NASA Technical Memorandum 105792

Real-Time Diagnostics for a Reusable Rocket Engine

T.H. Guo and W. Merrill
Lewis Research Center
Cleveland, Ohio

and

A. Duyar
Florida Atlantic University
Boca Raton, Florida

August 1992

NASA

Real-Time Diagnostics for a Reusable Rocket Engine

T. H. Guo and W. Merrill
Lewis Research Center
National Aeronautics and Space Administration
Cleveland, OH 44135

A. Duyar
Department of Mechanical Engineering
Florida Atlantic University
Boca Raton, FL 33431

ABSTRACT

A hierarchical, decentralized diagnostic system is proposed for the Real-Time Diagnostic System component of the Intelligent Control System (ICS) for reusable rocket engines. The proposed diagnostic system has three layers of information processing: condition monitoring, fault mode detection, and expert system diagnosis. The condition monitoring layer is the first level of signal processing. Here, important features of the sensor data are extracted. These processed data are then used by the higher level fault mode detection layer to do preliminary diagnosis on potential faults at the component level. Because of the closely coupled nature of the rocket engine propulsion system components, it is expected that a given engine condition may trigger more than one fault mode detector. Expert knowledge is needed to resolve the conflicting reports from the various failure mode detectors. This is the function of the diagnostic expert layer. Here, the heuristic nature of this decision process makes it desirable to use an expert system approach.

Implementation of the real-time diagnostic system described above requires a wide spectrum of information processing capability. Generally, in the condition monitoring layer, fast data processing is often needed for feature extraction and signal conditioning. This is usually followed by some detection logic to determine the selected faults on the component level. Three different techniques are used to attack different fault detection problems in NASA Lewis Research Center ICS testbed simulation. The first technique employed is the neural network application for real-time sensor validation which includes failure detection, isolation and accommodation. The second approach demonstrated is the model-based fault diagnosis system using on-line parameter identification techniques where input data are processed to estimate important parameters for the predefined fault detection algorithms. Besides these model based diagnostic schemes, there are still many failure modes which need to be diagnosed by the heuristic expert knowledge. The heuristic expert knowledge is implemented using a real time expert system tool called $G2^{TM}$ by Gensym Corp. Finally, the distributed diagnostic system requires another level of intelligence to oversee the fault mode reports generated by component fault detectors. The decision making at this level can be best done using a rule-based expert system. This level of expert knowledge is also implemented using $G2^{TM}$.

Introduction

In the effort of designing the real-time diagnostic system for the Intelligent Control System (ICS) of the Reusable Rocket Engine [1], a hierarchical, decentralized diagnostic system was proposed in [2] as the framework for the diagnostic subsystem for ICS research project. Figure 1 shows the proposed diagnostic system which has three layers of information processing. These are condition monitoring, fault mode detection, and expert system diagnosis. The condition monitoring layer is responsible for signal processing, signal conditioning, feature extractions, and pattern recognitions. Here, important features to be used in the diagnostic system are extracted from the incoming data stream and processed. The processed data are then used by the higher level fault mode detection layer to do preliminary diagnosis on potential faults at the component level. Because of the closely coupled nature of the rocket engine propulsion system components, it is expected that a given engine condition may trigger more than one fault mode detector. For example, a surge in the pump outlet temperature measurement on the low pressure

fuel turbopump (LPFTP) may trigger an alarm on the sensor failure detector as well as the LPFTP seal leakage fault mode detector. Expert knowledge is needed to resolve the conflicting reports from the various failure mode detectors. This is the function of the diagnostic expert layer. Here, the heuristic nature of this decision process makes it desirable to use an expert system approach.

Implementation of the real-time diagnostic system described above requires a wide spectrum of information processing capability. Figure 2 shows the current setup for the implementation of the distributed diagnostic system in the NASA-Lewis ICS group. Generally, in the condition monitoring layer, fast data processing is often needed for feature extraction and signal conditioning. This is usually followed by some detection logic to determine the selected faults on the component level. Three different techniques are used to attack different fault detection problems in NASA Lewis Research Center ICS testbed simulation [3]. The first technique is the neural network application for real-time sensor validation which includes failure detection, isolation and accommodation. The results of this neural network approach has been reported in details in [4,5]. The second approach demonstrated is the model-based fault diagnosis system using on-line parameter identification techniques where input data is processed to estimate important parameters for the predefined fault detection logic [6,7]. Besides these model based diagnostic schemes, there are still many failure modes which need to be diagnosed by the heuristic expert knowledge. The heuristic expert knowledge is implemented using a real time expert system tool called G2™ [3]. Finally, the distributed diagnostic system requires another level of intelligence to oversee the fault mode reports generated by component fault detectors. The decision making at this level can be best done using a rule-based expert system.

Neural Network Based Sensor Validation

In order to improve the operational reliability of the reusable rocket engine, it is necessary to validate the measured sensor data, isolate any failed sensor and recover the failed sensor measurements. There has been an extended effort in applying analytical redundancy to the sensor failure detection and isolation in the jet engine failure diagnosis problem [8]. In general, this approach utilizes the engine model and the Kalman Filter to detect the isolate sensor failures. Similarly, in the approach of a neural network based sensor validation, an autoassociative neural network is first trained to learn the relationships within the redundant sensor group and then used to estimate the sensor output as a group which is insensitive to a few corrupt sensors.

