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Application of Kalman Filters for the Fault Diagnoses of Aircraft Engine

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1. Introduction

Fault detection and isolation (FDI) logic plays a crucial role in enhancing the safety and reliability, and reducing the operating cost of aircraft propulsion systems. However, it is a challenging problem achieving the FDI task with high reliability. For this purpose, various approaches have been proposed in the literature.

In an on-line engine fault diagnoses, two tasks may use Kalman filter to carry out: 1) evaluation of on-line engine state variables to renew the on-board model; 2) diagnoses of on-line aircraft engine sensor/actuator fault. How to solve the above problems through application of Kalman filter is discussed in this paper.

A challenge in developing an on-line fault detection algorithm is making it adaptive to engine health degradation. If the algorithm has no adaptation capability, it will eventually lose its diagnostic effectiveness. To address this problem, the integration of on-line diagnostic algorithms was investigated. The Kalman filter estimates engine health condition over the course of engine's life. Then the on-board model could be re-constructed based on the estimated values of Kalman filter.

After all of the above, A Robust Kalman filter and a bank of Kalman filters are applied in fault detection and isolation (FDI) of sensor and actuator for aircraft gas turbine engine. A bank of Kalman filters are used to detect and isolate sensor fault, each of Kalman filter is designed based on a specific hypothesis for detecting a specific sensor fault. In the event that a fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors, from which a specific fault is isolated. When the Kalman filter is used, failures in the sensors and actuators affect the characteristics of the residual signals of the Kalman filter. While a Robust Kalman filter is used, the decision statistics changes regardless the faults in the sensors or in the actuators, because it is sensitive to sensor fault and insensitive to actuator fault.

W. C. Merrill, J. C. Delaat, and W. M. Bruton used a bank of Kalman filters for aircraft engine sensor FDI. This study successfully improved control loop tolerance to sensor failures, which were considered the most likely engine failures to happen under the harsh operating environment. In this study, actuator failure was not considered. In the study done by T. Kobayashi and D. Simon, a fault detection and isolation (FDI) system which utilizes a bank of Kalman filters is developed for aircraft engine sensor and actuator FDI in conjunction with the detection of component faults. The results indicate that the proposed

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FDI system is promising for reliable diagnostics of aircraft engine sensor and actuator. An analytical redundancy-based approach for detecting and isolating sensor, actuator, and component faults in complex dynamical systems, such as aircraft and spacecraft is developed by E. C. Larson, E.B. Jr. Parker, and B. R. Clark. This method has limited applications in practice. A Kalman filter was applied to aircraft sensor and actuator fault diagnosis by C. Hajiyev and F. Caliskan. Two different fault detection algorithms, namely multiple hypotheses testing and neural networks that analyze the sensor residuals generated with an extended Kalman filter (EKF) based on an un-faulted engine model were developed and implemented by R. Randal et al. These two algorithms have complementary performance, which is exploited in a fusion algorithm to enhance the overall detection & classification performance. An observer-based robust sensor fault detection approach was applied to a jet engine simulation by R. J. Patton and J. Chen. This method has limited applications in practice. A Kalman filter was applied for aircraft sensor and actuator fault diagnosis by C. Hajiyev and F. Caliskan. Those approach were based on the faults affected the mean of the Kalman filter innovation sequence. A sensor fault that shifted the mean of the innovation sequence could be detected and isolated. A Roubst Kalman filter was used to distinguish the sensor and actuator faults. But, this method could not used to isolate which actuator is faulty.

In general, in-flight diagnostic systems are designed at a nominal health, or non-degraded condition. This design condition becomes a reference health baseline for diagnostics. Any observed deviations in engine outputs from their reference condition values may indicate the presence of a fault. As the real engine degrades over time, in-flight diagnostic systems may lose their effectiveness. Engine health degradation is a normal aging process that occurs in all aircraft engines due to usage and therefore is not considered as a fault. However, similar to various faults, degradation causes the engine outputs to deviate from their reference condition values. When engine output deviations eventually exceed a certain level, the diagnostic system may misinterpret the health degradation as a fault and consequently generate a false alarm.

One approach to maintaining the effectiveness of in-flight diagnostic algorithms, when applied to degraded engines, is to periodically update or re-design the diagnostic algorithms based on the estimated amount of health degradation. Health degradation can be estimated by trend monitoring systems. Through the update based on the estimated health degradation, the health baseline of an in-flight diagnostic system can be shifted to the degraded engine, and thereby the system is able to effectively diagnose the presence of a fault.

The diagnosis approaches based on Kalman filter is the analysis of the residual signals. When the system operates normally, normalized residual signal in a Kalman filter is a Gaussian white noise with a zero mean and a unit covariance matrix. Faults change the system dynamics by causing surges of drifts of the state vector components, abnormal measurements, sudden shifts in the measurement sensor, and other difficulties such as decrease of instrument accuracy, an increase of background noise, reduction in actuator effectiveness etc., effect the characteristics of the normalized residual signals by changing its white noise nature, displacing its zero mean, and varying unit covariance matrix.

For linear dynamic system with white process and measurement noise, the Kalman filter is known to be an optimal estimator. Kalman filters are largely used in the jet engine community for condition monitoring purpose. At the same time Kalman filter are used in

the turbine engine for sensor fault diagnostics purpose. However this method can not or hardly distinguish the fault between sensor and actuator. A bank of Kalman filters and a robust Kalman filter are used to detect sensor and actuator faults. In addition, a bank of Kalman filters is used to detect which sensor is fault. Such technical are easy to implement in a real-time environment.

