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Takahisa Kobayashi
ASRC Aerospace Corporation, Cleveland, Ohio

Donald L. Simon
Glenn Research Center, Cleveland, Ohio

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Glenn Research Center
Cleveland, Ohio 44135

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ASRC Aerospace Corporation
Cleveland, Ohio 44135

Donald L. Simon
National Aeronautics and Space Administration
Glenn Research Center
Cleveland, Ohio 44135

ABSTRACT

In this paper, an enhanced on-line diagnostic system which utilizes dual-channel sensor measurements is developed for the aircraft engine application. The enhanced system is composed of a nonlinear on-board engine model (NOBEM), the hybrid Kalman filter (HKF) algorithm, and fault detection and isolation (FDI) logic. The NOBEM provides the analytical third channel against which the dual-channel measurements are compared. The NOBEM is further utilized as part of the HKF algorithm which estimates measured engine parameters. Engine parameters obtained from the dual-channel measurements, the NOBEM, and the HKF are compared against each other. When the discrepancy among the signals exceeds a tolerance level, the FDI logic determines the cause of discrepancy. Through this approach, the enhanced system achieves the following objectives: 1) anomaly detection, 2) component fault detection, and 3) sensor fault detection and isolation. The performance of the enhanced system is evaluated in a simulation environment using faults in sensors and components, and it is compared to an existing baseline system.

INTRODUCTION

Reliability is an important aspect in maintaining safety and efficient operation of aircraft gas turbine engines. To ensure reliability, aircraft engine electronic control systems are equipped with some level of redundancy for backup purposes in case of a failure. This redundancy has evolved from a simple hydro-mechanical backup to a dual-channel full authority digital electronic control (FADEC) [1-3]. In the dual-channel FADEC setup, a single engine parameter is measured by a dual-channel sensor,[†] and the FADEC receives the redundant measurements through dual channels. If a single channel fails, this failure is accommodated by utilizing the measurement on the other channel.

Such an accommodation action can be taken only if the identity of the faulty sensor and its failed channel are known. Thus, in order to fully utilize the available redundancy for sensor fault accommodation, the ability to diagnose the sensors on-line (real-time, in-flight) is required. The sensor fault detection and isolation process is initiated by cross-checking the redundant measurements of each dual-channel sensor. If both channels agree within a pre-established tolerance, the measurements on both channels are acceptable. If not, the cross-check fails, and one of the dual channels is considered faulty. A challenge arises in the subsequent process of identifying the faulty channel. Even if redundant measurements do not agree with each other, both of them may pass the range and rate checks [4]. Such a failure is called an in-range sensor fault and causes some difficulty in determining which channel is the failed one.

For the diagnosis of an in-range sensor fault, an analytical third channel is necessary as a referee in the decision making process [4]. In the triplex-channel setup, the redundant

[†] A dual-channel sensor is defined in this paper as a device which produces two measurements of the same engine parameter. The redundant measurements are referred to as channel A and channel B measurements. It is assumed that failures can occur in either one or both channels of the sensor.

measurements of a dual-channel sensor are compared against the referee (analytical third channel). The channel that disagrees most with the referee is likely the faulty channel. The analytical third channel is embedded within the FADEC in the form of an analytical representation of the real engine. This analytical representation is called an on-board engine model (OBEM). The OBEM captures the real engine's nominal behavior to some extent and provides expected engine output values in real time. In Ref. [5], a linear on-board engine model (LOBEM), which is composed of piecewise linear models generated at multiple operating conditions over the flight envelope, was utilized for the development of a baseline system for aircraft engine on-line diagnostics. This baseline system established the level of diagnostic performance which is potentially achievable in the field.

In this paper, an on-line diagnostic system that utilizes advanced techniques is developed to achieve a higher level of diagnostic performance. This system is referred to as an enhanced system, and it utilizes a nonlinear on-board engine model (NOBEM) and the hybrid Kalman filter (HKF) algorithm [6]. The NOBEM functions as the analytical third channel that provides expected engine output values in real time. The NOBEM is further utilized as part of the HKF algorithm. Based on the parameters generated by the NOBEM, the HKF estimates the engine output values which are used in the diagnostic process. Similar to the baseline system, the enhanced system achieves the following objectives: 1) anomaly detection, 2) component fault detection, and 3) sensor fault detection and isolation. The performance of the enhanced system is evaluated to determine its advantages over the baseline system.

In the following section, a review of the baseline system and its implementation challenge is given first. Then, the development of the enhanced system is described, followed by a discussion regarding how the influence of engine health degradation is accounted for by the enhanced system. Then, the diagnostic approach is applied to a large commercial aircraft engine model. The performance of the enhanced system is evaluated and compared to the performance of the baseline system using simulated faults in sensors and components.

NOMENCLATURE

BST	Booster
CFS	Component fault signature
FADEC	Full Authority Digital Electronic Control
FDI	Fault Detection and Isolation
HKF	Hybrid Kalman filter
HPC	High Pressure Compressor
HPT	High Pressure Turbine
LOBEM	Linear On-Board Engine Model
NOBEM	Nonlinear On-Board Engine Model
LPT	Low Pressure Turbine
OBEM	On-Board Engine Model
P2	Engine inlet pressure
P25	HPC inlet pressure
P_{amb}	Ambient pressure
PS3	Combustor inlet static pressure
T2	Engine inlet temperature
T25	HPC inlet temperature
T3	Combustor inlet temperature
T49	LPT inlet temperature
T_{amb}	Ambient temperature
TMHS23	BST metal temperature
TMHS3	HPC metal temperature
TMHS41	HPT nozzle metal temperature
TMHS42	HPT metal temperature
TMHS5	LPT metal temperature
TMHSBC	Combustor case metal temperature
TMHSBL	Combustor liner metal temperature
VBV	Variable bleed valve
VSV	Variable stator vane
WF36	Fuel flow
XN12	Fan speed, measured
XN25	Core speed, measured
XNH	Core speed, actual
XNL	Fan speed, actual
e	Environmental parameter vector
h	Health parameter vector
h_{ref}	Reference health condition vector
u_{cmd}	Control command vector
v	Sensor noise vector
x	State variable vector
y	Sensor output vector (controls/diagnostics)
z	Sensor output vector (ambient/engine inlet)

REVIEW OF THE BASELINE SYSTEM

The baseline system developed in Ref. [5] is composed of a linear on-board engine model (LOBEM) and fault detection and isolation (FDI) logic as shown in Fig. 1. The LOBEM runs in real-time and provides expected engine output values. In the triplex-channel setup, the dual-channel measurements are compared against each other and also against the output of the LOBEM. Based on discrepancies among the triplex channels, the FDI logic determines a root cause of the engine's anomalous behavior.

Since the LOBEM is developed to represent an aircraft engine at a specific health condition, it eventually becomes an obsolete representation as the real engine continues to degrade over its lifetime. Utilization of such an obsolete engine model in the diagnostic process corrupts on-line diagnostic capabilities. Thus, the LOBEM must be updated periodically so that it can accurately represent the real engine at a degraded condition. Through the periodic update of the LOBEM, the baseline system is able to maintain its diagnostic effectiveness regardless of health degradation.

