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Sensor Failure Detection for Jet Engines Using Analytical Redundancy

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SUMMARY

Analytically redundant sensor failure detection, isolation, and accommodation techniques for gas turbine engines are surveyed. Both the technology base and demonstrated concepts are discussed. Results from twenty five papers and reports are reviewed which document the development of the field from 1974 to the present. Demonstrations of analytically redundant techniques using engine simulations or full scale engines are included. Various differences among the three demonstrated approaches are discussed. Finally, ongoing Government programs are described.

INTRODUCTION

This paper surveys the use of analytical redundancy to improve turbine engine control system reliability. As shown in figure 1 an increase in control complexity has occurred in recent years and is expected to continue. This increased complexity has made it difficult to build reliable, low cost, low weight hydromechanical controls. On the other hand microprocessor based digital electronic technology allows complex control systems to be built with low cost and weight. However, these digital electronic controls do not have the maturity and therefore the demonstrated reliability of hydromechanical engine control systems.

A recent study of fault tolerant electronic engine controls (ref. 1) shows that sensor redundancy will be required to achieve adequate control system reliability. There are two types of sensor redundancy, hardware and analytical. Hardware redundancy (HR) uses multiple sensors to measure the same engine variable. Analytical redundancy (AR) uses a reference model of the engine to provide redundant estimates of a measured engine variable. HR is insensitive to failure type, hard or soft, since any discrepancy between two like sensors indicates a failure. (Hard failures are out-of-range or large in-range failures. Soft failures are small in-range or drift failures.) AR, however, distinguishes failure types. HR results in more costly, heavier, less practical, and less reliable systems than do various AR strategies (ref. 1). Consequently many researchers have investigated AR strategies.

The first objective of this paper is to survey the application of AR to the detection, isolation, and accommodation (DIA) of sensor failures for gas turbine engines. HR strategies are not covered. First, this survey reviews the theoretical and application papers which form the technology base of turbine engine AR research. Second, the status of four major, ongoing, application efforts are discussed. An analysis of this survey indicates some current technology needs. The second objective of this paper is to present NASA's current programs which address these technology needs.

AR Technology Base

This section describes those papers that document the AR technology base. Sixteen papers are considered. The papers are reviewed in essentially chronological order. The attributes of each paper are discussed in this section. These attributes are summarized in table I.

Mallhagen and Arpasi (ref. 2) presented the first (April 1974) use of sensor AR to improve engine control system reliability. A J85, single spool, turbojet with two sensed variables and three controlled variables was tested at a sea level, static condition. The inputs were compressor variable geometry, fuel flow, and exhaust nozzle area. The sensors were a magnetic pickup for rotor speed and a high response gage transducer for compressor static discharge pressure. Failure detection was accomplished by comparing the rate of change of the sensed variables with predetermined limits. Four consecutive out of range rates declared a failure. Since each sensor was tested for catastrophic, i.e., hard failure only, isolation is immediate. Failures are accommodated by replacement of the failed sensed value with a synthesized estimate. This synthesized variable is obtained from a tabulation of the synthesized variable as a function of remaining engine variables. Different tables were stored for steady-state and acceleration conditions. No explicit dynamical relationships were included.

The DIA logic was implemented in fixed point assembly language on a mini-computer. The implementation executed in a 15 msec time frame which allowed real-time interaction with the control. Testing in a sea level static test stand compared idle to full power step responses of rotor speed and thrust. For single failures steady-state speed was held to within 1 percent of its final value and 92 percent of maximum thrust was achieved. For two sensor failures steady-state speed was approximately 99 percent of its final unfailed value and thrust was 87 percent of maximum. Time to accelerate, however, had to be increased from 3 to 30 sec. Failures were induced at 50 percent power during a transient. Detection was reliable. The system also allows self-healing. An interesting feature of the DIA logic was its ability to learn, on line, all the data necessary to function. In a companion paper, Hrach, Arpasi, and Bruton (ref. 3) used a real-time nonlinear hybrid computer simulation of a two spool turbofan, the TF30-P-3 engine to demonstrate the DIA logic of reference 1 over a wide operating range. Four sensed variables; high pressure rotor speed, high and low pressure compressor discharge static pressures, and nozzle total pressure, and five inputs main fuel flow, nozzle area, afterburner fuel flow, and two compressor stage bleeds were considered. Again hard failure detection and isolation were obtained by individual rate checks.

Accommodation was achieved by replacement with averaged synthesized variables which were a function of the remaining good sensors (1,2, or 3). Synthesized variables were obtained from tabulations. However, the data were now stored as corrected values to allow a wide operating range. Data for the tables were collected at two operating points.

A real-time implementation of this DIA logic was programmed using assembly language in a minicomputer using a frame time of about 25 m/sec. Storage requirements include 4K Bytes for the logic and 0.2K Bytes for the tables. The logic was tested at 5 selected operating points (which include the 2 design points). Acceptable operation with no limit violations and approximately the same thrust was obtained for operation with 1, 2, or 3 of the 4 sensors failed.

For afterburning operation of the engine acceptable control was possible for only a single failure and with a severe rate limit on accelerations. This logic also incorporated learning or adaptive logic.

Ellis (ref. 4) (January 1975) studied the use of AR techniques using a nonlinear digital simulation of a two spool turbofan engine. The engine had five measured variables and two independent controlled variables. The DIA philosophy of this paper centers around estimates of the measured variables. First a multivariable linearized mapping (no explicit model dynamics) of corrected measurements to estimates is found. Since the engine has only two independent controls, it is assumed that only two measurements are required to generate an estimate. Taking unordered pairs of the 5 measured variables yields 10 estimates of each measured variable. A weighted average estimate is obtained by combining these ten-component estimates each weighted by its relative accuracy. Detection and isolation are accomplished by a threshold check on both sides of each weighted average estimate. If a weighted estimate is outside of the threshold corridor then all weighting factors associated with this estimate are set to zero. Weighted estimates are used by the control at all times. Only the weightings change as failures occur. Thresholds for the weighted estimates are obtained from sensor error statistics assuming Gaussian distributions.