More precisely, the goals of the neural network based sensor validation are to identify the failed sensor where its output is inconsistent with other measurements, and to generate an estimated value for the failed sensor. In order to apply the neural networks for sensor validation, the sensor measurements are first studied and a group of analytically redundant sensors are selected. In the study of SSME propulsion system, a group of flight sensors on the fuel system has been found to be strongly correlated. Figure 3 shows the inter-dependency of the sensor group. A special class of the autoassociative neural network is then trained to generate on-line estimates for all sensors whether normal or corrupt. The autoassociative neural network used here is a special selected type where first half of the neural network is to compress the data into a minimum order of representation and the second half the neural network is to recovery the encoded information. Figure 4 shows the structure of the autoassociative neural network for sensor validation. By doing the information compression and recovery, the neural network will be relatively insensitive to the errors generated by a single sensor. By comparing the incoming measurements with corresponding estimates, a sensor failure can be identified if a sensor reading departs from its estimated value while other sensor readings stay close to their estimates. Failed sensor isolation is done by replacing the failed sensor input (to the neural network estimator) with its estimated value. The neural network then can be used to detect consecutive sensor failures. The sensor validation scheme has been tested on the simulated sensor output data of the SSME operation. Figure 5 shows the output of the sensor validation scheme for the the combustion chamber inlet pressure (P_c) during a series of sensor failures. P_c is key a control parameter and a loss of the measurement can be fatal in the SSME operation. In the simulation, the P_c sensor was simulated to have its sensor value falling at the rate of 300 psi per second. It is observed that the estimated value follows very closely in despite of the sensor failures. The figure also shows the estimation of the failed PC sensor is held closely to its actual value during other sensor failures. Figure 6 shows a similar result on the sensor failure validation of another control variable, the Low Pressure Fuel Pump discharge temperature, during the multiple sensor failures.

2

Model Based Fault Detection

Model based fault detection is the technique that utilizes the nominal operation model to detect any abnormal operating behavior that can be classified into a specified structure. In order to develop a baseline operational reference model, a piecewise linear model of the Space Shuttle Main Engine was first developed in [9]. The performance model of the SSME can be described as:

$$x(n+1) = A\ x(n) + B\ u(n) + \omega(n) \tag{1}$$
$$y(n) = C\ x(n) + \eta\ (n)$$

where x, u and y are the state, the input and the output vectors. ω and η are process error vector and sensor measurement error vector respectively. A, B, and C are the system matrices.

The SSME model uses the positions of the control valves as its inputs to predict the performance variables: Chamber Pressure and Mixture Ratio. In [9], a system identification algorithm is developed to determine these parameters from the measurements of the input and output data. The A, B, C matrices obtained for this model are used as baseline process parameters of the system. Any changes of these parameters observed through real time identification, above preselected threshold values are used to detect and diagnose the failures.

Fault modes are classified into three different classes: actuator faults, sensor failures, and system performance degradations. Each fault mode has a different structure in its representations. For example, an actuator failure can be modelled by the following equation:

$$u_{af}(n) = F_a\ u(n) + f_{ao} \tag{2}$$

where $u_{af}(n)$ and $u(n)$ are the actual actuator output due to actuator failure and the requested actuator input respectively, the matrix F_a is a diagonal matrix and f_{ao} is a constant vector, both with appropriate dimensions.

Different values of matrix F_a and vector f_{ao} represent different types of faults of a specific actuator. They serve as the signature of actuator faults. Table 1 is the list of the expected fault parameters for the common actuator faults. The actuator fault detection can then be done by a special designed module which does the real-time estimation of the values of matrix F_a and vector f_{ao} using the most current input/output information and the *a priori* information of system matrices A, B, and C. This module considers only the actuation faults which affect the performance model. The module is described as a hypothesis module in [9]. Similarly, the sensor failures and system performance degradations are represented by different structures. Different fault parameters are then used to describe different types of faults in their classes. Two more hypothesis modules, for sensor failure and system degradation respectively, are used in this model based detection algorithm. Also, measured are the residues of these hypothesis modules which are calculated by the differences between the current measurements and their predicted values. The residues are the indication of the fitness of these models which can be translated into the confidence of the hypotheses. For example, in the case of an actuator fault, not only the fault signatures F_a and f_{ao} are expected to have some specific values associative to the fault, but also the residues generated in this module to be relatively small comparing to other hypothesis modules. Figure 7 shows the basic structure of this distributed diagnostic scheme. In the demonstration system at NASA-LeRC only the actuator faults are studied in detail and their on-line estimation algorithm is implemented. The estimated values of fault parameters are used to identify the place and type of the failed actuator as well as to estimate its failed position which is essential for controller to make the accommodation actions. Figure 8 shows the estimated fault parameters before and after an actuator failure (OPOV stuck). The parameter $F_a(1,1)$ which drops to 0.0 is an indication of the valve is no longer following the command. The bias term $f_{ao}(1)$ is then used to calculate the stuck position. Figure 9 is the calculated residue vector of the hypothesis module which indicates the high confidence of the model after the transition period of the estimation.

3

Rule Based Fault Detection

Rule based fault detection is used for the diagnosis of those fault modes which require the heuristic expert knowledge. Because of real-time requirement of the Intelligent Control System the expert system software G2™ by GENSYM Corp. was select because of its capability in dealing with real-time data. A G2 implementation of the rule based diagnostic system for High Pressure Oxidizer Turbopump failure modes is described in [3]. Expert rules are also used to resolve the conflict reports from the sensor failure detection module, the model based fault detection module, and the component fault detection modules.

There are three types of knowledge to be built into a typical G2 expert system: object classification, simulation formulae, and inference rules. As a typical knowledge based system, all objects in the application are described in terms of classes and subclasses. Each class has its own specific attributes. For example, all types of seals belong to a super class called SEAL which has common properties like flow rate, seal clearance, etc. Under this general description of a seal there are different subclasses of seals such as STEP-SEAL, LABYRINTH-SEAL, and SLINGER-SEAL [10]. Each of these subclasses of SEAL will have its own attributes which are specific to the subclass. Table 2 shows the object class definition in the HPOTP seal system. They are the building blocks for HPOTP seal knowledge model. Instances under a class can be created to represent physical objects. For example, PRIMARY-SEAL is an instance of STEP-SEAL. The relationships between objects ar established through connections. The values of the attributes of an object are obtained through three mechanisms: sensor inputs, simulation formulae, and inference rules. If a sensor measurement is available for a particular variable in the G2 knowledge base, an external sensor input can be connected to that variable. This is done by the real-time communication through GSI$_{TM}$ (G2 Standard Interface). In the NASA-LeRC ICS demonstration system the communication link of GSI handles more than 60 real-time sensor information for the G2 knowledge base. An attribute of an object can also receive its value through a simulation formula or from the conclusion of an inference rule when sensor data is not available. G2 rules contain expert's knowledge of what to conclude and how to respond to a given set of conditions. When the antecedent of a rule is evaluated (by the inference engine) as true, the rule is invoked and the action part of the rule is executed. The actions include: determining a variable's value, sending a value to an external destination, informing the user, activating or deactivating a specific set of knowledge base, etc. Figure 10 shows some of the rules used in the HPOTP seal problem diagnosis.

