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Online Model Parameter Estimation of Jet Engine Degradation for Autonomous Propulsion Control

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ABSTRACT

Jet engine components are subject to degradation over their lifetime of use. The effect of such degradation on the engine is to compromise performance and deteriorate operational characteristics. For autonomous flight control, since there is no pilot intervention it is necessary for the engine control system to maintain a nominal level of propulsion system thrust performance in an engine subject to changes in dynamics caused by aging and degradation. In this paper, two adaptive engine control techniques are investigated to recover the thrust performance of a degraded engine so that it is as close as possible to the thrust performance of a nominal (new) engine. The adaptive technologies are developed and demonstrated using a simulation representative of a modern fighter aircraft gas turbine engine. The first control technique consists of an adaptive onboard linear model embedded within the controller. Model-based estimates are used in closed loop with a proportional plus integral (PI) controller to maintain nominal thrust performance. The onboard model is tuned by parameter estimation using a Kalman filter to match the performance of the physical engine. The Kalman estimator uses measured engine outputs to estimate and adjust online the engine model health parameters, *i.e.* flows and efficiencies of the major engine components such as the fan, compressors and turbines. In simulation, the Kalman estimator provided accurate real time estimates of all ten engine health parameters with rapid convergence to the degraded engine state variables and outputs. Use of the estimated health parameters in the adaptive onboard model in closed loop with the PI controller corrected the thrust response of a severely degraded engine to be similar to that of a nominal engine. In the second adaptive control design technique, the nominal PI controller gains are adapted with a least squares method of controller parameter optimization in the frequency domain. In this technique, the adaptive PI controller parameters were estimated so that the closed loop frequency response of the degraded engine and adaptive controller matched the closed loop frequency response of a nominal engine and nominal PI controller. In simulation, use of the new adaptive controller to augment the control action of the existing nominal PI controller recovered the transient thrust response of the degraded engine to be close to that of the nominal engine and baseline controller. The techniques of engine model parameter estimation and controller adaptation can be combined to allow for implementation of an adaptive model-based propulsion control system that effectively maintains desired thrust performance levels in an engine subject to severe degradation.

NOMENCLATURE

Control Inputs:
WF36: Main Fuel Flow
A8: Exhaust Nozzle Throat Area
A16: Variable Bypass Duct Area
State Variables:
XNL: Fan (Low Pressure Spool) Speed
XNH: Compressor (High Pressure Spool) Speed
TMPC: Combustor Metal Temperature
Health Parameters:
SEDM2: Fan Efficiency
ZSW2: Fan Flow
SEDM7D: Low Pressure Compressor Efficiency
ZSW7D: Low Pressure Compressor Flow
SEDM27: High Pressure Compressor Efficiency
ZSW27: High Pressure Compressor Flow
ZSE41: High Pressure Turbine Efficiency
ZSW41: High Pressure Turbine Flow
ZSE49: Low Pressure Turbine Efficiency
ZSW49: Low Pressure Turbine Flow
Engine Variables and Components:
PLA: Power Lever Angle

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LPC: Low Pressure Compressor (Booster)
HPC: High Pressure Compressor
HPT: High Pressure Turbine
LPT: Low Pressure Turbine
FN: Thrust
ETR: Engine Temperature Ratio (T56/T2)
LEPR: Liner Engine Pressure Ratio (P56/P16)
T56: Exhaust gas temperature, at mixing plane.
T2: Fan face temperature
P56: LPT exit total pressure at mixing plane
P16: Total pressure in bypass duct
T27: Core Inlet Temperature
P27: Total Pressure at core inlet

INTRODUCTION

An onboard adaptive model-based propulsion control system will enable autonomous operation of a jet engine by providing the ability to accurately track and adjust performance parameters in the presence of engine deterioration. In the context of autonomous flight control, the adaptive model-based propulsion control system can deliver the desired thrust response to the vehicle management system where a pilot might otherwise have needed to manually adjust the throttle. This is particularly important for an aircraft with multiple engines, since asymmetric thrust response can result in an unacceptably large yawing moment. Also, the sluggish thrust response of a degraded engine would be an additional uncertainty for an autonomous vehicle management system performing transient maneuvers. One of the objectives of NASA's Autonomous Propulsion System Technology (APST) project is to develop in simulation an adaptive control system for aircraft gas turbine engine control. The adaptive control is required to maintain a nominal level of propulsion system thrust performance in an engine subject to slow changes in dynamics caused by aging and degradation.

To demonstrate the adaptive control objectives in simulation, a nonlinear aircraft engine model was linearized at an operating point to derive a linear state-space engine model as well as a linear onboard model. A linear control design about an operating point is an important step in the overall propulsion control design process. The linear models were also used for the Kalman estimator and adaptive controller design.

In this work, two separate approaches were considered for adaptation of the degraded engine control to recover thrust performance. The first approach was that of onboard model adaptation through extended state estimation using a Kalman filter, and the second approach was that of controller adaptation using parameter optimization in the frequency domain.

In Figure 1, a schematic of the first adaptive technique using a model-based control structure is shown. The plant is represented with a linear engine model, and a linear onboard model is included to track deterioration in the plant. A nominal PI controller was used for closed loop control with gains derived at the operating point from the nonlinear simulation gain-scheduled PI controller. One of the feedback parameters to the PI controller is thrust, which is an un-measurable output, so the onboard linear model was required to accurately estimate thrust. The accuracy of the model was achieved by online recursive estimation of the model parameters using measurable outputs from the engine such as temperatures and pressures. The estimation was performed using a Kalman filter to estimate the state variables of the degraded engine, this included the augmented state variables of the ten health parameters.

In Figure 2, a schematic of the second adaptive technique is shown. Here the recovery of thrust transient response for the degraded engine is addressed by controller adaptation. The nominal PI controller action was augmented by an adaptive controller to operate in closed loop with the degraded engine. The parameters of the adaptive controller were synthesized using a least squares technique of controller parameter optimization in the frequency domain. In this technique, the closed loop frequency response of the degraded engine and adaptive controller was matched with the closed loop frequency response of the nominal engine and nominal controller in a least squares sense.

The effect of engine degradation on thrust performance was investigated by compiling degradation data from literature[1]. This consisted of deterioration in the efficiency and flow characteristics for each of the engine component stages *i.e.* the health parameters. The data were used in a nonlinear component level model simulation to study the thrust response of a degraded engine.

Two adaptive techniques of model parameter estimation[2] and controller parameter optimization have been separately investigated in this work for recovering thrust performance of a deteriorated engine due to aging and component degradation. The initial linear control design about an operating point used for demonstrating these techniques is an important first step before extending and combining the techniques to linked linear models or nonlinear models across the full flight envelope.

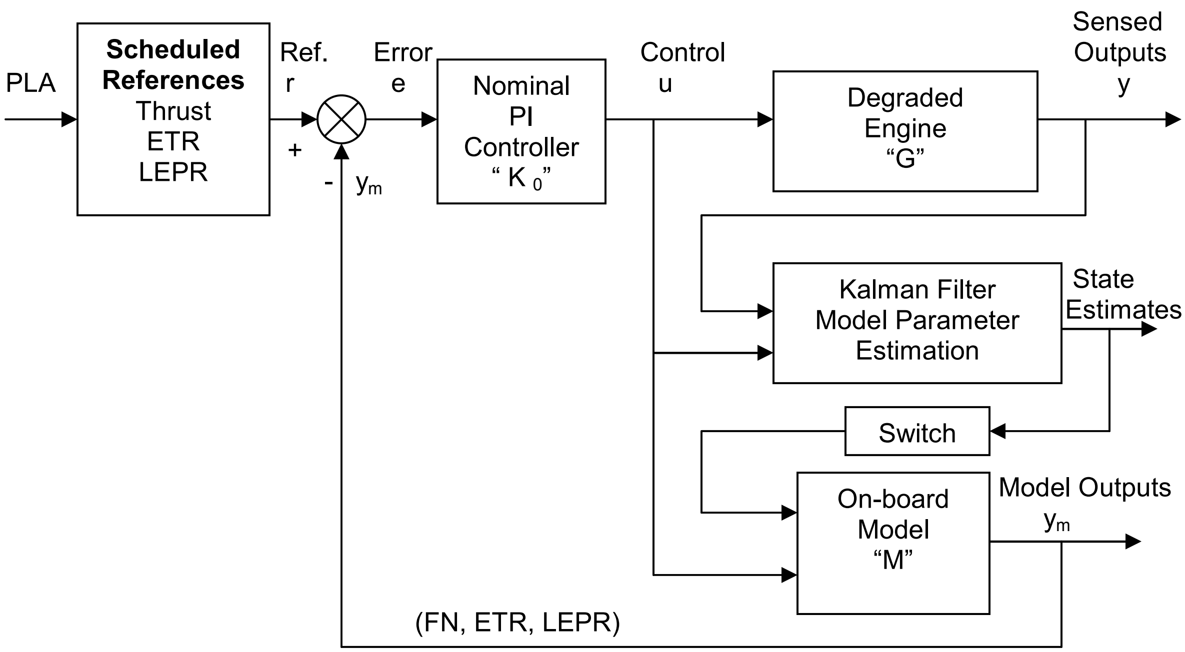

Figure 1: Adaptive Model Based Control Structure

- The Kalman Estimator is designed with the nominal engine model. It provides internal estimates of the state variables, which include the health parameters to account for degradation.
- The Adaptive Model action can be switched off by switching out the state feedback of estimated health parameters. The control will then revert back to using the nominal engine model.

