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Real-Time Fault Identification for Developmental Turbine Engine Testing*

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ABSTRACT

Hundreds of individual sensors produce an enormous amount of data during developmental turbine engine testing. The challenge is to ensure the validity of the data and to identify data and engine anomalies in a timely manner. An automated data validation, engine condition monitoring, and fault identification process that emulates typical engineering techniques has been developed for developmental engine testing.

An automated data validation and fault identification approach employing engine cycle-matching principles is described. Engine cycle-matching is automated by using an adaptive nonlinear component-level computer model capable of simulating both steady-state and transient engine operation. An automated model calibration process is also described. The model enables automation of traditional data validation, engine condition monitoring, and fault identification procedures. A distributed parallel computing approach enables the entire process to operate in realtime.

The result is a capability to detect data and engine anomalies in realtime during developmental engine testing. The approach is shown to be successful in detecting and identifying sensor anomalies as they occur and distinguishing these anomalies from variations in component and overall engine aerothermodynamic performance.

NOMENCLATURE

CLM	Component-Level Model
ETA	Efficiency
EUD	Engineering Unit Data
FG	Gross Thrust
FHV	Fuel Lower Heating Value
HPX	Power Extraction
MPI	Message Passing Interface
N	Rotational Speed
P	Total Pressure
PS	Static Pressure
SG	Specific Gravity
T	Total Temperature
W	Mass Flow Rate
WB	Air-Bleed Mass Flow Rate
WFB	Burner Fuel Flow Rate
WFAB	Augmentor Fuel Flow Rate

Greek Symbols

δ	Ratio of Measured Value to Baseline Model Value

Subscripts

0	Free Stream
1, 2, 3...	Engine Station Designation
ETA	Efficiency
HPC	High-Pressure Compressor
HPT	High-Pressure Turbine
LPC	Low-Pressure Compressor
LPT	Low-Pressure Turbine
WC	Referred Mass Flow Rate

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INTRODUCTION

Turbine engine testing at the Arnold Engineering Development Center (AEDC) is conducted to evaluate engine operation at a wide variety of simulated altitude conditions. Hundreds of sensors, each producing measurements at rates in excess of one hundred samples per second, are typically installed in the engine and test facility to measure aerothermodynamic performance. Consequently, a typical 8-hour test can produce 30 million samples of aerothermodynamic performance data. The challenge is to ensure the validity of the data, monitor the condition of the engine, and to promptly identify anomalies.

The countless variations of steady-state and transient engine operation and the necessity to delineate between sensor anomalies and abnormal engine deterioration, combined with the large volume of data, overwhelms the capabilities of traditional data validation methods (Malloy, 1993). Although traditional methods produce meaningful results, they are labor-intensive and time-consuming. Consequently, application of the methods is typically restricted to a fraction of the available data which diminishes the ability to detect anomalous data and intermittent events. An automated approach that emulates the traditional data validation and engine condition monitoring processes is needed to ensure a comprehensive assessment. Nonlinear component-matching engine models embody the physical relationships employed in the data validation and engine condition monitoring processes and can provide a basis for automating them. However, in order to provide a sound basis, the models must accurately represent the test engine.

Calibration of a model to accurately represent a specific engine is also a labor-intensive task. System identification techniques have commonly been applied to reduce the effort required to calibrate a model and have been used most effectively for calibrating simplified models to measurement sets for which data uncertainties are well defined. However, system identification techniques can exhibit numerical divergence as model complexity increases or as data uncertainties increase [(Friedland, 1969) (Trankle, 1982)]. Consequently, system identification techniques have not been effectively applied to complex transient models in a developmental test environment. Therefore, to take advantage of the relationships inherent in a component-matching model, a more effective calibration technique is required.

Fault identification capabilities have been demonstrated on systems for which major attributes of the system (e.g., components, configuration, control) remain unchanged and the same operating condition is repeated many times. A variety of approaches provides these capabilities, including expert systems, neural networks, and system identification techniques such as Kalman filtering. The system identification techniques rely on models that are well-defined for model-to-data closure and fault identification (Fitzgerald, 1971) while neural network techniques rely on a statistically significant number of samples at a selected operating condition (Doel, 1990). A component-level model for a developmental engine is not defined sufficiently for these techniques and undergoes frequent change to adapt to changes in the engine's attributes. Additionally, a developmental engine, because of frequent configuration changes, rarely repeats a specific operating condition, reducing the applicability of system identification and neural network approaches. Consequently, a fault identification approach that is able to adapt to engine system changes is required to enable an automated model-based approach to data validation and engine condition monitoring.