Conclusion

In this paper, different techniques used in the real-time diagnostic system for reusable rocket engine are described. A neural network based diagnostic system is used for on-line sensor failure detection, isolation and accommodation. A model based diagnostic system based on the nominal operation data is used to detect the actuator faults. Classification of actuator faults and the estimation of the fault severity are done by the estimation of selected fault parameters. An on-line knowledge system is used to detect those component faults which are traditionally done using heuristic expert knowledge. Rules are used to resolve the conflicting reports from different detection modules.

References

1.   Merrill, W. C. and Lorenzo, C. F., "A Reusable Rocket Engine Intelligent Control," 24th Joint Propulsion Conference, Boston, MA, July 11-13, 1988.

2.   Guo, T. H. and Merrill, W. C., "A Framework for Real-time Rocket Engine Diagnostics," 1990 Conference for Advanced Earth-to-Orbit Propulsion Technology, Marshall Space Flight Center, AL., May 15-17, 1990.

3.   Guo, T. H., "An SSME High Pressure Oxidizer Turbopump Diagnostic System Using G2™ Real-Time Expert System," Third Annual Health Monitoring Conference for Space Propulsion System, Cincinnati, Ohio, Nov. 13-14, 1991.

4.   Guo, T. H. and Nurre, J., "Sensor Failure Detection and Recovery by Neural Networks," Proc. Int. Joint Conference on Neural Networks, Seattle, WA, July 8-12, 1991.

5.   Lin, C.-S., Wu, I.-C. and Guo, T. H., "Neural Networks for Sensor Failure Detection and Data Recovery," to be presented in Int. Conference on Artificial Neural Networks in Engineering, St. Louis, MO, Nov. 10-12, 1991.

6.   Guo, T. H., Merrill, W. and Duyar, A., "Real-Time Diagnostics of the Reusable Rocket Engine Using On-Line System Identification," The Second Annual Health Monitoring Conference for Space Propulsion Systems, Cincinnati, OH, Nov. 14-15, 1990.

7.   Guo, T. H., Merrill, W. and Duyar, A., "A Distributed Fault-Detection and Diagnosis System Using On-Line Parameter Estimation," IFAC International Symposium on Distributed Intelligent Systems, Arlington, VA, Aug. 13-15, 1991.

8.   W. C. Merrill, J. C. DeLaat, and W. M. Bruton, "Advanced Detection, Isolation, and Accommodation of Sensor Failures: Real-Time Evaluation," *AIAA J. Guidance, Control Dyn.*, 11, No. 6, 1988.

9.   Duyar, A., Eldem, V., Merrill, W. and Guo, T., "State Space Representation of the Open Loop Dynamics of the Space Shuttle Main Engine," ASME *Journal of Dynamic Systems, Measurement, and Control*, Vol. 113, No. 4, December 1991.

10. Paxson, D. E., "A Model for the Space Shuttle Main Engine High Pressure Oxidizer Turbopump Shaft Seal System," The Second Annual Health Monitoring Conference for Space Propulsion Systems, Cincinnati, OH, Nov. 14-15, 1990.

ACTUATION FAILURE MODE	FAULT PARAMETERS			
	Fa11*	Fa22	fao1**	fao2
NORMAL	1	1	0	0
OPOV VALVE BALL SEAL LEAKAGE	1	1	c_1^+	0
FPOV VALVE BALL SEAL LEAKAGE	1	1	0	c_2
FPOV and OPOV VALVE BALL SEAL LEAKAGE	1	1	c_1	c_2
OPOV BLOCKAGE	1	1	$-c_1$	0
FPOV BLOCKAGE	1	1	0	$-c_2$
OPOV VALVE BALL SEAL LEAKAGE FPOV BLOCKAGE	1	1	$-c_1$	$-c_2$
OPOV VALVE STUCK	0	1	c_1	0
FPOV VALVE STUCK	1	0	0	c_2
OPOV & FPOV VALVE STUCK	0	0	c_1	c_2
OPOV RVDT FAILURE	0	1	c_1	0
FPOV RVDT FAILURE	1	0	0	c_2
OPOV and FPOV RVDT FAILURE	0	0	c_1	c_2