The next contribution to this area is documented in four reports by deSilva (refs. 5 and 6) and Wells (refs. 7 and 8). This series of reports applies Bayesian hypothesis testing to the detection of engine sensor failures. The engine studied is a simple turbojet with two outputs, speed and thrust and one input, fuel flow. A second order pseudolinear (PL) model of the engine was used on a mainframe computer to evaluate detection performance. A PL model consists of a dynamical, linear state space structure. However, individual coefficients within the linear structure vary as a nonlinear function of the state.

Bayesian hypothesis testing is implemented by 1) defining a risk function, and 2) determining from measured data the hypothesis that minimizes this risk. This risk function defines the penalty associated with selecting a false hypothesis. Assuming Gaussian noise statistics, the Bayesian hypothesis is also probabilistically most likely given the measured data. A "bank" of Kalman filters, one per hypothesis, used measured data and an engine model to generate state estimates and filter residuals. The hypothesis associated with the most likely set of residuals as determined by a likelihood ratio test was taken as the true hypothesis. The mode of operation associated with this hypothesis (failed speed sensor, no failure, etc.) was assumed true. The approach worked well in simulation studies of this simple case. This work represents the first application of AR to turbine engines based upon modern control theory. Difficulties with this approach include the requirement of a different Kalman filter for each failure mode hypothesis.

In June 1977 Spang and Corley (ref. 9) published an application of AR techniques as applied to the Quiet, Clean, Short Haul, Experiment Engine or QCSEE. This engine has seven measurements, fuel flow, compressor stator angle, fan speed, compressor speed, compressor discharge temperature and pressure, and turbine discharge temperature. Engine controls include fuel flow valve current and compressor stator blade torque motor current. In this study an extended Kalman filter approach was used to generate state estimates and residuals. A simplified nonlinear component model which is valid throughout the

engine operating envelope and a simplified feedback gain matrix operating on engine measurements were used to update the filter estimates and residuals.

Sensor failures were detected and isolated by a threshold comparison of the individual residual components. Thresholds were determined by sensor noise statistics. Only hard failures are considered. To accommodate failures, faulty measured values are replaced by sensor estimates from the filter. The approach was successfully demonstrated on a detailed, real-time, nonlinear hybrid computer simulation of the engine. The detection, accommodation and control logic was implemented in a microprocessor-based control also in real-time. Successful operation for single hard sensor failures was demonstrated at sea level static conditions for power chops and bursts in the idle to full take-off power range. This work, referred to as Failure Indication and Corrective Action or FICA, serves as the theoretical foundation for a significant portion of the work in the application of AR to turbine engines. Further applications based on FICA are given in a subsequent section.

Next, DeHoff and Hall (ref. 10) reported a largely theoretical study that developed a unified framework to achieve engine performance monitoring, trending, and sensor fault DIA. This framework is based upon maximum likelihood state and parameter estimation methods. A simple turbojet example was used to illustrate the application of a maximum likelihood based, on line, sequential processing, parameter estimation algorithm to the detection of sensor failures.

Sahgal and Miller (ref. 11) report on the design of a full order observer that reconstructs fan turbine inlet temperature for an F100 engine. The observer is based upon a 5th order scheduled state space model with four inputs, fuel flow, nozzle area and compressor and fan variable geometries and four outputs, fan and compressor speed, and compressor discharge temperature and pressure. Observer performance is compared with a full nonlinear digital simulation of the engine at sea level static conditions. The reconstructed temperature tracks the actual temperature quite well. The analytical study proposes to use the reconstructed temperature to accommodate for fan turbine inlet sensor failures.

The next three papers (refs. 12 to 14) by Leininger and Behbehani report the application of the generalized likelihood ratio (GLR) technique to the QCSEE. The GLR technique is a hypothesis based test with the time and type of failure unknown. Under linear, Gaussian assumptions, if the Kalman-Bucy filter residuals are found to be nonwhite, a failure is declared. Next, various likelihood ratios are compared to determine the most probable failure time and type. The GLR method was used to detect and isolate hard and soft failures. Both single and multiple actuator and sensor failures were considered.

Detection and isolation studies were conducted by simplified simulation of an under the wing QCSEE. This simulation included six outputs, fan and compressor speeds, engine inlet static pressure, fan inlet duct static pressure, combustor pressure and compressor discharge pressure and three inputs, fuel metering valve position, fan nozzle actuator position, and fan pitch angle. A linearized, eight state model was used in the Kalman-Bucy filter. Successful detection and isolation of multiple sensor and actuator failures with noisy sensors and imperfect modeling were demonstrated. Accommodation by control reconfiguration using nonsquare Multivariable Nyquist Array methods was proposed. Designs were obtained but not demonstrated by simulation.

A doctoral dissertation by Meserole (ref. 15) uses detection filter theory to design a detection filter that detects sensor failures in an F100 engine. Like the Kalman filter, the detection filter incorporates a dynamic process model and generates error residuals. However, unlike the Kalman filter a detection filter is designed to respond to a component failure with a residual that has a fixed, usually unique direction. Also this direction is independent of failure mode. Thus, sensor failures can be detected and isolated by detecting the occurrence of these fixed direction residuals. A sixth order state-space linear model with scheduled coefficients is used in the detection filter. Filter operation and detection capability are demonstrated using a detailed nonlinear digital simulation of the F100 engine. Fifteen components are checked for failure, the inlet pressure and temperature sensors, the fan and compressor speed sensors, the burner and augmentor total pressure sensors, the fan outer diameter discharge and turbine inlet total temperature sensors, the fuel system, the nozzle, bleed, fan guide vane, and compressor stator vane actuators, and the high and low pressure turbines. Five inputs are considered, fuel flow, nozzle area, fan guide vane and compressor stator vane positions, and bleed. Filter performance was studied for sensor failures and component changes (failures) at sea level static conditions for bias and scale factor changes. Failures were detected for 2 percent to 5 percent changes in one or more output measurements. Minimum failure size for successful isolation is summarized by component in table II.