In the following sections of this paper, the problem setup for sensor fault diagnostics based on the engine health degradation. The deterioration can be estimated by one Kalman filter. Then the on-board model can be re-constructed based on the estimated values of Kalman filter. At last a bank of Kalman filters is applied in fault detection and isolation (FDI) of sensors for aircraft gas turbine engine. At the same time, we assumed that only one of the sensors will fail at a time, and just only one actuator. Hence, detection and isolation between different actuators is not considered. The mean of the residual signals which from sensor measurements and their estimated values applied to detect and isolate sensor failures. An effective approach previously discussed in literature is to distinguish the sensor and actuator fault during a linear engine simulation.

2. Engine model

The engine model being used for this research is the nonlinear simulation of an advanced military twin-spool turbofan engine. Engine performance deterioration is modeled by adjustments to efficiency or flow coefficient scalars of the following four components: Fan (FAN), Booster (BST), High-Pressure Turbine (HPT), and Low-Pressure Turbine (LPT). These scalars representing the component performance deterioration are the health parameters. The engine state variables, health parameters, actuator, and sensor used in the current research are shown in Table 1.

State variable	Health parameters	Actuators	Sensors
XNL	FAN efficiency	w_{FB}	XNL
XNH	BST efficiency	A_8	XNH
	HPT efficiency		P_{31}
	LPT efficiency		P_6
			T_{45c}

Table 1. State Variables, Health Parameters, Actuators, and Sensors of the Engine Model

The FDI (Fault detection and isolation) logic uses the Kalman filter approach in order to estimate the state variables, health parameters, and engine output values from a given set of sensor measurements and control commands. A linear model under consideration is represented by the following state-space equations:

$$\begin{aligned} \dot{x} &= Ax + Bu + Lh + w \\ y &= Cx + Du + Mh + v \end{aligned} \quad (1)$$

where the vectors x , h , and u represent the state variables, health parameters and control commands, respectively. y is sensor measurement vector, w and v are the process and sensor noise, respectively, they are both assumed to represent Gaussian white noise. Their covariance matrices:

$$\begin{aligned}
 E[w(k)] &= 0; E[v(k)] = 0 \\
 E[w(k+\tau)w^T(k)] &= Q\delta(k\tau) \\
 E[v(k+\tau)v^T(k)] &= R\delta(k\tau)
 \end{aligned}
 \tag{2}$$

3. The estimation of health degradation

As shown in Fig.1, the on-board model and tracking filter are important part in the model-based control and diagnostics logic. This part uses two sets of input signals; sensor measurements and actuator position. The degradation of the real engine can be tracked by one Kalman filter based on the input signals. After the estimation of the Kalman filter, the on-board model can be shifted to the vicinity of the degraded engine.

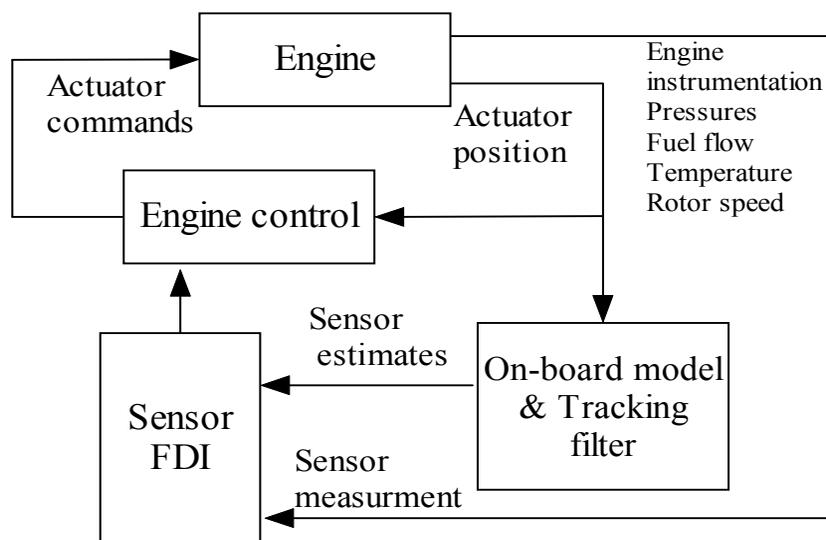


Fig. 1. Model-Based control and diagnostics logic

In the Kalman filter problem setup, the engine state vector is augmented with health parameters as follows:

$$\begin{aligned}
 \tilde{x} &= \tilde{A}\tilde{x} + \tilde{B}u + w \\
 y &= \tilde{C}\tilde{x} + Du + v
 \end{aligned}
 \tag{3}$$

where

$$\tilde{x} = \begin{bmatrix} x \\ h \end{bmatrix}, \tilde{A} = \begin{bmatrix} A & L \\ 0 & 0 \end{bmatrix}, \tilde{B} = \begin{bmatrix} B \\ 0 \end{bmatrix}, \tilde{C} = [C \quad M]$$

The estimated state vector \tilde{x}_e , the sensor measurements of y_e and the Kalman filter gain matrix can be found with the Kalman filter of the form:

$$\begin{aligned}
 \tilde{x}_e &= \tilde{A}\tilde{x}_e + \tilde{B}u + K(y - y_e) \\
 y_e &= \tilde{C}\tilde{x}_e + Du \\
 K &= P\tilde{C}^T R^{-1}
 \end{aligned}
 \tag{4}$$

where matrix P is the solution of the following steady-state Riccati equation:

$$\tilde{A}P + P\tilde{A}^T - P\tilde{C}^T R^{-1} \tilde{C}P + Q = 0 \quad (5)$$

4. Fault detection and isolation logic

When a fault occurs, the first step is to detect it as soon as possible. The approach used for model-based fault detection is composed of two steps as follow.