* Fa11 indicates the 1,1 element of the Fa matrix

** fao1 indicates the 1st element of the fao vector

+ C_1 & C_2 represent the bias terms

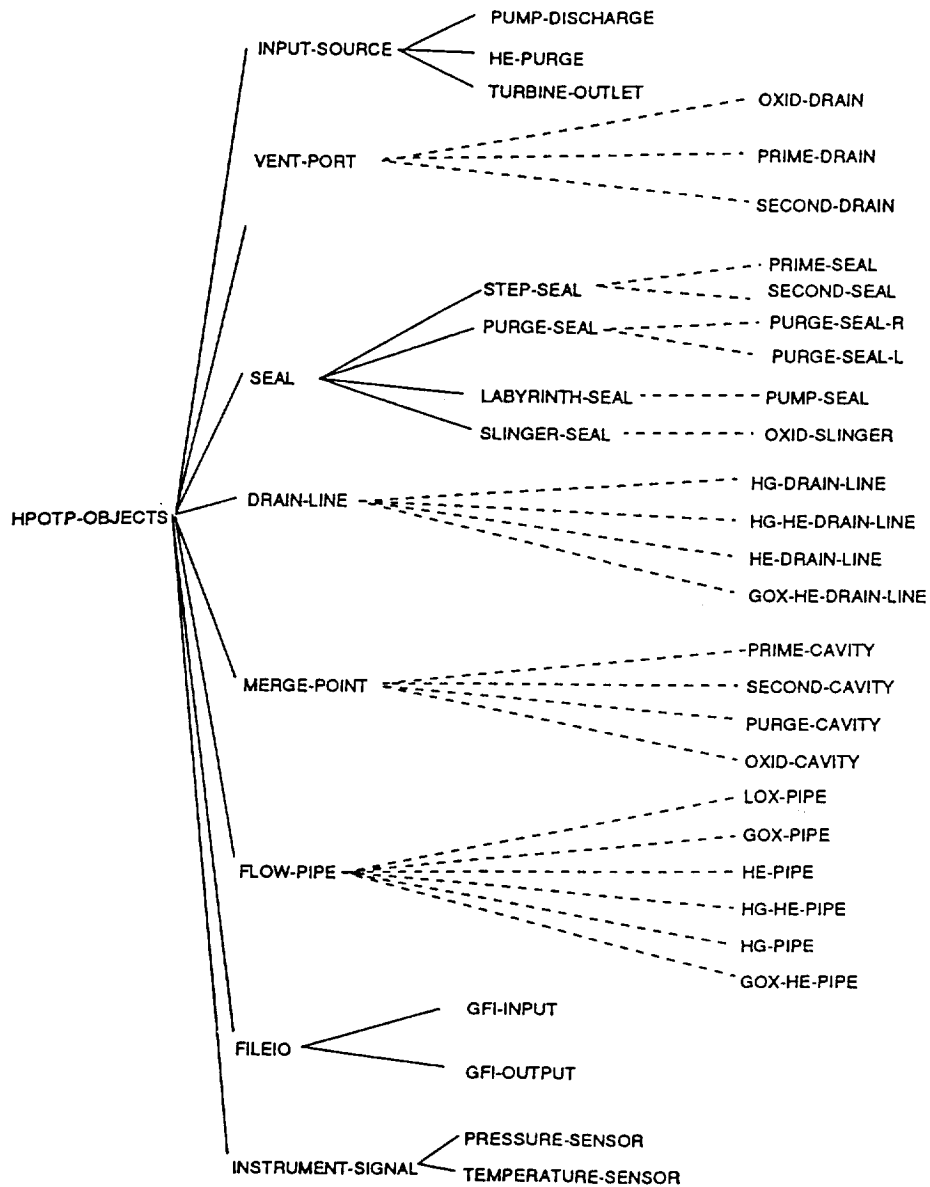Table 1. SSME Actuator Fault Signatures

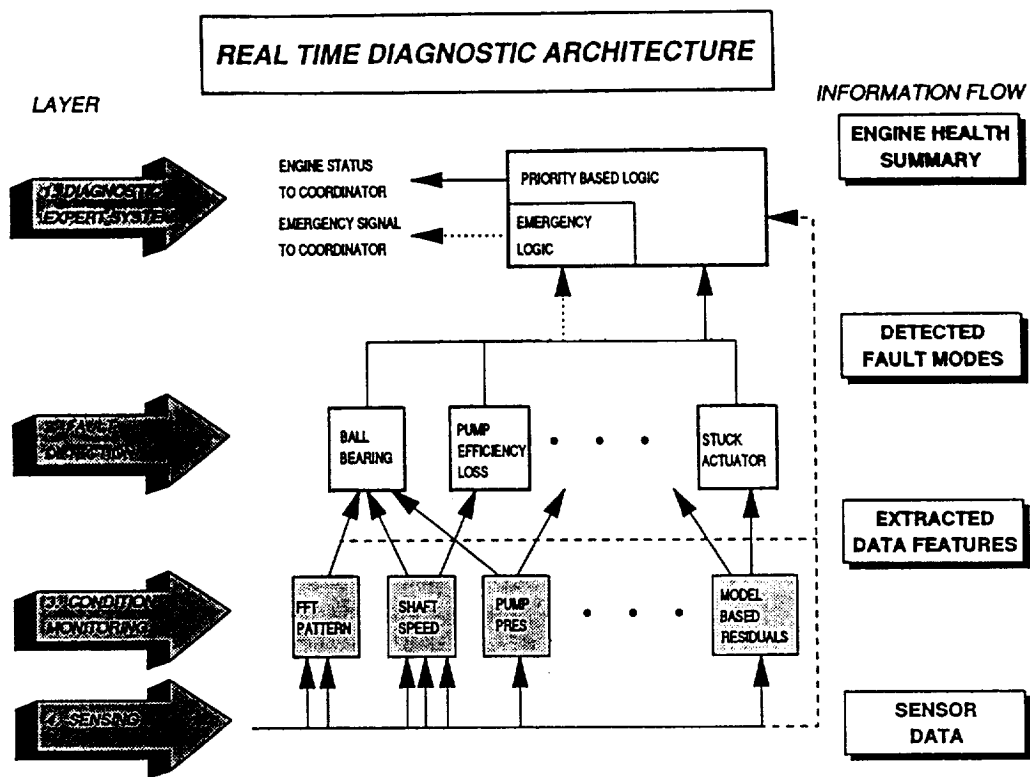Table 2 Class and Subclass Definition of the HPOTP Seal System

REAL TIME DIAGNOSTIC ARCHITECTURE

LAYER

INFORMATION FLOW

ENGINE STATUS
TO COORDINATOR

EMERGENCY SIGNAL
TO COORDINATOR

PRIORITY BASED LOGIC

EMERGENCY
LOGIC

ENGINE HEALTH
SUMMARY

BALL
BEARING

PUMP
EFFICIENCY
LOSS

• • •

STUCK
ACTUATOR

DETECTED
FAULT MODES

FFT
PATTERN

SHAFT
SPEED

PUMP
PRES

• • •

MODEL
BASED
RESIDUALS

EXTRACTED
DATA FEATURES

SENSOR
DATA

Figure 1 Distributed Diagnostic Architecture

On-line Parameter Est.

Neural Net

Real-Time Exp. Sys.

