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Sensory Prognostics and Management System Task 7 Report

June 2017

Final Report

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16. Abstract

The objective of this project is to develop a method to correctly identify and replace degraded electronic system line replaceable units (LRUs) to alleviate fault indications in aircraft propulsion systems. This information pinpoints specific LRU replacement candidates as they near their end-of-life (prognostics). This project defines the requirements to implement an automated, real-time electronic fault isolation system for a propulsion system small subsystem. The result of this project is identification of factors to be considered in applying the technology to larger aircraft systems.

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LIST OF SYMBOLS AND ACRONYMS

Ω	ohm
ARULE™	Adaptive Remaining Useful Life Estimator™
ATTF	Advanced Time-to-Failure
CIT	Compressor inlet temperature
CJC	Cold junction compensation
CVG	Compressor variable geometry
DAL	Development assurance level
DoE	Design of experiments
EEC	Engine electronic control
FADEC	Full-authority digital engine control
FD	Feature data
FFP	Fault-to-failure progression
FFS	Functional failure signature
FL	Failure Level
FNF	Fault not found
FV	Feature vector
HALT	Highly accelerated life testing
IO	Current output parameter
IOM	Current out minus
IOP	Current out plus
LRU	Line replaceable unit
LVDT	Linear variable differential transducer
MTBF	Mean time between failure
NIU	Nacelle interface unit
NM	Noise margin
OV	Output voltage
PD	Prognostic distance
PH	Prognostic horizon
RA	Relative accuracy
RTD	Resistance temperature detector
RUL	Remaining useful life
SoH	State of health
SSA	System Safety Analysis
T0	Ambient temperature
T2	Temperature at Station 2
TO	Takeoff
TTF	Time-to-failure
V_O	Output voltage
VOUT	Output voltage parameter
VOUTM	Voltage out minus
VOUTP	Voltage out plus

EXECUTIVE SUMMARY

The objective of the Sensory Prognostics & Management System project is to develop prognostics for propulsion system electronic line replaceable units (LRUs). Such prognostic capability allows for proactive engine maintenance and reduced operational disruption.

Project conclusions include the following:

1. Electronic prognostics can be minimally performed in legacy systems using operating data captured currently. Recorded data can be downloaded and subsequently evaluated to understand LRU circuit health. Limitation results from legacy system data not being recorded at optimum conditions to perform comprehensive prognostic analysis and LRU specific data being unavailable. Prognostic capability using legacy system data yields an indication of an LRU circuit degrading at a different rate than others on a multi-engine aircraft. The benefit is awareness of LRU circuit degradation and failure prediction when prognostic information is fused with historical circuit life data.
2. Minor changes to legacy systems allow for more accurate state of health predictions. Recording data during optimal prognostic analysis conditions makes accurate prognosis possible. Data acquired at conditions based on LRU characteristics provide information for use in analysis algorithms designed to evaluate LRU failure. Systems designed for prognostics can predict known electronics failure. Sense points added to LRUs allows for analysis and fault isolation to specific LRUs.
3. Unknown LRU failure modes can be prevented when used with algorithms developed to understand circuit health state. Algorithms can assess circuit health and warn of degradation even though LRU failure isolation may not be possible.
4. Electronic prognostics could reduce the need for system redundancy. Using prognostic analysis to predict failure and relying on maintenance action to replace components prior to failure makes redundant systems unneeded. Verification of effectiveness of prognostic analysis to accurately predict failure could allow for replacement of redundant systems as a means to address failure situations.
5. Certification of prognostic system features is related to existing system certification level and intent of the system. Certification impact must be evaluated in each instance and will vary depending on whether the system is new or modified.

Project success measurements indicate prognostic capability can predict failure for limited conditions in legacy systems. System modification or new design with prognostic intent can incorporate objectives to guide development resulting in achievement of goals. Agreed project success metrics are as follows:

- Reduce LRU “fault not found” removals by 65%.
- Improve accuracy of electrical LRU maintenance actions to yield at least 85% first time repair.
- Predict 65% of electrical LRU failures 10 hours prior to requiring maintenance.

Success of the first two metrics with legacy systems will require maintainer diligence during fault isolation to ensure an LRU is faulty prior to removal. Current legacy system data do not

support LRU diagnostics. Future prognostic-enabled systems can provide information to guide maintainer action and improve accuracy.

The identification of a degrading circuit with 10 hours remaining useful life (RUL) is achievable using relativistic prognostic analysis combined circuit failure history. LRU specific RUL estimation requires circuit modification to acquire data at additional locations.

The project proposal assumed data currently recorded on Rolls-Royce® engines could allow for prognostic analysis of electronic LRUs. Thorough data analysis from a prognostic perspective revealed data acquisition was not conducted during operating conditions or locations conducive to robust system prognostic assessment and did not support assessment of specific LRU health. The assessment identified modifications to acquire data that support comprehensive prognostic analysis.

The assessment revealed a method to evaluate similar circuits on a single aircraft to identify one exhibiting anomalous behavior compared to others. The method, referred to as relativistic prognostics, provides awareness of circuit degradation to allow preparation for subsequent LRU failure.

Legacy systems were designed to mitigate failure instead of predict it. Failure mitigation features built in to legacy systems guarantee safety. Any safety benefit from prognostic analysis is prediction and prevention of failure and unexpected disruption.

Taking advantage of prognostic analysis requires the system to be designed with prognostic intent. System data acquisition should be tailored to capture prognostic data during operating conditions and at locations that allow for prognostic analysis. Data acquisition at specific circuit locations allows for effective LRU health assessment.

Design intent drives certification impact. Prognostic analysis used with legacy system failure accommodation does not require certification. Certification for prognostic analysis algorithms and associated components does become necessary should prognostics be used to analyze safety-critical information.

Proving prognostic analysis effectiveness opens the possibility of using prognostics in predicting failure and allowing replacement of redundant systems. The analysis and entire prognostic system become safety critical. This concept requires significant development to approach implementation.

1. INTRODUCTION

1.1 PROGRAM OVERVIEW

The objective stated in the proposal for Task 7: Analysis Reporting of Results and Final Deliverable, was to "develop a method to correctly identify and replace degraded electronic system line replaceable units to alleviate fault indications in aircraft propulsion systems."

The project was initiated in August 2012 with a kickoff meeting at Rolls-Royce in Indianapolis. The result was an agreed project plan and a targeted completion of the program in 2015.

The agreed program metrics were:

- Reduce line replaceable unit (LRU) "fault not found" (FNF) removals by 65%.
- Predict 65% of electrical LRU failures 10 hours prior to requiring maintenance.
- Improve accuracy of electrical LRU maintenance actions to yield at least 85% first-time repair.

The chosen baseline aircraft was the subject aircraft powered by the Rolls-Royce® subject engine. Operational and LRU service data were identified for an aircraft requiring multiple service activities to clear a fault. Data from this aircraft provided information used to study applying prognostic analysis to this situation.

A circuit simulation was compiled for the temperature at station 2 (T2) compressor inlet temperature (CIT) sensor circuit to determine prognostic capability within the existing system. Each circuit component was evaluated and modeled at normal and operational limits to determine the failure modes that can be detected using the current system.

The conclusion was that deterministic prognostic analysis could not be performed with data from the current configuration T2 circuit data alone. The system final output value limits the decisions that can be made concerning system and LRU health. Anomalous behavior of various LRUs does not change the system output value significantly beyond the normal operating range.

Studying data from the operation of the baseline aircraft revealed a method to assess relative degradation of the same circuits of multiple engines on the same aircraft. Absolute remaining useful life (RUL) could not be determined with the available operating data alone, but information defining average circuit life could allow RUL determination of the anomalous circuit.

Data captured from the current circuit configuration limit the ability to perform comprehensive LRU diagnostics. An assessment determined that sense points placed at various locations in the circuit to gather data could allow for accurate LRU anomaly detection. The information provides insight into identification of data-acquisition capability yielding effective LRU assessment. The availability of additional circuit data provides LRU fault isolation detection.

Understanding the subject engine T2 sensor circuit prognostics propelled the project to apply the lessons learned to five additional LRU circuits. Six circuits had prognostic algorithms developed for use in evaluating test data from a benchtop simulation.

The simulation used functional subject engine hardware and degradation model effects applied to the hardware. Each LRU circuit was analyzed to discern failure modes and define failure limits and noise sources. Recorded data parameters were identified to enable algorithms to determine LRU health state.

Design of experiments (DoE) provided a framework to guide execution of the bench test simulation. The bench test consisted of two variable resistance boxes in the LRU circuit to separately simulate temperature change and LRU degradation.

The LRUs used in the simulation were as follows:

1. Relays and solenoids: fuel start solenoid
2. Cold junction compensation (CJC): resistance temperature detector (RTD) sensor embedded in full-authority digital engine control (FADEC)
3. Speed sensor: Engine rpm detector
4. Linear variable differential transducer (LVDT): compressor variable geometry (CVG) LVDT
5. CIT sensor: T2 RTD
6. Torque motor: CVG torque motor

Implementing relativistic electronic prognostics into an existing airborne system is detailed for the Rolls-Royce subject engine CIT on subject aircraft. Further potential enhanced electronic prognostic capability is proposed by modifying data acquisition for the system. The effective future use of electronic prognostic capability being used to predict and prevent failure does appear possible with additions to the current system.

Accurate electronic LRU prognostic capability is enabled by comparing data captured during consistent operating conditions against defined LRU design conditions. Capturing data that minimize variation and simplify analysis occurs during specific operating conditions.

Features added to the airborne system to allow for prognostic data acquisition must be certified to the existing system's development assurance level (DAL). Existing systems' original designs have accounted for all safety situations. Certification of added system features should be consistent with existing features. Added features must be compatible with existing functionality and require certification showing they do not adversely affect original system operation.

Ground-based prognostic analysis capability for existing systems would not require certification when it is intended to be used for aircraft service analysis. To perform prognostic analysis in a learning mode would not require certification of prognostic ground-based algorithms. However, using ground-based prognostic analysis software in activity affecting aircraft safety would require ground-based analysis software developed at an appropriate DAL.

Current aircraft systems architecture uses redundancy or the system safety assessment to ensure safety in case of failure. There is no safety benefit in predicting failure because mitigation is in place. Changes in aircraft system design, for which prognostic analysis results in elimination of redundancy, would provide cost and weight improvements. Elimination of redundant systems should result in improved reliability because of a reduced hardware count.

Specific system assessments provide examples of the detailed information required for prognostic enabling. There is no single formula to prognostic enable an electronic circuit or LRU. Each instance requires tailoring to use LRU or circuit-specific details to produce the desired result.

1.2 OBJECTIVES

The objective is to avoid system disruption and potential certification impact by providing a prognostic solution that is benign to current system operation. The goal is to identify diagnostic and prognostic methods that extract existing data signals from the system without disruption to system operation. These signals will be evaluated using prognostic algorithms to determine system health and annunciate any health degradation independent of system operation.

Task 2 evaluated the data available from operation of the subject engine to identify the baseline aircraft. The subject engine on the subject aircraft was chosen over the rest of the subject because it had more service information available.

The LRU selection criteria were derived through analysis of electronic fault conditions recorded for three Rolls-Royce engine lines managed at the Indianapolis site. The selection criteria evaluated the frequency of service events and LRU cost. For the subject engine data used in the study, 25% of all LRU multiple replacement events started with FADEC replacement.

Service records covering a 3-year period were compiled into a Pareto chart identifying the frequency of electronic LRU replacement (see figure 1). This information provided an indication of service action taken when a fault was annunciated by the FADEC for the circuit noted.

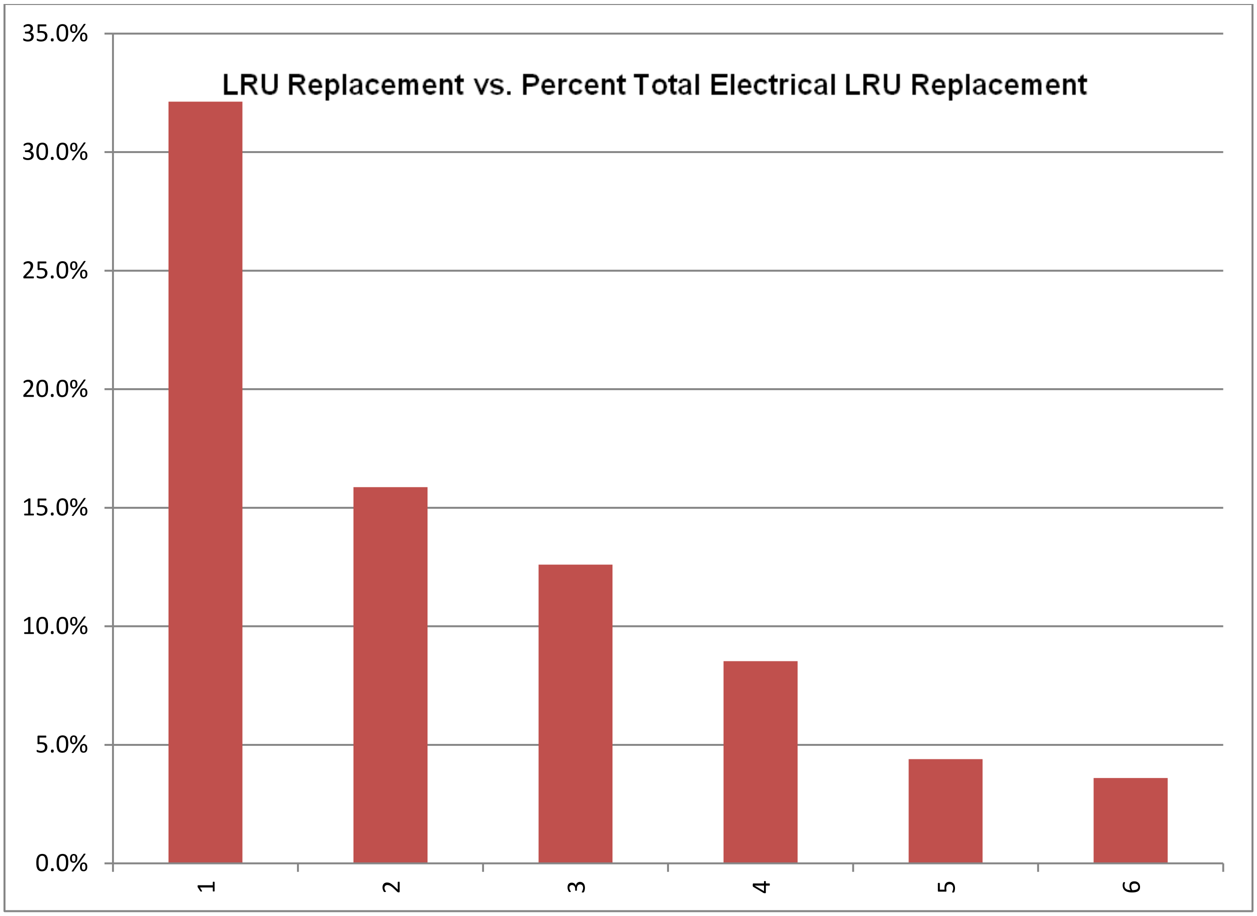

Figure 1. Subject engine electronic LRU Pareto

The fault annunciation indicates a disruption in the data stream for that circuit in service. Fault isolation done on the ground is intended to identify the faulty LRU. Some faults are not detectable on a static aircraft.

Troubleshooting LRU fault indications requires the maintainer to test each LRU in the circuit to determine whether it is operating correctly. It is not uncommon for a maintainer to replace an LRU to clear a fault and for the same fault condition to be annunciated shortly after the service action. The maintainer may replace an LRU to clear a fault even though fault isolation may not confirm the LRU is faulty.

The FADEC is the most serviceable LRU and is the first item replaced before doing a time-consuming circuit analysis to locate a faulty LRU. This results in 80% of returned FADECs being FNF. Each FNF FADEC carries a significant cost for return and functional checkout. That is the cost of four FADEC returns spent in nonproductive activity.

Because each FNF FADEC incurs a significant cost for each return, a better method for identifying faulty FADEC units that should be removed and replaced could save significant cost in FADEC returns and improve effectiveness of maintenance actions.

Low-cost LRUs are not serviced in the same manner as high-value LRUs, such as FADECs. Most low-value electronic LRUs (sensors, switches, etc.) are dispositioned by the maintainer during fault isolation and never analyzed for failure, so there is no process to confirm the LRU removed is faulty. If replacement of the LRU corrects the fault, it is assumed the LRU was faulty.

Faulty wiring harnesses frequently create fault indications that cannot be duplicated on the ground. Temperature and vibration environments that exist in flight cannot be replicated on the ground. Intermittent disruptions in circuit connectivity may trigger a fault during flight that is not detectable when the engine is not running.

The subject engine T2 sensor CIT circuit experiences fault indications for which the FADEC is replaced first and requires subsequent action to eliminate the fault. The objective of the project was to identify a method to guide the maintainer to replacing the faulty LRU.

The T2 sensor and the wiring harness appear on the Pareto chart and cost in the same range. Both are approximately 1.5% of the cost of replacing a FADEC. Therefore, replacing either of these LRUs prior to replacing a FADEC would be less costly from a replacement part perspective. Because servicing these LRUs is more difficult than FADEC replacement, a data-driven method to guide the maintainer to the faulty LRU would be helpful.

2. T2 SYSTEM DETAILED STUDY

An evaluation of the subject engine T2 circuit was undertaken in Task 3 to understand how currently recorded data relates to failures of the circuit (see figure 2). It was hoped that failure mechanisms could be identified using existing data that would allow prognostic analysis of the T2 circuit.

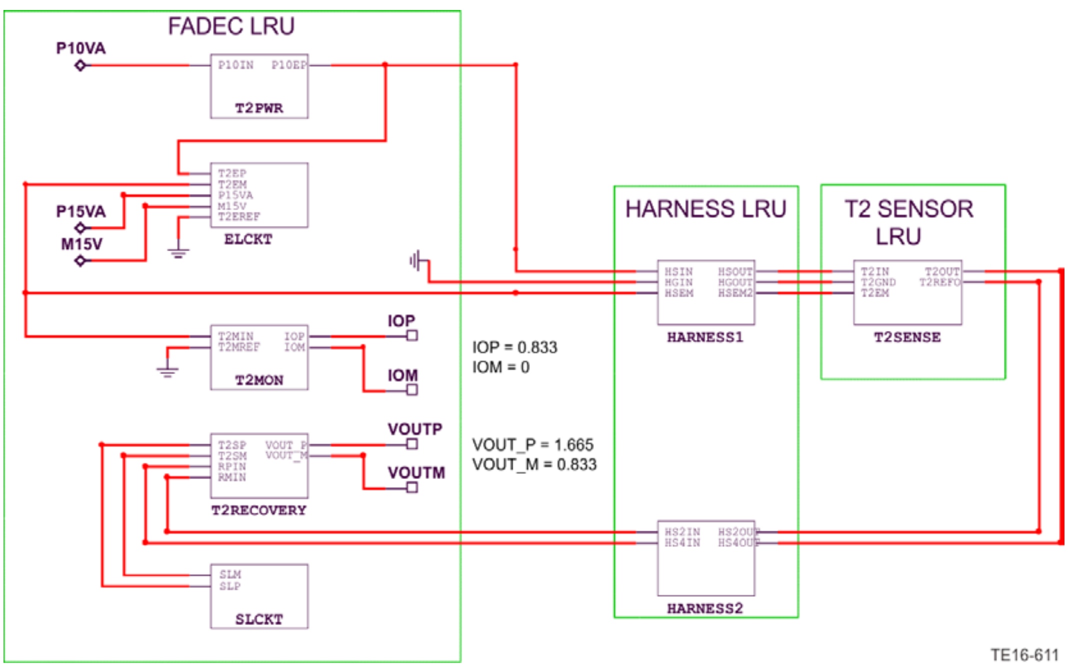

Figure 2. T2 circuit block diagram

The circuit was broken down into individual electronic components for each LRU and evaluated for failure rate and failure mode, along with identifying if the failure mode could be detected using prognostic analysis (prognostic enabled).

The individual T2 sensor electronic component simulations were combined into a system simulation model. The model was run with the components in healthy and failed states. Components that have a low likelihood of failure or cannot be prognostic enabled were not included in the simulation.

The model was run with all components in the healthy condition using the range of expected T2 temperature values to identify the normal range of T2 circuit signal output. This action established the expected circuit output and bounds the range of circuit output data values where normal circuit operation would not identify circuit degradation. The expected normal circuit operating window was defined as approximately 2.0–0.8 V for sensor resistance of 70–150 ohms (Ω).

The simulation provides an understanding of the circuit response for normal operation at any location in the circuit. The ability to simulate expected circuit values at known conditions allows identification of healthy and degraded LRU component states and the associated circuit values produced throughout the circuit. The current T2 circuit has limited LRU fault isolation assessment capability and data sense points within the engine electronic control (EEC).

Some LRU component failures result in circuit output values outside the normal operating range. It is not possible to identify a single faulted LRU with one of these failed components using only the existing circuit sense point. The visibility within the existing system does not allow accurate determination of the failing LRU using available information.

Individual component faults were introduced into the simulation circuit to develop information of fault effects on the circuit output value. Tables 1 and 2 capture the range of circuit output values when component faults are introduced. Injected faults resulting in output data values in the normal operating range do not provide indication the circuit is degraded. The output voltage parameter (VOUT) and current output parameters (IO) acronyms that have an “M” or “P” following them stand for voltage out minus (VOUTM), voltage out plus (VOUTP), current out minus (IOM), and current out plus (IOP).

Table 1. Nominal T2 circuit normal operating values

T2 sensor (Ω)	VOUTP	VOUTM	IOP	IOM
70	1.452	0.854	0.854	0
100	1.665	0.833	0.833	0
150	1.998	0.799	0.799	0

Table 2. Estimated degraded signal values and FADEC failed limits

VOUTP		VOUTM	
Degraded	Failed	Degraded	Failed
<= 1.40	<= 1.25	<= 0.79	<= 0.75
>= 2.00	>= 2.20	>= 0.85	>= 1.0

A T2 signal value in the normal output range of the circuit cannot be used by itself to provide information to make a diagnostic or prognostic decision. The only decision available using that output value is that the circuit is operating correctly. Degradation cannot be detected and fault isolation is not enhanced.

Table 3 identifies factors considered in assessment of LRU components. Identified are:

- Component location
- Component type
- Identifier
- Military Standard 217 failure rate
- Typical component failure mode
- Operating condition for failure detection (start, cruise, takeoff, etc.)

Not all electronic components were included in the simulation to simplify the simulation. Low-reliability (high likelihood of failure) components were included in the circuit simulation. High-reliability components were less likely to fail and were excluded from use for the simulation.

The circuit was analyzed to determine circuit output readings based on component failure indication. Analysis of failure results defined the bounds of functional detection of the data output. Each LRU was evaluated to identify diagnostic and prognostic capability.

Table 3. T2 circuit component evaluation

Block	Component				
	Type	ID	Failure rate	Failure mode	Detection mode
T2PWR	Resistor	R250	8.48E-04	Open circuit high resistance	Static degraded
ELCKT	Diode	D1	2.59E-03	Short circuit	Static
ELCKT	Diode	D2	2.59E-03	Short circuit	Static
ELCKT	Diode	D5	2.59E-03	Short circuit	Static
ELCKT	Transzorb	TZVAR1	6.24E-02	Drift 50%	Static
ELCKT	Transzorb	TZVAR2	6.24E-02	Drift 50%	Static
T2MON	Resistor	R2	6.26E-04	Open circuit	Static
T2MON	Resistor	R92	6.45E-04	Open circuit	Static
T2MON	Capacitor	C1	5.74E-04	Short circuit	Static
T2MON	Capacitor	C6	1.02E-03	Short circuit	Static
T2RECOVERY	Resistor	R11 (1)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R11 (2)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R11 (3)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R11 (4)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R12 (1)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R12 (2)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R12 (3)	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R13	4.02E-04	Open circuit	Static
T2RECOVERY	Resistor	R14	6.26E-04	Open circuit	Static
T2RECOVERY	Capacitor	C3	5.74E-04	Short circuit	Static
T2RECOVERY	Capacitor	C4	5.74E-04	Short circuit	Static
T2RECOVERY	Capacitor	C5	5.74E-04	Short circuit	Static
SLCKT	Capacitor	C7	1.02E-03	Short circuit	Static
SLCKT	Capacitor	C8	1.02E-03	Short circuit	Static
SLCKT	Capacitor	C9	1.02E-03	Short circuit	Static
SLCKT	Capacitor	C10	1.02E-03	Short circuit	Static
HARNESS1	Connector	HSIN	Use 1.000E-01	Intermittent	Dynamic
HARNESS1	Connector	HSOUT	Use 1.000E-01	Intermittent	Dynamic
HARNESS1	Connector	HSEM	Use 1.000E-01	Intermittent	Dynamic
HARNESS1	Connector	HSEM2	Use 1.000E-01	Intermittent	Dynamic
HARNESS1	Connector	HSIN to HSEM	Use 1.000E-03	Intermittent	Dynamic
HARNESS1	Connector	HSOUT to HSEM2	Use 1.000E-03	Intermittent	Dynamic
HARNESS1	Connector	HSIN to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS1	Connector	HSEM to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS1	Connector	HSOUT to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS1	Connector	HSEM2 to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS2	Connector	HS2IN	Use 1.000E-01	Intermittent	Dynamic
HARNESS2	Connector	HS2OUT	Use 1.000E-01	Intermittent	Dynamic
HARNESS2	Connector	HS4IN	Use 1.000E-01	Intermittent	Dynamic
HARNESS2	Connector	HS4OUT	Use 1.000E-01	Intermittent	Dynamic
HARNESS2	Connector	HS2IN to HS4IN	Use 1.000E-03	Intermittent	Dynamic
HARNESS2	Connector	HS2OUT to HS4OUT	Use 1.000E-03	Intermittent	Dynamic

Table 3. T2 circuit component evaluation (continued)

Block	Component				
	Type	ID	Failure rate	Failure mode	Detection mode
HARNESS2	Connector	HS2IN to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS2	Connector	HS4IN to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS2	Connector	HS2OUT to GND	Use 1.000E-03	Intermittent	Dynamic
HARNESS2	Connector	HS4OUT to GND	Use 1.000E-03	Intermittent	Dynamic

Note: ID statement XXX to XXX means the tested condition is either a pin-to-ground fault (e.g., HS4OUT to GND) or a pin-to-pin fault (e.g., HS2OUT to HS4OUT).

An electronic component with a measureable gradual decline in operating effectiveness over time is a candidate for prognostic enabling. Components that fail quickly and do not exhibit degradation prior to failure cannot be prognostic enabled.

One consideration in determining whether to include an electrical component in the simulation is the ability to detect degradation. The simulated failure modes were the most likely for the various components based on industry standard failure assessments of electronic devices. A simulation circuit was constructed that accounted for the components most likely to fail in the T2 circuit.

The simulation provided information about component-failure effects on the circuit output values. It provided an understanding of circuit operation when electronic components in the circuit fail. What became clear was there was little range in circuit output between normal operation and fault annunciation.

Each LRU has one or more circuits modeled as part of the simulation. Section 3.1 provides an example of that effort for the T2 sensor. Each part shown in the T2 circuit block diagram (see figure 2) was evaluated for the component failure response. Failure of individual components provided the circuit output value expected when components failed.

2.1 T2 SENSOR LRU CIRCUIT EVALUATION DETAIL EXAMPLE

Figure 3 shows the simulation model for the T2 sensor. The resistances represent the soldering and internal resistances between connector pins on the T2 housing and the temperature (varistor) sensor. The actual sensor is represented by a 100-Ω resistor, R1, having normal resistance ranging from 70–150 Ω.

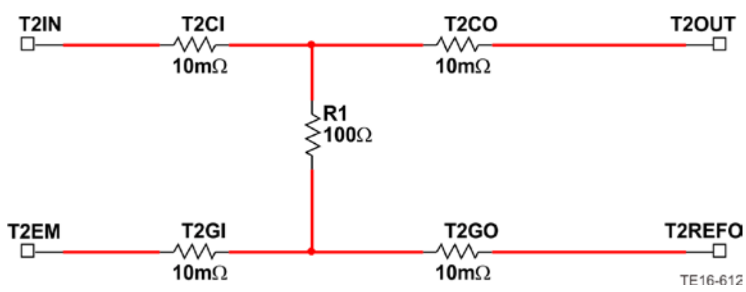

Figure 3. Simulation model for the T2 sensor

Referring to figure 2, table 1, and table 2, it is significant that:

1. As R1 decreases in value, the voltage at VOUTP decreases and the voltage at both VOUTM and IOP increases.
2. As R1 increases in value, the voltage at VOUTP increases and the voltage at both VOUTM and IOP decreases.

FADEC features prevent safety issues when there is a single-point failure in the T2 sensor circuit. The T2 sensor is a redundant system and has a backup circuit in case of failure of the primary system. The circuit in use is alternated each time FADEC power is applied. In addition to the backup sensor system, there are fault-tolerant systems built into the FADEC in case both sensors do fail. Failure creates a fault annunciation identifying the need to check the circuit.

Prognostic analysis compares operational data to previous values. The T2 sensor operates over a large temperature range. The temperature reported by the circuit is a function of the resistance indicated at the circuit sense points. T2 circuit information does not provide a way to compare resistance against temperature because the temperature reported relies on the sensor resistance. The FADEC has several backup mechanisms to ensure operation when a fault is identified. Slight differences in engine performance result because sensed T2 is not accurate when the sensor is degraded, even though it produces in-range circuit readings.

Circuit fault detection software does not indicate a fault until the circuit is at the failure limit. The circuit is designed to provide accurate T2 readings up to the failure point. Identification of circuit failure mechanisms could not be accomplished through analysis of existing circuit data.

T2 data are currently recorded only at takeoff (TO) and cruise conditions. Data variation at these conditions makes accurate prognostics impractical through evaluation of the T2 circuit data alone.

Not all components are prognostic enabled. The failure mechanism of some components does not allow prognostic analysis. The dominant failure mode of diodes is open circuit, and diodes in the protection circuit are normally not conducting. The normal operating voltages are not affected when the diodes fail open.

Tranzorbs can fail in a manner similar to diodes—failing short, then burning open. Neither of those two failure modes is detectable because the diodes with which they connect are not conducting.

Resistors typically fail because of an overload in current/voltage that causes the resistor material to overheat. The resistance increases, causing further heating, until the resistor gets hot enough to burn open. The T2 sensor current-limiting resistor R250 and the impedance-shunt resistor R92 are used in the FADEC recovery subcircuit. A change in the value of those resistors causes significant change in the voltages at the FADEC monitoring pins, and it could be possible to provide prognostic support for those resistors with the addition of sense points to isolate degradation.

Electrical harness connector pins fail because of vibration and motion stresses/strains. Connector-related faults typically do not manifest themselves as a hard open circuit. They typically appear as intermittent high-series-resistance faults having the following characteristics:

1. Very short duration events in the nanosecond range. The duration increases as time progresses to the point at which an event spans many processor clock cycles.
2. The effective resistance of the high-resistance events ranges from a value of less than 1 Ω to more than 1 M Ω.
3. The combination of the increase in duration and the increase in the value of the effective high resistance eventually causes an electrical anomaly of failure to correctly read or write fault data.

Wiring harness and connector issues seem to be a problem cause in this circuit. Connector pin problems start as short-duration events that do not register using the current system processor cycle time. The fault is shorter than the processing cycle. The amount of time for each fault becomes slightly longer and more frequent as the fault progresses. The intermittent fault duration equals, and then exceeds, the processor cycle at some point in the failure progression. The pin connector fault can be detected and prognostic calculations can begin.

It may be possible to perform prognostic analysis of electrical harness degradation. Using the information previously mentioned to create detection algorithms and capturing data when circuit disruption occurs could allow for harness-degradation identification. That hypothesis was not explored as part of this project because operational data were not available for confirmed harness problems.

