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Data Fusion for Enhanced Aircraft Engine Prognostics and Health Management

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Pratt & Whitney, East Hartford, Connecticut

December 2005

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Space Administration

Glenn Research Center

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Teaming Arrangement

Company/Agency	Role	Principal Investigator
Pratt & Whitney	Prime Contractor	Al Volponi
Intelligent Automation Corporation	Subcontractor	Tom Brotherton
Luppold and Associates	Subcontractor	Rob Luppold
NASA Glenn Research Center	Program Support	Don Simon (COTR)
NASA Dryden Flight Research Center	Flight Data Support	Mike Venti, Trindle Maine, John Orme, et al.

Although there was considerable synergy and technical contribution overlap between the primary members of the team in all areas during this development, the major responsibilities were as follows:

Company	Responsibility
Pratt & Whitney	Program Management, Technical Direction, and Analytical Support
Intelligent Automation Corporation	Data Management and Analytical Modules (Anomaly Detection and Empirical Modeling)
Luppold and Associates	System Integration and Analytical Modules (STORM and Data Alignment)

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CONTENTS

Section ***Page***

1. INTRODUCTION 1

2. BACKGROUND 2
   - 2.1 Chronology 2
   - 2.2 Architecture 4
   - 2.3 Engine Data 6
   - 2.4 Data Fusion Applicability 7

3. ANALYSIS MODULE OVERVIEW 10
   - 3.1 Data Alignment 10
   - 3.2 Lubrication System Modeling 10
   - 3.3 Gaspath Anomaly Detection 13
   - 3.4 Gaspath Analysis 14

4. GASPATH ALGORITHM FUSION 17
   - 4.1 Short- and Long-Term Filters 18

5. CONCLUSIONS 22

6. REFERENCES 23

FIGURES

Figure *Page*

1. Data Fusion Program Development Timeline 2
2. Generic Data Fusion Architecture 4
3. C17-T1 PHM Data Fusion Architecture 5
4. Measured Versus Predicted Oil Quantity 12
5. Measured Versus Predicted PN4SP 12
6. Gaspath Anomaly Detector Model 13
7. Gaspath Anomaly Detector Model 13
8. Graphical Depiction of Gaspath Anomaly Detector Output 14
9. Building the Empirical Element of the Hybrid Model 15
10. Implementing the Empirical Element of the Hybrid Model 15
11. Establishing the Zero Reference for Module Performance Tracking – Effect on the Tuners 16
12. Establishing the Zero Reference for Module Performance Tracking – Increase in Fault Visibility 16
13. Gaspath Analysis Algorithm Fusion Architecture 17
14. Short- and Long-Term Filter Response 18
15. Typical Small and Large Fuzzy Membership Functions 18
16. Example of a Nonpersistent Trend Shift 19
17. Example of a Persistent Trend Shift 19
18. Example Effect on Performance Tracking with Measurement Bias Insertion, Isolation, and Accommodation 20

TABLES

Table ***Page***

1. C17-T1 Instrumentation for Data Fusion 6
2. Data Fusion Potential: Information Overlap 9
3. Input Parameters for Empirical Lubrication Model 11

ACRONYMS

A

ACC	Active Clearance Control
AD	Anomaly Detection
ANN	Artificial Neural Network

D

DFRC	Dryden Flight Research Center

E

EDMS	Exhaust Debris Monitoring System
EGT	Exhaust Gas Temperature

F

FADEC	Full Authority Digital Electronic Control
FOD	Foreign Object Damage

G

GRC	Glenn Research Center

I

IDMS	Inlet Debris Monitoring System

M

MLP	Multi-Layer Perceptron
MPA	Module Performance Analysis

O

ODM	Oil Debris Monitoring

P

P&W	Pratt & Whitney
PHM	Propulsion Health Management

R

RBF	Radial Basis Function

S

STORM	Self-Tuning Onboard Real-time Model
SVM	State Variable Model

1. INTRODUCTION

Aircraft gas-turbine engine data is available from a variety of sources, including on-board sensor measurements, maintenance histories, and component models. An ultimate goal of Propulsion Health Management (PHM) is to maximize the amount of meaningful information that can be extracted from disparate data sources to obtain comprehensive diagnostic and prognostic knowledge regarding the health of the engine. Data fusion is the integration of data or information from multiple sources for the achievement of improved accuracy and more specific inferences than can be obtained from the use of a single sensor alone. The basic tenet underlying the data/information fusion concept is to leverage all available information to enhance diagnostic visibility, increase diagnostic reliability and reduce the number of diagnostic false alarms. This report describes a basic PHM data fusion architecture being developed in alignment with the NASA C-17 PHM Flight Test program. The challenge of how to maximize the meaningful information extracted from disparate data sources to obtain enhanced diagnostic and prognostic information regarding the health and condition of the engine is the primary goal of this endeavor. To address this challenge, NASA Glenn Research Center (GRC), NASA Dryden Flight Research Center (DFRC) and Pratt & Whitney (P&W) have formed a team with several small innovative technology companies to plan and conduct a research project in the area of data fusion, as it applies to PHM. Methodologies being developed and evaluated have been drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and fuzzy logic. This report will provide a chronology and summary of the work accomplished under this research contract.

2. BACKGROUND

2.1 CHRONOLOGY

Figure 1 provides a summary timeline for the development of the data fusion architecture and attendant analytical modules and support activities.

Figure 1. *Data Fusion Program Development Timeline*

This program was envisioned as an adjunct activity to a C17-T1 PHM program that had been awarded to P&W by NASA DFRC. One of the objectives of the PHM program was to flight test and evaluate several advanced sensors. This included the Stewart Hughes electrostatic inlet debris monitoring system (IDMS) and the exhaust debris monitoring system (EDMS), the SWANtech stress wave sensor, and several high frequency vibration sensors. This was in addition to an extended suite of gaspath, oil system, and airframe sensors. An oil debris monitoring system (ODM) was also planned, but was not installed during the Data Fusion program period.

In 2001, the C17-T1 PHM team was installing the advanced sensors and determining the entire suite of sensors that would be monitored, recorded, and archived for subsequent analysis. This planned repository of data would provide the requisite data for the fusion effort. Since the recording equipment and sensors would not be ready before 2002, this data would not be available until 1st Quarter 2002 at the earliest. For this reason, an alternate source of data was needed in order to begin the Data Fusion program activities planned for 2001. To this end, P&W supplied an F117-D01 transient field deck that could, at least, produce simulated gaspath flight data. At the same time, work began to develop an F117 Self-Tuning Onboard Real-time Model (STORM) that would provide a form of engine module performance tracking. The STORM system would be driven by the transient field deck that would act as the surrogate engine. This same (simulated) data would be used to develop an empirical gaspath anomaly detection (AD) system.

Persistent C17-T1 aircraft instrumentation problems, coupled with increased U.S. Air Force usage of the vehicle following the events of 11 September 2001, would ultimately limit (severely) the data available for this research effort. This forced a reliance on the F117 simulation data, which, in turn, would again limit the investigations to the engine gaspath. ***Figure 1*** depicts the relative dates when flight data was recorded. There were 11 flights in March 2002 and 3 flights in July 2003 where data was available. Unfortunately, there were difficulties in recording many of the parameters required for the Data Fusion program study, limiting the data's utility.

The primary accomplishments made within this program, given the constraints and the attendant year-to-year changes in scope driven by these constraints, can be summarized as follows:

- Definition of a general PHM-oriented data fusion architecture accommodating an array of sensors (structural health, gaspath, oil system, airframe, etc.) at different bandwidths.
- Development of data synchronization logic
- Identification and development of supporting analysis modules
  - Gaspath analysis
  - Empirical oil system modeling to produce analytical redundancy through virtual sensors (oil quantity, No. 4 bearing pressure)
  - Gaspath AD
- Preliminary vibration analysis without 1/rev tach signals
- Direct fusion of AD and gaspath analysis algorithms for detection and accommodation of measurement biases.

The chronological development of these items can be found in the technical narrative reports dating from 2001 through 2004. A summary overview of these items will be presented in Section 3. More detailed information can be found in the narratives.

2.2 ARCHITECTURE

The final (generic) architecture for PHM data fusion is presented in ***Figure 2***. A C17-T1 PHM specific architecture is depicted in ***Figure 3***.