The final paper to be discussed in this section, by Leininger (ref. 16) examines the impact of an inaccurate model on innovations-based detection and isolation procedures. The paper demonstrates that model inaccuracies appear as biases in the innovations (residuals). These biases are identified by a "student t" test. The "student t" test is then related to a recursive GLR detector using a sequentially updated Kalman filter. Model bias error is removed from the innovations data to remove the effect of model degradation and to allow more accurate soft and hard failure detection. Also, a finite width window sequential "t" test is used to update the bias term and provide a means of sensor failure detection and isolation. The theory was applied to an eighth order linear model of the QCSEE. Model eigenvalues were perturbed by 10 percent to simulate model error. The "t" test successfully removed the bias, tracked a sensor drift followed by a low frequency sinusoidal sensor bias, and exhibited a fail-heal-fail detection pattern for the sinusoidal test.

AR Technology Development

Based upon the encouraging, but preliminary results of the AR technology base, several technology development programs were begun. The overall objective of these programs is the full scale engine demonstration of improved control system reliability using AR technology. Four important AR development programs are discussed 1) Advanced Detection, Isolation, and Accommodation (ADIA), 2) Energy Efficient Engine (E³) FICA, 3) Full Authority Digital Electronic Control (FADEC) FICA, and 4) Digital Electronic Engine Control (DEEC) sensor DIA.

ADIA

The objective of the ADIA program is to demonstrate a viable DIA concept based upon advanced methodologies. The ADIA program consists of three parts:

development, real-time evaluation, and demonstration. The NASA Lewis Research Center provides overall program sponsorship and technical direction. Pratt and Whitney Aircraft, and their subcontractor, Systems Controls Technology, developed the ADIA algorithm. A real-time hybrid computer based evaluation and a full scale engine demonstration are currently being performed by the NASA Lewis Research Center. Each of these program parts is discussed below.

The development of the ADIA algorithm is reported by Beattie, et al. (refs. 17 and 18). Here advanced detection and filtering methodologies were compared to develop a viable ADIA concept. Comparisons were made on an F100 engine and F100 Multivariable Control (ref. 19) testbed system. The type and severity of sensor failures were carefully defined. Typical state-of-the-art transducers were selected. Failure characteristics were defined and quantified according to the predominant failure categories of out-of-range, drift, and noise. Next, a Failure Mode and Effects Criticality Analysis (FMECA) was conducted to classify the various failure modes as critical or noncritical. Critical failures result in surge, a 10 percent or larger thrust variation, or a rotor overspeed. This classification was accomplished over the full operating range of the F100 engine. Five competing DIA concepts were developed by combining available detection and filtering technologies. These five concepts were specifically formulated to span as many applicable technologies as possible.

Since competing technologies were to be compared, a scoring system was developed. The scoring system evaluated the concepts for 1) Performance Criteria - transient and steady-state minimum operation requirements, 2) Detection Performance - detection and isolation effectiveness, and 3) Figures of Merit - qualitative benefits of bettering the Performance Criteria. Using the scoring system and a simplified simulation of the testbed system, the five concepts were screened. Two concepts were selected for a more detailed comparison. Based upon this second screening, one concept was selected for evaluation on a detailed nonlinear simulation of the testbed system. This detailed evaluation included simulated sensor failures for both steady-state and transient operation throughout the entire operating range of the engine. This evaluation showed the ADIA approach 1) to be viable for gas turbine applications and 2) when compared to a parameter synthesis approach, to be more systematic and straightforward. This evaluation also pointed out two areas for improvement in the ADIA algorithm.

First, the accommodation filter was unacceptably biasing normal or unfailed steady-state operating point operation. A minor change in the accommodation logic improved steady-state operation by removing these unacceptable biases. This result is shown in table III. Here steady-state accuracy for the original, or baseline logic is compared with the revised logic at six operating points and various failed parameters. Data were obtained by hard failing a sensed parameter and observing the steady-state thrust before and after the failure. Estimation errors, for the failed parameter only, are also given. Notice that in every case an improvement in steady-state accuracy was obtained as measured by a smaller change in engine thrust.

Second, the simplified model used in the algorithms filter was not accurate enough at all flight conditions. To improve simplified model accuracy, additional linear, state-space model data were incorporated in a redesign of the simplified simulation. In total, linear state-space models at 76 different operating points that more uniformly span the entire flight envelope were used.

Individual elements of the state-space matrices were corrected to reduce data scatter and then scheduled by a nonlinear polynomial of selected model output variables over the flight envelope. This scheduled state-space system forms the basis of the simplified simulation. A more complete description of this modeling technology as applied to the development of a hypothetical turbofan engine simplified simulation (HYTESS) is given by Merrill, et al. (ref. 20). Figure 2 shows a transient response comparison for the nonlinear digital engine simulation and the ADIA simplified simulation for an idle power to intermediate power (PLA = 20° to 83°) step command. This comparison demonstrates the excellent estimation capability of the simplified simulation. The ADIA algorithm incorporates this simulation and Kalman filter logic to further improve these estimates.

The testbed system with ADIA and MVC logic is shown in figure 3. The algorithm consists of an extended steady-state Kalman filter, called the accommodation filter, that generates sensor estimates and residuals based upon a simplified, pseudo-linear model of the engine. These residuals are compared to thresholds for hard failure detection and isolation. A weighted sum of the squared residuals (WSSR) statistic is computed and compared to a threshold to detect soft failures. When a soft failure is detected, isolation is accomplished using a bank of five Kalman filters (one for each sensor) and likelihood ratio test of the five different filter residuals. After a failure is detected and isolated, the faulty information is removed from the accommodation filter by reconfiguration. Estimates of all sensor outputs are still produced but now they depend upon the set of unfailed measurements. The ADIA algorithm interfaces with the MVC algorithm in two ways. First, it supplies the linear quadratic regulator (LQR) with estimates of the engine outputs at all times. Second, it supplies the integral control logic with actual sensed values in the normal mode. An individual sensed value is only replaced with an estimate when a failure occurs and is detected and isolated.

Detailed evaluation results demonstrated the ability of the ADIA algorithm to completely cover hard sensor failures and most soft sensor failures. The hard failure results were excellent. All failures were covered with nearly instantaneous detection and isolation throughout the flight envelope. Accommodation transients were well within allowable ranges. Steady-state performance was good (see table III). On the other hand, soft failure DIA, especially for a full envelope design, represents a substantially more difficult task than hard failure DIA. In spite of this challenge, soft failure DIA performance was generally good. However, some soft failure modes remained uncovered.