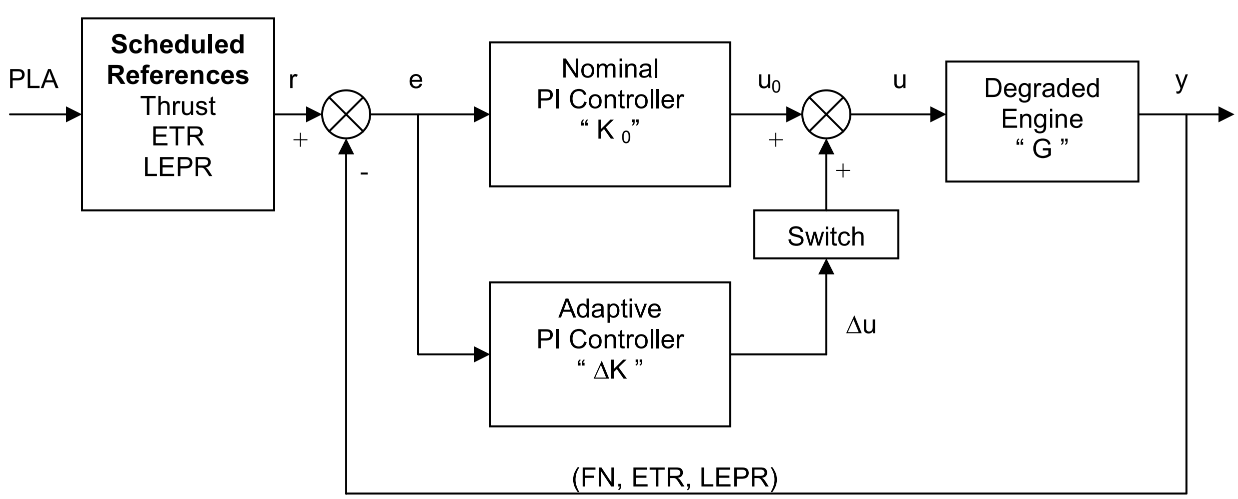

Figure 2: Controller Adaptation Structure

- The Adaptive PI Controller is: $K(s) = K_0(s)+\Delta K(s)$, where gains for $K(s)$ are calculated using a least squares parameter optimization algorithm in the frequency domain, to match the closed loop frequency response of the nominal engine $G_0(s)$ and nominal controller $K_0(s)$.
- The Adaptive Controller action "Δu" can be switched off using the switch or control limit authority. The control will then revert back to the nominal PI controller $K_0(s)$.

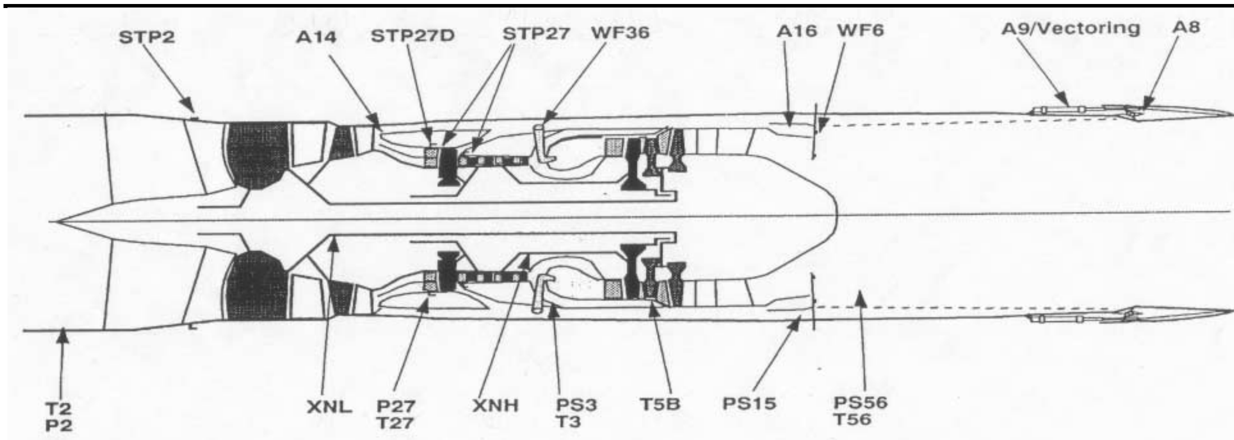

Figure 3: Jet Engine Schematic for Nonlinear Simulation

Actuators (Top Row):
STP2: Fan inlet guide vanes
A14: Bypass door (single to double bypass)
STP27D: Core driven fan stage tip stators
STP27: Compressor stators
WF36: Main fuel flow to combustor
A16: Bypass area
WF6: Afterburner fuel flow
A9: Nozzle exit area
A8: Nozzle throat area

Sensors (Bottom Row):
T2: Fan inlet temperature
P2: Fan inlet pressure
XNL: Fan speed
P27: Compressor inlet pressure
T27: Compressor inlet temperature
XNH: Core speed
PS3: Combustor inlet static pressure
T3: Combustor inlet temperature
T5B: LPT blade temperature
PS15: Bypass duct static pressure at mixing plane
PS56: LPT exit static pressure at mixing plane
T56: LPT exit temperature

Table 1: Degradation of Health Parameters

	Health Parameter	Effect of Initial Rub-In and Flight Loads	Degradation from **3000 Cycles** of Operation	Degradation from **6000 Cycles** of Operation
1	**Fan Efficiency**	-0.18 %	-1.50 %	-2.85 %
2	**Fan Flow**	-0.26 %	-2.04 %	-3.65 %
3	**LPC Efficiency**	-0.62 %	-1.46 %	-2.61 %
4	**LPC Flow**	-1.01 %	-2.08 %	-4.00 %
5	**HPC Efficiency**	-0.16 %	-2.94 %	-9.40 %
6	**HPC Flow**	-0.41 %	-3.91 %	-14.06 %
7	**HPT Efficiency**	-0.48 %	-2.63 %	-3.81 %
8	**HPT Flow**	+0.08 %	+1.76 %	+2.57 %
9	**LPT Efficiency**	-0.10 %	-0.538 %	-1.078 %
10	**LPT Flow**	+0.08 %	+0.2588 %	+0.4226 %

ENGINE MODEL

In Figure 3, a schematic of the engine model used for this study is shown along with the available actuators and sensors. This is a twin spool, dual bypass high performance gas turbine engine typical of a modern fighter aircraft. Some of the particular features of this engine are[3]: 1) Single stage fan with high pressure ratio, 2) A core driven fan stage booster (or low pressure compressor) with independent hub and tip stators, 3) High stage pressure rise mixed-flow compressor, 4) Double-annular combustor, 5) High and low pressure bleed, 6) High work extraction turbines, 7) Variable cycle capability with forward blocker doors and an aft variable area bypass injector, 8) Advanced exhaust nozzle technology. The nonlinear engine model is a component level model with an associated gain scheduled PI controller. It is coded in Fortran and is capable of simulating engine and controller dynamics together with the effects of health parameter degradation on key states and outputs. The nonlinear simulation was used to generate the linear models for both the degraded engine and the online model, and to obtain PI controller gains.

ENGINE DEGRADATION

The effect of engine degradation due to aging is modeled in the nonlinear simulation by modifying the efficiencies and flow capacities of key engine components such as: Fan, Low Pressure Compressor, High Pressure Compressor, High Pressure Turbine and Low Pressure Turbine. These efficiency and flow capacity parameters are known as engine health parameters, and the values of these parameters used in this paper corresponding to 3000 cycles of operation and 6000 cycles of operation are shown in Table 1. The numerical values are a percentage deviation from nominal, where a nominal engine is at 100% for each of the parameters. The data shown are derived from an available literature source on engine performance deterioration[1].