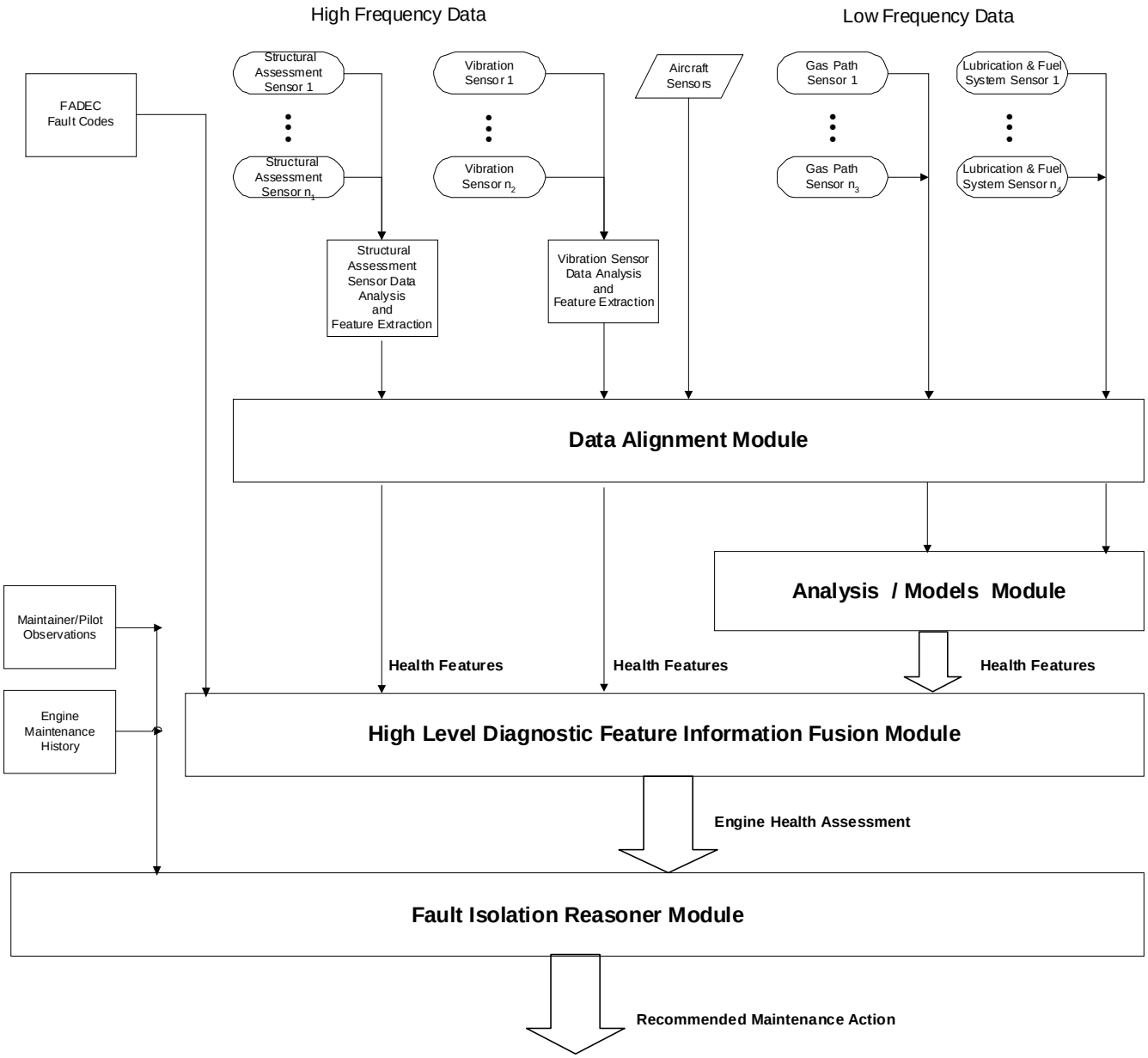

Figure 2. *Generic Data Fusion Architecture*

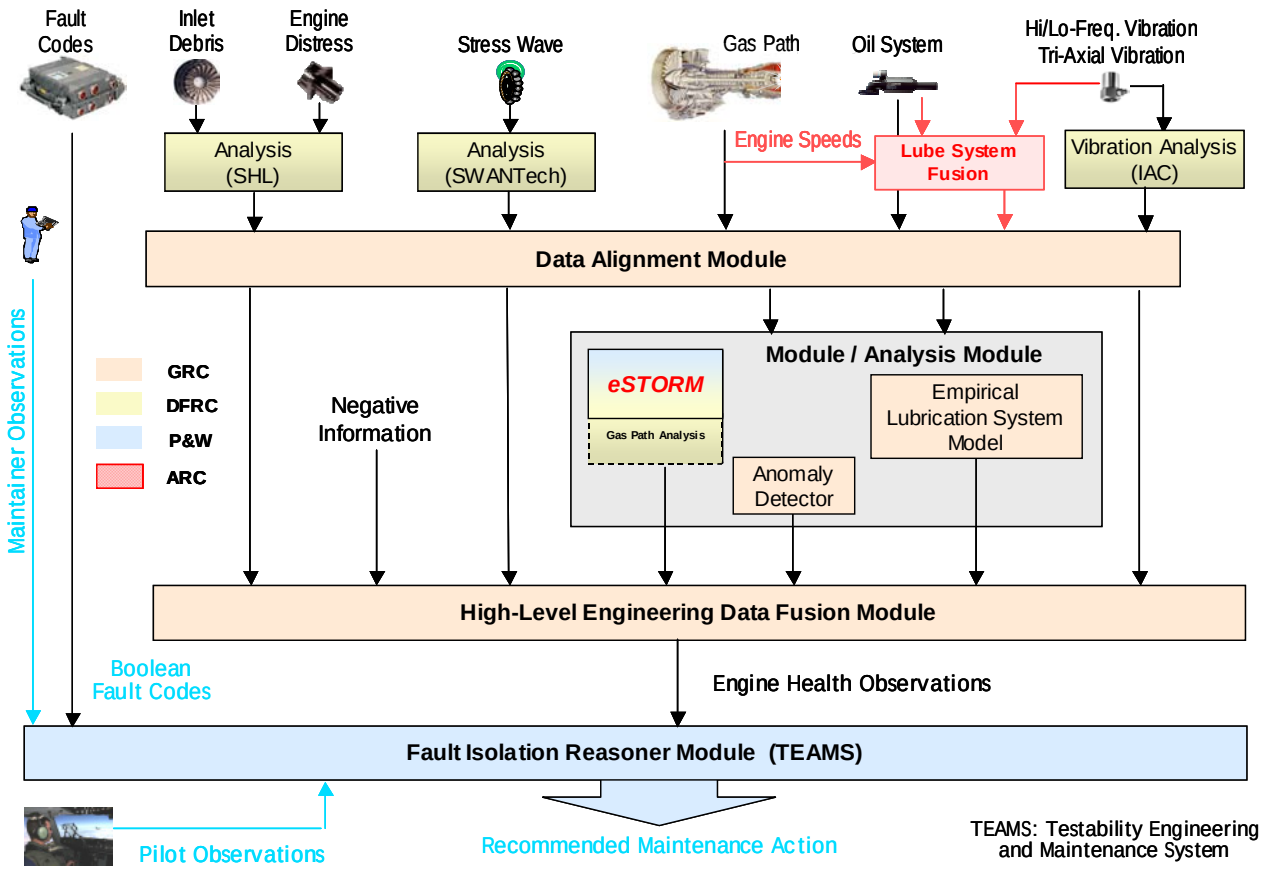

Figure 3. *C17-T1 PHM Data Fusion Architecture*

Both ***Figures 2*** and ***Figure 3*** illustrate the separation of high frequency and low frequency data and how they are processed. Gaspath, oil system and airframe data are typically low frequency in the 5 to 50 Hz bandwidth range, whereas the structural health and vibration monitoring can be in the 2 to 50 kHz range. The high frequency information content is preserved by analyzing these data with appropriate algorithms and exporting feature information at a low bandwidth (say, 1 to 20 Hz) for subsequent data synchronization with the lower bandwidth information in the data alignment module. The (unanalyzed) synchronized gaspath and oil system data is passed to an analysis module that provides for a real time assessment of engine module performance changes, oil system parameter synthesis, and gaspath AD. The feature information is presented to an information fusion module that combines this information to either corroborate or refute fault hypothesis and provide basic engine health assessment. This information could be combined with maintainer observations and full authority digital electronic control (FADEC) fault codes in a second tier of information fusion to produce the most probable maintenance action. It should be noted that the fusion modules were never realized in this program due to the data problems alluded to previously. The fusion process had to be downscoped to address only gaspath information that could be simulated with modifications to existing programs. This led naturally to fusing the physics-based gaspath analysis algorithm with the empirically derived AD system. An overview of the processing modules will be given in Section 3.

2.3 ENGINE DATA

The parameter list pertinent to the C17-T1 Data Fusion program is presented in ***Table 1***.

Table 1. *C17-T1 Instrumentation for Data Fusion*

Parameter	Sample Rate (Hz)	Engr. Units
Aircraft		
Mach No.	25	
Pressure Altitude	25	FT
Calibrated Airspeed	25	KNOTS
True Airspeed	25	KNOTS
Indicated Airspeed	25	KNOTS
Angle of Attack, (a)	50	DEG
Alpha Dot, (AOA Rate)	6	DPS
Roll Angle	50	FPS
Pitch Angle	50	FPS
Heading Angle	50	DEG
Roll Rate	50	DPS
Pitch Rate	50	DPS
Yaw Rate	50	DPS
Flight Path Angle	50	DEG
Altitude Rate	25	FPM
Total Temperature	10	Deg C
Total Pressure	25	IN HG
Static Temperature	10	Deg C
Static Pressure	25	IN HG
Commands		
High Press. Compressor Variable Vane Position	5	Inches
Station 2.5 Bleed Valve Position	5	% Open
Thrust Lever Angle	20	Degrees
High Pressure Turbine Clearance Valve Position	5	% Open
Low Pressure Turbine Clearance Valve Position	5	% Open
Air / Oil Heat Exchanger Valve Position	5	% Open
Oil/Fuel System		
Oil Quantity	2.5	Quarts
Fuel Temperature at Fuel/Oil Heat Exchanger	5	Deg C
Main Oil Temperature	5	Deg C
Main Oil Differential Pressure	5	PSIG
# 4 Bearing Compartment Exit Pressure	2.5	PSIG
Fuel Pump Exit Pressure	20	PSIA
#1, 2, 3 Bearing Compartment Exit Temperature	20	Deg C