Table IV is a summary of the evaluation of the soft failure DIA capability of the ADIA algorithm. Here data were obtained by injecting slow drift failures in various parameters at a variety of operating points throughout the envelope. Sixteen failure scenarios are presented. The estimation error or bias before failure isolation as well as the thrust change, and time to isolation are given for each scenario. Nine of the presented scenarios represent acceptable soft failure DIA performance. These scenarios include PT4, PT6, and FTIT coverage over a large portion of the flight envelope with small thrust deviations. One speed failure (N2) was also covered. Seven of the presented scenarios represent unacceptable performance. Five of these are rotor speed (N1 or N2) failures. Because the filter estimation process is strongly dependent on N1 and N2 measurements (particularly N2) a slow bias error in the speed signals will be tracked closely. Therefore the residuals will remain small and will not indicate a soft failure. As the filter is made less dependent on

rotor speeds, estimation accuracy decreases. This tradeoff requires more study and will be one of the subjects investigated in the real time hybrid evaluation phase.

The second part of the ADIA program is the real-time evaluation of the algorithm on a hybrid computer F100 engine simulation. A real-time microprocessor based implementation of the MVC and ADIA algorithms is required to complete this evaluation. DeLaat and Merrill (ref. 20) describe this implementation. Two 5 MHz Intel 8086 based microprocessors operating in a parallel processing environment are used to meet the update time requirement. The first computer contains a fixed point, assembly language, real-time implementation of the MVC which had been implemented and evaluated previously (ref. 22). The second computer contains the ADIA logic implemented in floating point FORTRAN. Floating point arithmetic was used since the Intel 8087 floating point coprocessor was available. FORTRAN was used because of the flexibility of programming in FORTRAN versus assembly language. Also, a good FORTRAN compiler for the 8086/8087 was available. This control hardware is currently being used with a hybrid computer engine simulation to evaluate the ADIA algorithm's real-time performance.

The third part of this program is the full scale engine demonstration of the ADIA algorithm. Current planning projects this evaluation to occur in the first quarter of 1985. The demonstration will take place in the NASA Lewis Research Center altitude test facility. The microprocessor hardware and software developed and evaluated in phase two of this program will be used in this demonstration.

E³ FICA

The E³ program is developing technology for improving the energy efficiency of future commercial transport aircraft engines. A FADEC based upon the bit-slice AMD 2901 microprocessor is used to implement the control and FICA logic for the engine developed under this program (ref. 23). The FICA logic is based upon the concept of Spang and Corley (ref. 9). Here, a sixth order extended Kalman filter is used to generate seven sensor estimates, fan and core speed, compressor inlet and discharge temperatures, turbine discharge temperature, fuel metering valve position, and compressor discharge static pressure. The Kalman filter uses a dynamic model of simplified engine aerothermodynamics and rotor dynamics. Actuator and sensor dynamic models are also included. This model accurately describes the engine over the full power range and flight envelope using simplified component modeling. The Kalman gain matrix is computed at a key operating point using a linearized engine model. Sensor failures are detected when the sensed versus estimated difference is greater than a prespecified tolerance. Out of range failures are also detected. The tolerance is estimated by statistical analysis and adjusted during simulation trials. Accommodation of failures is accomplished by replacement of sensed with estimated values. A nonlinear real-time simulation evaluation of the FICA logic showed that the filter estimate tracked the sensed values within the specified tolerance and successfully detected, isolated, and accommodated all hard sensor failures except fuel metering valve position. Multiple failures were also successfully handled. Tests with a reduced order implementation of the Kalman gain matrix that eliminated the three temperature sensors showed successful DIA with all sensors except core speed and fuel

metering position. The E³ FICA logic does not detect slow drift, i.e., soft, sensor failures.

FADEC FICA

Under the FADEC program (ref. 24), AR techniques (in particular FICA) were applied to two engines, a Joint Technology Demonstrator Engine (JTDE) and to the F404 afterburning turbofan engine. Each of these applications is discussed below.

The JTDE FICA was designed for a variable cycle engine with seven manipulated variables and nine sensed variables. The engine model used in the JTDE FICA is a second order, dynamic pseudo linear model valid throughout the flight envelope. The model is updated by an observer. Observer gains were chosen as the reciprocals of corresponding engine model steady-state gains at a high power condition. Gains were then adjusted to achieve adequate stability margins. For failure detection sensor model errors were compared to a preset threshold. Substitution of estimated variables was demonstrated using a simulation and subsequently a full scale engine. The engine demonstration was limited to sea level static conditions and single substitutions. Single substitutions for fan speed, compressor discharge static pressure, and compressor inlet temperature were successfully performed. Also demonstrated by simulation in this program was the application of FICA techniques to actuator sensor failures. In particular, fuel flow and nozzle area actuator hard out-of-range sensor failures were detected and accommodated.

The second application is the F404 FICA. The F404 is an afterburning turbofan engine with a rear variable area bypass injector (VABI) to permit selective cycle rematch. The VABI adjusts the bypass to core air ratio to match cycle demands. The engine includes five inputs and five outputs. A simplified, fourth order, component level model (ref. 25) is used in the FICA system. The model is accurate throughout the flight envelope and was implemented in FADEC microprocessor hardware in a 0.01 second update time increment. The model along with the FICA update logic was checked against actual engine operation during full scale engine tests at sea level static and altitude conditions from September 1981 to April 1982. Steady-state and transient model accuracies were judged to be excellent. Single, double, and triple substitutions of FICA generated estimates were successfully performed during the engine tests. These combinations are summarized in figure 4. Actuator FICA was also successfully demonstrated for exhaust nozzle hard open and closed failures. Thrust level in these cases was maintained by adjusting the gas generator speed reference schedule.

DEEC DIA

The DEEC system is a digital full-authority control system containing selectively redundant components and fault-detection logic. The system also contains a hydromechanical back-up control. Most of the sensors in the control are hardware redundant. However, failures of the inlet static pressure PS2, burner pressure, PB, and fan turbine inlet pressure, FTIT, are covered using a form of AR called parameter synthesis (PS).