The T2 circuit simulation is constructed with the output being monitored at the VOUT and current (IO) pins. Table 1 defines the nominal normal circuit output values when the T2 circuit simulation is executed in the normal operating condition.

One of the three LRUs (FADEC, T2SENSE, or HARNESS) is defined as having failed whenever the lowest voltage level at a monitor pin is less than an elected threshold.

Table 2 and an Advanced Time-to-Failure (ATTF) algorithm are used to estimate state of health (SoH) and RUL.

The quantity of failed T2 circuit components that can be detected as failed is approximately 60% of the total. Approximately 25% of all the potential failed conditions can be identified for each component; the number of “prognostic enabled” components is a little more than 5%. Compounding prognostic analysis is the small percentage of operating range of those components from the point their output goes beyond the normal operating range to the point of failure. A T2 signal value in this range by itself does not provide adequate information to make a diagnostic or prognostic decision as the sole source of data. The only decision available is the circuit is operating correctly when only that output value is available. A degradation cannot be detected.

The current T2 circuit design has limited prognostic information available. The only datum available is the final circuit output value at TO and cruise conditions. This single value allows assessment of the circuit health, and does not support the ability to determine the SoH of components. The design of the circuit creates electronic-component degradation, resulting in circuit output in the normal operating range.

The simulation provides the basis to explore various system solutions allowing prognostic assessment of the T2 circuit. The LRU simulation models provide expected signal changes associated with various component degradation conditions. Inserting individual component failures into the T2 circuit simulation produces signal variations at various circuit output locations. Outputs are tabulated to understand how the failures affect the output signal. The failures are classified for their detectability, depending on the change in signal output. A subsystem or component is prognostic enabled if there is a means to measure or collect condition-based data to be processed to produce one or more estimates to predict a future failure.

There are potentially two locations to access the signal data by modifying the current system. They are the following:

1. Data provided from the sensor to the FADEC.
2. Current provided to the sensor as measured within the FADEC excitation circuit (existing).

These sense point locations were considered when constructing the simulation model. The model output is analyzed at these points in the circuit. This approach allows assessment of the current circuit and the ability to implement lessons from this project to add sense points for improved prognostic capability.

Using the end of circuit output creates the challenge of determining which faulty LRU is creating the out-of-range condition. Data from only this location does not provide sufficient information to identify the degraded component. Multiple components have fault modes that produce output values outside the normal operating range, thereby indicating a failure. The output data available only at the end of the current circuit make it difficult to isolate which of the multiple components is creating the fault.

The T2 circuit is a simple circuit. A more complex circuit with additional electronic components and LRUs becomes even more difficult to predict RUL. There are more combinations of electronic components and LRUs that can lead to varying circuit values and increased complexity in isolating degraded components.

2.2 POSSIBLE DATA-ACQUISITION METHODS SUPPORTING PROGNOSTICS

Evaluation of the T2 circuit stimulated thought about how to acquire data useful in circuit assessment and prognostics.

The T2 circuit as defined reads data only at the end of the circuit internal to the FADEC. The detectable LRU failure modes do not produce unique signatures allowing isolation to a specific LRU; therefore, specific LRU health cannot be determined with available data. However, circuit health can be assessed using available data. LRU diagnostics require manual assessment to isolate the LRU causing the circuit anomaly.

T2 circuit output is captured consistently once per flight during TO. T2 data may be recorded during the cruise condition when data-recording criteria are satisfied, but data recording at the cruise condition is not guaranteed to occur during every flight. T2 data may also be recorded at intermittent conditions.

Failure-mode assessment concluded that the addition of sensors makes detectable failures progress at a rate at which data acquisition once per flight is adequate to predict RUL once degradation is recognized. T2 circuit data are captured once over flight at a single location at varying conditions. That defines the constraints of T2 circuit available data from the current system for use in prognostic analysis.

The T2 circuit evaluation spawned ideas of enabling data acquisition that facilitates effective prognostic analysis.

Data should be acquired at an operating condition that is conducive to detecting component degradation. Detectable T2 circuit failures are not sensitive to operating condition to identify degradation. Useful data can be acquired at any time during system operation.

The data-capture operating condition influences variability in the data and the need to account for it in calculations. It is desirable to capture data at a consistent condition to simplify data adjustment and facilitate tracking degradation.

T2 circuit data captured by the subject engine FADEC does occur at various temperatures. Resistance measurements from the T2 circuit are affected by temperature. Analysis algorithms must account for variation from the temperature chosen for degradation analysis.

Other LRU circuits can have different factors affecting data acquisition. Each circuit should be assessed to understand failure modes and opportunities to acquire data at a condition to determine SoH.

2.3 INTRODUCTION TO PROGNOSTIC ALGORITHMS

Ridgetop Group has developed methods and algorithms to perform prognostic analysis of electronic components. The method uses an algorithm to develop ATTF estimates using operational data from the components to estimate time to failure. The ATTF algorithm is applied for use in determining RUL.

Applying the ATTF process involves initial definition of the fault-detection level initiating data acquisition for the calculation. The detection threshold triggering data acquisition and starting the ATTF process is determined from knowledge of the component failure process. Degradation information defines a level of operation at which degradation becomes evident. The level can come from design information or field expertise.

The first step to applying the ATTF algorithm is to determine which components are prognostic enabled. LRU electronic components are identified as a subset of the complete list of electronic components in the circuit. The determination of being prognostic enabled is a function of the component type and how it is applied. In the Detection Mode column, identification of Degraded or Dynamic indicates a component is prognostic enabled.

Reaching the degradation threshold indicates the component is operating at a condition beyond the range of normality and is in the range of degradation. The component will not recover to normal conditions at this point. Data are analyzed to determine if degradation is detected during operation.

Degradation triggers data accumulation to provide comparison to the fault-to-failure progression (FFP) curve and calculation of RUL. The ATTF process continually analyzes data to determine if degradation has started (reaches degradation threshold). An assessment is performed once the data indicate degradation is initiated. Data will begin accumulating to establish the initial degradation process estimate for use by the FFP curve and calculation of RUL.

A table of failure provides a means to identify unique failure signatures. The table indicates detection capability and identifies characteristics to define a unique signature for a failure. The information from the table also helps to establish the conclusion that this failure can be accurately diagnosed using analysis algorithms for electronic hardware.

Table 4 is an example table (one item) that was helpful in understanding development of algorithms for the subject engine T2 circuit. Table 4 provides direction for things that should be considered when identifying degradation and failure information useful in algorithm definition.

Table 4. Example of failure information useful in algorithm development

Component ID	Failure rate	Failure mode	Detection mode	Failure mode information	LRU failure detection Scheme 1	LRU failure detection Scheme 2	LRU degradation information
T2 sensor resistor	0.000848	Open circuit	Static	10V excitation is lost	Both diff measurements are OV	All single ended measurements are at OV	Resistance is beyond 70-150 Ω

OV = output voltage

Unique signatures allow identification of various LRU failure modes. Multiple failure modes having a unique failure signature within a single LRU provide indication of a unique failure within the LRU. The unique degradation signature can provide identification of the specific failing LRU to the maintenance operator to assist in replacement. The simulation and evaluation can be used to prioritize potential visibility improvements benefiting accurate LRU fault identification.

Harness and connector open- and short-circuit conditions are seen as intermittent events prior to becoming a fixed-failure condition. The ability to sense these expected direct current signals can be used as an indication of unexpected high-frequency content on these signals. The addition of higher-frequency content provides a unique signature to differentiate harness issues from EEC or sensor issues. Diagnostic improvement is provided by diagnostic capability to accurately identify LRU faults. Specific failure signatures can be associated with specific LRUs, thereby identifying degrading conditions that can lead maintainers to LRUs for service actions.

Diagnostics does not address assessment of RUL of the system prior to failure. ATTF and RUL algorithms are defined and used to help identify trends indicating future failure. Prognostic capability is enabled through detection of changes over time and extrapolation of change to predict when failure will occur. Drift identified over time can be used to predict impending LRU failure when it begins to operate outside normal bounds.

FFP algorithms are defined based on theoretical degradation characteristics for electronic components. Experimental evidence is used to verify the signature curve. Multiple versions of an electronic component are tested to failure. Data recorded during testing is used to confirm or adjust the characteristic failure curve that is used for ATTF calculations.

The FFP signature curve represents the process of degradation to failure and starts at initiation of operational degradation of a component. The curve is defined using measured parameters that are used to adjust the curve fit using the actual acquired data. The curve, when plotted in an X-Y coordinate system, has the Y-axis representing the component degradation value and the X-axis representing the change in degradation time.

2.4 FFP SIGNATURE: DATA, MODELING, AND ATTF OPERATION

The theory on which the ATTF program algorithms are designed and developed for FFP signature and modeling is based in the following:

1. Components and devices degrade.
2. One or more electrical signals exhibit change that can be correlated to degradation.
3. Below a certain level of degradation (floor threshold), any measurement value of an electrical signal is defined to be small enough to declare an undamaged state (100% healthy).
4. At or above a certain level of degradation (ceiling threshold), any measurement value of an electrical signal is defined to be large enough to declare a failed state (0% healthy).

2.5 FFP SIGNATURE THEORY

Ridgetop's modular FFP signature modeling and processing technology is designed to apply condition-based signal data to provide accurate SoH and RUL estimates (see figure 4). Condition- based data indicate changes in the health state of the component. Data can be used as captured or transformed (if required) for use in analysis. The data are applied to the ATTF and FFP algorithms to identify and characterize the health of the device under investigation.

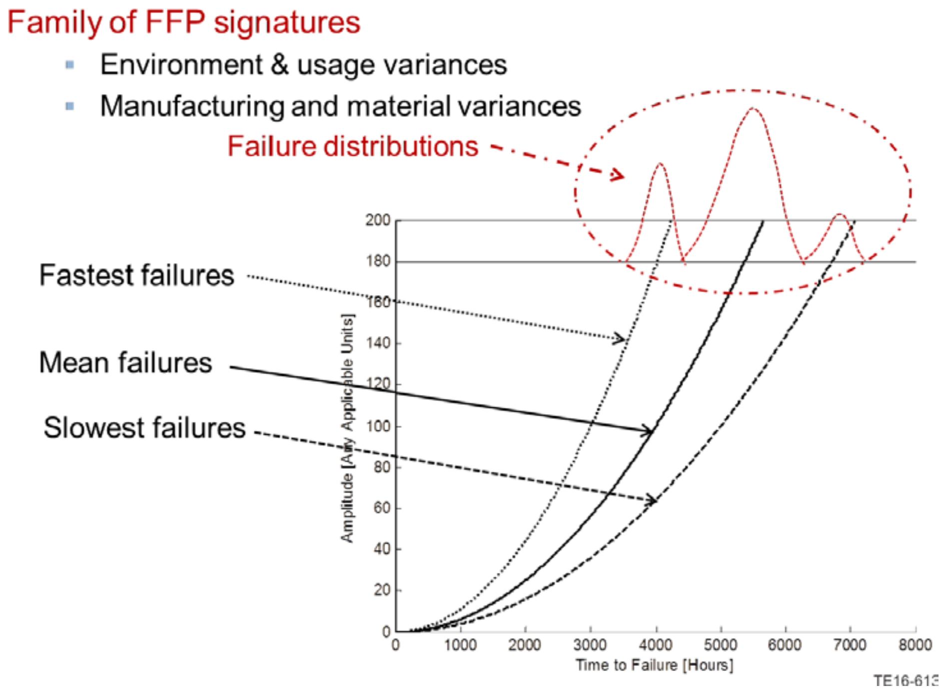

Figure 4. Family of FFP signatures and failure distribution

Ridgetop's methods and techniques are based on the theory that electronic component fault modes produce characteristic signatures in condition-based signal data. The signatures can be approximated by simple graphical models, such as piecewise linear and exponential functions to avoid extensive memory use and intensive computations to solve complex distributions (see figure 5).

Exponential: $f(\chi,\theta) = \frac{1}{\theta} e^{-\frac{x}{\theta}}$

Normal: $f(\chi,\mu,\sigma) = \frac{1}{\sqrt{2\pi\sigma}} e^{-(x-u)^2/2\sigma^2}$

Beta: $f(\chi,\alpha,\beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$

Weibull: $f(\chi,\theta,\lambda) = \frac{\lambda}{\theta} x^{\lambda-1}\, e^{-x^{\lambda/\theta}}$

Gamma: $f(\chi,\theta,\alpha,\beta) = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} x^{\alpha-1} e^{-x/\beta\theta}$

Figure 5. Examples of distribution functions

2.6 FFP SIGNATURE OPERATION: MODELING AND PROCESSING

The FFP signature modeling and processing performed by the ATTF programming algorithms is similar to extended Kalman filtering. Condition-based data and FFP signature models are used to perform measurement updates and time updates, extrapolate the updated model to calculate estimated time-to-failure (TTF) values, and produce SoH and RUL estimates. Processing includes analysis of multiple FFP signatures to identify fault-mode(s) resulting from degradation and eventual failure. Figure 6 depicts how the FFP signature model uses condition-based data to update the model. For each input data point, an expected FFP signature amplitude is calculated for the data time relative to the onset of degradation, and the difference in received and expected amplitude is adjusted using a weighting algorithm.

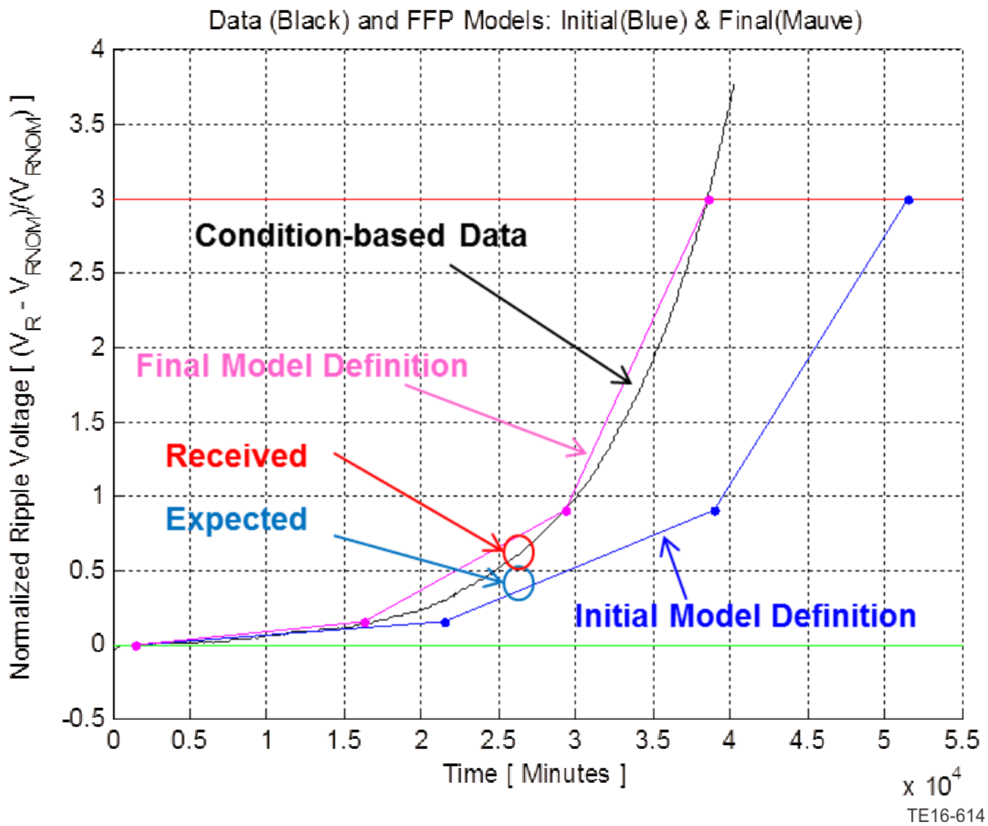

Figure 6. FFP modeling and processing, signature, and modeling overview

A measurement update is performed in figure 7A:

- The weighting algorithm uses the principal of inertia and momentum. A condition-based signature output does not make rapid changes in angular velocity.
- The algorithm favors keeping the model signature above the data signature to preferentially predicting TTF before actual time of failure. This reduces RUL/SoH "jitter" caused by low noise levels and accommodates "step-like" degradation. The initial (blue) and final (mauve) plots of the FFP signature model definition are shown.

A time update is performed in figure 7B:

- The change in model amplitude is used to adjust the signature model parameters to produce expected amplitudes with respect to time.
- The model is adapted to the data, the adapted FFP signature model is then extrapolated to estimate the TTF, and RUL and SoH are calculated:

  - RUL = TTF – data time
  - SoH = (RUL/TTF) * 100

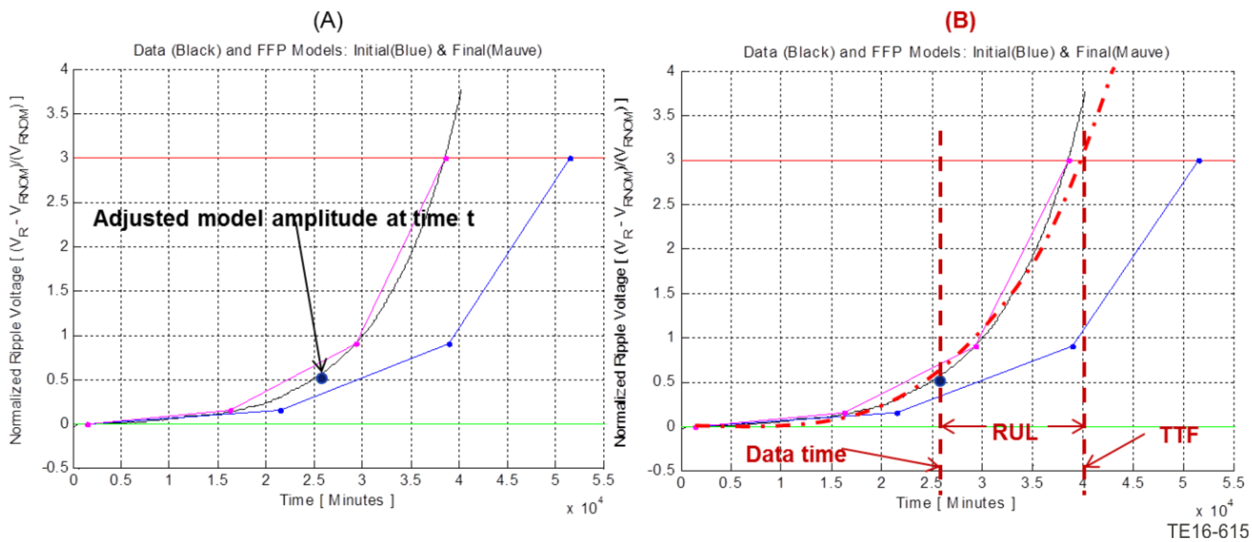

Figure 7. FFP modeling and processing, measurement, and time update

Effective prognostic analysis requires data at a consistent condition to enable comparison by prognostic algorithms. Algorithms must be designed to identify known degradation and failure modes. Data variation makes comparison of data captured at varying conditions impractical for analysis without “conditioning” it to remove the variation assessment against standardized operating conditions. Accurate prognostic analysis is impractical when variation is present in the system.

Several methods to extract prognostic features from noisy data include the following:

1. Compare data grouped by operating conditions and environment.
2. Include a second set of independent measurements.
3. Use normalized, differential comparisons.
4. Compare to like subsystem measurements taken at the same time.
5. Compare measurements against independently calculated measurements.

The accuracy of the algorithms used by the analysis program is demonstrated by the relative accuracy (RA) plots shown in figure 8, and the performance metrics are shown in figure 9. The RA data and the performance metrics use definitions defined by NASA (Abhinav Saxena, 2010). Figure 8 is the result of processing an FFP signature produced using the ATTF and FFP prognostic algorithms.

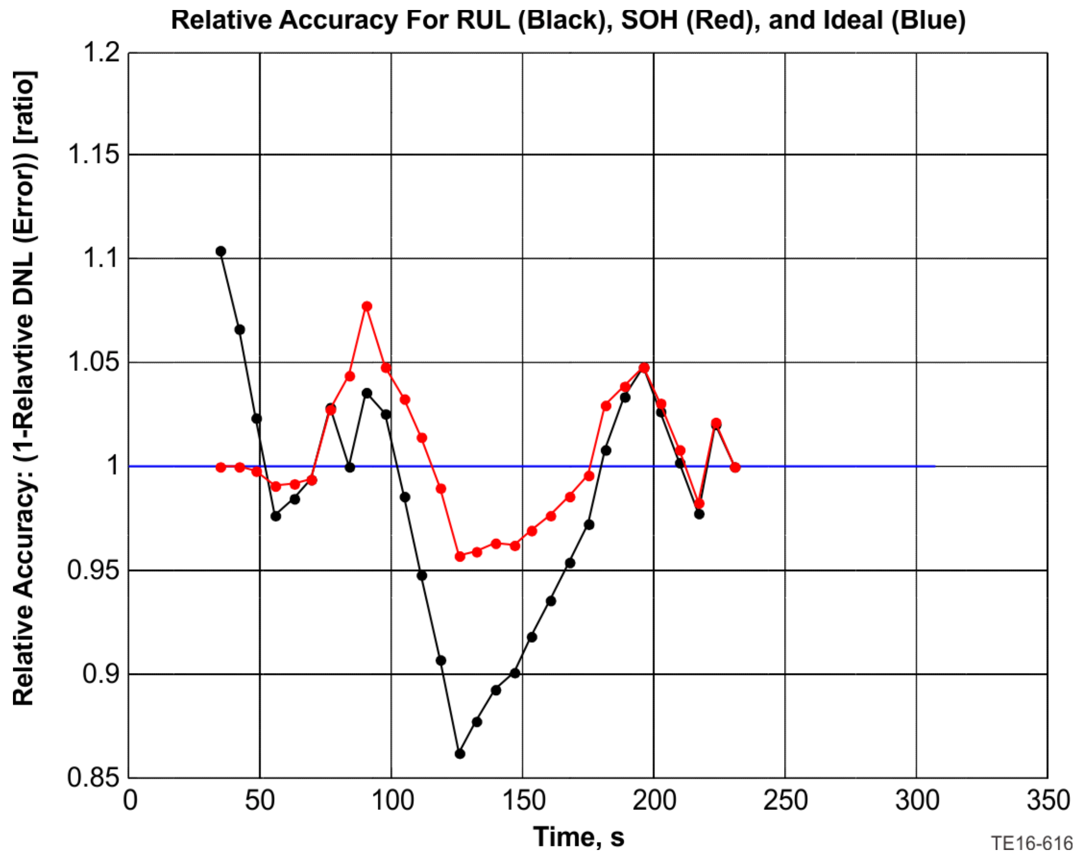

Figure 8. Example–RA plot

```
>> APERF('DATPH01');
Overall RUL accuracy:    1.019
Overall SOH accuracy:    0.996
Precision for RUL:      11.359 seconds
Precision for SOH:       0.030 percent
Mean Average for RUL:   -1.696 percent
Mean Average for SOH:    0.467 percent
>>
```

Figure 9. Example–performance metrics

A component or system that is thoroughly understood and has historical data supporting a known failure mechanism can be dispositioned using deterministic assessment. Deterministic prognostic methods use data specifically from the system being evaluated to assess operation against known conditions. Variables are a factor impacting health determination. A limited number of variables having a known relationship to health are conducive to deterministic assessment.

Components or systems with little history or many variables can benefit using relativistic assessment (explained in section 2.9). SoH change is compared to multiples of the same component operating in the same environment. If they all change the same way (no relative difference), it is the result of a common environmental factor. Relativistic SoH assessment provides information concerning rate-of-change variation between the same components in multiple systems (engines in this case). An absolute estimate of remaining SoH may be estimated by applying deterministic assessment when average RUL is known.

Data-acquisition methods influence the assessment process chosen. Data that can be measured directly from the system or component and are not influenced by related factors lend themselves to deterministic processing. Variation increases in cases in which assessment data are calculated using measured data (conditioned data).

Relativistic SoH assessment uses data from multiple applications of the same system operating in the same environment. Relativistic assessment provides indication of one component or system degrading at a different rate than other similar ones. Either data assessment method can be used with either data-acquisition method. Examples of data-acquisition variables are shown as follows:

1. A directly measured physical property indicates degradation and is not influenced by other factors (e.g., an RTD removed from an aircraft can have its resistance measured at a specific temperature and directly determine whether the resistance of the RTD has drifted out of specifications).
2. An indirectly measured physical property is determined using more than one type of measurement data to identify changes in property values due to degradation. The set of measurements is used to calculate the property value (e.g., fuel solenoid):

    a. Coil-resistance measurement provides an indication of health.
    b. Coil resistance changes because of degradation (windings short together).
    c. Coil resistance changes because of changes in temperature (thermal coefficient).
    d. Coil resistance is calculated using measured coil voltage and current.
    e. Temperature measurement is required to calculate resistance change because of temperature.
    f. Remaining coil resistance change is attributed to degradation.

An evaluation process is defined for each system/component type. The defined process is applied to each individual item to allow assessment of the SoH. Data are acquired and analyzed for each item to establish the degradation rate and to predict when the item will fail.

2.7 BENEFITS OF ELECTRONIC PROGNOSTICS

Prognostic analysis provides maintenance flexibility and avoids failure disruption in current Level A systems. Level A system LRUs are typically governed by limited dispatch restrictions. This requires an aircraft not be put into service if there is a failed LRU. Unexpected failure of an LRU results in having to repair the failed LRU at unexpected times and locations, resulting in a potential service disruption or delay. Prognostics have the potential to turn unexpected events into planned service actions.

Limited dispatch constraints require provisions be considered to manage unexpected events. Consideration must be given to repairing assets at remote locations requiring parts availability and service resource availability.

Failure of an LRU during a flight calls the redundant LRU into service. The aircraft will end up operating in a degraded condition in the unlikely scenario the backup LRU fails during flight. The availability of prognostic capability makes the calculated RUL of the LRU known so the failure scenario can be avoided.

Use of accurate prognostics could avoid unexpected events and allow planning for them. Inoperable system events become predicted and allow scheduling for optimized service conditions. The operator has more asset knowledge and improves management of operations.

Subsequent improvements in cost, air vehicle reliability, and potential safety will be realized if features are added to provide robust prognostic ability. Cost improvements include reduced maintenance activity plus the ability to optimize service event timing. Reliability improvements make aircraft operation more predictable, thereby allowing proactive maintenance and reducing unexpected service disruptions. Potential safety improvements will occur should methods be developed allowing additional critical component and system health assessments for predicting and reducing failure events.

Comprehensive use of prognostic solutions would provide planning and maintenance personnel with a prediction of RUL and a confidence factor to help guide LRU replacement decisions. This information would assist LRU isolation and provide maintenance action direction ensuring accurate first-time maintenance action.

2.8 DETERMINISTIC PROGNOSTICS

The deterministic-analysis method evaluates an electronic component using data to assess operation against specific criteria related to the component.

Assessment criteria are derived from design parameters, component standards, field service history, or other information defining how the component is expected to operate. This information establishes limits and provides guidance for development of algorithms to detect degradation.

The deterministic method establishes component health (SoH and RUL) using data collected from operation of the component.

2.9 RELATIVISTIC PROGNOSTICS

The relativistic prognostic method evolved during this project. Comparison of measured circuit output to other related temperatures on the aircraft was used to identify change between the two temperature values over time. The correlation between the measured and comparison data needed be understood. A known temperature measurement at one location provided an expected temperature value for the related measurement. Comparing the sensor of interest measurement to an accepted correlated sensor measurement provided difference knowledge of the two sensors.

Comparing temperature to another sensor assumes the comparison temperature is accurate. It is difficult to determine which sensor measurement is drifting when only two sensors are used in comparison and it is determined the measurements are no longer correlated. An additional confirmation is required to verify the comparison sensor. One method is to compare to a third sensor, whereas another option is to compare to the same calculation for the other engines on the aircraft.

Operating condition at the time of measurement is also a factor in comparison of temperature readings. Operating conditions must be comparable at the life calculation point to produce useful life degradation estimates. Operation at conditions other than those set for life calculation requires adjustment to use that data point in the life calculation.

Evaluation of the difference between the two sensor measurements (verified reference sensor) over time allows RUL determination. The magnitude and time change of the drift is evaluated to generate an RUL prediction.

Data currently acquired on subject-engine powered subject aircraft baseline aircraft do not enable prognostics or allow isolation of degrading LRUs in T2 sensor circuit. Data are used with fault software to indicate a failed LRU in the circuit. The faulty LRU is not identified and requires checking circuit LRUs to identify the faulty LRU.

Decisions that can be made concerning system and LRU health are limited because system data are available only for the circuit output value. Data acquisition occurs at varying conditions. Prognostic analysis using available data would require “normalization” of the data to a consistent condition for comparison. Anomalous behavior of the T2 circuit LRUs does not change the circuit output value significantly beyond the normal operating range. The system is significantly degraded and there is little RUL when faulted operation is recognized.

Circuit evaluation and assessment of available engine and aircraft data resulted in an analysis method to identify comparative degradation of a circuit on one engine of a multi-engine aircraft. This information can be used to identify a degrading T2 sensor circuit providing warning of a failure instead of the failure happening unexpectedly.

The current T2 circuit configuration is limited to data acquisition at the EEC interface point. This limits fault isolation to circuit assessment that can be performed at that location. Most of the LRU failure modes generate circuit output in the normal operating range of the circuit. A component failure resulting in circuit readings interpreted as normal values does not support improved degradation detection accuracy.

The subject engine T2 sensor circuit was chosen to develop and understand the challenges of prognostic analysis using legacy system data. The system was thoroughly evaluated to determine whether component degradation could be determined (prognostic enabled). Component reliability was considered to assess failure likelihood and identify locations where data acquisition would be desirable.

Evaluating subject engine T2 circuit data revealed faults occurring during both TO and cruise flight conditions. Fault events are plotted with T2 data to assess if anomalous circuit behavior is associated with fault indications (see figures 10–13). The wide range of operating conditions prevents identification of a characteristic to associate with fault occurrence.

The figures display the measured T2 value recorded on a single engine operated between the calendar dates of January 9 and February 28, 2011. The data in the figures are separated into two operating regimes, TO and cruise, showing the differences in temperature resulting from operation at various altitudes.