Based upon the information available in reference 1, the degradation level of a set of ten health parameters as a function of engine operating cycles was documented and plotted. Regression based curve fitting was used to interpolate between data points, as well as extrapolate to 6000 cycles in cases where information was not available. The degraded health parameter values at 3000 and 6000 cycles were introduced in the nonlinear simulation to evaluate degradation effects on engine and controller performance. In Figure 4, the decrease in efficiency and flow capacity for the Fan, Low Pressure Compressor and High Pressure Compressor versus cycles of operation is shown. The initial values of the plots represent the effect of flight loads and very early degradation known as rub-in. The subsequent data points represent degradation due to aging. The data points are average values of test measurements for a number of engines at each of the test flight cycles of operation. In Figure 5, a decrease in efficiency and increase in flow capacity for the High Pressure Turbine and Low Pressure Turbine with cycles of operation is shown. For the turbines, the available data measurements were up to 2000 flight cycles. For use in the simulation an assumed polynomial curve was fit to the available data and extrapolated to 6000 flight cycles of operation. It should be noted that with degradation of the engine, the flow capacity health parameter increases for the turbines.

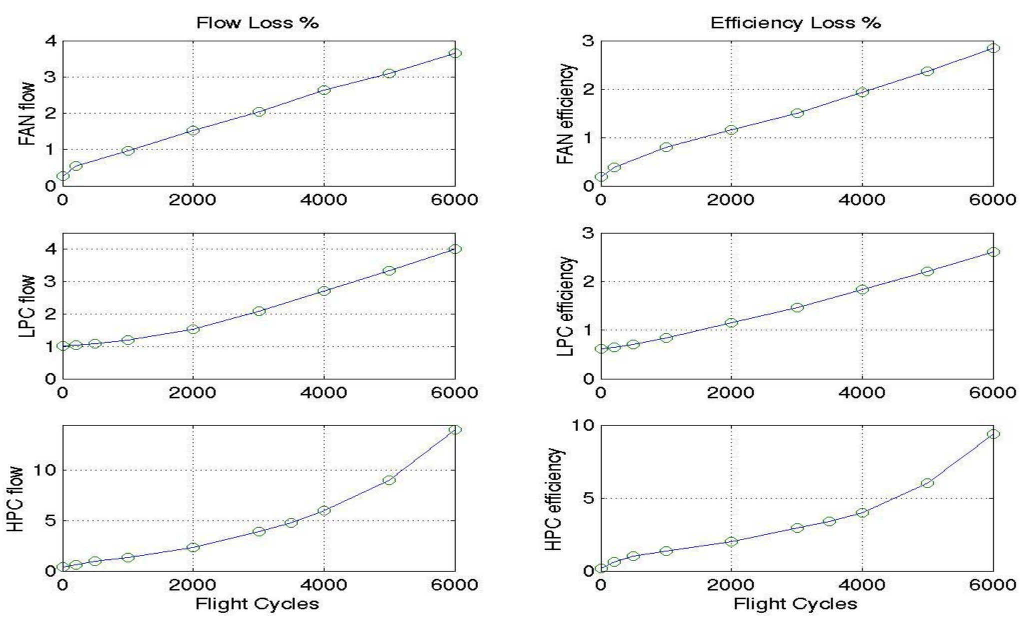

Figure 4: Health Parameter Degradation with Aging (FAN, LPC, HPC)

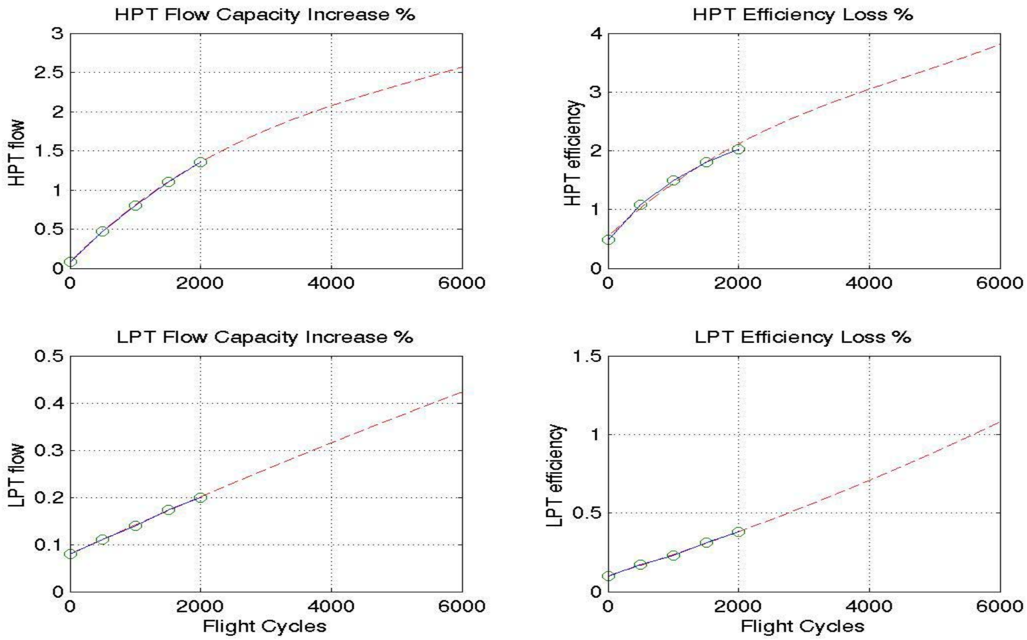

Figure 5: Health Parameter Degradation with Aging (HPT, LPT)
(Note: The extrapolated dashed lines are assumed curves for simulation only)