In PS an estimate of one measured variable is synthesized from an algebraic function of one or more different measured variables. This relationship is static, i.e., no explicit dynamics are included. If PS2 fails a range check, a synthesized PS2 is determined from PB, compressor speed, N2, and inlet total temperature, TT2. If PB fails, a synthesized PB is calculated from inlet total pressure, PT2, N2, and TT2. Fault detection of PB failures is based upon a comparison of measured and synthesized values. A comparison tolerance of ± 25 percent determines failures. This large tolerance precludes detection of soft failures. Both PS2 and PB failures are accommodated by substitution.

There are two groups of FTIT sensors. This allows hardware redundancy. However, if both FTIT sensor groups fail a range check, synthesized FTIT is substituted into the control. Synthesized FTIT is a function of PB and PT2.

The DEEC DIA logic was verified by closed-loop bench testing. Simulated sea level and altitude engine transients were performed. Faults were intentionally produced to evaluate DIA effectiveness. Subsequent sea level and altitude full scale engine tests uncovered no new problems with the DIA logic. A series of flight tests of an F15 aircraft with an F100 engine and DEEC control further demonstrated the DEEC Logic (ref. 26). During the flight program, the DEEC DIA logic did not detect any false alarms and did not cause any reversions to backup hydromechanical control. Two sensor failures occurred during the flight program. One, inlet temperature, was covered by redundant hardware. The second, exhaust nozzle pressure, failed to a high scale sensor limit. Appropriate accommodation action was taken by the logic in each case.

Neither of the two sensor failures encountered in the flight test program demonstrated the AR based logic of the DEEC DIA. Additional flight tests are planned for late 1984 which will incorporate intentional sensor faults to completely evaluate the DIA logic.

AR Technology Assessment

From the above survey an assessment of the relative state-of-the-art of applied AR can be obtained. The results presented in the technology base, and summarized in table I, demonstrate the feasibility of AR based DIA. In particular straightforward range or rate checks have provided successful detection of hard sensor failures. Further, advanced DIA approaches based upon advanced statistical decision theory and optimal filtering have demonstrated soft failure DIA feasibility. However, this soft failure DIA capability is obtained at the cost of increased computational complexity. This additional complexity consists of two parts: the filtering and decision making logic, and a more accurate, and therefore more detailed, model. These results also demonstrate a tradeoff between ability to accurately detect and time to detect. Where hard failures can be detected almost instantly, soft failures are reliably detected only after some finite amount of time. This time to detect is a function of threshold level, which determines detection reliability, model accuracy, and logic complexity.

Further results presented in the technology development section demonstrate AR based DIA capability for hard sensor failures on full scale engines over a limited range of power and flight conditions. Soft failure DIA has been demonstrated throughout the flight and power envelope but only on a detailed nonlinear simulation of the engine. Full scale engine testing remains

to be done. A study of the results of this development clearly emphasizes the fundamental importance that modeling plays in successful DIA. A model detailed enough for accurate DIA throughout the flight envelope is a significant technical challenge. Expectedly, when faced with a difficult technical problem, different approaches are pursued. Three different modeling approaches have been used: 1) Parameter Synthesis (PS), 2) Pseudolinear (PL), and 3) Simplified Component (SC). Both PS and SC approach have been used in successful hard failure DIA on full scale engines. The PL method has been demonstrated for both hard and soft failure DIA using a detailed nonlinear simulation. Each approach has its advantages and disadvantages.

The PS approach which was used in the DEEC DIA is simple to understand and straightforward to implement. Explicit dynamics are normally not included. However, this simplicity implies a less accurate model. Also, the most accurate interrelationships between measured and synthesized variables can not be easily or systematically identified. Model modifications are easily made.

The SC approach, which was used in the FADEC FICA, results in more accurate models than the PS approach. SC models are based upon detailed nonlinear engine simulations. Detail is selectively removed from the detailed simulation to maximize simplicity while maintaining accuracy. This process requires a great deal of judgment and is not straightforward or systematic. Additionally, simplified model performance is not easily predicted. An SC model relates naturally to the physics of the actual engine and is therefore readily understandable. However, modification of an SC model is not straight forward since changes in component performance can unpredictably effect model performance.

The PL modeling approach which is used in the ADIA algorithm, is a very organized, systematic approach. However, to achieve accuracy through a wide range of conditions requires a large amount of stored data. The relationship of a PL model with engine physics is not as straightforward as for an SC model. However, steady-state and dynamic model performance can be separated and modified independently. Due to the linear structure of the model equations, analysis and performance prediction is much easier with a PL model than with PS or SC models. Additionally, the complexity-accuracy tradeoff is more clearly defined for a PL model.

Current Programs

Currently four programs are underway to address technological needs in AR based DIA. These programs are ADIA, Robust DIA (RDIA), Multiple Engine DIA (MEDIA), and Analytical Redundancy for Engine Reliability Improvement (ARTERI).

ADIA

As stated in the technology assessment, soft failure DIA has not been demonstrated on a full scale engine. This is one of the main objectives of the ADIA program. As such, it represents the first serious attempt at soft failure DIA. Also, this program represents the first full envelope design, including design, development, evaluation, and full scale engine demonstration. To accomplish this program, a real-time microprocessor based implementation of the ADIA has been implemented and is being evaluated on a real-time hybrid engine simulation. This evaluation will establish an important data point on

the tradeoff between detection time and reliability, as well as algorithm complexity and detection capability. A successful full scale engine demonstration of hard and soft failure DIA will clearly establish AR based DIA as an accepted tool to improve engine control system reliability.

RDIA

NASA is currently pursuing basic research in Robust Detection, Isolation, and Accommodation (RDIA) of sensor failures. This research focuses on one fundamental question. How accurately must engine dynamics be modeled for successful DIA. A definitive answer to this question would establish the quantitative tradeoffs between complexity, detection time and detection performance. An alternative viewpoint would be to define the robustness of a DIA algorithm to model inaccuracies or uncertainty. Two contractors, Alphatech, Inc. and Systems Control, Inc. have identified two different approaches to the solution of this problem.