A fault identification approach is described. The approach relies on an automated real-time model calibration technique and emulates traditional fault identification processes. The technique focuses on single faults as each occurs rather than on the estimation of an optimal combination of all possible faults (AGARD-CP-448). The approach is adaptable to changes encountered in developmental turbine engine testing and relies on a basic component-matching model that represents the engine cycle (e.g., turbofan, turboshaft, turbojet). Industry-accepted engine modeling practices are combined with advanced fault diagnostic algorithms and parallel computer techniques to provide real-time fault identification including data validation and engine condition monitoring for steady-state and transient engine operation.

FAULT IDENTIFICATION APPROACH

To be effective, gas path analysis tools must identify component performance deviations and measurement errors. The model-based fault identification process consists of two main phases. The first phase of the fault identification process relies on a real-time model-based evaluation of test data to detect a probable fault resulting from measurement errors, engine component events, or a combination of the two. After a fault is detected, automated model simulation studies are performed to diagnose the most probable cause of the fault in near-real time. This detailed diagnostic information enables the analysis engineer to assess the relative probability of the fault and, in most cases, quickly identify and verify the actual cause of the fault. If necessary, additional test data may be acquired at previously tested stabilized engine operating conditions to increase the fidelity of the diagnosis. The following sections describe the adaptive engine model and the model-based fault identification approach.

Model Description

A component-level model (CLM), capable of simulating steady-state and transient engine operation, serves as the basis for the fault identification process. The CLM combines the physical relationships that govern engine operation with empirical relationships that describe individual component performance. The result is an adaptable model in which the effects of changes to engine attributes (e.g., components, configuration, controls) are incorporated by making corresponding changes to the model attributes. Additionally, the component matching approach quantifies the changes to engine performance interrelationships which provide a prediction capability for the fault identification process.

The CLM is an assembly of components constrained to operate in unison to simulate the engine (Chappell and McLaughlin, 1993). An augmented turbofan engine, for example, may include a variable-geometry fan and compressor, combustor, high- and low-pressure turbines, fan bypass duct, mixer, afterburner, and variable exhaust nozzle (Fig. 1). The component models combine thermodynamic process equations with empirically determined component performance relationships to simulate component performance. An iterative technique (McLaughlin, 1982) is used to satisfy a set of implicit rela-

[1]Real-time speed is defined as the speed required to continuously execute the model-based fault detection algorithms at an average execution rate of 100 Hz.

tionships that constrain the assembly to mass, momentum, and energy conservation principles. Measured engine control variables are used to govern model operation. The effects of rotor acceleration, heat transfer, and off-schedule variable geometry are included, providing a simulation of steady-state and transient engine operation ranging from engine starting conditions to maximum power. The CLM computes temperature, pressure, mass flow, and rotational speed for each intercomponent engine station as defined by Aerospace Standard 755.

Baseline component performance relationships are an integral element of the CLM; however, they are determined primarily for a baseline component configuration isolated from the engine assembly in a component rig test. Component performance variations that result from operation within the engine assembly are included by applying scaling parameters to the baseline performance relationships. The scaling parameters account for the effects of intercomponent interactions, component modifications, and off-schedule geometry. The scaling parameters are usually applied as scalars to flow, pressure ratio, and efficiency relationships and are defined as a ratio between measured values and baseline values. The scalars for the entire engine, comprised of the scalars from all the individual components, are the primary variables used to calibrate the engine model to a specific measurement set. The methods of determining the values of the scalars for the fault identification process is described in the following sections.

Model Calibration

The real-time fault identification process requires three distinct model calibration steps to minimize errors in the engine model that are often significant for developmental engine testing. First, a steady-state engine calibration is performed at a specified flight condition to document engine health at intermediate and part-power conditions. This is performed to calibrate the steady-state component characteristics at these conditions and to adjust the transient measurements using the more accurate and numerous steady-state data. Next, a transient calibration is performed to determine time-dependent effects. Finally, continuous real-time model calibration is performed to identify faults that may occur during subsequent developmental engine testing.

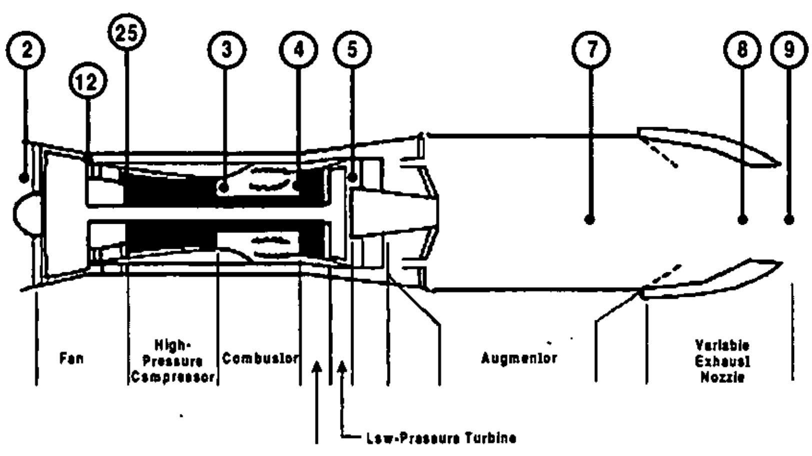

Fig. 1. Station designation for an augmented turbofan engine.