Parameter	Sample Rate (Hz)	Engr. Units
Gas Path		
N1	20	% RPM
N2	20	% RPM
Burner Static Pressure	5	PSIA
High Pressure Compressor Exit Total Temperature	5	Deg C
EGT Total Temperature	20	Deg C
Engine Inlet Total Temperature	5	Deg C
Engine Inlet Total Pressure	5	PSIA
Low Pressure Turbine Exit Total Pressure	5	PSIA
Fuel Flow	5	PPH
Low Pressure Compressor Exit Total Temperature	20	Deg C
Low Pressure Compressor Exit Total Pressure	20	PSIA
Structural Assessment Sensors		
Stewart Hughes IDMS Sensor # 1	12.5K	VDC
Stewart Hughes IDMS Sensor #2	12.5K	VDC
Stewart Hughes EDMS Sensor	12.5K	VDC
SwanTech Sensor #1 (Inlet Stator)	23.15K	VDC
SwanTech Sensor #2 (E-Flange)	23.15K	VDC
SwanTech Sensor #3 (Gearbox)	23.15K	VDC
SwanTech Sensor #4 (K-Flange)	23.15K	VDC
SwanTech Sensor #5 (#5 Bearing Oil Pressure)	23.15K	VDC
B-Flange High Frequency Acceleration	46.3K	g
B-Flange Low Frequency Acceleration	5.8K	g
P-Flange High Frequency Acceleration	23.15K	g
P-Flange Low Frequency Acceleration	5.8K	g
Gearbox High Frequency Acceleration	46.3K	g
Gearbox Channel 1 (X-axis Acceleration)	23.15K	g
Gearbox Channel 2 (Y-axis Acceleration)	23.15K	g
Gearbox Channel 3 (Z-axis Acceleration)	23.15K	g

Table 1 provides a listing of the parameters of interest to the Data Fusion program, along with their attendant sampling rates. Unfortunately, during the period of 2002 through 2004, only a handful of flights were made where data recordings were available. These flights experienced problems with instrumentation, so that the requisite information to develop much of the fusion capability was not available. This is summarized below.

Date	***Flight No.***	***Comments***
March 2002	658 to 664, 685	Eight flights in total; Air Force Certified Flight Test Instrumentation was inoperative; missing T25, P25 gaspath data required a STORM redesign to use the available data for analysis; few oil system parameters available; key input parameter BDL 14 missing; no vibration or advanced sensor data available.
July 2003	749, 752, 756	Three flights total; Air Force Certified Flight Test Instrumentation was inoperative during 749 and 752; became available on 756, but T25 data was corrupted; no advanced sensor data.

As a consequence of the unavailability of essential data, it was decided in late 2003 to abandon the original Data Fusion program goal and to proceed with the development of the gaspath performance and anomaly detection algorithms with a subsequent fusion between these two subsystems. This system will be described in a subsequent section of this report.

2.4 DATA FUSION APPLICABILITY

Early in the program, some effort was expended to determine to what degree data fusion would improve diagnostic capability and reliability in a gas turbine application. Much depends on the suite of measurements available to fuse and what informational overlap exists between these sources. For the purpose of establishing an appropriate generic architecture (as in ***Figure 2***) and investigating fusion possibilities, the following information sources were considered.

Engine Gaspath Measurements

These measurements consist of some subset of interstage pressures and temperatures, spool speeds, fuel flow, etc. Depending on the engine type, this subset can range from four flight parameters to as many as twelve. In addition, measurements such as inlet temperature, pressure, Mach number and altitude define the flight condition and aid in the normalization of the main gaspath parameters.

Oil/Fuel System Measurements

These measurements consist of various oil system temperatures, pressures, fuel temperature, and delivery pressure. Advanced sensors indicating oil quality, oil debris monitoring sensors, and oil quantity measurements may be available.

Vibration Measurements

Some form of vibration monitoring is typically performed on most engines. This monitoring is usually on the low spool to measure fan and low-pressure turbine (LPT) vibration, but may include high spool vibration probes, as well as specific bearing and gearbox vibration measurements.

Structural Assessment Sensors

These sensors aid in assessing structural integrity of the engine. Examples include inlet debris and exhaust debris monitors, acoustic sensors, high bandwidth vibration sensors, multi-axis vibration, and blade tip clearance monitors.

FADEC Codes

The electronic engine control performs a myriad of performance tests on signal condition and fidelity. Cross channel checks can aid in determining whether or not a main engine sensor is drifting, going out of limit, or failing. Checks on bleed valves, active clearance control, and variable geometry can provide independent information regarding engine health and the health of various engine subsystems.

Onboard Engine Models

Accurate engine models embedded within the FADEC or residing within a dedicated PHM hardware unit can be used to generate virtual engine measurements to aid in detecting faulty engine instrumentation or confirming degraded engine performance. STORMs have been developed for this purpose. These models adapt themselves to changing conditions observed in the engine's measurement suite, providing virtual sensors that can be used to estimate engine module degradation.

Maintenance/Analysis History

Information regarding the performance disposition of the major modules that comprise the engine can potentially be used as *a priori* information to support the identification and estimation of performance changes within a Module Performance Analysis (MPA) program. Similarly, knowledge of past maintenance actions and

past analysis results may also be used to aid in differentiating between engine component performance faults and engine controls and accessories malfunctions, such as bleed leaks, cooling problems, and similar problems.

Companion Engine Data

On multi-engine aircraft, information from the companion engines might be used to provide additional independent confirmation of instrumentation problems and engine events.

Negative Information

This pertains to a reasoning methodology more than an actual source of information. Negative information constitutes conditions that were not present, but would, or should, have been perceived under the hypothesis that a certain fault scenario exists. In mathematical parlance, it is referred to as proof by contradiction. For example, if Active Clearance Control (ACC) was not enabled (i.e., there was a faulty operation) then exhaust gas temperature (EGT) should increase. If EGT was not observed to increase, then the original assumption is probably false (i.e., ACC must be working properly). This type of information would best be employed in an expert system-like structure that governs the overall analysis and processing of the engine data.

With such a wealth of potential information, the manner by which to combine or fuse information for the stated diagnostic goal must be decided. In general, data can be fused at different levels, for example:

- Sensor level fusion where multiple sensors measuring correlated parameters (e.g., oil pressures, exhaust gas temperatures, etc.) can be combined
- Feature level fusion, where analysis information resulting from independent analysis methods (e.g., component performance changes, event detection) can be combined.
- Decision level fusion, where diagnostic actions (e.g., damage assessments, maintenance advisories) can be combined.

The level of fusion that is appropriate will, in general, depend on many factors, including available sensors, models, analysis algorithms, data monitoring and recording specifics (continuous vs. discrete data), and computing platform. In the case of engine diagnostics, it can be argued that different levels of information fusion will be required depending on whether the system is for a military or a commercial application. In military applications, dedicated PHM systems using independent engine monitoring and analysis hardware and/or direct FADEC involvement are not uncommon. In these scenarios, data is collected and analyzed in real time, onboard the aircraft during flight. In commercial applications, much of the data collected is discrete in nature (several data points per flight, typically at takeoff and cruise). This information is downloaded to ground-based computer systems for subsequent analysis and trending. In addition, advanced sensors are used more in the military environment (as in the C17 T1 program) than in commercial applications, where the historical trend is to minimize sensors and data collection hardware.

To provide the most generic and expandable system for a wide variety of engine applications with varied instrumentation and data sources, the decision was made to perform the information fusion at the feature level (the general architecture depicted in ***Figure 2***). This scheme provides for the potential inclusion of a variety of sensors, standard, special, low frequency, and high frequency, as well as other pieces of relevant diagnostic information that might be in the form of fault codes, maintenance records, and observations. The general structure provides for information synchronization to align the data to a common timeframe, analysis modules for salient feature extraction, and high-level fusion. Applying this to the C17-T1 specific measurement suite gives rise to the architecture depicted in ***Figure 3***.

Investigating the fusion potential for the C17-T1 measurement suite (assuming all instruments were fully operational), it appeared that there was little information overlap relative to common engine fault scenarios. ***Table 2*** enumerates the top candidates in order of fusion potential.

Table 2. *Data Fusion Potential: Information Overlap*

Event	***Measurement System***	***Comment***
FOD	Gaspath	STORM
	IDMS/EDMS	Local system fusion
	Vibration SWAN	May require higher level of event severity
Bleed Leak/Failure	Gaspath	STORM
	Anomaly detector	Empirical modeling
	Bleed temperature/pressure	Not currently available on C17-T1
Lubrication Leak/Loss	Lubrication system sensors (OTs and OPs)	--
	SWAN	May require higher level of event severity
General Vibration Events	Standard vibration, high frequency vibration, tri-axial vibration, SWAN	Possible analysis/algorithm fusion

As can be seen in ***Table 2***, a foreign object damage (FOD) event provides the greatest overlap among the sensor information available. The oil system is fairly detached from the gaspath system, which, in turn, is fairly detached from the structural sensor data. Some form of algorithm fusion that could take advantage of different processing methodologies, modeling techniques (empirical vs. physics) is possible.

The final outcome of this program is predicated on an algorithm fusion between an empirical gaspath anomaly detection system and a hybrid (empirical and physics) model-based gaspath analysis methodology that extends the functionality of the latter. Before describing this system, we will briefly return to a brief general overview and discussion of the fusion process and elements contained within it.

