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Implementation of a Model Based Fault Detection and Diagnosis for Actuation Faults of the Space Shuttle Main Engine

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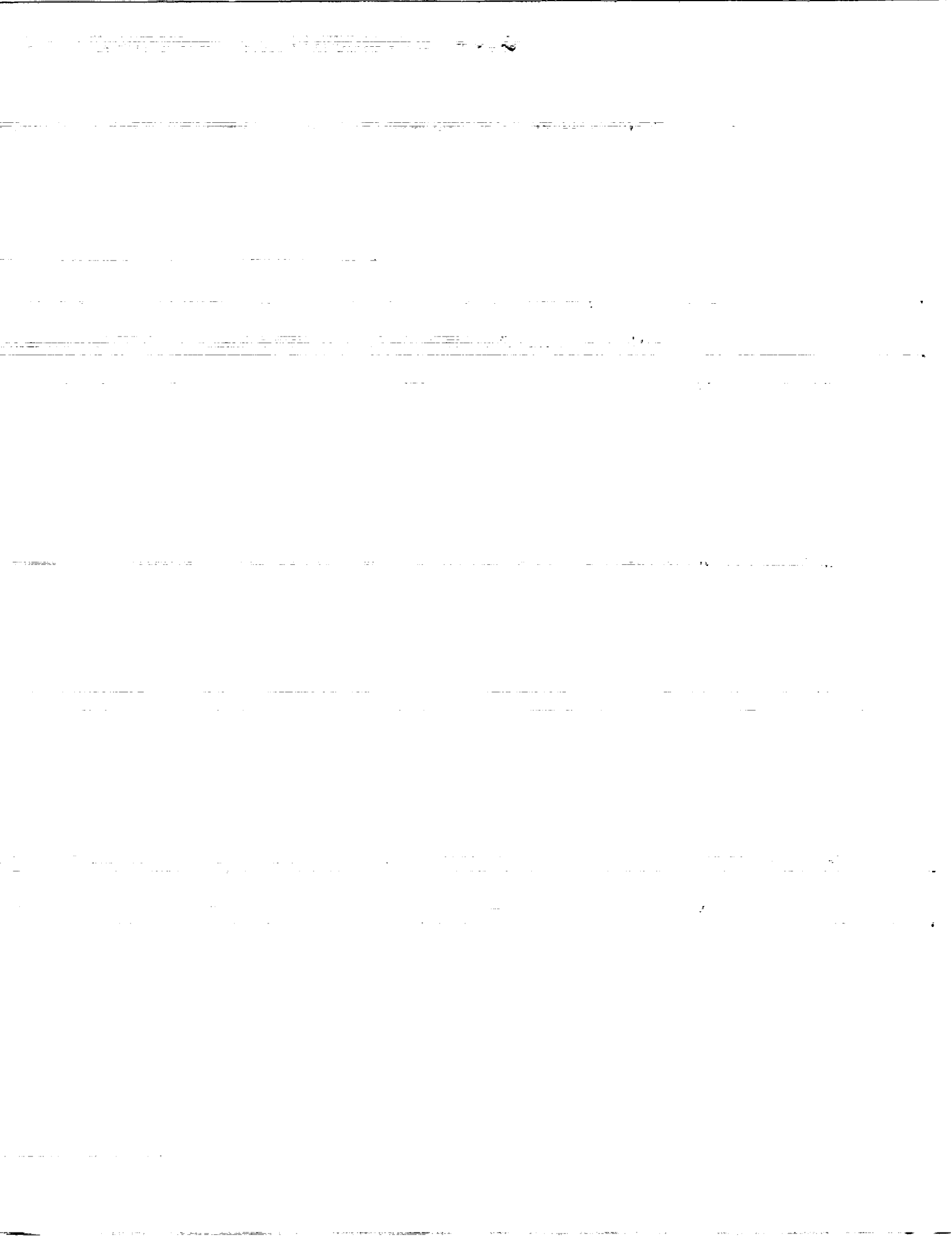**NASA**