Step 1- Steady-State Performance Calibration. A steady-state performance calibration is performed at a specified flight condition to establish engine health at intermediate and part-power conditions and update the baseline component characteristics. Estimation accuracy is enhanced using a detailed spatial array of measurements at each of the measurement stations. The spatial array of measurements is ultimately combined to determine the mean station averages. Corrections for steady-state flow profile errors associated with single-element time-dependent probes are determined from the test data. After completion of the steady-state model calibration, the model serves as a baseline to characterize steady-state engine operation and engine health at intermediate and part-power conditions.

Step 2 - Transient Calibration. The transient calibration process estimates the effects of sensor lags, profile errors, heat transfer, and volume dynamics. Test data are acquired during a rapid intermediate-to-idle power sweep (engine deceleration), followed by a rapid idle-to-intermediate power sweep (engine acceleration) to characterize time-dependent effects. Estimation accuracy is enhanced using time-dependent data sampled at 100 samples per second.

The calibration approach must extract reliable values from data with normal measurement noise and permit identification of a wide variety of faults during both steady-state and transient engine operation. A number of data filtering and smoothing algorithms (where the sampling interval is estimated from data obtained at times both prior to and after the time being considered) were evaluated. Compared to filtering algorithms, smoothing algorithms provide a substantial improvement in real-time estimation accuracy and fault detection capability. Exponential-type filters were found to be insensitive to many common sensor failure modes and abrupt changes in system performance which must be identified during developmental engine testing.

Corrections for transient lag in aerothermodynamic temperature measurements are estimated directly from the test data. All other aerothermodynamic sensors provided satisfactory responses such that corrections for transient time lag were small and could be effectively compensated for in conjunction with other time-dependent effects. Multiple temperature and/or pressure sensors are used at each measurement station to minimize the effects of transient profile errors associated with single-element probes. Rotor dynamic effects are determined using rotor polar moments of inertia obtained from the engine manufacturer and speed derivatives obtained from the smoothed data. The combined effects of heat transfer, volume dynamics, sensor lag, and other transient effects such as tip and seal clearance changes are estimated from the test data. The empirical method for estimating the combined effects of heat transfer and volume dynamics is well-suited for real-time fault identification and avoids inaccurate estimates relative to metal mass, heat-transfer coefficients, and calculation of metal temperature derivatives. Time-dependent effects were found to be weakly related to flight condition and could be assumed constant.

Step 3 - Real-Time Model Calibration. The real-time model calibration approach focuses on estimating changes in engine component flows and efficiencies which provide the foundation for real-time fault identification. Changes in engine component flows and efficiencies are calculated 20 times per second during steady-state engine operation and 100 times per second during transient engine operation.

The process of choosing an optimal set of test measurements and model calibration factors requires, to a large extent, evaluation of all possible combinations of test measurements and model calibration scale factors. Model-based simulation studies were conducted to choose appropriate test measurements and model calibration scale factors for identification of data and engine component faults. The selected set of test measurements and model calibration scale factors reflects extensive studies conducted using actual engine test data obtained during developmental engine tests. Typical test measurements used for real-time calibration of an augmented turbofan engine (Fig. 1) include engine inlet and free-stream conditions (P_2, T_2, and P_0), engine inlet mass flow rate (W_2), fan tip discharge conditions (P_{12} and T_{12}), high-pressure compressor inlet condiiions (P_{25} and T_{25}), high-pressure compressor discharge conditions (P_3 and T_3), fuel lower heating value (FHV), burner fuel flow (WFB), augmentor fuel flow (WFAB), high-pressure spool horsepower extraction (HPX_{HPT}) and bleed flow rate (WB3), fan and high-pressure compressor rotor speeds (N_{LPC} and N_{HPC}), and variable-geometry measurements. Typical calibration scale factors varied for a turbofan engine model include fan and compressor map flow and efficiency scalars ($\delta_{WC,LPC}$, $\delta_{ETA,LPC}$, $\delta_{WC,HPC}$, and $\delta_{ETA,HPC}$) and high- and low-pressure turbine map efficiency scalars ($\delta_{ETA,HPT}$ and $\delta_{ETA,LPT}$). The CLM provides an accurate prediction of measured and unmeasured parameters that reflect the current status of the test article and include the effects of off-schedule variable geometry, sensor lags, profile errors, heat transfer, and volume dynamics.

