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ABSTRACT

This paper presents an application of a fault detection and diagnosis scheme for the sensor faults of a helicopter engine. The scheme utilizes a model-based approach with real time identification and hypothesis testing which can provide early detection, isolation, and diagnosis of failures. It is an integral part of a proposed intelligent control system with health monitoring capabilities. The intelligent control system will allow for accommodation of faults, reduce maintenance cost, and increase system availability.

The scheme compares the measured outputs of the engine with the expected outputs of an engine whose sensor suite is functioning normally. If the differences between the real and expected outputs exceed threshold values, a fault is detected. The isolation of sensor failures is accomplished through a fault parameter isolation technique where parameters which model the faulty process are calculated on-line with a real-time multivariable parameter estimation algorithm. The fault parameters and their patterns can then be analyzed for diagnostic and accommodation purposes.

The scheme is applied to the detection and diagnosis of sensor faults of a T700 turboshaft engine. Sensor failures are induced in a T700 nonlinear performance simulation and data obtained are used with the scheme to detect, isolate, and estimate the magnitude of the faults.

INTRODUCTION

On-line fault detection and diagnosis is an area with great potential for high payoff, especially in the battlefield environment. The ability to detect and isolate a fault as it happens allows a decision to be made immediately about the viability of the system and the likelihood of completing the mission. In a situation where the unavailability of a system may have much direr consequences than merely the loss of some information or capability, every possible piece of data helps in gaining the advantage.

Sensor malfunctions are particularly pernicious because they might cause a mission to be terminated when all systems are actually functioning properly. Prime examples of this come from the Space Shuttle where numerous sensor failures over the years have caused subsystem shutdowns and aborted launches at great expense as well as posing potential danger to the astronauts.

It is well known that the variables in complex systems are often correlated and that this information can be used to detect and isolate incorrect sensor readings. This technique allows sensor failures to be isolated, and it allows lost or incorrect values to be recovered using the remaining valid measurements (DeLaat and Merrill 1984, Guo and Nurre 1991).

A proposed intelligent control system contains the sensor fault detection, isolation, and accommodation scheme coordinated with complementary schemes for the actuators and components (Figure 1). If the differences between the estimated and sensed system outputs exceed some threshold values, the fault detection logic will initiate a parameter estimation algorithm which determines the type and magnitude of the failure. This is achieved through the use of fault parameters, variables defined to convert the model from that of the fully functioning system to that of an impaired one as their values move off nominal. Once the fault is isolated, the control system will accommodate it if possible (Litt 1990).

The test bed for this research is the T700 turboshaft engine, which is used in pairs in the army's Blackhawk and Apache helicopters. It is a 1600 horsepower-class modular two-spool engine consisting of a gas generator and a free power turbine (Figure 2). In the simplified model used here there is one input: fuel flow, W_f. There are four measured output variables: gas generator speed, N_g, interturbine gas temperature, T_{45}, interturbine gas pressure, P_{45}, and power turbine torque output, Q_{PT}. Should any of the sensors fail, the engine would appear to be malfunctioning and, if the faulty measurement were fed back through the control system, the engine would operate off the design point.

SENSOR FAULT DETECTION AND ISOLATION

The Sensor Fault Detection and Isolation scheme is developed using a fault model. A simplified linear perturbation model has been developed which switches between several point models for full envelope coverage (Duyar, Gu, and Litt 1992). The simplified model at an operating point is of the standard form

$$\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y(k) &= Cx(k) \end{aligned} \tag{1}$$

The variables in these point models are all normalized with their zero values corresponding to the operating point. We assume that the (A, B, C) realization of the system is in α-canonical form (Eldem and Duyar 1993). Lack of space precludes a thorough presentation here, but, very briefly,

$$\begin{aligned} C &= [0 \vdots H^{-1}] \\ A &= A_0 + KHC \end{aligned} \tag{2}$$

where K is a deadbeat observer gain (Kwakernaak and Sivan 1972), and A_0 is nilpotent, i.e. $A_0^{\mu}=0$ for some $\mu > 0$. There are several other requirements which are listed in the references.

The model is created by substituting the equation for A from (2) into (1), evolving (1) through time from 0 to k, and rearranging, thus

$$y(k) = CA_0^k x(0) + \sum_{i=1}^{k} CA_0^{i-1}[KH \; \vdots \; B]\begin{bmatrix} y(k-i) \\ u(k-i) \end{bmatrix} \tag{3}$$

The fact that A_0 is nilpotent is important because it allows (3) to be simplified to

$$y(k) = \sum_{i=1}^{\mu} CA_0^{i-1}[KH \; \vdots \; B]\begin{bmatrix} y(k-i) \\ u(k-i) \end{bmatrix} \tag{4}$$

when $k \geq \mu$. Once in this form, the unknown parameters can be identified using a least squares technique. This way the initial model is developed.