1. Generate residual signals from the sensor measurements and their Kalman filter estimated values.
2. Compare the residuals with thresholds to make fault detection detections.

System noise, measurement noise and modeling uncertainty are key factors that affect detection performance.

A propulsion system with fault detection and isolation logic is shown in Fig. 2. The Kalman filters use two sets of input signals; sensor measurements and control commands. Sensor measurements are corrupted by noise. The difference between them is simply defined as a fault. In this paper, the sensor and actuator failures are “soft failures”. Soft failure is defined as inconsistencies between true and measured sensor values that are relatively small in magnitude and thus difficult to detect by a simple range-checking approach.

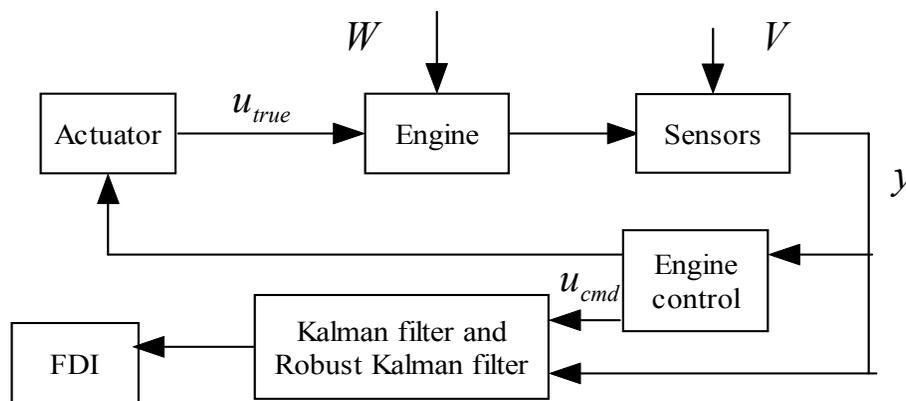


Fig. 2. Fault detection and isolation logic.

4.1 Fault detection algorithm for sensor

In this paper, an approach based on a model with a bank of Kalman filters is used for sensor fault detection and isolation. The sensor and actuator fault are “soft fault”. Soft fault is defined as inconsistencies between true and measured sensor values that are relatively small in magnitude and thus difficult to detect by a simple range-checking approach, whereas “hard” fault are larger in magnitude and thus more readily detectable.

Each Kalman filter is designed for a specific sensor fault. In the event that a fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors. By monitoring the residual of each filter, the specific fault that has occurred can be detected and isolated. The structure for sensor FDI using a bank of Kalman filters is shown in Fig. 3. The bank of Kalman filters contains 5 Kalman filters where 5 is the number of sensors being monitored. The control input and a subset of the sensor measurements are fed to each of the 5 Kalman filters. The sensor which is not used by a particular filter is the one being

mentioned by that filter for fault detection. For instance, the i^{th} filter uses the sensor subset that excludes the i^{th} sensor. Hence each Kalman filter estimates the augmented state vector using 4 sensors. Filter #1 uses all sensors except sensor #1, filter#2 uses all sensors except sensors#2, and so on. So, filter #1 is able to estimate the augmented state vector from fault-free sensor measurements, whereas the estimates of the remaining filters are distorted by the fault in sensor #1.

For each filter, the residual vector:

$$e^i = y_e^i - \hat{y}^i \quad (6)$$

When we got the residual, the weighted sum of squares residuals for each of the Kalman filters were calculated as:

$$WSSR^i = V^i (e^i)^T (\Sigma^i)^{-1} e^i \quad (7)$$

where $\Sigma^i = \text{diag}[\sigma^i]^2$. The vector σ is the noise standard deviation, and the additional weigh V^i is the weighting factor.

The statistical function as in (6) has χ^2 distribution consider the following two hypotheses :

H_0 : system operates normally,

H_1 : fault occurs in the system.

If a confidence probability a is given, the threshold can be found as in. The following gives the detection theory:

$$H_0 : WSSR^i \leq \lambda_i \quad (8)$$

$$H_1 : WSSR^i \geq \lambda_i$$

where λ_i is the threshold.