IMPLEMENTATION OF A MODEL BASED FAULT DETECTION AND DIAGNOSIS TECHNIQUE FOR ACTUATION FAULTS OF THE SPACE SHUTTLE MAIN ENGINE

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ABSTRACT

In a previous study, Guo, Merrill and Duyar, 1990, reported a conceptual development of a fault detection and diagnosis system for actuation faults of the space shuttle main engine. This study, which is a continuation of the previous work, implements the developed fault detection and diagnosis scheme for the real time actuation fault diagnosis of the space shuttle main engine. The scheme will be used as an integral part of an intelligent control system demonstration experiment at NASA Lewis. The diagnosis system 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 for improved control systems with enhanced performance and 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 (Merrill and Lorenzo, 1988) with fault detection, diagnostics and accommodation capabilities. This paper focuses on the development of a model based fault detection and diagnosis (FDD) system which 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 (Massoumnia, 1986, Wunnenberg and Frank, 1987, Clark, 1978, Montgomery and Caglayan, 1974, Willsky, 1976, Beard, 1971, Jones, 1973, Wilbers and Speyer, 1989, Ge and Fang, 1988, Chow and Wilsky, 1984, Patton et al, 1989, Potter and Sunman, 1977). 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 utilizes signals generated by a mathematical model of the system being considered. These signals are then compared with actual measurements obtained from the system. The comparison is done using the residual quantities which 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.

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 in order to accomplish fault isolation. A set of parity relations or a set of unknown input observers (Frank, 1990), each assigned to be sensitive to a different fault, can be used for this purpose.

All the fault detection schemes are either explicitly or implicitly 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 a more direct approach than the others. This approach has been used for fault detection in a d.c. motor and pipe system by Filbert and Metzger, 1982. In this approach fault decision logic can also employ the estimates of some physical parameters (Isermann, 1984, Walker and Baumgarten, 1991) such as efficiency, fuel consumption, etc., which can effectively be used in fault diagnosis logic.

It is believed that the success of a FDD scheme depends on the accurate and appropriate modelling of the faulty process. The model of the faulty process defines the effects associated with faults. If the faulty process is modelled to distinguish the faults, then the residuals carry meaningful information that can be used for diagnostics purposes. In this study, this is accomplished by incorporating the notion of fault parameters (Watanabe and Himmelblau, 1983) in the model of the faulty process. These fault parameters are estimated by using a real time multivariable parameter estimation algorithm (Duyar, Eldem, Merrill and Guo, 1990). It is assumed that no more than one type of fault in the categories of either actuation or 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 diagnostics purposes.

In a previous study, Guo, Merrill and Duyar, 1990, reported a conceptual development of an FDD system for actuation faults of the space shuttle main engine (SSME). This study, which is a continuation of the previous work, implements the developed FDD scheme for the real time actuation fault diagnosis of the SSME.

In this paper, the development of the nominal linear model of the SSME is first presented. Next, the model of the faulty process is presented. Then, the fault diagnosis scheme based on the estimation of fault parameters is discussed. Finally, the results obtained through the implementation of the FDD scheme for actuation faults of the SSME are presented. The fault detection and diagnosis technique used in this study was previously reported in papers (Duyar, Eldem and Saravanan, 1990, Guo, Merrill and Duyar, 1990, Duyar and Eldem, 1991). However, the results of the real time implementation are new and are presented in this paper.

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MODEL OF THE NORMAL PROCESS

It is assumed that the dynamics of the SSME can be modelled as a discrete time linear system described by the following state equations

$$x(n+1) = A\ x(n) + B\ u(n) \tag{1}$$

$$y(n) = C\ x(n) \tag{2}$$

where x, u and y are the kx1 state, the px1 input and the qx1 output vectors respectively and A, B, C are the nominal matrices of the system with appropriate dimensions. It is assumed that the system is in α-canonical form (Duyar, Eldem, Merrill and Guo, 1990) such that the following relations hold:

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

$$A = A_0 + K\ H\ C \tag{4}$$

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

$$(H\ C)_{ri}\ A_0^{\mu_i} = 0 \tag{6}$$

$$(H\ C)_{ri}\ A_0^l\ K_{cj} = 0 \quad for\ l \geq 0, \ \wedge \ l < \mu_i - \mu_j \tag{7}$$

Here K is a deadbeat gain and A_0 and H are lower left triangular matrices. A_0 is determined by the observability indices $\{\mu_i\}$. The observability index which is the maximum of μ_i's is denoted by μ. $(HC)_{ri}$ denotes the i'th row of HC while K_{cj} denotes the j'th column of K.