The major implementation challenge that must be addressed for the baseline system is the complexity involved in

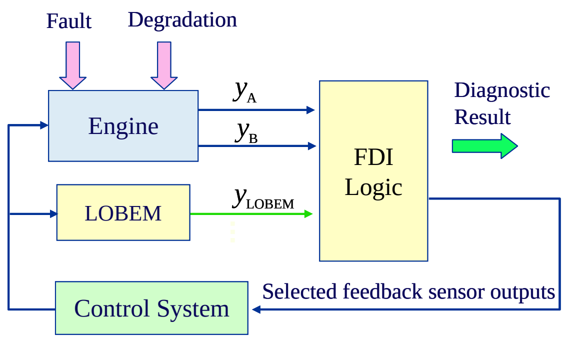

FIGURE 1. STRUCTURE OF THE BASELINE SYSTEM FOR ON-LINE DIAGNOSTICS

the update process. In order to update the LOBEM, piecewise linear models must be re-generated at a degraded health condition. This re-generation process may have to take place on a ground-based computer with human intervention. Furthermore, after the re-generation process, the piecewise linear models must be uploaded to the FADEC. Such complexity raises a number of questions regarding the practicality of this approach.

The complex process of updating an on-board engine model must be addressed before any on-line diagnostic algorithms that utilize the model can be viable. In the following section, the enhanced system is developed to address the above implementation challenge.

DEVELOPMENT OF THE ENHANCED SYSTEM FOR ON-LINE DIAGNOSTICS

The structure of the enhanced system is shown in Fig. 2. The enhanced system is different from the baseline system in the following two aspects: 1) utilization of a nonlinear OBEM instead of a linear OBEM and 2) utilization of the HKF

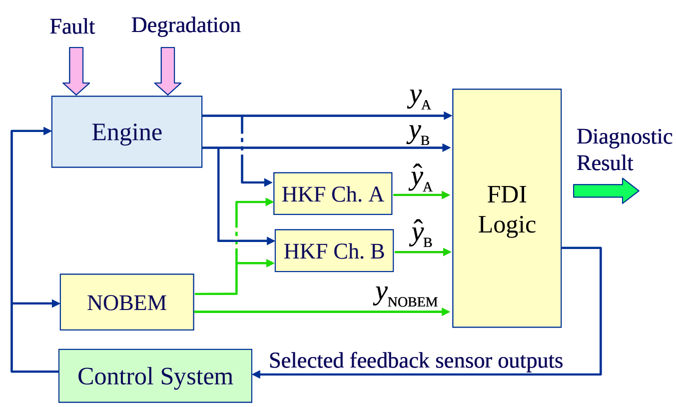

FIGURE 2. STRUCTURE OF THE ENHANCED SYSTEM

algorithm. The NOBEM functions not only as the analytical third channel but also as part of the HKF algorithm [6]. The HKF algorithm utilizes the parameters generated by the NOBEM in order to estimate the engine output values. The estimated engine outputs are used by the FDI logic in conjunction with the output of triplex channels. The elements of the enhanced system are described in this section.

Hybrid Kalman Filter

An aircraft engine under consideration for on-line diagnostics is described by nonlinear equations of the following form:

$$\begin{aligned} \dot{x} &= f\left(x, h, u_{cmd}, e\right) \\ y &= g\left(x, h, u_{cmd}, e\right) \end{aligned} \tag{1}$$

The vectors x, u_{cmd}, and e contain state variables, control command inputs, and environmental parameters, respectively. The vector h contains health parameters that indicate the engine health condition. Health parameters are efficiencies and flow capacities of the engine components such as compressors and turbines. As they deviate from their nominal health condition, the performance delivered by each component degrades. For given inputs, the nonlinear functions f and g generate the state derivative vector $\dot{x}$ and engine output vector y. The engine outputs are measured by sensors with dual-channels A and B as follows:

$$\begin{aligned} y_A &= y + v_A \\ y_B &= y + v_B \end{aligned} \tag{2}$$

The vectors v_A and v_B represent the zero-mean, normally distributed white noise that corrupts the measurements on dual channels.

The enhanced on-line diagnostic system utilizes a NOBEM in the following form:

$$\begin{aligned} \dot{x}_{NOBEM} &= \bar{f}\left(x_{NOBEM}, h_{NOBEM}, u_{cmd}, z\right) \\ y_{NOBEM} &= \bar{g}\left(x_{NOBEM}, h_{NOBEM}, u_{cmd}, z\right) \end{aligned} \tag{3}$$

The vectors x_{NOBEM} and y_{NOBEM} contain the state and output variables of the NOBEM, respectively, while the vector z contains the measured parameters which define the flight condition. The vector h_{NOBEM} contains health parameters that indicate the health condition of the NOBEM. The health condition prescribed by this vector is called the "health baseline" since it is the reference health condition at which the NOBEM operates.

Based on the state and output vectors of the NOBEM, the HKF equation is formulated as follows:

$$
\begin{aligned}
\dot{\hat{x}}_{\mathrm{A}} &= A\left(\hat{x}_{\mathrm{A}} - x_{NOBEM}\right) + K\left(y_{\mathrm{A}} - \hat{y}_{\mathrm{A}}\right) \\
\hat{y}_{\mathrm{A}} &= C\left(\hat{x}_{\mathrm{A}} - x_{NOBEM}\right) + y_{NOBEM}
\end{aligned}
\tag{4}
$$

One HKF is set up for each channel as shown in Fig. 2; the above equation represents the HKF for channel A. The subscript "A" is replaced by "B" for the HKF on channel B. The vector $\hat{x}_{\mathrm{A}}$ represents the estimate of x in Eq. (1), while the vector $\hat{y}_{\mathrm{A}}$ represents the estimate of y_{A} in Eq. (2). The state space matrices A and C are derived off-line through the linearization of the NOBEM. During the linearization process, the health baseline of the NOBEM is set to a specific health condition (e.g., nominal health). The matrix K represents the Kalman gain. Similar to the general linear Kalman filter approach, the matrices A, C, and K are derived at multiple operating conditions, defined by altitude, Mach number, and power setting, in order to cover a wide operating range of the aircraft engine. Once derived, these matrices are saved in table lookup form for real-time execution of Eq. (4).

Construction of Fault Signals

Based on the triplex channels ($y_{\mathrm{A}}, y_{\mathrm{B}}, y_{NOBEM}$) and the estimates of dual HKFs ($\hat{y}_{\mathrm{A}}, \hat{y}_{\mathrm{B}}$), various signals are constructed for diagnostic purposes. The first signal is constructed through the comparison of measurements on channels A and B. There are a total of m engine parameters which are measured by m dual-channel sensors. For each measured parameter, the residual is computed as follows:

$$
r^{i} = \frac{y_{\mathrm{A}}^{i} - y_{\mathrm{B}}^{i}}{\sigma_i}, \qquad i = 1, \ldots, m \tag{5}
$$

where σ_i indicates the standard deviation of the measurement uncertainty of the i^{th} sensor. The residual in Eq. (5) is called the "dual-channel residual." The dual-channel residual for each sensor is compared against a pre-established threshold, τ_{DR}^{i}. If the dual-channel residual does not exceed the threshold, the redundant measurements on both channels are acceptable. Otherwise, at least one of the dual channels is faulty. This process can only determine whether at least one channel of the dual-channel sensor is faulty, but not which channel is faulty.

