# Sensor Failure Detection for Jet Engines Using Analytical Redundancy

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THIS paper surveys the use of analytical redundancy (AR) to improve turbine engine control system reliability. Over the past 35 years hydromechanical implementations of turbine engine control systems have matured into highly reliable units. However, as shown in Fig. 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, lightweight 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.

Thus, in an effort to improve the overall demonstrated reliability of the digital electronic control system, various redundancy management techniques have been applied to both the total control system and to individual components. One of the least reliable of the control system components is the engine sensor. In particular, a study of fault-tolerant electronic engine controls[1] shows that sensor redundancy will be required to achieve adequate control system reliability. There are three types of sensor redundancy: direct, analytical, and temporal. Direct, or hardware, redundancy uses multiple sensors to measure the same engine variable. Typically, a voting scheme is used to detect failures. Analytical redundancy uses a reference model of the engine and redundant information in dissimilar sensors to provide an estimate of a measured variable. Estimates and measurements can be used in a variety of ways to detect failures. Temporal redundancy uses redundant information in successive samples of the output of a particular sensor to determine failures. Range and rate checks are simple and often used examples of temporal redundancy.

Hardware redundancy is insensitive to failure magnitude since any detectable discrepancy between two like sensors indicates a failure. Thus, hardware redundancy handles hard (out-of-range or large in-range) failures as well as soft (small in-range or drift) failures. Analytically redundant schemes can distinguish failure type and, in fact, can be made sensitive to a particular type, such as soft failures. Range and rate checks are simple and reliable detection methods, but are limited to hard failures. Often range and rate checks are combined with analytical redundant schemes to cover both hard and soft failure types. As shown in Ref. 1, hardware redundancy results in more costly, heavier, less practical, and less reliable systems than do various analytical redundancy strategies. Since cost, weight, and reliability are important drivers in turbine engine control systems design, many researchers have investigated analytical redundancy strategies.

State-of-the-art digital electronic control schemes, such as that for the PW2037 engine,[2] make use of a combination of hardware and analytical redundancy to provide adequate system reliability. Here, dual-redundant sensor measurements and a synthesized or estimated measurement are compared to detect sensor failures. This approach is comparable to that used in the aircraft control for the F8 digital fly-by-wire aircraft.[3] In each case a two-step approach is used. First the dual sensors are compared to determine if a discrepancy exists. Then a comparison is made to the estimate to isolate the faulty sensor. Operation continues with the good sensor. Here analytical redundancy allows system operation after both sensors have failed to furthwr improve system reliability. Eventually, as AR-based techniques improve, additional reliance on AR strategies would allow single-sensor operation with the resultant savings in cost and weight.

The objective of this paper is to survey the application of analytical redundancy to the detection, isolation, and accommodation (DIA) of sensor failures for gas turbine engines. This includes those approaches that use software implementations of temporal redundancy combined with analytical redundancy. Hardware redundant strategies are not covered. This survey first reviews the theoretical and application papers which form the technology base of turbine engine analytical redundancy research. Second, the status of important ongoing application efforts is discussed. Also included is a review of the PW2037 engine control system sensor AR strategy. This is the first operational engine to include AR-based strategies. Finally, an analysis of this survey indicates some current technology needs.

## AR Technology Base

In this section, papers that document the AR technology base will be reviewed. Sixteen papers are considered. The papers will be reviewed in essentially chronological order. The attributes of each paper, as discussed in this section, are summarized in Table 1.

Wallhagen and Arpasi[4] 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 com-

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**Table 1 Summary of papers describing the application of analytical redundancy methods to turbine engine control**