3. ANALYSIS MODULE OVERVIEW

In a data fusion effort, of equal importance as the data itself is the repertoire of analysis tools required to reduce, analyze, and interpret the information collected. For the application at hand, a set of specialized algorithms employing both physics-based and empirical methodologies has been employed. These include:

1. Data alignment for synchronizing the raw data/information to a common sample rate for subsequent analysis
2. Gaspath anomaly detection that offers an empirical model of nominal gaspath behavior, with quantitative metrics for inferring the level of departure from normal when applicable
3. Gaspath analysis that provides for the isolation, estimation, and tracking of engine module performance faults
4. Lubrication system modeling taking the form of empirically derived models for estimating oil quantify and bearing pressure.

A brief synopsis regarding the nature of these algorithms is given below. A detailed description of the theory, structure, and implementation of these analytical modules can be found in the quarterly program technical narratives and annual program progress presentations.

3.1 DATA ALIGNMENT

As ***Table 1*** indicates, the information being collected on the C17-T1 ranges dramatically in bandwidth from 2.5 to 50 Hz for the low frequency sensors, and from 5.8 to 46.3 kHz for the high frequency sensors. Referring to the system architecture in ***Figures 2*** and ***3***, the high frequency information will be processed by specialized algorithms to capture the salient information content of the signal and distilled to low bandwidth feature information at approximately 1 Hz. As a precursor to eventual information fusion, this data, along with the remaining low frequency sensor signals, is time synchronized to a common sampling rate. For this application, the data alignment frequency is 20 Hz and is accomplished by up and down sampling of the raw signal.

3.2 LUBRICATION SYSTEM MODELING

The original intent of the oil system modeling effort was to provide an empirically derived model of the sensed oil system parameters for the purpose of analytical redundancy and fault detection. Because of the instrumentation and data collection difficulties alluded to previously, the work in this area has taken the form of empirically derived models for estimating oil quantity (POILQ) and No. 4 bearing pressure (PN4SP) from other available engine oil system measurements (main oil temperature and pressure), gaspath measurements, and other engine and flight parameters (a total of 14 input parameters) (***Table 3***).

Table 3. *Input Parameters for Empirical Lubrication Model*

Parameter Name	***Description***
ptfuel	Fuel temperature at fuel/oil heat exchanger
ptoil	Main oil temperature
poilp	Main oil differential pressure
pfc	Air/oil heat exchanger valve position
ptt2	Engine inlet total temperature
ppt2s	Engine inlet total pressure
pacwf	Fuel flow
pn1	N1
pn2	N2
mach	Mach number
palt2	Pressure altitude (hp)
hdot	Altitude rate
alpha	Angle of attack
ptrasl	Thrust lever angle

Initially, artificial neural networks (ANNs) were considered for modeling the lubrication system data; however, due to computational burden in training these ANNs, simple linear models were considered. Those models took the form:

$$y(t) = c_1 u_1(t) + c_2 u_2(t) + \ldots + c_p u_p(t) \qquad \textit{Equation 1}$$

where *y(t)* is the target variable at time $t, u_i(t)$ are the corresponding input variables, and c_i are the input weighting coefficients. There are *p* variables used as input to the model. The linear modeling problem is to estimate the c_i given *training* data. It was found that linear models fit the lubrication data as well as the neural net models. To further reduce complexity, a model reduction process using a backwards elimination approach was applied to identify the optimal subset of input variables for both models (POILQ and PN4SP). This resulted in models with seven input variables, albeit, different variables for each model. An example of the response for the oil quantity parameter versus the actual measured oil quantity is given in ***Figure 4***.

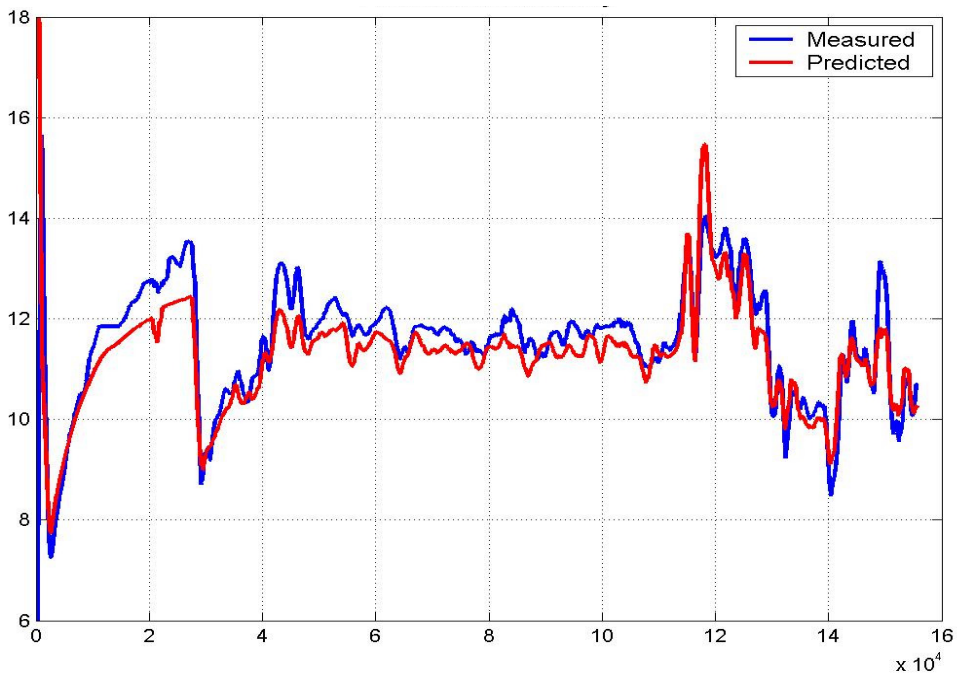

Figure 4. *Measured Versus Predicted Oil Quantity*

Similar results for No. 4 bearing pressure (PN4SP) appear in ***Figure 5***. In this plot there is a comparison between measured PN4SP (blue) and estimates using a one variable model (green) and a six variable multi-layer perceptron ANN (red).

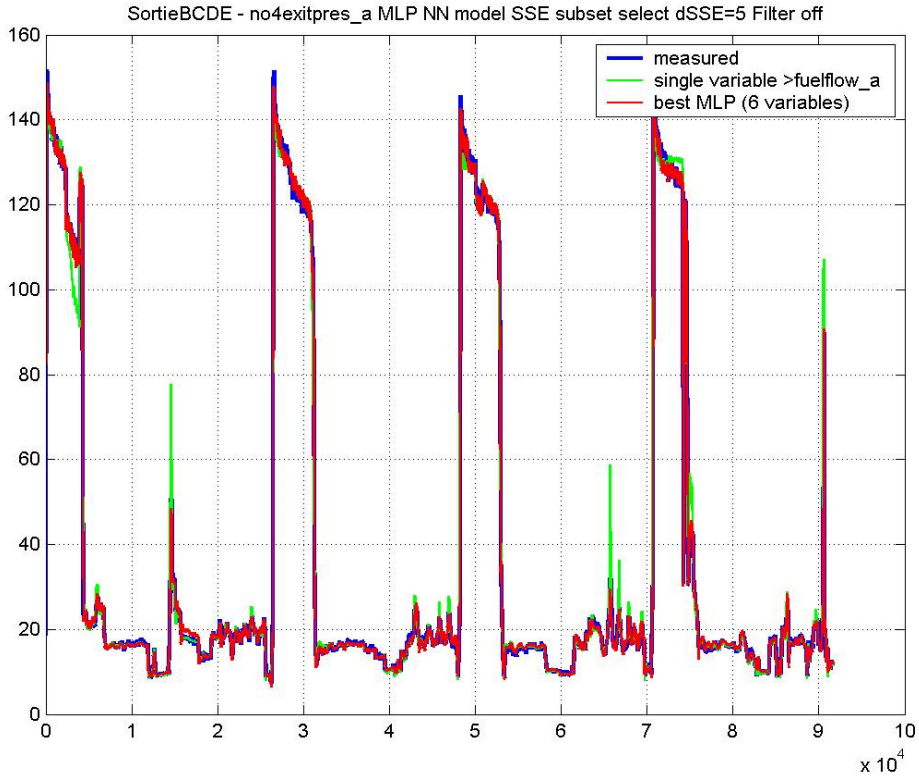

Figure 5. *Measured Versus Predicted PN4SP*

3.3 GASPATH ANOMALY DETECTION

A PHM system generally has provisions for the detection and isolation of known fault conditions. During the course of engine operation, however, it is possible to encounter fault conditions or other off-nominal situations that were never anticipated, never modeled (or incorrectly modeled), or never encountered in previous engine operation. Such events can be referred to as anomalies and it is prudent to provide for the detection of such occurrences.

To address unanticipated anomalies, empirical models developed from a statistically significant sample of nominal engine operation data can be used to form the basis for an anomaly detector. These types of models typically take the form of ANNs and are trained to output normal engine operation measurement estimates. When compared to actual measurements, they provide a basis for making a statistical determination as to whether or not the observations at hand conform to what is considered *normal* operation. An empirical model of the gaspath components was developed for the F117 engine. The underlying modeling mechanism is a radial basis function (RBF) ANN. During the training process for these types of ANNs, the training data is self-organized into a group of classes. Each class is modeled by an n-dimensional Gaussian function, referred to as a radial basis function. These functions capture the statistical properties and dimensional interrelationships between the input and output engine data parameters. The structure of an RBF ANN is depicted in ***Figure 6***.

