Toward an intelligent, deterioration accommodating controller for aging turbofan engines

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ABSTRACT

A method for accommodating engine deterioration via a scheduled linear parameter varying quadratic Lyapunov function (LPVQLF)-based controller is presented. The LPVQLF design methodology provides a means for developing unconditionally stable, robust control of linear parameter varying (LPV) systems. The controller is scheduled on the engine deterioration index, a function of estimated parameters that relate to engine health, and is computed using a multilayer feedforward neural network. Acceptable thrust response and tight control of exhaust gas temperature (*EGT*) is accomplished by adjusting the performance weighting on these parameters for different levels of engine degradation. Nonlinear simulations demonstrate that the controller achieves specified performance objectives while being robust to engine deterioration as well as engine-to-engine variations.

NOMENCLATURE

A,B,C,D	state space model system matrices
CLP	subscript denoting closed-loop system
EDI	engine degradation index
EPR	engine pressure ratio
FN	engine net thrust
G	block diagram representation of plant
I	identity matrix
K	subscript denoting controller, block diagram representation of controller
L, M	state space health parameter augmentation matrices
LMI	linear matrix inequality
LPV	linear parameter varying
LPVQLF	linear parameter varying quadratic Lyapunov function
p	health parameter vector
P	Lyapunov function matrix for unforced system, scheduling parameter space
s	Laplace variable
SM	stall margin
SMD	stall margin deviation
T5, EGT	exhaust gas temperature
u	system input
v	controller inputs
V	Lyapunov function
VBV	variable bleed valve
VSV	variable stator vane
w	exogenous system inputs
W	Lyapunov function matrix for forced system
$\mathbf{W}_{var}$	frequency-dependent performance weights for variable *var*
WF	engine fuel flow
x	state variable vector
y	system output
z	unmeasured system outputs related to control system performance
δ	deviation from steady state operating condition
Δ	block diagram representation of model uncertainty
$\rho(t)$, ρ	scheduling parameter for engine deterioration

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1.0 INTRODUCTION

Turbofan engine performance varies from engine to engine due to manufacturing tolerances, aging, and deterioration caused by use[1]. Generally the control system developed for the engine is robust enough to keep it operating within acceptable boundaries for several thousand flight cycles, even though the degradation will eventually require the engine to be overhauled as limits are reached. These limits include operability constraints such as maximum temperatures, minimum stall margins, and performance constraints such as the FAA's rise time requirement for thrust in commercial engines. Exhaust gas temperature (*EGT*) increases as the engine ages and is used as an indicator of the engine's internal condition, i.e., unmeasurable temperatures that can lead to thermomechanical fatigue (TMF) of engine components. *EGT* is usually at a maximum during the take-off phase of flight, and if it reaches a specified threshold it signifies that the engine needs to be overhauled. Stall margin, or the distance an engine component is operating from the stall line on its performance map, tends to decrease with age, increasing the risk of an engine stall during transient operation.

Turbofan engines typically control Engine Pressure Ratio (*EPR*) or fan speed to generate the desired thrust, since thrust can not be measured directly during flight. As the engine is used, manifestations of wear such as turbine blade erosion, larger clearances, etc., degrade the engine's performance. In order to achieve the same fan speed or *EPR* as in a new engine, a deteriorated engine must run hotter and/or faster. This shift from nominal operation increases with use, and eventually reaches the point where the engine's performance can not be maintained without compromising the life of its components. While regulated variables are maintained at their setpoints regardless of engine degradation, the non-regulated parameters shift from their nominal values with deterioration[2]. Additionally, in the degraded engine, the actual thrust output, which is indirectly controlled through the regulation of other variables, may be shifted from the expected value.