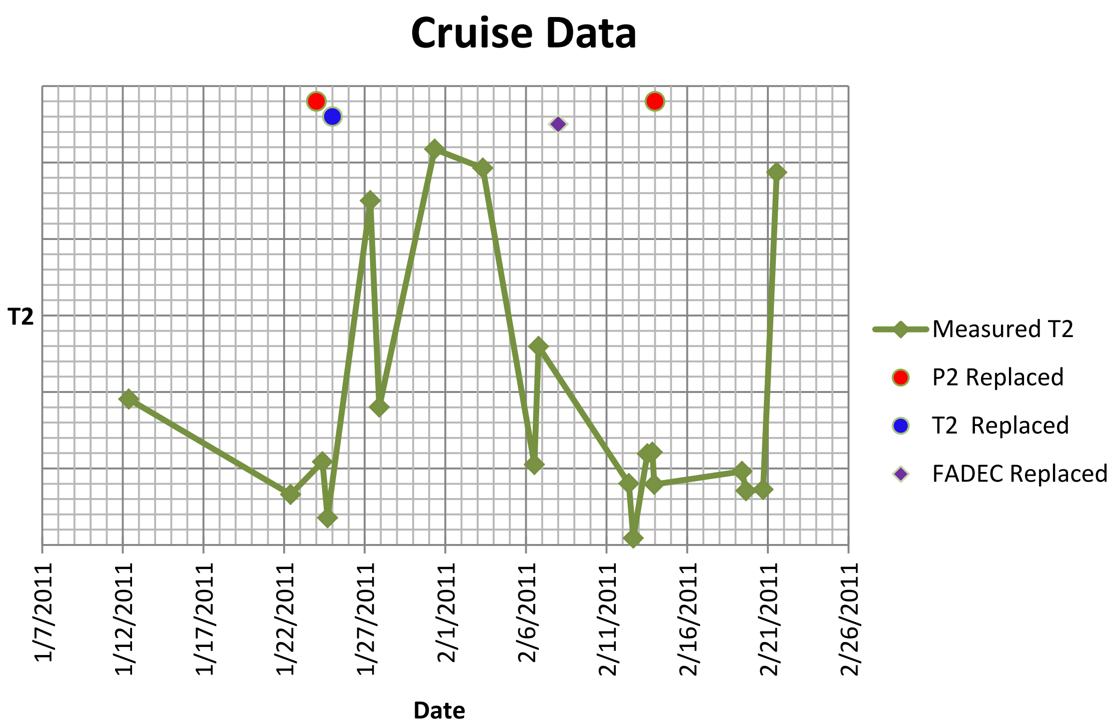

Figure 10. T2 temperature near fault events during cruise operation

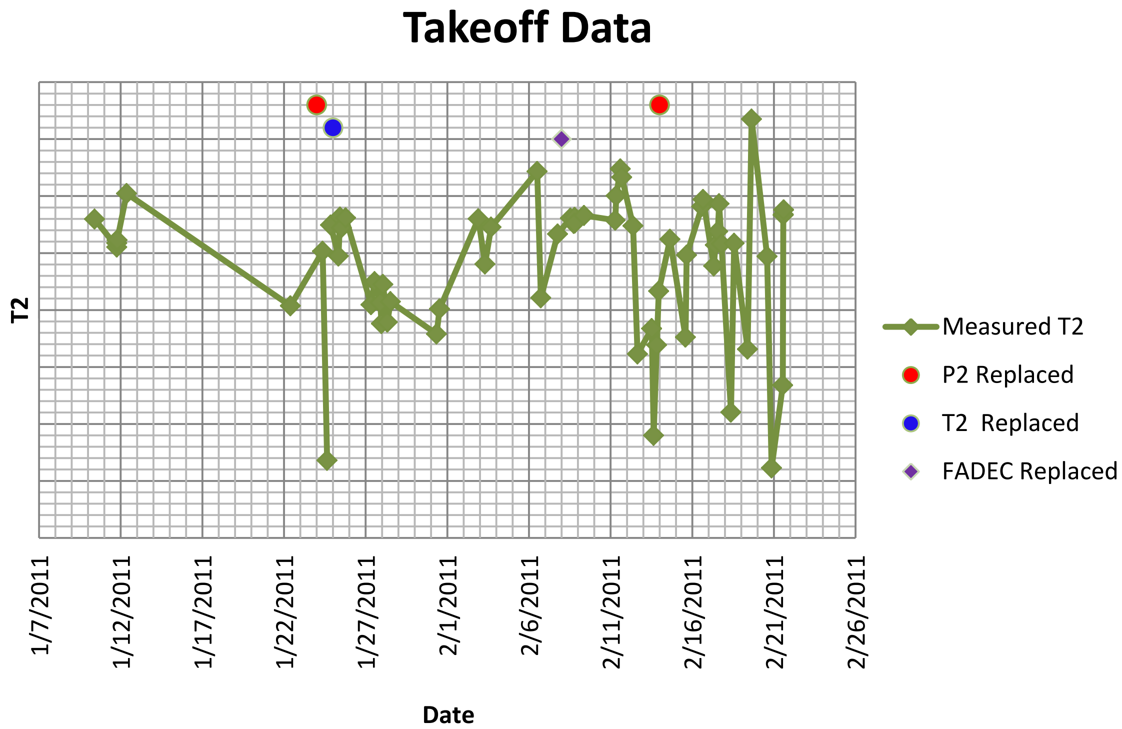

Figure 11. T2 temperature near fault events during TO operation

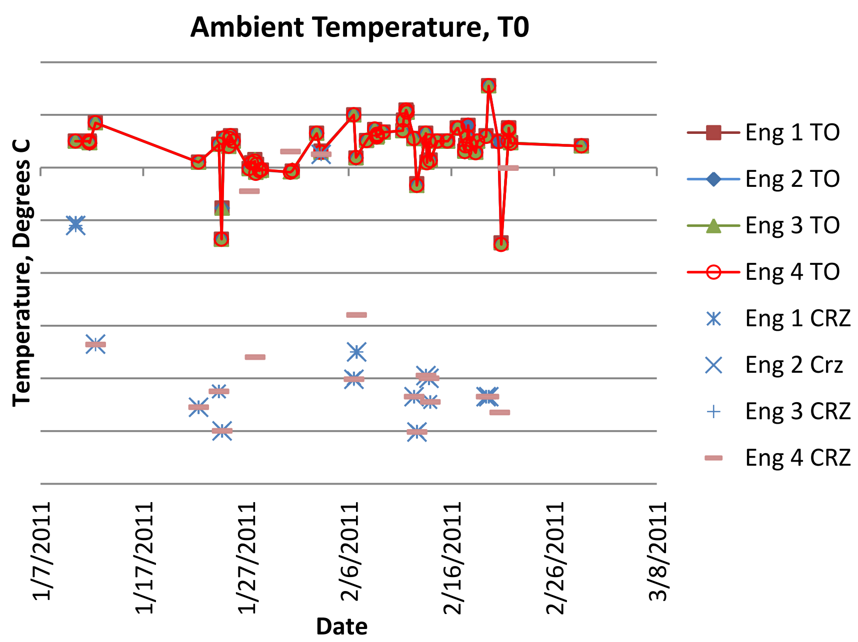

Figure 12. Ambient temperature readings of multiple engines on a single aircraft at cruise and TO

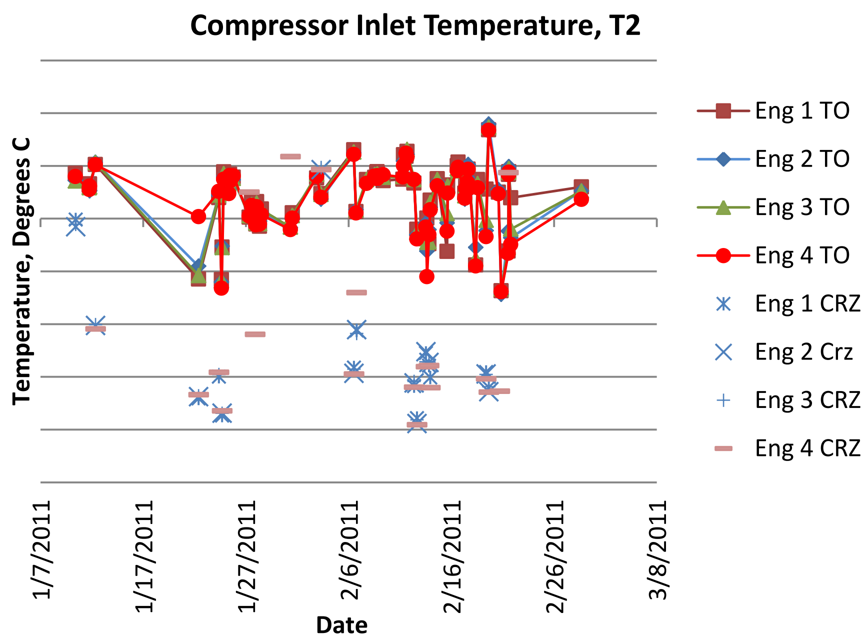

Figure 13. CIT (T2) readings of multiple engines on a single aircraft at cruise and TO

Included in figures 10–13 are symbols indicating maintenance event types related to T2 faults (the Y parameter is for graph placement only) annunciated by the FADEC system shown on the date of occurrence. The events occurred on the engine within a short period of time. Faults were annunciated and action was taken to replace the LRU identified by the maintainer as faulty. Four maintenance actions occurred within 1 month to address related faults. Replacement of the T2 sensor resolved fault occurrences until reoccurrence a month later.

The figures demonstrate the variation associated with using only the measured T2 circuit value to assess health. Data scatter using this single piece of information does not provide clear direction for interpretation of the T2 sensor circuit accuracy. Using T2 data must be done in conjunction with other data to understand the validity of the measurement.

Available aircraft operational data contain altitude, Mach number, flow-path temperatures and pressures, and engine accelerometer vibration data. The data proved useful in establishing the relationship of other temperatures to expected T2 values for use within prognostics.

Comparison of rate of change in the T2 circuit of multiple engines on the same aircraft can use the single circuit sense point currently existent to provide information to indicate relative circuit state. Inadequate information exists to determine the circuit absolute state from existing data. Comparing all engines on one aircraft can provide insight into degradation and a pending fault indication of the T2 circuit of one engine. Isolation of a faulty LRU in the circuit still requires manually checking the LRUs to identify the failed LRU.

A decision was made to compare the CIT circuit temperature readings to ambient temperature (T0). All engines are ingesting the same ambient air, and the data source is the aircraft T0 sensor. That analysis revealed a consistent small temperature difference between CIT and T0. Evaluating differences in the small temperature delta made the T2 reading variation more prominent (see figures 14 and 15).

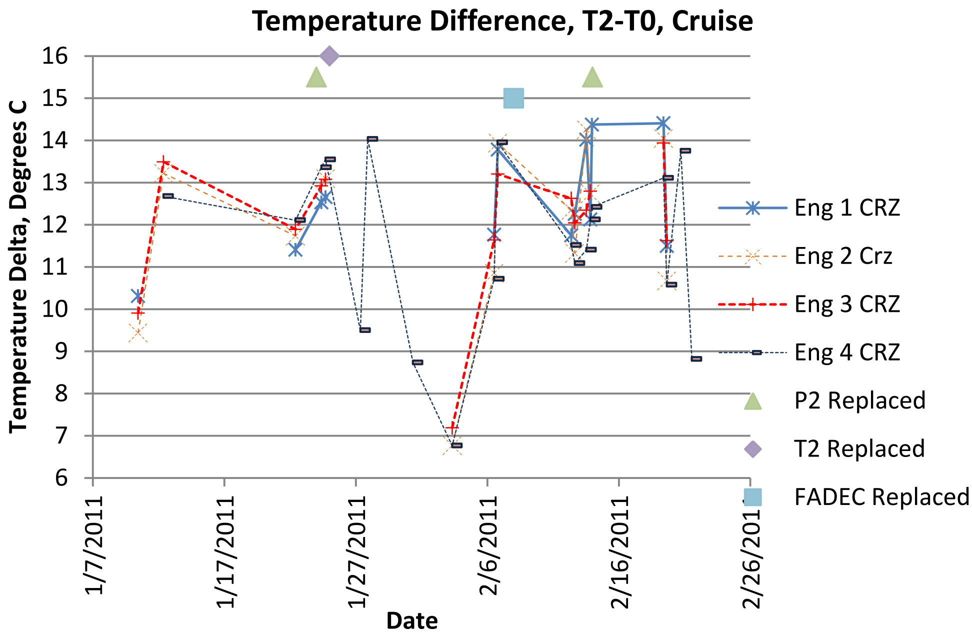

Figure 14. T2-T0 temperature differentials, all engines, cruise condition (note that missing engine data indicate cruise stability criteria were not satisfied)

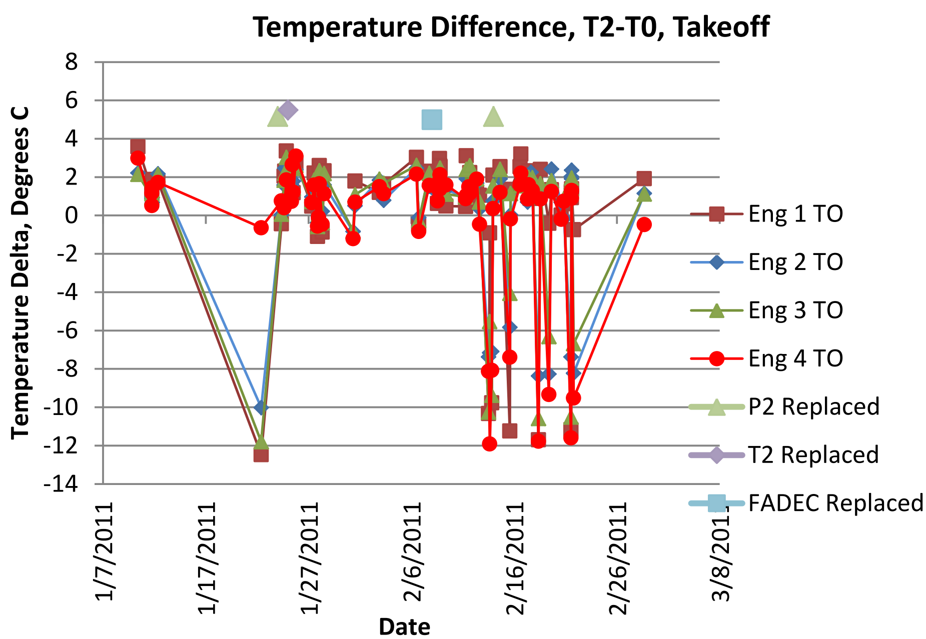

Figure 15. T2-T0 temperature differentials, all engines, TO condition

It was noted that the temperature difference is greater at cruise condition than TO. Figure 16 examines the same data using engine 4 as a baseline. It indicates that though the temperature difference between T2 and T0 is greater at cruise, the same is true for all engines. Figure 17 shows the data for engine 4 independent of the other three engines.

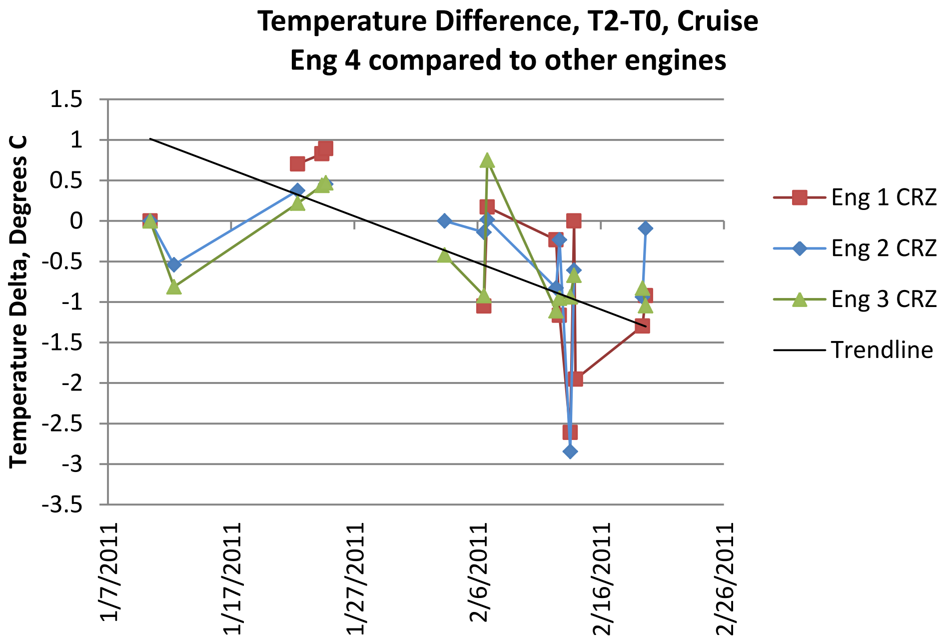

Figure 16. T2-T0 temperature differentials, comparison to engine position 4, cruise condition (note that missing engine data indicate cruise stability criteria was not satisfied)

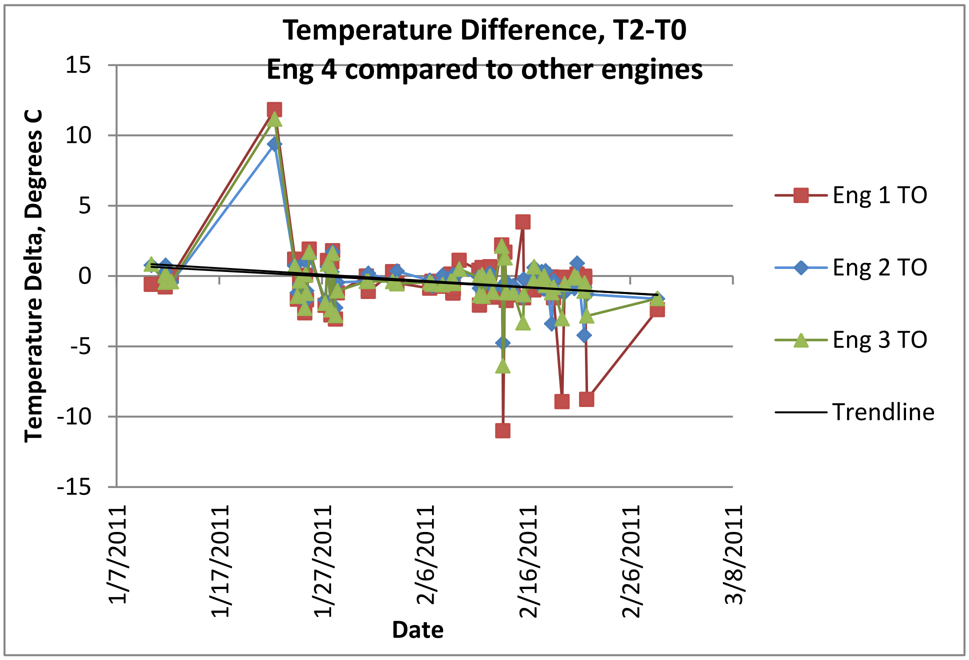

Figure 17. T2-T0 temperature differentials, comparison to engine position 4, TO condition

Figures 14 and 15 respectively show variation of the T0 and the T2 sensor reading of the CIT. The data in each figure were taken at different sensors on four different engines during the same flights. Data taken during TO and cruise operating regimes are separated. The absolute temperatures differ due to operation at different altitudes.

The T2 circuit evaluation provided evidence that degradation should be accompanied by a change in circuit resistance. The detailed aircraft specific data available around failure events did not cover long enough durations to confirm circuit resistance degradation. The detailed data covered a duration of 2 months. The temperature difference between T2 and T0 (ambient) exhibited approximately a 1°C trend change during that time (see figure 18). That change was in the range of data scatter and prevented a conclusive decision stating circuit degradation. The data did support the idea of the presence of resistance change indicating degradation.

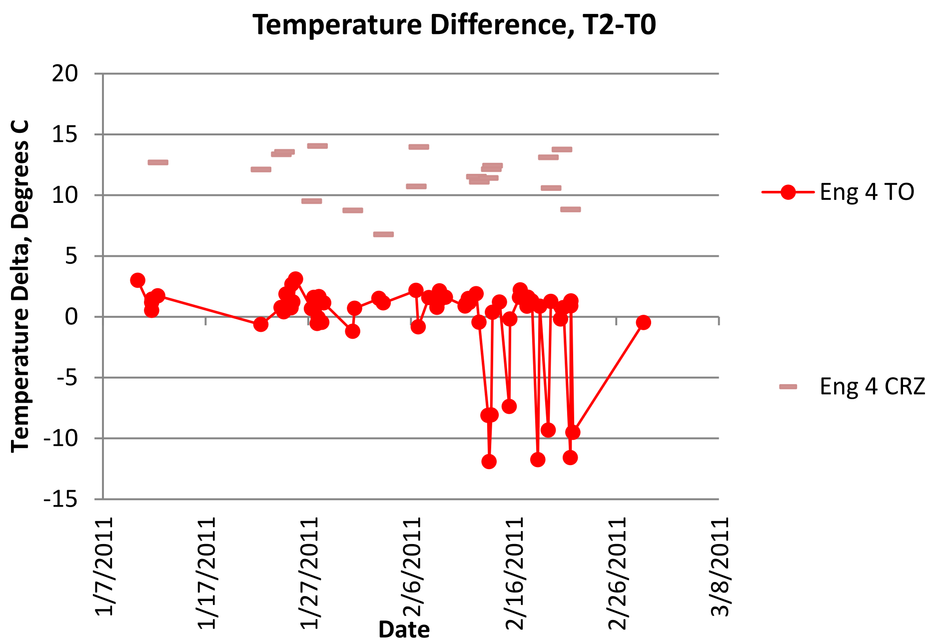

Figure 18. Engine 4 T2-T0 indicates 7 "events"

The CIT temperature change was compared to the other three engines on the aircraft (see figures 16 and 17). All engines demonstrated similar readings, except a few data points.

Study of data from all engines installed on the same aircraft revealed a different degradation rate when looking at engine 4. Engine 4 had a trend of decreasing difference between T2 and T0 not exhibited by the other three engines on the aircraft. This was not obvious when looking at the CIT alone or the T2-T0 difference. Data variation for engine 4 was similar to other engines. The decreasing trend was not evident until the T2-T0 delta for the other engines was compared to that of engine 4.

Examination of the correlation of T2 to T0 revealed a consistent delta for all engines, depending on mode of operation (see figures 14 and 15). There is a high degree of correlation between T2 and T0 for all engines. Further study of data brought recognition that the consistent delta of

T2-T0 could be compared against other engines at the same operating condition, yielding a deviation from one another near 0 (see figures 16 and 17). The result shown in figure 19 indicates the variance in temperature differential (T2-T0) is less than 5º at both TO and cruise conditions.

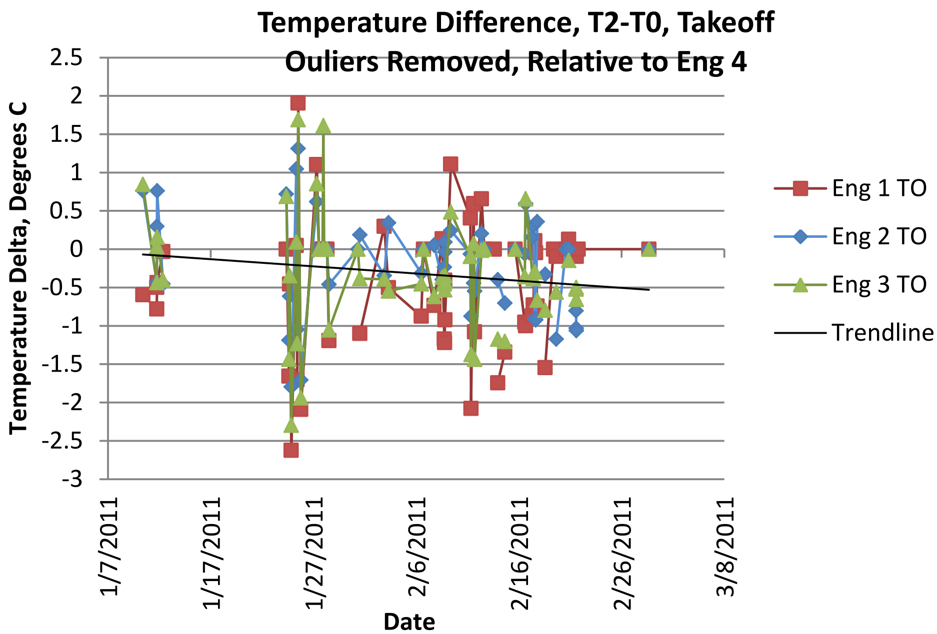

Figure 19. Comparison of T2-T0 to engine position 4, TO

It is concluded that T2-T0 engine differential temperatures can be used to extract an FFP signature to support prognostic capability for temperature drift. It would be possible to determine which engine was experiencing the temperature drift by treating the comparisons as a multivariate dataset.

This information provided a method to assess circuit degradation when compared to the other T2 circuits on the aircraft. Assessment of the T2 circuit of all engines on the aircraft against T0 minimizes variation and allows for identification of one engine circuit degrading relative to the others.

A viable prognostic approach based on modeling and processing an FFP signature that extracts a temperature divergence trend has been identified. The approach is facilitated using two different correlated temperature measurements and ambient and compressor inlets for multiple engines on the same aircraft. These two temperatures from multiple engines provide seven pieces of comparison information to determine the accuracy of the measured T2 circuit value for the sensor of interest (T2, engine 4).

This array of available temperature data provides a source of information to compare temperatures for the sensor of interest to correlated temperatures of other sensors. Temperature data from the other engines provide a comparison and confirmation of data for the sensor of interest when the other engines are being operated in a similar fashion.

It may be possible to identify anomalies in any of the T2 sensor circuits used in the comparison. Using data from multiple engines being operated in a similar fashion allows identification of data that are anomalous in any of the information being used.

Figure 17 data have several points that are divergent from the normal condition. It is hypothesized these are harness anomalies, but it is not possible to confirm that idea using the data available. The January 22 event in which all engines except engine 4 exhibited a data shift indicated a connection discontinuity in engine 4. Several points for engine 1 showed sporadic variation in approximately mid-February.

An underlying assumption is that it is unlikely that drift due to harness issues in one engine will occur at the same time in other engines. There were several instances of more than one engine exhibiting out-of-limits readings. The assumption that out of limits is a result of harness issues results in a question of whether there may have been high engine vibrations aggravating the harness issues. No indication was noted in the service logs.

It was observed that there were trends of increasing differential values.

Figures 16–18 examine the correlation of T2–T0 through calculation of the difference between their measurements. Figure 15 shows the difference between T2 and T0 for all engines on one aircraft. In addition, the figures demonstrate that, with the exception of nine records, there is a high degree of correlation between T2 and T0 for all engines. The reason for the nine exceptions in the differential measurements is not fully known. Assuming those spikes occur for a reason or reasons not related to temperature drift, these nine records are excluded. The result shown in figure 20 indicates the variance in temperature differentials is less than 5º.

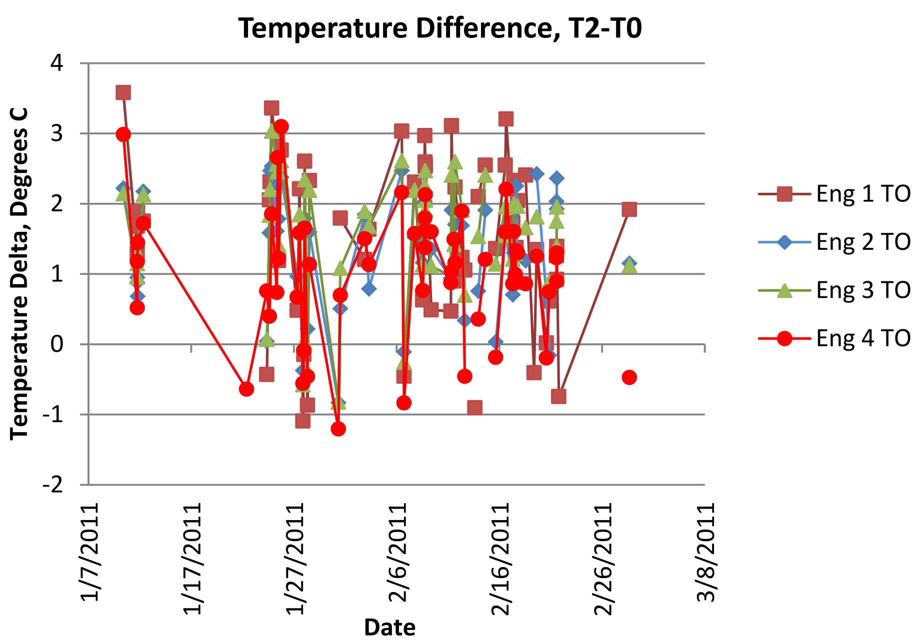

Figure 20. T2-T0 data for all engines after removal of outliers

A limit for data assumed to be invalid for potential harness discontinuity issues was applied to help minimize data variation. The general tight dataset for the T2-T0 led to declaring an outlier limit of +/-5°C from average. Elimination of outliers decreased data scatter more. The standard deviation for T2-T0 was less than 2°C for cruise and less than 1°C at TO condition.

Elimination of data variation allowed for a conclusive assessment of data among the engines on a subject aircraft. Identification of a specific degrading LRU cannot be made, but the evaluation can identify a degrading T2 circuit and provide warning prior to a failure. A failed T2 circuit LRU is no longer unexpected.

A failure limit has not been associated with this analysis. No average circuit life value is defined for the subject engine T2 circuit. Availability of that value should allow comparison of the relative life of the T2 circuit for the engines and identify a level defining failure. That detailed analysis was not attempted because the circuit failure did not exist.

Figures 18 and 20 show the effect of eliminating outliers in the data. Outliers associated with hypothesized spurious harness events at TO reduce the slope of the trendline almost 5 times (0.0444 to 0.0094). The number of occurrences and relative time both influence trend improvement by elimination of outliers.

Prognostic enabling of T2 sensor and FADEC system LRUs using only the existing T2 temperature measurement is not possible. Valid temperatures measured at the sensor can vary from -65°C–150°C. It is necessary to know the temperature the T2 circuit is expected to produce to understand whether the measurement delivered to the EEC from the sensor through the harness is correct. Use of the T0 reading for correlation of T2 provides that needed information.

The comparative analysis described herein has application to multiple situations in which relative data are available. One situation that directly presents itself is the similar relationship of ambient pressure (P0 sensor) and compressor inlet pressure (P2). It may be possible to use similar methods in establishing analysis methods relating temperature and pressure sensors.

Comparison of measured circuit output to other related temperatures on the aircraft can identify change between the comparison values over time. The correlation between the measured and comparison data must be understood to be useful. A known temperature measurement from a different location provides a correlated temperature value indicating the sensor of interest measurement. Comparing the sensor of interest measurement to an accepted correlated sensor measurement provides difference knowledge of the two sensors. Evaluation of the difference between the two sensor measurements over time allows for RUL determination. If the difference progresses consistently over time (drift), the magnitude and time change of the drift is evaluated to generate an RUL prediction.

Comparison of the sensor of interest to measurement of an additional correlated different single sensor is useful when it is difficult to determine which sensor measurement is drifting. An additional correlated sensor measurement provides information to identify the drifting sensor.

The T2 circuit normal operating range is -65°–150°C. T2 circuit output readings within that temperature range are expected to be normal. Looking at only the circuit temperature value does not allow an assessment of circuit health. It is helpful to know what T2 value is expected from the circuit to determine how well the circuit (and subsequently the LRUs) is operating. Using the T0 value as a reference provides a baseline to make that assessment.

The ability to understand the T2 circuit value compared to other engine operating conditions provides information to assess SoH and RUL when compared to other engine T2 circuits. Comparison of T2 and related engine data over time provides information concerning degradation of the T2 circuit. The degradation process can be characterized and compared to known circuit degradation signatures to estimate the circuit life.

The LRU operating models provide the ability to assess the T2 circuit in various LRU (sensor, harness, EEC) health states. The LRU component health states are varied and input producing the electrical values of the T2 circuit at any location.

The circuit simulation allows assessment of response to inserted LRU faults at current system measurement points and additional sense points. The simulation provides a source to identify optimized data acquisition locations to help isolate LRU faults. These additional data sources will also allow more accurate assessment of individual LRU SoH and RUL instead of the current system, which yields only the indication of a system fault condition (T2 value outside normal operating range).

2.10 PROGNOSTICS CAPABILITY INVESTIGATIONS

Figure 21 represents the data acquisition and analysis system for the subject engine. Four of them power the C130-J project baseline aircraft. Data acquisition occurs onboard the aircraft while it is in operation. The data allow system post-flight assessment using ground-based analysis tools. This system architecture provides effective health management of the engine systems and identifies LRU faults. It is envisioned that the prognostic analysis described would parallel, if not become part of, the health-management architecture.