The sensor fault model is built on top of (1) in the form

$$\left.\begin{aligned} x(k+1) &= Ax(k) + Bu(k) \\ y_s(k) &= F_s Cx(k) + f_{s0} \end{aligned}\right\} \tag{5}$$

where $y_s(k)$ is the set of normalized sensor readings at time k. In the case where all sensors are fully functional, F_s is the identity matrix and f_{s0} is the zero vector, thus reducing (5) to (1). The diagonal matrix F_s accounts for changes in sensor gain while a non-zero f_{s0} represents bias errors. Substituting and rearranging as before

$$y_s(k) = F_s CA_0^k x(0) - \sum_{i=1}^{k} F_s CA_0^{i-1} KHF_s^{-1} f_{s0} + \sum_{i=1}^{k} F_s CA_0^{i-1}\left[KHF_s^{-1} \; \vdots \; B\right]\begin{bmatrix} y_s(k-i) \\ u(k-i) \end{bmatrix} + f_{s0} \tag{6}$$

Using the nilpotency of A_0 to simplify (6) we get

$$y_s(k) = f_{s0} - \sum_{i=1}^{\mu} F_s CA_0^{i-1} KHF_s^{-1} f_{s0} + \sum_{i=1}^{\mu} F_s CA_0^{i-1}\left[KHF_s^{-1} \; \vdots \; B\right]\begin{bmatrix} y_s(k-i) \\ u(k-i) \end{bmatrix} \tag{7}$$

when $k \geq \mu$. Once a failure is detected, an on-line estimation technique calculates values for the fault parameters, f_{s0} and F_s. As long as F_s is nonsingular, the value of the parameters along with some simple logic provides an assessment of the type and magnitude of the error. In the case where F_s

becomes singular, implying that the gain of a sensor became zero, a logical check can be used to determine which sensor has failed.

SIMULATION SETUP

A full nonlinear simulation of the T700 turboshaft engine subjected to a load (Ballin 1988) is used in the simulation test bed to represent the engine in question (Kurtkaya 1992). The fault detection and hypothesis testing modules run in parallel with the nonlinear simulation as shown in Figure 1. The time step used is 60 ms. All programs are written in FORTRAN and are embedded in Model-C, a control analysis and simulation package.

Past controller outputs together with the sensor readings are fed through the fault detection model described by (7) and the resulting estimate of the set of sensed variables is compared to those received from the simulation at the current time step. The differences, or residuals, are checked against threshold values which, when exceeded, activate the fault detection scheme.

Initially, the system is assumed to be functioning normally, thus the value for F_s is identity and f_{s0} is the zero vector implying no multiplicative sensor gain error and no sensor bias, respectively. The fault detection scheme contains models appropriate for each type of failure, i.e. actuator, component, and sensor. Just as the sensor fault parameters are associated with the C matrix as shown in (5), the actuator fault parameters are associated with the B matrix of (1) and the component fault parameters are associated with the A matrix (Duyar *et al.* 1991). Fault models similar to (7) are derived for the actuator and component failures. When the residual exceeds the activation threshold, an on-line parameter estimation scheme is initiated which calculates the fault parameters, e.g. F_s and f_{s0} in the sensor case.

It is important to run the parameter estimation scheme using data from the impaired system so that the results are not skewed by pre-failure information. Therefore, the parameter estimation module begins collecting data only after the activation threshold is exceeded. A recursive least squares technique with a forgetting factor of 0.98 is used to compute the value of the fault parameters. The models of the actuator, component, and sensor failures are developed in parallel and the three sets of fault parameters are computed simultaneously.

At each time step the resulting fault parameters are passed to the hypothesis testing module, actually a battery of simple logical checks, which determines what fault occurred using the identified parameters. The logic assumes that only one failure occurs at a time. The result is checked by confirming that the selected model using the identified fault parameters produces a smaller sum of the squared errors (residuals) over a fixed time than do the other estimated models using their fault parameters. In this case a moving window of five data points was used for summing the squares of the residuals before comparing the models, resulting in a delay of at least 0.3 seconds (5 samples $\times$ 0.060 seconds/sample) before the error is isolated and its magnitude estimated. This data length is selected to produce reliable results in relatively few samples.

RESULTS

Testing was performed at the 96% power level. Results for two types of faults are presented: gas generator speed sensor bias, and multiplicative gain error of the gas generator speed sensor.

For the first case, a sensor bias of 1.8% of nominal was introduced to the nonlinear simulation's gas generator speed sensor's output at the start of the run. As soon as the bias was added, the misinformation, which was fed back for control purposes, disrupted all of the other output variables and caused the engine to operate off of the design point. The fault parameters were first computed after the impaired system was sampled twice, i.e. 0.12 seconds after the threshold was exceeded. Figure 3 shows how the fault parameters corresponding to the multiplicative sensor gain converged immediately to their correct values of 1.0 as determined through recursive least squares, indicating no sensor gain failure. Figure 4, on the other hand, shows that the bias on the N_g sensor converged to approximately 0.018 while the other bias values stayed within the normal expected variation around zero. Figure 5 shows the results of the hypothesis testing using the fault parameters determined for each type of failure. The sums of the squared errors over a five sample moving window for each type of failure were computed beginning with the sample after the fault parameters had been first estimated, i.e. 0.18 seconds after the threshold was exceeded. It can be seen that the sensor fault parameters provided a much better match to the simulated failure than either the actuator or component faults parameters did.