In this work the objective is to maintain consistent steady state and transient thrust response (rise time less than five seconds), even in the presence of degradation, which precludes the use of *EPR* or fan speed as the controlled variable. Currently some engines achieve consistent acceleration and deceleration by controlling the derivative of core speed[3], but not all engines use this control mode, and it does not address the steady state shift in thrust introduced by deterioration. Direct thrust control, however, can deal with both of these issues. There is currently significant interest in direct control of thrust using such approaches as model predictive control and model-based control because of their ability to reduce fuel consumption and *EGT*, and generally optimise overall engine performance[4-6]. However, because thrust is not directly measurable in flight, for any of these methodologies to be implemented a reliable thrust estimate is required. This has led to several different approaches to thrust estimation using standard sensor measurements which have been validated in simulation[4-9], and progress is being made toward an engine test of model predictive control within the next few years[5]. In this work thrust is controlled directly, with the assumption that a reliable estimate is available. (No thrust estimation algorithm is implemented here, but a scheme demonstrated using the same engine model has been shown to be sufficiently accurate for closed loop control over a wide range of operating conditions and deterioration levels[10]. Additionally the controller minimises exhaust gas temperature, in terms of the steady state value and in excursions during transients, while maintaining acceptable component (estimated) stall margins to overcome the operability problems associated with traditional controllers applied to aging engines. To meet these goals, a robust linear parameter varying (LPV) controller[11] is designed to accommodate a range of degradation using sets of gains scheduled on the engine degradation index (EDI). The linear parameter varying quadratic Lyapunov function (LPVQLF) design methodology provides a means for developing unconditionally stable, robust gain scheduled control of nonlinear plants with appropriate Jacobian linearisations across an operating envelope, i.e., linear parameter varying (LPV) systems. The LPV controller is applied to a nonlinear simulation of a large commercial turbofan engine. This paper is organised as follows: Section 2 describes the characteristics of engine degradation and its accomodation using LPV control, Section 3 presents an overview of the LPV controller development process via quadratic Lyapunov functions, Section 4 provides the pertinent details concerning the design of LPV thrust/*EGT* controllers for a large turbofan engine, Section 5 presents the results of nonlinear simulation testing of these controllers and Section 6 presents conclusions and future work. Due to the proprietary nature of the models used for controller development, the results presented are suitably normalised or in terms of deviations.

2.0 ENGINE DEGRADATION AND LPV CONTROL

To develop the LPV controller, models of the engine ranging from nominal to fully degraded need to be generated. Off-nominal values of specific internal engine parameters representing component efficiencies and flow capacities are often used to account for these performance variations. These adjustment parameters are called health parameters[12] because they indicate the level of engine deterioration. The equations describing the degraded engine's behavior are given by

$$\begin{aligned}\dot{\mathbf{x}}(t) &= f(\mathbf{x}(t),\mathbf{u}(t),\mathbf{p})\\ \mathbf{y}(t) &= g(\mathbf{x}(t),\mathbf{u}(t),\mathbf{p})\end{aligned} \quad \ldots (1)$$

where $\mathbf{p}$ represents the vector of health parameters. When obtaining a standard linear point model of an engine, the health parameters are treated like inputs,

$$\begin{aligned}\delta\dot{\mathbf{x}}(t) &= \mathbf{A}\delta\mathbf{x}(t) + \mathbf{B}\delta\mathbf{u}(t) + \mathbf{L}\delta\mathbf{p}\\ \delta\mathbf{y}(t) &= \mathbf{C}\delta\mathbf{x}(t) + \mathbf{D}\delta\mathbf{u}(t) + \mathbf{M}\delta\mathbf{p}\end{aligned} \quad \ldots (2)$$

Depending upon how the health parameters manifest themselves, the system dynamics may or may not change with degradation. Equation (2) clearly illustrates that steady state is only obtained when the $\mathbf{x}(t)$ and $\mathbf{u}(t)$ vectors shift to compensate for $\mathbf{p}$, and the output equation shows how nonzero values of $\mathbf{p}$ can produce additional steady state shifts in the output variables. These equations also imply that degradation causes shifts in the engine's trim values,

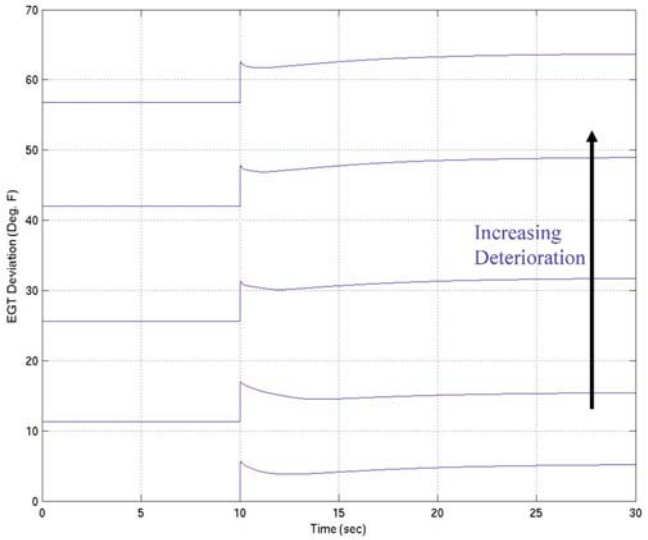


Figure 1. Open loop *EGT* response (deviation from nominal) to a 2% increase in fuel flow for several levels of deterioration.

