JOURNAL OF GUIDANCE, CONTROL, AND DYNAMICS
Vol. 17, No. 1, January–February 1994

Fault Detection and Diagnosis in Propulsion Systems: A Fault Parameter Estimation Approach

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The paper presents the development of a fault detection and diagnosis (FDD) system with applications to the Space Shuttle main engine. The FDD utilizes a model-based method with real-time identification and hypothesis testing for actuation, sensor, and performance degradation faults.

Introduction

THERE is a growing demand to improve the control systems of liquid propulsion rocket engines for enhanced performance with increased reliability, durability, and maintainability. This demand can be met by improving the individual reliabilities of system components and also by an intelligent control system[1] with fault detection, diagnostics, and accommodation capabilities. This paper focuses on the development of a model-based fault detection and diagnosis (FDD) system that can be used as an integral part of such an intelligent control system.

During the last two decades of the development of fault detection methods, the so-called model-based fault detection approach has received considerable attention. These schemes basically rely on the idea of analytical redundancy. As opposed to physical redundancy, which uses measurements from redundant sensors for fault detection purposes, analytical redundancy is based on the signals generated by the mathematical model of the system being considered. These signals are then compared with the actual measurements obtained from the system. The comparison is done by using the residual quantities that give the difference between the signals being measured and the signals being generated by the mathematical model. Hence, the model-based fault detection and diagnosis can be defined as the determination of faults of a system from the comparison of the measurements of the system with a priori information represented by the model of the system through generation of residual quantities and their analysis.

In the absence of noise and modeling errors, the residual vector is equal to the zero vector under fault-free conditions. Hence, a nonzero value of the residual vector indicates the existence of the faults. When noise and modeling errors are present, their effect has to be separated from the effect of faults. In the simplest case, this is done by comparing the residual magnitudes with threshold values. Using the distribution of the residuals under fault-free conditions, one can determine threshold values to minimize false alarms and missed detections by selecting the level of confidence.

Received March 6, 1992; revision received Feb. 12, 1993; accepted for publication Feb. 27, 1993.

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The basis for the isolation of a fault is the fault signature, i.e., a signal obtained from a diagnostic model defining the effects associated with a fault. A diagnostic model is obtained by defining the residual vector in such a manner that its direction is associated with known fault signatures. Furthermore, each signature has to be unique to one fault to accomplish fault isolation.

Since the generation of residual quantities is a central issue in model-based FDD schemes, it will be briefly reviewed in this section. Survey papers by Frank,[2] Gertler,[3] Willsky,[4] and Isermann[5] discuss the rich variety of approaches that have been proposed for the generation of residuals. These approaches can be classified as observer- or filter-based approaches, a parity relations approach, and parameter estimation approaches. The first two classes are closely related because it has been shown by Massoumnia[6] that a parity relations approach is equivalent to using deadbeat observers.

The basic idea within the observer- or filter-based approaches is to estimate the outputs of the system from the measurements or a subset of measurements by using either Luenberger observer(s) in a deterministic setting or filter(s) in a stochastic setting. Then the output estimation error or innovations in the stochastic case are used as a residual. The flexibility in selecting observer gains has been fully exploited in the literature, yielding a rich variety of fault detection schemes.

The parity relations approach is based on checking the consistency of the mathematical relations between the outputs (or a subset of outputs) and inputs. These relations may lead to direct redundancy, which gives the static algebraic relations between the sensor outputs, or temporal redundancy, which gives the dynamic relations between inputs and outputs.

All of the fault detection schemes either explicitly or implicitly are based on the assumption that faults cause changes in parameters of the system. In the parameter estimation approach system parameters are estimated on-line to monitor these changes for fault detection and diagnostics purposes. Therefore, it is a simpler and more direct approach than the others. In this approach fault decision logic can also employ the estimates of some physical parameters[5] such as efficiency, fuel consumption, etc., which can effectively be used in fault diagnosis logic.

It is believed that the success of an FDD scheme depends on the accurate and appropriate modeling of the faulty process. The model of the faulty process defines the effects associated with faults. If the faulty process is modeled to distinguish the faults, then the residuals carry meaningful information that can be used for diagnostics purposes. Therefore, the main attention of this work is devoted to the modeling of the faulty process. This is accomplished by incorporating the notion of fault parameters[7] in the model of the faulty process. These fault parameters are estimated by using a real-time multivariable parameter estimation algorithm.[8] It is assumed that no more than one type of fault in the categories of either actuation, sensor, or component faults can occur at the same time. Hence, fault parameters are estimated based on different hypotheses of the type of faults. The fault parameters and their patterns are then analyzed for diagnostic purposes.