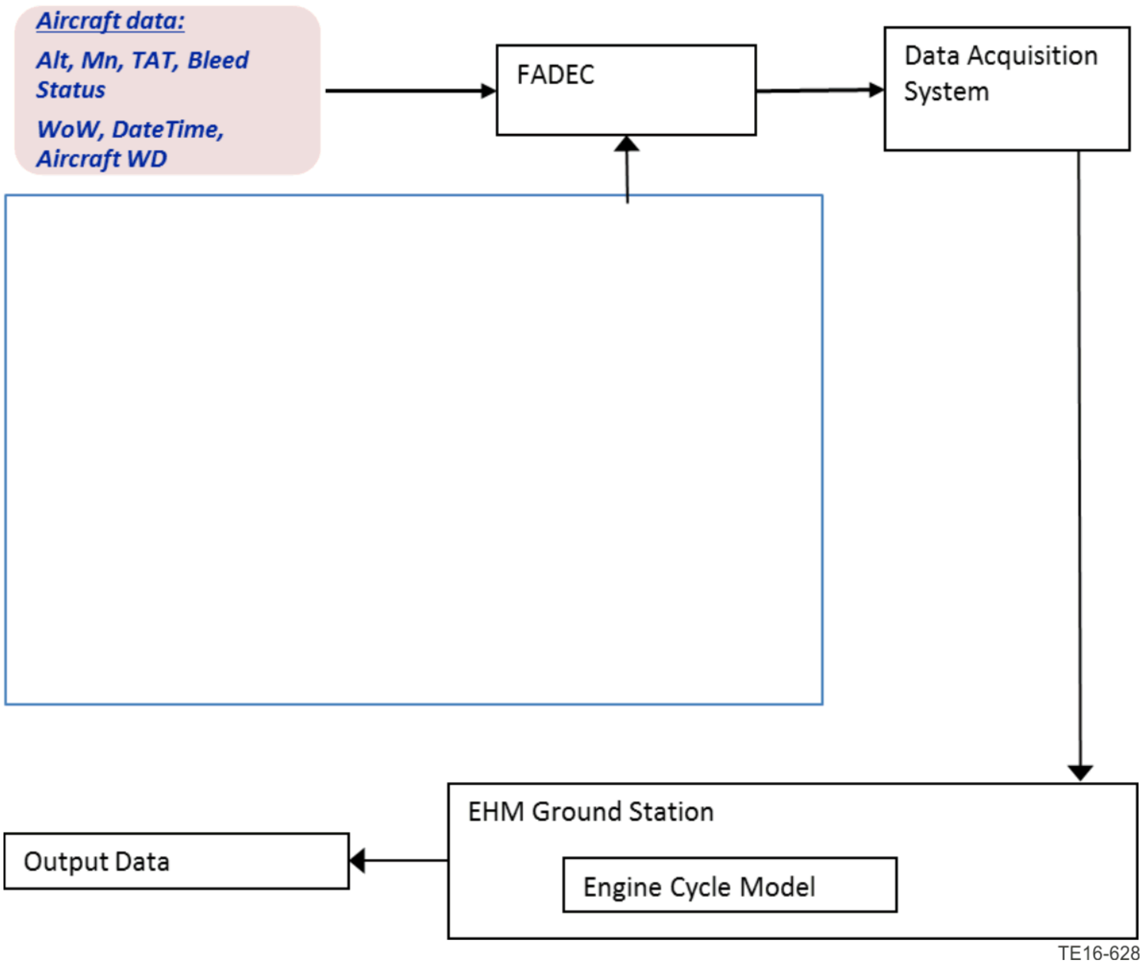

Figure 21. High-level diagram of turboprop jet engine[1]

Task 5 covers the design and development of prognostic-enabling algorithms of five groups of LRUs. The effort provides a proof-of-feasibility demonstration for developing prognostic methods. The LRUs are as follows:

1. Relays and solenoids–fuel start solenoid
2. CJC–RTD sensor embedded in FADEC
3. Speed sensor–engine rpm detector
4. LVDT–CVG LVDT
5. CIT sensor–T2 RTD

One of the limitations of the current T2 circuit is the ability to access data at only one point in the circuit. Adding data sense points to the system architecture provides the ability to isolate failure to specific areas of the circuit.

The ability to insert data-acquisition points at strategic locations in the circuit improves diagnostic and prognostic certainty. The ability to assess operation at known circuit locations provides precise ability to isolate the degraded conditions associated with specific electronic components and, more accurately, predict RUL and SoH. This capability would provide warning of component degradation and ultimately prevent unexpected system failure and potential safety compromise.

Developing electronic component prognostic analysis methods involves specific historical component failure data. Specific subject engine component parameter data available for application to use in determining LRU health defines data to use in calculations. Previous prognostic algorithm development experience is helpful, and developing a computer simulation to apply prognostic algorithms during development provides insight into the ability to predict RUL.

LRU failure mode, effect, and criticality analyses; hardware test beds; and previous Ridgetop Group activity provide historical data for testing condition-based prognostics. Figure 22 refers to the information and steps required to generate prognostic algorithms.

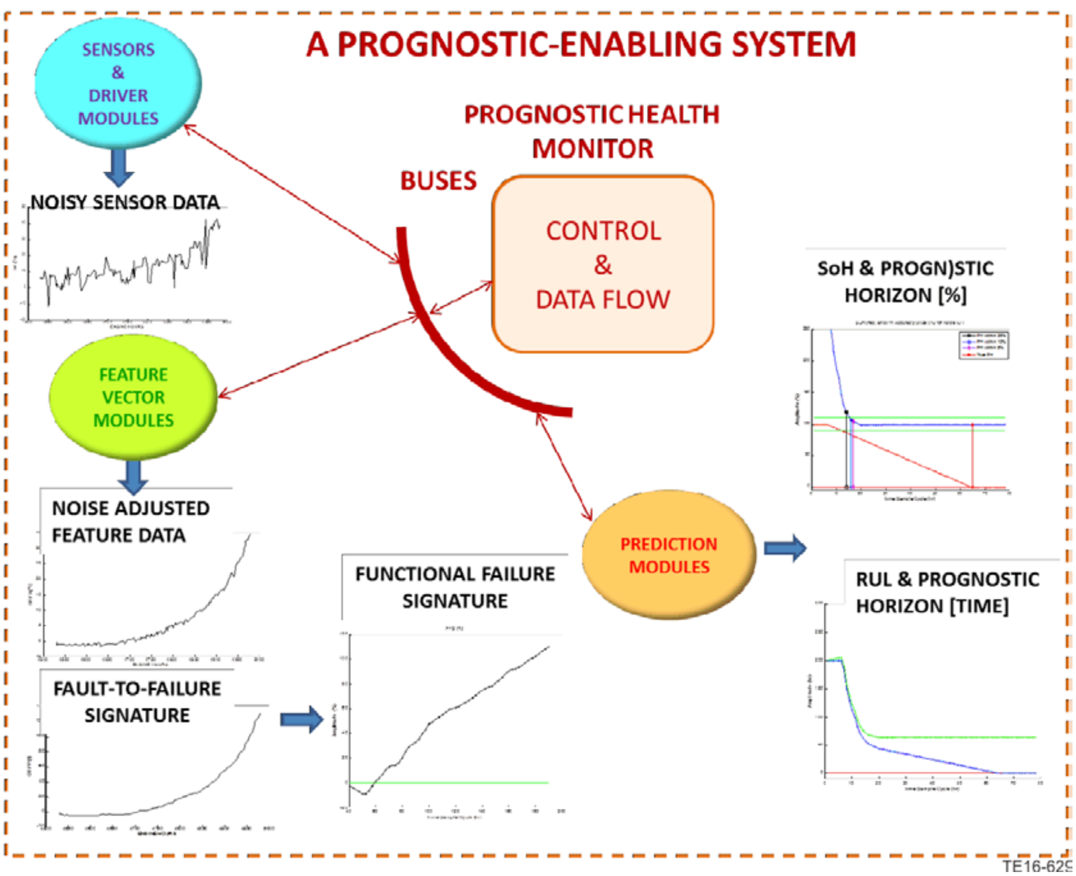

Figure 22. Example of sensor data transformation to prognostic information

Feature data (FD) are condition-based information from an LRU or system exhibiting changes correlated to damage. FD used in algorithm development is derived from system information identifying parameters as important. Data type and operating condition are factored into defining healthy and anomalous situations the algorithm must detect.

Field data can be noisy and include characteristics related to more than one mode of damage. FD are conditioned using algorithms that include data fusion, data transformation, and data conditioning. An example of data fusion is the use of voltage and current data to calculate resistance. An example of data transformation is to use calculated resistance values, measured temperature values, and the relationship between resistance and temperature to calculate changes in resistance with respect to nominal resistance. An example of data conditioning is noise mitigation using subtraction and data-smoothing methods.

Conditioned FD are transformed into feature vectors (FVs) using canonicalization algorithms. An FV is a term related to machine learning and is an n-dimensional vector of numerical features that represent an object. FVs can represent characteristics other than physical. Defining FVs includes computing differences, subtracting nominal values, subtracting noise margins (NMs), and transforming to ratios to create FFP signature data. The divisor to transform FFP signature data to ratios is a value representing 1% degradation of the item of interest (as determined by functionality). Multiplying the ratio by 100 puts FFP degradation in terms of percent. When an FFP is further divided by a percent value of failure level (FL) and the result multiplied by 100, the FFP is transformed into a functional failure signature (FFS).

FFSs have features useful for processing to produce prognostic information, such as SoH and RUL. FFS also features the absence of data-sensitive units of measure, such as amperes, volts, ohms, etc. FFS value indicates the following:

- Negative FFS value represents 100% health—no significant degradation.
- FFS values between 0 and 100 represent degraded health.
- FFS values of 100 or more indicate functional failure.

The process to demonstrate the creation and application of prognostic enabling analysis of electronic LRUs is shown in figure 23.

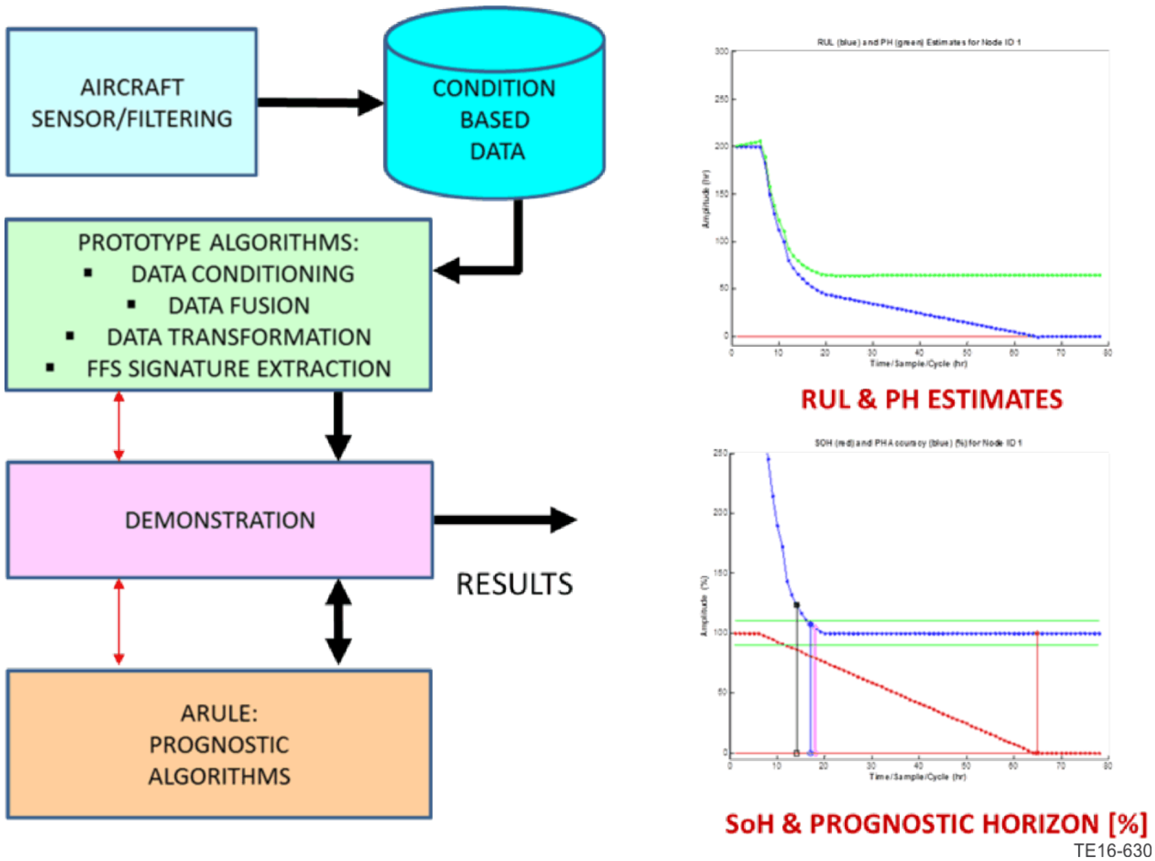

Figure 23. Architecture block diagram of the demonstration

Information is compiled concerning LRU failure mechanisms. LRU failure information is fused with mathematical knowledge to create algorithms identifying LRU health state. The algorithms are further evolved to indicate the level of functional failure of the specific LRU (using specific failure information).

The “demonstration” block in figure 23 is the process in which the derived health information is used to evaluate data from an LRU test simulating degradation of the LRU.

Required information concerning LRU failure includes:

- Declared FL—defined by operational limit of component.
- Onset of degradation—FFP reaches zero point where operational response begins to change.
- Failed—occurs when the FFP reaches the declared FL.
- Prognostic horizon (PH)—predicted time of functional failure.
- Prognostic distance (PD)—the distance at which estimated PH is within a specified percent of the true PH.

Effectiveness of analysis algorithms is evaluated as their convergence of PH and PD.

Figure 24 shows prognostic information of interest. SoH ranges in value from 100% (no degradation) to 0% (functional failure has occurred). An ideal SoH transfer curve is a straight line between 100% and 0%. An estimated PH is the predicted time of functional failure (including event No., sample No., and so on). RUL is the time between detection of decradation and functional failure. An ideal PH would have a magnitude equal to the true PH for all measurements. This is not possible in practice because of the following:

1. Prognostic estimation is not performed and the RUL estimate is a fixed value until degradation is detected.
2. The prediction algorithm needs time to converge from a fixed estimate to the PH.

Figure 24. Graph showing relationship to prognostic information of interest

There are three performance metrics of particular significance that apply to any prognostic algorithm:

1. When does the prognostic prediction converge to a solution in which the estimated PH is within a specified variance, such as 25%, 10%, or 5%? That occurrence is the PD.
2. What is the estimated SoH at PD?
3. What percentage is PD with respect to the maximum possible PH?

An Adaptive Remaining Useful Life Estimator™ (ARULE™) feature called Prognostic Analysis provides the following performance metrics:

- Prognostic information for node ID1: DXDATIVP1.txt
    - Estimated start of degradation at 6.0 (hr)
    - Estimated time of functional failure at 65.0 (hr)
    - PD for PH within 10.0% = 47.5 (hr) at 17.0 (hr); SoH = 81.1 %; prognostic distance (PD/PDMAX) = 80.5 %
        - PH within 25% at 14.0 (hr); SoH = 86.3 %; PD = 50.5 (hr); PD/PDMAX = 85.6 %
        - PH within 10% at 17.0 (hr); SoH = 81.1 %; PD = 47.5 (hr); PD/PDMAX = 80.5 %
        - PH within 5% at 18.0 (hr); SoH = 79.3 %; PD = 46.5 (hr); PD/PDMAX = 78.8 %

Leading indicators of failure provide key information describing the degradation process specific to the item of interest. They are usable for producing SoH and RUL estimates.

An FFP signature is useable in prognostic algorithms. It is not optimal because of the following:

1. Different FLs.
2. Non-intuitive relationship to state of health.
3. Use of the term “fault-to-failure” is interpretable as a physical failure of a component, device, or assembly.

FFP signature usability is improved by converting to an FFS signature and then to SoH. Functional failure occurs when a device, component, or assembly fails to operate at a required level of functionality but has not physically failed. The prognostic program, ARULE, processes FFS data and produces RUL estimates at each point after degradation has been detected. ARULE estimates when functional failure will occur.

Task 5 executed a bench test failure simulation of the LRU groups chosen to test the analysis algorithms developed. Testing consisted of setting up a good LRU on the test bench to gather the required data for input to the algorithms for prognostic assessment. Degradation of the good LRU was simulated using resistance inserted in the test circuit to change circuit output. Resistance was varied during testing to simulate differing amounts of degradation.

Resistance was added into the circuit to simulate varying temperature operation of the circuit without needing a temperature chamber. The temperature resistance was inserted similarly but separately from degradation resistance. Knowing the circuit characteristics and how temperature changes resistance provided a simple method to simulate different temperature operation.

Temperature and degradation parameters were adjusted during testing, and data were recorded at each test point. Data were recorded at three simulated operating temperatures for simulated degradation between 0% and 100% for each LRU. The resulting data matrix consisted of approximately 100–200 points. Appendix A contains an example test data set for the LVDT. Simulation temperatures were -40°, -10°, and 15°C.

Moving prognostic analysis to a level of safety-critical electronic LRU prediction puts a higher level of certification into effect. Using prognostics to accurately predict and prevent failure by forecasting LRU removal requires certification of such software.

Continual system evolution introducing updated reliability data presents a challenge. A system depending on reliability data for calculation input needs to have the ability to be changed as additional information is learned through the system lifecycle. Life predictions could be extended or reduced as information is revealed during the system life cycle. Ability must be provided to update the predictive system to prevent premature part removal or unexpected failure leading to potential safety issues.

Ground-based system software and reliability data used to avoid safety-critical component failure become safety critical. The ability to update reliability data through the product life cycle and assure calculation accuracy becomes a certification issue. Certification of a system intended to be changed throughout the life cycle may require new assessment of certification.

2.10.1 Using Legacy System Data Currently Recorded for Prognostics

Rolls-Royce legacy EEC systems typically record operational data from Level A control systems. The subject engine used on the subject aircraft also records data in the nacelle interface unit (NIU), which is a Level A system.

LRU circuits in Rolls-Royce electronic systems certified to DAL A have built-in redundant features to prevent degraded operation from affecting safety. Estimating RUL and predicting failure does not improve safety in these systems.

Legacy system data may be useful in the determination of circuit health when the recorded data can be applied to determining SoH. Data could be used as recorded if operating-condition variability does not affect determination of health state. It is unlikely that recorded data can be used for prognostic analysis because legacy data acquisition requirements did not consider capturing data for use in prognostics. Legacy data systems on Rolls-Royce engines typically record sensor information for trending engine-performance degradation. Some circuits store operational data that can be useful for LRU health assessment.

The circuits also monitor output and check for faulty operation. Data triggering fault events could be useful in predicting failure if they are stored.

Legacy system engine data are often fused with complementary system data for use in prognostic analysis. The T2 sensor circuit used comparison of two temperature data sources to determine SoH compared to other engines on the aircraft. The assessment provides warning of a degrading circuit. Comparison of degradation of systems operating at the same conditions produces a relative degradation rate. The RUL cannot be determined from the limited engine data available.

Relativistic prognostics provide a degradation rate of one circuit/LRU relative to others on the aircraft. This information can be used to prepare prior to annunciation of a fault, thereby allowing prompt action to minimize disruption.

Systems with a DAL lower than Level A typically do not impact safety of flight. A failed LRU results in degradation of circuit operating effectiveness. The aircraft can continue to operate with a system that is not fully functioning because it has been determined it is not a safety concern. The aircraft can operate effectively as determined by the System Safety Analysis (SSA).

Prognostic capability provides no safety benefit to systems designed to safely operate in the case of a failed LRU. The safety assessment shows the aircraft does not have to be removed from service in the instance of a failure event. Prognostic capability does not add disruption avoidance because the aircraft can be dispatched with failed LRUs in these systems.

Prognostic health analysis would not affect safe operation of those systems because they have been predetermined to be able to operate safely with a failure. Prognostics could prevent system operation in the degraded state by allowing replacement of an LRU before it actually fails.

To apply prognostics to current aviation electronic systems would be a maintenance benefit. Safety effects of LRU failures are mitigated in design.

It is desirable to minimize variation in data used to perform prognostic analysis of degradation. Data acquisition at a repeatable operating condition is one way to reduce variation. The most repeatable operating condition for subject engine data acquisition is "cruise." There is still variation in data because data acquisition constraints are within a range of operation. Relativistic prognostics minimize the impact of variation by making use of data taken at the same condition for all engines.

Using data from multiple engines on a single aircraft allows comparison of data taken at the same condition for the same system on each. Data captured during cruise will be close to the same operating condition for all engines. This allows for comparison of the circuit responses between engines. Data from the engines can be evaluated to identify a difference in degradation rate between them. Comparison of data from three or more engines allows establishment of "normal" operation when at least two engines operate in nearly the same manner. Abnormal degradation can be identified when compared to "normal" operation.

The subject engine is programmed to record data during a defined steady-state cruise condition. Using data recorded at the consistent operating condition facilitates accurate degradation prediction. Data capture at this condition reduces variation and eliminates the need to account for data variation when performing relativistic prognostic analysis. Comparing engines on one aircraft takes advantage of operating in the same environmental conditions and reduces variation.

The ability to compare engine flight data against each other is facilitated by the engines operating in harmony. The result is similar operating data conditions minimizing variation allowing comparison of their response. Multiple engines in the same operating condition and environment allow comparison to reveal differences in their response and determine relative degradation.

Use of data captured during operation allows assessment of operational anomalies that are not repeatable when conducting on-ground diagnostic checks. Data captured in flight have the influence of running engines (vibration and temperature) that is not replicated when performing ground maintenance diagnostics. Degradation parameters that are influenced by vibration and temperature can be accounted for in data captured during engine operation.

Combining degradation-rate information with historical circuit-failure information provides circuit RUL. A differing circuit-failure rate of one engine compared to others on the same aircraft can provide circuit RUL for that engine when the others are considered to be failing at the normal rate.

Determination of the degrading circuit LRU can be derived using LRU historical data to define specific FFS indicating LRU failure. Signatures that are unique to failure of one LRU in the circuit can be used in pinpointing an LRU for replacement.

Data recorded currently in a legacy airborne system that is usable for prognostic analysis does not require airborne system modification and has no certification impact.

Analysis using existing operational data from multiple engines on the same aircraft is performed post-flight on the ground. The aircraft system is not affected when providing data for prognostic analysis.

2.10.2 Changes to Legacy Systems to Enhance Prognostic Capability

Legacy electronic systems can be modified to enable data acquisition to perform effective prognostic analysis. Capturing data at specific operating conditions useful for prognostic analysis permits RUL assessment. Adding data-acquisition capability requires software modification. Memory and processor capability may need to be added to capture large amounts of new data.

Additional data sense points in the circuit provide isolation and allow location of anomalous circuit and LRU operation. Systems intended to isolate specific LRU health require modifications to capture data for each applicable LRU. The addition of circuit sense points requires hardware modification in conjunction with software modification to capture new data. LRUs must be modified to include sense points to acquire health information to be prognostic enabled.

Modification of hardware or software of a certified airborne system will impact system certification. Modification to a certified airborne system requires certification to confirm the changes do not adversely affect system operation. Recertification could range from exercising part of the system directly affected by change to complete system recertification.

Deterministic prognostics can be performed when changes are made to the airborne data-acquisition system. Prognostic-enabled systems can be designed and implemented to use specific prognostic recording condition capability. System configuration and prognostic intent determine required data acquisition specifications.

Specific data-acquisition locations enabling deterministic prognostic analysis provide information for prognostic analysis of overall circuit and LRU health.

Legacy-system prognostic data-acquisition capability requires consideration of the failure mechanism in defining the data-capture location. The same information provides guidance in defining the data-acquisition operating condition. The analysis method is dependent on data-acquisition location and condition. Data-acquisition location and condition should be implemented consistent with identified degradation mechanisms.

LRUs require additional sensing locations to perform thorough prognostic analysis of the sensing circuit and isolate faulty LRU degradation.

Circuits consisting of multiple LRUs are not capable of fault isolation of specific LRU degradation without multiple sense points. Data are required at specific system points to identify the circuit location of degradation. Multiple data-acquisition points (at least one per LRU) provide insight into the circuit location creating anomalous behavior. System anomaly location allows isolation of the defective LRU and subsequent replacement to restore operation.

Adding critical system sense point features requires testing to confirm they do not interfere with safe system operation. Feature addition may drive additional failure mitigation in safety-critical systems. Backup functionality must be provided if failure of a sensing feature creates a critical system failure. Typical current critical systems use a redundant backup mechanism that negates the need for additional capability.

Task 3 evaluated the subject engine T2 circuit and prioritized failure points to identify the degrading LRU. Of the failure points identified in Task 3, 30% have unique signatures defining specific component failures. This allows actuate unit-level diagnostics to be possible through additional visibility throughout the circuit.

Relativistic prognostic analysis can be performed using data acquired from modified legacy airborne electronic systems. There should be no unique data-recording needs to perform relativistic prognostics. Acquired data targeted for specific assessment can be used to perform relativistic prognostics.

Modification of legacy systems provides the opportunity to acquire data to detect wiring-harness degradation. Wiring-harness anomalies are difficult to confirm using on-ground diagnostic techniques. Specific data-acquisition conditions targeted to identify harness degradation could enable harness prognostics.

Harness degradation does have a unique failure signature that creates short-duration signal disruptions. Disruption duration gradually increases as degradation progresses. Vibration that occurs on the engine during operation aggravates harness degradation. The disruption duration will eventually become long enough to span a full FADEC cycle.

Harness problems manifest themselves as random data disruptions. An increasing frequency of data disruption is indicative of a need to correct a harness problem. Changes in data-acquisition conditions can be made to address data for detection of harness degradation. Random signal spikes seen in LRU data analysis are attributed to harness degradation. Monitoring the progression of increasing fault-annunciation trigger events prior to fault annunciation could provide the ability to predict harness failure.

Higher frequency data-capture rates would be helpful to detect and predict early wiring harness degradation and avoid sporadic fault annunciation and data disruption. A higher data-capture frequency would likely require a new processor. That would be a significant system change requiring complete recertification. Prognostic capability for wiring degradation would need to be thoroughly evaluated to justify implementation in a legacy system.

Multiple sense points in a circuit would be helpful in fault isolation. Sense points in LRUs, including the harness, would provide confidence in isolating the source of degradation and circuit faults. Previous Ridgetop experience points to wiring degradation being detectable. Harness fault-detection capability was not confirmed in this project.

Information leading to fault annunciation could be useful for prognostics if it was stored for subsequent use. If the data used to assess fault detection logic were recorded prior to failure, it could provide information useful for prognostics. This hypothesis would require system modification to confirm, which was beyond the scope of this project.

Fault annunciation triggers fault isolation ground maintenance. Fault isolation performed on the ground with the engine stopped does not stimulate the harness fault and is not likely to be found. Other LRUs are often mistakenly removed during fault isolation because maintainers are unable to reproduce harness degradation.

Adding operational data access points would allow specific data acquisition tailored to performing LRU prognostic analysis. The system could be designed with prognostics in mind by providing system operating data at locations to support prognostic assessment.

2.11 PROGNOSTICS FOR FUTURE SYSTEMS

The design of prognostic-enabled future avionics electronic systems should incorporate adequate circuit sense points to detect individual LRU or circuit degradation. Data-acquisition software must be configured to record data at conditions to perform prognostic analysis.

Prognostic ability providing specific LRU RUL allows service and replacement of a degrading LRU at an opportune time that avoids operational disruption and logistic complications. These capabilities provide business benefits to operations activities.

Component-part storage and maintenance activity can be centralized when failures become predictable. Parts do not have to be stored at multiple locations to accommodate the situation of a failure preventing asset usage. Known failure times allow scheduling service activities and potentially facilitate consolidation of part storage and service locations.

A cost/benefit analysis should be performed to decide whether adding prognostic capability to an electronic system is cost effective. Prognostic ability provides no added safety benefit to future systems designed to satisfy existing constraints. Current safety considerations require redundant systems to avoid single-point failure of safety-critical components. Noncritical systems are required to continue to operate with no safety impact when a single LRU failure occurs. There is no need to prevent failure because the system must operate safely in the event of failure. Current system-design constraints eliminate failure as a safety concern.

Existing system-design constraints need to be revised for prognostics to provide system-safety benefits. Prognostics will not provide a safety benefit as long as safety events are mitigated by designing them to have no operational effect.

Prognostic analysis may provide lower cost by substituting redundant Level A features with prognostic analysis to predict and avoid electronic failures. Safety considerations would need to be incorporated, thereby eliminating the potential of failure during operation of safety-critical systems.

Could prognostics capability be used to reliably predict failure and direct maintenance action instead of building in redundant systems? The idea of using prognostic capability to replace redundancy needs to be proven before it can be incorporated.

Prognostic enabling of a new system requires it to be designed with insight to known failure modes. Existing and previously used features and components have identified failure modes to consider in the safety assessment. Data acquisition requirements defining the conditions to assess health and predict RUL should use the safety assessment for guidance. Sense points and data-capture conditions should be implemented to capture indications of identified failure modes. The benefit of using these features results in advanced indication of LRU failures and avoiding operational disruption.

The cost of testing a new system should not be significantly impacted by adding prognostic capability during the design of a new system. The testing and certification protocol for new system design is significant. The feature types that would be implemented to enable prognostic capability are typically tested during certification. Variation in testing of more system features will be minimal in overall certification-testing costs. Test time and effort will slightly increase to develop related ground-based features. Airborne system complexity and test effort should decrease with elimination of redundancy-related features. Added features must be accounted for in design and development of a new product.

Demonstrating the reliability of prognostics can be approached in multiple ways. One possible approach is to conduct predictive assessment of LRUs or circuits in which data currently exist. Another approach would be to perform a minor modification of an existing circuit to acquire prognostic data for use with analysis software. A further possibility is to design a test system to specifically acquire and analyze data to prove prognostics while still using redundant safety features.

The use of prognostic analysis as a method to prevent failure of electronic safety features will require significant effort before it is proven as an alternative to current safety methods.

2.12 GROUND-BASED ANALYSIS SYSTEMS

Ground-based analysis systems using legacy system data would not require certification for advisory SoH calculations. Legacy systems are designed to accommodate electronic LRU failures using redundant systems or SSA determination that failure is not safety critical. They are designed and certified to be airworthy with failure of an electronic component.

Ground-system analysis algorithms must be defined and developed addressing the unique failure and data variation of each LRU. A data-management system is required to store and access data as needed.

Post-flight ground-based analysis allows identification of degradation following a flight and permits maintenance action prior to failure for the majority of electronic failures. Failure that progresses from being identified to occurrence in two flights is not a good candidate for prognostic analysis, because the failure progression is too rapid to effectively use prognostic analysis.

Prognostic capability applied to a legacy system does not reduce safety. Degrading electronic components are addressed using legacy fault annunciation. Safe system operation with failed components is guaranteed using redundancy or SSA.

The ground-based analysis system contains prognostic algorithms having the ability to analyze incoming data and creating output defining the health state of the system being analyzed. Analysis results do not drive maintenance activity. SoH and RUL information is advisory for legacy systems designed to address failure and maintain safe operation.

Performing prognostic analysis requires a mechanism to make acquired airborne data available for use. Most aircraft systems have the ability to transfer airborne system data to a ground-based system. Prognostic data can be made available for analysis using the same process.

Maintenance history must be recorded and used as input in calculation of RUL. Installation of new components is used to initialize the life-history calculation. Part of the ground-analysis system must have part replacement information for use in prognostic analysis.

Analysis output needs to be made available to the user and stored for use for subsequent analysis. The Ridgetop analysis method uses the latest three data points for calculation. This avoids the need to store excessive data and reduces calculation complexity.

Ground-based analysis systems used for components that are safety critical will require certification. Assurance of system integrity is necessary in the case of prognostic assessment replacing redundant features. The parts of the system used for safety-critical analysis are the same as those previously defined.

Certification of ground-based analysis systems requires confirming the interaction of all parts of the system to produce accurate results. Certification of ground-based safety-critical systems may reveal new requirements to be considered in certification.

Prognostic assessment of electronic systems must be proven and accepted before certification of ground-based systems is needed.