Alphatech, Inc. bases their research on redundancy, or parity relations. These relationships among the measured system variables incorporate all possible redundant information available. Modeling uncertainty affects the reliability of these parity relations. For a quantified level of uncertainty, all parity relations can be ranked from most to least reliable. This allows the more reliable parity relations to be used to generate DIA strategies that are as robust to uncertainty as possible.

Systems Control Technology (SCT) bases their research on recent advances in robust control system design. Model uncertainty effects on DIA robustness will be quantified using conic sector uncertainty properties. Here uncertainty that is bounded in a conic sector in the frequency domain and which then propagates through a system, remains bounded by a conic sector. These sectors determine quantitatively the performance/robustness tradeoff. This frequency domain description of uncertainty along with frequency shaped linear quadratic filter design theory allow the DIA strategy to be designed in the frequency domain. This frequency shaped filter will yield innovations that are optimally robust to model uncertainty. Thus, sensor failure detection based upon these innovations will also be robust.

MEDIA

A current NASA program is investigating a variation of hardware redundancy to improve soft failure DIA capability. In this contracted feasibility study, General Electric Corp. examined a multiengine approach (in this case two engines) to soft failure DIA. The underlying principle is to use a like sensor measurement from one engine as redundant information to improve DIA capability on another engine. This approach incorporates a model of potential engine differences, an average engine model, and decision logic. By looking at the sum and differences of redundant sensed values for the two engines, measured average and differential performance is obtained. These are compared to the average and difference engine models contained in the DIA logic. This additional information allows improved DIA performance over a single engine concept. This concept was demonstrated using a digital nonlinear engine simulation.

ARTERI

The final program, ARTERI is sponsored by the US Navy. ARTERI started in October 1983 and is a three year program. Its objectives are to develop AR techniques based upon FICA to the point where they may be employed in a full scale engine development program. Both hard and soft failures must be covered over the full range of engine power and flight conditions. A detection filter approach is proposed to extend FICA to include a soft failure DIA capability. Also, to be included is a thorough investigation of the ability of the logic to discriminate among sensor, actuator, and engine failures. The results will be evaluated on a full range nonlinear transient simulation. This simulation will include models for the extended FICA and FADEC control logic. The results will then be demonstrated on a full scale Joint Technology Demonstrator Engine in 1986.

CONCLUDING REMARKS

The technology base for AR based sensor failure DIA strategies for gas turbine engines has been surveyed. Several observations and conclusions are made. First the technology base often builds or expands upon technology developed for aircraft controls. This is particularly true of hypothesis based techniques. However, less stringent reliability requirements and more adverse sensor environments are pushing the engine controls designer to AR rather than HR solutions to reliability requirements. Secondly, modeling is the key issue in the success or failure of AR techniques. Three types of models are used. Each has its advantages and disadvantages and no clear preferred type emerges. Finally, simulation or full scale engine testing has conclusively shown the feasibility of AR based DIA for hard failures. Soft failure DIA has been demonstrated, so far, only by simulation. The results were very encouraging but not totally successful. Work remains to be done in this area.

Three on-going Government sponsored programs that address soft failure DIA were summarized. One of these programs will supply a complete theoretical understanding of robust DIA concepts. The second showed the feasibility of multiengine DIA concepts. The third will extend FICA technology to full scale engine development. Finally, the ADIA program will be taken to a full scale engine test to demonstrate a soft failure DIA capability.

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TABLE I. - SUMMARY OF PAPER ATTRIBUTES

Paper	Testbed system	Reference model	Type of DI	Type of A	Computer environment	Evaluation	Number of sensors	Miscellaneous
Wallhagen and Arpasi	J85 turbojet	PS	Hard failures via rate limit threshold	Replacement	Real time mini computer	Sea level static	2	
Hrach, Arpasi and Bruton	TF30 real time hybrid simulation	PS	Hard failures via rate limit threshold	Replacement	Real time mini computer	5 operating conditions through flight envelope	4	Extension of paper 1
Ellis	Turbofan nonlinear digital simulation	PS and PL	Threshold check of weighted average estimate	Estimates always used by control. Weighted average modified	Digital simulation	Sea level static (SLS)	6	
Wells and de Silva	Nonlinear model of turbojet	PL with bank of filters	Bayesian hypothesis	None	Digital simulation	SLS	2	
Spang and Corley	QCSEE real time hybrid simulation	SC with Kalman filter	Threshold comparison of filter residuals.	Substitution	Real time digital control	SLS	7	
Dehoff and Hall	Single spool turbojet	SC	Maximum likelihood	None	Digital simulation	SLS	1	Theoretical study
Sahgal and Miller	F100 nonlinear simulation	PL	None	Substitution	Digital simulation	Two conditions	4	
Leininger and Behbehani	QCSEE nonlinear simulation	PL	GLR	None	Digital simulation	SLS	6	Theoretical and application study
Meserole	F100 nonlinear simulation	PL	Detection filter	None	Digital simulation	SLS	15	Theoretical and application study
Leininger	QCSEE simulation	Linear	"t" test	None	Digital simulation	SLS	3	Theoretical study of model uncertainty

TABLE II. - MINIMUM FAILURE SIZE FOR A DETECTION
FILTER DESIGNED FOR AN F100 ENGINE

Detection: 2 percent to 5 percent change
in one or more output measurements.

Isolation

	Minimum failure size, percent	
	Engine state	
	Steady	Unsteady
Output sensors	2	5 to 10
Inlet sensors	2	5 to 10
Fuel system, exhaust nozzle	5 to 10	10 to 20
Compressor vanes, fan vanes	10 to 30	20 to 60
Rotor efficiencies	2	5 to 10

TABLE III. - STEADY STATE COMPARISONS

Flight operating point	Failed parameter	Baseline DIA algorithm		Revised DIA algorithm	
		Estimation error	Thrust change, percent	Estimation error	Thrust change, percent
0/0/24°	N1	+100	+5.3	+55	+2.1
0/0/83°	PT4	-5.5	-3.1	-4.2	~ 0
10k/0.75/83°	N1	+15	-2.2	+60	~ 0
20k/0.3/40°	PT6	-0.49	-4.9	-0.33	+1
20k/0.3/83°	N2	-70	-5.5	-70	+0.15
60k/1.2/83°	PT6	-0.18	+7.1	-0.36	-0.09