Engine Status Report

G2

Diagnostic Expert System

Sensor
Failure
Report

Sensor
Validation

Model Based
Fault Detection
(Actuator Failures)

Component
Fault Detection

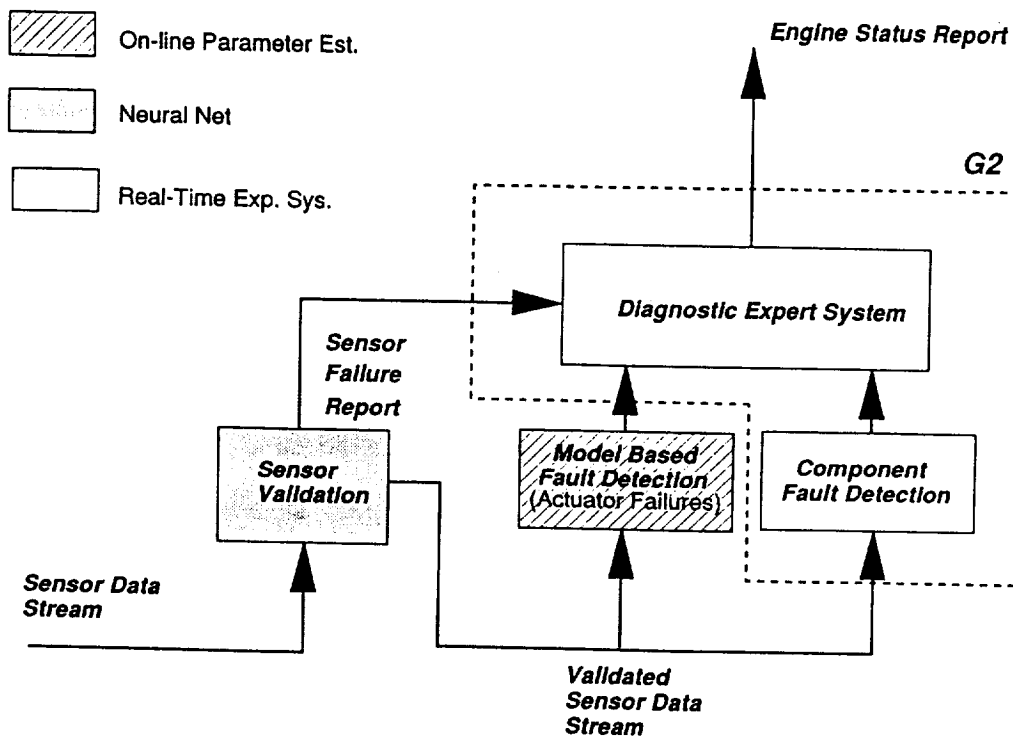Sensor Data
Stream

Validated
Sensor Data
Stream

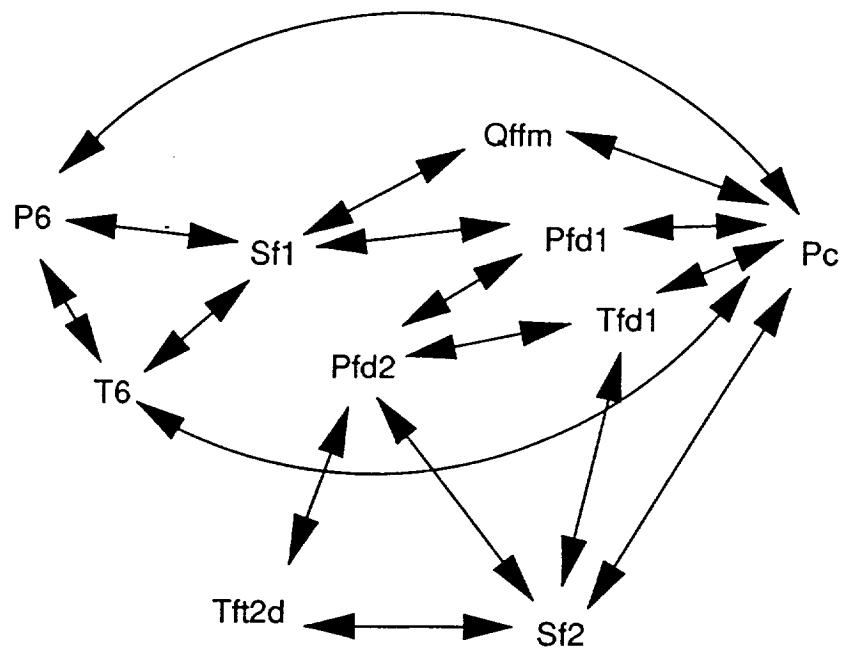Figure 2. ICS Real-Time Diagnostic System

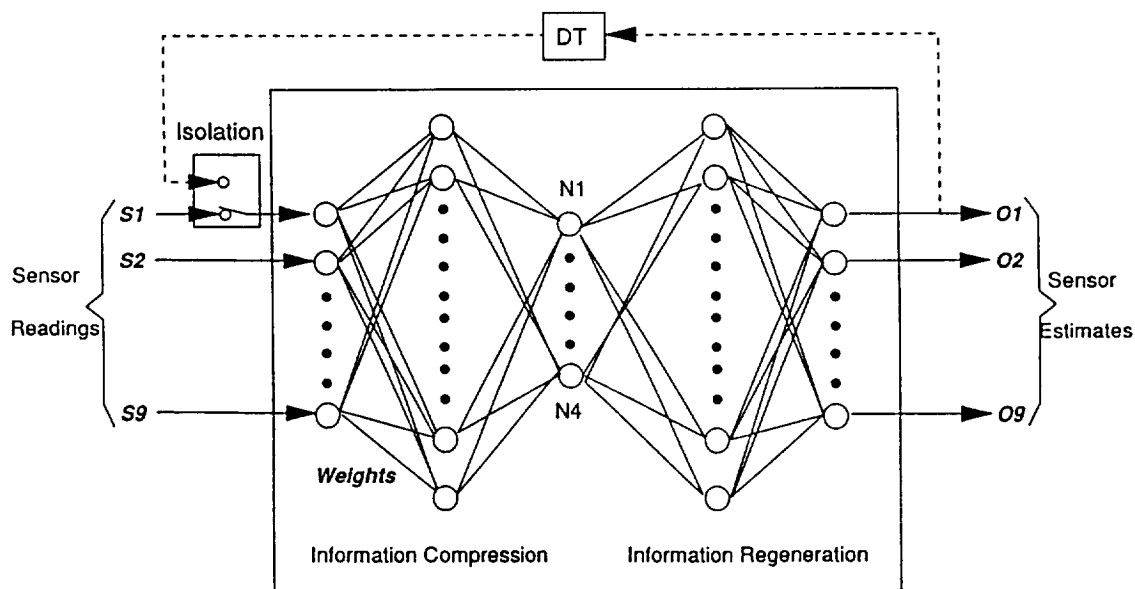**Figure 3** Influence Sensor Map of SSME Fuel System