Initially, the model of the faulty process is developed. This is followed by the section describing the diagnostic model. Then a fault diagnosis scheme based on the estimation of fault parameters is discussed. Finally, the results obtained through the application of this technique for the actuation and sensor faults of the Space Shuttle main engine (SSME) are presented. Preliminary results of the work discussed here were previously reported in several conference papers.[9-11]

Model of the Faulty Process

Consider a discrete time linear system described by the following state equations:

$$x(n+1) = Ax(n) + Bu(n) \tag{1}$$

$$y(n) = Cx(n) \tag{2}$$

where x, u, and y are the $n \times 1$ state, the $p \times 1$ input, and the $q \times 1$ output vectors, respectively. The A, B, and C are the known nominal matrices of the system with appropriate dimensions. The process noise, measurement noise, and modeling errors due to uncertainties in the parameters are not included for mathematical simplicity. It is assumed that the system is in α-canonical form[8] such that the following relations hold:

$$C = [0 \; : \; H^{-1}] \tag{3}$$

$$A = A_0 + KHC \tag{4}$$

$$A_0^{\mu} = 0 \tag{5}$$

$$(HC)_{r_i} A_0^{\mu_i} = 0 \tag{6}$$

$$(HC)_{r_i} A_0^k K_{c_j} = 0 \quad \text{for } k \geq 0 \text{ and } k < \mu_i - \mu_j \tag{7}$$

where K is a deadbeat gain, and A_0 is a lower left triangular structure matrix that consists of zeros and ones only. A_0 is determined by the observability indices $\{\mu_i\}$; $(HC)_{r_i}$ denotes the ith row of HC, whereas K_{c_j} denotes the jth column of K.

The model of the faulty process is developed by considering the cause/effect relations for faults as associated with the parameters of the system. Actuation, sensor, and component faults of the system are considered. Sensor faults due to the multiplicative error and bias are modeled as

$$y_s(n) = F_s y(n) + f_{s0} \tag{8}$$

where $y_s(n)$ and $y(n)$ are the sensor measurement and the actual output of the process, respectively; the matrix F_s is a diagonal matrix, and f_{s0} is a constant vector, both with appropriate dimensions.

The actuation faults are modeled in a similar way as

$$u_a(n) = F_a u(n) + f_{a0} \tag{9}$$

where $u_a(n)$ and $u(n)$ are the actual actuator output and the requested actuator input, respectively. The matrix F_a is a diagonal matrix, and f_{a0} is a constant vector, both with appropriate dimensions.

In the case of the system component faults, it is assumed that the structure of the system, i.e., the observability indices, remains the same, whereas the system matrix A is affected. The new system matrix under faulty conditions becomes A_f and can be described as

$$A_f = A_0 + K_f HC \tag{10}$$

The parameters F_a, F_s, f_{a0}, f_{s0}, and A_f are referred to as fault parameters in this study. Under normal operating conditions, the fault parameters F_a and F_s are equal to identity matrices, whereas the vectors f_{a0} and f_{s0} are equal to the zero vectors. Under faulty operating conditions, the fault parameters change, reflecting the effect of fault. For example, a stuck actuator valve will cause the corresponding element of F_a to change from a value of unity to a value of zero. A valve ball seal leakage will manifest itself as a change in the corresponding element of f_{a0} from a value of zero to a nonzero value.

Using Eqs. (8–10) in Eqs. (1) and (2), the open-loop dynamics of the faulty process can be modeled as

$$x(n+1) = A_f x(n) + BF_a u(n) + Bf_{a0} \tag{11}$$

$$y(n) = Cx(n) \tag{12}$$

$$y_s = F_s y(n) + f_{s0} \tag{13}$$

The preceding equations can be used to obtain the state, the output, and the measured output of the faulty process in terms of the nominal system parameters, fault parameters, input, and the measured output as

$$x(n) = \sum_{i=1}^{\mu} A_0^{i-1}(Bf_{a0} - K_f HF_s^{-1} f_{s0}) + \sum_{i=1}^{\mu} A_0^{i-1}[K_f HF_s^{-1} \; : \; BF_a] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{14}$$