In addition to the comparison between the dual channels, the comparison of the dual channels against the model output is performed as follows:

$$
\begin{aligned}
r_{\mathrm{A}}^{i} &= \frac{y_{\mathrm{A}}^{i} - y_{NOBEM}^{i}}{\sigma_i} \\
r_{\mathrm{B}}^{i} &= \frac{y_{\mathrm{B}}^{i} - y_{NOBEM}^{i}}{\sigma_i}
\end{aligned}
\tag{6}
$$

The residual in Eq. (6) is called the "analytical residual." The analytical residual computed for each channel of each sensor is compared against a pre-established threshold, τ_{AR}^{i}. The NOBEM generates the expected output values of the engine operating without any faults. If an analytical residual exceeds a threshold, it indicates the existence of an anomaly.

The analytical residual is further utilized to construct a component fault signal (CFS) for each of the dual channels as follows:

$$
\begin{aligned}
CFS_{\mathrm{A}} &= \sum_{i=1}^{m} \left(\frac{r_{\mathrm{A}}^{i}}{\tau_{AR}^{i}} \right)^2 - \alpha \\
CFS_{\mathrm{B}} &= \sum_{i=1}^{m} \left(\frac{r_{\mathrm{B}}^{i}}{\tau_{AR}^{i}} \right)^2 - \beta
\end{aligned}
\tag{7}
$$

where

$$
\alpha = \max_{i=1,\ldots,m} \left\{ \left(\frac{r_{\mathrm{A}}^{i}}{\tau_{AR}^{i}} \right)^2 \right\}, \quad \beta = \max_{i=1,\ldots,m} \left\{ \left(\frac{r_{\mathrm{B}}^{i}}{\tau_{AR}^{i}} \right)^2 \right\} \tag{8}
$$

As discussed in Ref. [5], the CFS is computed specifically for the purpose of component fault detection. The scalars α and β in Eq. (8) are the maximum ratio of the analytical residual to the threshold τ_{AR}^{i} for channel A and B, respectively, among the m dual-channel sensors. These scalars correspond to the analytical residual of a given channel that is largest in magnitude with respect to its threshold. This maximum ratio value is subtracted from the summation in Eq. (7). Since a sensor fault causes a prominent increase in the analytical residual of one faulty sensor, the CFS value is unaffected by a single sensor fault. On the other hand, a component fault generally causes an increase in the analytical residuals of multiple sensors, and therefore the CFS value will increase when a component is faulty. As such, an increase in the CFS value indicates the existence of a component fault. The CFS for each channel is compared against a pre-established threshold, τ_{CFS}. When the CFS exceeds the threshold in at least one channel, it indicates the existence of a component fault.

Up to this point, the signals generated from the triplex channels are computed in the same way as those used in the baseline system [5]. In conjunction with these signals, the enhanced system utilizes the following residuals generated by the HKF:

$$
\begin{aligned}
\hat{r}_{\mathrm{A}}^{i} &= \frac{y_{\mathrm{A}}^{i} - \hat{y}_{\mathrm{A}}^{i}}{\sigma_i} \\
\hat{r}_{\mathrm{B}}^{i} &= \frac{y_{\mathrm{B}}^{i} - \hat{y}_{\mathrm{B}}^{i}}{\sigma_i}
\end{aligned}
\tag{9}
$$

The residual in Eq. (9) is called the "estimation residual." The estimation residual computed for each channel of each sensor is compared against a pre-established threshold, τ_{ER}^{i}. When the engine experiences a fault, the estimation accuracy of the HKF becomes poor, causing some increase in the estimation residuals. Such an increase, however, occurs in an unpredictable manner. For instance, a fault in a particular sensor does not necessarily cause a large increase in the estimation residual of that particular sensor. Instead, the estimation residuals of multiple sensors may exhibit a moderate increase. This can happen since the HKF algorithm is formulated based on the assumption that no fault exists in the system. When at least one of the estimation residuals exceeds a threshold in either channel, it indicates the existence of an anomaly in the corresponding channel.

Fault Detection and Isolation (FDI) Logic

The various signals discussed in the previous section are compared against their respective thresholds. When any of those signals exceeds a threshold, it indicates anomalous engine behavior due to a fault. Based on the threshold violation occurring from the engine, the FDI logic determines a root cause of the problem based on the following assumptions:

- Only one sensor may be faulty at a time, i.e., either one or both channels of this sensor may be faulty at a time.
- Multiple components may be faulty at a time.
- Only one of the above two conditions occurs at a time.

The FDI logic indicates one of the following conditions: 1) sensor fault detected, 2) sensor fault isolated, 3) component fault detected, and 4) anomaly detected. Each of these conditions is discussed in the following section, and a flow chart of the FDI logic is given in the Appendix.

Sensor Fault Detection. The FDI logic indicates that "a sensor fault is detected" when one of the dual-channel residuals in Eq. (5) exceeds the threshold τ_{DR}^{i}, but all other signals remain below their corresponding thresholds. This scenario happens depending on the fault magnitude and the threshold values. In this condition, the identity of a faulty dual-channel sensor is determined, but the identity of its failed channel cannot be determined.

Sensor Fault Isolation. The FDI logic indicates that "a sensor fault is isolated" when the dual-channel residual of a particular sensor exceeds the threshold τ_{DR}^{i}, and also at least one of the following conditions is met:

- This sensor's analytical residual exceeds the threshold τ_{AR}^{i} in one channel. The channel in which the threshold violation occurs is identified as the failed one.
- At least one of the estimation residuals exceeds the threshold τ_{ER}^{i} in one channel. The channel in which the threshold violation occurs is identified as the failed one. When multiple estimation residuals exceed the threshold, all threshold violations must occur in the same channel.

The first bullet is the same logic used in the baseline system. The second bullet is specific to the enhanced system which utilizes the HKF algorithm. When one of the above two conditions occurs in both channels instead of only one or when the above two conditions occur in different channels, it is considered that both channels of a particular sensor are faulty.

Component Fault Detection. The FDI logic indicates that "a component fault is detected" when all dual-channel residuals remain below the threshold τ_{DR}^{i}, and also the following condition is met:

- The CFS exceeds the threshold τ_{CFS} in at least one channel.

This is the same logic used by the baseline system. The HKF algorithm makes no contribution in detecting a component fault. As mentioned earlier, the estimation performance of the HKF is corrupted in an unpredictable manner when the engine experiences any fault. As a result, the estimation residuals do not reveal whether the fault exists in a sensor or in a component. They simply reveal the existence of a fault in the engine. Therefore, the estimation residuals generated by the HKF are not used to detect a component fault.