Figure 4 Autoassociative Neural Network for Sensor Validation

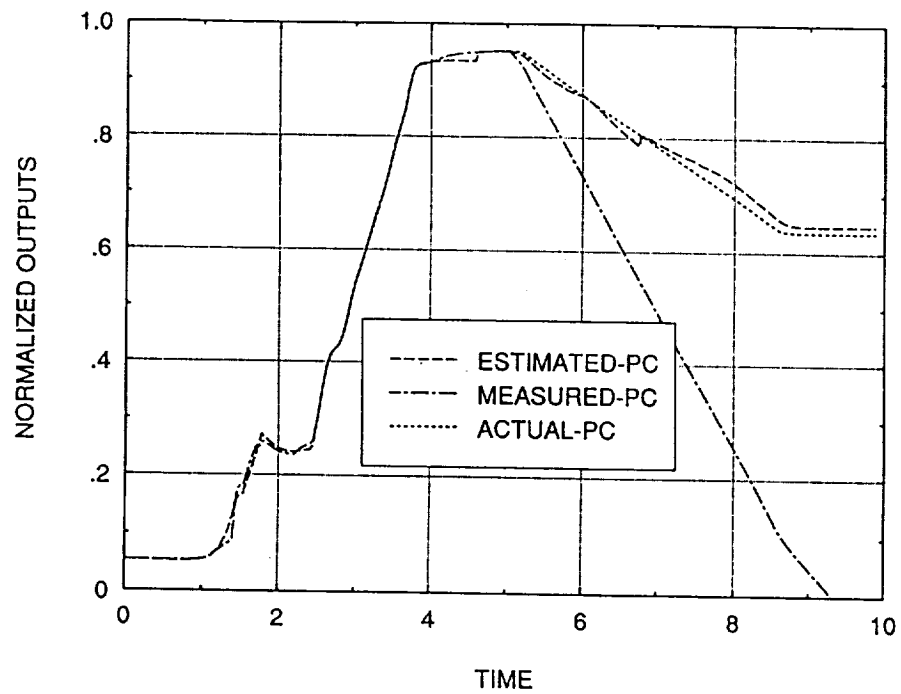SENSOR FAILS: SF2 AT 4.1, PC&QFFM AT 5.1, TFD1 AT 6.1, & T5 AT 7.1

Figure 5 Chamber Inlet Pressure (Pc) sensor recovery during a series of sensor failures