For the second case, the original unity gain of the N_g sensor was scaled by a multiplicative gain of 0.1 at the start of the run. Figure 6 shows the multiplicative gain fault parameters as determined by the recursive least squares technique from past data. It took significantly longer to converge than the previous example did but eventually the parameter corresponding to the N_g sensor's gain converged to about 0.1 while the other three hovered near 1.0. Figure 7 displays the estimated values of the bias parameters, which, after some initial hunting, converged to approximately 0.0.

The maximum time it takes to achieve a good identification depends upon how quickly the fault parameters converge, which can vary from almost instantaneously to several seconds as demonstrated by the examples. In general, however, with the combination of logic used to examine the fault parameters and the windowed residual information, it is usually possible to identify a failure and estimate its magnitude in a short period of time.

CONCLUSIONS

A scheme to detect, isolate, identify and estimate the type and magnitude of sensor faults in a T700 turboshaft engine has been developed and demonstrated. It is an integral part of a proposed Intelligent Control System.

The injection of a fault caused the residual to exceed the threshold value and trigger the identification scheme. Once running, the scheme produced accurate results, usually in under a second. The identified fault parameters can be used in the state equation to cancel the bias or eliminate the incorrect gain, thereby accommodating the sensor faults and allowing the closed loop system to run as if unimpaired.

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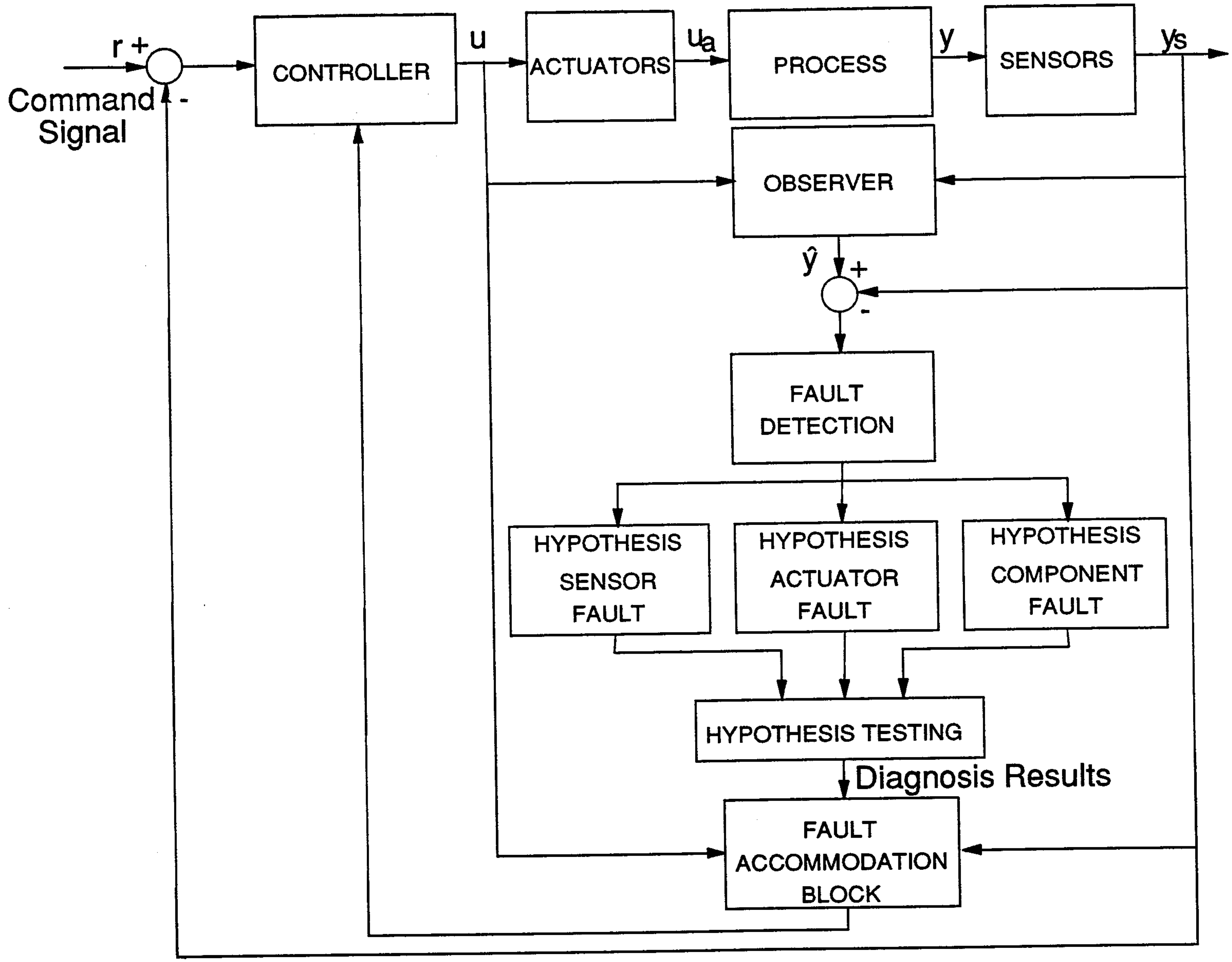