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and it is these shifts that can result in unacceptable operation. Figure 1 presents the effect of engine deterioration on exhaust gas temperature (*EGT*) open loop response (deviation from nominal) to a 2% change in fuel flow. A shift in trim is clearly evident, with a less pronounced change in *EGT* dynamic response.

In general, the health parameters vary slowly enough with time that they are treated as constants in Equation (2). Trending of the health parameters can be achieved by an estimation algorithm known as a tracking filter. Tracking filters have been successfully used to estimate health parameters from measured variables[13], allowing more accurate tracking of unmeasured engine variables such as thrust and stall margin. In this work it is assumed that reliable estimates of the health parameters, thrust, and stall margin are available.

As mentioned previously, the LPV controller is scheduled on EDI. Here the health parameters are each assumed to change as functions of EDI from new (0%) to fully deteriorated (100%), with some variation about a nominal degradation profile (engine-to-engine variation). For the present study, a multilayer perceptron neural network is used to map estimated engine health parameter values (assumed to be provided by a tracking filter) back to the scalar EDI to accommodate uncertainties associated with the health parameters. Desired response of engine thrust and exhaust gas temperature (*EGT*) is accomplished by adjusting the performance weighting on these variables for different levels of engine degradation. Model uncertainty (i.e., engine-to-engine variation) is also incorporated into the design. Figure 2 presents an overview of the deterioration-tolerant LPV controller.

3.0 LINEAR PARAMETER VARYING CONTROLLERS BASED ON QUADRATIC LYAPUNOV FUNCTIONS

Unconditional stability of parameter dependent controllers is provided via development and solution of a suitable Lyapunov equation, which incorporates the dynamic characteristics of the closed loop system. The linear parameter varying (LPV) system considered here is such that all time dependence in the system is correlated to the parameter dependence on time, with each set of state space matrices used for controller design a function of the EDI, $\rho(t)$.

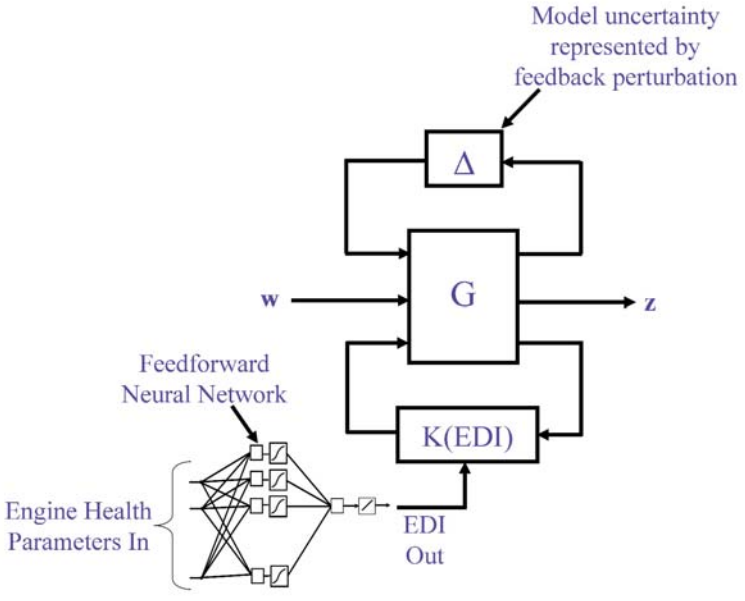


Figure 2. Overview of turbofan engine deterioration-tolerant LPV controller.