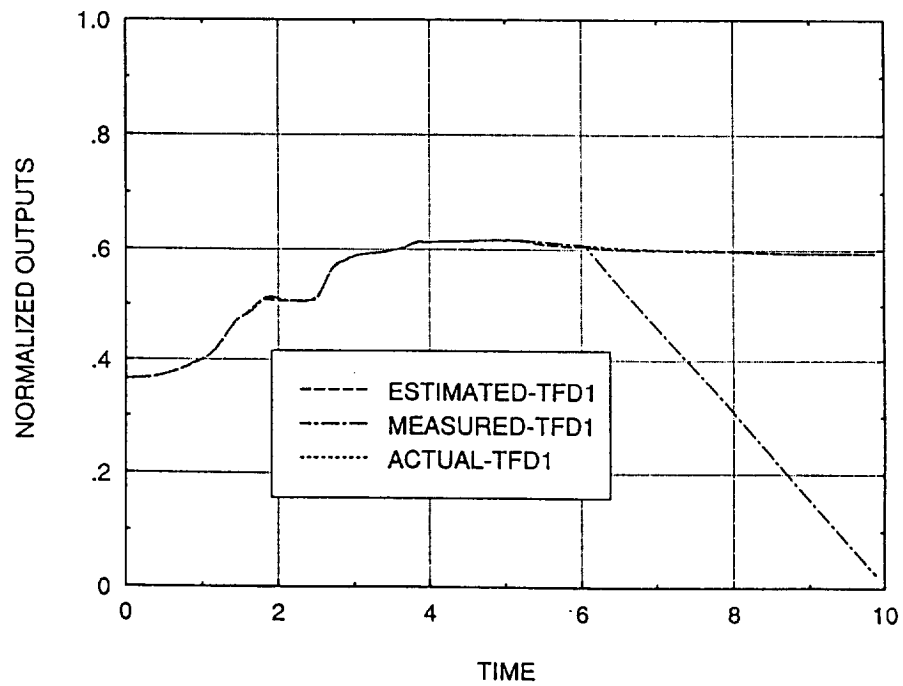SENSOR FAILS: SF2 AT 4.1, PC&QFFM AT 5.1, TFD1 AT 6.1, & T5 AT 7.1

Figure 6 LPFP discharge Temperature sensor recovery during a series of sensor failures
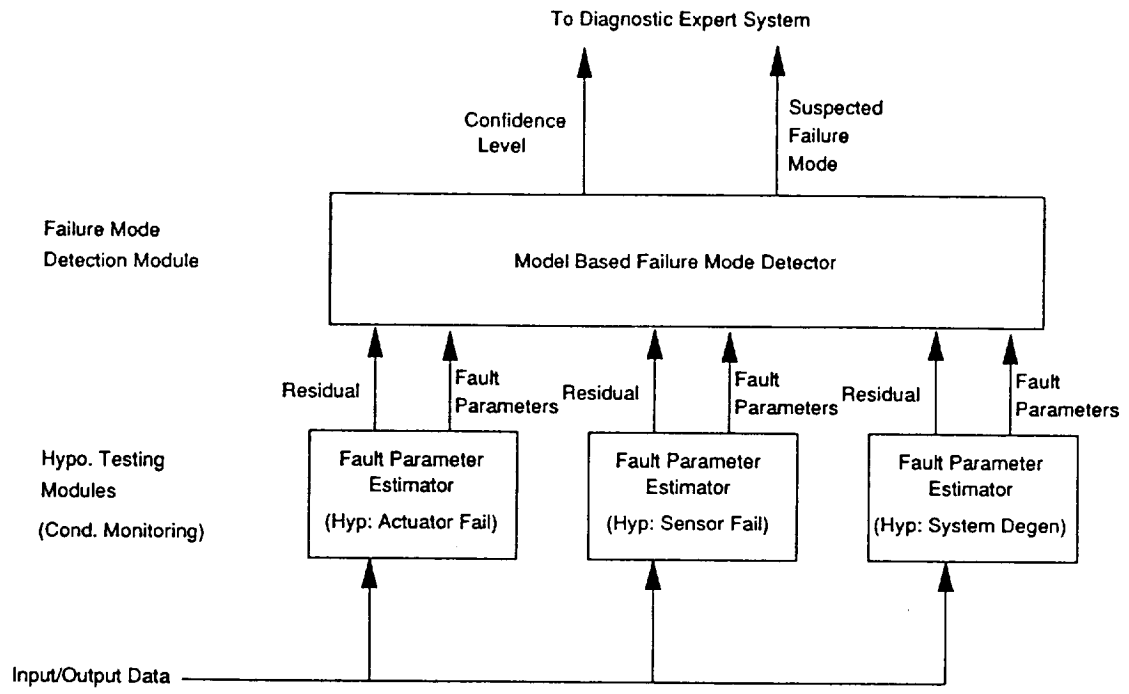
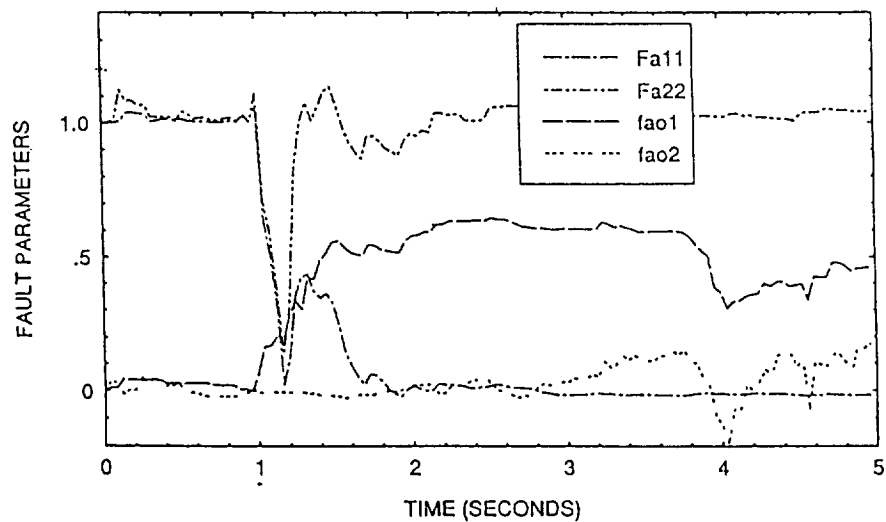**Figure 7** Model-Based Fault Detection and Diagnostic System

Figure 5. OPOV Valve Stuck at Time = 1.0 Sec.

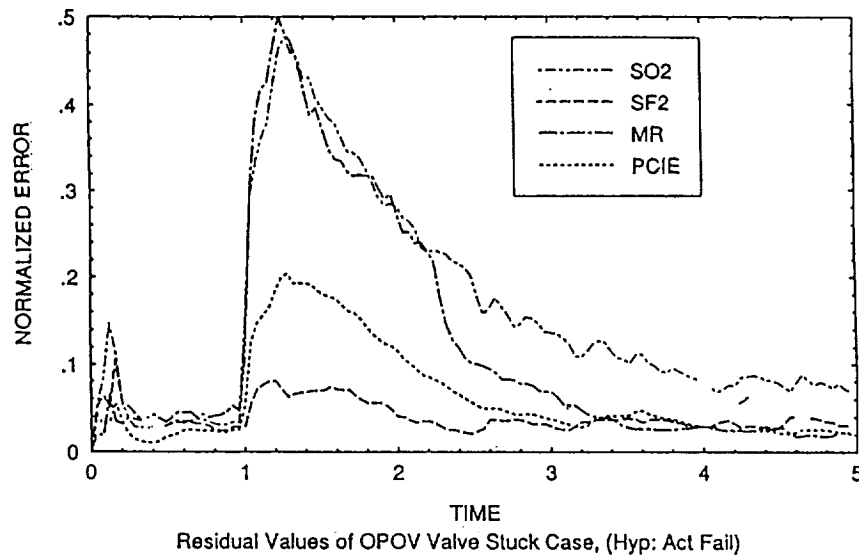**Figure 8** Estimated Fault Parameters on OPOV Valve Stuck

TIME

Residual Values of OPOV Valve Stuck Case, (Hyp: Act Fail)

Figure 9   Residue of the Hypothesis Module on OPOV Valve Stuck

if the status of any step-seal is failed then change the color-pattern of the step-seal so that foreground-color is cyan

if (the pressure of cavity-1 < 125) and (the pressure of cavity-2 > 25) then conclude that the status of second-seal is failed

if the pressure of cavity-1 > 400 and the down-pressure of hg-line-1 > 50 then conclude that the status of prime-seal is failed

if (the pressure of oxid-cavity-1 > 55) and (the temperature of oxid-cavity-1< 380) and (the down-pressure of OXID-SLINGER <150) then conclude that the status of OXID-SEAL is failed

if (the pressure of cavity-2 > 14) and (the pressure of purge-cavity < 62) then conclude that the status of purge-seal-r is failed