It also should be noted that the enhanced system only indicates the existence of a component fault without identifying the specific faulty components. To determine the identity of faulty components, the measurements must be further processed through an algorithm, such as a bank of Kalman filters which was demonstrated in Ref. [7].

Anomaly Detection. The FDI logic indicates that "an anomaly is detected" when it determines that something is abnormal, but it is unable to classify the anomaly into one of the three categories previously listed. This occurs when all dual-channel residuals remain below the threshold τ_{DR}^{i}, and also at least one of the following conditions is met:

- At least one of the analytical residuals exceeds the threshold τ_{AR}^{i} in either channel.
- At least one of the estimation residuals exceeds the threshold τ_{ER}^{i} in either channel.

Again, the first bullet is the same logic used in the baseline system, whereas the second bullet is specific to the enhanced system. The analytical residuals and estimation residuals are affected by faults in sensors and components. Therefore, the specific identity of a fault cannot be inferred from the threshold violation of these signals. In this case, the FDI logic only indicates the existence of an anomaly.

INFLUENCE OF ENGINE HEALTH DEGRADATION

The on-line diagnostic system is designed to detect and isolate a fault as early as possible while avoiding false alarms. To achieve this objective over the lifetime of an aircraft engine, it is necessary to account for the influence of engine health degradation on engine behavior. Engine health degradation is a normal aging process that occurs in all aircraft engines as a result of usage, whereas a fault is an abnormal event that happens unexpectedly. Engine health degradation is not considered as a fault, but its influence on the engine performance grows over time. Since the off-nominal engine behavior induced by health degradation is undistinguishable from the anomalous engine behavior induced by a fault, the on-line system eventually loses its diagnostic effectiveness if health degradation is not accounted for in the diagnostic process. An example of such loss of diagnostic effectiveness due to health degradation is discussed in Refs. [8,9] for the case of sensor fault diagnostics based on neural networks.

The health condition of an engine is defined by the vector h in Eq. (1) which contains health parameters. The health condition at an instant of time can be expressed as follows:

$$h = h_k + \Delta h \tag{10}$$

The vector h_k represents health degradation. Since health degradation progresses gradually over the lifetime of an engine, h_k is treated as a constant vector in the time scale at which the on-line system operates (i.e., real-time operation). The subscript k indicates the time index of a much longer time scale at which the change in health degradation takes place (i.e., k may increment once every few flights or few days). The vector Δh represents a component fault that can occur abruptly at any instant of time. The on-line diagnostic system aims to detect this component fault when it happens. If there is no component fault, health degradation defines the health condition of the engine at a given instant.

As discussed earlier, the NOBEM in Eq. (3) operates at a specific health condition (e.g., nominal health condition) defined by the vector h_{NOBEM}, and this health condition is called the health baseline. As long as the health baseline and the true health condition of the real engine are in close proximity, the NOBEM accurately represents the real engine's performance. As the engine continues to degrade, the difference between the true health condition and the health baseline increases. With such an increase of health condition mismatch, the NOBEM becomes a poor representation of the real engine and consequently corrupts the diagnostic capability of the on-line system. To address this problem, the NOBEM must be adjusted or updated periodically so that it can operate in the vicinity of the true health condition of the real engine.

The update process for the NOBEM is completed by setting the health baseline as follows:

$$h_{NOBEM} = \hat{h}_k \tag{11}$$

The vector $\hat{h}_k$ represents the estimate of health degradation h_k. As demonstrated in Ref. [10], health degradation is estimated by a trend monitoring algorithm periodically over the course of the engine's life, and it is assumed that this health estimate is provided to the on-line system. This update process through Eq. (11) also completes the necessary step for updating the HKF; it is not needed to update the linear component of the HKF (A, C, K in Eq. 4). Therefore, the NOBEM and the HKF are updated in a relatively simple manner, and this simplicity is a major advantage of utilizing the NOBEM, instead of the LOBEM. As discussed in Ref. [5], in order to update the LOBEM to a new health baseline, the piecewise linear models must be re-generated at the new health condition. Such complexity can raise a number of practical issues in utilizing the LOBEM.

The periodic update of the health baseline is critical to maintaining the enhanced system's diagnostic effectiveness over the lifetime of an engine. Through this update, the influence of health degradation on analytical residuals, CFS, and estimation residuals is kept to a minimum. The significance of this update was demonstrated in Ref. [10]. The dual-channel residuals are the only signals that are not affected by health degradation.

APPLICATION OF THE ENHANCED ON-LINE DIAGNOSTIC METHODOLOGY

The enhanced on-line diagnostic system requires a nonlinear engine model that can be executed in real time. In this section, a description of an aircraft engine model is given first. This engine model is used as the NOBEM of the enhanced system. The same engine model is also used to represent a real engine in the evaluation study presented later. Then, a description of the HKF is given, followed by a discussion of selecting the threshold values used by the FDI logic.

Engine Model

The engine model used in this paper is a nonlinear simulation of an advanced high-bypass turbofan engine, a typical power plant for a large commercial aircraft. This engine model has been constructed as a component-level model, which consists of the major components of an aircraft engine. The engine model captures highly complex engine physics while being designed to run in real time. Engine performance deviations from the nominal health condition are modeled by adjustments to efficiency and flow capacity scalars of the following five components: fan (FAN), booster (BST), high-pressure compressor (HPC), high-pressure turbine (HPT), and low-pressure turbine (LPT). There are a total of 10 adjustments that are called health parameters. The engine state variables, health parameters, actuator variables, and environmental parameters are shown in Table 1.

There are a total of 11 measured parameters (y and z) that are available to the digital control unit of this engine. Table 2 shows seven measured parameters (y) along with their standard deviations given in percent of steady-state values at the ground maximum power condition. These parameters are measured by dual-channel sensors with channels A and B. In this paper, the same statistical characteristics are used for both channels. The control action and diagnostics are based on those sensed variables. Table 3 shows four additional measured parameters (z) along with their standard deviations given in their actual engineering units. These four parameters indicate the ambient and engine inlet conditions, and they are used to operate the enhanced on-line diagnostic system over the flight envelope. Faults in these parameters are not considered in this paper.

The nonlinear engine model is used in the subsequent sections to represent a real engine in Eq. (1). The engine operates at given health conditions, and its flight condition is specified by the three environmental parameters listed in Table 1. This engine operates in closed loop with a control system described in Ref. [6]. In the current control architecture, the power lever angle (PLA) is converted to desired corrected fan speed (an indicator of thrust). The control system adjusts actuation variables to cause the corrected measured fan speed to match the desired value. The closed-loop system runs at the frequency of 50 Hz.

The nonlinear engine model is also used as the NOBEM. The NOBEM operates at the flight condition defined by the three measured parameters: T_{amb}, P_{amb}, and T2. From these measurements, the NOBEM calculates altitude, Mach number, and temperature deviation from the standard day condition. The NOBEM receives the three control commands generated by the control system.