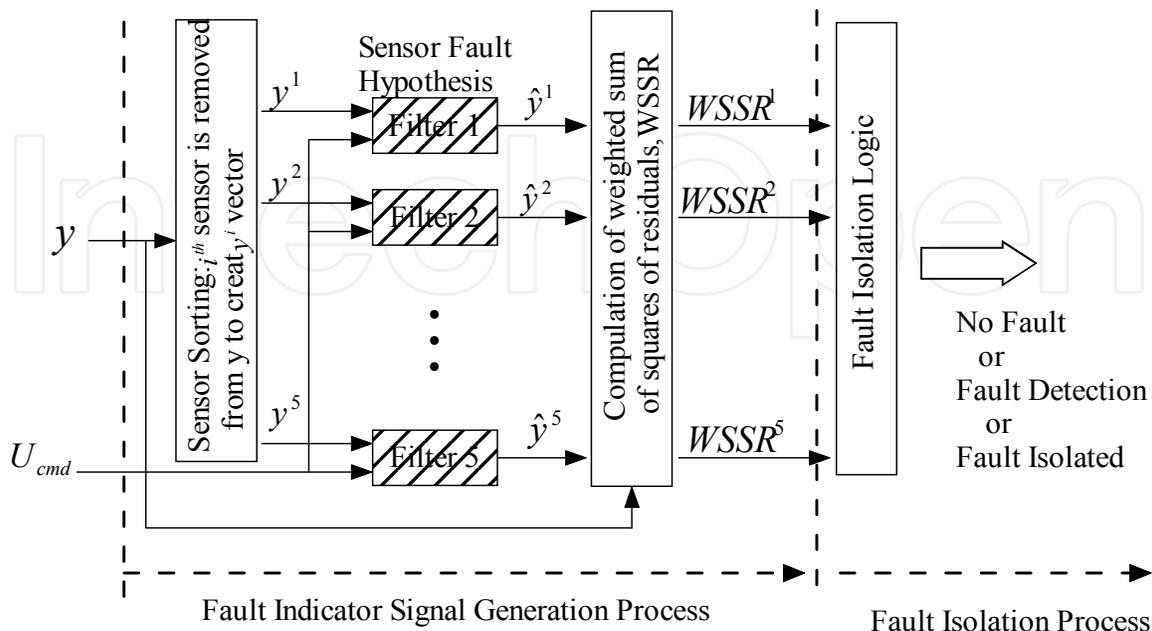


Fig. 3. Sensor fault detection isolation using bank of kalman filters

4.2 Fault detection algorithm for actuator

When a large discrepancy between commanded and true actuator positions does exist due to an actuator fault, it may cause significant errors. A Robust Kalman filter may be designed in order to isolate the sensor and actuator faults. A Kalman filter that satisfies the Dolye-Stein condition is referred to as Robust Kalman filter.

The Doly-Stein condition is expressed as follow.

$$K(I + H\phi K)^{-1} = B(H\phi B)^{-1} \quad (9)$$

Here K is Kalman filter gain, I is unit matrix, $\phi = (sI - A)^{-1}$, A is the system matrix in continuous time, B is the control distribution matrix in continuous time. H is the system measurement matrix. The Kalman filter satisfies the Doly-Stein condition called Robust Kalman filter.

For Kalman filters, $K = P_q C^T R^{-1}$,

With P_q defined by the Riccati equation

$$AP + PA^T - PC^T R^{-1} CP + Q_q = 0$$

As usual we take $Q = Q^T > 0$ and $R = R^T > 0$ with $(A, Q^{1/2})$ and (C, A) stable and observable, respectively. For Kalman filters, they represent given process noise and measurement noise intensities. They are treated more freely as design parameters which we can select to suit broader purposes. In particular, let

$$\begin{aligned} Q_q &= Q_0 + q^2 BVB^T \\ R &= R_0 \end{aligned} \quad (10)$$

Where Q_0 and R_0 are noise intensities matrix for the nominal plant, V is any positive definite symmetric matrix. With these selections, the observer gain for $q = 0$ corresponds to the nominal Kalman filter gain. However, as q approaches infinity, the gains are to satisfy as follow

$$\frac{K R K^T}{q^2} \rightarrow BVB^T \quad (11)$$

Solutions of (11) must necessarily be of the form: $\frac{1}{q} K \rightarrow BV^{1/2} (R^{1/2})^{-1}$

Where $V^{1/2}$ and $R^{1/2}$ denote square root of V and R , respectively, i.e.

$$(V^{1/2})^T V^{1/2} = V, \quad (R^{1/2})^T R^{1/2} = R.$$

Then a Kalman filter satisfying with (9) will be a Robust Kalman filter.

Because of the q factor, the Robust Kalman filter (RKF) is not an optimum filter. The value of the q must be chosen carefully, if q is chosen small the RKF is a Kalman filter and becomes sensitive to actuator failures, on the other hand, if it is chosen large, noise effects increase and unexpected result occur in the RKF.

5. Simulation results 1

The bank of Kalman filters was implemented on the nonlinear dynamical model of an aircraft engine with faults in sensors and the estimation of degraded engine as shown in Fig.4. The nonlinear dynamical model generates five sets of real signals at a given state. The sensor fault can be added on those signals directly. There are five sensors may be fault: High-pressure spool speed (XNH) sensor, Low- pressure spool speed (XNL) sensor, Booster exit pressure (P31) sensor, LPT exit pressure (P6) sensor, LPT inlet temperature (T45c) sensor.

Health degradation can be estimated by trend tracking filter. One Kalman filter was used to estimate the degradation of the real engine. If there were no degradation and no fault, the values of $WSSR1-5$ go to zero, as shown in Fig.5. However, if the HPT efficiency degrades by 2% and the on-board model does not shift to the vicinity of the degraded engine then the in-flight diagnostic systems may lose their effectiveness, as shown in Fig.6. The values of the $WSSR1-5$ grow rapidly and all of them exceed the threshold. It causes a false alarm. This is because shifts in measured engine outputs are induced not only by faults but also by engine degradation. Estimation of the degraded engine is critical to the fault detection and isolation system.

Fig.7 shows that Kalman filter can estimate the degradation accurately. After this the on-board model can be shifted to the vicinity of the degraded engine, and the in-flight diagnostic system may be effective. The Kalman filter estimates engine health condition over the course of engine's life. Based on the estimated health condition, the on-board model is updated. When we add the fault at 10 steps and stop at 200 steps in the LPT inlet temperature measurement sensor and at the same time HPT efficiency degrades by 2%, the in-flight diagnostic system can detect and isolate the fault. As shown in Fig.8, $WSSR1-WSSR4$ grow rapidly but the $WSSR5$ remains small. The results indicate that there is a fault in T45c sensor.