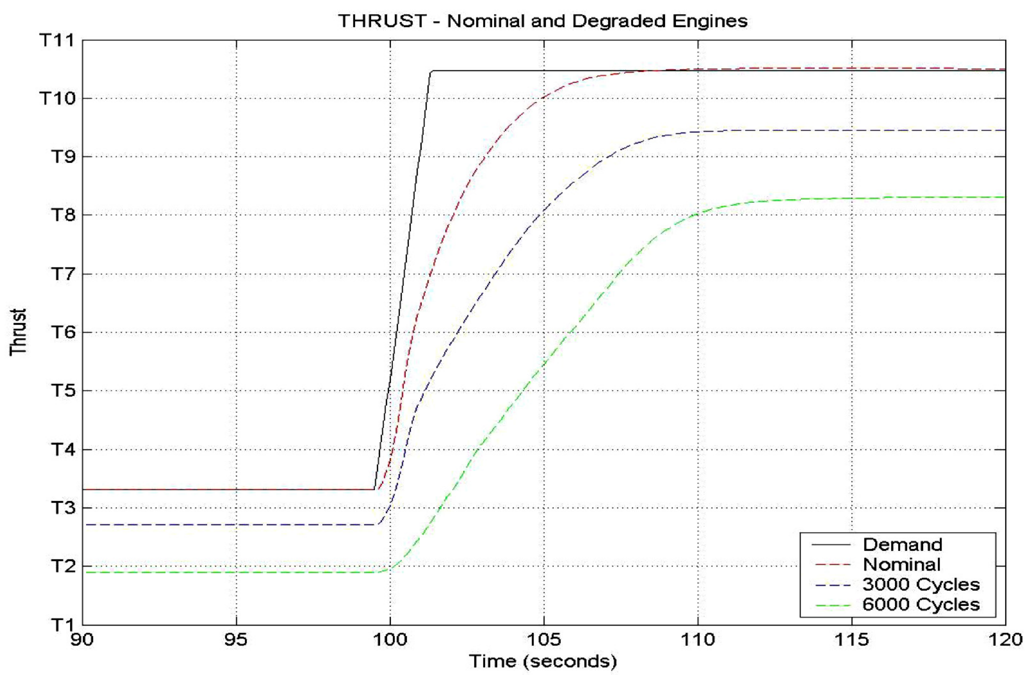

Figure 6: Thrust Response to Step in Thrust Demand

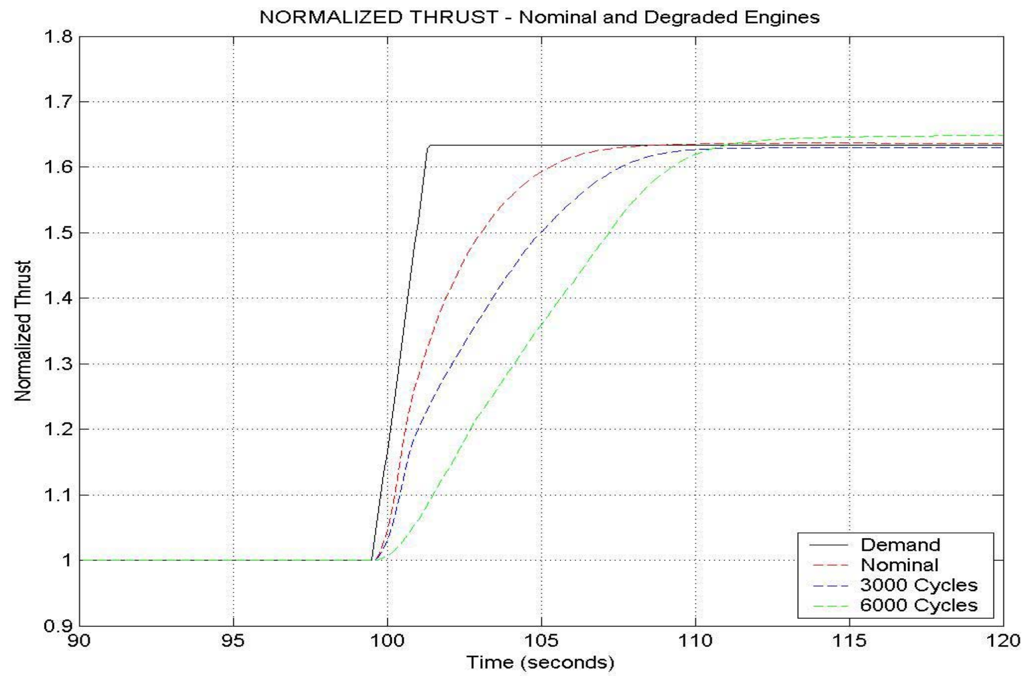

Figure 7: Normalized Transient Thrust Response

Degradation Effects on Engine Performance

The effect of component health parameter degradation on engine performance was investigated using the nonlinear engine simulation in closed loop with its nominal gain-scheduled PI controller. The system was given an initial PLA command of 35 degrees, and was allowed to run to an initial steady state value for all three engine state variables (XNL, XNH and TMPC), then a step change in PLA from 35 to 45 degrees was introduced at 100 seconds, and the response of thrust was observed for nominal and degraded engines.

Thrust Response to Step Change in Thrust Demand

The transient and steady state responses for nominal and degraded (3000 and 6000 cycle) engines were simulated. In each case the nonlinear simulation was run with the nominal PI controller and an associated on-board model tuned to a nominal engine. Thrust response results for each simulation scenario are shown in Figure 6.

It can be seen from Figure 6 that a significant steady state error between thrust demand and actual thrust exists for the degraded engines. The operating point shift can be attributed to inaccurate estimates from the online model which does not account for degradation effects on engine outputs such as thrust, ETR and LEPR, which are used for feedback to the PI controller. The model-based control used in this nonlinear engine simulation is an advanced control architecture that allows the engine to be controlled on un-measurable parameters such as thrust and stall margin, and is not conventional for most engine propulsion control systems. The steady state thrust discrepancies shown in Figure 6 are to be expected for a model-based controller that is not tuned to account for degradation of engine components.

Normalized Transient Thrust Response

In Figure 7, the effect of engine degradation on normalized thrust is shown in order to compare the transient thrust response of nominal and degraded (3000 and 6000 cycle) engines. The solid line represents a 63% increase in thrust demand corresponding to a PLA change from 35 to 45 degrees. It can be seen that with increasing engine degradation the closed-loop transient thrust response becomes more sluggish as compared to the nominal engine thrust response.

ADAPTIVE CONTROL TECHNIQUES

Two separate techniques to adapt the engine control system were used to recover thrust performance in an engine subject to changes in dynamics caused by deterioration due to aging and component degradation. These include an onboard model parameter estimation technique using extended state estimation with a Kalman filter as was shown in Figure 1, and an adaptive controller run in parallel with the nominal controller as was shown in the control system configuration of Figure 2. When switched on, the adaptive controller augments the action of the nominal controller to recover the degraded engine thrust performance. Simulations of these linear models and control systems were developed in the Simulink® environment, to form the basis for the adaptive model-based control system design.

Linear Model

The nonlinear engine model is linearized at an operating point (*i.e.* PLA, Altitude and Mach Number), to have the following form:

$$\dot{x}(t) = A\,x(t) + B\,u(t) + E\;p(t)$$
$$y(t) = C\,x(t) + D\,u(t) + F\;p(t)$$

where:

p(t): is the vector of health parameters. In this work the health parameters are assumed to be time invariant.

For estimation of the health parameters, the vector *p* is augmented to the state variables in vector *x*, and for the case where the health parameters are required as inputs to the engine, the vector *p* is included in the input vector *u*.

The linear state-space *A, B, C, D* matrices[4] are the sensitivity matrices containing the partial derivatives calculated during linearization of the nonlinear model. For the Kalman filter estimator, and in the *linear degraded engine model*, the $\widetilde{A}$ *and* $\widetilde{C}$ matrices include the health parameter sensitivity matrices *E* and *F* respectively, since the health parameters are treated as extended state variables that need to be estimated. While, for the *linear onboard model* the $\widetilde{B}$ *and* $\widetilde{D}$ matrices include the matrices *E* and *F* respectively, since the health parameters are treated as inputs to the model.

This yields the more familiar form of the linear state space engine model as:

$$\dot{\widetilde{x}}(t) = \widetilde{A}\widetilde{x}(t) + \widetilde{B}\widetilde{u}(t)$$
$$y(t) = \widetilde{C}\widetilde{x}(t) + \widetilde{D}\widetilde{u}(t)$$

Where:

For the linear degraded engine model (i.e. the Plant):

$\widetilde{u}(t)$: Are the 3 inputs of WF36, A8 and A16.

$\widetilde{x}(t)$: Is a 13 element state vector consisting of the 3 engine state variables XNL, XNH, TMPC, and 10 augmented state variables representing the health parameters.

$y(t)$: Are the 24 outputs, including engine outputs and sensor measurements. Of these, 14 outputs corresponding to sensor measurements are selected for the Kalman Filter estimation in Figure 1, and the 3 outputs of (FN, ETR, LEPR) are used for direct feedback to the PI controller in the parameter optimization simulation in Figure 2.

For the linear onboard model:

$\widetilde{u}(t)$: Is a 13 element input vector consisting of the 3 inputs WF36, A8, A16, and the 10 health parameters as inputs.

$\widetilde{x}(t)$: Is the state vector consisting of the 3 engine state variables XNL, XNH, TMPC.

$y(t)$: Are the 24 outputs corresponding to engine outputs and measurements. The 3 outputs of (FN, ETR, LEPR) are the only ones that are used for feedback to the PI controller for model-based control.

Use of the linear models for control, and the algorithms and implementation of the two control techniques of adaptive model-based control using a Kalman estimator, and that of controller adaptation by parameter optimization in the frequency domain, are discussed in the next two sections.

ADAPTIVE MODEL-BASED CONTROL

The system was implemented using separate linear models for the degraded engine and the onboard nominal model as shown in Figure 1. The linear model representing the degraded engine was preset with health parameter values representative of 6000 cycles of operation. A multivariable three input three output PI controller was used, with the gains and regulator control modes[3] derived from the nonlinear simulation at the point of linearization of the degraded engine. A Kalman filter estimator was designed using a linear nominal engine model to estimate the state variables of the engine, this included the augmented state variables for the health parameters. The adaptive model-based control loop consists of the Kalman filter estimating the state variables and health parameters of the degraded engine and feeding this information to the onboard linear model. This adapted onboard model is used to estimate thrust, ETR and LEPR for feedback to the PI controller. The errors between the scheduled references and the adapted onboard model estimates are used by the PI controller to calculate the control inputs to the engine.