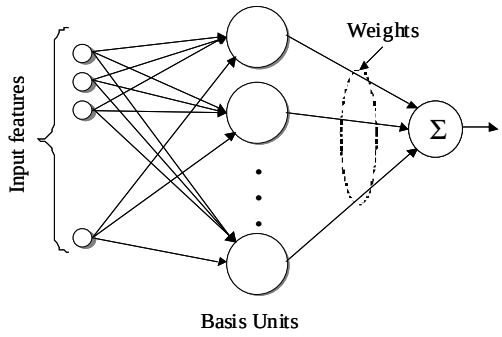

Figure 6. *Gaspath Anomaly Detector Model*

The gaspath AD for the F117 is configured as a set of several RBF ANNs, each representing a particular flight regime or operational characteristic to enhance the accuracy of the overall detector. For example, there is an RBF ANN for steady state operation with and without stability bleed off-take, acceleration, and deceleration. Simple regime recognition logic controls the selection of the appropriate RBF ANN. Preprocessing of engine parameters in terms of standard day corrections and range normalization are made prior to input into the ANN. The primary output of the system is a (fuzzy-like) detection variable that takes on the values between 0 (anomalous data) and 1 (normal data). A threshold and median filtering is applied to the output to produce a discrete binary parameter to serve as a detection flag. A representation of this model is depicted in ***Figure 7***.

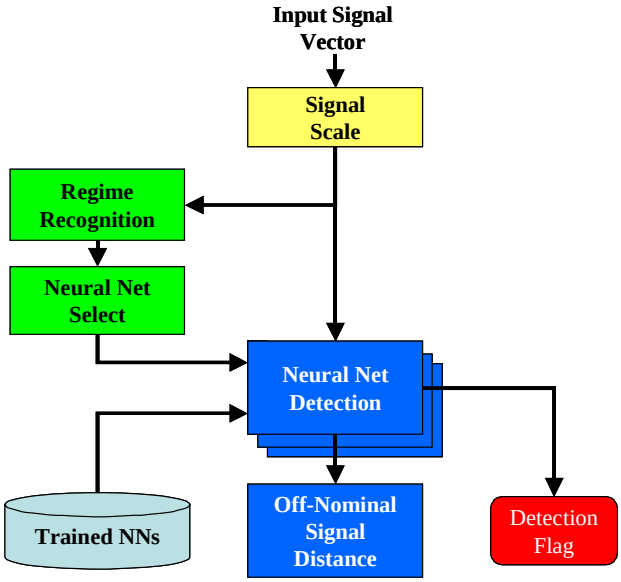

Figure 7. *Gaspath Anomaly Detector Model*

In addition to the binary AD output parameter, individual input parameter distance measures are available that quantify each parameter's contribution to the data's classification as normal or anomalous. Collectively, these provide an empirical signature for anomalous data and are particularly helpful in determining in-range sensor faults. A graphical depiction of the output for a segment of an actual C17-T1 flight with a simulated fuel flow bias added (as an anomaly) is given in ***Figure 8***.

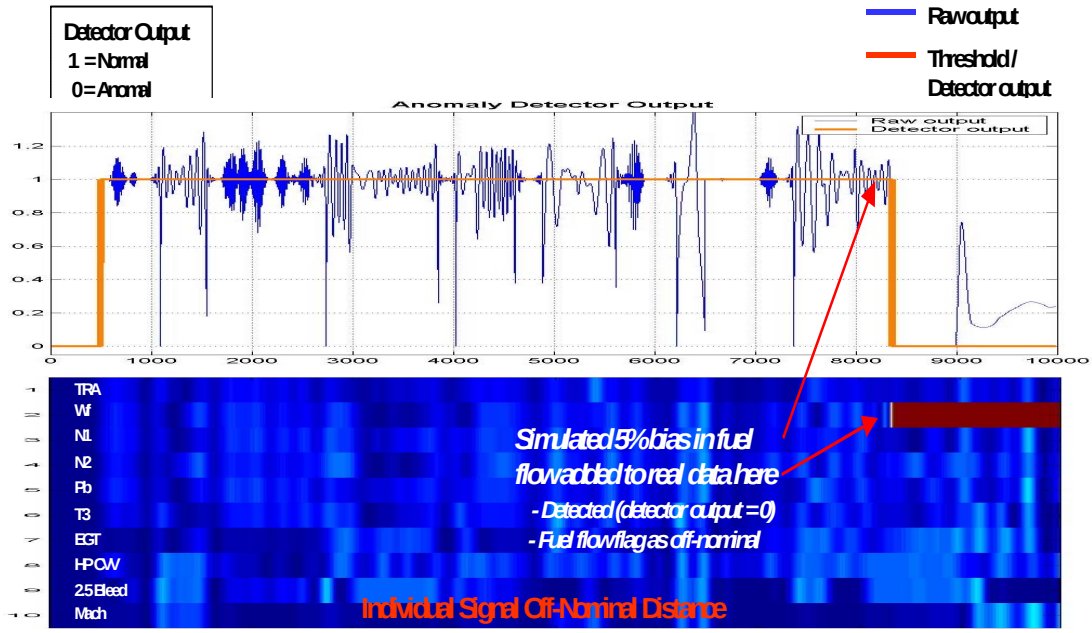

Figure 8. *Graphical Depiction of Gaspath Anomaly Detector Output*

The upper chart in ***Figure 8*** portrays the raw output (blue) and the threshold (binary) output (orange) of the AD for nominal operation and an implanted (simulated) fuel flow fault. The lower chart is a color-coded graphical representation of the individual input parameter distance measures, where blue signifies normal and red signifies abnormal.

3.4 GASPATH ANALYSIS

Traditional gaspath analysis provides for the isolation, estimation, and tracking of engine module performance faults. As a three decade-old practice, it has been the subject of considerable research. A variety of methods of gaspath analysis have evolved as disparate techniques like optimal estimation, fuzzy logic, ANNs, Bayesian Belief Networks, and Kalman filters. The efficacy of any of these methods depends on many factors and is somewhat application dependent, although they all share the same characteristic of assessing change in performance relative to some reference. In the context of the present application, a modified Kalman filter approach was chosen, with the frame of reference being the monitored engine at time of installation.

For the C17-T1, the reference level is obtained through a hybrid engine model. This hybrid model representation of the monitored C17-T1 engine consists of a simple real time physics-based state variable engine model (SVM) coupled with an empirically determined modeling element. The empirical element takes the form of a multi-layer perceptron (MLP) ANN that models the difference between the subject engine (at installation) and the SVM. The above elements, in combination with a Kalman filter observer acting on the residuals between the hybrid model and the monitored engine, provides the requisite process for performing the gaspath analysis. Thus the hybrid gas turbine engine model consists of both physics-based and empirically derived constituents. Physics-based models would consist of piecewise linear or nonlinear aerodynamic-thermal models of varying complexity; SVM is a simple example. In contrast, empirical models are derived solely on the basis of collected data. A typical architecture for such a hybrid model that might be used for the purpose of engine performance tracking is depicted in ***Figures 9*** and ***10***. ***Figure 9*** illustrates a typical configuration where an empirical modeling process captures the difference between the physics-based engine model and the actual engine being monitored. The engine performance estimation process in this architecture will take the form of a Kalman filter observer. This configuration (in its most simplistic form) is given in ***Figure 10***.

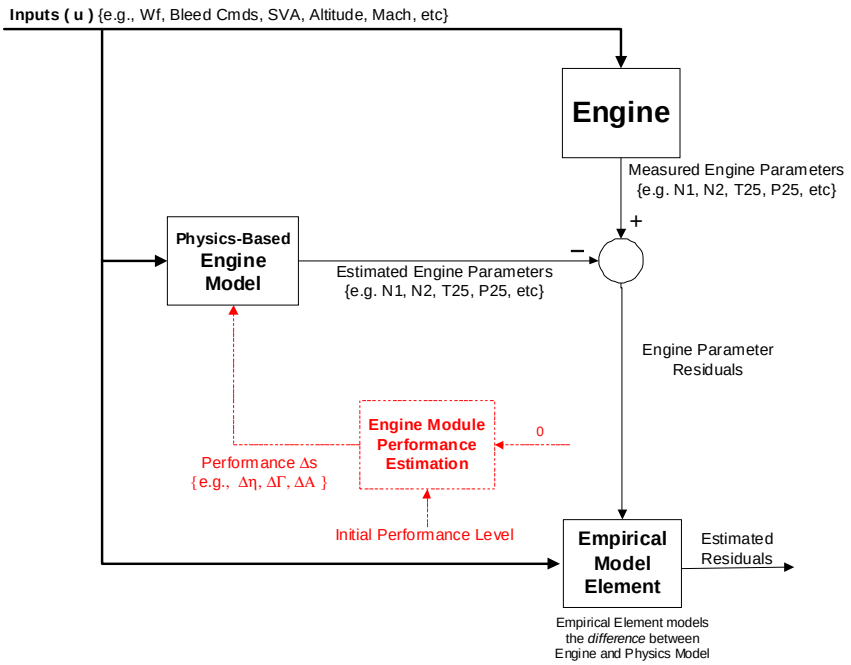

Figure 9. *Building the Empirical Element of the Hybrid Model*

The combination of the empirical element and the physics-based model provides a more faithful representation for the particular engine being monitored. This provides more meaningful residual information from which an engine performance change assessment can be performed, since potential (physics-based) model inaccuracies and shortcomings have been effectively removed by virtue of the empirical element. It should be noted that the hybrid approach has advantages over a purely empirical model approach, in that the latter tend to require considerably more data (to model all of the physics) and tend to be quite large in comparison with the former, which appears to be fairly robust and small in size.