Figure 1. Model Based Fault Detection and Diagnosis Scheme

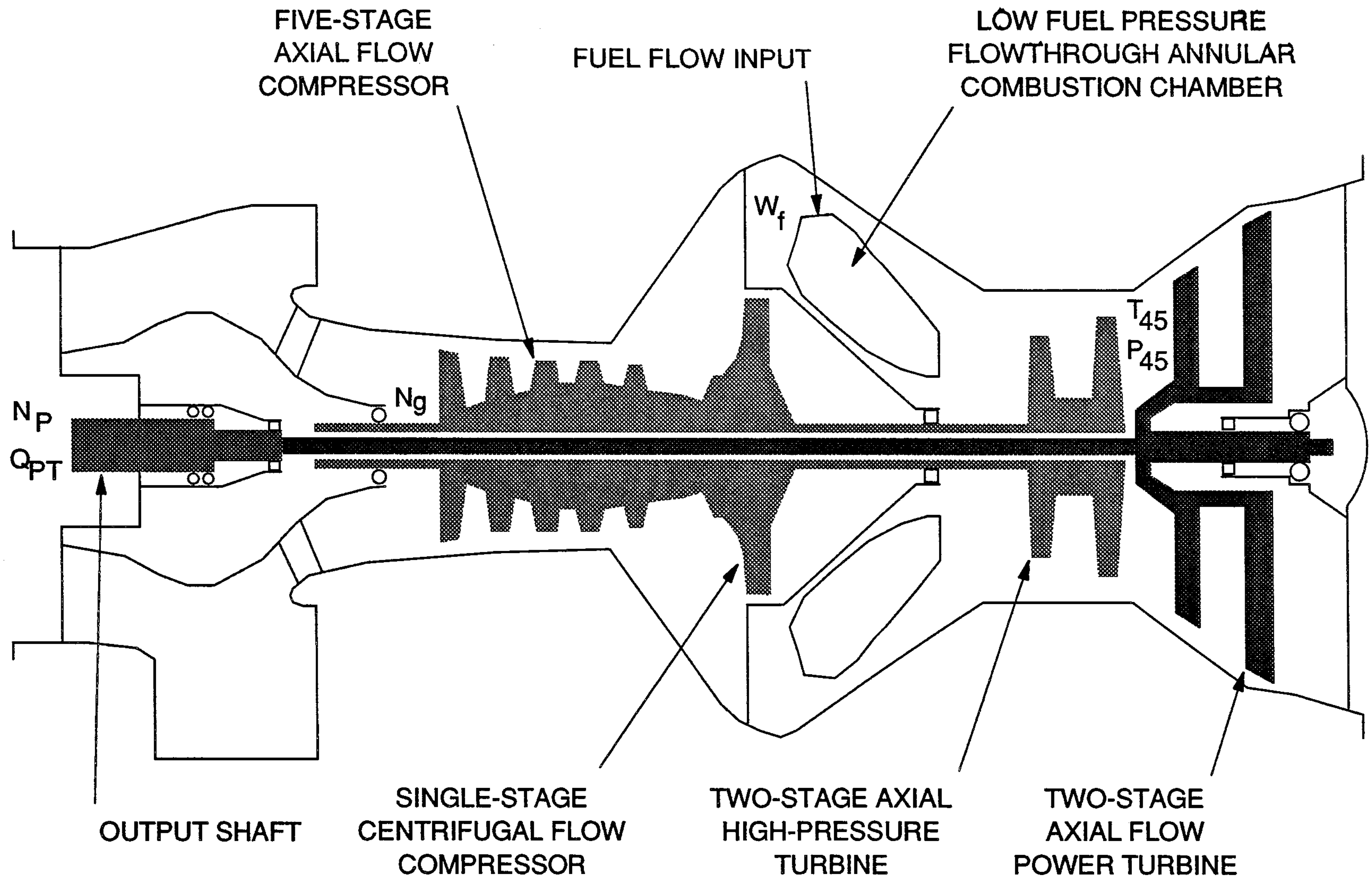

Figure 2. Cross section of a T700 turboshaft engine

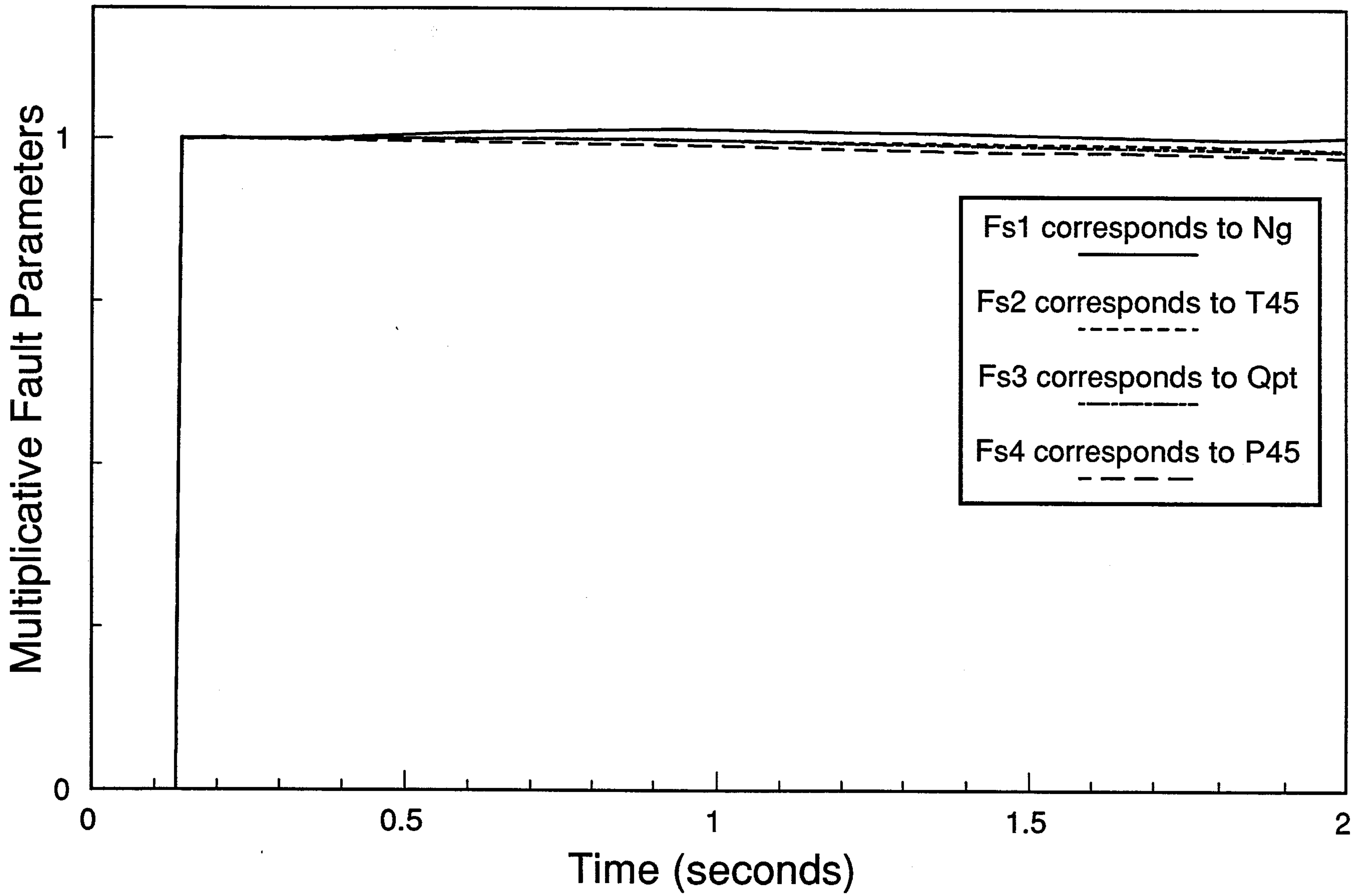

Figure 3. Estimates corresponding to a 1.8% bias in the Ng sensor output

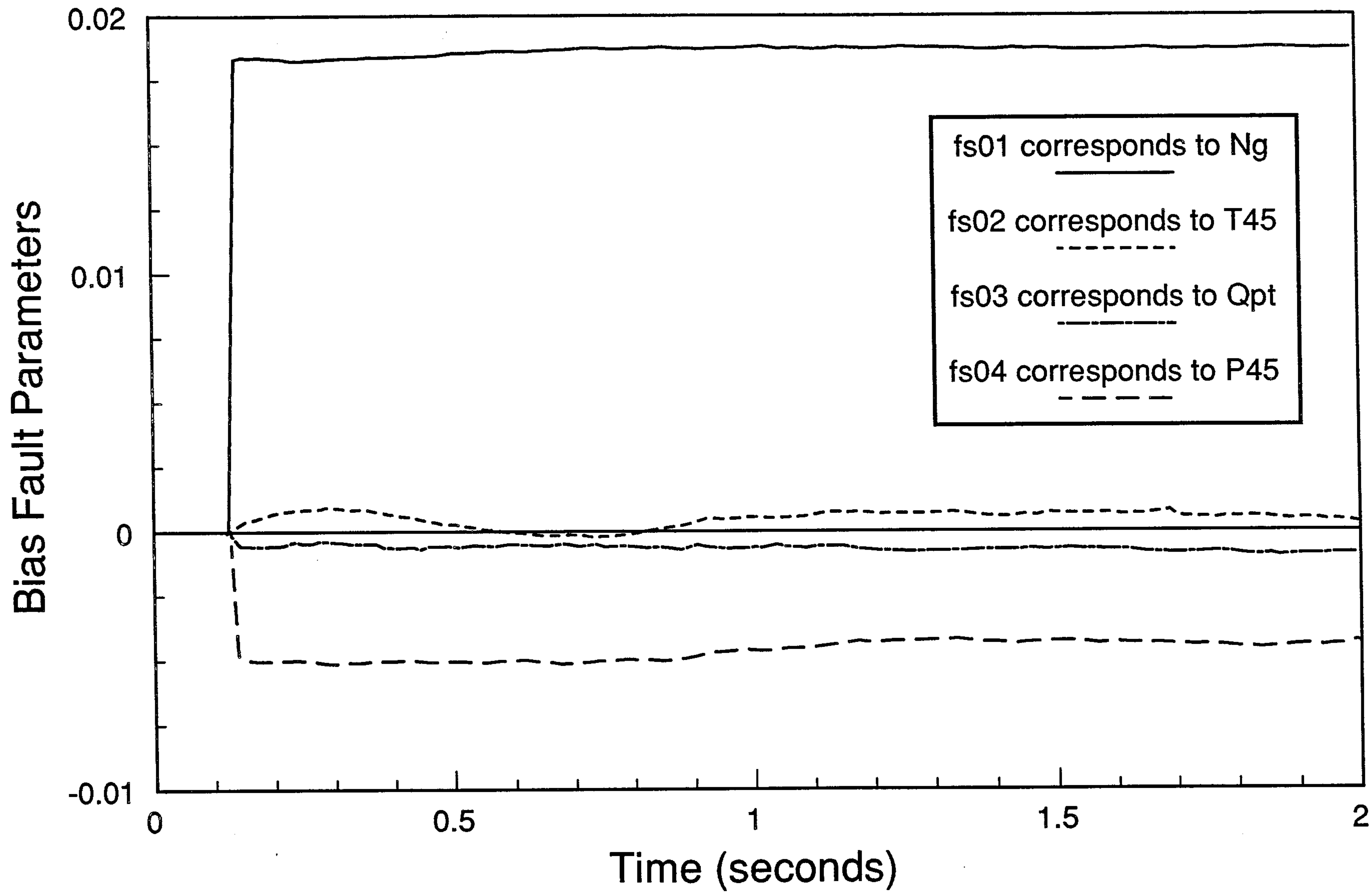

Figure 4. Estimates corresponding to a 1.8% bias in the Ng sensor output

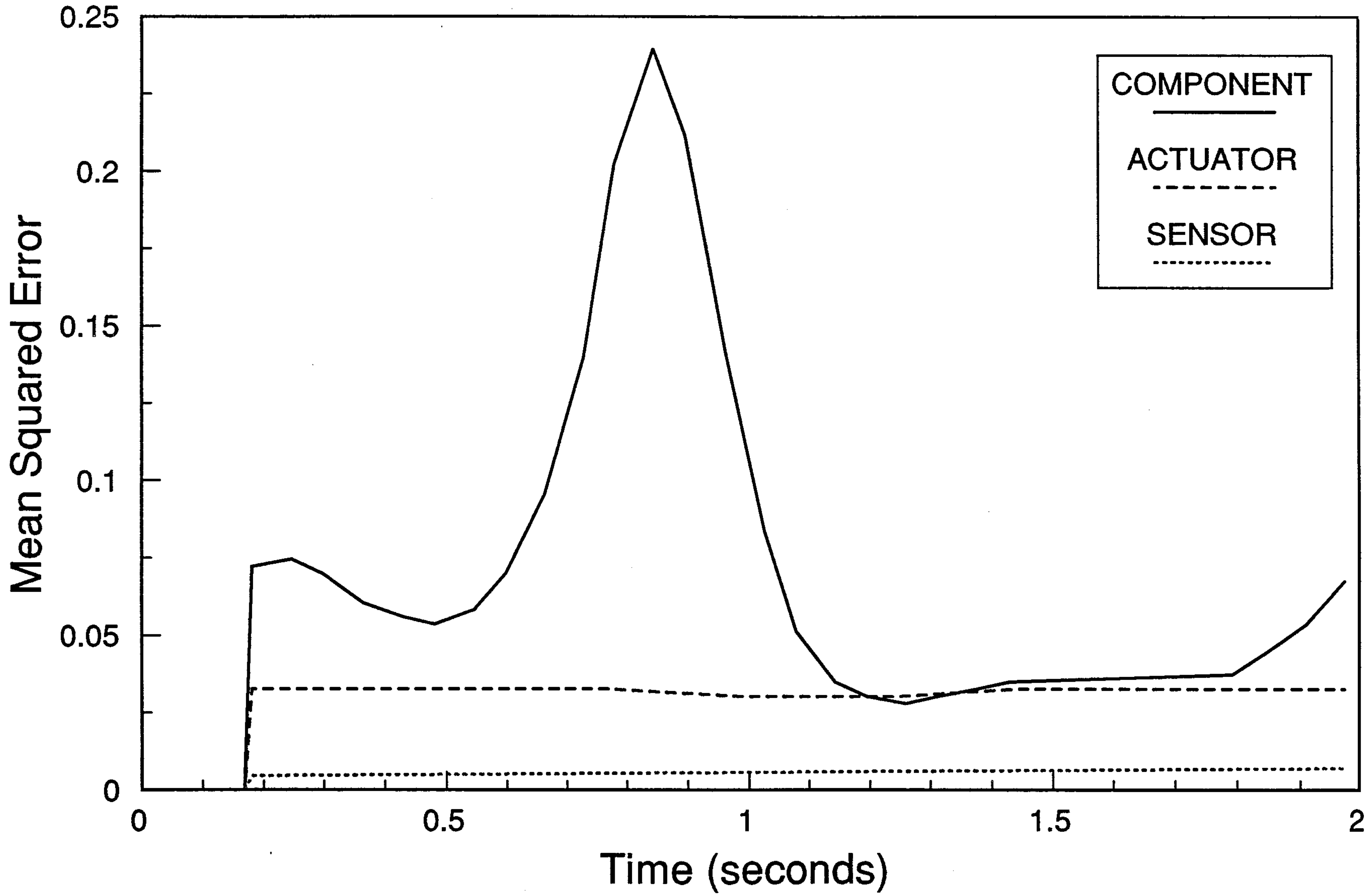