| Paper: Reference No(s). | Paper: Authors | Testbed system | Reference model | Type of DI | Type of A | Computer environment | Evaluation | No. of sensors | Miscellaneous |
|---|---|---|---|---|---|---|---|---|---|
| 4 | Wallhagen and Arpasi | J85 turbojet | PS | Hard failures via rate-limit threshold | Replacement | Real-time minicomputer | SLS | 2 | |
| 5 | Hrach et al. | TF30 real-time hybrid simulation | PS | Hard failures via rate-limit threshold | Replacement | Real-time minicomputer | Five operating conditions through flight envelope | 4 | Extension of Ref. 4 |
| 6 | Ellis | Turbofan nonlinear digital simulation | PS, PL | Threshold check of weighted-average estimate | Estimates always used by control weighted-average modified | Digital simulation | SLS | 6 | |
| 7-10 | Wells and de Silva | Nonlinear model of turbojet | PL with bank of filters | Bayesian hypothesis | None | Digital simulation | SLS | 2 | |
| 11 | Spang and Corley | QCSEE real-time hybrid simulation | SC with Kalman filter | Threshold comparison of filter residuals | Substitution | Real-time digital control | SLS | 7 | |
| 12 | DeHoff and Hall | Single-spool turbojet | SC | Maximum likelihood | None | Digital simulation | SLS | 1 | Theoretical study |
| 13 | Sahgal and Miller | F100 nonlinear simulation | PL | None | Substitution | Digital simulation | Two conditions | 4 | |
| 14-16 | Leininger and Behbehani | QCSEE nonlinear simulation | PL | GLR | None | Digital simulation | SLS | 6 | Theoretical and application study |
| 17 | Meserole | F100 nonlinear simulation | PL | Detection filter | None | Digital simulation | SLs | 15 | Theoretical and application study |
| 18 | Leininger | QCSEE simulation | Linear | "t" test | None | Digital simulation | SLS | 3 | Theoretical study of model uncertainty |
| 19,20 | Weiss et al. and Pattipati et al. | F100 linear | Linear | SPRT | None | Digital simulation | SLS | 5 | Theoretical study of model uncertainty |
| 21 | Emami-Naeini et al. | F100 linear | Linear | Hypothesis | Frequency-weighted filter estimates | Digital simulation | SLS | 5 | Theoretical study of model uncertainty |
| 22 | Brown et al. | F110 nonlinear | Linear | Threshold checks | Substitution | Digital simulation | SLS | 9 | Application to multiple engines |

Key: PS = parameter synthesis, SC = simplified component, PL = pseudolinear, SLS = sea level static, SPRT = sequential probability ratio test, and GLR = generalized likelihood ratio.

pressor 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 the 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 minicomputer. The implementation executed in a 15-ms 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% of its final value and 92% of maximum thrust was achieved. For two sensor failures, steady-state speed was approximately 99% of its final unfailed value and thrust was 87% of maximum. Time to accelerate, however, had to be increased from 3 to 30 s. Failures were induced at 50% 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 of the data necessary to function.

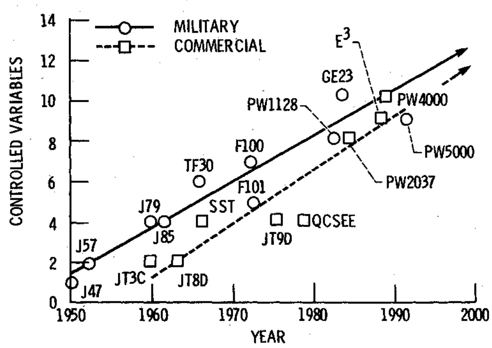


**Fig. 1 Trends in control complexity of aircraft turbine engines.**

In a companion paper, Hrach et al.[5] used a real-time nonlinear hybrid computer simulation of a two-spool turbofan, the TF30-P-3 engine, to demonstrate the DIA logic of Ref. 4 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 (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 0.025 s. Storage requirements include 4K bytes for the logic and 0.2K bytes for the tables. The logic was tested at five selected operating points (which include the two design points). Acceptable operation with no limit violations and approximately the same thrust was obtained for operation with 1-3 of the 4 sensors failed. For afterburning operating 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[6] (January 1975) studied the use of AR techniques using a nonlinear digital simulation of a two-spool turbofan engine. The engine has 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 five measured variables yields ten 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[7-10] by de Silva and Wells. 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 model of the engine was used on a mainframe computer to evaluate detection performance. A pseudolinear model consists of a dynamical, linear state-space structure where 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 lowest risk Bayesian hypothesis is also probabilistically most likey given the measured data. A "bank" of Kalman filters, one per hypothesis, uses 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, is taken as the true hypothesis. The mode of operation associated with this hypothesis (failed speed sensor, no failure, etc.) is assumed true. The approach worked well in simulation studies of this simple case. This work represents the first application of analytical redundancy 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[11] published an application of AR techniques to the quiet, clean, short-haul, experimental engine (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 vane torque motor current. In this study an extended Kalman filter approach is used to generate state estimates and residuals. A simplified nonlinear component model that is valid throughout the engine operating envelope and a simplified feedback gain matrix operating on engine measurements are used to update the filter estimates and residuals. Sensor failures are detected and isolated by a threshold comparison of the individual residual components. Thresholds are 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 are implemented in a microprocessor-based control; also in real time. Successful operation for single hard sensor failures is 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 (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[12] report 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 is 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[13] 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 fifth-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[14-16] 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 is used to detect and isolate hard and soft failures. Both single and multiple actuator and sensor failures are considered.