TABLE IV. - STEADY STATE RESULTS OF SLOW DRIFT FAILURE TRANSIENTS

ADIA algorithm						
Flight operating point	Failure parameter	Parameter bias before DIA	Change in thrust before DIA, percent	Time for DIA, sec	Comments	Performance
0/0/24°	P6	7.5 psi (42)	-4.5	0.490		A
0/0/40°	N1	1333 rpm (12.1)	-44.5	1.994		U
0/0/83°	PT4	46.5 psi (12.7)	-0.1	3.080	Filter noisy during FDIA	A
0/1.2/83°	FTIT	90° F (5.2)	-2.2	2.53		A
10K/0.75/50°	PT4	40.5 psi (19.6)	-0.2	2.664		A
10K/0.75/83°	PT6	9 psi (21.8)	-1.5	0.572		A
20K/0.3/40°	N2	Undetected	-----	Undetected	Unstable diverging	U
20K/0.3/83°	N2(-)	Undetected	-----	Undetected	Unstable	U
20K/0.3/83°	N2	1415 rpm (11.4)	-4.5	3.518		A
25K/1.0/83°	PT4	46.5 psi (18.1)	-0.2	3.066		A
25K/2.2/83°	PT4	False alarm	-----	-----	PT4 and PT6 false alarms prior to failure	U
40K/0.6/40°	N2	Miss	> -48	-----	2000 rpm drift miss	U
40K/0.6/83°	PT6	6.75 psi (63.7)	-0.5	0.448		A
45K/2.2/83°	P4	-56.4 psi(-24.5)	-0.16	3.750		A
60K/1.2/83°	N2	2000 rpm (15.8)	-19.4	5.016	System oscillatory after failure induced	A
65K/2.5/83°	P6	-3.75 psi (-27.4)	+24.7	0.400	Drift caused system to go unstable	U
					FTIT false alarm	U

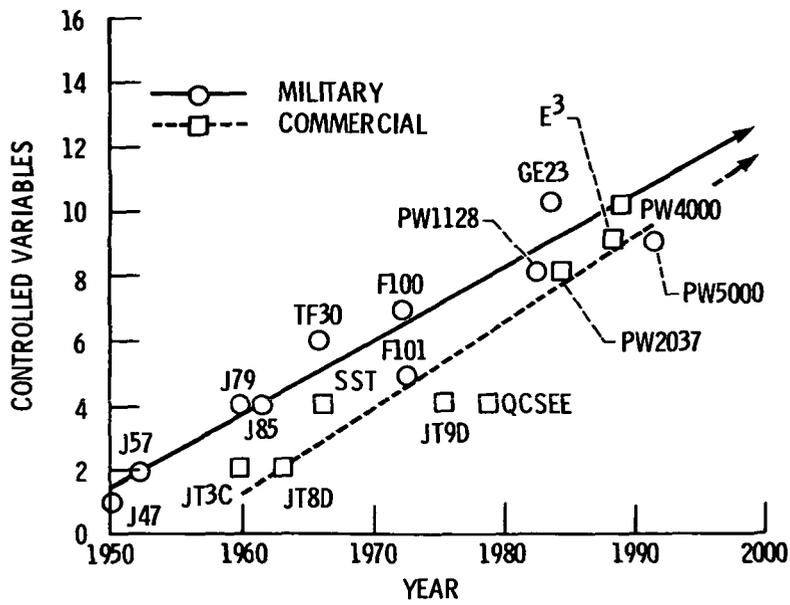


Figure 1. - Trends in control complexity of aircraft turbine engines.

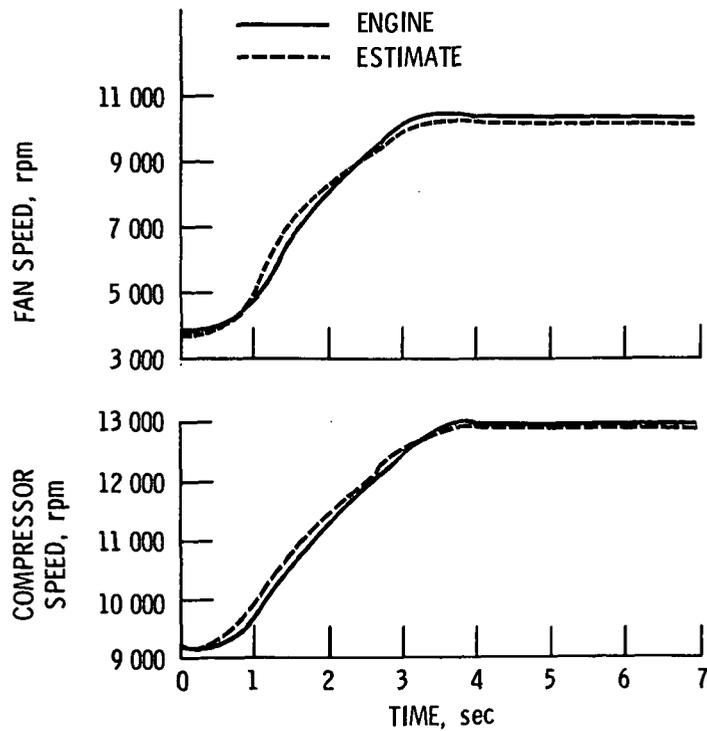


Figure 2. - Transient response comparison of nonlinear digital simulation (engine) and the ADIA simplified simulation (estimate). Flight conditions: altitude, 0 ft; Mach number, 0; power lever angle, 20° to 83° at 0.2 sec.