3. PROPOSED PROGNOSTICS SYSTEM ARCHITECTURE/BACKGROUND

General aircraft electronics system architectures are represented in figure 25. Prognostic methodology is applicable to components that have detectable failure modes. Some components that fail rapidly (instantly) cannot be prognostic enabled because there is no degradation process. The project takes the simplified approach of exploring in detail how to implement capability into a single circuit. Understanding the impact on this single circuit will allow extrapolation to implementation in more complex systems, including the complete aircraft. The project explored methods to detect, isolate, and predict electronic LRU degradation and failure. The methodology developed is applicable to electronic components in general.

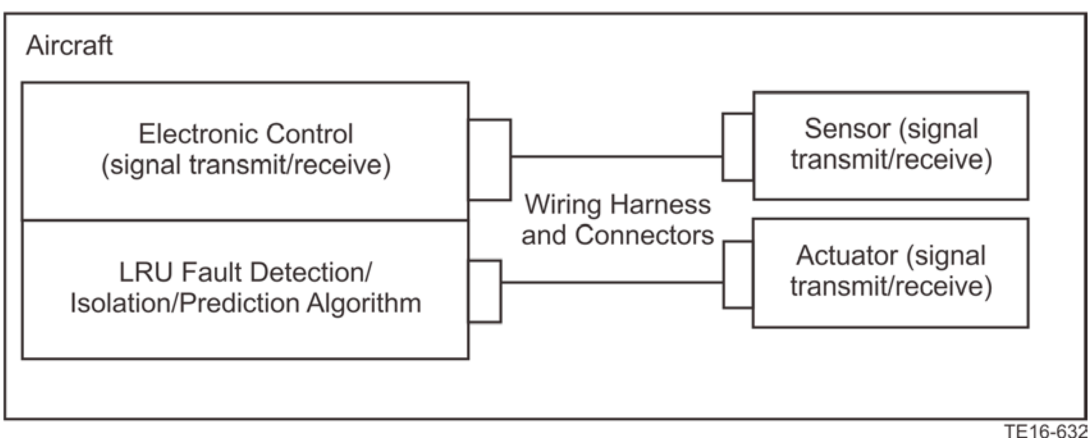

Figure 25. Aircraft system block diagram

The subject engine T2 circuit was chosen initially to study prognostic implementation. Additional LRU circuits were brought into the project to provide a broader perspective of prognostic methods.

Current aerospace applications can benefit from prognostics by producing reduced service cost and disruption created by proactive maintenance. Future potential benefit comes from the logic becoming verified as capable of detecting equipment degradation and accurately identifying the expected failure time of electronic components. Current aircraft safety-critical systems use redundant features to prevent single-point failures.

Evaluation of the T2 circuit using prognostic methods requires data beyond the circuit alone to be able to effectively determine circuit health. Modification to insert additional sense points in the circuit provides the ability to isolate LRUs to determine when they are operating correctly. Evaluation of circuit health is limited to stating it is operating within known limits when only knowing circuit operational limits. The wide range of operation does not allow pinpointing anomalous circuit behavior without comparing the output to expected behavior at a known operating condition.

Use of additional sense points in the circuit is not possible in existing systems. Use of additional sense points requires knowledge of the T2 circuit expected output to evaluate circuit health. Determination of LRU component condition requires information to identify the expected output value of the T2 circuit.

The T2 circuit simulation has been applied to determine additional data sense points in the T2 circuit that allow for accurate LRU fault identification and prognostics.

Inserting additional sense points in the circuit provides the capability to identify the response of LRU components independent of other system components. The ability to read and understand the circuit values of the individual LRUs supports identification of each LRU condition. With information available at the LRU sense points, the ability exists to gather data relating to the specific LRU over time to allow determination of RUL.

The variation in engine operating conditions makes it necessary to understand the T2 circuit temperature being sensed to interpret the LRU component values. Determination of the T2 circuit expected values is achieved when the sensed T2 temperature is known. As a check against the T2 temperature produced by the T2 circuit, other sources of expected T2 temperature are required.

It is possible to track the difference between the expected and actual T2 value over time. Additional sense points associate the degradation process to a specific component or LRU. It is also helpful with prognosis of faults to identify and quantify failure progression.

Data-processing capability is needed to determine the expected T2 value and to evaluate the difference between the measured and expected T2 value. RUL determination requires comparison to previous difference values and assessment of duration of change. This method could be performed by an onboard maintenance computer system if processing capability is available. Maintenance actions can only be performed on the ground.

LRU prognostic capability completed post-flight supports maintenance action. In-flight data acquisition supports post-flight analysis and can be done on current systems with adequate data-storage capacity. Required data-storage capacity is a function of the analysis method used. Continuous data acquisition allows selection of data acquired during operation at any condition. Snapshot data acquisition (during a specified condition) reduces data selection to operation when data are captured, which may not be optimal for the analysis being performed.

The comparison of multiple data sources over time provides information to be used for prognostics. Comparison of similar data sources (same temperature location using different sensors) provides the simplest comparison. EEC circuits include redundant sensor information (two separate signals) that is compared within the EEC as a method of validity check for signals received. These data are not used for anything additional and are not stored. Capturing the difference values between redundant sensors and evaluating them as time progresses is a source of data that could be useful in determining if a sensor is degrading.

Analysis of these data would be useful in a system for which redundant system sensors are housed separately. Systems using redundant sensors housed in the same component (as in this system) would see reduced benefit from sensor comparison information. Redundant sensors housed together as a single LRU are replaced together. Identification of a single-lane sensor fault occurs today. The instance of an LRU returned for repair could benefit from knowledge of sensor history and health.

Because redundant sensors are designed to provide backup for control-system functions, they will read very close data values during normal operation. If the difference in readings increases over the life of the sensors, it would indicate degradation of one of the sensors. This information alone does not identify a failed sensor.

In the current T2 circuit design, the circuit output is assessed only at one location in the circuit. Variation in that reading over the life of the circuit would indicate change in LRU components that degrade as they age (sensor/EEC). The remaining LRU in this circuit, the wiring harness, exhibits a failure condition of intermittent connection.

Use of data beyond the T2 circuit electrical condition provides additional information for use in determining circuit health. The circuit has a range of acceptable electrical output values that are bounded by the expected temperature the circuit must measure. Knowing the accuracy of the electrical value within those limits provides insight into the circuit health. A source of data to compare the T2 circuit measured value against the expected value provides an accuracy check to track circuit changes. The ability to identify and track changes provides information to assess RUL.

History exists with use of thermodynamic engine-cycle analysis models for engine-health management. These models use steady-state data gathered during flight to conduct off-board analysis used in engine-performance assessment. These models use multiple gas-path measurements as information input to allow convergence to a solution representing steady-state engine operation. T2 is one of the gas-path parameters calculated in that solution. The engine cycle model T2 value could be used for comparison to the measured T2 value.

Trending of several T2-related parameters has been explored to evaluate use as a simplified T2 estimate for comparison to the measured value. Preliminary assessment identifies variation requiring correlation to understand acceptable use and possible additional parameters for inclusion to improve accuracy.

Possible sources of data outside the T2 circuit include other aircraft system temperatures that can be compared to the T2 circuit temperature. Correlation to engine system operation is required. In line with that approach, the FADEC system provides data that could be useful. There are persistence counters that determine if intermittent faults are occurring. They prevent nuisance fault annunciation until a predetermined number of continuous processing cycles indicate the fault is actually problematic.

FADEC systems minimize the impact of intermittent circuit discontinuities. The persistence counter allows short disruptions in data acquisition to occur without annunciating every minor incident. The persistence counter annunciates a fault after a set number of consecutive data processing cycles occur when valid data are not available. The piece of information available from persistence counters that could be useful in diagnostics and prognostics is the count of minor disruptions prior to activating the persistence counter. For instances in which disruptions occur prior to fault annunciation, counting and tracking the disruptions could provide insight into the failure mechanism and possibly prognostic input to predict RUL.

As an example, intermittencies that occur infrequently and begin to increase in occurrence and duration could be indicative of a pending electrical connector failure. Tracking the number of persistence counter events would allow identification of a trend, if present, to indicate a connector problem and possibly predict impending failure.

Currently, persistence counter events are not recorded or tracked.

The identified data sources and evaluation methods could be implemented as software on current hardware systems for which memory and processing capability support additional software. Data outside the T2 circuit requires assessment in conjunction with the T2 circuit simulation to understand the effectiveness of using that information in determining circuit and LRU health.

Implementation of the identified analysis methods impacts aircraft safety and certification as a ground-based system. LRU diagnostics and prognostics are most useful when the aircraft is not in service. Data acquisition while the aircraft is in-flight is a critical aspect of producing accurate solutions to identify faulty and degrading LRUs. Post-processing of flight data on the ground allows maintenance actions to be defined that reduce service disruption and burden to aircraft systems with data processing. This approach reduces impact to the flight system's data-acquisition memory and the processing required to capture the necessary data.

A prognostic-enabled aircraft electronics system should be designed to provide specific prognostic information, which consists of data gathered at locations and conditions required to understand and predict health. Prognostic intent determines the data required.

The system should be designed with prognostics in mind, and the type of prognostic analysis to be used should be considered. System-design intent can be to generate information to predict circuit or specific component RUL. Data acquisition and analysis need to be coordinated to produce the desired results.

The desired prediction capabilities are enabled by the location of data sensors. Overall circuit prognostics can be conducted with sensing capability placed at one location in the circuit. That location will influence what can be learned with the data acquired. Multiple sensor locations allow fault isolation within the circuit. The sensor location facilitates identification where the circuit fault exists. The data-acquisition and analysis algorithms can be tailored to identify specific fault conditions aiding maintenance activity and LRU repair.

The location of data acquisition features to enable prognostic analysis is a function of number sensors and conditions when data are recorded. The system architecture requires data acquisition hardware and software to acquire prognostics data. The onboard system architecture is adjusted using the data-storage capacity to support the analysis desired.

The circuit and LRU data acquired onboard must be available for ground analysis, subsequent storage, and maintenance action. It provides operational information and history used in prognostic analysis. Historical operating and maintenance information must be stored in the ground data for use in analysis.

The ground-based analysis and data-storage architecture can be the same for any system. Architecture size variation is driven by analysis feature count and the number of data points recorded for analysis. System processor requirements and data-storage needs will be dependent on many user-specific factors.

Ground-based system efficiency is affected by data processing and storage capacity. The anticipated amount of data to be managed and the complexity of analysis algorithms will factor into ground-system definition.

Figures 26–28 show an architecture identifying the parts of a prognostic-enabled engine-control system. The figures display system feature relationships and demonstrate data flow. The figures show a general architecture of the system components. The detailed aircraft-based components depict one channel of a DAL A engine-control system (when applicable). The redundant features required to ensure safety of the system are depicted only once. The control system has an additional channel, as noted. Lower DAL systems do not require redundancy and would be configured as shown.

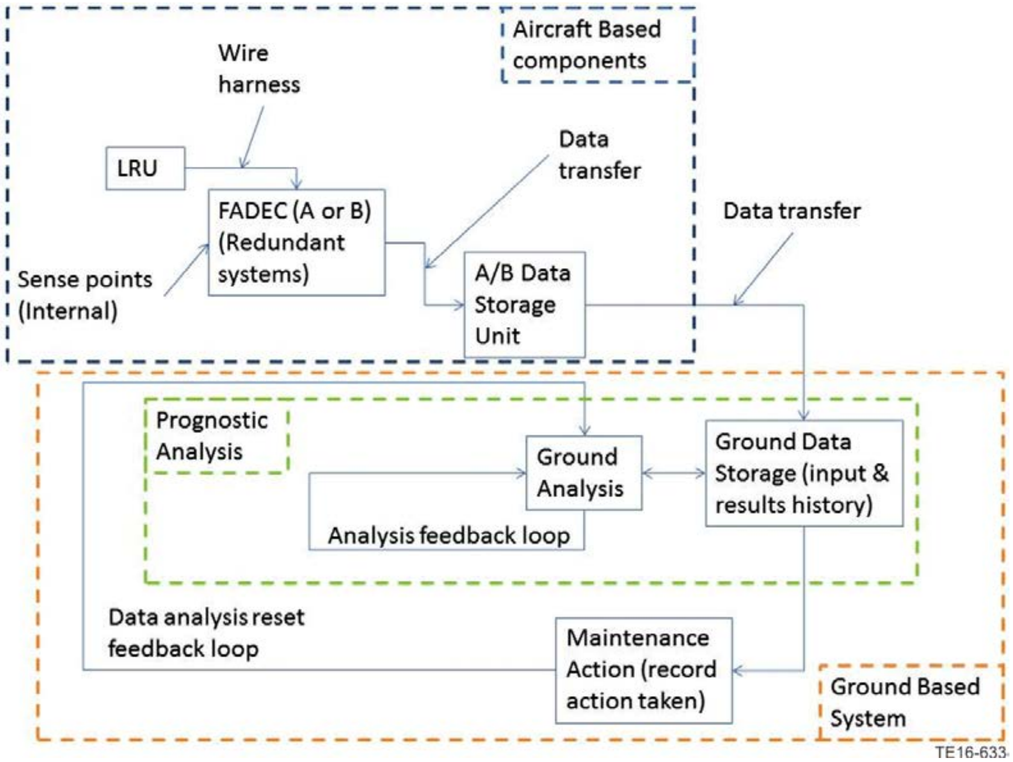

Figure 26. Prognostic system architecture using existing airborne system (ground-based system added to enable prognostics)

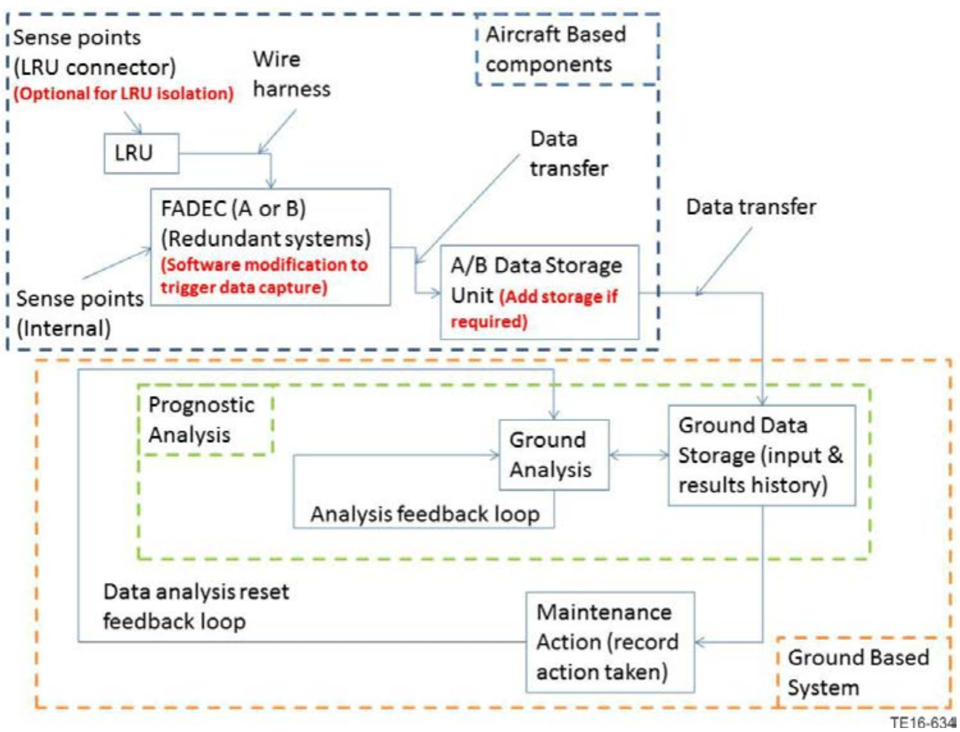

Figure 27. Prognostic system architecture using modified airborne system (Note that items in red highlight changes to airborne system)

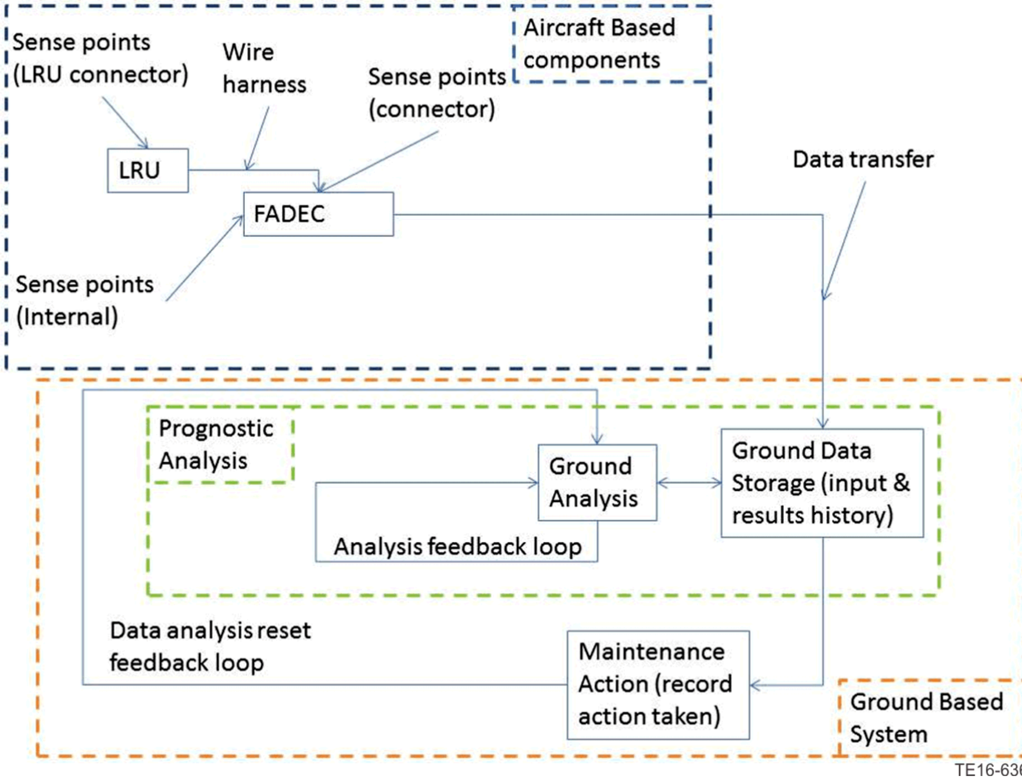

Figure 28. Prognostic system architecture for future airborne systems

Figures 26–28 contain a data-storage unit in addition to a FADEC. It is possible the data-storage feature could be combined with the control. It is shown separately to potentially take advantage of the lower DAL associated with data storage without control.

The information in the following sections considers differing scenarios for implementing prognostics and provides examples related to the current subject engine electronics system.

3.1 PROGNOSTICS USING DATA FROM EXISTING SYSTEMS

Rolls-Royce legacy EEC systems typically record operational data from Level A control systems. The subject engine used on the subject aircraft also records data in the NIU, which is a Level A system.

LRU circuits in Rolls-Royce electronic systems certified to DAL A have built-in redundant features to prevent degraded operation from affecting safety. Estimating RUL and predicting failure does not improve safety in these systems.

Airborne systems certified at lower DAL use the SSA to confirm that failure does not cause a safety concern. Prognostic analysis could be beneficial in these systems by predicting and preventing failure. Safety is not compromised when a component fails. Safe operation of these systems has been predetermined to be able to operate safely with a failure. Prognostic analysis could avoid operation in the degraded state.

The safety assessment shows the aircraft does not have to be removed from service in the instance of a failure event. The aircraft can be dispatched with failed LRUs in these systems. Prognostics could prevent system operation in the degraded state by allowing replacement of an LRU before it actually fails.

Prognostic capability is enabled through detection of parameter changes over time and extrapolation to predict failure occurrence. Prognostic assessment using existing system data is difficult. Prognostic data acquisition was not considered when designed. The design intent was to provide system functional information.

Some of the recorded engine performance data can be used to predict system health and calculate RUL using analysis algorithms designed to use available data. Opportunities may exist to use data acquired by legacy systems to assess electronic LRU health should data be recorded at conditions conducive to understanding health.

Legacy data systems on Rolls-Royce engines typically record sensor information for trending engine performance degradation. Some circuits store operational data that can be useful for LRU health assessment.

The circuits also monitor output and check for faulty operation triggering fault annunciation. Data triggering fault events could be useful in predicting failure if it is stored.

Fault annunciation for the subject engine is a non-dispatch situation. Fault detection is not prognostic. It annunciates that a circuit is beyond its defined operational limits and requires maintainer fault isolation action to identify and replace a faulty LRU.

Accurate prognostic assessment is facilitated by performing analysis at a consistent operating condition, thereby allowing determination of heath-state change. The ideal method is to identify an operating condition producing useful health data that is executed consistently when the engine is operated. The frequency of repetition for capturing the data is a function of the expected degradation rate of the component. A slow degradation rate (many operation cycles) can be captured once per cycle and provide adequate warning of failure. A rapid failure rate (as few as a few engine cycles) requires multiple data-acquisition points every time the engine is used.

A consistent data-acquisition condition reduces the necessity to “adjust” the data to the defined assessment condition. Acquiring data at varying operating conditions introduces variation that must be accounted for by calculating how operational variation affects failure propagation.

One of the limitations driving assessment of the current T2 circuit is the ability to access data at only one point in the circuit. The existing system provides data at the endpoint of the circuit in the EEC. The simulation circuit assessment occurs using this location. Applying this limitation to the simulation provides the ability to understand whether LRU health can be assessed and if it can be made using the existing system architecture.

The in-depth knowledge gained during the T2 circuit simulation assisted development of the idea of doing relativistic prognostics. The relativistic method does not assess the specific LRU against design information to determine its health. It compares the degradation rate of multiple-engine

T2 circuits on the same aircraft. This information can be used to provide notice of an impending circuit failure.

Engine operational data are captured for certain circuits (sensors) by the control system. It is possible to use the data from multiple engines on the same aircraft to determine degradation differences of like systems on those engines. A further benefit is that all engines on a single aircraft are similarly operated. Data can be analyzed from the same operating condition and will be very close to the same for all engines. All engines on a single aircraft will also be operating in the same environment.

Data variation leads to analysis uncertainty. Using data recorded at the consistent operating condition facilitates accurate degradation prediction. Data capture at a specific condition reduces variation and eliminates the need to account for data variation when performing relativistic prognostic analysis. Comparing engines on one aircraft takes advantage of operating in the same environmental conditions and reduces variation.

Data acquired from multiple engines operating in similar conditions helps reduce variation in analysis and provides a data source to conduct robust analysis.

Legacy system engine data are often fused with complementary system data for use in prognostic analysis. The T2 sensor circuit used comparison of two temperature data sources to determine state of health compared to other engines on the aircraft. The assessment provides warning of a degrading circuit. Comparison of degradation of systems operating at the same conditions produces a relative degradation rate.

Relativistic prognostics provide a degradation rate of one circuit/LRU relative to others on the aircraft. This information can be used to anticipate annunciation of a fault allowing prompt action when it does occur to minimize disruption.

It is desirable to minimize variation in data used to perform prognostic analysis of degradation. Data acquisition at a repeatable operating condition is one way to reduce variation. The most repeatable operating condition for subject engine data acquisition is “cruise.” There is still variation in data because data acquisition constraints are within a range of operation. Relativistic prognostics minimize the impact of variation by making use of data taken at the same condition for all engines.

Using data from multiple engines on a single aircraft allows comparison of data taken at the same condition for the same system on each. Data captured during cruise will be close to the same operating condition for all engines. This allows for comparison of the circuit responses between engines. Data from the engines can be evaluated to identify a difference in the degradation rate between them. Comparison of data from three or more engines allows for the establishment of “normal” operation when at least two engines operate similarly. Abnormal degradation can be identified when compared to “normal” operation.

The ability to compare engine flight data against other engines is facilitated by the engines operating in harmony. The result is similar operating data conditions minimizing variation allowing comparison of their response. Multiple engines in the same operating condition and environment allow comparison to reveal differences in their response and determine relative degradation.

Use of data captured during operation allows for the assessment of operational anomalies that are not repeatable when conducting on-ground diagnostic checks. Data captured in flight has the influence of running engines (vibration and temperature) that is not replicated when performing ground maintenance diagnostics. Degradation parameters that are influenced by vibration and temperature can be accounted for in data captured during engine operation.

Combining degradation rate information with historical circuit failure information provides circuit RUL. A differing circuit failure rate of one engine compared to others on the same aircraft can provide circuit RUL for that engine when the others are considered to be failing at the normal rate.

Determination of the degrading circuit LRU can be derived using LRU historical data to define specific FFS indicating LRU failure. Signatures that are unique to failure of one LRU in the circuit can be used in pinpointing an LRU for replacement.

Data recorded currently in a legacy airborne system that are usable for prognostic analysis do not require airborne system modification and have no certification impact.

Analysis performed using existing operational data from multiple engines on the same aircraft is performed post-flight on the ground. The aircraft system is not affected when providing data for prognostic analysis.

Figure 26 represents an existing legacy aircraft electronics system and ground-based features to perform prognostic analysis. This architecture uses data recorded using an unmodified airborne system with ground-based analysis algorithms developed specifically considering existing data usage and system information.

The ground-based system uses some existing capability such as data transfer and storage. Development of all prognostic analysis algorithms will be required. A complete ground-based system enabling prognostic analysis needs to be assembled and tested.

The functional definition of each element in figure 26 is defined in the following:

- LRU—electronic sensor or actuator in circuit prognostic analysis is applied; data sent to FADEC
- Wire Harness—connection for data transfer between LRU and FADEC
- FADEC—contains software defining circuit function for control of LRU and data provided for capture
- Data Transfer—general method of sharing data between two elements noted; could be multiple forms (wire harness, data bus, wireless)
- Data Storage—capture operating data to be subsequently downloaded for analysis on the ground
- Ground Data Storage—long-term data retention to be used in prognostic analysis historical and record keeping

- Maintenance Action—system input for maintaining record of current and historical maintenance activity; identifies component replacement time and related information
- Ground Analysis—compiles algorithms and data to achieve prognostic analysis and directs output to specified recipient

The following sections pertain to how the subject aircraft T2 circuit is relativistic prognostic enabled. It serves as an example of information to consider when defining a relativistic prognostic-enabled system.

3.1.1 Subject Aircraft T2 Circuit Evaluation

Real-time prognostics was the original vision. Several issues became clear in studying implementation of a real-time prognostic analysis system:

- Replacement of electronic system LRUs cannot be accomplished in "real-time." The aircraft must land before any service action can take place.
- Real-time airborne analysis software could be costly to certify. Certification requirements are dependent on the function of the software and associated features. At a minimum, software interfacing with the control system will need to be certified to prove no detrimental operation to the control.
- Current systems implement mitigation that guarantees safe aircraft operation in the event of failure of an electronic LRU. LRU failure can be tolerated without compromising aircraft safety.
- Prognostic analysis provides information to predict and prevent failure. Service action to address LRU failure is identified prior to failure and can be performed to prevent failure.

Real-time prognostic analysis is not cost justified with existing system constraints. The ability to identify impending failure eliminates the reason to perform real-time analysis.

The above process led to the conclusion that a ground-based analysis system was a more effective solution. A ground-based system can provide warning of impending failure and avoid software certification issues when used to assist maintenance for systems with failure mitigation. Data transfer and analysis capability make post-flight analysis achievable shortly after aircraft landing. Add the fact that effective analysis identifies degradation several flights before failure and reduces unexpected maintenance actions.

Prognostic capability for the T2 circuit uses resistance drift identification over time to identify impending LRU failure. Deterministic prognostic analysis is not possible using existing T2 sensing capability. The circuit is designed to provide acceptable temperature measurement over the defined range of sensor operation. A fault is issued if the temperature reading reaches an out-of-range value, but there is no way to determine whether the reading is accurate using only the T2 circuit readings.

The Task 3 simulation established which components of the T2 circuit have high probability failure according to military standard 217 reliability prediction methods. The high probability failure mode components guided assessment of analysis methods for the T2 circuit. Degradation of the T2 circuit electronic components could not be differentiated using only the single sense point in the existing system. The circuit design prevents determination of resistance reading related to temperature using only circuit data. It is not possible to determine the state of health of the T2 circuit as it currently exists.

Task 3 identified sense points that could be useful to calculate accurate LRU degradation. The system simulation model allowed investigation of additional sense points providing improvements to system diagnostic capability. Additional sense points make it possible to isolate circuit components. Capturing data at optimized operating conditions provides data tailored to prognostics.

A table of failure effects at each of the potential sense points provides a means to identify unique failure signatures seen at the sense points (see table 5). The table identifies detection capability at the sense points. Identification of a unique signature value for a failure yields the conclusion that this failure can be accurately diagnosed by the EEC or related electronic hardware. Unique signatures allow identification of each failing LRU. A unique signature provides identification of the specific degrading LRU to point the maintainer to replace the LRU. The simulation and evaluation can be used to prioritize visibility improvements benefiting accurate LRU degradation and, ultimately, failure.

In table 5, the signatures unique to the individual component failures are identified in yellow. The signatures that are unique to the LRU are identified in orange.

The evaluation identified three system improvements that could be added without incurring reliability degradation or T2 signal accuracy. These system improvements provide visibility to accurately identify the appropriate LRU for repair of failure modes of the T2 circuit.

The subject engine T2 sensor circuit operating data were used to develop relative prognostics. T2 sensor circuit design, fault, and operating information is used to define analysis algorithms. T2 circuit readings are recorded during normal operation of the engine.

Using the T2 data from the multiple engines on the aircraft provides a comparison of degradation rates to identify an abnormal engine. Another T0 reading available in the system serves as a reference to determine if the T2 circuit reading is degrading. T0 is an aircraft sensor available to all engines. It serves as a common reference for comparing the individual T2 sensors.

Table 5. Component failure effects for T2 circuit

Bock	Comp type	ID	Failure rate	Failure mode	Task 3 detec-tion mode	Notes concerning failure mode	LRU detection scheme using existing 2 differential measurements	LRU detection scheme using single-ended measurements of 4 points	LRU detection scheme using frequency-to-voltage converter	LRU detection scheme using external isolation verification circuit	LRU detection scheme using new A2D points	What other things could be done to see this failure?
T2PWR	Resistor	R250	8.48E-04	Open circuit	Static	10V excitation is lost	Both diff measurements are 0V	All single-ended measurements are at 0V	No indication of intermittency			
T2PWR	Resistor	R250	8.48E-04	High resistance	Degraded	10V excitation is lower voltage due to more losses.	Current and voltage scale, so this is not seen as a problem unless a windowing limit is exceeded	No benefit				Set expected current and voltage ranges to identify losses or errors with 10V excitation path.
ELCKT	Diode	D1	2.59E-03	Short circuit	Static	VOUTM is pulled to ~0.9V	Difficult to identify (differentially within performance range)	VoutM is at 0.9 (below expected range), but VoutP is within an expected range.				
ELCKT	Diode	D2	2.59E-03	Short circuit	Static	VOUTM is pulled to ~0.9V	Difficult to identify (differentially within performance range)	VoutM is at 0.9 (below expected range), but VoutP is within an expected range.				
ELCKT	Diode	D5	2.59E-03	Short circuit	Static	VOUTM is pulled to ~0.9V	Difficult to identify (differentially within performance range)	VoutM is at 0.9 (below expected range), but VoutP is within an expected range.				
ELCKT	Tranzorb	TZVAR 1	6.24E-02	Drift 50%	Static							
ELCKT	Tranzorb	TZVAR2	6.24E-02	Drift 50%	Static							
T2MON	Resistor	R2	6.26E-04	Open circuit	Static	IOP drifts to ground	Loss of current measurement but not voltage measurement	All points but IOP are in expected ranges				

Note: Yellow indicates unique individual component failures. Orange indicates unique LRU failures.