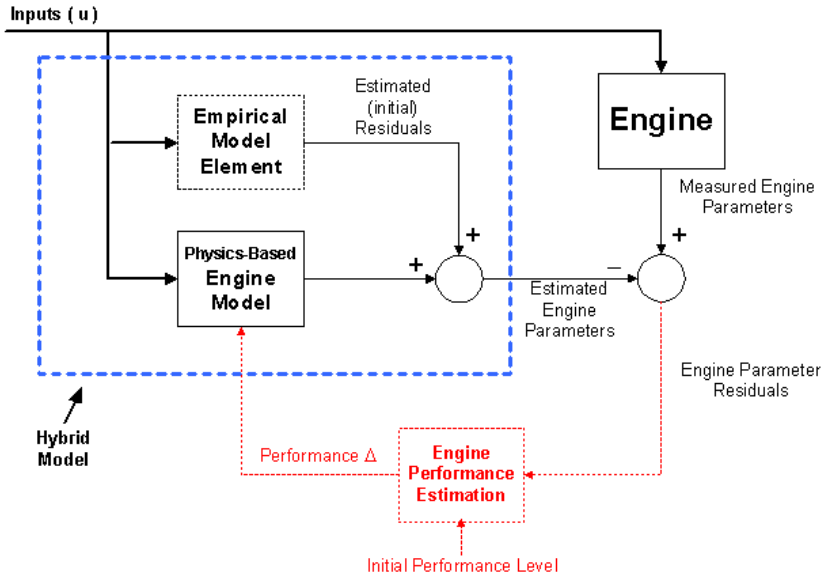

Figure 10. *Implementing the Empirical Element of the Hybrid Model*

In ***Figures 9*** and ***10***, the output from the Kalman filter observer labeled tuners refers to a vector of module performance changes (from installation) that are estimated from the measurement residual input to the Kalman filter. These tuners are tracked over time for diagnostic purposes. They are also fed back to the SVM to update the model measurement predictions that in closed loop are forced to match the actual engine measurements (on the average), driving the residuals to zero. The empirical element (MLP ANN) in the hybrid representation is required to mitigate the effects (on the tuners) of model inaccuracies and deficiencies. ***Figure 11*** illustrated this effect on the tuners for actual C17-T1 engine data.

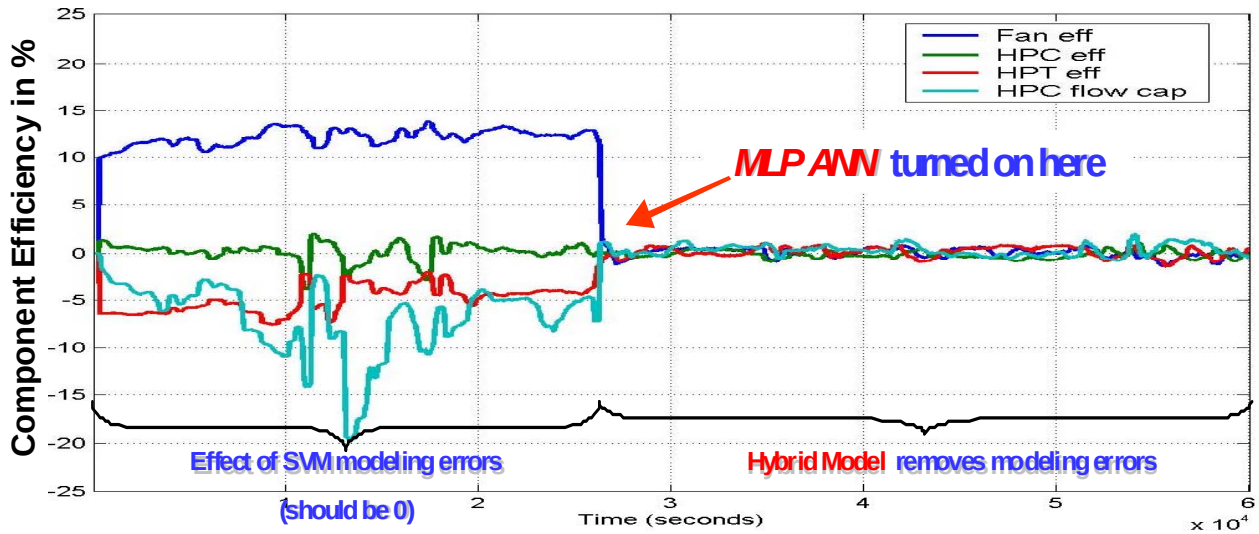

Figure 11. *Establishing the Zero Reference for Module Performance Tracking – Effect on the Tuners*

Once the reference level is established (zero on the average) for the module performance deltas, only then can component deterioration be effectively tracked over time. The marked increase in fault visibility with such an approach is illustrated in ***Figure 12***. This hybrid model configuration is referred to as enhanced STORM (eSTORM).[1]

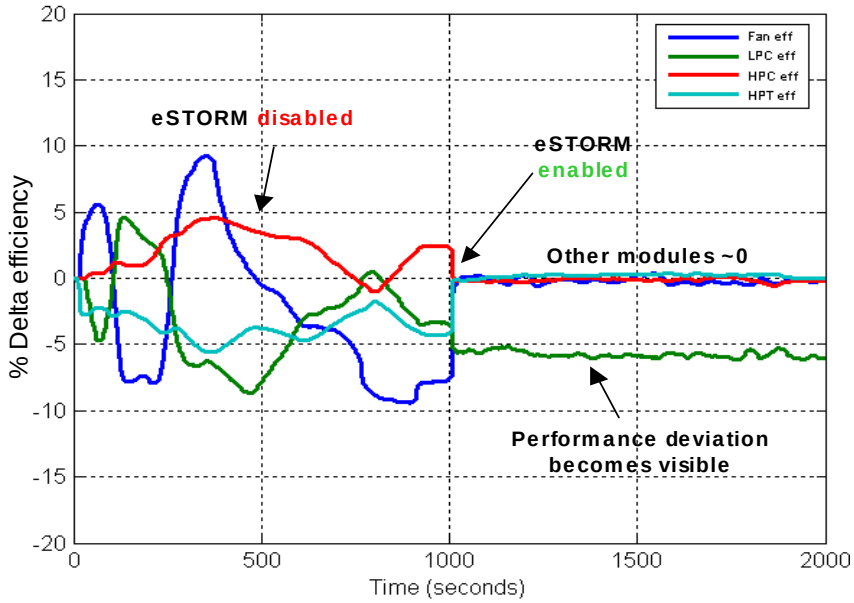

Figure 12. *Establishing the Zero Reference for Module Performance Tracking – Increase in Fault Visibility*

4. GASPATH ALGORITHM FUSION

One of the deficiencies in the gaspath analysis approach described in the previous section is its intolerance to measurement error. The presence of a measurement bias would cause an attendant deviation in the performance tracking tuners in the system's attempt to drive the (offending) measurement residual back to a zero level. In this instance, the tuners become a mathematical artifact for accommodating the measurement error. The problem is that the assessment erroneously applies the blame of a measurement error to a module performance fault or a combination of module performance faults. What is described in this section is a novel approach of combining (or fusing) two gaspath algorithms, namely AD and eSTORM in such a way as to extend the features of both approaches taken independently. In particular, we extend the gaspath analysis (in eSTORM) to detect and accommodate measurement bias without corrupting the module performance tracking (tuners). This fusion methodology involves only the gaspath parameters and was possible to model and demonstrate with the use of simulated engine data, thereby allowing the fusion work to continue in light of the data acquisition problems experienced in the C17-T1 PHM program.

The system we will describe consists of eSTORM, AD, and a high level fusion module using some fuzzy logic, with attendant signal processing elements that allowed fault event detection, annunciation, and accommodation. The system was designed to address rapid shifts in both performance faults and measurement error (biases). Signal processing elements were developed to mitigate the number of false alarms that might be driven by processing and signal uncertainties.

The overall strategy that was employed made use of signal processing logic to test for parameter deviation persistency to detect and distinguish true deviations from parameter/system noise induced deviations. The heart of the persistency logic consisted of tracking eSTORM and AD output parameters by both short- and long-term median filters. The divergence between these two types of filters was used to detect the initial onset of a parameter trend, as well as its degree of persistency. The persistency logic considered initial large deviations (between short- and long-term filtered parameters) followed by a subsequent convergence back to small deviations, which were the central indicator that a persistent trend shift had occurred. The quantification of large and small deviations was made through the use of fuzzy membership functions. Attendant logic was used to classify a detected trend as either a performance fault or a measurement (sensor) fault. A functional block diagram for the overall fusion is depicted below in ***Figure 13***.

