JOURNAL OF AIRCRAFT
Vol. 39, No. 3, May–June 2002

Adaptive Estimation of Aircraft Flight Parameters for Engine Health Monitoring System

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An adaptive control approach to the implementation of on-line estimation of aircraft flight parameters for the engine health monitoring system is presented. The adaptive estimation system enables a fast reliable data prediction to replicate the missing or misleading data caused by malfunctions in the sensors or communication links, thereby compensating for the deficiency of data that can trigger fault diagnoses of engine health. The estimation method features the integration of an autoregression model and a self-tuning adaptation algorithm for one-step-ahead estimation, in which the manufacturer's baseline values are used as an input in conjunction with an adaptive input adjusted to minimize the estimate error deviated from the snapshot data taken from satellites. The entire system is implemented through the parameter identification and optimization in an attempt to minimize the estimate error. Stability of this adaptive estimation system is investigated, and discrete-time simulations of in-flight parameter estimation will also be presented to show the effectiveness of the present approach.

I. Introduction

An engine condition monitoring (ECM)[1] system is used at Delta Air Lines to monitor the aircraft engine conditions of various Delta fleets when cruising in air. The ECM program was originally developed by Pratt and Whitney to compare each aircraft's engine condition to baseline values for the flight parameters of fuel flow (FF), exhaust gas temperature (EGT), low-pressure rotor speed (N1), high-pressure rotor speed (N2), engine pressure ratio, airborne vibrations, oil pressure, and temperature, etc. These in-flight parameters are referred to as engine health readings taken at the data points under the cruising condition wherein the Mach, altitude, and outside air temperature are held steady long enough to take a snapshot of flight data. The snapshot is automatically taken by an aircraft communications addressing and reporting system (ACARS)[1] installed onboard. The baseline values are supplied by the engine manufacturers, which have been calibrated to fit various fleet-engine configurations in the preflight testing process. The deviation between snapshots and baseline values demonstrates a trend curve that characterizes the engine health under the cruising condition. Thus the ECM system is able to trace the trend curves of FF, EGT, N1, and N2 to monitor the engine condition, in which a watch-list program has been developed to calculate the correlation coefficients[2] of 20 consecutive data from the sequential flights in order to detect the engine faults. If diagnosed to be malfunctioning, the engines will be taken off the plane for maintenance.

The performance of the ECM system relies on the consistent snapshot data downloaded from the ACARS system. However, the data acquisition and transmission system might not work properly so as to deteriorate the quality of flight data. For instance, single values or portions of the input-output data are missing as a result of malfunctions in the sensors or communication links. On the other hand, certain measured values are in obvious error as a result of the measurement failures, which are so-called outliners.[2] Above all, the measured values are vulnerable to the outside disturbances causing the misleading data in reading. The effects considered herein on the ACARS system are all adverse and result in failure of trend watch-list analysis or even in unreliability of the ECM system, which normally requires the consecutive data in the sequential flights to assess the engine health. These problems can be resolved by means of parameter estimation; however, some issues must be taken into consideration in advance, such as the 1) estimation model must be updated online along with the input-output data to adapt the varying characteristics of flight parameters under the different operating conditions, 2) estimate calculation has to be efficient to accommodate all Delta fleets prior to flight operation, and 3) estimation structure must remain unchanged for the different fleets, wherein conventional estimation method does not seem entirely effective and satisfactory for such purposes. The objective of this paper is thus to replicate the missing or misleading data inherent in the ECM system from the standpoint of adaptive estimation: in particular, an adaptive control algorithm[3] incorporating an autoregression model[2] is considered.