The T2 data are only measured at one location in the circuit of each engine. The location serves to provide circuit fault detection data and allows assessment of circuit health. A single circuit measurement location provides no ability to isolate degrading LRUs. The T2 temperature value that is recorded to analyze engine performance and used for control is measured using this location.

The T2 sensor is an RTD whose dominant degradation mode is the increasing resistance of the sensor. Change in resistance at a known temperature indicates that the sensor element is degrading. The resistance change for each individual T2 engine sensor is determined by comparison to the T0 common aircraft sensor (T2-T0).

The T2 fault-detection logic provides information indicating when the circuit is nonfunctional. The software is continually checking circuit functionality. The logic does not trigger data storage that would be useful for prognostics.

The wiring harness connecting the T2 sensor to the FADEC is susceptible to degradation in the form of intermittent connection. A faulty connection can trigger fault indication.

It may be possible to determine harness degradation through monitoring occurrence of CIT signal “spikes.” The current subject engine CIT circuit data examined around service events revealed random spikes. If conditions are satisfied, the subject engine only stores CIT data during two snapshot conditions per flight. An increasing frequency of the occurrence of spikes could indicate a harness problem triggering faults instead of the CIT sensor or FADEC.

Harness degradation is difficult to identify during the fault isolation process performed on the ground. Harness degradation explains repeated maintenance action to address fault indication in the same circuit causing replacement of good LRUs.

Compilation of operating data gathered prior to harness replacement maintenance activities could result in identification of a unique fault signature, thereby indicating harness degradation. Algorithms indicating harness degradation could be defined based on data related to confirmed harness-replacement events. Direction could be provided to the maintainer to examine the circuit for harness problems as the primary fault. However, that effort and confirmation of the hypothesis requires effort beyond the scope of this project. There was no faulty wiring harness and no way to simulate one.

Intermittent connection problems start as a short-duration interruption in signal continuity aggravated by vibration. The short duration of interruption is not likely to be seen during the signal-processing cycle, except intermittently when disruption occurs at the moment data are captured. The problem progresses with connector pin contact degrading and disruption in the signal lengthening in duration. The disruption will be recognized more frequently as the signal-disruption length approaches the circuit-data processing interval.

The existing T2 sensor system could be configured to warn of intermittent signal disruption and track increasing occurrence as an indicator of harness connector issues. Definitive detection of connector degradation using current data capture constraints is not possible prior to intermittent disruptions generating fault indication. Fault indication is triggered when signal disruption occurs for one-fifth of the circuit-data capture cycle (1 second). A fault indication will occur before data-capture conditions allow confirmation of the situation.

Intermittent signals will trigger circuit fault annunciation dictating maintenance action. Increasing T2 data spike frequency could provide an indication of connector degradation. An algorithm to tell the maintainer there is an indication of harness connection issues should be investigated. It was not possible to duplicate this failure mode during testing, and additional flight data were not explored.

Wiring faults, such as open or short circuits, are less common, but can occur. An open circuit can manifest itself as a resistance change prior to total failure and wire breakage. This is the failure mechanism that occurs in a harness. A short circuit is likely to present itself as a sudden failure and has limited degradation detection.

The FADEC portion of the T2 sensor circuit contains several features that could indicate T2 circuit degradation. The FADEC features that degrade are resistive elements. Resistor degradation is progressive and distinctive from the random disruption produced by connector degradation. Resistive elements in the T2 circuit differ. Their failure rate will vary. It is not possible to differentiate degradation in the T2 FADEC circuit with a single-circuit sense point.

Prognostic analysis of the T2 circuit of an engine with only one sense point in the circuit can determine the degradation rate of the circuit. Using a reference temperature source, circuit output can be correlated and corrected to a reference condition for comparison over time. RUL cannot be accurately assessed for the component-driving circuit degradation without a method to isolate the degradation location in the circuit. RUL for degradation mechanism of the LRUs may differ. An analysis producing a safe circuit assessment would be based on the lowest life LRU in the circuit to prevent unexpected failure.

Maintenance action based on this type of evaluation provides the warning that a failure is progressing and provides the earliest predicted occurrence possible. The manual fault isolation process cannot identify a degrading LRU, only a failed one. Planning maintenance action to isolate and replace an LRU based on the circuit prediction may result in replacing an LRU with remaining life. Failure of the LRU may not occur at the circuit predicted time.

Additional sense points in the T2 circuit would provide the ability to isolate the degradation source to a specific LRU.

Manual fault isolation is required to determine what LRU to replace when using a single sense point. Maintenance to detect the degrading LRU prior to fault annunciation cannot be accomplished until degradation parameters of the LRUs are defined.

The evaluation of degradation of a T2 sensor circuit on a single engine provides little information by itself. It provides warning of impeding failure. The prediction is the earliest possible occurrence. The degrading LRU cannot be identified. The maintainer does not have information to perform fault isolation until failure has occurred.

The ability to compare circuit degradation among all engines on one aircraft (three or more engines per aircraft) reveals whether the degradation rate coincides with other engines or is unique. A failure rate that tracks with the other engines on the aircraft indicates degradation that is occurring as a result of environmental or operational factors and is “normal.”

Evaluating life of the T2 circuit on a single engine provides warning of degradation. Evaluation yields RUL of the lowest life component in the T2 circuit that has been prognostic enabled. A degrading component driving degradation other than the lowest life component means the predicted RUL will be lower the actual RUL.

An LRU degradation rate that tracks differently from the majority (two or more) of those on the aircraft indicates an anomaly in the circuit/LRU that differs. Accurate RUL prediction can be provided by comparing degradation information to other engines on the aircraft. RUL determination can be made using comparison of the anomalous rate to the normal rate.

Temperature measurement at the cruise condition offers a consistent measurement condition for all engines of the subject aircraft to be compared. The common atmospheric condition and stable engine operating condition of all engines provides minimal variation.

Cruise data are not captured on every flight, but TO data are available from every flight. The TO data introduce more variation than cruise data. A method was developed to assess T2 circuit operation between all engines on a single aircraft.

The T2 circuit produces a temperature value based on circuit voltage and resistance. Known voltage is input into the sensor, and resistance determines the temperature reading. Resistance change (sensor failure mode) cannot be detected when looking only at the circuit output over time. Resistance defines the circuit temperature output.

The circuit temperature reading needs to be compared to a reference temperature to determine if the temperature difference varies over time. The many operating conditions that can exist result in multiple calculations to extract data at a standardized comparison condition.

Calculating the temperature difference between the measured T2 and a temperature reference (T0) yields a result that can be compared to the result for other engines on the aircraft. The temperature difference should be the same for healthy T2 sensors. All engines typically operate synchronously and all in the same ambient environment (T0).

The temperature difference (T2-T0) is at or near the same value for all engines. Anomalous behavior can be recognized if one engine starts to deviate from the “normal” data. The calculation is simplified (T2-T0) for the multiple engines and variation is minimized because they are operating the same.

Adding historical circuit mean time between failure (MTBF) is useful (if available) as input for calculating RUL. An RUL for the engine degrading differently can be determined assuming the circuit MTBF as RUL for the normal engines.

Relative prognostic evaluation as defined uses engine operating data acquired from legacy systems combined with additional data. It requires no modification to the aircraft on-board system. All engines on one aircraft have the same inlet temperature and engine speed at the operating condition. Cruise data for the subject engine on the subject aircraft are captured when specified stability criteria are continually satisfied for 2 minutes.

The only data parameter that varies from point to point is temperature. The resistance difference attributable to temperature change is calculated to align temperature readings between data points to allow comparison at different operating conditions.

T2 data recorded during operation of subject engines revealed intermittent spikes in the T2 signal. It is hypothesized that these intermittent spikes are wiring harness connector faults being captured during T2 data recording. The intermittent spikes can be eliminated to make the data useful for T2 sensor degradation analysis.

Assuming the "spikes" are the result of intermittent connector fault leads to tracking the frequency of occurrence of the spikes. The data acquisition is not frequent enough in legacy systems to make accurate harness degradation RUL predictions. Data disruption will become problematic before accurate RUL predictions can be made using legacy systems.

It is likely that fault annunciation will occur before a prognostic algorithm can positively predict failure. Fault detection is checked every 20 msec and is annunciated after a count of 10 consecutive occurrences. A disruption of 200 msec will trigger fault annunciation. The data-acquisition frequency of 1 second is 5 times longer than the fault time.

A prognostic algorithm can be configured to warn that intermittent faults are detected and suggest harness inspection. The awareness of perceived harness intermittency could point the maintainer toward harness maintenance if fault isolation does not reveal a failed LRU.

The T2 circuits on one aircraft can be accurately compared to determine when one circuit is degrading faster than the others using the temperature-adjusted data and deleting intermittent data spikes. This data can provide "relative" RUL of the degrading system compared to the normal systems on the aircraft.

3.1.2 T2 Circuit Prognostic Simulation Results

Flight data from in-service subject aircraft guided T2 circuit analysis algorithm development. The T2 data for all engines on one aircraft recorded during multiple flights were analyzed. The data chosen were previous to and during multiple T2 circuit faults, resulting in multiple LRU service events.

Studying the data plots revealed several points that led to prognostic analysis algorithm development:

- Temperature data taken at cruise condition has less variation than the TO data.
    - T2 temperature readings are related to T0.
    - Difference between T2 and T0 is consistent for all engines.
    - Comparison of all engines on one aircraft identifies anomalous behavior.

The method of adjustment for different temperature readings between measurements using the coefficient of thermal resistance to normalize sensor data was enacted. It also led to awareness of “intermittent spikes” in temperature readings and developing criteria to reduce their impact on SoH calculations.

A bench test degradation simulation was performed to assess relative prognostics algorithms developed for the T2 circuit. The simulation was conducted using a T2 circuit containing functional LRUs (sensor, wiring, and FADEC) and simulating sensor degradation by varying resistance. DoE was used in formulating a test matrix to account for variation in inlet temperature and sensor resistance.

The test setup simulated variation of temperature and T2 sensor degradation. The measured simulated sensor degradation data were then evaluated using the relative prognostic algorithms to compare to three other healthy sensor simulations. The healthy sensor simulation data accounted for inlet temperature variation but not for degradation.

Table 6 lists the accuracy of relativistic prognostics for various circuits.

Table 6. Accuracy of calculated versus simulated SoH

	Simulated SoH	75%	50%	25%
CJC sensor	Simulated failure point	76	76	76
	Calculated failure point	72.8	70.8	72.8
	Accuracy at SoH	95.79%	93.16%	95.79%
CIT	Simulated failure point	126	126	126
	Calculated failure point	116.2	125.6	125.4
	Accuracy at SoH	92.22%	99.68%	99.52%
Speed sensor	Simulated failure point	226.2	226.2	226.2
	Calculated failure point	237.1	218.8	228.2
	Accuracy at SoH	95.40%	103.38%	99.12%
CVG LVDT	Simulated failure point	89	89	89
	Calculated failure point	107.8	93.5	92.9
	Accuracy at SoH	82.56%	95.19%	95.80%

3.1.3 T2 Circuit Prognostic System Requirements

The use of relativistic prognostic analysis is possible using data available from the existing airborne system on the subject engine for certain LRU circuits. The objective of performing prognostic analysis for an existing aircraft application must satisfy the requirement of using data captured by the system to perform analysis. The ability to perform prognostic analysis without modification to the existing airborne system is determined by the data available for analysis.

The subject-engine T2 circuit data are captured during operation of each flight when specific stability criteria are satisfied. The legacy system requirements originally were to capture operating data for use in evaluation of engine performance. The prognostic objectives in a legacy system in which changes are difficult to implement are to identify information that can be useful in predicting electronics degradation. Analysis algorithms that consider available data and system operating constraints must be developed to provide definition of circuit degradation. The details of algorithm development are specific to each system and require system knowledge to design effective algorithms.

Data currently captured by the subject-engine system for the T2 circuit consist of snapshots taken during TO and cruise when specific conditions are met. Cruise data are not acquired for every flight. The control system incorporates multiple features to compensate for variation in T2 conditions that make it impractical to determine accuracy of the T2 measurement for an individual engine circuit.

Comparison of change of T2 data readings for engines on the same aircraft provides the ability to determine when a T2 sensor circuit is degrading at an accelerated rate. Degradation knowledge provides insight of an impending "failure." Fusing prognostic information with circuit failure history and individual part service history can provide an estimated RUL.

Data acquisition requirements are established for a legacy aircraft, and prognostic system requirements and capabilities are limited by that constraint. The subject engine T2 circuit analysis algorithms were developed through evaluation of available captured data and discovery of useful relationships allowing an understanding circuit operation.

Algorithm development uses the following facts:

- Operating data are captured during aircraft flight.
- The CIT sensor in each engine should measure the same delta compared to the aircraft-mounted ambient air temperature sensor that is recorded. The measurement of T2-T0 should be equal for all engines on one engine captured at the same condition. Using this measurement eliminates the need to compensate for differing T0s.
- Determination of differences in this temperature value when compared to other engines on the aircraft. Difference of 2.5°C from other engines indicates degradation initiation. Temperature difference of 25°C is declared failed.
- Noise is assumed to be caused by wiring faults resulting in sporadic "spikes" in recorded temperature followed by the subsequent reading returning to normal. These conditions were discarded for the prognostic analysis.
- Tracking the temperature difference condition provides a degradation rate and estimated time to failure (RUL) compared to normally degrading T2 circuits on other engines on the aircraft.

This information is used to derive various algorithms to assess change in the T2 circuit and estimate RUL.

The following is an assessment of the ability of other subject engine circuits studied in Task 5 to be prognostic enabled using current legacy data acquired:

- Fuel start solenoid—no data recorded in legacy applications
- CJC sensor—no data recorded in legacy applications

- Speed sensor—sensor output voltage (OV) allowing assessment of degradation is not recorded
- CVG LVDT—no data recorded in legacy applications
- CVG torque motor—no data recorded in legacy applications

The T2 circuit is the only subject engine circuit of those evaluated with recorded data that can be used to perform ground-based analysis.

3.2 MODIFICATION OF EXISTING SYSTEMS TO ENABLE PROGNOSTICS

To acquire data that enable prognostic capability requires modification to existing systems. Performing effective prognostic analysis requires data captured at conditions for use in deterministic prognostic analysis. Information should be gathered at consistent operating conditions to decrease variation to facilitate accurate prognostic analysis.

Data-acquisition conditions defined to facilitate prognostic analysis require software modification. Additional data storage may be required if there is not enough spare storage space for additional data.

Prognostic enabling does not change any features currently existing in legacy systems. Prognostic capability adds features that provide data aimed at moving electronic LRU failures from unexpected to predicted.

Adding prognostic features to existing systems can affect certification. The certification impact of software modification or adding sensing features to a circuit is determined by the DAL of the system that is modified.

Fault-detection data acquisition enables circuit analysis to annunciate circuit failure. The same data-acquisition features can be used to acquire additional information useful for circuit prognostics. The data-acquisition features used for fault detection can be prognostic enabled to acquire data at specific conditions suited to prognostic analysis. This requires a software change defining the conditions to acquire data and defining data-storage specifications.

The addition of data-sensing features in LRUs allows degradation analysis of the LRU along with isolation of health. LRU modification is required to add data sense points. Data detection also requires software to manage acquisition. System memory is required to accommodate additional data acquisition.

Figure 27 defines the electronic system architecture showing the aircraft system configured to capture prognostic data for use in circuit or LRU analysis. The system will require a software change at a minimum to collect data at conditions for prognostic analysis. The prognostic requirements will determine whether hardware modifications are necessary to achieve the desired prognostic capability.

The ground-based system contains the same features as figure 26 for existing systems. The same architecture and components are necessary. The analysis algorithms will differ to use airborne data captured specifically to enable comprehensive prognostic analysis.

The T2 circuit simulation provided the ability to look into the T2 circuit using additional sense points to detect and identify the LRU in a degrading or failed circuit. This solution provides a method to satisfy the diagnostic aspect of the project and point to predict a degrading LRU prior to failure.

Enabling prognostic analysis requires knowledge of the normal and failed circuit operation. To understand the health of the LRUs in the circuit prior to failure, the expected output of the circuit should be known to allow its determination if the circuit is operating accurately. Identification of anomalous operation initiates further analysis to determine LRU degradation, thereby causing the change to expected output.

A method must be identified to determine the accuracy of the T2 circuit output to detect unexpected circuit behavior triggering prognostic analysis. Several methods have been postulated and must be evaluated.

Airborne system data in addition to the T2 circuit provide information to understand the effectiveness of the electrical reading produced by the T2 circuit. Multiple data sources provide checks to determine overall engine-system operation and compare the T2 circuit value against other sensor values. The comparison of the expected T2 value to the actual T2 circuit value provides a deviation that is used to detect changes in circuit operation. If the circuit shows a trend of increasing deviation from the expected output over time, an FFP signature can be initiated. ARULE and ATTF algorithms can then be applied to calculate RUL and SoH.

Sources of expected temperature values include other engine sensors and synthesized temperatures from the EEC. Airframe temperatures and other engines provide additional sources of temperature data for comparison purposes. The thermodynamic engine cycle model offers a source of comparison data using many of the data sources noted as input to converge on a steady-state operating solution.

Data scatter can be reduced by defining data-acquisition conditions that minimize input data variation. Engine startup offers an excellent condition to gather data for systems in which degradation can be detected before the component is fully operational. The engine uses a defined start process each time. Measuring T2 circuit data during engine start results in T0 being the only variable to consider in health assessment.

Data-acquisition variation must be accounted for in prognostic algorithm development. Data variation should be adjusted to create data that can be used in degradation detection at a standard condition. Lack of data scatter reduction results in uncertainty.

Another possibility for acquiring data for use in prognostics analysis is to perform a system self-test. The idea of a self-test is not practical to evaluate as part of the simulation. Self-tests are a standard feature in electronic systems and implementation impact, and its effectiveness is well known.

The functional definition of each element in figure 27 is defined in the following:

- LRU—electronic sensor or actuator in circuit prognostic analysis is applied. Data sent to FADEC. A sensor added to the LRU provides data concerning health and facilitates electronic LRU isolation.
- Wire Harness—connection for data transfer between LRU and FADEC.
- FADEC—contains software defining circuit function for control of LRU and data provided for capture. Software modification is required to acquire prognostic-enabling data.
- Data Transfer—general method of sharing data between two elements noted. Could be multiple forms (wire harness, data bus, wireless).
- Data Storage—capture operating data to be subsequently downloaded for analysis on ground. Additional data storage may be required to allow capture of information for prognostics.
- Ground Data Storage—long-term data retention to be used in prognostic analysis, historical, and record keeping.
- Maintenance Action—system input for maintaining record of current and historical maintenance activity. Identifies component replacement time and related information.
- Ground Analysis—compiles algorithms and data to achieve prognostic analysis and directs output to specified recipient.

The following subsections pertain to how the subject engine torque motor can be prognostic enabled. This serves as an example of modification of a legacy system when defining a prognostic-enabled system.

3.2.1 System Modification Example Detail, Subject Engine Torque Motor

Fault detection provides indication of failure. The subject engine fault detection identifies failure of a circuit. Fault annunciation is the only information recorded. No operating data are captured, so fault detection does not provide operating data concerning the circuit. The maintainer must perform fault isolation to identify the failed LRU in the faulted circuit. Software modification to store operating data associated with fault-event occurrence could provide data for use in prognostic circuit analysis.

Circuit fault detection information provides circuit requirements defining failure. This information can be used in defining analysis algorithm limits to assess the circuit. Declared onset of degradation must be defined to evaluate the circuit SoH.

Software modification should be made to capture data at conditions providing information conducive to circuit/LRU analysis. Data acquisition at existing circuit sense points can prognostic enable the circuit. Additional sense points provide the ability to assess the location of anomalous circuit behavior.

Existing system circuit sense points used in conjunction with sense points added to other circuit LRUs provide the ability to isolate degradation of the circuit to specific LRUs. Availability of data from multiple sense points provides the ability to detect degradation of the circuit in addition to the individual LRUs.

The addition of sense points in the CVG torque motor allows for the gathering of operating data specific to the motor. In conjunction with the existing FADEC circuit sensors, it is possible to evaluate degradation of the FADEC and the CVG torque motor independently. Software needs to be added to the system that identifies when to acquire data from the CVG torque motor and FADEC sense points.

The ability to record prognostic data at LRU sensing locations requires optimized conditions to acquire data specifically for prognostic analysis. The data-acquisition conditions for the torque motor are as follows:

- Detect (sense) the start of the positioning command.
- Wait approximately one-fourth of the nominal time for the repositioning of the vanes.
- Measure current at approximately one-half of the nominal time for repositioning of the vanes.
- Record the average value of the current measurements.

The data-acquisition conditions were defined based on operation and characteristics of the torque motor. Figure 29 shows the high current at the beginning and end of actuation with the half-stroke load being what is used in prognostics.

Modification of LRUs for prognostic enablement brings additional data-storage needs. Software changes are required to capture data at the proper time. Airborne storage capacity needs to be added to capture the LRU data.

Airborne system software and data-storage modifications provide data to analyze specific LRU health. Ground-based data-analysis capability uses the data to enable determination of LRU health.

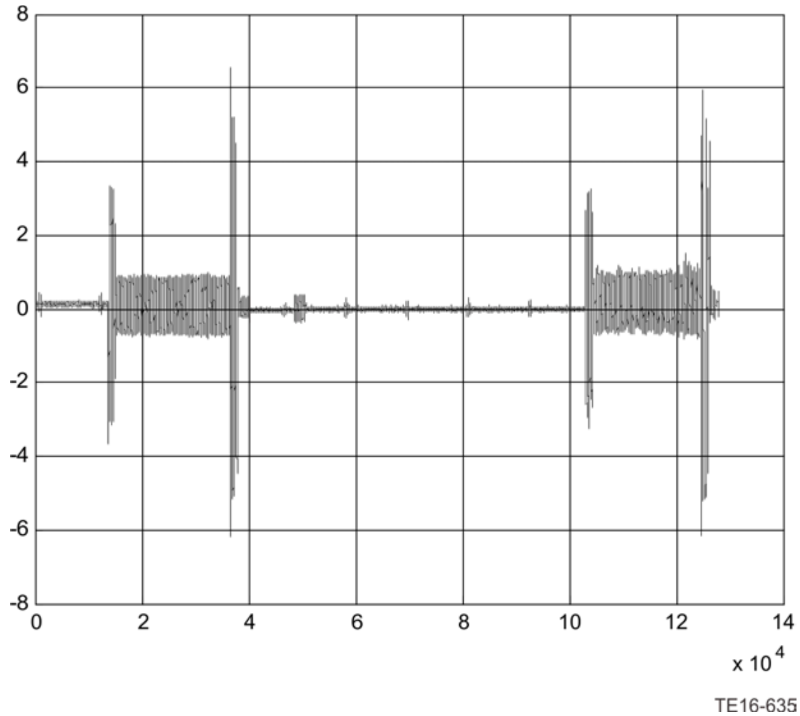

Figure 29. Example of non-uniform amplitude of motor current during positioning

Ground-based algorithm development should consider data-acquisition capabilities in defining analysis. Several factors influence analytical software definition. Analysis objectives must align with data-acquisition design. Design intent to detect individual LRU degradation requires the analysis to be defined to assess data at the time and point they are detected.

Data analysis compares detected torque motor current to commanded current. Degradation is indicated when operating current is higher than scheduled current. Limits used in algorithm development are the following:

- Nominal current is 20 mA
- Degradation starts when operating current exceeds 5% (21 mA)
- Functional failure occurs when current exceeds 41.5 mA
- NM = 6%

FD is defined as = where I_0 = 10 mA

NM =

FV is defined as =

FFP is defined as =

FFS is defined as = where FL = 50%

The FFS algorithm calculates a number against a 100% metric defining SoH. At 100%, the LRU is failed and SoH is 0.

Analysis algorithms are defined to process data acquired from specific LRUs. Algorithms are developed based on data specific to an LRU. The data used with the algorithms must be from the correct LRU.

3.2.2 CVG Torque Motor Prognostic Simulation Results

Deterministic prognostic algorithms were developed and tested using data gathered from bench testing functional LRUs to simulate degradation. Testing was conducted using a DoE to address specific conditions for each LRU tested. The test circuit incorporated variable resistance to simulate degradation and temperature changes independently.

Accuracy is determined as the failure point predicted by the algorithm at the simulated SoH divided by the simulated failure point.

Table 7 lists the accuracy of deterministic prognostics.

Table 7. Accuracy of calculated vs. simulated SoH

	Simulated State of Health	75%	50%	25%
Fuel Start Solenoid	Simulated failure point	189	189	189
	Calculated failure point	191.5	189.7	189.3
	Accuracy at SoH	98.69%	99.63%	99.84%
CVG Torque Motor	Simulated failure point	73.5	73.5	73.5
	Calculated failure point	76.8	76.4	75.6
	Accuracy at SoH	95.70%	96.20%	97.22%

Ground-based prognostic analysis is effective for failure modes with a "fuse" length of multiple flights to predict degradation prior to failure. Failure progression rates must be considered in defining prognostic systems. Most failure modes progress at a rate slow enough to allow for ground-based analysis. Slow failure progressions allow notification and subsequent corrective action before failure occurs.

Failures that progress quickly are not good candidates for ground-based analysis. Degradation that occurs in less than a single flight needs to be addressed by a different means because maintenance action cannot be performed prior to failure. Rapid failure progression (less than one flight) requires safety considerations if the system is expected to compensate for failure. Prognostic analysis is not effective for failures with a short prognostic window.

3.2.3 CVG Torque Motor Prognostic System Requirements

Modification of the CVG torque motor system to enable prognostic analysis requires data in addition to what is currently available from the subject engine airborne system. The objective of capturing data for prognostic analysis use is to define conditions that provide insight into degradation.

The ability to perform prognostic analysis is determined by many factors. The CVG torque motor failure modes identify data and conditions to be captured in the onboard system during operation.

The onboard system requires the ability to sense data at an LRU location that is able to provide information pertinent to failure. Software is required for defining the operating condition to acquire data at the sense point(s). Software definition also needs to include information on data storage to facilitate the data download process.

Information used to define airborne system-data-acquisition changes that enable prognostic analysis includes:

- Typical failure results in increasing current to effect required operation. Install a sense point in the torque motor to acquire current readings when commanded.
- Torque motor operating characteristics lead to current measurement being recorded at the middle point between initiation and completion of actuation. Data-acquisition software defined to detect the start of actuation and commanded duration (both defined and available from the control) divided by two as the condition to capture the torque motor current reading and comparing it to demand. Software also needs to define storage criteria for captured data. Data could be captured during any execution during operation.

Data download from the airborne data-acquisition system to the ground-based analysis system can take multiple forms. How it gets to the ground for analysis is less important than when it gets to the ground. Data-transfer requirements are dependent on the time from detection to failure. The download interval must be shorter than the time from detection to failure to ensure detection is annunciated prior to failure. The maximum download interval must be less than the time from detection to failure, preferably less than half that duration, to allow prediction and notification for the performance of maintenance and the prevention of failure.

Prognostic analysis requires three degraded readings to establish an RUL estimate. Data acquisition for the torque motor can occur multiple times per flight because there are no constraints on the condition for data capture.

There currently are no data for this circuit to base download frequency definition. Post-flight data download would be sensible until the failure mechanism degradation rate is determined to establish a maximum acceptable data download limit. Increased download and analysis frequency is beneficial to improving awareness of degradation and maximum time for maintenance response.

Fast degradation rate failures require prompt action. Analysis frequency can assist with maintenance planning and minimize operational disruption. Frequent data download and analysis increase the time notification at degradation onset and provide more options to perform maintenance activity.

Analysis algorithms are developed using torque motor data that enable assessment of health state. Algorithm development incorporates the data acquisition considerations stated above and design features to determine torque motor health state.

- Analysis development considerations:

  - Demanded and actual current are recorded for subsequent comparison.
  - Difference between demanded and actual current is tracked over time.
  - Degradation is confirmed when the difference reaches 2.5°C difference between the temperature value for the CIT sensor and the average temperature values for other CIT sensors on the aircraft.
  - RUL is determined based on failure at 25°C or a greater difference between the temperature value for the CIT sensor and the average temperature values for other CIT sensors on the same aircraft.

Capturing data during the engine start cycle produces a consistent operating condition for the torque motor with temperature being the only variable. Comparing torque motor data taken during engine start allows for identification of operating response changes indicating degradation of torque motor health.

3.2.4 Additional LRU Circuit Prognostic System Requirements

The following is an assessment of the ability of other subject engine circuits studied in Task 5 to be prognostic enabled by modifying the system to acquire data and perform analysis:

3.2.4.1 Fuel Start Solenoid

- Hardware Modification—Circuit operational data need to be captured for use in ground-based analysis algorithms. Study of the solenoid reveals capability is required to measure voltage and current at the solenoid to determine SoH. The sense point to acquire data can be placed at several locations and influences algorithm complexity. The FADEC has circuit-sensing capability for use in fault identification that can assist prognostic analysis. Use of this sense point allows assessment of circuit effects that include wiring harness and FADEC. Analysis algorithms using data acquired at this point must be configured to account for variation from all the circuit components and to factor in effects for multiple components. Solenoid modification to insert a sense point at the solenoid acquires data strictly indicating solenoid health. Analysis algorithms for a sense point in the solenoid can be simplified to address solenoid issues only.
- Airborne Software Modification—Software must be modified to acquire T0, voltage, and current to understand solenoid health. A clock is required to determine time since engine shutdown and determine if data satisfy the shutdown criteria. Data need to be available from the FADEC to determine engine start and shutdown rpm or operating mode. Deterministic prognostic methods to analyze the solenoid require data capture from the individual engine being evaluated. Software needs to define the operating condition to record data. The condition is defined to satisfy the operating condition for which the analysis algorithm is designed.

- Ground-Based Analysis Algorithm Development—Evaluation of solenoid use and failure determined data acquisition should occur during engine start. A requirement to acquire data after a minimum shutdown time ensures the solenoid is at T0 to minimize data variation. The fuel start solenoid is cycled once per flight. The failure mechanism is gradual. Shutdown time can affect the number of recorded data points between good data points. The failure rate and the frequency of acquired data points determine the adequacy of data acquisition to provide failure prediction. The minimum shutdown time may have to be reduced and data variation factors increased if the minimum shutdown time is infrequently satisfied.
- Deterministic analysis algorithms use T0 to calculate temperature effects to normalize solenoid operation to a constant condition for comparison to previous data. Change in solenoid resistance indicating an increase or decrease in resistance triggers degradation tracking and RUL calculation degradation. RUL calculation is activated when degradation is confirmed.

3.2.4.2 CJC Sensor

- Hardware Modification—No hardware modification is required to assess T0 of the CJC in the FADEC. The CJC is used to compensate for electronic equipment temperature in the FADEC. The temperature is currently sensed but not recorded.
- Airborne Software Modification—Software must be defined to record CJC temperature when the engine starts. A minimum time since shutdown ensures data are taken at T0 conditions. This requires clock information be available to determine the time since shutdown. FADEC data are required to determine state (shutdown or start) or engine rpm (to determine state). T0 recording could be helpful to allow temperature adjustment of the CJC reading to a standard temperature.
- Ground-Based Analysis Algorithm Development—Relativistic prognostic analysis is used because the FADEC contains several temperature compensation tools that affect the recorded temperature. It is not possible to determine whether the recorded temperature is the CJC or another source. Relativistic analysis comparing the other CJCs on the aircraft should result in minimal variation because all sensors should be at ambient condition. Software must compare CJC temperature at the start of operation for all engines on an aircraft.
- Comparison of all CJC sensors on one aircraft allows detection of anomalous behavior of a CJC. Comparison can be made several ways or with a combination of multiple comparison methods. The basic comparison mechanism is to calculate a difference between the sensors and a common reference and determine that difference. The minimum shutdown time requirement allows CJC temperature to consistently approach ambient. The temperature comparison could be done by comparison to the raw measured value of each engine sensor. Change in resistance indicating an increase or decrease triggers degradation tracking and RUL calculation. RUL calculation is activated when degradation is confirmed.