$$y(n) = \sum_{i=1}^{\mu} CA_0^{i-1}(Bf_{a0} - K_f HF_s^{-1} f_{s0}) + \sum_{i=1}^{\mu} CA_0^{i-1}[K_f HF_s^{-1} \; : \; BF_a] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{15}$$

$$y_s(n) = f_{s0} + \sum_{i=1}^{\mu} F_s CA_0^{i-1}(Bf_{a0} - K_f HF_s^{-1} f_{s0}) + \sum_{i=1}^{\mu} F_s CA_0^{i-1}[K_f HF_s^{-1} \; : \; BF_a] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{16}$$

Diagnostic Model

As mentioned earlier, several techniques may be used to generate the residual vector to be used as the diagnostic model. In this work the fault parameters are used as the residual vector that makes the diagnostic model. Fault parameters can be used to isolate faulty components. They can also be used to determine the size of faults that may be needed for accommodation purposes. Hence, a real-time identification of fault parameters using measurements of the input and output data and with the knowledge of nominal system parameters is proposed in this study for fault detection and diagnostic purposes.

To obtain fault parameters, Eqs. (6) and (8) may be used as a single diagnostic model. A close look at these equations, however, reveals that fault isolation may not be possible if multiple faults occur. For this reason, three different models—each monitoring different faults in actuation, sensor, and component fault categories—are used as diagnostic models. It is assumed that no more than one fault may occur at the same time. With this assumption, Eq. (16) can be rewritten for actuation faults as

$$y_s(n) = \sum_{i=1}^{\mu} CA_0^{i-1} Bf_{a0} + \sum_{i=1}^{\mu} CA_0^{i-1}[KHF_a^{-1} \; : \; BF_a] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{17}$$

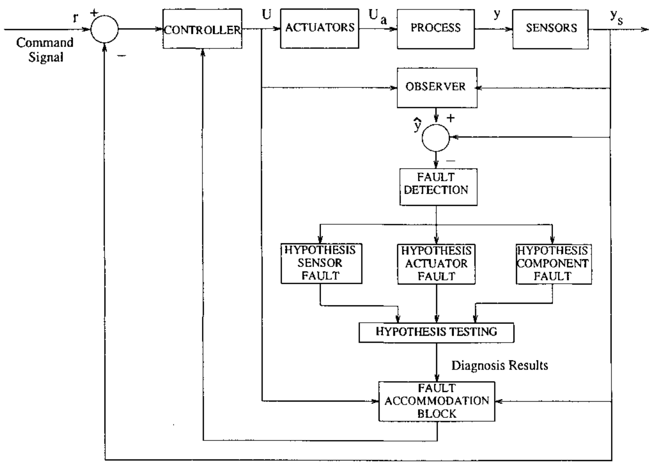

Fig. 1 Model based fault detection and diagnosis scheme.

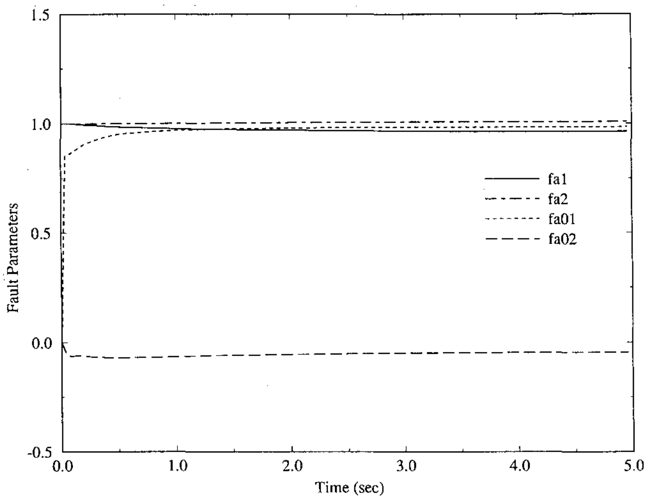

Fig. 2 OPOV leakage at time $t = 0.0$ s.