Fault Detection

The issue of detecting faults during developmental turbine engine testing with newly developed hardware at never-before-tested conditions is extremely complex. Therefore, the real-time model-based fault identification approach is used to supplement existing approaches that consider on-site calibrations, online monitoring of instrumentation systems, comparison of redundant measurements, steady and non-steady measurements, and measurement to predicted responses [(Malloy, 1993) (Davis et al., 1996)].

The fault detection approach relies on interpretation of measured and predicted responses and interrelationships throughout the propulsion system quantified by the CLM. A simultaneous multipoint analysis is used to provide a relative assessment of measurement error and changes in component performance. The multipoint analysis includes the following:

1. Interpretation of differences between predicted and measured aerothermodynamic measurements for the time being considered (to validate modeling assumptions and detect measurement errors);

2. Interpretation of changes in component flows and efficiencies using data immediately prior to and during the time being considered (to detect abrupt faults); and

3. Interpretation of changes in component flows and efficiencies using data considerably prior to and during the time being considered (to detect slower faults such as engine degradation or sensor drift).

A weighted root-sum-square fault detection parameter is calculated as a measure of the probability of a fault. The fault probability is a function of time-dependent changes in component flows and efficiencies, the ability to predict test measurements not directly used in the real-time model calibration process, and changes in component flows and efficiencies relative to baseline values. The sensitivity of the fault detection system is varied to maximize the probability of detecting faults, and to minimize the probability of false alarms. Sensitivity is increased when measurement uncertainties are lower (e.g., stabilized operating conditions at higher power settings). Further increases in sensitivity result at previously tested conditions and configurations (e.g., no hardware or instrumentation system changes). Some reduction in sensitivity is made to account for higher data and model uncertainties during engine starts.

Fault Diagnosis

Once a fault is detected, an automated model-based methodical search is performed to isolate the most probable cause of the fault. The probability of accurately diagnosing the fault is increased, as previously stated, by emulating the diagnostic process performed by the analysis engineer. Specifically, the automated model-based fault diagnnsis approach concentrates on identifying measurement errors which are the most probable faults. If the fault cannot be attributed to measurement error, the fault is interpreted as a change in component or overall engine performance.

Once a fault is detected, the fault diagnostic system concentrates on identifying individual sensor faults and tries to identify the erroneous measurement and the magnitude of the error. The calibrated CLM (calibrated with data immediately prior to detection of the fault) is used to assess the probability of measurement errors. Each measurement is sequentially perturbed, varying magnitudes to determine the mnst probable cause of the fault (e.g., fuel flow is perturbed ± 5 percent in 0.5-percent increments, then airflow is perturbed, etc.) The model-based diagnostic approach relies on interpretation of measured and predicted responses and interrelationships throughout the propulsion system quantified by the CLM. Due to the highly nonlinear interrelationships throughout the propulsion system, multiple perturbatinns of varying magnitudes are required to evaluate fault probabilities accurately. The measurement error probability is the inverse of the fault detection parameter. The error probability considers differences between predicted and measured parameters and both rapid and slow changes in component flows and efficiencies.

REAL-TIME COMPUTING APPROACH

Effective use of existing engine models in a real-time test environment often requires significant improvements in execution speed (often by several orders of magnitude). Distributed workstation networks have been chosen as the target architecture for this work at the AEDC. Benefits of using distributed workstation networks include better availability, increased flexibility (workstations can be used independently by several users during periods when no testing is performed), affordability, and scaleability of distributed architectures.

An eight-processor parallel distributed machine (Biegl et al., 1997) was built to provide an inexpensive development environment. The machine consists of eight Pentium® PC clones interconnected via a high-speed (100 Mb/sec) Ethernet network (Fig. 2). Each node has four network ports: one of these is a standard 10 base-2 (coaxial) port, the other three are high-speed 100 base-T (twisted pair) ports. The coaxial ports are used for "standard" network traffic while the high-speed ports are used for application-level communications. The high-speed ports are connected in a hubless point-to-point scheme to build an eight-node hypercube. To keep things simple, off-the-shelf hardware and software were used. Every processor runs a copy of the Linux® operating system. The parallel machine also includes system management tools (small collection of shell scripts added to the standard Linux distribution) to facilitate control of the distributed processors. The Message Passing Interface (MPI) [MPI Standard] has been ported to this environment to provide application-level communication services over the high-speed ports. Special user-level network device drivers were developed for MPI to control the high-speed Ethernet ports without the need to use operating system calls.