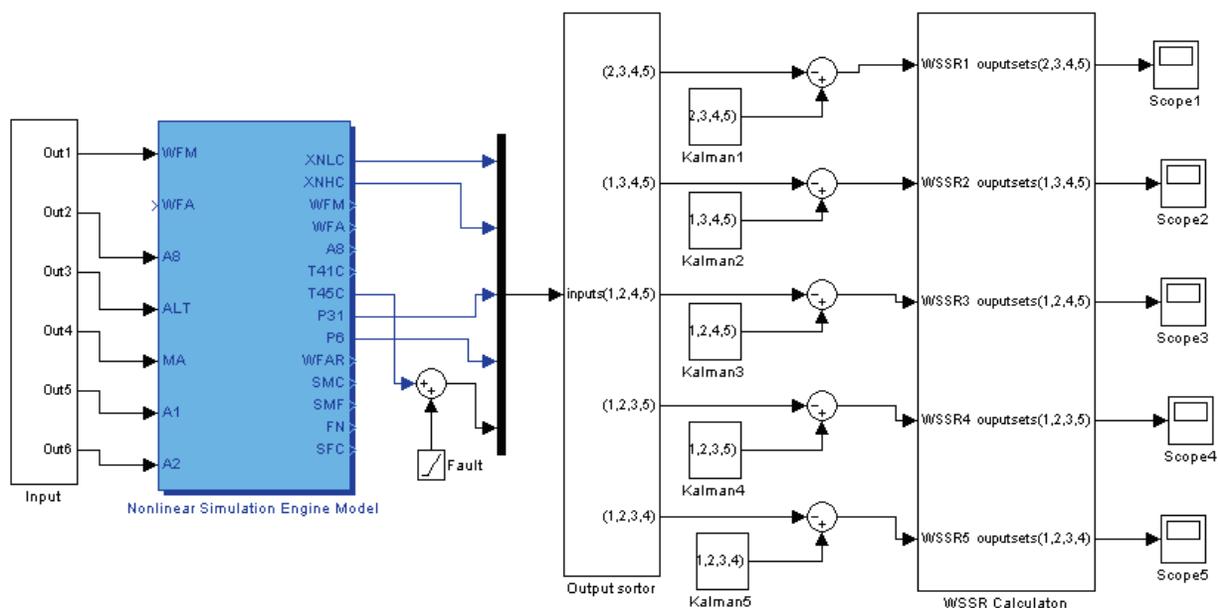


Fig. 4. The simulation architecture of Sensor fault detection isolation using bank of kalman filters

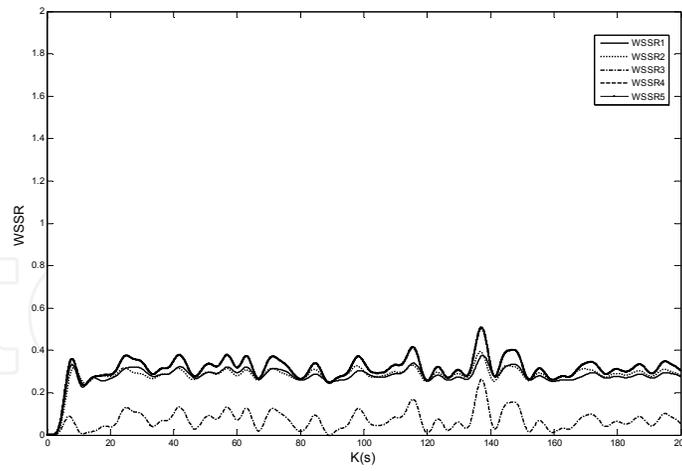


Fig. 5. The value of $WSSR1 - 5$ when no fault and no degradation exist

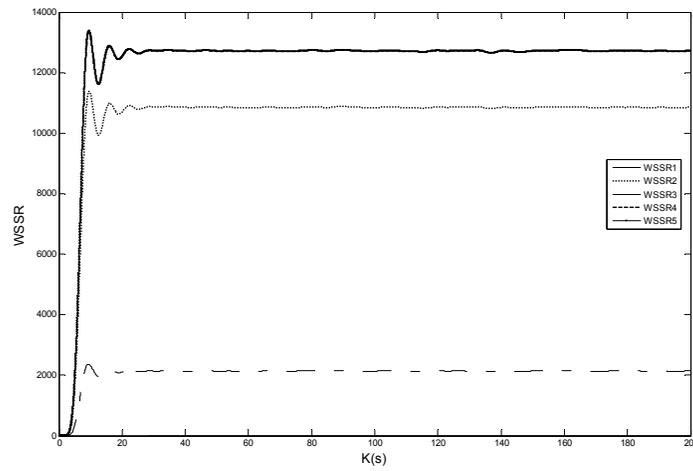


Fig. 6. The value of $WSSR1 - 5$ when the HPT efficiency degrades by 2% and no fault exist.