Kalman Filter Estimator

A Kalman filter based estimator in continuous time is used in the adaptive model-based control approach[5]. As described earlier, the purpose of this filter is to estimate state variables of the degraded engine, including health parameters which are treated as augmented state variables in the linear engine model. The general form of the filter equations follow:

Given a continuous plant with the System Model:

$$\dot{x}(t) = Ax(t) + Bu(t) + Gw(t)$$

where: w(t)~N(0, Q) is the uncertainty in the system model

and Measurement Model:

$$y(t) = Cx(t) + Du(t) + v(t)$$

where: v(t)~N(0, R) is the uncertainty in the measurement model

and the inputs *u(t)* are known, also the white noise vectors *w(t), v(t)* satisfy:

$E(w) = 0;\ E(v) = 0;$
$E(ww^T) = Q;\ E(vv^T) = R$ and $E(wv^T) = 0$

the State Estimate is given by:

$$\dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K\,(y(t) - C\,\hat{x}(t) - Du(t))$$

which minimizes the steady-state "state estimation" error Covariance:

$$P = \lim_{t\to\infty} E(\{x-\hat{x}\}\{x-\hat{x}\}^T)$$

The error Covariance is propagated as:

$$\dot{P} = AP + PA^T + GQG^T - KRK^T$$

The Kalman Gain is calculated by solving the Riccati equation for the covariance matrix to yield:

$$K = PC^T R^{-1}$$

The output estimates are given by:

$$\hat{y}(t) = C\hat{x}(t) + Du(t)$$

The design parameters of the Kalman filter were formulated as follows:

x(t): The nominal engine model is used here with 13 state variables, corresponding to the 3 engine state variables, and 10 health parameters.

Q : The uncertainty in the system model is a (13x13) diagonal matrix, corresponding to the engine and health parameter state variables. The standard deviation of the uncertainty for each engine state variable was set at 1% of the variables steady state value, and at 0.5% for each of the health parameter values.

R : The uncertainty in the measurement model is a (14x14) diagonal matrix, corresponding to the 14 engine outputs selected for the estimation process. The standard deviation of the uncertainty for each measurement was set at 0.2% of its steady state value.

The Kalman filter was designed using Matlab®, and implemented in the linear simulation as a Simulink® state space object.

Results of Kalman Estimation and Control

Figure 8 shows linear simulation results of thrust and engine temperature ratio (ETR) from the adaptive model-based control evaluation. The initial conditions and state variables are set to represent a cruise operating point. The first 150 seconds show the nominal onboard model and the degraded engine without the adaptive model-based control. The thrust level of the degraded engine is about 14% less than the nominal engine model which closely tracks the command reference. Similarly, the degraded engine has an ETR of approximately 18% more than the nominal engine. At time 50 seconds a PLA change is introduced requesting an increase in thrust. At time 150 seconds the Kalman estimates of the model health parameters are switched in, thereby bringing the adaptive onboard model into the loop. The estimates of the health parameters at this time have converged to the degraded engine state variables. The adapted onboard model and nominal PI controller action enables the degraded engine to closely follow the thrust and ETR command references.

Kalman Filter State Estimation of Engine State Variables

Figure 9 shows the actual values of the engine state variables (XNL, XNH, TMPC), and the Kalman filter estimates of these state variables during the simulation. The Kalman filter by design strives to minimize the error in the state estimates based on the degraded engine sensor measurements and the model estimates of the output measurements. It is seen from the plots that the state estimates converge very accurately to the actual values of the state variables within the first 50 seconds.

Estimation of Health Parameters

In Figures 10 and 11 the Kalman filter health parameter estimates obtained from this simulation are shown. They exhibit accurate convergence of the health parameter estimates to their actual values for each of the degraded engine component stages. The Kalman filter estimation is active continuously, irrespective of whether the estimates are switched into the control loop via the adapted model. In this simulation the adaptive model was switched in at 150 seconds, at this point most of the health parameter estimates had converged to their true values corresponding to the degraded engine state. It can be seen in Figure 10 that the Kalman estimates of the efficiencies and flows for the Fan (SEDM2, ZSW2) and the High Pressure Compressor (SEDM27, ZSW27) converge within 50 seconds, while for the Low Pressure Compressor the efficiency (SEDM7D) takes about 200 seconds to converge. In Figure 11 the High Pressure Turbine efficiency and flow (ZSE41, ZSW41) converge in about 50 seconds while the Low Pressure Turbine efficiency and flow (ZSE49, ZSW49) take about 200 seconds to converge. The convergence rate of the state estimates for the different health parameters depends on the values of variance chosen for the different elements of the Q and R uncertainty matrices used in the Kalman filter estimator design, and in this example it also appears to depend on the sensitivity of a health parameter to the error between the measured and estimated values of the sensor outputs.

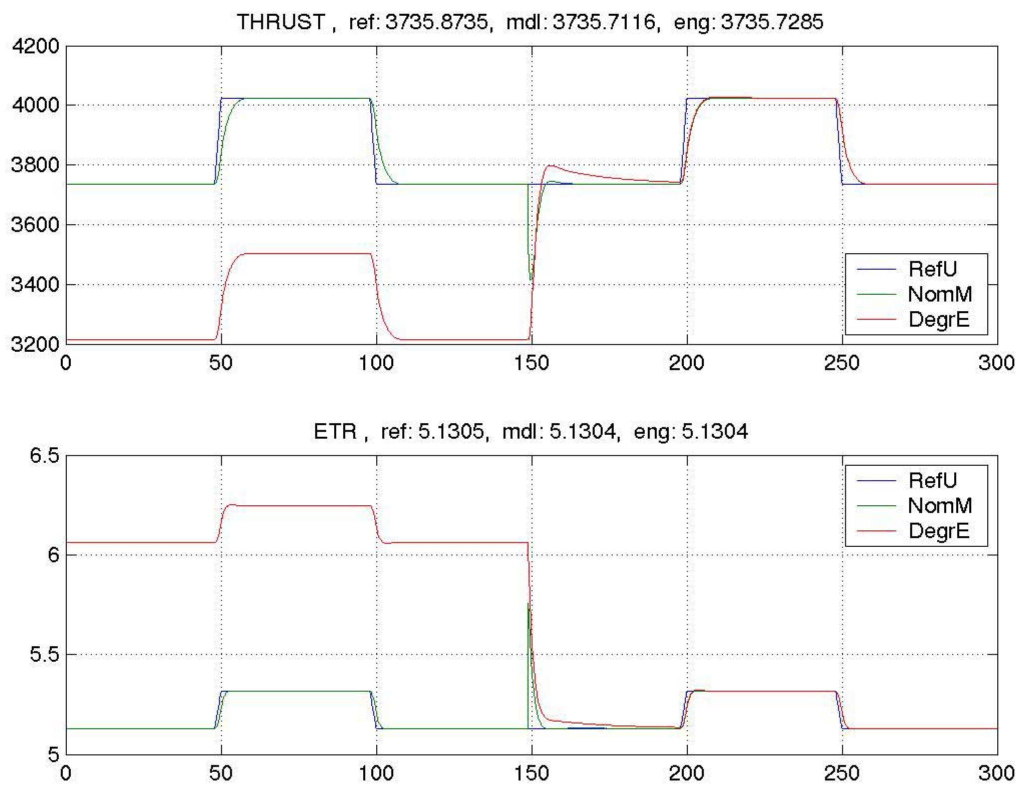

Figure 8: Adaptive Model Based Thrust & ETR Control
(For THRUST and ETR at steady state conditions, **ref**=Command Reference, **mdl**=Model Output and **eng**=Degraded Engine Output, and inside the Figure: **RefU**=Command Reference, **NomM**=Nominal Model, **DegrE**=Degraded Engine)

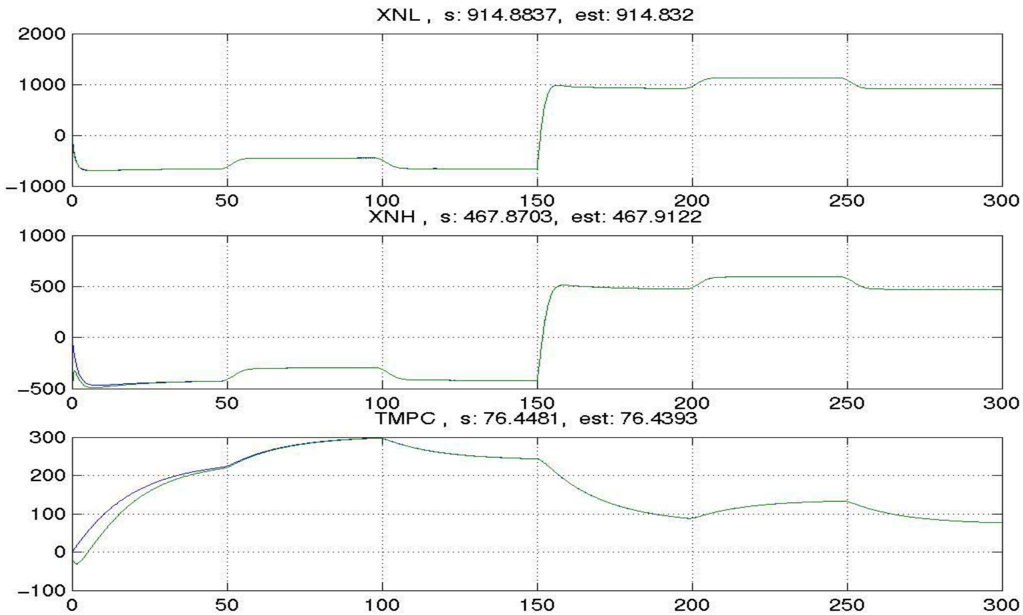

Figure 9: Engine State Estimation by Kalman Filter
s: True Value of State Variable (**blue line** in figure)
est: Estimate of State Variable (**green line** in figure)