3.2.4.3 Speed Sensor

- Hardware Modification—The speed sensor circuit does not require modification to assess the sensor circuit OV. The sensor circuit triggers a speed pulse when voltage switches from positive to negative. Known maximum OV is not required for correct sensor operation. Maximum OV change is beneficial to understanding sensor degradation of the coil windings. No hardware modification is required because voltage is already monitored to identify a shift from positive to negative. On-board software requires modification to record the maximum coil voltage at a specific condition.

- The existing speed sensor circuit voltage measurement is in the FADEC. The captured data value includes voltage effects caused by wiring harness anomalies. Any analysis algorithms developed using the existing sense point must factor in variation and uncertainty associated with having the wire harness anomalies in the data stream.
- The speed sensor could be modified to provide the OV at the sensor. This eliminates the need to consider harness effects in the data.
- Airborne Software Modification—Speed sensor degradation cannot be detected by evaluating currently recoded sensor signal data. The only data currently recorded is the zero crossing point.
- Degradation can be predicted using evaluation of the sensor-signal maximum OV. The speed sensor circuit does not require modification because the sensor circuit voltage is monitored to detect the zero crossing (voltage = 0). Modification of the LRU would allow for recording of the sensor signal voltage at the sensor, thereby reducing harness impact on the data. Locating a sense point in the LRU allows isolation of the sensor in the circuit. Data measurement in the FADEC includes wiring anomalies in the data stream. Airborne data-acquisition software must capture the peak sensor voltage produced by the sensor coil. Data are to be acquired during engine startup when each engine reaches a fixed idle speed. T0 must also be recorded to allow temperature compensation.
- Ground-Based Analysis Algorithm Development—Software must assess the specific sensor unit data against the voltage when the unit was initially installed to identify degradation. The measured voltage is adjusted using the measured T0 to calculate voltage at the reference temperature.

3.2.4.4 CVG LVDT

- Hardware Modification—The CVG LVDT circuit must be modified to acquire the transducer coil voltage. A sense point added to the LVDT coil allows isolation of the LVDT specific data. The existing circuit has sensing capability to perform fault identification that, if recorded, could enable circuit prognostics.
- Airborne Software Modification—CVG LVDT degradation can be detected by evaluating coil OV. Software modification to capture coil OV enables prognostic analysis. Specific data-acquisition conditions can be defined to capture data during engine start to reduce variation. Data capture during normal operation can be used but introduces additional data variability and requires additional analysis software to compensate for variation.
- Additional parameters must be recorded concurrently with the LVDT voltage. T0 and commanded voltage should also be recorded for use during analysis.
- Ground-Based Analysis Algorithm Development—Software must assess the specific LVDT data against what is commanded. Relativistic prognostic analysis can be used when operating data are acquired. Deterministic prognostic analysis can be performed

when engine start data have been recorded. Deterministic analysis also requires information about initial installation voltage to identify degradation.

3.2.4.5 CIT Sensor

T2 sensor relativistic prognostic details are discussed in section 3.1.1.

3.2.4.6 CVG Torque Motor

CVG LVDT prognostic details are discussed in section 3.2.1.

4. ESTIMATING PROGNOSTICS IMPLEMENTATION COST

Task 5 demonstrated prognostic algorithm analysis functions using bench test data simulating degradation of five LRUs. Algorithm development involved steps to define multiple (approximately 9 per LRU) algorithms for testing. The information developed in Task 5 forms the basis to define scale factors for use in defining future prognostic systems.

The analysis methods simulated in Task 5 used a legacy engine control circuit incorporating an individual sensor or actuator to perform simulation of LRU degradation. The simulation circuit consisted of a sensor or actuator, a wiring harness, and a FADEC. The circuit sensing location for the bench test was located at the FADEC electrical connector. Test instrumentation was set up to monitor operation and read data at that location. This setup facilitated insertion of resistance values to simulate LRU degradation and temperature variation.

The positive results verifying the prognostic algorithms against the simulated degradation provided confidence in an understanding of what is required to create a prognostic system and identify how to implement electronic prognostics.

To prognostic enable an individual sensor or actuator LRU or circuit requires data storage and analysis capability specifically related to the LRU or circuit. Data sense points in LRUs and circuits provide data to analyze LRU health state without having to account for additional component health factors affecting analysis.

Prognostic health assessment capability is limited using the current subject engine circuits because of having only a single data sense point in a circuit. Capturing data isolating only LRU health parameters captured at specific conditions to enable analysis algorithms formulated to detect the LRU health provides more comprehensive LRU assessment than using currently available data.

Use of existing data sense points in the FADEC allows assessment of relative circuit health to identify a circuit that is degrading differently from others on the aircraft. This relativistic prognostic method can provide assessment of circuit degradation compared to other engines using existing system data.

Software modifications that trigger data capture at optimal prognostic conditions are the minimum change to effectively enable prognostic analysis. Existing data sense points can be used in conjunction with system software modification to enable data capture. Software needs to define data storage and acquisition conditions for capturing prognostic analysis data.

Optimum prognostic effect and benefit is enabled when LRUs are evaluated using data acquired consistent with important operating characteristics. LRU operational awareness makes it possible to identify data useful in analysis. Additional data storage hardware may be required to provide needed space.

It is difficult to estimate the cost of all added features to enable system prognostics without defining required system function. Varying system capability affects the cost of implementing prognostics. Cost is approximated for individual prognostic-enabling features. Total system cost is dependent on system definition.

Certification of a system is the largest development expense. Certification cost of adding prognostic features to a legacy system is a function of system heritage. Definition of added system features depends on the desired prognostic ability. Certification cost for modification of the legacy system is dependent on the modifications.

Below is an estimate of incremental cost to add a single prognostic feature to enable a Level A qualified airborne system:

- Additional circuit sense point in LRU $5/unit ($15,000 development cost)
- Additional data storage and processing hardware $20/unit ($10,000 development cost)
- Additional data acquisition software development $20,000/one-time cost

The cost of adding prognostic enablement of one electronic feature for a Level A qualified airborne system is approximately $45,000 in development cost. Individual cost of additional features will be reduced because of project efficiency and volume.

The estimated airborne software cost includes writing and verifying the software and will vary relating to complexity.

Certification represents the largest cost in implementing electronic prognostics. Using existing airborne system data requires no expenditure. Certifying software modification enabling prognostic data acquisition could cost as little as $100,000. Certification cost relating to prognostic features in a new product system is estimated at ~$1,000,000 total cost.

Ground-based software developed to analyze acquired airborne data needs to be considered. The cost of analysis software development will vary depending on the complexity of the analysis. The LRU assessment performed in Task 5 utilized approximately 9 algorithms to analyze the data for each LRU.

An estimated 200 hours per LRU is used as an average for writing and testing ground-based prognostic software once all pertinent factors are defined and available. Recurring costs will be incurred for data analysis once the analysis software is deployed for use.

A cost of $5 is estimated for each incident of ground-based analysis of airborne data. The actual cost will vary depending on analysis frequency and subsequent use of results.

The ground-based analysis software is not subject to certification when using legacy system data. It has no effect on airborne systems that have safety-critical failure prevention features built into their design. Electronic prognostics used in safety-critical systems would need to be certified.

4.1 CONSIDERATIONS IN IMPLEMENTING PROGNOSTICS

Electronic systems using prognostics are designed to detect known failure modes. Degradation, and ultimately failure, may not be detected in the case of an unknown failure mode. The possibility of not detecting previously unknown failure modes creates an issue for relying on prognostic evaluation of safety-critical systems.

Conditions may arise that are not anticipated. Prognostic analysis could be beneficial in identifying general circuit operational degradation not related to specific failure modes. Analysis algorithms designed to assess degradation of circuit function could identify circuit anomalies similar to fault software. The design of data acquisition and algorithms to assess and predict system-level operation provides confirmation for anticipated conditions and provides potential warning of problems that do not have LRU failure detection identified. A degrading circuit could be identified without needing data to isolate a specific faulty LRU.

Data are the first part of enabling prognostic analysis. Data definition requires details identifying parameters to be acquired and operating conditions to capture them. This definition comes from various aspects of the system design and failure modes to be detected.

Knowledge of failure modes provides information concerning data to be acquired. Known failure modes guide selection of parameters captured for health analysis. These parameters must be captured at an appropriate condition during operation to be useful in health analysis algorithms.

Failure mode knowledge provides parameter information, expected or historical failure rates, and noise source input for analysis algorithm development. Algorithm development is focused on how to make operating data represent a consistent analysis condition.

Acquisition during a consistent operating condition minimizes data correction to conduct data comparison at a “standardized” condition. Variation in analysis condition must be accounted for by correcting acquired data to a standard condition allowing comparison of operation at the same condition. Variation effect on operating should be quantified allowing data adjustment to a standard condition. Acquired data that cannot be standardized or corrected must be accounted for as unaccounted variation.

Failure rate determines the feasibility of detection using ground-based analysis. Failure that occurs during one flight cycle will not be detected using ground-based post-flight analysis; therefore, failure cannot be predicted and prevented. An alternative to ground-based post-flight prognostic analysis is necessary.

Ground-based prognostic analysis is effective in detecting degradation occurring over multiple flights or data acquisition cycles. Data are available to the analysis system post-flight and maintenance action can be identified.

The maximum data-acquisition and analysis-interval period is determined based on the knowledge of the most rapid known failure rate. The longest interval between data acquisition and analysis that allows for identification of degradation is half the period of most rapid-failure conditions. This interval guarantees at least one data point and identification of degradation prior to failure, but it cannot estimate failure time with only one data point.

The prognostic algorithms require three data points following onset of degradation to predict RUL. Data acquired once per flight will require three flights before an RUL prediction can be determined. If only downloaded post-flight, data acquired more frequently (multiple points per flight) may not be transferred to the ground for analysis to initiate maintenance action for rapidly degrading circuits.

On-board data acquisition frequency requires consideration of failure rate, operating conditions, maintenance action, and possibly more. Multiple data-acquisition points per flight allow rapid data accumulation and subsequent estimate of RUL when analyzed. This would make sense for rapidly evolving failures. Variation in data-acquisition conditions may lead to increased uncertainty in calculating RUL, at which point the failure progression rate is a factor. A rapidly progressing failure would not be a good candidate for data acquisition once per flight. Data should be recorded at a condition that occurs multiple times per flight to be able to establish failure rate and predict failure, thereby ensuring adequate warning and time for maintenance action.

The promptness of data processing is also a factor in implementing identified maintenance action. Immediate data download and analysis in the ground-based system allows for near-term maintenance should the predicted RUL dictate that action is required.

Delayed data processing lengthens the window for prediction and potential maintenance action. Promptness of data download, analysis, and failure rate should be factored into system design and considered in defining processes.

Data download frequency also impacts response to identified action. The most sensible scenario is downloading upon completion of a flight. Less frequent data download lengthens identification and potential corrective action.

More frequent data acquisition, download, and analysis could allow for increased prediction accuracy. And increased prediction accuracy could facilitate increasing service intervals, thereby extending component usage and holding off replacement until closer to failure.

End-to-end system design must be considered to create the ability to respond to anticipated conditions.

A “smart” analysis tool could monitor and adjust the algorithms as data are acquired over time. The required method was not explored in this project and adds a level of complexity to algorithm development and certification. Creation of smart, self-learning prognostic tools may be a future endeavor when prognostic methods become accepted as valid.

4.2 DEFINITION OF INFORMATION TO ENABLE PROGNOSTICS

Enabling prognostic analysis methods requires an understanding of the system and components to be prognostic enabled. The level of prognosis (LRU or system) needs to be determined and built into the analysis tools and methods to ensure expected results. Data acquisition must support analysis to produce desired results.

Expected degradation mode and resultant failure determines data analysis methods. Analysis methods define the input data required from the airborne system. Specific parameters and operating conditions for data acquisition enable data-analysis success.

An understanding of failure mechanisms can be gained by analysis of historic failures in existing systems. Examination of failed LRUs should identify root cause and lead to methods for detecting degradation prior to failure. Parameters important to failure detection will direct the location of sense points.

Reliability estimations can provide guidance when developing analysis algorithms for new systems. Circuit-design assessment using reliability data can be used to identify algorithm needs.

Recorded parameter details are used in defining software to acquire data useful for analysis. Recorded parameter operating conditions must detect degradation and minimize variation. Failure detection is possible only at specific conditions, which dictate data acquisition timing.

The subject engine CVG LVDT evaluated in this project is an example of a situation in which a specific condition is required to facilitate effective data analysis. Measuring current at the transducer-commanded midstroke position is the most consistent operating condition to capture data for health assessment. Operating temperature variation is not a factor in current measurement.

Flexible data-acquisition timing allows for the selection of data to maximize the amount available for use in analysis. Flexibility of recording conditions can delete data post-flight that are not beneficial in calculation. Analysis algorithms can be defined to “adjust” data for analysis.

A consistent operating condition for data acquisition ensures circuits or LRUs operating at similar conditions for each recorded data point. This minimizes data correction (if any) needed to make a degradation assessment.

Several of the subject-engine circuits addressed in this project are proposed to use engine start data if a minimum non-operational time has been reached. Data gathered at this condition need adjustment to account only for different temperature readings.

An unknown degradation mode may not be detected when the analysis method and the acquired data monitored do not detect specific failure symptoms. Analysis algorithms can be designed to identify circuit degradation and warn of LRU failure modes.

Algorithms designed to identify circuit-level operational anomalies may provide awareness of circuit changes not identified by those designed for specific LRU failure modes. Analysis is defined to check circuit functional parameters to determine operational efficacy of the LRU circuit. It confirms the degradation identified using the specific degradation algorithm and identifies circuit degradation not seen by an algorithm designed to identify a specific failure mode.

The algorithms needed to evaluate circuit response and track degradation over time require different information than algorithms for performing prognosis of health and providing RUL of electronic LRUs. Analysis algorithms may be tailored to consider the data-acquisition location dependent on the component design and expected failure mode.

Algorithms designed to assess the circuit health create redundant analysis tools for use to detect degradation in safety-critical circuits. The detection methods should be targeted to evaluate expected circuit output. The circuit output is important to determining circuit functional safety, not specific LRU degradation.

The data-acquisition location is a factor in identifying circuit degradation and helps isolate faulty circuit components. The system-analysis software can be similar for assessment of circuit performance. Location of data acquisition is helpful in analyzing where circuit degradation is occurring.

Enabling system prognostics for circuits having safety implications requires data assessment of the circuit output to determine healthy and degraded operation. Detecting health data at multiple locations in the system allows for isolation of component degradation in the system. Specific data-acquisition locations allows for specific LRU degradation identification and replacement of the correct component using diagnostic algorithms.

LRUs using data-acquisition capability to isolate information from an LRU permit specific analysis targeted to identify degradation of the LRU. Analysis algorithms formulated to use the LRU data evaluate the LRU specifically to identify degradation and provide RUL relating to the LRU.

4.3 PROGNOSTIC METHODS TO DETERMINE STATE OF HEALTH

Two different prognostic methods were identified in Task 5. The deterministic method compares operating data of a system or LRU to itself and design criteria to determine health. The relativistic prognostic method compares data from multiple components of the same type operating in the same environment at the same conditions to identify one that is degrading at a different rate than the others.

The deterministic method uses system or LRU data acquired at specific operating conditions as input data for analysis algorithms. Data are compared to known operational information to characterize detected degradation. Characterization data used in algorithms can be from design, test, or service information. Analysis quantifies variation from expected operation and estimates SoH and RUL.

Parameters acquired for use in performing prognostic analysis are identified using information concerning LRU or circuit design and operation. Data that are important to determining health are acquired at the required operating condition and location of the LRU or circuit. Information on failure modes or degradation mechanism defines the condition when parameters are recorded.

Analysis algorithms are defined to use acquired data to determine circuit or LRU health. Algorithms process data to adjust for parameter variation, and input data are also smoothed to minimize fluctuation caused by data scatter. Results are compared to expected characteristics to determine degradation rate and estimate RUL.

The relativistic method uses data acquired from the evaluated circuit or LRU on multiple engines on the same aircraft. Variation is minimized by comparison of data at the same operating condition. The comparison identifies degradation differences between engines and allows understanding of how the like components' health compares to the others in the same environment.

LRU or circuit operational data are acquired on the aircraft to enable health detection. Parameters are captured that provide information important to health assessment. Parameters are captured for a specific LRU or circuit of each engine on the aircraft, and data are captured at the same operating condition or time to minimize variation in data.

The data capture condition for relativistic analysis is most important to be consistent among all engines. The capture criteria can be based on the operating condition of all engines being in a specified window or at the same time to minimize environmental variables. Knowledge of system design and prognostic intent are helpful in ensuring data are available that support prognostic goals.

The relativistic method enables prognostic capability to predict RUL of the abnormally degrading circuit or LRU. Expected life of the evaluated circuit or LRU must be known to estimate the circuit or LRU RUL. The circuits or LRUs degrading at the similar rate are assumed to be "normal." The circuit or LRU degrading differently is compared to the circuit or LRU degrading at a normal rate, thereby allowing a degradation estimation. Assuming the normal RUL is known, RUL can be estimated of the degrading circuit or LRU.

The normal RUL value can be applied to the normal circuit or LRU to establish the relationship of time and limits for normal RUL. The abnormally degrading circuit or LRU degradation curve can use the relationship to the normal circuit or LRU degradation curve to compare how degradation occurs and where it intersects the failure limit.

4.4 DATA ACQUISITION TO SUPPORT PROGNOSTIC METHODS

Data used in prognostic analysis must be captured at the correct location and operating condition for the analysis to provide accurate prediction. Knowledge of system or LRU design and operation is used in analysis algorithm design. This same information is required to define data acquisition to support algorithm execution.

Data acquisition is defined in conjunction with analysis algorithm design to produce the desired results. Analysis intended to reveal circuit health uses different data than analysis intended to assess specific LRU health. Data acquisition needs to be tailored to support analysis algorithms.

Circuit health analysis can be assessed with minimal data. Analysis algorithms should assess critical circuit function and be able to identify function changes. Assessment of circuit health may be determined by the duration taken to complete an action. Another could be the maximum voltage achieved during an action. The objective is to assess degradation of circuit operation.

Data used for prognostic evaluation should be fit for purpose. The number of data acquisition locations chosen depends on prognostic intent. The data source location and acquisition condition should be consistent with the method of evaluation to produce expected results.

Being able to diagnose individual LRUs of a circuit consisting of multiple LRUs will require multiple data-acquisition locations. The data acquired for evaluation should be consistent with evaluating LRU functionality. LRU degradation detection avoids removal of LRUs while they are serviceable.

Data to identify specific LRU feature degradation must provide an understanding of the specific feature health. The data must capture the critical feature determining LRU health, which should be determined in defining the prognostic system and its intent.

Detecting overall circuit health and being able to track circuit state requires a data source only at one location. It also requires specific algorithms designed to detect information indicating the functional health of the circuit. Data acquisition operating condition determines the type of prognostic analysis that can be performed. Data captured at specific conditions enables deterministic prognostic analysis. General operation data acquisition can be used for relativistic analysis.

4.5 DATA ANALYSIS OPTIONS TO SUPPORT PROGNOSTIC METHODS

Options for prognostic analysis influence the accuracy and effectiveness of results. Knowledge of degradation and failure mechanisms allows analysis to be formulated properly. Uncertainty concerning these processes leads to checking and continual refinement of calculations as information is learned to generate useful assessment.

Optimum analysis is achieved using algorithms configured in relationship to the system. The degradation mode determines multiple analysis factors. The condition in which operating data and parameters are optimally recorded comes from degradation knowledge. The limit of functional failure used in analysis comes from knowing at which point the circuit or LRU becomes incapable of performing as intended.

Knowledge of the operating environment of the circuit or LRU provides input for the analysis algorithms to account for, and adjust for variation in, parameter data. The algorithms can incorporate features to adjust data for known variation, thereby allowing data comparison at consistent conditions. Expected data noise sources can be corrected analytically by factoring out known levels or rejecting data that are beyond defined limits.

The parameters chosen to record for the subject engine speed sensor are the peak voltage produced when the rotating feature passes through the sensor coil. The reading is compared to nominal output voltage ( ) of the sensor when first measured. The normal OV is known to range between 46 mV and 53 mV. This information provides the variable parameter that is input to calculations. The fixed voltage values are used as values for calculations defining functional limits.

The speed-sensor design defines the normal operating range to have a variation of 10%. Degradation is considered to have initiated when voltage goes beyond that level. Measurement of the circuit voltage has an uncertainty value of 4%.

The failure mode of the sensor is shorted coil windings. The sensor is considered failed when maximum coil voltage has dropped 25% from the initial value.

There are no environmental factors that need to be considered in determining speed-sensor health. The voltage measurement is not affected by temperature or other operating factors of the aircraft.

Certification requirements are related to functional intent of the system. Circuits subject to certification because of their normal function will have data-acquisition features certified to confirm no adverse circuit functions. There should be no certification requirement for ground-based analysis software that is used to specify maintenance action. Systems defined to meet current safety requirements have redundant features to handle failures.

4.6 FUTURE USE OF ELECTRONIC PROGNOSTICS

The use of prognostics in future electronics systems can go forward using the architecture and system configuration described in figure 28. That approach results in minor system cost increase and can be introduced near-term following airborne system certification of prognostic features added to Level A systems. Modifying current electronic systems to implement prognostics yields minimal safety benefit.

A departure from current system design and safety requirements could potentially reduce system cost, weight, and complexity. Redundant systems could be eliminated and the safety constraints to produce the benefits noted with proper design consideration.

Proven prognostic capability could prevent failure instead of incorporating features to function in case unexpected failure occurs. Features could be built into the system to prevent aircraft flight in the case failure is predicted and maintenance is not conducted and logged. There are numerous details that must be considered to implement this philosophy.

The system architecture shown in figure 28 indicates that data processing and management are ground based. A ground-based analysis system that guarantees an aircraft will not fly with a system that can fail during an upcoming flight is a Level A system. This requires certification of all aspects of the system, including data transfer, which has not been previously certified.

Level B systems are allowed to operate with system failures that are proven in the SSA to be noncritical. Level B system requirements address failure situations in design and do not necessitate redundant systems. Systems at Level B and below can be modified as defined in section 3.2 and produce no safety impact. Electronic prognostics could be used as an option and effectively improve safety by preventing aircraft flight with any systems that may fail during flight.

Proven electronic prognostic ability could be applied in conjunction with verified maintenance to provide ensured safe operation. Proof will be required to confirm that prognostics are accepted and to guarantee safe operation. RUL information from prognostic analysis can prevent dispatch when RUL is lower than a specific value. Limited dispatch features would have predicted time to failure and avoid operating with a likely near-term failure. The move from unexpected to predicted failure events allows elimination of redundancy and a move to proactive maintenance when prognostics have been proven. Improvements from this change include system cost and weight reduction and reliability improvement. Predictive maintenance reduces operating cost by removing a requirement to perform maintenance wherever a failure occurs. Therefore, maintenance moves from an unexpected to a planned event. By using predictive maintenance, repair can be scheduled and performed at a specified time and location prior to failure. Failure prevention results in safer aircraft operation.

The ground-based processes require certification. The analysis algorithms and the process to ensure accurate use of data becomes critical. Maintenance action records and engine configuration tracking must be ensured to have accurate and timely input to the system. The estimated cost of a prognostic maintenance system is beyond the scope of this project. The variations in system design options create many possible solutions affecting cost. The cost trade of determining design safety-critical systems as redundant or pursuing prognostic maintenance implementation will require determination for the individual application.

The functional definition of each element in figure 29 is defined as follows:

- LRU—electronic sensor or actuator in LRU prognostic analysis is applied; data is sent to FADEC.
- Wire harness—connection for data transfer between LRU and FADEC.
- FADEC—contains software-defining circuit function for control of LRU and defines data-acquisition criteria; captures operating data to be subsequently downloaded for analysis on ground.
- Data transfer—general method of sharing data between airborne and ground system; could be multiple forms (wire harness, data bus, or wireless); requires certification.
- Data storage—capture operating data to be subsequently downloaded for analysis on ground; requires certification.
- Ground data storage—long-term data retention to be used in prognostic analysis, historical, and record keeping; requires certification.
- Maintenance action—system input for maintaining record of current and historical maintenance activity; identifies component replacement time and related information. Requires certification.
- Ground analysis—compiles algorithms and data to achieve prognostic analysis and directs output to specified recipient; requires certification.

4.6.1 Proving Prognostics for the Future

Proving prognostic analysis effectiveness before prognostic methods are designed into safety-critical applications requires a method of confirmation. The idea of using prognostic maintenance in place of redundancy for safety-critical systems requires proof that electronic prognostic analysis works. Proving the concept can take a couple paths.

One approach is to search for an existing system with captured data that can be used to test prognostic algorithms. Algorithms can be designed around system design parameters to allow for understanding of initial system-development constraints. Data can be analyzed and results can be used to revise algorithms based on field experience. The revised algorithms provide an indication of the level of improvement that field data can provide.

Another approach to proving the effectiveness of prognostic analysis is modifying an existing noncritical system to incorporate prognostic capability. The methods identified in section 3.2, could be used in a system. Data can be acquired during operation to provide evaluation of effectiveness of prognostics. Any prognostic enabling features must be confirmed to not adversely impact the system.

Using data from an existing system would result in the most expeditious path to proving prognostics. Prognostics could potentially be in a state to start implementing new system designs with prognostic capability by using previous system knowledge. The number of systems identified that have data available to prove prognostic methods and the effort expended will be factors in making prognostic maintenance move forward.

The path of developing and testing prognostic systems from scratch would take longer to generate proof of prognostics than existing systems. The major constraint is the time involved in generating failures in the field. Accelerated life testing could be used, but there is still a question regarding the data relative to real use conditions.

The benefit of proving the effectiveness of prognostics is the potential use in reducing the need for redundancy in safety systems. If prognostics can be proven to be reliable to predict component failure, the need for redundant systems can be reduced or eliminated. Accurate RUL prognosis allows elimination of system redundancy.

It is postulated that correctly configured system design and associated algorithms could monitor system function instead of failure mode detecting gradual degradation. Current redundant systems use fault-detection algorithms to identify when a circuit fails to function. Algorithms could be formulated to identify circuit functional degradation prior to failure. Applying prognostic methods to the information can provide an RUL to guide maintenance action. Circuit prognostic analysis can use current circuit history as a method for verifying circuit prognostics.

The circuit and LRU prognostics create redundancy using prognostics. A degrading LRU would be identified by the LRU prognostic analysis. The circuit functional analysis provides a backup that identifies circuit degradation should an identified failure mode not be detected. The circuit analysis does not point to a specific LRU requiring service action to detect the degrading component prior to failure.

Current fault isolation procedures provide information to detect failed LRUs. Procedures to identify degrading LRUs prior to failure during fault isolation will be required.

The event of sudden undetectable failure could not use prognostics and would require features to avoid operational failure. There could be multiple solutions to accommodate this requirement. One method would be to use alternative circuit design that eliminates failure modes that do not result in detectable degradation prior to failure. The alternatives may result in circuit design complexity and cost but should reduce those effects on the system when redundancy is eliminated.

Another possible solution may be the creation of local redundancy rather than entire-system redundancy. This approach entails creating circuits with instantaneous failure features that are backed up in the circuit design if a failure occurs. The feasibility and cost would need to be evaluated independently.

Another method to account for sudden failure is the use of a model in the case of unexpected failure of a component. The currently defined failure-detection algorithm can be used to activate a circuit model to operate as backup for a failure.

Other approaches may be identified when the paradigm is shifted for how to address system design pertaining to safety. Potential methods need to be evaluated to determine if they are acceptable. The concept of eliminating redundancy needs to be thoroughly evaluated.

4.6.2 Certification of Future Prognostics

Electronic prognostics will be proven effective when comparison of calculated and confirmed state match. Confirming predicted and actual RUL requires running LRUs to failure. Using existing system data or modifying an existing system to enable prognostics allows for the use of LRUs until failure without concern for system safety.

Use of stored data from an existing system that captures data allowing for prognostic analysis would provide the fastest way to prove prognostic capability. Stored data allowing analysis of LRU degradation and calculation of RUL through its life cycle provides understanding of the failure process. Accurate maintenance records provide information concerning actual LRU life to compare to calculations. The information to prove prognostic algorithms exists.

Modification of an existing system will provide a longer path to proving prognostics. The system must be modified to acquire the needed data. Actual data acquisition and analysis are performed subsequent to modification. Failure of the LRU and confirmation of analysis results can be time consuming.

The approach of using existing data or modifying an existing noncritical circuit to acquire data is done for the purpose of proving that prognostic analysis is accurate. Prognostic analysis must be proven to result in failure estimates agreeing with actual LRU failure before it can be considered for use in safety-critical applications.

An alternative approach is to perform LRU testing using highly accelerated life testing (HALT) to quickly drive LRUs to failure. This method provides a way to test parts to failure without the lengthy timespan involved in testing in the actual operating environment. This test method does not prove the actual failure process. Failure is accelerated by concentrating known failure mechanisms in a shorter time or at a higher level than actual operation.

Prognostic algorithms used with the HALT test method would be tailored to the test conditions to accurately predict failure. This approach proves capability and accuracy to predict failure using information related to the operation of the LRU.

The use of prognostic analysis can be implemented in non-safety-critical systems with little impact. Design of the system is such that a system failure does not create a safety concern. Implementation of any prognostic-enabling feature that has a possibility to create a system malfunction is handled within the system-design constraints.

Near-term implementation of prognostic analysis could be beneficial to prove long-term prognostic effectiveness. Modification of a non-safety-critical system could be performed to support establishing prognostic knowledge. Changes to a non-safety-critical system would have minimal if any impact on system safety due to consideration in original system design.

Consideration could be given to implementing prognostic analysis concurrently with redundancy in safety-critical applications. This provides a side-by-side comparison of the two ways of addressing failure. Prognostic enabling existing safety-critical LRUs or circuits maintains accepted failure-mitigation techniques while adding the ability to acquire prognostic data to perform analysis. It would require certification of airborne system changes associated with the implementation of prognostic data acquisition. That can be a costly activity but results in a low-risk approach to understanding electronic prognostics. Analysis software used during development would not require certification.

Proving electronic prognostics are reliable and predicable must be accomplished before they are considered for predicting failure in safety-critical systems. Proof of the acceptability and predictability of prognostics methods must be established and understood before it is applied to prevent safety-critical failures.

Establishment and understanding of prognostic methods must be independent of, and prior to, certification activities. Certification will address compliance to the proven methodologies established for prognostics. Established prognostic method requirements must be in place for assessment of prognostic feature certification. Certification of electronic failure prediction would be difficult and costly. Certification is aimed at demonstrating that a newly designed system performs as it is intended. An established prognostic method forms the basis to certify that prognostic capability is properly implemented. There are many steps required prior to certification to guarantee system safety with the use of prognostics.

The concept of using prognostic analysis in place of redundancy requires different considerations prior to the elimination of redundant features in safety-critical systems. Implementing this idea removes the possibility of using a backup system in case of an expected safety-critical system failure. Preventing failure by using proven prognostic analysis eliminates the need for system redundancy.

Prognostic algorithms and data acquisition must be in place to enable detection of known failure modes with ample time to permit maintenance action prior to failure. Failure modes resulting in insufficient warning time to perform LRU replacement require redundancy to be maintained. LRU circuits requiring redundancy for specific failures should be evaluated to determine the benefit of incorporating any prognostic features.

Airborne aspects of data acquisition and storage become critical. Data acquisition must be guaranteed to be reliable and accurate. Airborne data acquisition encompasses hardware and software certification. Airborne hardware certification will be required for data acquisition components. That process should be familiar and applicable to ground-based hardware certification. The ground-based hardware supporting RUL analysis and maintenance activity requires certification.