In the current study, the same engine model is used to represent a real engine and the NOBEM. Typically, there will be a mismatch between the real engine and its mathematical representation due to unmodeled and incorrectly modeled physical phenomena. Such a mismatch can be a cause of false alarms. To account for the influence that the mismatch may have on the diagnostic system, the health condition mismatch between the engine and the NOBEM is utilized to set the threshold levels. The health condition mismatch captures in some degree the mismatch that exists in the real environment.

TABLE 1. ENGINE MODEL VARIABLES

State Variables	XNL, XNH, TMHS23, TMHS3 TMHSBL, TMHSBC, TMHS41 TMHS42, TMHS5
Health Parameters	FAN efficiency, FAN flow capacity BST efficiency, BST flow capacity HPC efficiency, HPC flow capacity HPT efficiency, HPT flow capacity LPT efficiency, LPT flow capacity
Actuators	WF36, VBV, VSV
Environmental Parameters	Altitude, Mach Number, Ambient Temperature

TABLE 2. STANDARD DEVIATIONS OF CONTROLS AND DIAGNOSTICS SENSORS (σ IN % OF STEADY-STATE VALUES AT GROUND MAXIMUM POWER CONDITION)

Sensors (y)	σ (%)
XN12	0.25
XN25	0.25
P25	0.50
T25	0.75
PS3	0.50
T3	0.75
T49	0.75

TABLE 3. STANDARD DEVIATIONS OF AMBIENT AND ENGINE INLET SENSORS (σ IN ACTUAL UNITS)

Sensors (z)	σ
T_{amb}	5.0º F
P_{amb}	0.1 psi
T2	5.0º F
P2	0.1 psi

Hybrid Kalman Filter Design

The HKF is composed of the NOBEM and the linear component (A, C, K in Eq. 4). The NOBEM operates as described in the previous section. The NOBEM is the core of the enhanced system since it functions not only as the analytical third channel but also as part of the HKF algorithm. The linear component, which is integrated with the NOBEM in the HKF structure, is derived off-line from the NOBEM through the following steps. First, the NOBEM is linearized at specific operating conditions. At each linearized point, a Kalman gain matrix K is computed based on the matrix pair [A, C]. Then, the piecewise linear matrices are saved in table lookup form. As the real engine moves from one operating condition to another, the piecewise linear matrices are interpolated based on a scheduling parameter.

The same HKF design that appeared in Refs. [6,11] is used in this paper. The linear component was generated by linearizing the NOBEM along the steady-state power setting line at a cruise flight condition. During the linearization, the health baseline was set to the nominal health condition. For the interpolation of the piecewise linear matrices, the HKF's estimate of corrected fan speed is used as the scheduling parameter. When the HKF was implemented in a simulation environment, it was discretized to run at the frequency of 50 Hz. The parameters used by the HKF are corrected based on the engine inlet condition T2 and P2 [12].

Selection of Threshold Values

In the enhanced on-line diagnostic system, various signals are constructed based on the triplex channels ($y_{\mathrm{A}}, y_{\mathrm{B}}, y_{NOBEM}$) and the HKF estimates ($\hat{y}_{\mathrm{A}}, \hat{y}_{\mathrm{B}}$), and they are compared against the thresholds. Since the enhanced system classifies the root cause of the problem based on the threshold violations occurring from the engine, the selection of threshold values is an important task in order to achieve the desired diagnostic performance.

There are many thresholds that need be determined for the enhanced system. First, the threshold τ^i_{DR} for the dual-channel residual in Eq. (5) must be determined for each of the *m* sensors. Similarly, the threshold τ^i_{AR} for the analytical residual in Eq. (6) must be determined for each of the *m* sensors. The same threshold value is used for both channels of each sensor. Furthermore, the threshold τ_{CFS} for CFS in Eq. (7) must be determined, and the same threshold value is used for both channels. The total number of thresholds mentioned so far is 2*m*+1, and these thresholds are also used by the baseline system [5]. For comparison purposes, the same threshold values used by the baseline system are used by the enhanced system.

The enhanced system utilizes additional signals that are constructed from the HKF's estimate. For the estimation residual in Eq. (9), the threshold τ^i_{ER} must be determined for each of the *m* sensors. The same threshold value is used for both channels of each sensor. Therefore, the total number of thresholds for the HKF-based signals is *m*. The threshold values are determined through Monte-Carlo simulation; the engine and the HKF are run with different levels of health condition mismatch between them. This mismatch causes the estimation residuals to vary over some range. The thresholds are set to values higher than the maximum values that the estimation residuals can reach due to the mismatch used in the Monte-Carlo simulation. The process of determining the threshold values is discussed in detail in Refs. [6,11].

The total number of thresholds for the enhanced system is 3*m*+1. In the current setup, all signals (dual-channel residuals, analytical residuals, CFS, and estimation residuals) are processed by a low-pass filter with a cutoff frequency of 1.0 rad/sec (0.16 Hz) and then compared against the thresholds. A threshold violation is declared when any of the signals persistently exceeds its corresponding threshold. For this study, a threshold violation is declared when a threshold is exceeded 25 consecutive time steps (0.5 sec). This persistency test is carried out to ensure the existence of a fault. Based on the threshold violations occurring from the engine, the FDI logic determines the root cause of the anomaly. The low-pass filter design and persistency test are adjusted based on the engineering judgment of the designer. The performance of the diagnostic system will vary with those design factors.

PERFORMANCE EVALUATION

In this section, the performance of the enhanced system is evaluated in the same way the baseline system was evaluated in Ref. [5]. The evaluation is conducted in a simulation environment using faults in sensors and components. The simulation setup for the enhanced system is shown in Fig. 2. The nonlinear engine model is used to represent the real engine. Since accommodation of sensor faults is beyond the scope of this paper, the measurements on channel A are used as feedback inputs to the control system regardless of fault existence. Sensor faults are injected into channels A and B individually to investigate the effect of control action.

The enhanced system is evaluated at a cruise condition, and the threshold values at this operating point are shown in Table 4.[‡] It should be noted that the threshold values for the estimation residuals are relatively small. This is due to the fact that the Kalman filter, in general, accurately estimates the measured parameters even in the presence of uncertainty; the Kalman filter tends to tune its state estimate in order to maintain its output estimate in good agreement with the measured parameters.

With the threshold values in Table 4, the enhanced system should possess a level of robustness similar to that of the baseline system. This aspect is investigated in the following section using engine health degradation as uncertainty that can cause false alarms.

TABLE 4. THRESHOLD VALUES AT CRUISE CONDITION

Sensors	τ_{DR} (σ)	τ_{AR} (σ)	τ_{ER} (σ)
XN12	± 2.0	± 3.6	± 0.4
XN25	± 2.0	± 5.0	± 0.7
P25	± 2.0	± 1.5	± 0.9
T25	± 2.0	± 1.4	± 0.7
PS3	± 2.0	± 1.7	± 0.8
T3	± 2.0	± 1.6	± 0.6
T49	± 2.0	± 1.6	± 0.7

$\tau_{CFS} = 1.2$

[‡] For full flight envelope evaluation, different threshold values should be used at different operating points, and the adaptive threshold approach discussed in Ref. [6] could be used during transient operation.