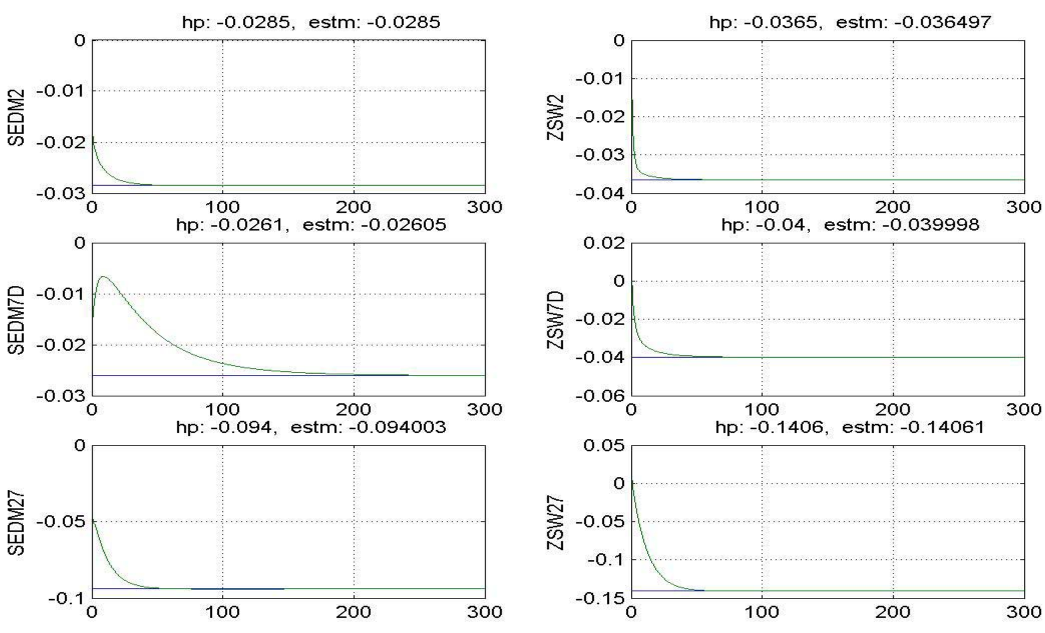

Figure 10: Kalman Filter Estimates of Health Parameters (FAN, LPC, HPC)
hp: True Value of Health Parameter (**blue line** in figure)
estm: Estimate of Health Parameter (**green line** in figure)

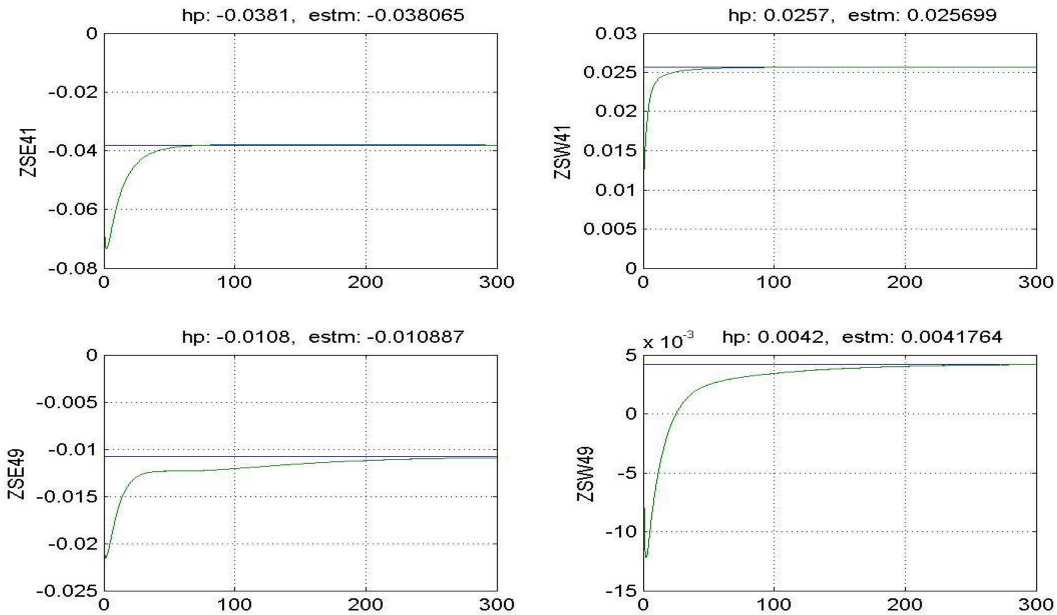

Figure 11: Kalman Filter Estimates of Health Parameters (HPT, LPT)
hp: True Value of Health Parameter (**blue line** in figure)
estm: Estimate of Health Parameter (**green line** in figure)

CONTROLLER ADAPTATION BY PARAMETER OPTIMIZATION

For the design and demonstration of this technique a linear degraded engine was derived from the nonlinear engine model by linearizing about an operating point representative of 6000 cycles of operation, which represents a severely degraded engine, almost at the end of its useful life. The eigenvalues of the *A* matrix of the degraded engine model were further shifted to give a linear engine transfer function that has a very sluggish thrust response in closed loop with a nominal PI controller. This highly degraded closed loop response was created to demonstrate the capability of the controller parameter optimization technique used in this work for adapting the nominal controller parameters. In this technique, the closed loop frequency response of the degraded engine and adaptive controller was matched in a least squares sense with the closed loop frequency response of the nominal engine and nominal PI controller, to yield the adaptive controller parameters.

Controller Adaptation

Parameter optimization is a wide field, in which Edmunds' algorithm[6] represents a readily workable technique. The algorithm is a means of synthesizing a controller $K(s)$ for a degraded engine $G(s)$, which aims to make the resulting closed loop transfer function:

$$T(s) = G(s)\,K(s)\,[\,I + G(s)\,K(s)\,]^{-1}$$

approach a specified target closed loop transfer function $T_0(s)$ of a nominal controller $K_0(s)$ and nominal engine $G_0(s)$ over a given frequency range, where:

$$T_0(s) = G_0(s)\,K_0(s)\,[\,I + G_0(s)\,K_0(s)\,]^{-1}$$

Some key aspects of the algorithm are that the structure of the controller $K(s)$ is assumed to be specified, and a select number of the controller parameters are to be modified to optimize the agreement between $T(s)$ and $T_0(s)$. In the Edmunds' algorithm a simplifying approximation is that only the numerator elements of the controller are considered unknown by restructuring the problem, to allow the optimization to be a linear least squares optimization. In this paper, the Edmunds' approximation is not used, and a more general problem is considered where both numerator and denominator parameters can be optimized, if necessary, in the chosen controller structure. The general case is a nonlinear problem, and the solution is obtained by the use of a nonlinear least squares unconstrained optimization technique.

Structure of the controller

A multivariable PI controller structure is chosen for *K(s)*, in which each element of the (3 input x 3 output) structure is proportional + integral. This structure is based on the high power engine temperature ratio (ETR) control mode[3] of the nonlinear engine simulation PI controller, and has the following form:

$$K(s)=\begin{bmatrix} \left(k_{P11}+\frac{k_{I11}}{s}\right) & \left(k_{P12}+\frac{k_{I12}}{s}\right) & \left(k_{P13}+\frac{k_{I13}}{s}\right) \\ \left(k_{P21}+\frac{k_{I21}}{s}\right) & \left(k_{P22}+\frac{k_{I22}}{s}\right) & \left(k_{P23}+\frac{k_{I23}}{s}\right) \\ \left(k_{P31}+\frac{k_{I31}}{s}\right) & \left(k_{P32}+\frac{k_{I32}}{s}\right) & \left(k_{P33}+\frac{k_{I33}}{s}\right) \end{bmatrix}$$

The three inputs to the controller are the errors in FN, ETR and LEPR, and the outputs of the controller are the changes to WF36, A8 and A16, which are used as control commands to the engine.