This paper uses an adaptive estimation scheme intended to compensate the deficiency of flight data for the ECM system enhancement in monitoring the engine health condition. Included in the closed-loop system is the integration of an autoregression model and a self-tuning adaptation algorithm for one-step-ahead estimation, in which the manufacturer's baseline values are used as an input in conjunction with an adaptive input automatically adjusted to minimize the estimate error derived from the subtraction between the estimated and measured data taken from satellites. In this way a first-order regression model is developed in the discrete-state format for open-loop estimation, whereas the adaptive estimation is implemented by an adaptive controller for closed-loop error compensation. It is known[4,5] that the adaptive control is very effective in tracking and error regulation when there exists measurably uncertain disturbances acting on the system, which makes this method well suited here to the online estimation problem against the uncertainties upon the flight parameters. Various estimation strategies have been studied to achieve the adaptive capability for signal processing. Some of them reviewed as references here are Kalman filter, forgetting factor, recursive least squares, and least mean squares.[2] The investigation of these papers was aimed at using different approaches to adapt the respective estimator adjustable to changes in the signals so as to continuously strive to optimize the estimate performance. As for comparison, a mean-square-fit equation[6] is applied to calculate the estimate error between the estimated and measured traces for each approach considered in this paper. Stability of overall estimation system is also analyzed to quantify the stable margin of the adaptive estimation system developed in the present paper.

Received 2 August 2001; revision received 10 December 2001; accepted for publication 11 December 2001.

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The outline of remainder of this paper follows. First, the derivation of an adaptive estimation algorithm is introduced for use in conjunction with an autoregression model for the adaptive estimation, following the stability analysis of this adaptive estimation system. Then, the implementation of the adaptive estimation system is detailed in conjunction with the parameter optimization against the estimate error. Finally, simulation results of adaptive estimation of in-flight parameters are presented for discussion.

II. Adaptive Estimation System

As just alluded to, the estimation system must be capable of handling the in-flight parameters for varying fleet-engine configurations and be robust to the substantial uncertainties throughout the ACARS system; therefore, an adaptation scheme seems particularly well suited to serve for such estimation purposes. In the present paper we make concurrent use of an adaptive control as well as an autoregression estimation and assess its applicability to the adaptive estimation of the ECM system. An adaptive controller is thus integrated with the merits of each particular estimator included. First, it is known that the autoregression model is very effective in estimating the measured output signal as long as the plant model is of the linear least-squares architecture. Then, when system parameters vary along with uncertainties adding adaptation into the autoregression model can enable the resulting system to deal with the varying plant parameters such that the estimate error as a result of fleet variations and uncertainties is greatly reduced.

A. Model Development

The development of the estimation network and parameter adjustment mechanism follows the adaptive control algorithm. Figure 1 shows a block diagram of the proposed adaptive estimation system. As demonstrated in Fig. 1, the adaptive control is attributed to the model-reference type, which requires a reference model against which system performance is measured. The reference model is a relatively simple spreadsheet of baseline values that are automatically calculated in the ECM system via a lookup table vs the variables of attitude, temperature, Mach, etc., when the ACARS system takes a snapshot under the cruising condition. The purpose of the baseline values is two-fold: 1) an input $U_{\text{base}}(t)$ to the linear estimator and 2) a reference input to the adaptive controller. In Fig. 1, t stands for the current state in a discrete-time sequence; likewise, $(t-1)$, the preceding state, and $(t+1)$, the next state. Then, corresponding to the transient responses, the error $e(t-1)$ can be obtained by defining $e(t-1) = y^\star(t-1) - y(t-1)$, where $y^\star$ and y indicate the measured and estimated outputs, respectively. The error