In the development of the model of the normal process the data is generated from the nonlinear simulation of the SSME (Rockwell, 1981). The simulation is implemented on an AD100 computer using the ADSIM simulation language. An off-line system identification technique developed by Eldem and Duyar, 1989, is used to obtain the linear model of the SSME covering the power level ranging from 70% to 100%. The inputs of the model are controller commands of the rotary motions of the valve actuators for the fuel prebumer oxidizer valve (FPV), the oxidizer prebumer oxidizer valve (OPV), the coolant control valve (CCV), and the oxidizer prebumer fuel valve (OPFV). The outputs of the linear model are the chamber inlet pressure, P_{ci}, and the mixture ratio, MR.

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Four uncorrelated, three-level pseudo random sequences are used as the input perturbation signals to excite the system. The amplitude of the input signals correspond to the maximum observed deviations of the respective inputs during a typical mission. The sequences have a clock time of 0.04 seconds and a length of 242.

The nominal parameters of the linear model are identified as:

$$A_0 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix}; \quad K = \begin{bmatrix} .0258 & .0279 \\ -.2669 & -.0162 \\ -.0572 & .0043 \\ .9988 & .0155 \\ 0 & .2670 \end{bmatrix};$$

(8)

$$B = \begin{bmatrix} -.1707 & .2003 & -.0101 & .0111 \\ .22 & .4159 & .0013 & .0088 \\ -.6656 & .6191 & -.0259 & .023 \\ -.0198 & .0475 & .0009 & -.0033 \\ -.2445 & .1339 & -.0205 & .0034 \end{bmatrix}; \quad H = I; \quad C = [\, 0 : I\,];$$

The validity of the estimated parameters of the system is checked by comparing the responses obtained from the identified system with the responses of the nonlinear simulation. Both a state variable filter and the model of the identified system is used for comparison purposes. The state variable filter utilizes the measurements of both the output and the input to estimate the next value of the output. The model of the identified system utilizes only the measurement of the input data to predict the output and the state variables. The comparison of these responses during the maximum structural dynamic loading (MAX-Q) portion of the main stage of operation for a typical mission of the SSME indicate good agreement as shown in figure 1.

MODEL OF THE FAULTY PROCESS

The model of the faulty process is developed by considering the cause and 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, bias and broken wire is modelled as

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

(9)

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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 modelled in a similar way as

$$u_a (n) = F_a \, u(n) + f_{a0} \tag{10}$$

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 remain the same while the system matrix A is affected. The new system matrix under faulty conditions becomes A_f, and can be described as:

$$A_f = A_0 + K_f \, H \, C \tag{11}$$

The parameters F_a, F_s, f_{a0}, f_{s0}, and K_f are referred to as fault parameters in this study. Using equations 9 - 11 in equations 1 and 2 the open loop dynamics of the faulty process can be modelled as:

$$x(n+1) = A_f \, x(n) + B \, F_a \, u(n) + B \, f_{a0} \tag{12}$$

$$y(n) = C \, x(n) \tag{13}$$

$$y_s = F_s \, y(n) + f_{s0} \tag{14}$$

DIAGNOSTIC MODEL

In this work fault parameters are used as the residual vectors which make the diagnostic model. Fault parameters can be used to isolate faulty components. They can also be used to determine the size of faults which 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 diagnosis purposes.