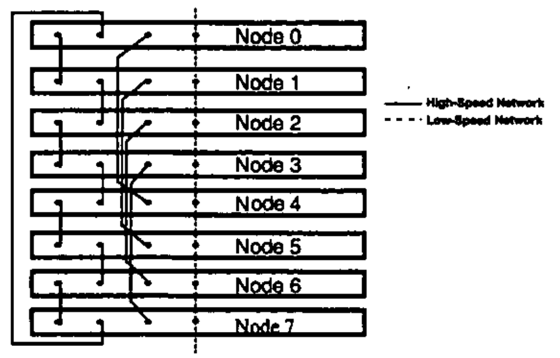

Fig. 2. Schematic of eight-processor parallel distributed machine.

Implementation of the nonlinear CLM and the processing of large amounts of data imposed a considerable computational burden, not only in terms of cycle time, but also in terms of convergence control of the nonlinear model. Two approaches were employed to counter these burdens. The first was to simultaneously balance the cycle equations and minimize errors between the model and the data. The second was to optimize the combination of perturbation variables and cycle constraints associated with the nonlinear CLM in order to maximize the accuracy of the simulation and ensure convergence with minimal iteration. Effective use of the partials correction in the modified Raphson solver (McLaughlin, 1982) minimizes the need to recalculate derivatives.

"Task level" parallel processing, in conjunction with the above improvements, was used to provide a real-time computing capability. Explicit algnrithmic parallelization of existing FORTRAN software requires a thorough understanding of the algorithm used and explicit distribution of the different functional blocks to different processors. The advantage of explicit parallelization is that frequently, a much higher level nf parallelizatinn can be obtained than with instructinn-level parallelizing compilers. Explicit calls to the underlying communication library are made at the points where synchronization and/or data exchange is necessary. Parallel computing processes shown to greatly enhance the real-time computing capability include simultaneous calibration of cnmponent maps, calculation nf engine processes (cycle balancing), and integratinn of dynamic quantities (rotor and gas dynamics) for time-dependent data.

Demonstrated Increases in Execution Speed

The model-based fault detection algorithms executed at about 20 percent of real-time speed on a 100-MHz Pentium platform. Attempts to run the software on available high-performance single-processor workstations did not result in real-time operation. The effectiveness of the Pentium platform and parallelized software was evaluated using an 89-sec test maneuver. Figure 3 shows the average processing speed as a function of the number of worker processors employed. The results convincingly show that the 8-processor Pentium system is fully capable of executing the parallelized model-based data validation and fault detection algorithms in real time.

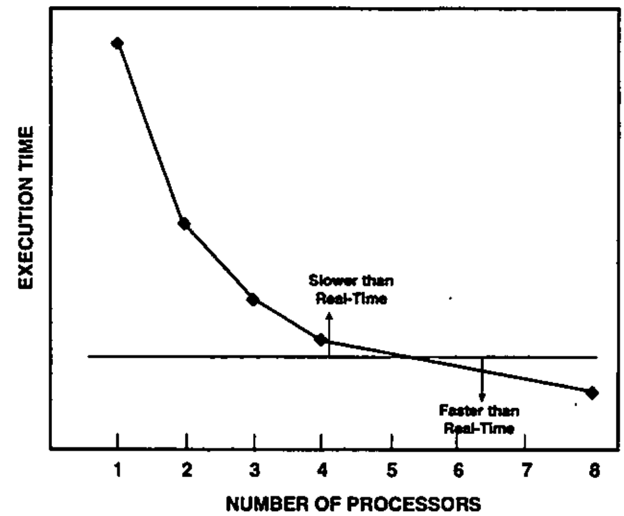

Figure 3. Pentium Platform Effectiveness

TEST RESULTS

The fault detection and diagnostic algorithms were evaluated using data from two distinctly different modern military turbofan engines undergoing ground test development at simulated altitude test condiiions. Data from hundreds of sensors were recorded at rates up to 100 samples per second to characterize aerothermodynamic engine performance. Both engines were tested over a wide range of steady-state and transient engine operating conditions enabling a comprehensive assessment of the suitability of the approach for developmental engine testing.

The three-step model calibratinn process is an integral part nf the fault identification process. Accurate predictinns from the CLM are a key element of the fault detectinn and diagnostic processes. Figure 4 shnws a prediction of engine thrust compared to engine test data after model calibration. Predicted thrust provides an independent measure nf the real-time model calibration capability, since measured thrust is not used during the calibration process. The close agreement between measured thrust and predicted thrust demonstrates the accuracy provided by the model calihration capability.