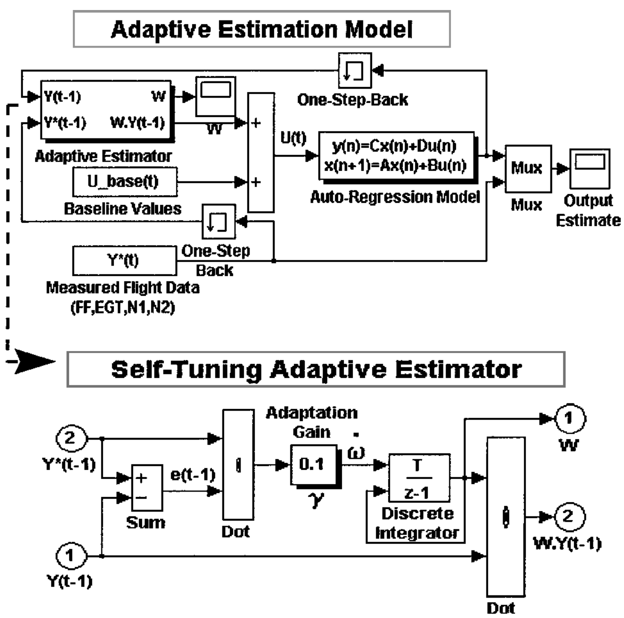

Fig. 1 Block diagram of an adaptive estimation system.

signal is regulated through the adaptive controller characterized by a variant adaptation law in compensating for fleet variations as well as parameter uncertainties. A complete derivation of this adaptive estimation synthesis is presented as follows.

Let us begin with the description of the autoregression model in the adaptive estimation system. The autoregression model is constructed by the state-variable equations in the discrete format, such as

$$x(t+1) = Ax(t) + Bu(t), \qquad y(t) = Cx(t) + Du(t) \quad (1)$$

in which x is the state variable, y the output estimate, u the input variable, and $[A,\ B,\ C,\ D]$ the state parameters. The values of the state parameters will be determined through the system identification process. As a consequence, four sets of values of state parameters will be identified for the flight parameters: FF, EGT, N1, and N2, respectively. Then, the values of the state parameters are fixed for use in Eq. (1) regardless of the effects of the fleet-engine variations, which should be taken care of by an adaptive control as introduced next. Moreover, for estimate efficiency we restrict the regression system to the lowest first-order so as to avoid a sophisticate adaptive design as required if a higher-order regression model is employed in Eq. (1).

To facilitate an adaptive capability in the model as shown in Eq. (1), we derive the input of the autoregression model into the following equation:

$$u(t) = U_{\text{base}}(t) + \omega y(t-1) \quad (2)$$

where the former is a lookup table of baseline values generated from ECM database and the latter denotes an adaptive input. The adaptive input uses the just-estimated output multiplied by an adaptation parameter. The adjustable parameter ω is adjusted for the adaptive input through a first-order differential equation governed by

$$\dot{\omega} = \gamma y^\star(t-1)e(t-1) \quad (3)$$

where γ is a positive adaptation gain that is selected from stability considerations to obtain the well-behaved and stable responses in the adjusting mechanism. According to a Massachusetts Institute of Technology (MIT) rule,[3–5] the adjustable parameter ω is fine tuned in the manner as shown in Eq. (3) to minimize a loss function specified by $J(\omega) = \frac{1}{2}e^2$, whereas the adaptation parameter is instantaneously changed in the direction opposite to the gradient of the loss function. Based on a MIT rule for adaptive control, the sensitivity of the error signal with respect to the adaptation parameter is given by $\partial e/\partial\omega = -y^\star$, which contributes to the formulation of the right-hand side of Eq. (3). In this way ω is driven by the error signal in the negative gradient direction through the first-order differential equation.

To mechanize this adaptive estimation algorithm, one must solve the differential equation (3) by the discrete integrator[6] with a fixed sample time of unity so as to be consistent with the discrete integration in Eq. (1). The value of ω is then multiplied with the preceding estimate, and the resulting product yields an adaptive input added to the current baseline input in Eq. (2). Given the input, the first-order difference equation (1) updates the next state value while computing the current estimate output. Then, the estimate output is set one step backward into the adaptive controller for the next discrete integration of Eqs. (1) and (3) in the closed-loop system. Overall estimation system is implemented according to the flight data of a majority fleet at Delta Air Lines, which will be the topics in the next section.