**Table 2 Minimum failure size for a detection[a] filter designed for an F100 engine**

| Isolation | Minimum failure size, %, Engine state: Steady | Unsteady |
|---|---|---|
| Output sensors | 2 | 5-10 |
| Inlet sensors | 2 | 5-10 |
| Fuel system, exhaust nozzle | 5-10 | 10-20 |
| Compressor vanes, fan vanes | 10-30 | 20-60 |
| Rotor efficiencies | 2 | 5-10 |

[a]2-5% change in one or more output measurements.

Detection and isolation studies are conducted by simplified simulation of the 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[17] uses detection filter theory to design a detection filter that detects sensor failures in an F100 engine. Similar to 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 2-5% changes in one or more output measurements. Minimum failure size for successful isolation is summarized by component in Table 2.

A paper by Leininger[18] 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 Student's "t" test. The "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% 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.

The next three papers present basic research in robust detection, isolation, and accommodation 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 different approaches have been identified to the solution of this problem.

The research of Refs. 19 and 20 is based upon the concept of 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. A three-step design process is presented. First, the parity relations are rank-ordered using a robustness metric. That set of relationships with acceptable robustness is identified. Second, the coverage (probability of detection for all failures) for this set of relationships is assessed. Finally, the ability of the set of parity relations to distinguish each failure mode from the others is assessed, again using a metric-based analysis. Iterations through this process are possible in order to expand the original set of relationships and to improve coverage or distinguishability by incorporating decreasingly robust parity relations. The parity relations can be generated efficiently from either a time- or frequency-domain description of the average process. The average process is defined as

$$\bar{A} = \sum_{\ell=1}^{n} \rho_\ell A_\ell$$

where $A_\ell$ represents the $\ell$ th set of model parameters and $\rho_\ell$ the a priori probability that $A_\ell$ is correct. The methodology has been applied to the preliminary design of a robust DIA system for an F100 engine.

The research of Ref. 21 is based upon the extension of recent advances in robust control system design to sensor DIA and estimator design. Model uncertainty effects on DIA robustness are 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 yields optimally robust innovations to model uncertainty. Thus, sensor failure detection based upon these innovations will also be robust.

The design process makes use of a threshold selector. The threshold selector determines the minimum detectable failure size for a given noise level, failure type, false-alarm rate, and model uncertainty description. This threshold selector determines maximum achieveable performance for the given set of constraints. Optimally robust (to modeling errors) residuals are generated using filters designed using the internal model principle and frequency shaping. The results of this methodology are applied to the preliminary design of sensor DIA logic for an F100 engine.

The final paper in this section[22] is an investigation of a variation of hardware redundancy to improve soft failure DIA capability. This feasibility study examines 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 obtainable. 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 is demonstrated using a digital nonlinear simulation of two F110 engines.

## 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. These important AR development programs are 1) Advanced Detection, Isolation, and Accommodation (ADIA), 2) Energy-Efficient Engine ($E^3$) FICA, 3) Full-Authority Digital Electronic Control (FADEC) FICA, 4) Digital Electronic Engine Control (DEEC) sensor DIA, and 5) Analytical Redundancy Technology for Engine Reliability Improvement (ARTERI). Also included is a discussion of the sensor redundancy approach used on the PW2037 engine.