To obtain fault parameters three different models, each monitoring different faults in actuation, sensor, and component fault categories are used as the diagnostics model. It is assumed that no more than one fault will occur at any given time. With this assumption, the measured output of the faulty process can be rewritten for actuation faults as

$$y_s(n) = \sum_{i=1}^{\mu} CA_0^{i-1} Bf_{a0} + \sum_{i=1}^{\mu} CA_0^{i-1}[KH : BF_a] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} , \tag{15}$$

for sensor faults as

$$y_s(n) = f_{s0} + \sum_{i=1}^{\mu} F_s CA_0^{i-1} KHF_s^{-1} f_{s0} + \sum_{i=1}^{\mu} F_s CA_0^{i-1}[KHF_s^{-1} : B] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} , \tag{16}$$

and for component faults as

$$y_s(n) = \sum_{i=1}^{\mu} CA_0^{i-1}[K_f H : B] \begin{bmatrix} y_s(n-i) \\ u(n-i) \end{bmatrix} \tag{17}$$

The proposed diagnostic scheme compares the output of the faulty process with the output of the normal process to generate residuals. It uses a two step approach. The first step is composed of a group of hypothesis testing modules (HTM) in parallel processing to test each class of suspected faults. Each module is designed solely to process the input/output data under a specified hypothesis and generate the signature data for fault diagnostics purposes. The second step is the fault diagnosis module which checks all 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 figure 2. 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, C, and the input/output data to estimate the fault parameters, F_a and f_{a0}.

Upon 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

$$e_{ij}(n) = y_{si}(n) - \hat{y}_i(n/n-1, H_j) \tag{18}$$

$$SEE = \left(\sum_{i=1}^{n} e_{ij}^2 / \sum_{i=1}^{n} y_{si}^2\right)^{1/2} \tag{19}$$

Here subscript i and j refers to the i'th output and j'th class of faults. H_j is the hypothesis that the fault belongs to the j'th class of faults. The SEE is calculated at each step with the most recent estimate of the fault parameters and is used to accept or reject the hypothesis.

The fault diagnosis module examines all 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 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. Also a nonzero component of f_{so} shows a bias between the command input and the actual input to the system.

FAULT DETECTION AND DIAGNOSIS OF THE SSME: ACTUATION FAULTS

The FDD system based on fault parameter estimation is applied to the diagnosis of actuation and sensor faults on the space shuttle main engine. SSME dynamic responses to a stuck FPV fault is simulated using the nonlinear simulation with the closed loop control system active. In this case the valve stops responding to the input command. The magnitude of the bias, f_{ao1}, depends on the valve stuck position and the desired position of the operating condition.

Figure 3 shows the faulty output and the estimate of the expected output corresponding to a stuck FPV at 3.8 seconds. Figure 4 shows the output estimate error. The estimates of both the multiplicative and bias fault parameters are shown in figures 5 and 6. As illustrated in these results, both the fault isolation and the magnitude estimation is accomplished with this approach.

CONCLUSION

A fault detection and diagnosis system based on fault parameter estimation is implemented for the real time diagnosis of the SSME actuation faults. It is shown that the real time identification can effectively be used 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. The developed FDD system has the added advantage that in the case of actuation and sensor faults, a priori knowledge about fault signatures are not needed.

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(a) Mixture ratio, mr.