B. Stability Analysis

The stability of the proposed adaptive estimation system is investigated using a continuous-time model derived from Eqs. (1) and (3) under the criteria of asymptotic stability theory.[3,7] We consider the adaptive input in Eq. (2) for stability analysis and modify the input to be $u = \omega y$, where the adaptation parameter is updated by

$\dot{\omega} = \gamma y^\star(y^\star - y)$. Thereby, the state variable equation (1) becomes

$$\dot{x} = Ax + Bu = Ax + B\omega(Cx + Du)$$
$$= Ax + BC\omega x + BD\omega^2 y = \cdots$$
$$= \left[A + BC\omega \sum_{i=1}^{n+1} (D\omega)^{i-1}\right] x + BD^{n+1}\omega^{n+2} y \quad (4)$$

when one repeatedly substitutes the input and output variables by $u = \omega y$ and $y = Cx + Du$, respectively. Now, if $n \to \infty$, $\|D\omega\| < 1$, and $\|B\|$ is finite, Eq. (4) yields

$$\dot{x} = [A + BC\omega/(1 - D\omega)]x \quad (5)$$

which indicates that such a state-variable equation is asymptotically stable if and only if the eigenvalue is negative, implying $[A + BC\omega/(1 - D\omega)] < 0$ provided that $\|D\omega\| < 1$. As a result, the inequality equations of $[A + BC\omega/(1 - D\omega)] < 0$ and $\|D\omega\| < 1$ represent the criteria of asymptotic stability for the proposed adaptive estimation system, which can be used to validate a system implementation that will be discussed in the following section. The study described in this section can now be applied to bring about an adaptive estimation design for the ECM system. System implementation of an adaptive estimator will be the topic in the next section.

III. System Implementation

The implementation of the adaptive estimation system proposed in this paper includes the determinations of the state parameters in Eq. (1) and an adaptation gain in Eq. (3). The state parameters are identified by a least-squares method, wherein the regression model is treated as a black box in conjunction with the data of the baseline input $U_{\text{base}}(t)$ and the measured output $y(t)$ given from the historical flight records. We chose a majority fleet of the Boeing 757-200 model as a candidate for the state-parameter identification. Figure 2 shows the baseline and measured data of the flight parameters FF, EGT, N1, and N2 retrieved from a B757-200 fleet. In Fig. 2 each plot contains 222 data points dated from 8 October to 28 November in 2000. These snapshot data have been assured that no watch-list alerts happened to such fleet during the period of flight time. The flight data are preprocessed by normalizing their magnitudes into a range between zero and two prior to estimation so that the same value of γ in Eq. (3), determined later, can be applied for all Delta fleets and $\|\omega\|$ can be well bounded to enable the inequality relationship $\|D\omega\| < 1$ in the sense of asymptotic stability. The first-order, zero-delay, single-input, and single-output autoregression model is chosen for use in the system identification process, wherein a polynomial transfer function is generated and converted to a state-space model in the canonical form.[2,6] In this way the autoregression model is thus identified with four sets of replaceable values of state parameters as listed in Table 1.

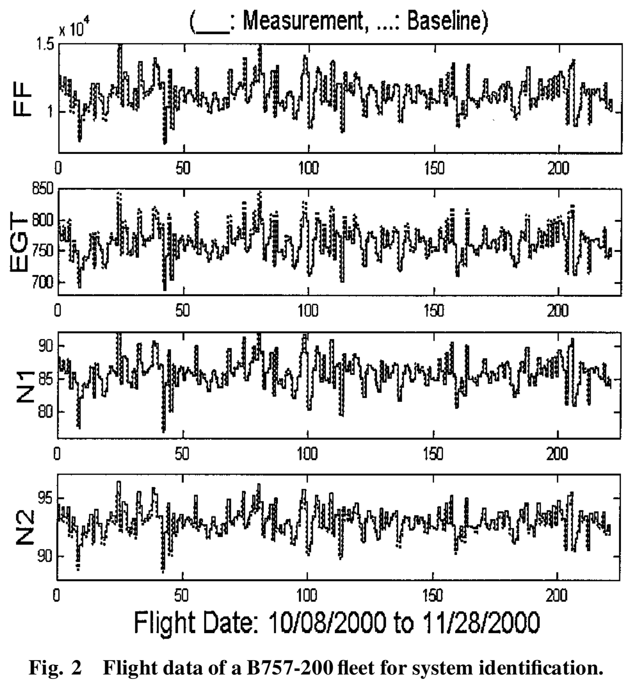

Fig. 2 Flight data of a B757-200 fleet for system identification.