### 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 development of the ADIA algorithm is reported by Beattie et al.[23,24] 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 (MVC)[25] 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 was conducted to classify the various failure modes as critical or noncritical. Critical failures were defined as those that resulted in surge, a 10% 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 methodologies. These five concepts were specifically formulated to span as many applicable methodologies as possible.

Since competing methodologies were to be compared, a scoring system was developed. The scoring system evaluated the concepts for 1) exceeding minimum transient and steady-state operation requirements, 2) detection and isolation effectiveness, and 3) the qualitative benefits of bettering the requirements of item 1. 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 engine operating range. This evaluation showed the ADIA approach to be: 1) viable for gas turbine applications, and 2) when compared to be a parameter synthesis approach, 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. Second, the simplified simulation used in the algorithm's filter was not accurate enough at all flight conditions. The bias problem was removed by a minor change in the accommodation logic to improve steady-state operation. This result is shown in Table 3. 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. To improve simplified simulation accuracy, additional linear, state-space model data were incorporated in-

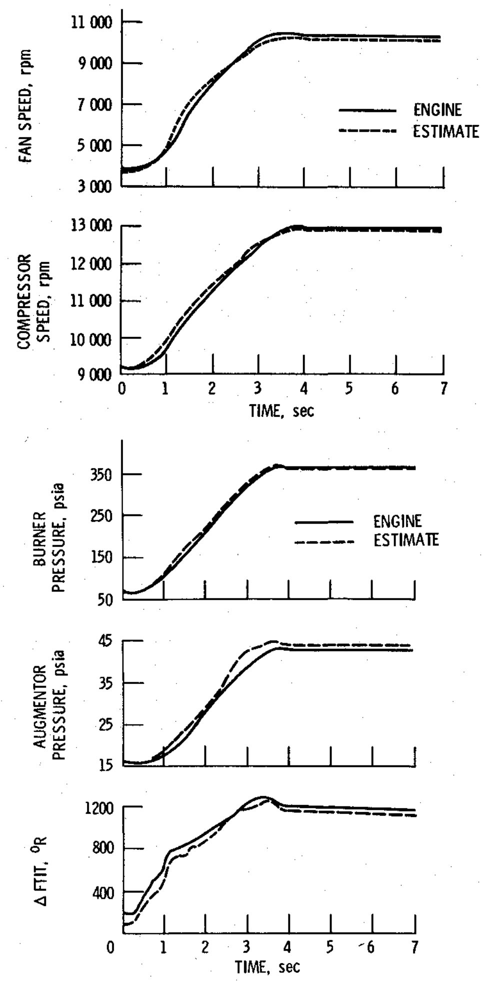


**Fig. 2 Transient response comparison of nonlinear digital simulation (engine) and the ADIA simplified simulation (estimate). Flight conditions: altitude, 0 ft; Mach number, 0; power level angle, 20-83 deg at 0.2 s.**

**Table 3 Steady-state comparisons of thrust change and estimation error for baseline and revised DIA algorithms**

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

to 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.[26] 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 = 20-83 deg) step command. This comparison demonstrates the excellent estimation capability of the simplified simulation. The ADIA algorithm incorporates this simulation and Kalman filter logic to improve these estimates further.

The testbed system with ADIA and MVC logic is shown in Fig. 3. The algorithm consists of an extended steady-state Kalman filter, called the accommodation filter, that generates sensor estimates and residuals based upon the previously described simplified engine simulation. 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 a 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, however, 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 cover completely 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 3). 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 4 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 burner pressure (PT4), exhaust pressure (PT6), and fan turbine inlet temperature (FTIT) failure 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[27] describe a preliminary 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 that had been implemented and evaluated previously.[28] The second computer contains the detection and accommodation 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 vs assembly language. Also, a good FORTRAN compiler for the 8086/8087 was available. Subsequent work has incorporated a third microprocessor into the implementation. In