Robustness to Engine Health Degradation

The enhanced system has been developed with some degree of robustness to uncertainty that exists in the real application environment. Such robustness, however, is not at the level that can prevent the enhanced system from diagnosing health degradation as a fault. In this section, it is determined how much the engine can degrade before the enhanced system starts indicating the existence of a fault.

In this study, the health baseline of the NOBEM is set to the nominal health condition, while the engine degrades gradually over its lifetime along a degradation profile as discussed in Ref. [10]. A degradation profile defines the health condition h_k in Eq. (10) at the k^{th} sample point which may increment once every few flights or few days. The engine fully deteriorates at the 300^{th} sample point.

For the health degradation profile used in Ref. [5], the enhanced system indicated the existence of a component fault when the health condition of the engine reached the 38^{th} sample point of the degradation profile. For the baseline system, it was the 37^{th} sample point at which the engine's health degradation was detected as a component fault. The level of health degradation at this point is far from the condition where a maintenance action is necessary. Thus, the diagnostic result, if trusted, can lead to an unnecessary maintenance action or inspection. To avoid such an undesirable scenario, the health baseline of the NOBEM must be periodically updated as shown in Eq. (11).

The above study was further continued using different degradation profiles in order to compare the robustness of the enhanced system to that of the baseline system. For each degradation profile tested, the enhanced system indicated the existence of a component fault or an anomaly at the same or similar sample point as the baseline system did. This means that the two systems possess a similar level robustness to health degradation. The robustness to health degradation or other uncertainties can be adjusted by modifying the threshold values. The thresholds for the enhanced system have been set so that the robustness of the enhanced system is similar to that of the baseline system. With this setup, fault detection and isolation capabilities of the two systems can be compared in a fair manner.

Sensor Fault Diagnostics

The capability to detect and isolate a biased sensor is evaluated in this section. A bias is injected into channel A or B of a single sensor at a time. The health condition of the engine and the health baseline of the NOBEM are set to the nominal health. In the presence of a sensor bias, the closed-loop system is trimmed at a cruise operating condition. Then, the simulation in Fig. 2 is run at steady-state for 100 seconds. When any of the signals (dual-channel residuals, analytical residuals, CFS, and estimation residuals) exceeds a threshold for 25 consecutive time steps, a threshold violation is declared. Based on the threshold violations occurring from the engine, the FDI logic determines the root cause.

Table 5 shows the sensor fault diagnostic result when a bias is injected into channel A (closed-loop configuration). The Anomaly Detection column shows the level of bias at which the enhanced system detects the existence of an anomaly. At this point, the nature of the anomaly cannot be determined; the anomaly could be a sensor or a component fault. The Sensor Fault Detection column shows the level of bias at which the enhanced system detects a faulty dual-channel sensor. At this point, the identity of the faulty sensor is determined, but the identity of the faulty channel cannot be determined. The Sensor Fault Isolation column shows the level of bias at which the enhanced system identifies the faulty channel of a faulty sensor.

It can be seen in Table 5 that the sensor fault detection is achieved at the bias magnitude of 1.8σ across all sensors. The same result was obtained for the baseline system. This is due the fact that the threshold for dual-channel residuals is set to the same value for all sensors (Table 4). The enhanced system outperforms the baseline system in anomaly detection; it detects an anomaly when a sensor bias of smaller magnitude exists. While the baseline system uses the analytical residuals to detect an anomaly, the enhanced system uses the estimation residuals in addition to the analytical residuals. The estimation residuals which are generated by the HKF algorithm help to detect an anomaly of smaller magnitude. These signals also help the enhanced system to isolate a fault in the XN12 and XN25 sensors. For the rest of the sensors, fault isolation is achieved at the same level that the baseline system achieved.

When a bias was injected into channel B (open-loop configuration), the result was very similar to the result shown in Table 5 (closed-loop configuration). Thus, control actions appear to have minimal influence on the enhanced system's performance at the cruise condition considered in this study. This was not the case for the baseline system; the baseline system performed differently depending on the channel being biased. When a bias exists in a feedback sensor, the control system adjusts its commands. As a result, the relationship between engine parameters changes after the occurrence of a fault. This change in relationship is captured by the NOBEM

TABLE 5. SENSOR BIAS DIAGNOSTIC RESULTS

	Anomaly Detection (σ)	Sensor Fault Detection (σ)	Sensor Fault Isolation (σ)
XN12	--- / ---	1.8 / -1.8	2.4 / -2.3
XN25	--- / ---	1.8 / -1.8	3.2 / -2.9
P25	0.8 / -0.8	1.8 / -1.8	1.8 / -1.8
T25	1.2 / -1.3	1.8 / -1.8	1.8 / -1.8
PS3	1.1 / -1.2	1.8 / -1.8	1.8 / -1.8
T3	1.2 / -1.2	1.8 / -1.8	1.8 / -1.8
T49	1.4 / -1.5	1.8 / -1.8	1.8 / -1.8

but not by the LOBEM. Therefore, the enhanced system is able to maintain its diagnostic performance regardless of control actions.

Component Fault Detection

The capability to detect component faults is evaluated in this section. The health condition of the engine and the health baseline of the NOBEM are set to the nominal health. A component fault is represented by an abrupt shift in a health parameter, and it results in transient operation of the closed-loop system until the engine settles to new trim point. After the injection of a component fault, the engine is run for 100 seconds during which a diagnostic result is generated continuously by the enhanced system. Because of the transient operation, the enhanced system may indicate the existence of an anomaly for a certain period and then indicate the existence of a component fault. During this simulation run, if the enhanced system indicates the existence of a component fault at least once, it is considered that the component fault is detected. If the enhanced system does not indicate the existence of a component fault but indicates the existence of an anomaly at least once, it is considered that an anomaly is detected. If none of the above occurs (i.e., the enhanced system indicates that a fault does not exist), it is considered that the enhanced system misses the component fault.

Table 6 shows the component fault scenarios used in this evaluation study. The same scenarios were used in the evaluation of the baseline system. Fault scenarios 1 through 5 represent single-component fault cases while fault scenarios 6 through 9 represent multiple-component fault cases. For each fault scenario, four levels of component damage are considered for evaluation. At each damage level, the efficiency and flow capacity of the faulty component(s) are independently shifted through a random process within the range shown in the table. This range is considered to encompass reasonable failure scenarios. All component shifts are made in the negative direction, except for HPT and LPT flow capacities which are shifted in the positive direction. At each damage level of each fault scenario, 100 fault cases are generated by randomly shifting health parameters. Thus, a total of 3600 component fault cases are used in the evaluation. These component fault cases are identical to those used in the evaluation of the baseline system.

Table 7 shows the result of the component fault diagnostics. There are three possible diagnostic results that the enhanced system may produce: 1) component fault detection, 2) anomaly detection, and 3) missed detection. In each cell of the table, the number of component fault cases that resulted in each of the three possible conditions appears in the aforementioned order. The best result that the enhanced system can achieve is 100/0/0. The result 0/100/0 indicates that the enhanced system detects the existence of an anomaly but cannot determine the nature of the anomaly. The result 0/0/100 indicates that the enhanced system completely misses the component faults.