(b) Chamber inlet pressure, pcie.
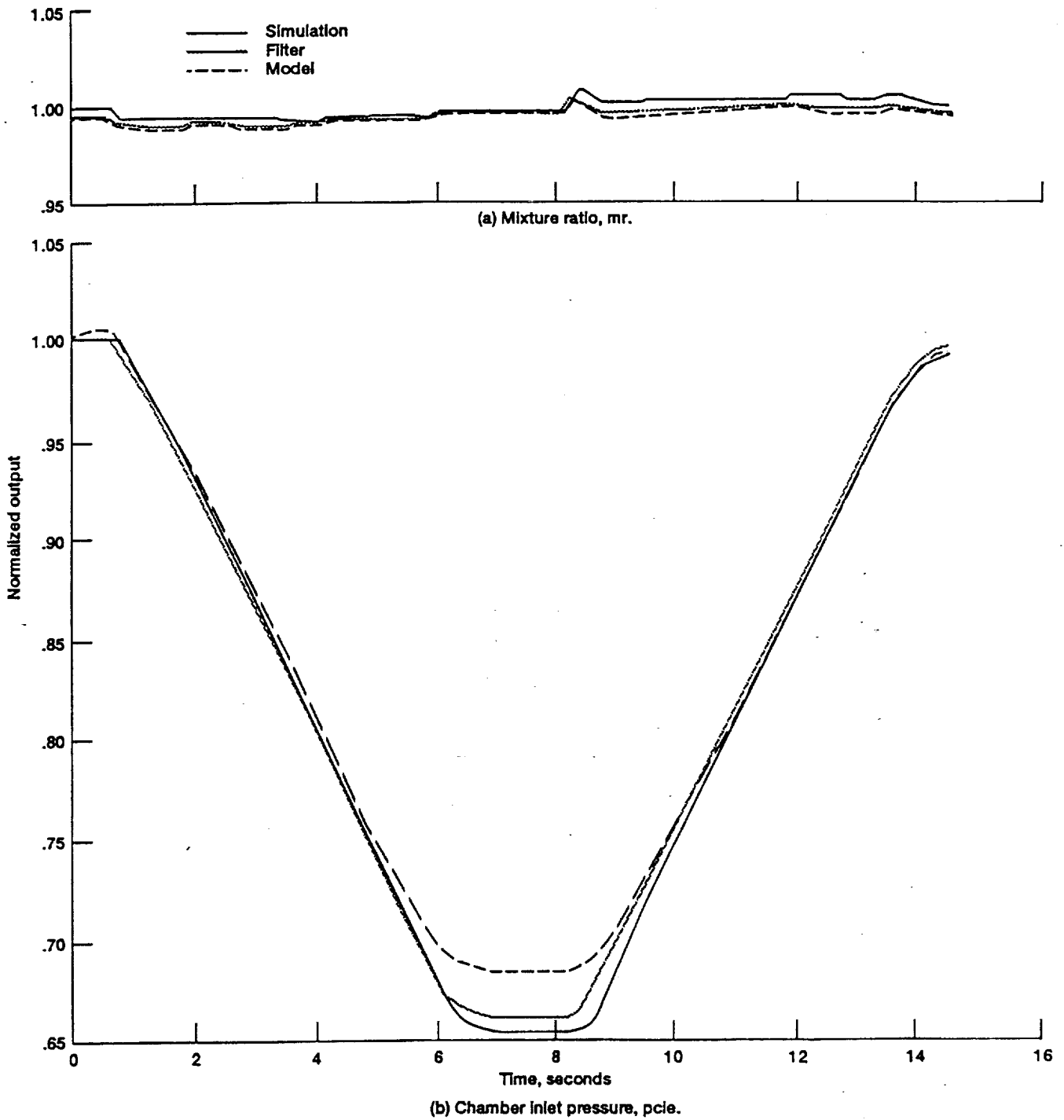
Figure 1.—Comparison of the response of the nonlinear simulation with the identified system.