and for sensor faults as

$$y_s(n) = f_{s0} - \sum_{i=1}^{\mu} F_s C A_0^{i-1} K H F_s^{-1} f_{s0} + \sum_{i=1}^{\mu} F_s C A_0^{i-1} [K H F_s^{-1} \; : \; B] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{18}$$

and for component faults as

$$y_s(n) = \sum_{i=1}^{\mu} C A_0^{i-1} [K_f H \; : \; B] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{19}$$

Residuals $r(n)$ for each category of faults are generated by using the difference between the sensor output $y_s(n)$ and the estimated output of the normal process $\hat{y}(n)$ as

$$r(n) = y_s(n) - \hat{y}(n) \tag{20}$$

The estimated output of the normal process is obtained by using a deadbeat observer as

$$y_s(n) = \sum_{i=1}^{\mu} C A_0^{i-1} [K H \; : \; B] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{21}$$

where the observer gain K is defined by Eqs. (4–7).

Hence, the proposed diagnostic scheme uses a two-step approach. The first step is composed of a group of hypothesis testing modules (HTM) processed in parallel to test each class of suspected faults. Each module is solely designed to process the input-output data under a specified hypothesis and to generate the signature data for fault diagnostics purposes. The second step is the fault diagnosis module that checks all of the information obtained from the HTM level, isolates the fault, and determines its magnitude.

There are three hypothesis testing modules on the first data processing layer in the proposed diagnostic system as shown in Fig. 1. These modules are used for on-line identification of fault parameters corresponding to each hypothesis of actuation, sensor, or component faults. For example, under the hypothesis of an actuation fault the corresponding module uses the known nominal system matrices A, B, and C and the residuals generated from the input-output data to estimate the fault parameters F_a and f_{a0}.

On the estimation of the fault parameters, it is also necessary to determine the validity of the hypothesis. This is accomplished by comparing the output estimate obtained using the fault parameters with the actual measured output. For this purpose the output estimate error and the standard error of estimate (SEE) are defined as

$$e_{ij} = y_{si}(n) - \hat{y}_i(n/n-1, H_j) \tag{22}$$

$$\text{SEE} = \left(\sum_{i=1}^{n} e_{ij}^2 \Big/ \sum_{i=1}^{n} y_{si}^2 \right)^{1/2} \tag{23}$$

where subscripts i and j refer to the ith output and jth class of faults, and H_j is the hypothesis that the fault belongs to the jth class of faults. The SEE is calculated at each step with the most

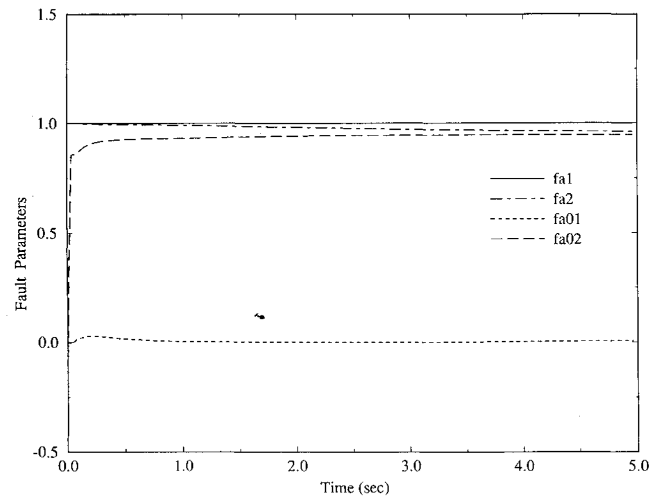

Fig. 3 FPOV leakage at time $t = 0.0$ s.

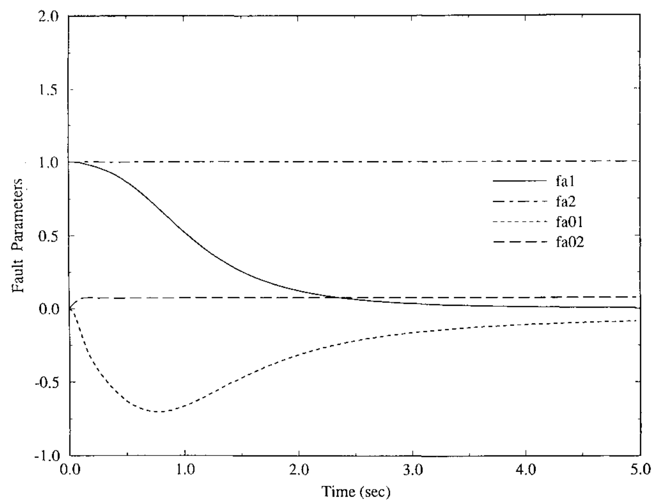

Fig. 4 OPOV stuck valve at time $t = 0.0$ s.

recent estimate of the fault parameters and is used to accept or reject the hypothesis.