TABLE 6. COMPONENT FAULT SCENARIOS

Fault Scenario	Faulty Components
1	FAN
2	BST
3	HPC
4	HPT
5	LPT
6	FAN & BST
7	BST & HPC
8	FAN &BST & HPC
9	HPT & LPT

Damage Level	Range of Fault Magnitude
1	[1%, 2%]
2	[2%, 3%]
3	[3%, 4%]
4	[4%, 5%]

The result in Table 7 shows that the enhanced system is able to detect the fault in HPC, HPT, and LPT. It has some difficulty in detecting BST faults when the fault level is 2 or below. The enhanced system encounters the most difficulty in detecting FAN faults. The same tendency was exhibited by the baseline system. As discussed in Ref. [6], this is due to the fact that the measurement shifts induced by FAN faults are difficult to observe through the sensor set used in this study.

The enhanced system indicates the existence of a component fault in 2374 cases out of 3600 component fault cases (65.9%), whereas the baseline system detected the component faults in 2495 cases (69.3%). In both the enhanced and baseline systems, the CFS is used to detect a component fault. When the engine experiences a component fault, the relationship between engine variables changes and becomes “off-design” with respect to the original relationship before the incident. This change in the relationship is captured by the NOBEM but not by the LOBEM. In the baseline system, the CFS increases due to a component fault and also due to the off-design relationship induced by the component fault. Therefore, an increase in CFS is much more prominent in the baseline system than in the enhanced system, resulting in a better component fault detection capability for the baseline system.

The enhanced system, however, outperforms in detecting engine’s anomalous behavior; the enhanced system indicates the existence of an anomaly in 421 cases whereas the baseline system did so in 104 cases. This means that the enhanced system misses a lesser number of component faults. The missed detection rates for the enhanced and baseline systems are 22.4% (805 cases out of 3600) and 27.8% (1001 cases out of 3600), respectively. This difference is attributed to the estimation residuals generated by the HKF algorithm. The

TABLE 7. COMPONENT FAULT DIAGNOSTIC RESULT

Fault Scenario #	Faulty Components	Level 1	Level 2	Level 3	Level 4
1	FAN	0 / 0 / 100	0 / 0 / 100	0 / 8 / 92	24 / 27 / 49
2	BST	0 / 0 / 100	0 / 56 / 44	0 / 100 / 0	83 / 17 / 0
3	HPC	34 / 10 / 56	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
4	HPT	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
5	LPT	66 / 0 / 34	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
6	FAN/BST	0 / 0 / 100	0 / 21 / 79	0 / 99 / 1	86 / 14 / 0
7	BST/HPC	38 / 36 / 26	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
8	FAN/BST/HPC	43 / 33 / 24	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
9	HPT/LPT	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0

Each cell shows the number of component fault cases that resulted in the following three categories:
Component fault detection, anomaly detection, and missed detection

enhanced system uses the estimation residuals, in addition to the analytical residuals, to detect an anomaly. The estimation residuals generated by the HKF algorithm help to detect the engine's anomalous behavior induced by component faults more frequently than the baseline system does. Anomaly detection does not reveal the nature of the anomaly. However, by further investigating the data generated by on-line systems, the identity of the detected anomaly can be determined as discussed in Ref. [5].

DISCUSSION

The enhanced system is different from the baseline system in two respects. One is that the enhanced system utilizes the NOBEM while the baseline system utilizes the LOBEM. The other is that the enhanced system utilizes the HKF algorithm while no estimation algorithm is included in the baseline system. A significant benefit of utilizing the NOBEM instead of the LOBEM is that the NOBEM can be updated to a new health baseline through a much simpler process than that for the LOBEM. The benefit of utilizing the HKF algorithm, however, is not as obvious. Since the HKF algorithm adds complexity to the on-line diagnostic system, it should be making a contribution which justifies the cost of implementing the algorithm. To determine the benefit of the HKF algorithm, another diagnostic system, called a sub-enhanced system, was evaluated. The sub-enhanced system is identical to the enhanced system except that it does not utilize the HKF algorithm. From another perspective, the sub-enhanced system is identical to the baseline system except that it utilizes the NOBEM as the analytical third channel, instead of the LOBEM. Through the comparison of the sub-enhanced system's performance to that of the enhanced system, the contribution of the HKF algorithm can be determined.

The sub-enhanced system was evaluated in the same way the enhanced system was evaluated. Table 8 shows the sensor fault diagnostic result for the sub-enhanced system. A noticeable difference between the sub-enhanced and enhanced systems is in their capability to isolate a bias in the XN12 and XN25 sensors. In particular, a bias in the XN25 sensor must be quite large to be isolated by the sub-enhanced system. For the rest of the sensors, the enhanced system slightly outperforms the sub-enhanced system; the enhanced system detects sensor biases of smaller magnitude as anomalies.

Table 9 shows the component fault diagnostic result for the sub-enhanced system. Since both the sub-enhanced and enhanced systems use the CFS alone to detect component faults, they exhibit the identical success rate; component faults are detected in 2374 cases out of 3600 (65.9%). The main difference between the two systems is their capability to detect the engine's anomalous behavior. The sub-enhanced system indicates the existence of an anomaly in 145 cases, whereas the enhanced system does so in 421 cases. This difference translates to the missed detection rates of 30.0% for the sub-enhanced system and 22.4% for the enhanced system. Since the missed detection rate for the baseline system was 27.8%, the utilization of the NOBEM, instead of the LOBEM, as the analytical third channel worsens the fault detection capability.

TABLE 8. SENSOR BIAS DIAGNOSTIC RESULTS FOR SUB-ENHANCED SYSTEM

	Anomaly Detection (σ)	Sensor Fault Detection (σ)	Sensor Fault Isolation (σ)
XN12	--- / ---	1.8 / -1.8	3.3 / -3.4
XN25	--- / ---	1.8 / -1.8	5.0 / -5.0
P25	1.3 / -1.4	1.8 / -1.8	1.8 / -1.8
T25	1.2 / -1.3	1.8 / -1.8	1.8 / -1.8
PS3	1.5 / -1.6	1.8 / -1.8	1.8 / -1.8
T3	1.4 / -1.5	1.8 / -1.8	1.8 / -1.8
T49	1.4 / -1.5	1.8 / -1.8	1.8 / -1.8

TABLE 9. COMPONENT FAULT DIAGNOSTIC RESULT FOR SUB-ENHANCED SYSTEM

Fault Scenario #	Faulty Components	Level 1	Level 2	Level 3	Level 4
1	FAN	0 / 0 / 100	0 / 0 / 100	0 / 5 / 95	24 / 20 / 56
2	BST	0 / 0 / 100	0 / 0 / 100	0 / 38 / 62	83 / 17 / 0
3	HPC	34 / 10 / 56	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
4	HPT	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
5	LPT	66 / 0 / 34	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
6	FAN/BST	0 / 0 / 100	0 / 0 / 100	0 / 3 / 97	86 / 1 / 13
7	BST/HPC	38 / 27 / 35	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
8	FAN/BST/HPC	43 / 24 / 33	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0
9	HPT/LPT	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0	100 / 0 / 0

Each cell shows the number of component fault cases that resulted in the following three categories:
Component fault detection, anomaly detection, and missed detection

Such a disadvantage, however, is compensated through the utilization of the HKF algorithm in the enhanced system.