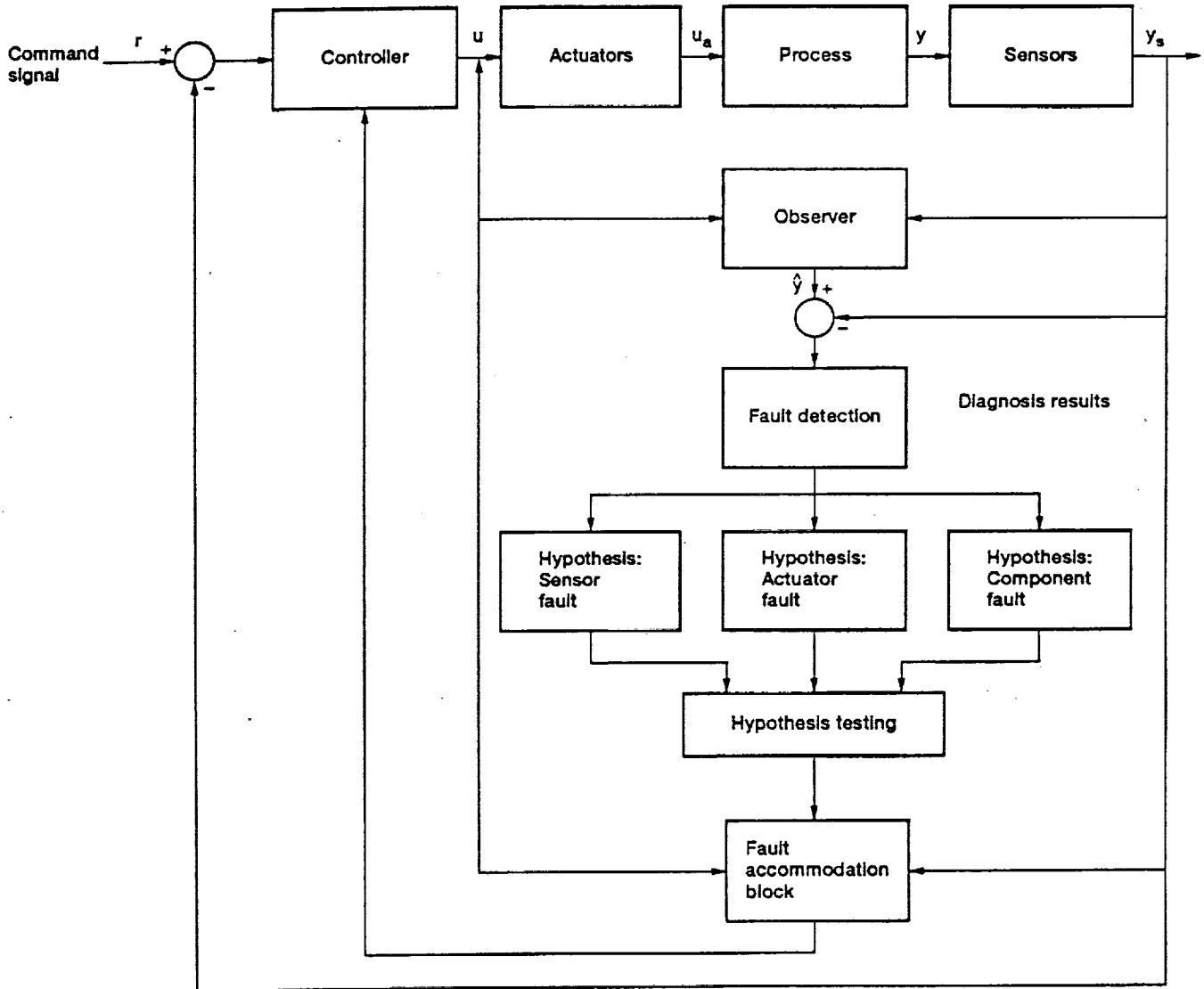
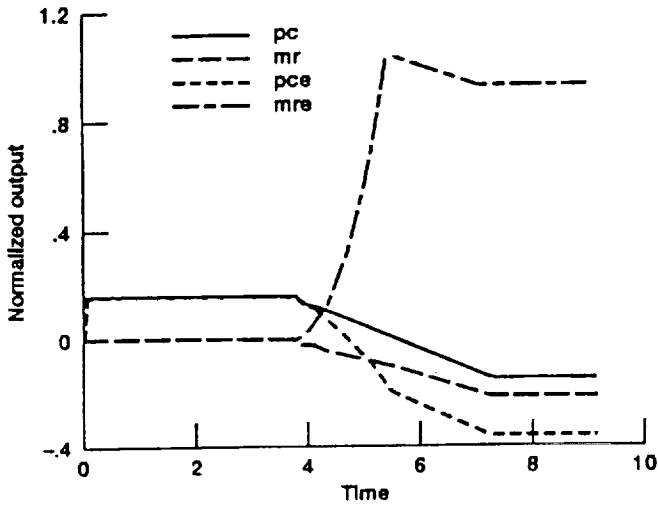Figure 2.—Model based fault detection and diagnosis scheme.