Software certification for airborne systems is a familiar activity. Ground-based analysis and maintenance activity software will require the same rigor to be applied to safety-critical systems. Certification activities to physically demonstrate all possible failures that can be predicted would not be possible with the amount of variation in failure factors. Certification of the analysis system can be demonstrated to be effective when prognostic methods are accepted to be effective. Certification could be demonstrated by activating each prognostic variable to prove the calculations respond as expected. Certification activity would have to test each combination of variables to demonstrate that the system response to various data inputs produces the expected output.

Replacement of redundancy with prognostic analysis can be accomplished using ground-based analysis algorithms, except in the case of instantaneous or very rapid failures. There is no benefit to making analysis software airborne because maintenance cannot be performed remotely by the electronic system. Airborne prognostic software may prove beneficial for fault accommodation of rapid failure events, but that scenario is beyond the scope of this topic.

Ground-based analysis software for safety-critical systems is safety critical and must be certified as such. Analysis software must be certified to Level A. The software and the processes associated with maintenance activity become critical. The information must be used in prognostic analysis to accurately predict RUL. Maintenance record accuracy and reporting timeliness are necessary to determining the health of critical systems relying on prognostics. The process for reporting maintenance activity must be certified as Level A.

Maintenance activity reporting affects the calculated RUL. The RUL calculation should have associated limits defining the LRU replacement window and a non-operational limit. The LRU replacement window is determined as the time before the non-operational limit is reached that allows LRU replacement prior to failure. Such factors as parts and service logistics and aircraft operation would set when the LRU replacement window should be annunciated.

The non-operational limit is the point at which the LRU is predicted to fail. LRU operation beyond that limit is likely to result in failure. The earliest possible occurrence of failure defines the non-operational limit for prognostics to be used in place of redundancy. All variance must be considered to determine the earliest failure possible to prevent failure during operation when no backup is present.

Certification of a safety-critical prognostic maintenance-analysis system instead of certification of a redundant system will have more working pieces than a redundant system. It is not clear that a benefit exists for one approach over the other. All variables should be considered by the system designer in making a decision.

Cost and risk factors should be considered in deciding whether a safety-critical electronic system should be designed using redundancy or prognostic maintenance. The primary risk factor to consider for prognostic maintenance is the consequence of unpredicted failure with no backup features for activation.

The cost to design, implement, and certify each type of system design should be considered. The redundant system requires one-time design of the system. Additional cost is incurred in defining and certifying redundancy features to implement the mechanism to activate the backup system.

The design of the system function and the subsequent cost of a prognostic maintenance system is the same as for a redundant system. The analysis software requires development and Level A certification for each LRU or circuit for which it is applied.

The maintenance action tracking system and process guaranteeing information fed back to the RUL calculations can be the same for all LRUs or circuits. Certification of that process and the associated software and features could be performed once. There would be no reason to certify the entire process for each LRU or circuit. Certification would be required to confirm that each specific LRU or circuit's input and output data are available to the RUL calculation.

The process of proving the effectiveness of prognostic analysis is considered to be established prior to approaching the design of a system that relies on prognostics to prevent failure. Certification activity is related to verification of the defined system functioning properly within the operating constraints identified.

Use of prognostic maintenance brings another cost that cannot be verified without additional effort. Removing a functional (though degraded) LRU leaves useful life in the LRU. The cost of the remaining life should be factored into the cost tradeoff in determining design of the system. Additional effort would be expended in determining remaining life by testing removed LRUs to failure. The effort to test removed LRUs to failure would not provide benefit unless the information could be used to adjust analysis factors subsequent to algorithm certification. Algorithm tailoring of certified calculations based on test data would promote continued exploration and development of prognostic methods. If considered, the concept of modifying certified safety-critical algorithms requires rethinking and exploration.

The possibility exists that unexpected failure modes could occur that are unaccounted for in LRU analysis. Circuit functional analysis is intended to identify degrading circuits to prevent unexpected failure. It is possible this feature may not provide failure warning in the case of an unknown failure condition. This possibility currently exists in the case that fault-detection software is not in place to identify unknown failure modes. Several approaches could be included in the system to effectively add a redundant capability in the instance an unidentified failure mode occurs.

A circuit functional degradation algorithm could provide assessment of the circuit function to provide degradation indication not detected by the LRU degradation algorithm. The circuit algorithm would detect degradation of the circuit function and warn of impending failure in case the LRU RUL warning is not annunciated. Specific failure information would not be provided and degradation detection would be required.

A circuit model could be included in the system that would be activated in the case of circuit results being out of range. Out-of-range detection could be part of the circuit that would activate the circuit model to direct circuit operation if circuit degradation is detected. This solution is an alternative to degradation detection and would allow limited asset service continuation.

4.6.3 Future Prognostics System Requirements

Future systems will be closely related, if not integral, to control systems. Proven prognostic methods could open the possibility of reduced control-system complexity. Effective prognostic capability provides an opportunity to be proactive about failure instead of addressing it when it occurs.

Current control-system philosophy relies on mitigation when failure occurs. Critical systems are designed with redundant systems as backup in case of primary system failure. Noncritical systems allow for operation at a reduced capability level for a short time when there is a failure. Predicting failure and addressing failure prior to occurrence removes the need for redundancy in critical systems and prevents operation at reduced capability in noncritical systems. Proving prognostic capability and designing it into new systems could prevent failure and improve safety.

Proving prognostics capability requires significant effort before being applied to safety-critical systems to predict and prevent failure. A starting point to proving prognostics is gathering data for existing systems (noncritical) that can safely be run to failure. Data can be processed through prognostic analysis algorithms for comparison to actual failure. Comparison of calculated prognostic analysis algorithms to actual failure event information can then be used to improve prediction methods.

The definition of when prognostic methods are proven will depend on the functionality that needs to be proven. There are no safety implications for noncritical systems that can function with failed components. The safety case for that system has taken safety into account and assessed no safety impact for a failure. Prognostic methods can be developed and proven using modification to these existing systems to acquire data and perform analysis on the ground with no safety impact.

When prognostic methods have matured to a point of correctly predicting failure occurrence of noncritical system LRUs, it becomes possible to consider the concept of replacing redundant systems with prognostics.

The use of prognostics to prevent failure instead of using redundant critical safety systems to address failure requires verification of the ground-based features used in tracking part usage. Guaranteed timely availability of airborne data to conduct accurate ground-based analysis prior to failure must be confirmed. Accurate part replacement records are required as input to RUL calculation and tracking. Part location and use history become critical for RUL calculation. Accurate information storage and availability must be verified to support analysis algorithms.

Maintenance action tracking and verification must be implemented to guarantee components are replaced when indicated. The information must also be available for the use of analysis algorithms. The systems defined for managing this information will require certification. It should be possible to conduct the ground-based part tracking and maintenance action data-system certification once. Minor algorithm changes can be certified as part of subsystem recertification and not total system recertification. Ground-based part tracking and maintenance action data-system development and certification costs are not addressed as part of this project.

Prognostic analysis algorithm development is detailed in section 2.10. The analysis requirements are a function of the system being analyzed. Algorithms for prediction of critical system failure prevention will incorporate prognostic analysis method improvements defined at the time the system is developed.

5. CONCLUSIONS

Accurate prediction of electronic circuit and sensor failure requires system design and failure understanding to create algorithms capable of detecting failure mechanisms. The system needs to be designed with prognostics in mind using operating data that enable analysis.

Data acquisition needs to provide information supporting prognostic analysis algorithms. Existing legacy system data are recorded to provide an understanding of system operation. Data to enable prognostic analysis should be recorded at conditions and locations that reveal system degradation and health indicators. Data from current legacy systems rarely provide information useful for prognostics.

Modification of legacy data acquisition systems to capture additional data-enabling prognostics would provide a method to perform effective prognostic analysis. Modification of certified airborne systems requires recertification, and recertification cost is dependent on modification extent.

Subject-engine line replaceable units (LRUs) are removed many times in attempts to address faults using the easiest possible maintenance action. Additional maintenance actions and service disruptions occur when removal does not correct the fault. Maintenance action continues until the faulty LRU is replaced and functionality is restored.

Use of existing legacy airborne electronic system data to perform prognostic analysis creates no certification or cost issues for the airborne system. Prognostic capability is enabled by creation of ground-based analysis algorithms that use existing airborne data. Cost will be incurred to develop algorithms. Existing system data enable limited prognostic ability.

Prognostic algorithms used to analyze legacy system data do not require certification. The airborne system is certified, and the information provided from ground-based algorithms is advisory and has no impact on system safety.

The use of existing legacy system data provides limited prognostic understanding. Legacy system data capture was not created to record information that is important to predicting health. Locations and operating conditions for data capture are not optimized to enable prognostic analysis.

The use of legacy system data to perform prognostic analysis can be enhanced using data from sources outside the circuit itself. A combination of circuit output information and comparison of the expected values for other parameters provides the ability to assess T2 circuit health. The ability to detect degradation relative to other circuits can provide awareness of and preparation for pending failure.

Development of modified legacy systems enabling prognostic analysis should start with the use of existing system knowledge to create advisory-level results. Legacy system modification to capture additional data tailored to enabling prognostics would be beneficial. The system informs operators of potential impending failure and allows them to change suspect LRUs prior to failure.

The system needs to be modified to support the capture of data that are useful for prognostic analysis. Prognostic algorithms rely on data captured at specific locations and conditions for supporting the analysis process. The airborne system modifications need to capture the data identified during algorithm development. Data acquired to satisfy prognostic needs would make accurate prediction possible.

Removed LRUs can provide information to assess the effectiveness of predicted remaining useful life (RUL). The failing system could be left installed until failure to compare to prediction accuracy. Information collected would help build confidence for potential use in safety-critical applications to predict failure. Existing systems can operate safely when LRU failure occurs.

The addition of more sense point locations in the circuit allows more comprehensive circuit analysis and LRU isolation. Acquiring data at more locations in the circuit allows analysis to determine the location of anomalous behavior.

System modification with prognostic analysis intent should be designed to acquire data at operating conditions that support prognostic assessment. The airborne system design may require additional memory capacity to accumulate health parameters.

The simulation data created during the algorithm development process was originally envisioned as having degradation associated with usage time. During the development of the assessment methods, many of the data-acquisition conditions turned out to be related to cold start to help reduce temperature-induced variation. Another method that reduced temperature variation is relativistic analysis, in which multiple items are compared at the same operating condition and are considered to be at or near the same temperature.

In assessing health and degradation, it was determined that the time factor (x-axis of many graphs) is determined as a function of operation of the item being assessed. Other factors included when data can be acquired and factors that degrade the item. So the applicable usage factor could be one of several parameters. That parameter must be the same for the assessment and must be factored into the consideration of results.

When assessment is performed at cold-start conditions, the usage factor would be the number of engine starts. The amount of time the item is operated between starts may be a factor in degradation rate and should be factored into algorithm development if required to be considered. Applicability of that consideration is determined by design or experience. For the simulation performed in this report, the factors for choosing assessment at cold start were:

- Minimizing potential certification impact through data acquisition prior to the engine system becoming operational.
- Reducing assessment variation by minimizing operational differences when data are acquired.

Choosing operating time as a usage factor should be considered when the item being evaluated is affected by the amount of time it is used.

The certification impact of adding prognostic data acquisition would address the addition of features to a safety-critical system. Safety-critical circuits have multiple redundant safety features that mitigate the safety impact of a failure condition. There is no single LRU failure in these circuits that could compromise safe operation. LRU failure would be annunciated requiring corrective action.

Legacy system modification requires certification to confirm that no safety impact is caused by the modifications. System certification scope would be commensurate with the system development assurance level and would require appropriate certification activity.

Hardware certification of additional processor or memory capacity would be the same as existing systems requiring certification. Additional computational processing or memory capacity supporting added software and data storage requires hardware certification.

Removed LRUs can provide information to assess the effectiveness of predicted RUL. The failing system could be left installed until failure to compare to prediction accuracy. Information collected would help build confidence for potential use in safety-critical applications to predict failure. Existing systems can operate safely when LRU failure occurs.

It is anticipated that the prognostic capability described can be used to identify degrading LRUs and point maintainers in the direction of the likely faulty component to achieve first-time repair success. The analysis can identify LRUs that are degrading and recommend replacement of the LRU. Identification of degrading LRUs will save the cost of unnecessary replacement of a good, operational LRU.

There is benefit in identification of LRUs that are degrading but have yet to fail. Proactive action to remove LRUs approaching failure can prevent disruption and allow continual asset availability. Prediction of failure allows planning for maintenance action at a time and place that is conducive to the most effective opportunity.

The information presented in this report evolved as the bench test progressed. Ridgetop's prognostic work prior to that was focused on analysis using the deterministic method to evaluate electronic components against their own degradation process. The relativistic analysis method was developed using the ability to evaluate multiple items of the same type in the same environment. Comparing degradation against the same type item operating in the same environment (the same aircraft) on multiple engines produced the opportunity to assess the item against its own historic health evaluation. Filtering the data and operations helps in removing information that is not operationally consistent and can complicate analysis.

The value of comparing degradation to items that should be experiencing similar degradation was noted in reviewing data and information to understand the current prognostic capability. Quickly evident factors are item age and differences in the part life cycle. The simplifying assumption in this work is that all the items being compared started life when data recording was initiated (initial use). For field units, it is not likely that all the items being compared will have started life at the same point in time, except on a new aircraft.

A complication that would need to be addressed when using the relativistic method in service is the differing point in the degradation life cycle. The degradation rate typically increases as components near end of life. The relativistic method can identify that increasing degradation rate compared to other similar items. The LRU circuit requires additional information to understand where it stands in the degradation curve, assuming the curve is known.

The relativistic analysis method does require at least three “relative” comparisons to be effective. In the case of the subject engine, the aircraft system contains multiple engines. There are many aircraft in service today with dual-engine configurations or, in the case of many military aircraft, single-engine applications. Relativistic evaluation could be used when comparing operation of twin-engine aircraft. Twin-engine diagnosis creates a challenge in discerning which of the two engines is operating normally.

It would be possible to compare fleet assets, but it would be more complicated to match operational data for comparison in a fleet environment. The effectiveness of evaluation of multiple aircraft in a fleet needs to be studied to determine if the method is effective.

Prognostic analysis could be implemented at this time in limited cases in which currently acquired data can be used to produce predictive insight. Circuits would need to be evaluated to determine their applicability to prognostics. The airborne system requires no modification to support this effort.

System modification to acquire data specifically for prognostics would require recertification of the airborne system. The failure safety features of legacy systems allow for a safe environment to determine the effectiveness of prognostic assessment in a low-risk environment. Prediction could be made, and LRUs run to a fault condition to compare predicted results with actual results.

Current legacy-system architecture limits prognostic enabling of many components in current systems. Future systems designed to be prognostic could use alternative architecture that considers the use of prognostic-enabled components.

Proven prognostic effectiveness could lead to potentially replacing system redundancy with predictive analysis to prevent failure.

5.1 REDUCE LRU FAULT NOT FOUND REMOVALS BY 65%

The logic behind Success Metric 1 is based on evaluation of service event data. Full-authority digital engine control (FADEC) returns from the subject engine result in 80% (4 out of 5) yielding fault not found (FNF) diagnosis. Elimination of half of the FNF returns would result in 67% FNF returns, thereby yielding a 65% improvement. That level of improvement should be achievable with successful implementation of prognostic methods.

The following information was used in deriving this metric:

- Faulty FADEC returns go from 20% to 33%:

    - From 1 in 5 (0.20) to 1 in 3 (0.33) faults (0.33/0.20 = 1.65)
    - Therefore, 65% improved

- FADECs are the only items in the T2 sensor circuit that are returned for refurbishment. That statement is true for many of the subject-engine electronic circuits. The FADEC is the only LRU returned and identified as FNF.
- 80% of the subject engine FADEC returns are FNF. Therefore, identifying one faulty returned FADEC results in the return of 5 FADECs total.
- Therefore: 65% improvement of 5 FADEC returns = 3.25 FADEC returns when a circuit fault is identified. FADEC FNF returns cost $5000 each.

The ability to satisfy this metric using data for a single engine for prognostic analysis is not feasible using the current subject-engine data-acquisition system. Current system data are acquired at only one data sense point, and that does not allow circuit prognosis, only circuit fault annunciation. Use of existing system data does not allow fault isolation to the FADEC or any specific LRU.

Manual LRU diagnostic operations must be performed to isolate a faulty LRU in the circuit. Data acquisition at only one sense point allows fault annunciation but does not support electronic fault isolation. Data-acquisition location and conditions must be optimized for prognostics analysis.

The current subject-engine fault isolation procedures require manual inspection of the circuit LRUs to isolate the faulty LRU. Ineffective checks lead to removal of the wrong LRU and costly repeated maintenance activity until the fault is corrected.

The erroneous LRU replacement maintenance activity could be reduced with a solution available that used airborne system data to guide the maintainer to a likely failed LRU. The maintainer could perform the diagnostic operation for the identified faulty LRU and confirm the diagnosis before servicing the LRU. The system output could provide a prioritized listing of likely LRU failures for the maintainer to follow for further diagnostic checks if the initial diagnosis does not confirm the LRU faulty.

The probabilistic procedure for recommending LRU replacement does not guarantee reduced FNF incidents. It adds data to the diagnosis process that the maintainer must heed to be effective. Maintainers performing LRU diagnostics as specified would not remove FNF FADECs. The concept of adding probabilistic analysis to guide the maintainer in LRU diagnosis has not been studied, and data are not available to estimate the effectiveness of the process.

Relativistic prognostic assessment can provide circuit-degradation warning prior to fault annunciation. Specific LRU degradation cannot be identified. Circuit LRU diagnostics must still be performed. Circuit degradation identification allows preparation to act on a fault annunciation.

Modifications to the current subject engine system could add LRU sense points to provide prognostic capability and isolation of the degrading LRU in the circuit. Adding sensing capability to the LRU circuit outside the FADEC (current system) provides the ability to predict individual LRU RUL and isolate a degrading LRU. This information can be used to direct the maintainer to the LRU requiring replacement without performing a physical test to confirm LRU failure.

Enhanced data availability provides reduced FNF removals of the FADEC. Maintenance action to remove the most readily accessible LRU in the circuit would be guided by electronic data to assist in determination fault isolation. FNF LRU removals should be reduced if accurate diagnostic algorithms that recommend the faulty LRU and the maintainer use the algorithm information to remove the LRU identified.

Data analysis to detect and accurately identify LRU degradation cannot be implemented prior to legacy-system modification-enabling prognostic assessment. Minimal prognostic information can be formulated using existing system data. Metric success will require maintainer diligence until additional data become available.

5.2 PREDICT 65% OF ELECTRICAL LRU FAILURES 10 HOURS PRIOR TO REQUIRING MAINTENANCE

Success Metric 2 considered the ability to accurately predict an LRU failure in time to be able to avoid service disruption. Ridgetop noted a 72-hr threshold as a U.S. military requirement.

The identification of a degrading circuit with 10 hour RUL is achievable for the majority of electronic component failures.

Achieving this objective will be difficult using existing system data. The single sense point and limited data acquisition at conditions not meant to yield prognostic enabling data make specific LRU analysis difficult. Relativistic prognostics have been noted as a method to assess circuit degradation. The result of the analysis produces a warning of impeding circuit failure and fault annunciation. LRU degradation can be predicted if captured data are available that can be used to understand degradation and exhibit a failure signature.

Data constraints using existing system information prevent comprehensive LRU prognostics until data acquisition is enhanced with added system data. The previous discussion addressing current system limitations that are limiting prognostic ability also applies here. Achieving this objective by modifying data acquisition is possible. Prognostic enabling modifications can be made by tailoring the data to produce predictive assessment. Data recorded at the right location at the correct condition provides information to produce RUL determination.

Data-acquisition requirements to perform specific LRU degradation analysis are dictated by algorithm definition. Analysis methods are developed using system knowledge design, service history, and other sources. Algorithms can be developed by applying the knowledge to prescribe methods to determine LRU health. Simulation testing provides insight into the effectiveness of algorithm development and allows refinement.

Insertion of additional sense points in circuits provides the ability to isolate LRU degradation over time and thereby enables determination of RUL. Data acquisition at discreet locations would enhance circuit diagnostic capability and allow LRU isolation.

The T2 circuit study identified the limited number of components that can be identified as failed as equaling 60% of the total circuit. The target of predicting 65% of failures is achievable if the high-failure-rate components for a circuit are prognostic enabled. Circuits with high-failure-rate components that are not prognostic enabled will not meet the criteria. This metric is not achievable for the current T2 circuit. The T2 circuit contains approximately 5% prognostic-enabled components. Prognostic effectiveness for this criterion is dependent on circuit architecture and the percentage of prognostic-enabled components. The number of prognostic-enabled components and the reliability of those components may prevent reaching the 65% value of this metric.

Looking at the LRU simulations, the ability to detect failed components is approximately 60% of the total selected components. Of all the potential failed conditions for each component, approximately 25% can be identified. Prognostic capability is much lower. The major issue is the number of “prognostic-enabled” components being a little more than 5%. Compounding that issue is the small percentage of operating range of those components from the point their output goes beyond the normal operating range to the point of failure.

Relative prognostics can provide degradation information using existing system data. It can be used to identify a circuit having a heightened likelihood of degradation compared to other engines on the same aircraft in circuits. It is not possible to accurately predict RUL to isolate the degrading LRU in the degrading circuit using existing system data. LRU circuits currently recording operating data (pressures, temperatures, speeds) can be used to predict relativistic prognostic RUL. To meet the 10-hour prediction threshold requires data to be reported no more than 5 hours between reports once degradation has been identified. Definition of initiation of degradation and failure limits requires system information and an understanding of relativistic algorithms.

The subject engine current operating environment creates data approximately every 2 hours of operation. With data availability at that frequency, relative prognostics can be applied to predict failure for LRUs that have data regularly recorded. Using relative degradation to identify a degrading LRU circuit can predict RUL within 10 hours of failure of the limit identified in the RUL algorithms. The RUL algorithms must consider the variables affecting RUL calculation. Because faulty LRU isolation is not possible in the existing circuit, the relative prognostic method should be configured to predict the most conservative circuit RUL. In conjunction with RUL limit annunciation, the physical LRU diagnostic must be performed to identify the LRU causing degradation. The LRU diagnostic typically identifies failure and does not provide information to determine degradation.

System enhancements add sense points and additional data-acquisition conditions to enable prognostics. System definition can be targeted to meet these criteria. LRU failure rate information provides direction that is useful in algorithm development, and it also influences data-acquisition rates.

5.3 IMPROVE ACCURACY OF ELECTRICAL LRU MAINTENANCE ACTIONS TO YIELD AT LEAST 85% OF FIRST-TIME REPAIR

Success Metric 3 is based on the number of accurate electronic LRU replacements today and the opportunity for improvement.

The 3-year scope of the subject engine service action database contains 1741 electronic LRU fault events, of which 360 had to be repeated 1 or more times. The current first-time electronic LRU repair rate is 74%. To reach 85% first-time repair, the number of repeat repairs needs to be reduced by 118 of the 360.

The combination of circuit evaluation and prognostic tracking of LRU degradation will provide information to accurately identify faulty LRUs requiring replacement:

- First-time electronic LRU rate (1-(360/(1741-360)) = 74%.
- To reach 85%, errant first-time repair rate needs to decrease from 360 by 118 or
- 1- (360-118)/1741-118
- In 21% of subject engine electronic LRU removal and replacement events, 2 or more service actions were required to clear the fault.
- Therefore, 21% x 85% = 21% reduction in repeat service events, resulting in 4% repeat service events.

Prognostic enabling circuit components again is a factor affecting achievement of this metric.

Implementation of the prognostic algorithms will improve maintenance-action accuracy only if the algorithms are used to help maintainers perform diagnostic analysis. The existing data-acquisition system on the subject engine provides information that can be used to identify circuit degradation. The available data are not adequate to enable specific LRU diagnostics, so it is not possible direct maintenance action using the existing system data. The manual individual LRU diagnostics are needed to confirm a failed LRU prior to removal.

Using additional LRU life data compiled from fleet operation, specific engine-operation data and probabilistic algorithms derived from that data can provide data defining prioritized LRU failure likelihood. Using the information to direct the maintainer to the LRU needing diagnostic analysis should improve maintenance accuracy.

Modifying the subject-engine system to monitor individual LRU health enables identification of health and isolation of faulty LRUs. The addition of sense points to LRUs (sensor, actuator, etc.) facilitates isolation of faults between the LRU and the FADEC. The FADEC contains sensing capability to determine functional health of the LRU circuit. Sense points at both the FADEC and LRU provide data to differentiate which LRU of the circuit is degraded.

The individual LRU data can be analyzed to produce RUL for each monitored LRU and can be prioritized to indicate the LRU most likely to need replacement. The following conclusions are noted from this effort:

1. Aviation electronic systems provide data that can potentially generate estimates of RUL. Benefit includes predicting and avoiding unexpected failures leading to service disruptions. Relative prognostics can provide this capability for circuits where operating data are stored.
2. System modification to acquire prognostic data at specific locations and conditions based on identified circuit-degradation knowledge enables prognostic analysis. These data allow assessment of the LRU or circuit against known parameters.
3. Prognostic analysis could be evolved to benefit safety by predicting and eliminating electronic component failure. This effort can use circuit data and analysis to evaluate components that can be operated to failure and compared with analytical results.
4. Aviation electronic systems could replace redundant safety features with prognostic analysis to prevent failures. Significant prognostic analysis verification must occur and safety requirements must be modified to allow prognostics in this fashion.
5. The effectiveness of prognostic analysis is highly dependent on data-acquisition conditions and parameters being available. Acquisition of prognostic-tailored data and system-design-enabling prognostics provide the most capable and accurate prognostic results.

The following two prognostic methods provide flexibility and opportunity to assess degradation of electronic circuits or LRUs using legacy data and data specifically for prognostics:

- Relativistic prognostic analysis identifies an item on a multiple-engine aircraft that is degrading at a different rate than other engines. This can be done using existing engine data. An estimated RUL can be determined when combined with component life data. This method may be applicable for fleet assessment.
- Deterministic prognostic analysis provides assessment of individual circuits or LRUs. Data acquisition and analysis algorithms are developed to determine health compared against known characteristics. Data captured to perform this type of analysis can also be used for relativistic analysis.

New aircraft electronic systems should be designed with prognostics in mind. The location and timing of data acquisition are defined to allow maximum prognostic accuracy. Systems designed to achieve the best possible predictive analysis produce operational benefit by preventing unexpected failure (disruption) and making them planned events. Prognostic systems do not provide additional safety benefits for systems designed to be failure tolerant.

Aircraft cost, weight, and reliability improvement are available from eliminating redundant systems. Prognostics may provide that benefit if reliable and accurate methods can be proven. Certification requirements will need to be addressed if prognostic analysis is to be used as replacement of redundancy in safety-critical systems. Certification of ground-based analysis systems and their connection to airborne and service systems must be addressed.

6. REFERENCES

1. Saxena, A., Roychoudhury, I., Celaya, J., Saha, S., Saha, B., and Goebel, K. (2010). Requirements specification for prognostics performance–an overview. . Atlanta, GA.

APPENDIX A—LINEAR VARIABLE DIFFERENTIAL TRANSDUCER TEST DATA

Test No.	Test setup	Coil degradation, %	Measured voltage, V	Functional failure signature
1	4	0.00	1.235	-7.83898
2	4	0.50	1.222	-10.5932
3	4	1.00	1.21	-13.1356
4	4	1.50	1.1985	-14.9364
5	4	2.00	1.192	-13.5593
6	4	2.50	1.181	-11.2288
7	4	3.00	1.169	-8.68644
8	4	3.50	1.158	-6.35593
9	4	4.00	1.147	-4.02542
10	4	4.50	1.136	-1.69492
11	4	5.00	1.126	0.423729
12	4	5.50	1.115	2.754237
13	4	6.00	1.1	5.932203
14	4	6.50	1.095	6.991525
15	4	7.00	1.085	9.110169
16	4	7.50	1.0761	10.99576
17	4	8.00	1.066	13.13559
18	4	8.50	1.057	15.04237
19	4	9.00	1.047	17.16102
20	4	9.50	1.038	19.0678
21	4	10.00	1.03	20.76271
22	4	10.50	1.0215	22.56356
23	4	11.00	1.0128	24.40678
24	4	11.50	1.004	26.27119
25	4	12.00	0.9958	28.00847
26	4	12.50	0.9877	29.72458
27	4	13.00	0.9798	31.39831
28	4	13.50	0.9718	33.09322
29	4	14.00	0.964	34.74576

Test No.	Test setup	Coil degradation, %	Measured voltage, V	Functional failure signature
30	4	14.50	0.956	36.44068
31	4	15.00	0.9489	37.94492
32	4	15.50	0.9413	39.55508
33	4	16.00	0.934	41.10169
34	4	16.50	0.9265	42.69068
35	4	17.00	0.9193	44.2161
36	4	17.50	0.9123	45.69915
37	4	18.00	0.9055	47.13983
38	4	18.50	0.8989	48.53814
39	4	19.00	0.8922	49.95763
40	4	19.50	0.8854	51.39831
41	4	20.00	0.8788	52.79661
42	4	20.50	0.8726	54.11017
43	4	21.00	0.8663	55.44492
44	4	21.50	0.86	56.77966
45	4	22.00	0.8538	58.09322
46	4	22.50	0.8477	59.38559
47	4	23.00	0.8418	60.63559
48	4	23.50	0.836	61.86441
49	4	24.00	0.83	63.13559
50	4	24.50	0.8244	64.32203
51	4	25.00	0.8185	65.57203
52	4	25.50	0.813	66.73729
53	4	26.00	0.8075	67.90254
54	4	26.50	0.802	69.0678
55	4	27.00	0.7965	70.23305
56	4	27.50	0.7912	71.35593
57	4	28.00	0.786	72.45763
58	4	28.50	0.7807	73.58051
59	4	29.00	0.7756	74.66102
60	4	29.50	0.7705	75.74153

Test No.	Test setup	Coil degradation, %	Measured voltage, V	Functional failure signature
61	4	30.00	0.7655	76.80085
62	4	30.50	0.7607	77.8178
63	4	31.00	0.7558	78.85593
64	4	31.50	0.751	79.87288
65	4	32.00	0.7464	80.84746
66	4	32.50	0.7415	81.88559
67	4	33.00	0.737	82.83898
68	4	33.50	0.7323	83.83475
69	4	34.00	0.728	84.74576
70	4	34.50	0.7234	85.72034
71	4	35.00	0.719	86.65254
72	4	35.50	0.7148	87.54237
73	4	36.00	0.7105	88.45339
74	4	36.50	0.70064	90.54237
75	4	37.00	0.702	90.25424
76	4	37.50	0.698	91.10169
77	4	38.00	0.6938	91.99153
78	4	38.50	0.6897	92.86017
79	4	39.00	0.6857	93.70763
80	4	39.50	0.6818	94.5339
81	4	40.00	0.6778	95.38136
82	4	40.50	0.674	96.18644
83	4	41.00	0.6703	96.97034
84	4	41.50	0.6666	97.75424
85	4	42.00	0.6626	98.60169
86	4	42.50	0.6589	99.38559
87	4	43.00	0.6551	100.1907
88	4	43.50	0.6516	100.9322
89	4	44.00	0.6481	101.6737
90	4	44.50	0.6445	102.4364
91	4	45.00	0.641	103.178

Test No.	Test setup	Coil degradation, %	Measured voltage, V	Functional failure signature
92	4	45.50	0.6374	103.9407
93	4	46.00	0.6339	104.6822
94	4	46.50	0.6305	105.4025
95	4	47.00	0.6271	106.1229
96	4	47.50	0.624	106.7797
97	4	48.00	0.6206	107.5
98	4	48.50	0.6172	108.2203
99	4	49.00	0.6143	108.8347
100	4	49.50	0.6109	109.5551
101	4	50.00	0.6078	110.2119