Propulsion control schedules and engine hardware often vary significantly from basic design conditions during developmental engine testing. The situation is compounded by the use nf specific propulsion control laws and schedules developed during engine tests to tune overall system performance to match individual missinn roles. The capability to identify measurement errors and anomalous changes in component performance during control logic development is a formidable task because changes to the control laws may result in atypical, but

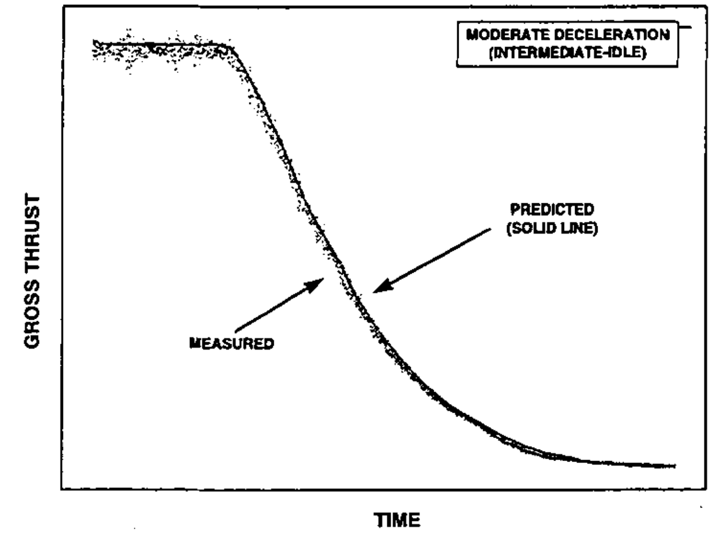

Fig. 4. Predicted and measured gross thrust.

valid, engine operation. False alarms and incorrect diagnoses will result unless the control law changes are reflected in the fault identification analyses. For example, potentially anomalous engine behavior or anomalous measurement of engine airflow is indicated in Fig. 5 by an erratic, rather than uniform, increase in engine airflow for a moderate engine acceleration. However, the erratic change in airflow is a result of control law manipulation and represents valid engine operation. The real-time portion of the calibration process, discussed previously, inherently accounts for the control law changes and results in a confirmation of valid engine operation for the data shown in Fig. 5. The fault identification process correctly reported no faults, thus demonstrating its suitability for developmental engine testing.

Sensor faults identified during transient engine operation using the model-based approach include the identification of a slowly responding pressure measurement used in the determination of engine inlet airflow. The fault was initially identified as an engine airflow measurement anomaly indicated by differences between normal and faulty airflow indications as shown in Fig. 6. The differences are evident near the end of the deceleration and, to a lesser extent, in the steady portion of the data immediately prior to and following the deceleration. Further investigation revealed the root cause as a crimped pressure line which affected the transient airflow measurement. The diagnosis demonstrated the applicability to transient engine operation by identifying a faulty time response that is not detectable during steady-state engine operation.

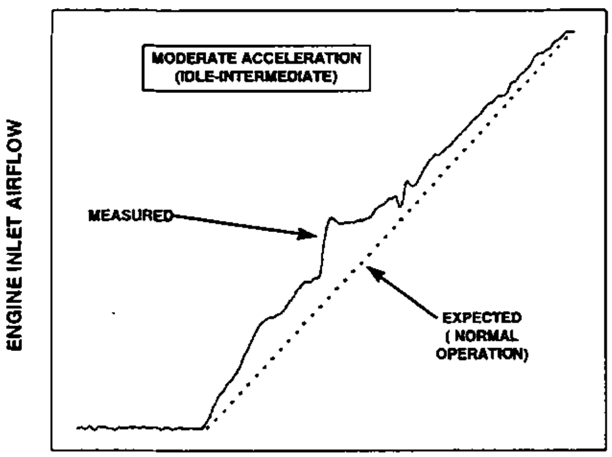

Fig. 5. Effects of propulsion control schedules on airflow measurement.

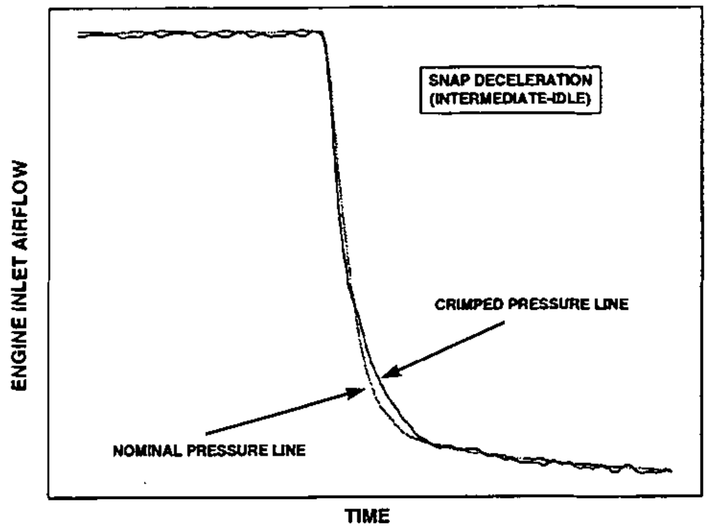

Fig. 6. Effect of slowly responding pressure measurement on airflow measurement.