Figure 5. Hypothesis testing results for a 1.8% bias in the Ng sensor gain

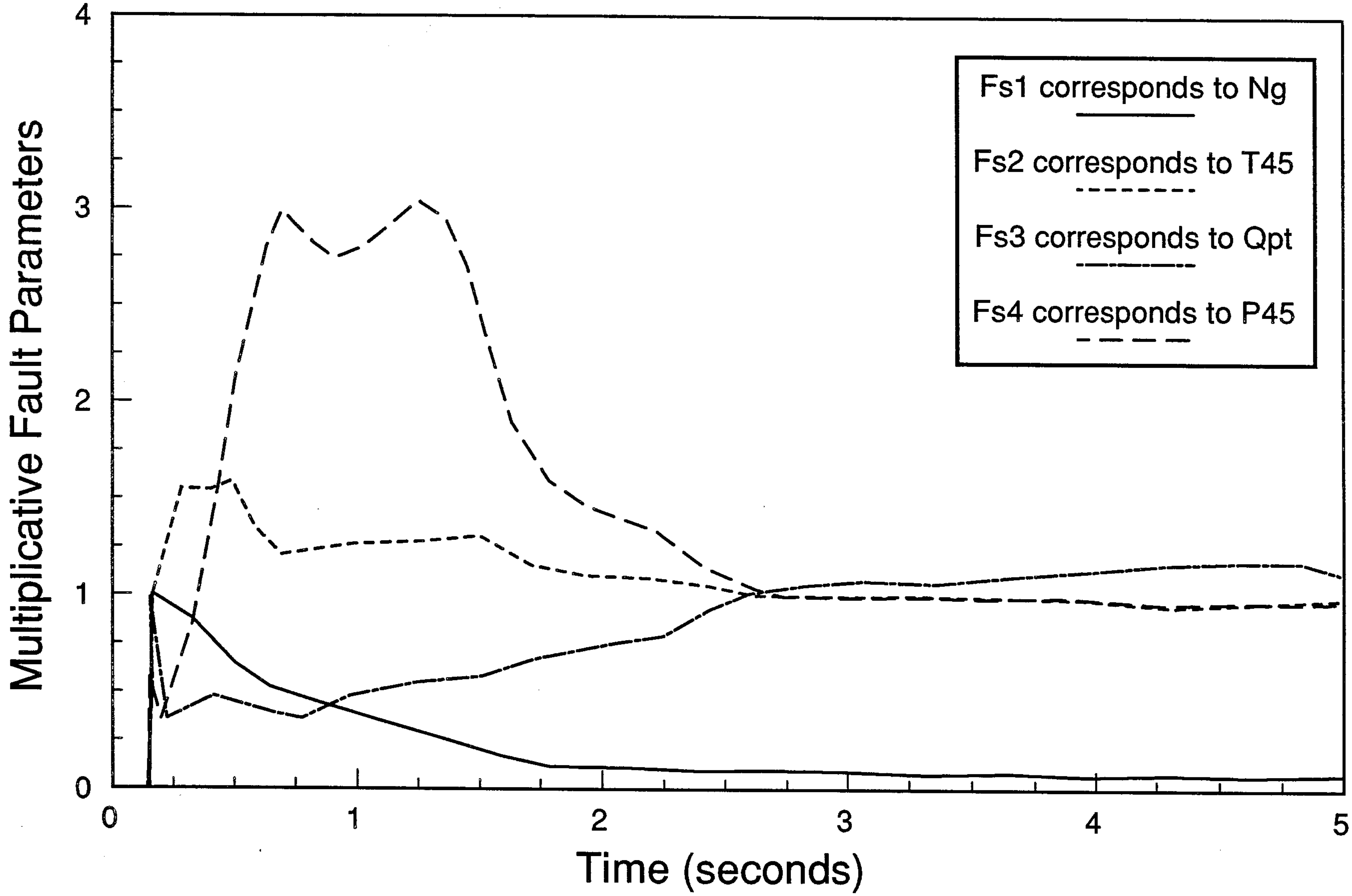

Figure 6. Estimates corresponding to a 0.1 multiplicative gain in the Ng sensor

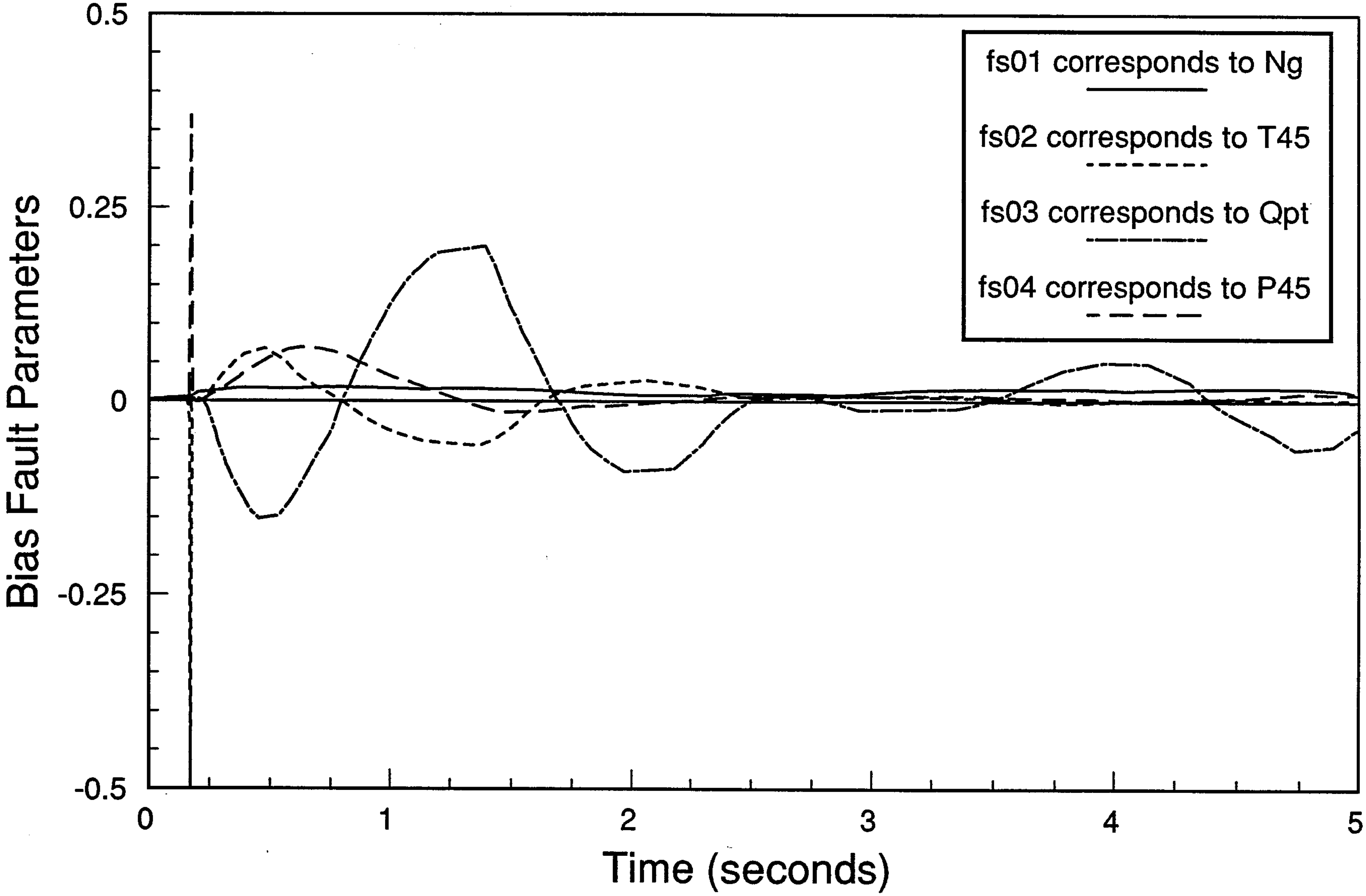

Figure 7. Estimates corresponding to a 0.1 multiplicative gain in the Ng sensor

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13. ABSTRACT ***(Maximum 200 words)***

This paper presents an application of a fault detection and diagnosis scheme for the sensor faults of a helicopter engine. The scheme utilizes a model-based approach with real time identification and hypothesis testing which can provide early detection, isolation, and diagnosis of failures. It is an integral part of a proposed intelligent control system with health monitoring capabilities. The intelligent control system will allow for accommodation of faults, reduce maintenance cost, and increase system availability. The scheme compares the measured outputs of the engine with the expected outputs of an engine whose sensor suite is functioning normally. If the differences between the real and expected outputs exceed threshold values, a fault is detected. The isolation of sensor failures is accomplished through a fault parameter isolation technique where parameters which model the faulty process are calculated on-line with a real-time multivariable parameter estimation algorithm. The fault parameters and their patterns can then be analyzed for diagnostic and accommodation purposes. The scheme is applied to the detection and diagnosis of sensor faults of a T700 turboshaft engine. Sensor failures are induced in a T700 nonlinear performance simulation and data obtained are used with the scheme to detect, isolate, and estimate the magnitude of the faults.

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