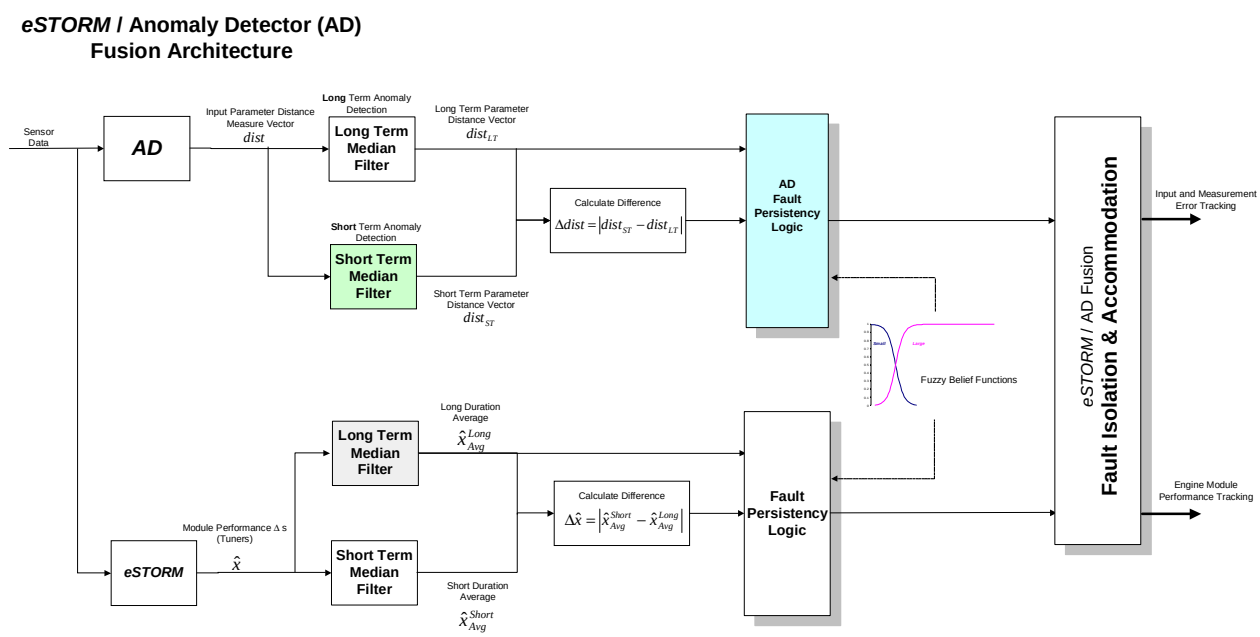

Figure 13. *Gaspath Analysis Algorithm Fusion Architecture*

4.1 SHORT- AND LONG-TERM FILTERS

The short- and long-term filters may take many forms. The basic requirement for the filters is that they exhibit a measurable difference in response to a step change, as illustrated in ***Figure 14***.

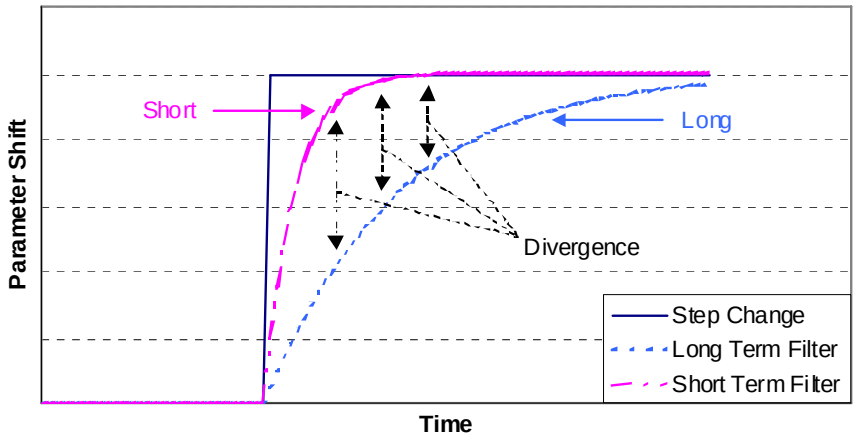

Figure 14. *Short- and Long-Term Filter Response*

The arithmetic difference (termed divergence) between these two filtered signals provides the requisite information for determining whether the monitored signal has sustained a persistent shift. This is applied on a parameter-by-parameter basis for each of the monitored engine parameter (residual) signals.

The divergence parameter vectors provide the information to assess whether a persistent shift has occurred. The process makes use of fuzzy membership functions to assess whether or not the divergence is large or small. Although these membership functions can take many forms, the sigmoid functions depicted in ***Figure 15*** are illustrative of the concept.

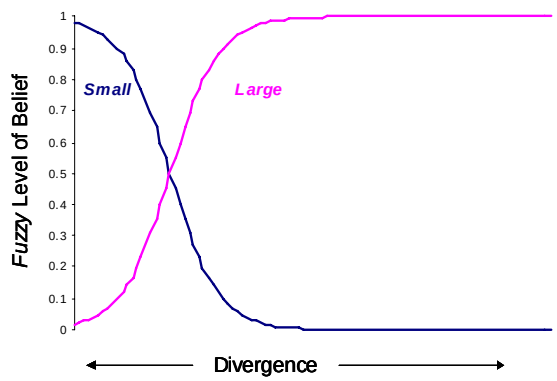

Figure 15. *Typical Small and Large Fuzzy Membership Functions*

To assist in the fault isolation associated with detected parameter shifts, a very long filter is maintained for each

parameter to establish a reference level from which the transgression was observed. These are calculated in the same manner as the long filtered parameters, with appropriate filter constants.

An example of a nonpersistent trend shift (in a measured parameter) is illustrated in ***Figure 16***, while an example of a persistent trend shift by comparison is depicted in ***Figure 17***.

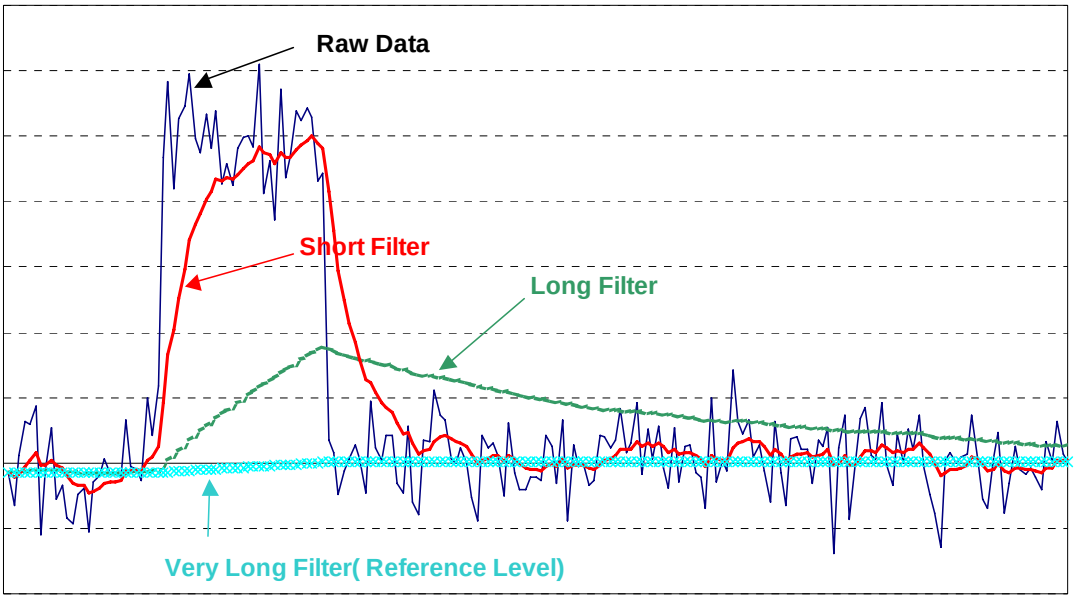

Figure 16. *Example of a Nonpersistent Trend Shift*

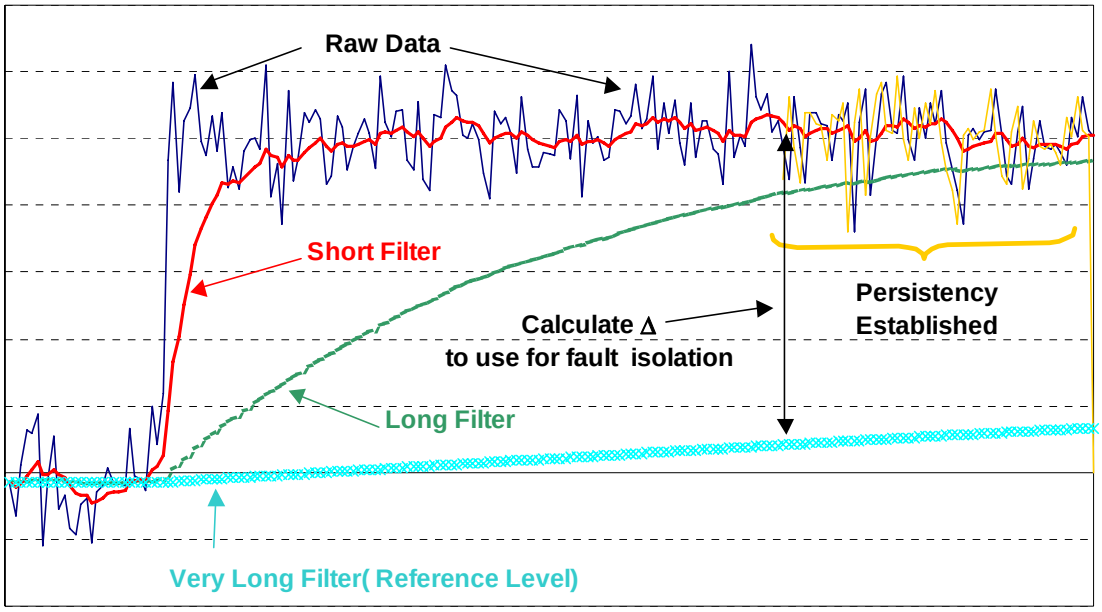

Figure 17. *Example of a Persistent Trend Shift*

The approach taken in the algorithm fusion was to use the AD outputs to indicate that a shift in (at least one) measured parameter had taken place. The AD outputs a distance measure for each of the gaspath parameters (see previous discussion on AD). A divergence between the short- and long-term filtered values of these metrics would give an indication if an excursion has taken place. If the excursion is short-lived (as in ***Figure 16***), no further action is taken. If, however, the indicated trend shift endures, (i.e., the excursion is persistent), a delta calculation is performed (for each gaspath parameter) between the present (persistent) value and the reference value. This provides a vector of gaspath deltas that embodies a signature that describes the underlying fault. At this juncture, a variety of isolation procedures are available to identify the fault and assess its relative magnitude. The particular isolation procedure used in this application is similar to that described in *The Use of Kalman Filter and Neural Network Methodologies in Gas Turbine Performance Diagnostics: A Comparative Study.*[2]

An illustration of the effect of the fused algorithm is depicted in ***Figure 18***.