Data anomalies are equally likely to occur during steady-state and transient engine operation and the wide range of engine operating conditions enabled detection and diagnosis of a number of sensor faults while demonstrating a low occurrence of false alarms. The fault identification approach is most sensitive during steady-state engine operation at high power settings and is capable of detecting very small (less than 1 percent) errors (Fig. 7). Common data anomalies that have been identified using the model-based approach include identification of sensor biases, drifts, level shifts, and excessive noise.

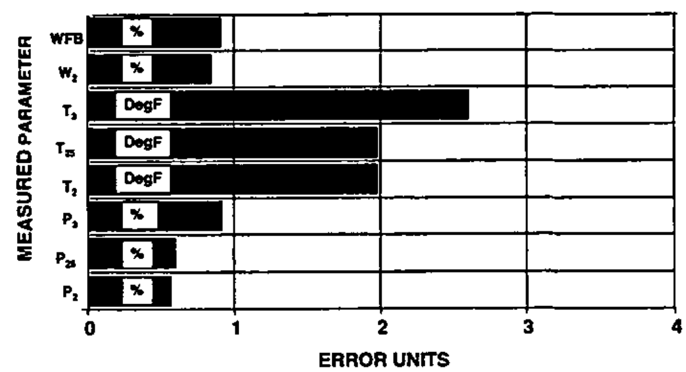

Fig. 7. Minimum detectable faults for selected parameters (sea-level-static intermediate rated power).

An important function of the fault identification capability is its ability to distinguish between measurement anomalies and engine anomalies. Data for a steady-state engine operating condition were chosen for clarity to illustrate the capability to distinguish between measurement and engine anomalies. For steady-state engine operation, data in Fig. 8 seem to indicate the occurrence of an engine anomaly implied by an abrupt reduction in compressor efficiency and a corresponding reduction in flow capacity. The effects of the observed changes in compressor performance were also seen in other parameters throughout the engine as would be expected with a deviation in compressor performance. Superficial inspection of the data leads to a conclusion that a compressor anomaly exists.

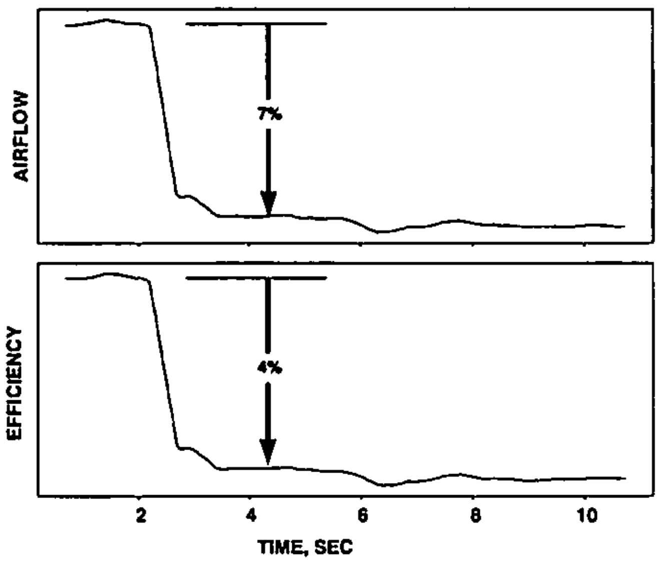

Fig. 8. Abrupt change in compressor performance during steady engine operation.

However, the fault identification process diagnoses the effects of a faulty P_3 measurement on related cycle parameters, correctly identifies the P_3 measurement anomaly, and distinguishes it from an apparent engine anomaly. The high probability of a P_3 anomaly, as determined by the fault identification process, is shown relative to the probability of other measurements in Fig. 9. In contrast, if the probability of a P_3 error had also been low, a compressor anomaly would have been diagnosed. Independent analysis using traditional methods confirmed the anomalous P_3 diagnosis.

Important to note in the anomalous P_3 diagnosis is that the fault was detected early in the event (Fig. 10), clearly exceeding the fault detection threshold. Although the P_3 measurement eventually shifted to 95 percent of its true value (i.e., 5-percent error), the fault was identified while the error was approximately 1.5 percent. The P_3 fault, which was indicative of other faults that were identified, demonstrated the capability of the model-based approach to successfully detect and diagnose sensor anomalies as they occur and distinguish these anomalies from variations in component and overall engine performance.