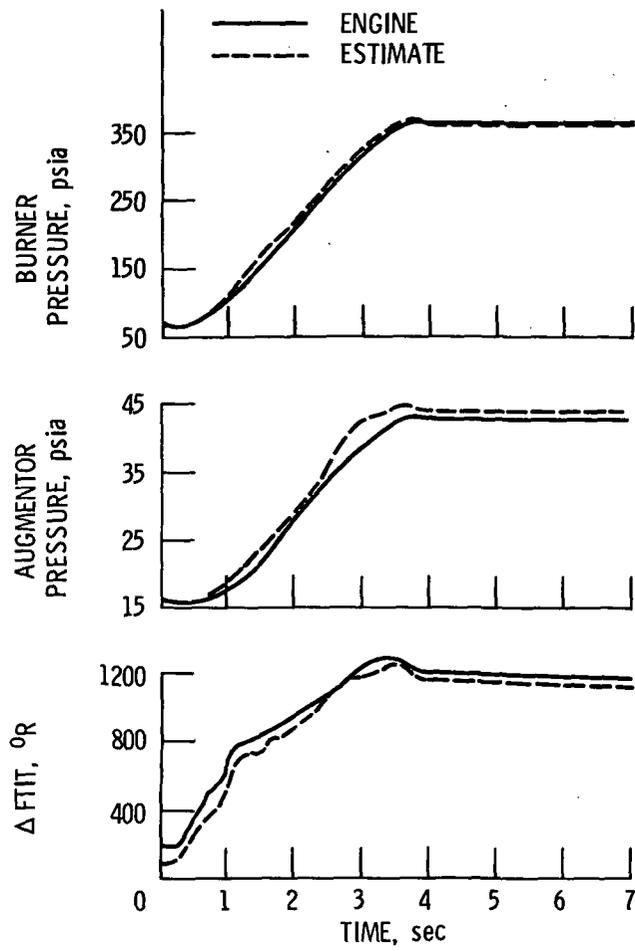


Figure 2. - Concluded.

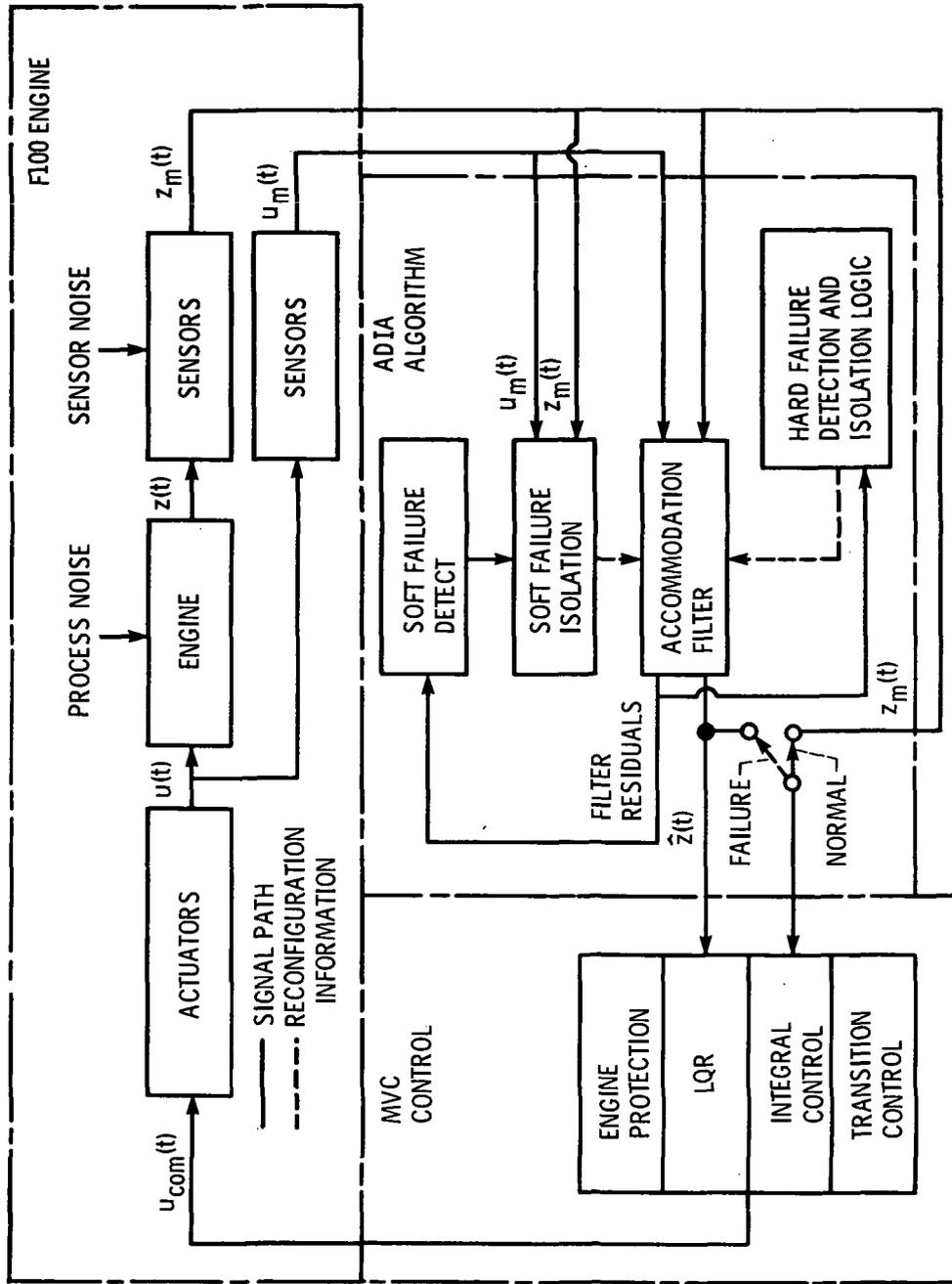


Figure 3. - F100 testbed system with ADIA algorithm and MVC control.

STEADY STATE & TRANSIENT

SENSORS	SINGLE FAILURE SLS	DUAL FAILURES			TRIPLE FAILURES 25K/1.0M
		SLS	25K/1.0M	35K/0.8M	
PS3	○	○ ○ ○ ○ □	△ ○ △ △	□ □ □ □	□ □ □ □
NF	○	○	△	□	□ □ □
T56	○	○	○	□	□ □
T25	○	○	△	□	□ □
NG	○	○	△	□	□ □
WFM	○	□			

- 20% TO 100% TO 20% DRY THRUST
- 30% TO 100% TO 30% DRY THRUST
- 30% TO MINIMUM A/B TO 30% DRY THRUST
- △ 30% TO MAXIMUM A/B TO 30% DRY THRUST

Figure 4. - F404 FICA sensor substitution results.

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