The difference in the diagnostic performance between the enhanced and sub-enhances systems is the contribution of the HKF algorithm. The comparison study reveals that the HKF algorithm does indeed provide improved performance.

CONCLUSION

An on-line diagnostic system which utilizes dual-channel sensor measurements was developed for the aircraft engine application. This system was referred to as the enhanced system because of its utilization of advanced technologies: the nonlinear on-board engine model (NOBEM) and the hybrid Kalman filter (HKF) algorithm. The performance of the enhanced system was evaluated using simulated faults in sensors and components, and its advantage over an existing baseline system was investigated. The enhanced system outperformed the baseline system in detecting anomalous engine behavior induced by sensor and component faults. It indicated the existence of an anomaly when sensor biases of relatively small magnitude existed. The enhanced system also indicated the existence of an anomaly more frequently than the baseline system when the engine experienced a component fault.

The enhanced system also has a practical advantage over the baseline system. In general, on-line diagnostic systems must be adjusted or updated as an aircraft engine degrades over its lifetime. Otherwise, the on-line systems eventually lose their diagnostic effectiveness since they are not able to discern the difference between off-nominal engine behavior induced by health degradation and anomalous engine behavior induced by faults. In order to update the baseline system, its linear on-board engine model (LOBEM) must be re-generated at the estimated health condition. On the other hand, the enhanced system is updated by feeding the estimated health degradation values into the NOBEM. This relatively simple update process is a major advantage of the enhanced system over the baseline system. Through this update, the diagnostic performance of the enhanced system is maintained over the lifetime of an aircraft engine.

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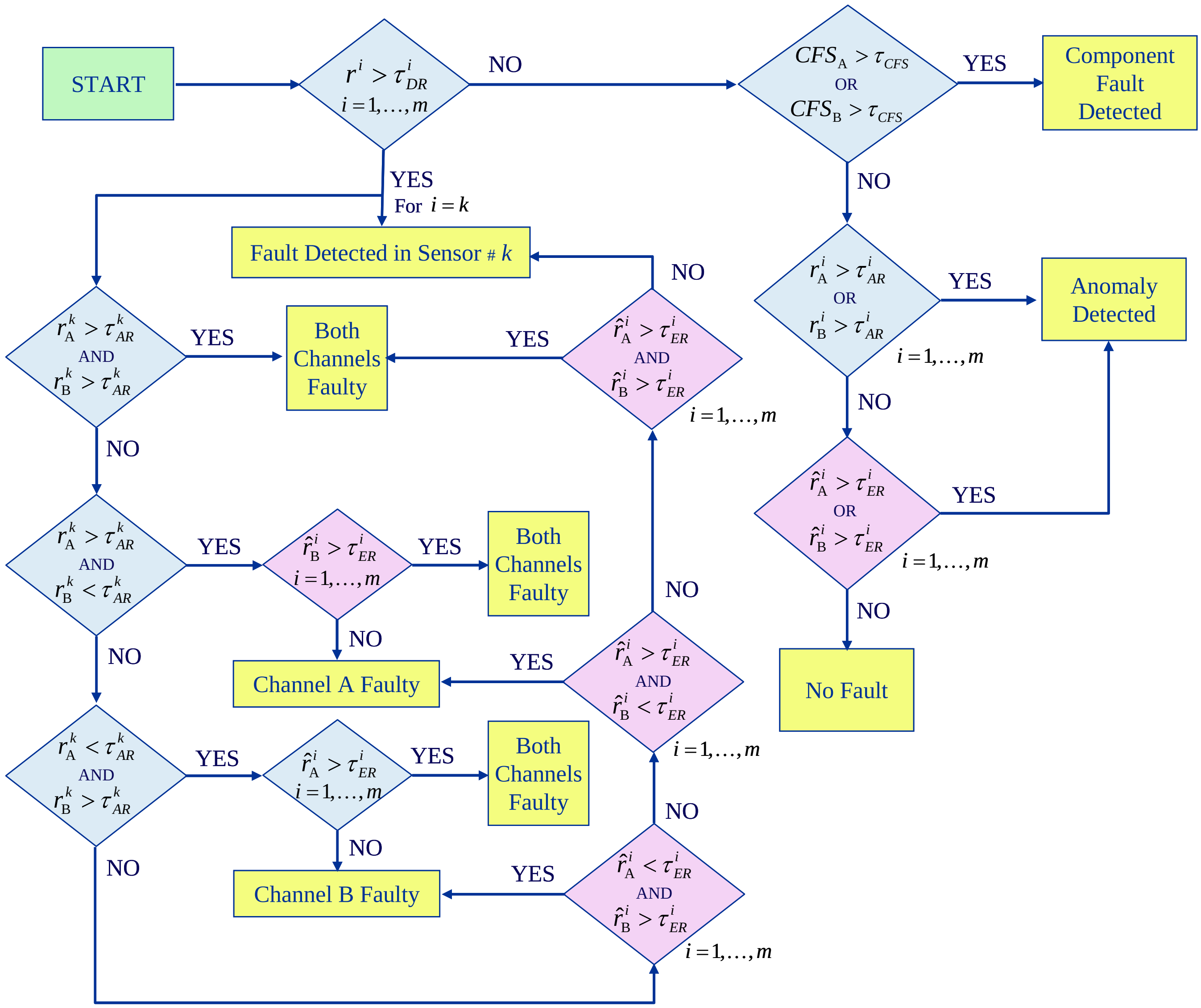
APPENDIX

FLOW CHART OF THE FAULT DETECTION AND ISOLATION LOGIC



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13. SUPPLEMENTARY NOTES

14. ABSTRACT
In this paper, an enhanced on-line diagnostic system which utilizes dual-channel sensor measurements is developed for the aircraft engine application. The enhanced system is composed of a nonlinear on-board engine model (NOBEM), the hybrid Kalman filter (HKF) algorithm, and fault detection and isolation (FDI) logic. The NOBEM provides the analytical third channel against which the dual-channel measurements are compared. The NOBEM is further utilized as part of the HKF algorithm which estimates measured engine parameters. Engine parameters obtained from the dual-channel measurements, the NOBEM, and the HKF are compared against each other. When the discrepancy among the signals exceeds a tolerance level, the FDI logic determines the cause of discrepancy. Through this approach, the enhanced system achieves the following objectives (1) anomaly detection, (d) component fault detection, and (3) sensor fault detection and isolation. The performance of the enhanced system is evaluated in a simulation environment using faults in sensors and components, and it is compared to an existing baseline system.

15. SUBJECT TERMS
Aircraft engine diagnostics; Fault detection and isolation; On-board engine model; FADEC; On-line diagnostics; Dual-channel sensors; On-board engine model; Kalman filter

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