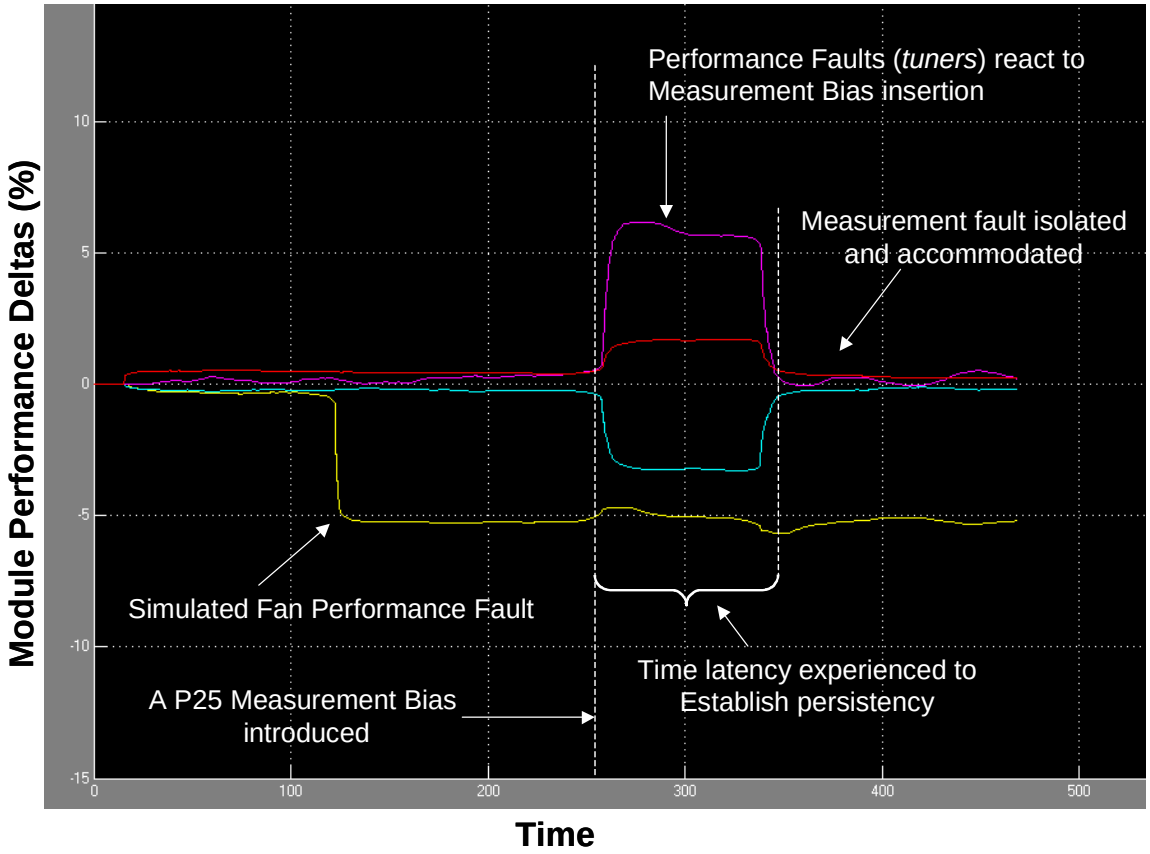

Figure 18. *Example Effect on Performance Tracking with Measurement Bias Insertion, Isolation, and Accommodation*

Figure 18 depicts the example effect on the performance tracking (tuners). The plot begins (at time 0) with a nominal engine. Shortly after 100s, a simulated fan fault is introduced and tuners react by tracking the fan efficiency excursion. At approximately 250s, a P25 measurement bias is introduced. The tuners react by absorbing the measurement bias; the eSTORM system explains away the measurement bias as a combination of module performance faults. This is what would happen in a traditional gaspath analysis system (in real time). Since the

[2] A. Volponi, *The Use of Kalman Filter and Neural Network Methodologies in Gas Turbine Performance Diagnostics: A Comparative Study,* ASME 2000-GT-547, IGTI Turbo Expo 2000, Munich; accepted for *Transactions of the ASME*, Journal of Engineering for Gas Turbines and Power.

system only knows module performance faults, it will interpret all measurement signatures as some combination of these faults. Sensor error (bias) faults are typically not included in these real time analysis systems, as the number of faults would then exceed the number of measurements. In such a system, the perturbation in the tuners (observed after time = 250s) would continue unabated, at least until the measurement bias is removed.

In the fused system, the AD would detect the excursion at 250s. After what appears to be approximately 100s, persistency is established and a measurement delta vector is computed. A fault isolation is then performed, thereby isolating the P25 bias. After this identification, the bias can be accommodated by either applying the bias estimate (from the isolation process) to cancel the signal, or, (in a dual channel FADEC), by switching to the alternate measurement channel (the approach taken here for simplicity). In either event, the bias is effectively removed and the tuners return to their pre-biased state.

5. CONCLUSIONS

While the Data Fusion program fell short of demonstrating a working information fusion system for the C17-T1 aircraft, largely because of data acquisition problems, it did provide a research vehicle for establishing a general approach and architecture for the incorporation of such a system. Central to the program work was the identification and development of several key modules, particularly, the analysis elements. With respect to these modules, it was demonstrated that there is a good potential for deriving a viable virtual oil quantity measurement. This is particularly important for commercial engine applications where features such as oil consumption rate are of interest; however, oil quantity measurements during flight are not available to monitor this feature in real time.

Although not mature, significant progress was made in defining and developing a gaspath AD system. System studies yielding a configuration require several regime-dependent detectors. For example, steady-state operation and transient acceleration and deceleration all required separate detector models. Separating bleed *on* and bleed *off* operations also resulted in increased accuracy.

Finally, the (algorithm) fusion of the AD and a real time gaspath analysis system (eSTORM) was able to demonstrate the (positive) impact of fusing disparate information sources. Although restricted to the gaspath because of simulation constraints, it was possible to demonstrate a marked improvement in the classical gaspath analysis. In particular, it was demonstrated that measurement bias could be detected, estimated, and accommodated so that module performance tracking could proceed without corruption.

6. REFERENCES

1. Brotherton, T., Volponi A., Luppold, R., Simon, D. L., 2003, "eSTORM: Enhanced Self Tuning On-board Real-time Engine Model," Proceedings of the 2003 IEEE Aerospace Conference, Vol. 7, March 8-15, 2003, pgs. 3075-3086.

2. Volponi, A., *The Use of Kalman Filter and Neural Network Methodologies in Gas Turbine Performance Diagnostics: A Comparative Study*, ASME 2000-GT-547, IGTI Turbo Expo 2000, Munich; accepted for *Transactions of the ASME*, Journal of Engineering for Gas Turbines and Power.

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13. ABSTRACT ***(Maximum 200 words)***

Aircraft gas-turbine engine data is available from a variety of sources, including on-board sensor measurements, maintenance histories, and component models. An ultimate goal of Propulsion Health Management (PHM) is to maximize the amount of meaningful information that can be extracted from disparate data sources to obtain comprehensive diagnostic and prognostic knowledge regarding the health of the engine. Data fusion is the integration of data or information from multiple sources for the achievement of improved accuracy and more specific inferences than can be obtained from the use of a single sensor alone. The basic tenet underlying the data/information fusion concept is to leverage all available information to enhance diagnostic visibility, increase diagnostic reliability and reduce the number of diagnostic false alarms. This report describes a basic PHM data fusion architecture being developed in alignment with the NASA C–17 PHM Flight Test program. The challenge of how to maximize the meaningful information extracted from disparate data sources to obtain enhanced diagnostic and prognostic information regarding the health and condition of the engine is the primary goal of this endeavor. To address this challenge, NASA Glenn Research Center, NASA Dryden Flight Research Center, and Pratt & Whitney have formed a team with several small innovative technology companies to plan and conduct a research project in the area of data fusion, as it applies to PHM. Methodologies being developed and evaluated have been drawn from a wide range of areas including artificial intelligence, pattern recognition, statistical estimation, and fuzzy logic. This report will provide a chronology and summary of the work accomplished under this research contract.

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