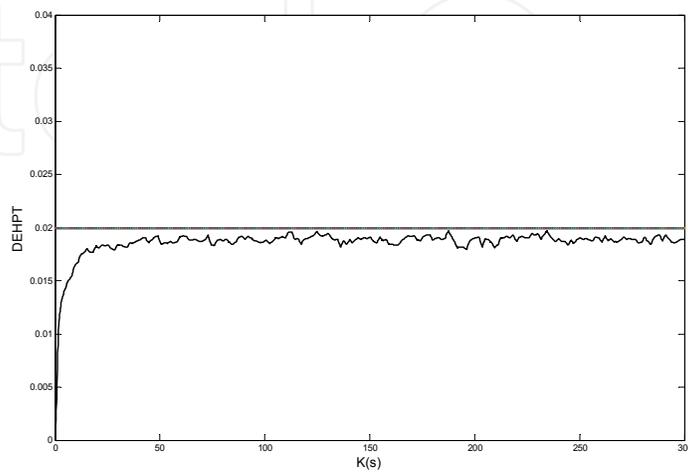


Fig. 7. The estimation of Kalman filter when the HPT efficiency degrades by 2%

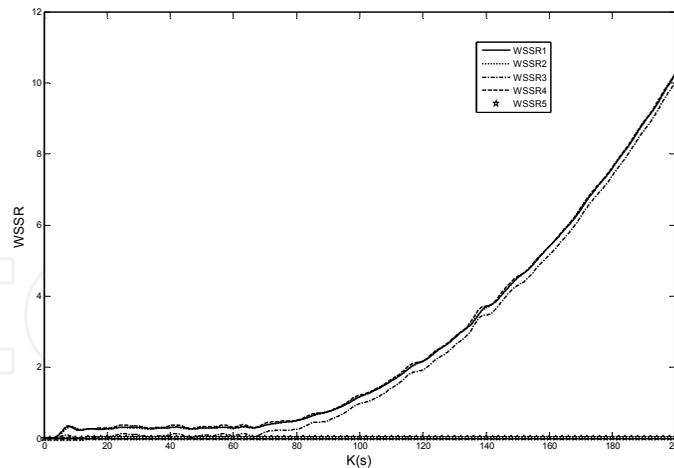


Fig. 8. The value of $WSSR$ -5 when there is a fault in T45c sensor and HPT efficiency degrades by 2%

5. Simulation results 2

The bank of Kalman filters and a Robust Kalman filter (RKF) were implemented on the nonlinear dynamical model of an aircraft with faults in sensors and actuator. The use of the RKF is very useful in the isolation of sensor and actuator as it is insensitive to the latter failures.

The RKF was used to isolate whether the detected fault is a sensor fault or an actuator fault, when we add the fault at 20 steps and stop at 200 steps in the low-pressure spool speed measurement sensor, the plot for the RKF estimate is shown in Fig. 10 and when a fault occurs in the sensor, $WSSR$ grows rapidly, and after 50 steps it exceeds the threshold. Then, when the fault is in the actuator, the plot for the RKF estimate is similarly shown in Fig. 9. The detection of actuator fault is not possible when the RKF is used. Hence, Fig. 9 and Fig.10 illustrate that the RKF can detect the sensor faults, and cannot detect the actuator faults. On the other hand, if we use Kalman filter (KF) to isolate sensor or actuator fault, the values of $WSSR$ are shown in Fig. 11 and Fig. 12. Whatever there is a fault in the sensor or in the actuator, the value of $WSSR$ exceeds the threshold. So, KF is sensitive to both sensor and actuator fault and RKF are not sensitive to actuator fault. In this case, RKF and KF should be united to distinguish sensor or actuator fault.

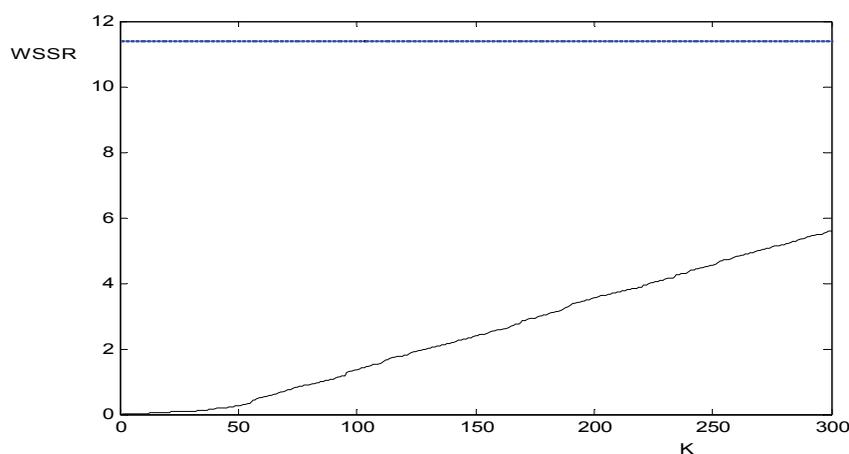


Fig. 9. Detection of actuator fault with RKF.

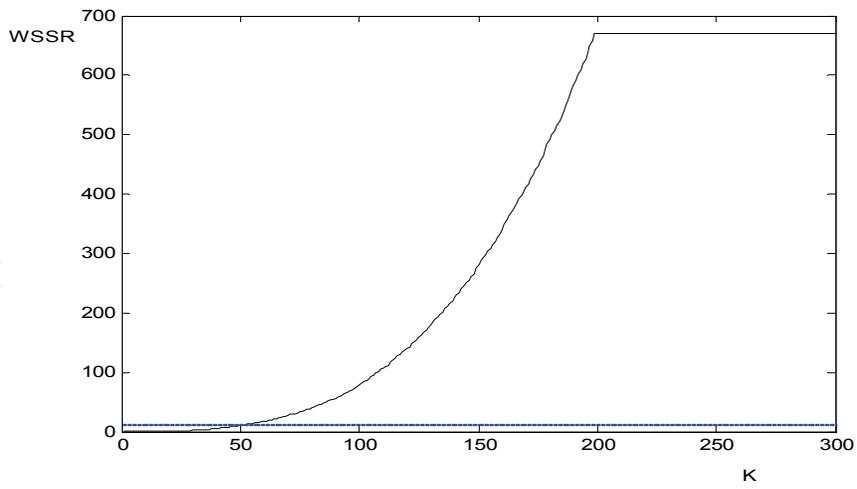


Fig. 10. Detection of sensor fault with RKF.