Synthesis of this controller requires the identification of a coefficient *Matrix* θ defined as:

$$\theta=\begin{bmatrix} k_{P11} & k_{P12} & k_{P13} \\ k_{I11} & k_{I12} & k_{I13} \\ k_{P21} & k_{P22} & k_{P23} \\ k_{I21} & k_{I22} & k_{I23} \\ k_{P31} & k_{P32} & k_{P33} \\ k_{I31} & k_{I32} & k_{I33} \end{bmatrix}$$

Parameter Optimization Algorithm

The Error Function over a defined frequency range is:

$E(s) = [\, T_0(s) - T(s)\,]$

Collecting the unknown controller coefficients into θ, yields:

$K(s)=K(s,\theta)$

and:

$E(s,\theta) = \{\, T_0(s) - G(s)\, K(s,\theta)\, [I + G(s)\, K(s,\theta)]^{-1} \,\}$

The design problem becomes one of suitably *minimizing* $E(s,\theta)$ *by choice of* θ. A least squares minimization is performed in the frequency domain over a

defined frequency set: $\{\, \omega_k : k = 1,\dots\dots,p \,\}$

i.e.:

Minimize over $\{\, \omega_k \,\}$ $\quad \| E(j\omega,\theta) \|^2$

by choice of θ

The cost function is an element by element form, if E has elements $\{\, e_{ij} \,\}$, the cost function can be expressed as:

$$\| E(j\omega,\theta) \|^2 = \sum_k \sum_i \sum_j \left| e_{ij}\left(j\omega_k,\theta\right) \right|^2$$

In practice the cost function lacks flexibility because it gives equal weighting to each element of E; a more satisfactory cost function includes frequency weighting for each input-output combination as:

$$\| E(j\omega,\theta) \|^2 = \sum_k \sum_i \sum_j \left| v_{ij}(\omega_k)\, e_{ij}\left(j\omega_k,\theta\right) \right|^2$$

where the element-by-element weightings v_{ij} can be used to increase or decrease the importance of certain terms, for instance to achieve diagonal dominance or decoupling of certain input-output relationships.

The minimization of the above cost function is approached in this work as a problem of unconstrained nonlinear optimization. A gradient search method is used to find the optimal θ. Each element $\{e_{ij}\}$ can be split into target and achieved parts.

$$Let \;\; e_{ij} = z^t_{ij} - z_{ij}$$

where: superscript t denotes *target*

The cost function may then be re-written as:

$$\| E(j\omega,\theta) \|^2 = (y_t - y)^T \; (y_t - y)$$

where the column vectors y_t and y contain successive elements of the weighted target and achieved values:

$$
y_t = \begin{bmatrix} v_{11}(\omega_1)\ z^t_{11}(\omega_1) \\ \vdots \\ v_{mn}(\omega_1)\ z^t_{mn}(\omega_1) \\ \vdots \\ \vdots \\ \vdots \\ v_{11}(\omega_p)\ z^t_{11}(\omega_p) \\ \vdots \\ v_{mn}(\omega_p)\ z^t_{mn}(\omega_p) \end{bmatrix}
$$

and:

$$
y = \begin{bmatrix} v_{11}(\omega_1)\ z_{11}(\omega_1) \\ \vdots \\ v_{mn}(\omega_1)\ z_{mn}(\omega_1) \\ \vdots \\ \vdots \\ \vdots \\ v_{11}(\omega_p)\ z_{11}(\omega_p) \\ \vdots \\ v_{mn}(\omega_p)\ z_{mn}(\omega_p) \end{bmatrix}
$$

where: $m=3$ and $n=3$ are the dimensions of the indices for the controller parameters.

and, y is in turn a nonlinear function of θ : $y = f(\theta)$, the gradient of y for each parameter θ is given by the Jacobian matrix J with elements:

$$
J_{ij} = \frac{\partial y_i}{\partial \theta_j} \quad \{at\ \theta^*\}
$$

A gradient search method that re-calculates the Jacobian at each new guess of the parameters θ is used in the optimization procedure, which uses a Matlab function from the optimization toolbox[7]. The search algorithm uses a quasi-Newton method with a mixed quadratic and cubic line search procedure. The overall technique is essentially an unconstrained nonlinear minimization of the objective function to yield the optimal values of the controller parameters in a least squares sense.

Controller Parameter Optimization Results

The controller parameter optimization technique was implemented following the architecture shown in Figure 2. For this evaluation a linear engine simulation was used. The simulation results are shown in Figures 12, 13 and 14. The controller has a 3x3 structure corresponding to the three controlled outputs of thrust, ETR and LEPR of the engine. In Figure 12 the bode magnitude plot is shown for thrust error input to delta thrust output. The blue line shows the closed loop frequency response of the nominal controller, $K_0(s)$, and nominal engine, $G_0(s)$. The green line shows the nominal controller, $K_0(s)$, with the degraded engine, $G(s)$, where the degradation in response for low and high frequency ranges is evident. The red line shows the adapted controller, $K(s)$, with the degraded engine, $G(s)$, and the recovery of the thrust response, particularly in the lower frequencies is clearly evident, where the response closely matches the nominal engine and controller.

In Figure 13, the closed loop time domain response to a change in thrust demand corresponding to a PLA change from 30 to 48 degrees is shown. Again, the blue line is the nominal engine and controller thrust response, the green line is the nominal controller with the degraded engine showing a sluggish thrust response, and the red line is the adapted controller with the degraded engine showing the recovery of the thrust response to closely match the nominal engine and controller.

In Figure 14, the change in the control inputs to the engine are shown. For the case with the adapted controller and degraded engine, the fuel flow rises rapidly to compensate for the sluggish thrust response of the deteriorated engine. In a real engine with acceleration schedule constraints, the rapid rise in fuel flow may encounter a rate limit, thereby limiting the adaptive controller action. The steady state value of fuel flow for the degraded engine is higher than that of the nominal engine, this indicates that the open-loop thrust output decreases for a deteriorated engine, and for this engine to achieve the same thrust output level of a nominal engine more fuel is injected in closed-loop control. The large change in fuel flow for the degraded engine shown here, is due to the excessive deterioration induced in the engine transfer function to demonstrate the recovery capability of the adaptive controller.

In an actual implementation, the controller parameters can be updated offline at the end of each flight cycle. Depending on the duration of a flight cycle and the flight conditions encountered, the controller parameters can be updated after a number of flight cycles.