Table 1 Model parameters of an adaptive estimation system

Symbol	A	B	C	D
FF	0.0132	0.0132	1.0	1.0024
EGT	0.0864	0.0787	1.0	0.9117
N1	−0.0096	−0.0097	1.0	1.0091
N2	−0.0329	−0.0341	1.0	1.0368

Table 2 Optimization results of an adaptation law design

$\varepsilon_{\text{fit}}(\gamma, \boldsymbol{p})$	FF	EGT	N1	N2
$\gamma = 1.0$	135.677	6.919	0.216	0.366
$\gamma = 0.5$	100.066	6.418	0.195	0.292
$\gamma_{\text{opt}} = 0.1$	89.975	6.156	0.180	0.291
$\gamma = 0.05$	94.140	6.180	0.187	0.292
$\gamma = 0.01$	105.967	6.255	0.188	0.293
$\gamma^{\text{o}} = 0.0$	108.230	6.262	0.220	0.360

As already discussed, the adaptive input design demonstrated in Eq. (2) is to handle the parameter uncertainties and fleet variations. An optimization approach is presented to find the optimum solution of the adaptation gain γ appearing in Eq. (3) in order to minimize the estimate error specified by a mean-squared-fit equation.[6] The optimization problem is formulated to minimize the mean-squared-fit value so that the following optimization problem is expressed by:

Minimize:

$$\varepsilon_{\text{fit}}(\gamma, p) = \frac{\|\boldsymbol{Y}(p) - \boldsymbol{Y}^\star(p)\|}{\sqrt{\rho[\boldsymbol{Y}(p)]}} \quad (6)$$

Subject to:

$$\phi(\gamma) = \dot{z} - F(z, \gamma) = 0, \qquad z = \begin{bmatrix} y \\ \omega \end{bmatrix}$$

$$F(z, \gamma) = \begin{Bmatrix} [D\gamma y^\star/(1 - D\omega)](y^\star - y) + BC\omega/(1 - D\omega) + A \\ \gamma y^\star(y^\star/y - 1) \end{Bmatrix} y \quad (7)$$

where $\varepsilon_{\text{fit}}(\gamma, p)$ is the cost function (mean-squared-fit equation) of flight parameter p; $\boldsymbol{Y}(p)$ the vector of estimated data of flight parameter p; $\boldsymbol{Y}^\star(p)$ the vector of measured data of flight parameter p; $\rho[\boldsymbol{Y}(p)]$ the size of vector $\boldsymbol{Y}(p)$; and $\phi(\gamma)$ the equality constraint function. The equality constraint function in Eq. (7) is derived by rearranging Eqs. (1) and (3) into the continuous-time format. In Eqs. (6) and (7) the optimization program uses the polytope algorithm[8] to seek the optimum solution of the design variable γ to minimize a cost function $\varepsilon_{\text{fit}}(\gamma, p)$. The lower bound is imposed on the design variable being positive. Along the procedure of optimization, the differential equations inside the equality constraint function are numerically integrated to obtain the time-history responses that are discretely sorted at an even interval for the determination of the cost function defined in Eq. (6).