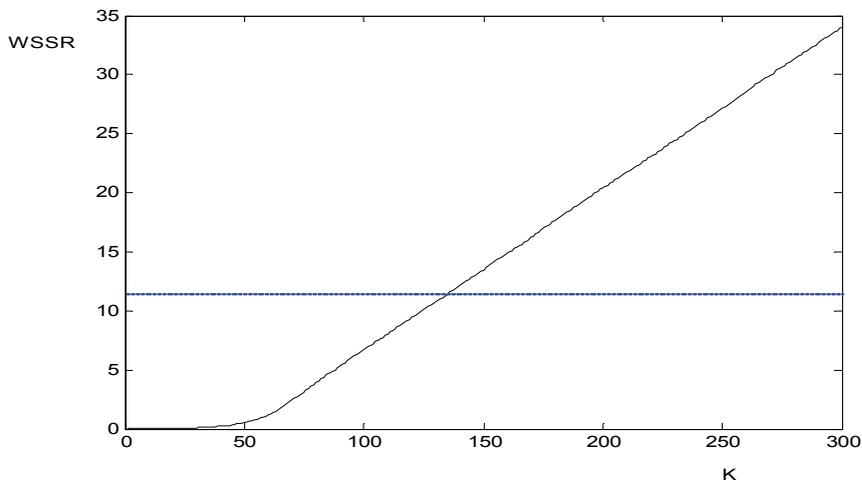


Fig. 11. Detection of actuator fault with KF.

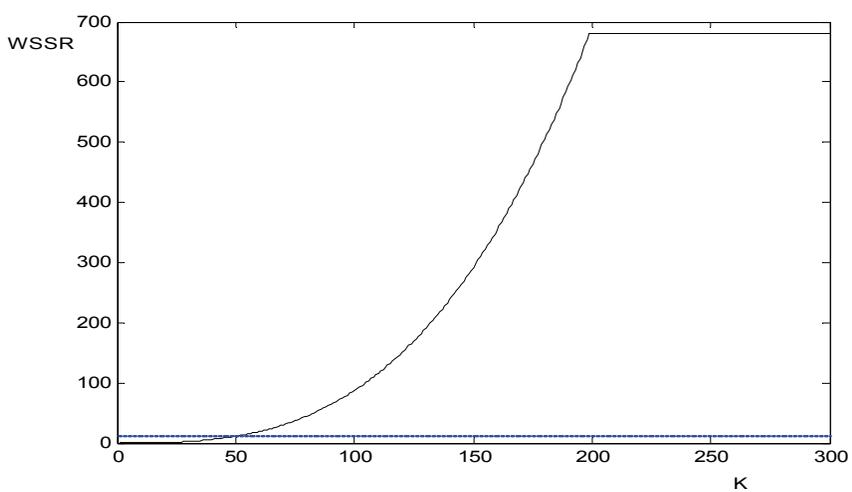


Fig. 12. Detection of sensor fault with KF.

In this paper, there are four sensors may be fault, i.e. low-pressure spool speed sensor, high-pressure spool speed sensor, high-pressure compressor exit pressure sensor, low-pressure turbine exit temperature sensor.

When the low-pressure spool speed measurement sensor is faulty, as above mentioned, all filters except for filter 1 will use a corrupted measurement. Filter 1 will be able to estimate the engine outputs from fault-free sensor measurements, whereas the output estimates of the remaining filters (i.e., filters 2, 3 and 4) will be distorted by the fault in sensor 1. The value of $WSSR$ and threshold for the 4 Kalman filters are shown in Fig. 13(a)-(d) respectively. The values of $WSSR$ for Kalman filter 2, 3 and 4 are also seen to be high whereas the value of $WSSR$ for the Kalman filter 1 goes to zero. In this way we can successfully detect which sensor is faulty. The low-pressure spool speed measurement sensor is not used by filter 1. Hence, this sensor is faulty.