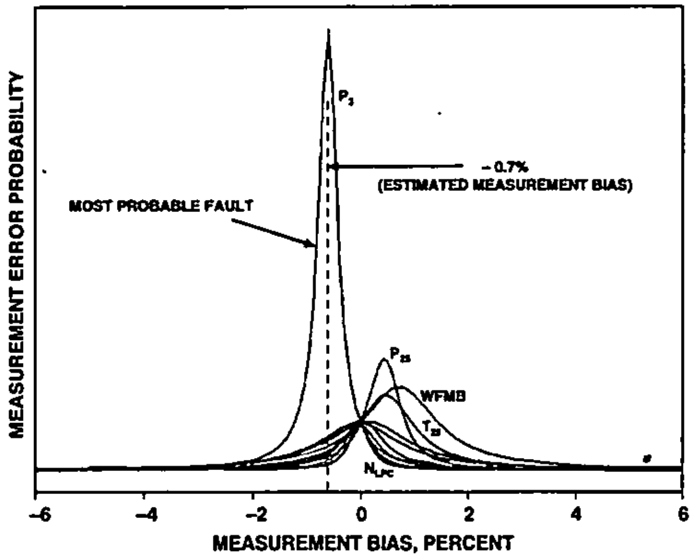

Fig. 9. Fault identification and estimate of bias.

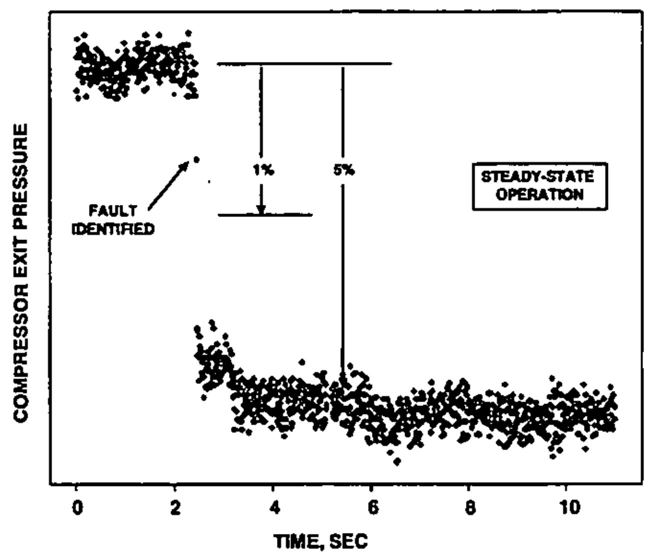

Fig. 10. Abrupt change in compressor exit pressure during steady engine operation.

SUMMARY

A new capability for real-time fault identification during developmental turbine engine testing has been developed and demonstrated. The capability automates a model calibration process and emulates traditionally manual approaches. A parallel computing approach enables real-time operation of the processes.

The model-based fault identification approach has been demonstrated on steady-state and transient test data, successfully detecting and identifying anomalous measurements and distinguishing these from unusual variations in component and overall engine performance. A component-level model provides the basis for fault identification and an automated model calibration process ensures adequate model fidelity. In addition, the component-level model enables automation of fault detection and diagnostic techniques that generally rely on engine cycle-matching principles.

The technique has been demonstrated during developmental turbine engine testing at simulated altitude conditions to assess the viability of the approach both in terms of the functionality of the model-based approach and the required computational speed. The results indicate that the technique is capable of detecting and diagnosing abrupt changes in measurements.

FUTURE WORK

The component modifiers used for the real-time model adaptation and data validation processes allow the engine to be reasonably characterized and the data to be adequately validated during online operations. Additional development is required to further minimize the errors in the system model and more accurately validate the test data.

A variety of interactive tools is currently available for use in developmental engine tests that permit more detailed diagnostics of steady-state data (and if necessary, backward chaining to identify the fault). Due to observability constraints imposed by the specified instrumentation and test conditions at the time of the identification, some loss of diagnostic resolution of data anomalies results from lumping together component modifiers and measurements used in the model-based diagnostic system (e.g., burner fuel flow (WFB) is a function of measured fuel heating value, specific gravity, viscosity, fuel temperature, turbine flow meter output, etc.). Future work includes linking the model-based fault identification approach with other fault diagnostic systems to better analyze all available information.

The current system is optimized to identify data anomalies, which occur much more frequently than engine anomalies. Additional computational power is required to run two sets of algorithms: one optimized to detect and diagnose data anomalies, and the other optimized to detect and diagnose engine anomalies. Finally, additional work is required to minimize the test time, cost, and effort required to calibrate the engine model over the full engine operating range and flight envelope.

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