Based on the model parameters in Table 1 as well as the recorded data from Fig. 2, the optimization of the adaptive estimator is carried out by implementing four adaptive estimations for the flight parameter of FF, EGT, N1, and N2, respectively. The feasible starting point is specified to be $\gamma^{\text{o}} = 0$, which in fact yields a case of regression estimation alone. Some optimization results are included in Table 2. It can be seen that the optimum solution has been found to be $\gamma_{\text{opt}} = 0.1$, which results in the minimum of cost functions of FF, EGT, N1, and N2. The estimate errors associated with $\gamma^{\text{o}} = 0$ are vastly reduced if applying the adaptive control with the adaptation gain $\gamma < 1.0$. The adaptation gain γ is then fixed to the value of 0.1

to tune the adaptation parameter ω in Eq. (3) as for generating an adaptive input in Eq. (2).

The procedure described in this section can now be used to bring about a complete design of adaptive estimation model for the ECM system. Numerical simulations have been implemented and will be discussed in the following section.

IV. Simulation Results

The model parameters of an adaptive estimation system for simulations are summarized in Table 1. Four types of aircraft were selected for adaptive estimation simulation during the years of 1995–2000, and they are B757-200, B727-200, MD-88 (McDonnell Douglas), and MD-90. The adaptive estimation has been simulated for the prediction of FF, EGT, N1, and N2 in comparison with the actual data and the baseline values. Although simulated through 7000 data points recorded from 1995 to 2000, only a portion of data points were demonstrated in each simulation for a clear highlight of graphics.

In the first simulation the baseline values of a B757-200 fleet are specified to the inputs of FF, EGT, N1, and N2, respectively. Figures 3a–3d show the numerical results of this simulation dated from 20 July to 8 October in 1995. The results associated with the adaptive estimation are indicated by a solid line, whereas those with the measured data are indicated by a dashed line. The dotted trace represents the baseline values. It can be seen that the traces of the estimated, measured, and baseline data are close to one another, and the three traces of N1 even overlap closely, implying a good trend estimation for this B757-200 plane.

The second simulation is conducted for a B727-200 fleet operating from 12 March 1999 to 20 May 2000. The B727-200 planes use Pratt and Whitney JT8D-15 engines different from PW2037 engines installed in B757-200 planes. Under the adaptive estimation the discrete time-histories in Figs. 4a–4d represent the traces of estimation for FF, EGT, N1, and N2, respectively. As can be observed in Fig. 4, the estimation of N1 shows a better performance among the others. Moreover, the baseline values of FF, EGT, and N2 deviate from the measured data; however, the estimated traces still present a good prediction close to the measured traces. Above all, the results in Fig. 4 demonstrate that the adaptive estimator is capable of dealing with the sudden changes along the traces of flight data.

Figures 5 and 6 present the estimation results of an MD family such as MD-88 and MD-90 fleets. Figures 5a–5d show the simulation results for a MD-88 fleet dated from 9 September to 9 December

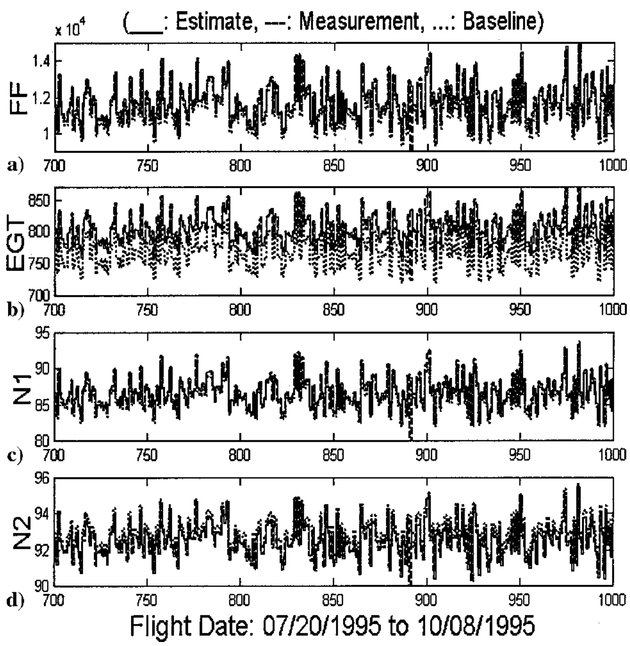

Fig. 3 Simulation results of a B757-200 fleet under adaptive estimation.