The fault diagnosis module examines all of the estimated fault parameter values and SEEs and generates a conclusion of the faulty status of the system. This is done by 1) comparing the fault parameters against the predetermined signatures, 2) comparing the SEEs against the preselected thresholds, and 3) comparing the relative magnitude of the SEEs among all of the hypothesis testing modules. For the case of actuation faults, if the estimated fault parameter F_a is not equal to the identity matrix I, then it is concluded that the input gain matrix has changed, which corresponds to a stuck actuator valve. Also, a nonzero component of f_{a0} shows a bias between the command input and the actual input to the system.

Fault Detection and Diagnosis of the SSME: Actuation and Sensor Faults

The FDD system based on fault parameter estimation developed in this study is applied to the diagnosis of actuation and sensor faults of the Space Shuttle main engine. The modeling of the SSME dynamics is accomplished in a previous study by Duyar et al.[8] This work is further extended to cover a wide range of operations by using a piecewise linear model[12] with two inputs and four outputs. Nominal matrices are obtained from the piecewise linear model developed in this previous study. The inputs considered were the oxidizer preburner oxidizer valve (OPOV) and the fuel preburner oxidizer valve (FPOV). The outputs are the mixture ratio (MR), the chamber inlet pressure (PCIE), and the speeds of the oxidizer and fuel preburners (NOP and NFV, respectively). In the aforementioned studies, the accuracy of the simplified model is verified by comparing its outputs with the outputs obtained from a nonlinear performance simulation of the SSME, referred to as the digital transient model (DTM), developed by Rockwell International Corporation's Rocketdyne Division.[13]

SSME dynamic responses to actuation and sensor faults are simulated using the DTM with the closed-loop control system active. The types of faults in each category are induced in a manner to simulate the actual faults observed on the SSME as reported by Glover et al.[14] The operating condition selected for this study is 100% rated power level with a nominal mixture ratio of 6.026. A sampling time of 0.04 s is used.

Figures 2–4 show the identified fault parameters for simulated actuation faults. In Figs. 2 and 3 fault parameters corresponding to valve ball seal leakage are shown. The magnitude of the bias f_{a0} is directly related to the leakage flow rate. Figure 4 shows fault parameters corresponding to a stuck valve. In this case, the valve stops responding to the input command. The magnitude of the bias f_{a01} depends on the valve stuck position and the desired position of the operating condition. Figures 5 and 6 show results obtained for simulated multiplicative and additive sensor faults. As illustrated in these results, both the fault isolation and the fault magnitude estimation can be accomplished with this approach.

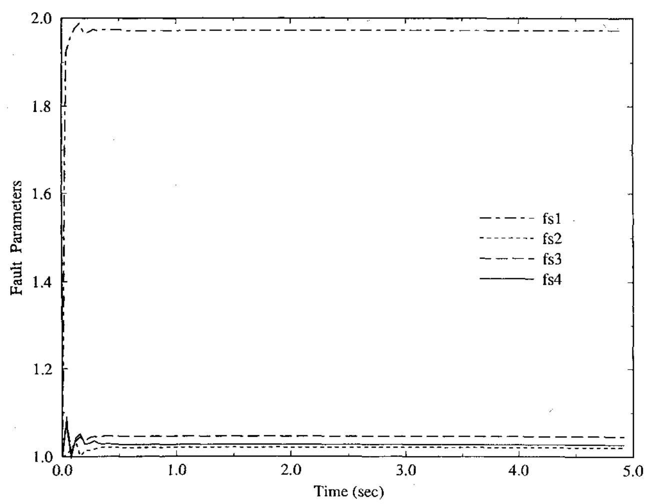

Fig. 5a Multiplicative fault in PCIE sensor.