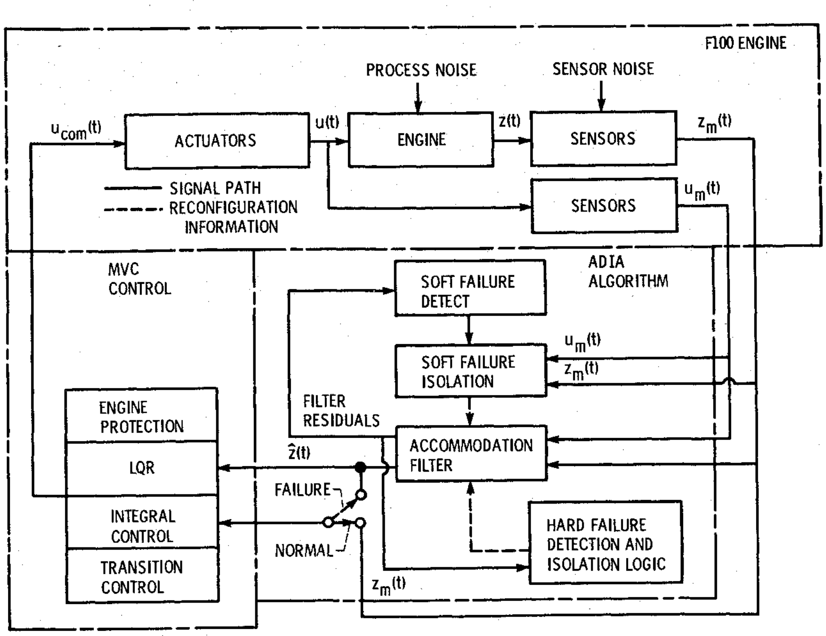


**Fig. 3 F100 testbed system with ADIA algorithm and MVC control.**

this third computer the five isolation filters are implemented, again using floating-point FORTRAN. 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 1986. The demonstration will take place in the NASA Lewis Research Center Altitude Test Facility. The microprocessor hardware and software developed and evaluated in phase 2 of this program will be used in this demonstration.

### $E^3$ FICA

The $E^3$ program is developing technology to improve 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.[29] The FICA logic is based upon the concept of Spang and Corley.[11] Here, a sixth-order extended Kalman filter is used to generate seven sensor estimates: fan and core speeds, 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 vs 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 values 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. The $E^3$ FICA logic does not detect slow drift, i.e., soft, sensor failures.

### FADEC FICA

Under the FADEC program,[30] AR techniques (in particular, FICA) were applied to two engines, a Joint Technology Demonstrator Engine (JTDE) and 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 pseudolinear 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 performed successfully. 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.

A second application of the FICA technology was to the F404 engine. The F404 is an afterburning turbofan engine with a rear variable-area bypass injector to permit selective cycle rematch. The rear injector 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[31] 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-s 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.[32] Steady-state and transient model accuracies were judged to be excellent. Single, double, and triple substitutions of FICA-generated estimates were performed successfully during the engine tests. These combinations are summarized in Fig. 4. Actuator FICA was also demonstrated successfully 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[33] is a digital full-authority engine control containing selectively redundant components and fault-detection logic. The system also contains a hydromechanical

**Table 4 Steady-state results of slow drift failure transients for the ADIA algorithm**

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

[a] A = acceptable, U = unacceptable.

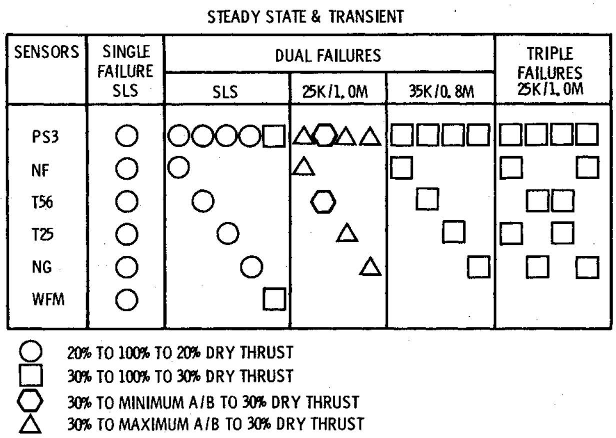


**Fig. 4 F404 FICA sensor substitution results.**

backup 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.