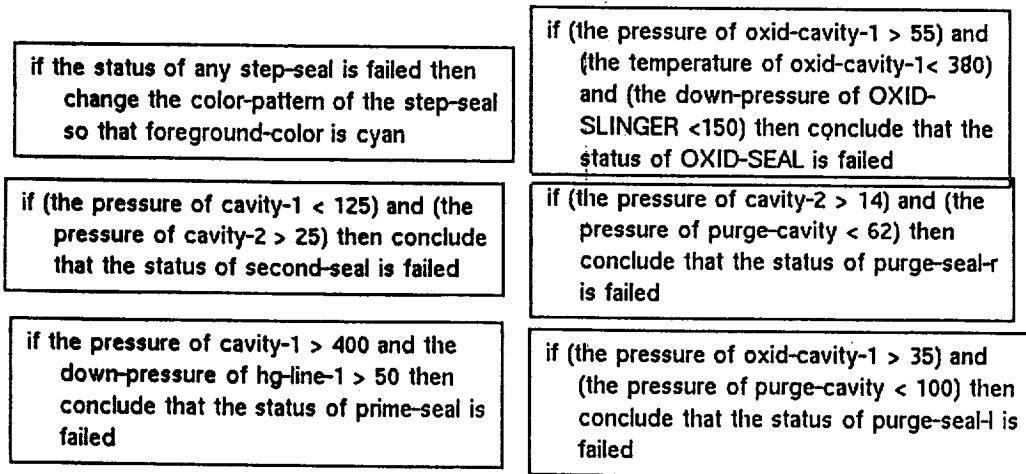if (the pressure of oxid-cavity-1 > 35) and (the pressure of purge-cavity < 100) then conclude that the status of purge-seal-l is failed

Figure 10   Examples of G2 Rules in HPOTP Seal Diagnosis

12

REPORT DOCUMENTATION PAGE

Public reporting burden for this collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington, VA 22202-4302, and to the Office of Management and Budget, Paperwork Reduction Project (0704-0188), Washington, DC 20503.

1. AGENCY USE ONLY (Leave blank)	2. REPORT DATE	3. REPORT TYPE AND DATES COVERED
	August 1992	Technical Memorandum

4. TITLE AND SUBTITLE

Real-Time Diagnostics for a Reusable Rocket Engine

6. AUTHOR(S)

T.H. Guo, W. Merrill, and A. Duyar

5. FUNDING NUMBERS

WU–582–01–41

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)

National Aeronautics and Space Administration
Lewis Research Center
Cleveland, Ohio 44135–3191

8. PERFORMING ORGANIZATION REPORT NUMBER

E–7222

9. SPONSORING/MONITORING AGENCY NAMES(S) AND ADDRESS(ES)

National Aeronautics and Space Administration
Washington, D.C. 20546–0001

10. SPONSORING/MONITORING AGENCY REPORT NUMBER

NASA TM–105792

11. SUPPLEMENTARY NOTES

T.H. Guo and W. Merrill, NASA Lewis Research Center, Cleveland, Ohio. A. Duyar, Department of Mechanical Engineering, Florida Atlantic University, Boca Raton, Florida 33431. Responsible person, T.H. Guo, (216) 433–3734.

12a. DISTRIBUTION/AVAILABILITY STATEMENT

Unclassified - Unlimited
Subject Category 63

12b. DISTRIBUTION CODE

13. ABSTRACT (Maximum 200 words)

A hierarchical, decentralized diagnostic system is proposed for the Real-Time Diagnostic System component of the Intelligent Control System (ICS) for reusable rocket engines. The proposed diagnostic system has three layers of information processing: condition monitoring, fault mode detection, and expert system diagnostics. The condition monitoring layer is the first level of signal processing. Here, important features of the sensor data are extracted. These processed data are then used by the higher level fault mode detection layer to do preliminary diagnosis on potential faults at the component level. Because of the closely coupled nature of the rocket engine propulsion system components, it is expected that a given engine condition may trigger more than one fault mode detector. Expert knowledge is needed to resolve the conflicting reports from the various failure mode detectors. This is the function of the diagnostic expert layer. Here, the heuristic nature of this decision process makes it desirable to use an expert system approach. Implementation of the real-time diagnostic system described above requires a wide spectrum of information processing capability. Generally, in the condition monitoring layer, fast data processing is often needed for feature extraction and signal conditioning. This is usually followed by some detection logic to determine the selected faults on the component level. Three different techniques are used to attack different fault detection problems in NASA Lewis Research Center ICS testbed simulation. The first technique employed is the neural network application for real-time sensor validation which includes failure detection, isolation and accommodation. The second approach demonstrated is the model-based fault diagnosis system using on-line parameter identification techniques where input data are processed to estimate important parameters for the predefined fault detection algorithms. Besides these model based diagnostic schemes, there are still many failure modes which need to be diagnosed by the heuristic expert knowledge. The heuristic expert knowledge is implemented using a real time expert system tool called G2™ by Gensym Corp. Finally, the distributed diagnostic system requires another level of intelligence to oversee the fault mode reports generated by component fault detectors. The decision making at this level can be best done using a rule-based expert system. This level of expert knowledge is also implemented using G2™.

14. SUBJECT TERMS

Diagnostics; Expert systems; Artificial intelligence; Controls

15. NUMBER OF PAGES

14

16. PRICE CODE

A03

17. SECURITY CLASSIFICATION OF REPORT	18. SECURITY CLASSIFICATION OF THIS PAGE	19. SECURITY CLASSIFICATION OF ABSTRACT	20. LIMITATION OF ABSTRACT
Unclassified	Unclassified	Unclassified	

NSN 7540-01-280-5500

Standard Form 298 (Rev. 2-89)
Prescribed by ANSI Std. Z39-18
298-102

National Aeronautics and
Space Administration

Lewis Research Center
Cleveland, Ohio 44135

Official Business
Penalty for Private Use $300

FOURTH CLASS MAIL

ADDRESS CORRECTION REQUESTED

Postage and Fees Paid
National Aeronautics and
Space Administration
NASA 451

NASA