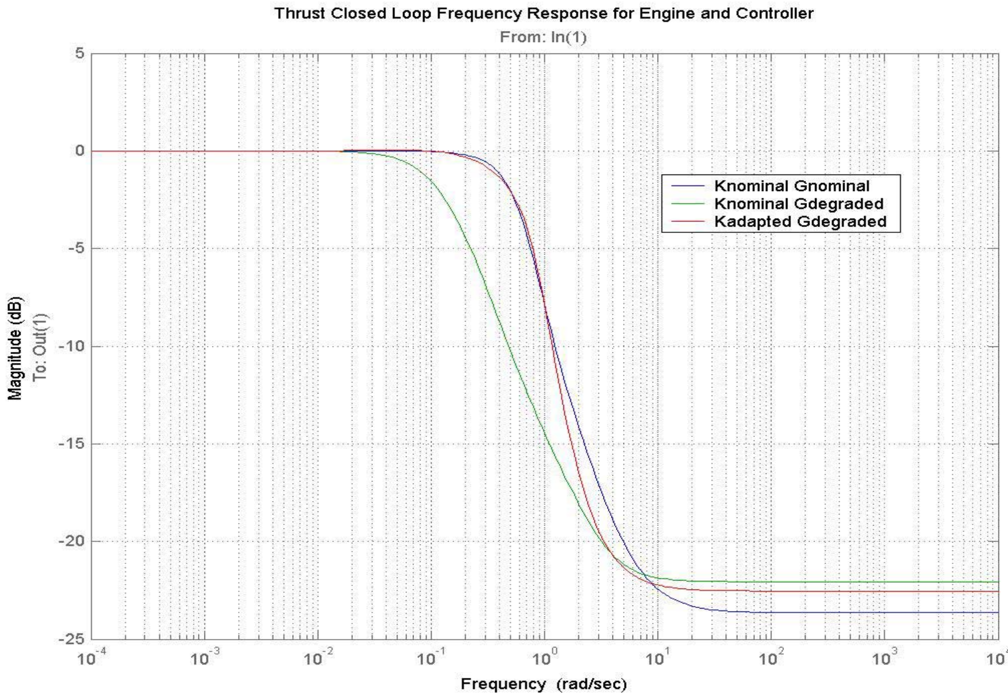

Figure 12: Bode Magnitude Plot of Closed Loop Thrust Frequency Responses

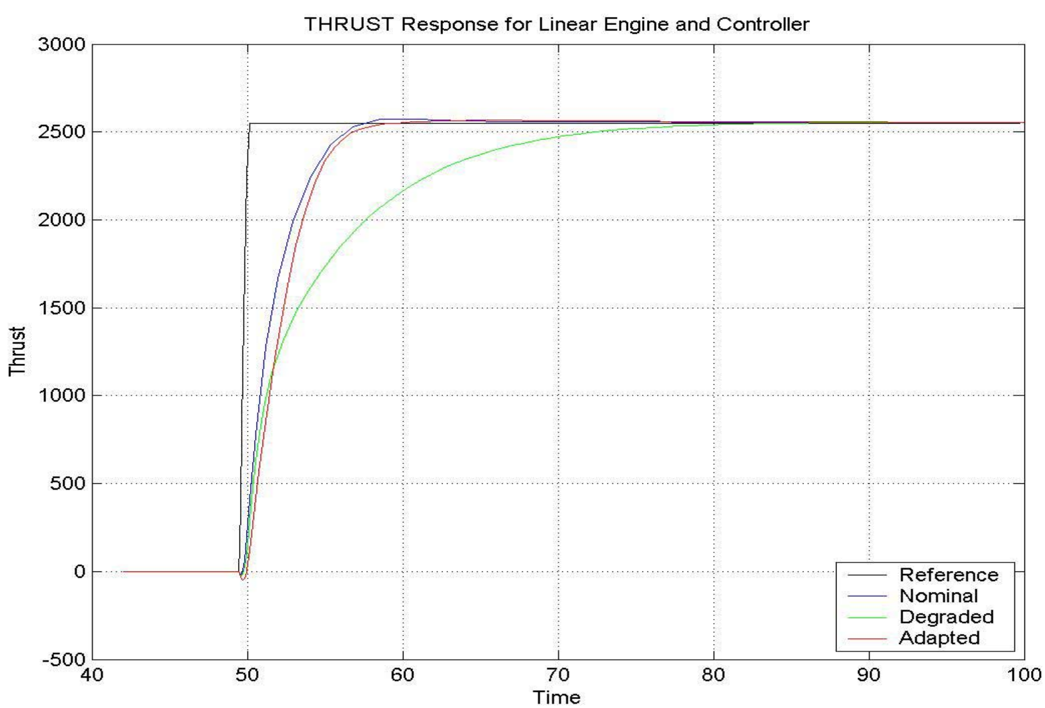

Figure 13: Closed Loop Thrust Responses for Linear Engine

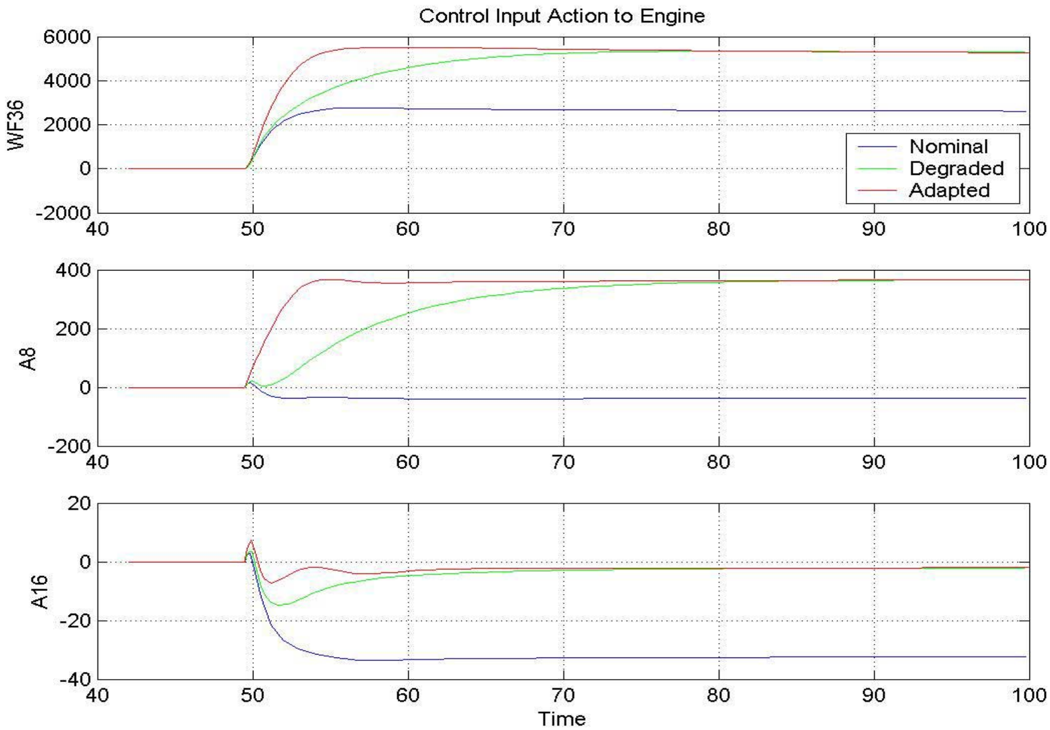

Figure 14: Control Inputs to Linear Engine due to Thrust Demand Change

CONCLUSIONS

A simulation of a modern high performance gas turbine engine for fighter aircraft was used to study the effects of engine health parameter degradation on thrust performance as well as engine and controller dynamics. Health parameter values were compiled for degraded engines at 3000 and 6000 cycles of operation, and it was found that the thrust performance for degraded engines was increasingly sluggish with increasing engine degradation as compared to a nominal engine. To address similar degradation effects simulated in the linear environment, two separate adaptive control techniques where evaluated. First, an adaptive model-based control configuration using online Kalman filter estimation of degraded engine health parameters was designed to compensate for the degradation due to aging. The Kalman estimator provided accurate real-time estimates of all ten engine health parameters, and this allowed the control system to quickly regulate steady-state thrust in response to engine degradation. The second technique of controller parameter optimization was used to ensure that the transient thrust performance of the degraded engine matches the nominal engine in closed loop. To accomplish this, the PI controller parameters were adapted so that the frequency response of the closed loop transfer function of the degraded engine and adaptive controller matched the closed loop frequency response of the nominal engine and baseline PI controller in a least squares sense. The parameter optimization was performed using a nonlinear unconstrained gradient search optimization technique. The adaptive PI controller action was used to augment the nominal PI controller action with the degraded engine in closed-loop. In simulation, the adaptive controller recovered the thrust performance of the severely degraded engine to match the thrust performance of the nominal engine and controller.

The initial linear control design about an operating point shown in this paper is an important first step in the overall propulsion control design process. For future work, the single operating point design can be extended across the full flight envelope by linearizing at multiple operating points and using linked linear models across the flight envelope. The techniques of model parameter estimation and controller parameter optimization shown here, can be combined into an integrated model-based adaptive control system that can recover steady-state and transient response of un-measurable parameters such as thrust and stall margin. In the context of autonomous flight control the onboard adaptive model-based propulsion control system can deliver the desired thrust where a pilot might otherwise have needed to manually adjust the throttle.

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Jet engine components are subject to degradation over their lifetime of use, and this can lead to a deterioration in thrust performance of the engine. For autonomous propulsion control, it is desirable for the engine control system to maintain a nominal level of propulsion system thrust performance in an engine subject to changes in dynamics caused by aging and degradation. In this paper, two adaptive control techniques are investigated to recover the thrust performance of a degraded engine so that it is as close as possible to the thrust performance of a nominal (new) engine. The first technique consists of an adaptive onboard linear engine model tuned by parameter estimation using a Kalman filter, and used in closed loop with a PI controller to maintain nominal thrust performance. In the second technique, the nominal PI controller gains are adapted with a least squares method of controller parameter optimization in the frequency domain, so that the closed loop frequency response of the degraded engine and adaptive PI controller matches the closed loop frequency response of a nominal engine and nominal PI controller. Use of the new adaptive controller recovered the closed-loop transient thrust response of the degraded engine to nominal levels.

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