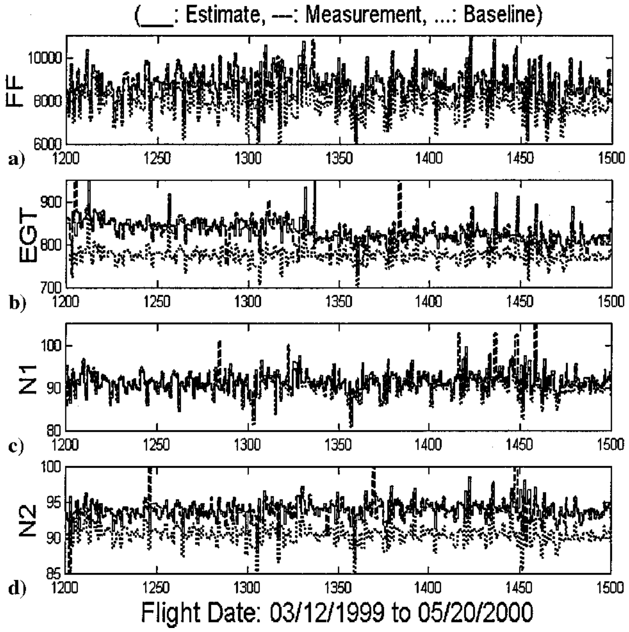

Fig. 4 Simulation results of a B727-200 fleet under adaptive estimation.

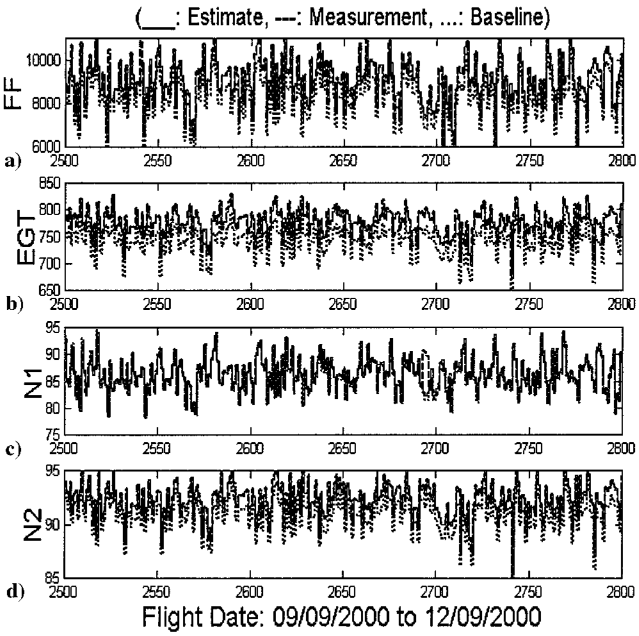

Fig. 5 Simulation results of a MD88 fleet under adaptive estimation.

in 2000, whereas those in Figs. 6a–6d are for a MD-90 fleet dated from 7 September to 2 December in 2000. The MD-88 planes use Pratt and Whitney JT8D-219 engines, while the MD-90 planes adopt International Aero Engines V2528-D5. In Figs. 5 and 6 it can be observed that the estimate errors are greatly eliminated in the traces of FF, EGT, N1, and N2 under the adaptive estimation system regardless of the fleet-engine variations. Although not shown in Figs. 3–6, the discrete time histories of the adaptation parameter are bounded by $\|\omega\| < 0.1$ for the cases of B757, B727, MD-88, and MD-90 planes.

Now, we take an EGT sample of MD-90 (total 7000 data points from 1995 to 2000) to benchmark the alternate estimation algorithms such as Kalman filter, normalized gradient, and forgetting factor.[6] The comparison results are listed in Table 3. The adaptive estimation algorithm proposed in this paper inquires the lowest order of system with no delays in modeling to perform the least estimate error in the fast estimation.