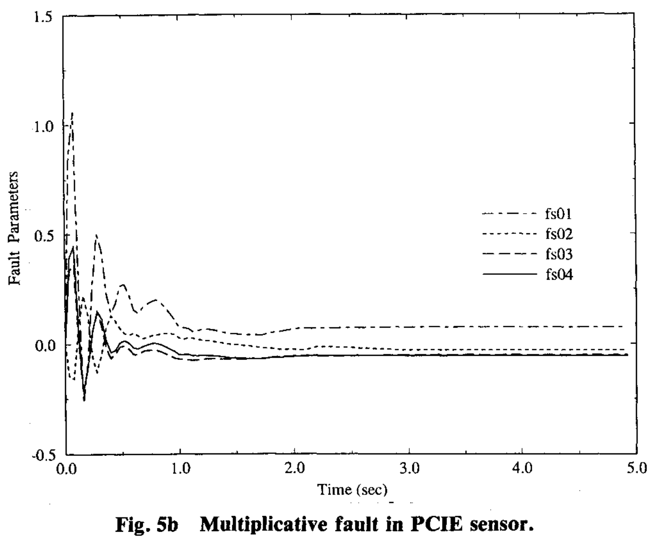

Fig. 5b Multiplicative fault in PCIE sensor.

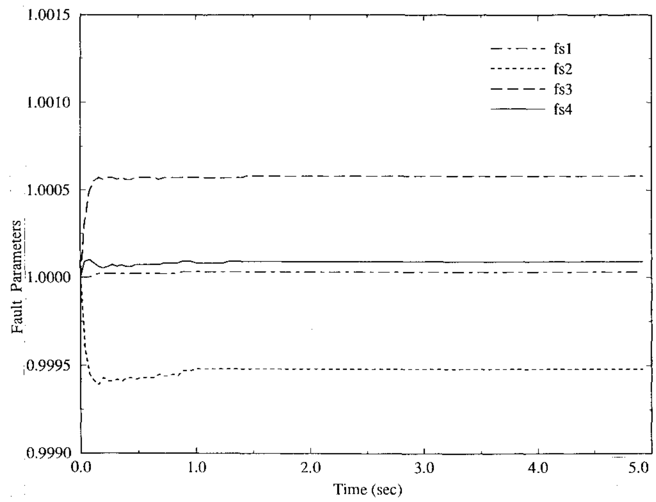

Fig. 6a Bias in the mixture ratio sensor.

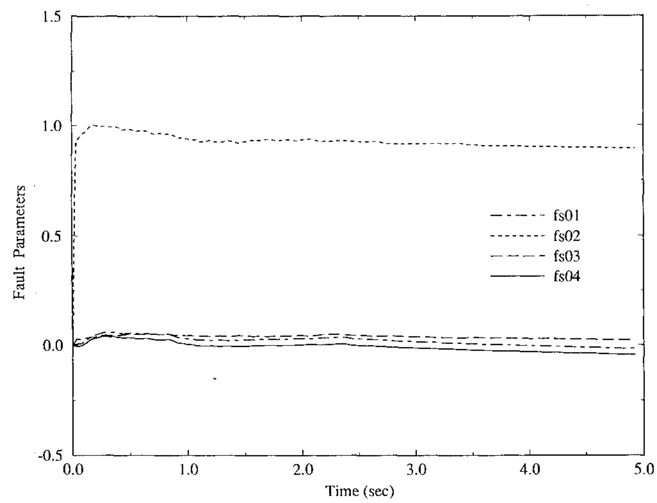

Fig. 6b Bias in the mixture ratio sensor.

Conclusions

A fault detection and diagnosis system based on fault parameter estimation is developed for actuation, sensor, and component faults. The validity of the FDD system is demonstrated by applying it to the SSME for actuation and sensor faults. In the case of SSME actuation and sensor faults, it is shown that the parameter estimation approach can be used effectively for fault diagnosis purposes. It is a direct approach and therefore reduces the detection, isolation, and magnitude estimation tasks to the task of comparing fault parameter values before and after the occurrence of a fault. Fault parameters can also be used for accommodation purposes because they are used to estimate the fault magnitudes. The FDD system developed has the added advantage that, in the case of actuation and sensor faults, a priori knowledge about fault signatures is not needed. Therefore, this approach can improve the SSME safety over the current redline schemes.

Further research is needed to apply this scheme to the component faults and to determine the type and quality of measurements for the real-time implementation. The real-time implementation of this study for the actuation faults of the SSME is currently being studied as an integral part of the intelligent control system demonstration project at NASA Lewis Research Center.

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