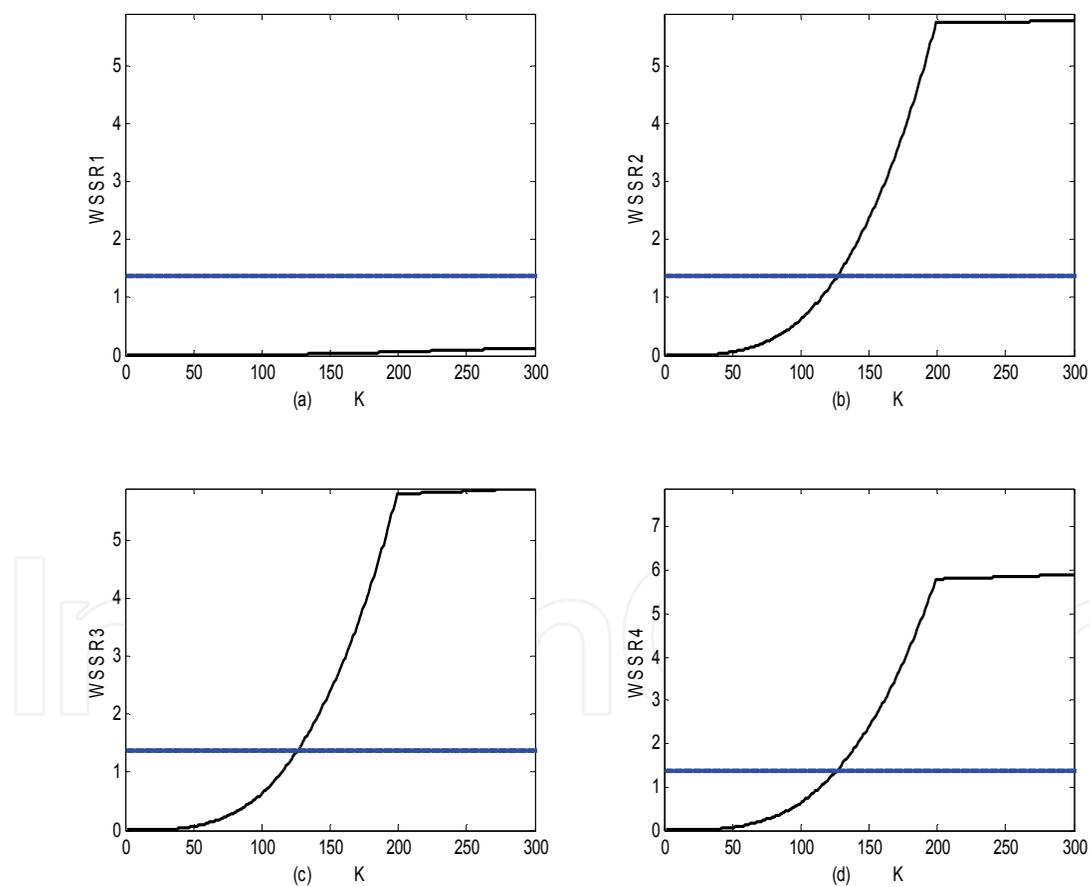


Fig. 13. Fault detection of low-pressure spool speed measurement sensor when a bank of Kalman filters is used.

6. Conclusion

In this paper, aircraft engine sensor fault diagnostics based on the estimation of health degradation was investigated. The tracking filter estimates engine health condition over the course of engine's life. Through this integration, the on-line fault detection algorithm is able to maintain its diagnostic effectiveness as the aircraft engine degrades over its lifetime.

The integrated approach was investigated in a simulation environment using a nonlinear engine model. The evaluation result showed that this approach is essential to maintain on-line fault detection capability in the presence of health degradation.

In this paper, an approach has been proposed to detect and isolate the aircraft sensor and actuator failures occurred in the aircraft control system. A bank of Kalman filters were used to detect and isolate sensor failures, each of Kalman filter is designed based on a specific hypothesis for detecting a specific sensor fault. In the event that a fault does occur, all filters except the one using the correct hypothesis will produce large estimation errors, from which a specific fault is isolated. Failures in the sensors and actuators affect the characteristics of the residual signals of the Kalman filter. When the Kalman filter is used, the decision statistics changes regardless the faults in the sensor or in the actuator. While a Robust Kalman filter is used, it is easy to distinguish the sensor and actuator fault.

7. References

- Lakshminarasimha, A. N., Boyce, M. P., and Meher-Homji, C. B. (1994). Modeling and Analysis of Gas Turbine Performance Deterioration. *Journal of Engineering for Gas Turbines and Power*, Vol.116, January 1994, pp46-52.
- Diakunchak, I. S. (1992). Performance Deterioration in Industrial Gas Turbines. *Journal of Engineering for Gas Turbines and Power*, Vol. 114, April 1992, pp. 161-168,.
- Tabakoff, W., Lakshminarasimha, A. N., and Pasin, M. (1990). Simulation of Compressor Performance Deterioration Due to Erosion. *Journal of Turbomachinery*, pp. 78-83, Vol.112, January 1990.
- Batcho, P. F., Moller, J.C., Padova, C., and Dunn, M.G. (1987). Interpretation of Gas Turbine Response Due to Dust Ingestion. *Journal of Engineering for Gas Turbines and Power*. Vol.109, July 1987 pp. 344-352.
- Richardson, J.H., Sallee, G. P., and Smakula, F. K. (1979). Causes of High Pressure Compressor Deterioration in Service. Paper AIAA-79-1234, AIAA 15th Joint Propulsion Conference, Las Vegas, NV, 1979.
- Luppold R H, Roman J R, Gallops G W, Kerr L J.(1989). Estimating in-Flight Performance Variations Using Kalman Filter Concepts. AIAA-89-2584, AIAA/SAE/ASME/ASEE 25th Joint Propulsion Conference, July 10-12 1989, Monterey, CA,1989.
- Lambert H.H. A Simulation Study of Turbofan Engine Deterioration Estimation Using Kalman Filter Techniques. NASA-TM-104233.
- Kobayashi, T., and Simon, D.L.(2004), Evaluation of an enhanced bank of Kalman filters for in-flight aircraft engine sensor fault diagnostics. NASA/TM_2004 - 213203.

Xue Wei, Guo Ying-qing. (2007). Troubleshooting soft failure of aircraft engine sensor with sequential probability ratio. *Journal of Aerospace Power*, Vol.22, 2007, 1925-1929.

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The Kalman filter has been successfully employed in diverse areas of study over the last 50 years and the chapters in this book review its recent applications. The editors hope the selected works will be useful to readers, contributing to future developments and improvements of this filtering technique. The aim of this book is to provide an overview of recent developments in Kalman filter theory and their applications in engineering and science. The book is divided into 20 chapters corresponding to recent advances in the field.

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