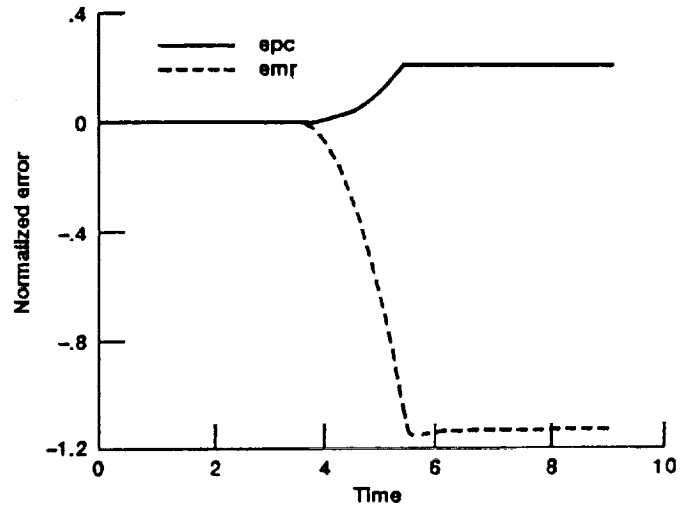Figure 3.—Faulty output and the estimate of the normal output (FPV stuck).

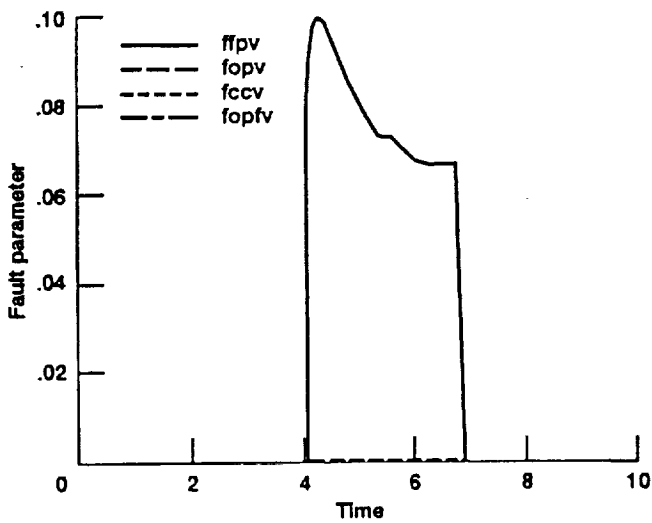Figure 4.—Output estimate error (FPV stuck).

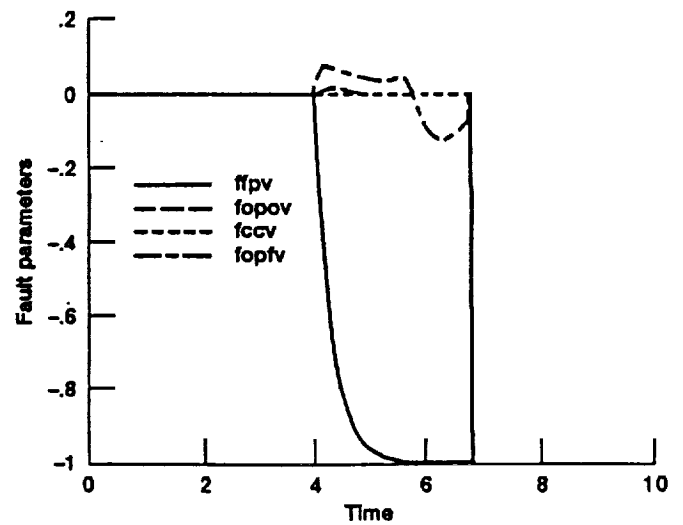Figure 5.—Bias fault parameters, f_{a0} (FPV stuck).

Figure 6.—Multiplicative fault parameters, F_a (FPV stuck).

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