In parameter synthesis 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 $\pm 25\%$ 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.[34] 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[35] which will incorporate intentional sensor faults to evaluate completely the DIA logic.

**ARTERI**

ARTERI is a three-year development program, started in October 1983. 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 then will be demonstrated on a full-scale Joint Technology Demonstrator Engine in 1986.

**PW2037**

The PW2037 engine is a modern, high-bypass-ratio turbofan engine and is the first to incorporate a competely digital, full-authority electronic control system.[2] The control is engine-mounted and dual-channeled to meet reliability requirements. As part of the control's redundancy managemnt strategy, a combination of hardware and software sensor redundancy is used to ensure engine operability whenever the capability is available. Dual hardware is used for seven sensors (two speeds, two pressures, two temperatures, and thrust lever angle). All of these sensors are covered by channel-to-channel comparisons, as well as software range and rate checks, to detect failures. In the case of the two engine speeds and the two pressures, sensor failures are further covered by comparisons to synthesized estimates. In the case of a dual-channel failure (both low-spool-speed sensors, for example), operation continues using the synthesized estimate of low spool speed. The two pressures and high spool speed are synthesized from low spool speed using a parameter synthesis method. Low spool speed is synthesized from high spool speed.

## AR Technology Assessment

From the preceding 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 1, demonstrate the feasibility of AR-based DIA. In particular, straightforward range or rate checks have provided successful detection of hard sensor failures. Futher, 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 reliabily detected only after some finite amount of time. This time to detect is a function of threshold level, which determines detection reliability, required 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 an engine. Full-scale engine testing remains to be done. State-of-the-art operational systems, such as the DEEC and the PW2037 control, use only limited AR in combination with more extensive hardware redundancy.

The work presented in this survey clearly emphasizes the fundamental importance of modeling in successful DIA. A model detailed enough for accurate DIA throughout the flight envelope is a significant technical challenge. Expectantly, when faced with a difficult technical problem, different approaches are pursued. Three different modeling approaches have been used: 1) parameter synthesis, 2) pseudolinear, and 3) simplified component. Both the parameter synthesis and simplified component modeling approaches have been used in successful hard failure DIA on full-scale engines. The pseudolinear method has been demonstrated for both hard and soft failure DIA using detailed nonlinear simulations. Each approach has its own advantages and disadvantages.

The parameter synthesis approach, which was used in the DEEC DIA and the PW2037, is simple to understand and straightforward to implement. Explicit dynamics normally are not included. However, this simplicity implies a less accurate model. Also, the most accurate interrelationships between measured and synthesized variables cannot be identified easily or systematically. Model modifications are made easily.

The simplified component approach, which was used in the FADEC FICA, results in more accurate models than the parameter synthesis approach. Simplified component 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. In addition, simplified model performance is not easily predicted. A simplified component model relates naturally to the physics of the actual engine and, therefore, is readily understandable. However, modification of a simplified component model is not straightforward since changes in component performance can have an unpredictable effect on model performance.

The pseudolinear modeling method 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 pseudolinear model with engine physics is not as straightforward as for a simplified component 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 pseudolinear model than with parameter synthesis or simplified component models. In addition, the complexity/accuracy tradeoff is defined more clearly for a pseudolinear model.

## Concluding Remarks

This paper has surveyed the technology base and technology applications for analytical redundancy (AR)-based sensor failure detection, isolation, and accommodation (DIA) strategies for gas turbine engines. Several observations and conclusions are made. Comparisons of PW2037 technology with that of the F8 digital fly-by-wire program, or the approach used in the ADIA program with that proposed by Montgomery and Caglayan,[36] show that engine AR technology often builds or expands upon technology developed for flight controls. Also, modeling is the key issue in the success of AR techniques. Three types of models are used. Each has its advantages and disadvantages and no clear preferred type emerges. Because of this strong dependence of performance on modeling accuracy, fundamental questions about detection performance and robustness have been posed and addressed in recent robust DIA programs. Finally, simulation or full-scale engine testing has conclusively shown the feasiblity of AR-based DIA for hard failures. Soft failure DIA has been demonstrated, thus far, by simulation only. The results were very encouraging but not totally successful. Work remains to be done in this area.

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