Table 3 Comparison of alternate estimation algorithms

Method/Parameter	ε_{fit}(EGT)	Order	Delay	Speed
Adaptive regression	3.7	1st	0	1st
Kalman filter	22.5	6th	1	3rd
Normalized gradient	26.6	6th	1	4th
Forgetting factor	22.5	6th	1	2nd

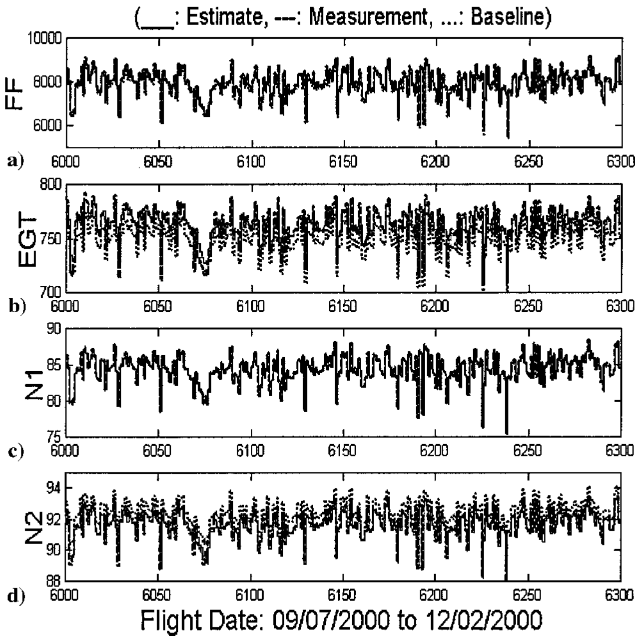

Fig. 6 Simulation results of a MD90 fleet under adaptive estimation.

The adaptive estimation of the flight monitoring system under the presence of baseline values has been shown to match the actual data when the adaptive estimator is invoked. The estimate errors have been effectively suppressed through an adaptive estimation system. The simulation results in Figs. 3–6 thus validate the applicability of the proposed adaptive estimation design for the engine health monitoring system.

V. Conclusions

In this paper the problem of parameter estimation on the aircraft engine health monitoring system has been proposed and analyzed under the adaptive estimation system. The adaptive estimation has been shown to be applicable and suitable for compensating the deficiency of flight data in the engine condition monitoring system when conducting the trend and watch-list analyses for the engine health diagnosis. The basic idea of the proposed estimation strategy is to adjust the adaptation parameter to minimize the estimate error as the result of forming a closed loop in the autoregression model, in which adaptive estimation is facilitated to accommodate fleet variations and to compensate for uncertainties upon the flight parameters. The autoregression model is developed by a first-order differential equation and automatically adjusted by an adaptive control law through the input of system. The stability of the adaptive estimation system was analyzed to deduce two inequality equations as the necessary criteria to ensure the adaptive system was asymptotically stable. The adaptive estimation system has been implemented by identifying the regression model and optimizing the adaptation law according to the historical flight data of a majority fleet. The entire estimation system was formulated into an ease-to-code format and has been proven suitable to work for various fleets operated at Delta Air Lines.

Numerical simulations of the proposed estimation strategy are shown to be suitable for the engine health monitoring system to be used actively against the deficiency of flight data taken from the ACARS system. The simulation results indicate that the estimate error is considerably reduced by the adaptive estimation system regardless of fleet variations and changes of parameter characteristics. The benchmark study shows that the proposed estimation algorithm outperforms the existing estimation algorithms in terms of accuracy, order of system, and computational speed.

Acknowledgment

The authors wish to acknowledge the technical support from Warren B. Bledsoe, Principal Engineer in the Flight Operations Engineering Department of Delta Air Lines, to complete this paper.

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