Consider first an unforced, time-invariant nonlinear system of the form

$$\dot{\mathbf{x}}(t) = f(\mathbf{x}(t)) \quad \ldots (3)$$

with origin $\mathbf{x}(0)$. The above is *Lyapunov stable* if a positive definite function, $V(\mathbf{x})$, exists such that

$$\dot{V}(x) = \frac{\mathrm{d}V(\mathbf{x})}{\mathrm{d}\mathbf{x}} f(\mathbf{x}) \quad \ldots (4)$$

is negative semi-definite. If Equation (4) is negative definite, the origin is asymptotically stable. For linear time invariant (LTI) systems

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) \quad \ldots (5)$$

and a candidate Lyapunov function takes the form

$$V(\mathbf{x}) = \mathbf{x}^T\mathbf{P}\mathbf{x} \quad \ldots (6)$$

with

$$\dot{V}(\mathbf{x}) = \mathbf{x}^T(\mathbf{A}^T\mathbf{P} + \mathbf{P}\mathbf{A})\mathbf{x} \quad \ldots (7)$$

If a matrix $\mathbf{P}$ can be found such that $(\mathbf{A}^T\mathbf{P} + \mathbf{P}\mathbf{A})$ is negative (semi) definite then the system is asymptotically (Lyapunov) stable[14]. For forced LTI systems

$$\dot{\mathbf{x}}(t) = \mathbf{A}\mathbf{x}(t) + \mathbf{B}\mathbf{u}(t) \quad \ldots (8)$$
$$\mathbf{y}(t) = \mathbf{C}\mathbf{x}(t)$$

the Bounded Real Lemma[14] provides a Lyapunov-like stability criterion, i.e., the system is internally exponentially stable and

$$\left\|\mathbf{C}\left(s\mathbf{I} - \mathbf{A}\right)^{-1}\mathbf{B}\right\|_{\infty} < 1 \quad \ldots (9)$$

if and only if the matrix $\mathbf{X} = \mathbf{X}^T > 0$ provides a solution to

$$\mathbf{A}^T\mathbf{X} + \mathbf{X}\mathbf{A} + \mathbf{X}\mathbf{B}\mathbf{B}^T\mathbf{X} + \mathbf{C}^T\mathbf{C} < \mathbf{0} \quad \ldots (10)$$

Consider a nonlinear system approximated by an LPV system, where $\rho(t) \in \mathbf{P}$, $\mathbf{P}$ being the space of all possible parameter trajectories,

$$\begin{bmatrix} \dot{\mathbf{x}}(t) \\ \mathbf{z}(t) \\ \mathbf{y}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{A}(\rho(t)) & \mathbf{B}_w(\rho(t)) & \mathbf{B}_u(\rho(t)) \\ \mathbf{C}_z(\rho(t)) & \mathbf{D}_{zw}(\rho(t)) & \mathbf{D}_z(\rho(t)) \\ \mathbf{C}(\rho(t)) & \mathbf{D}_w(\rho(t)) & 0 \end{bmatrix} \begin{bmatrix} \mathbf{x}(t) \\ \mathbf{w}(t) \\ \mathbf{u}(t) \end{bmatrix} \quad \ldots (11)$$

with the feedback controller defined as

$$\begin{bmatrix} \dot{\mathbf{x}}_K(t) \\ \mathbf{u}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{A}_K(\rho(t)) & \mathbf{B}_K(\rho(t)) \\ \mathbf{C}_K(\rho(t)) & \mathbf{D}_K(\rho(t)) \end{bmatrix} \begin{bmatrix} \mathbf{x}_K(t) \\ \mathbf{y}(t) \end{bmatrix} \quad \ldots (12)$$

The corresponding closed-loop LPV system is represented by

$$\begin{bmatrix} \dot{\mathbf{x}}_{CLP}(t) \\ \mathbf{z}(t) \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{CLP}(\rho(t)) & \mathbf{B}_{CLP}(\rho(t)) \\ \mathbf{C}_{CLP}(\rho(t)) & \mathbf{D}_{CLP}(\rho(t)) \end{bmatrix} \begin{bmatrix} \mathbf{x}_{CLP}(t) \\ \mathbf{w}(t) \end{bmatrix} \quad \ldots (13)$$

where

$$\mathbf{x}_{CLP} = \begin{bmatrix} \mathbf{x}^T & \mathbf{x}_K^T \end{bmatrix}^T \quad \ldots (14)$$

and

$$\mathbf{A}_{CLP}(\rho) = \begin{bmatrix} \mathbf{A}(\rho) + \mathbf{B}(\rho)\mathbf{D}_K(\rho)\mathbf{C}(\rho) & \mathbf{B}(\rho)\mathbf{C}_K(\rho) \\ \mathbf{B}_K(\rho)\mathbf{C}(\rho) & \mathbf{A}_K(\rho) \end{bmatrix} \quad \ldots (15)$$

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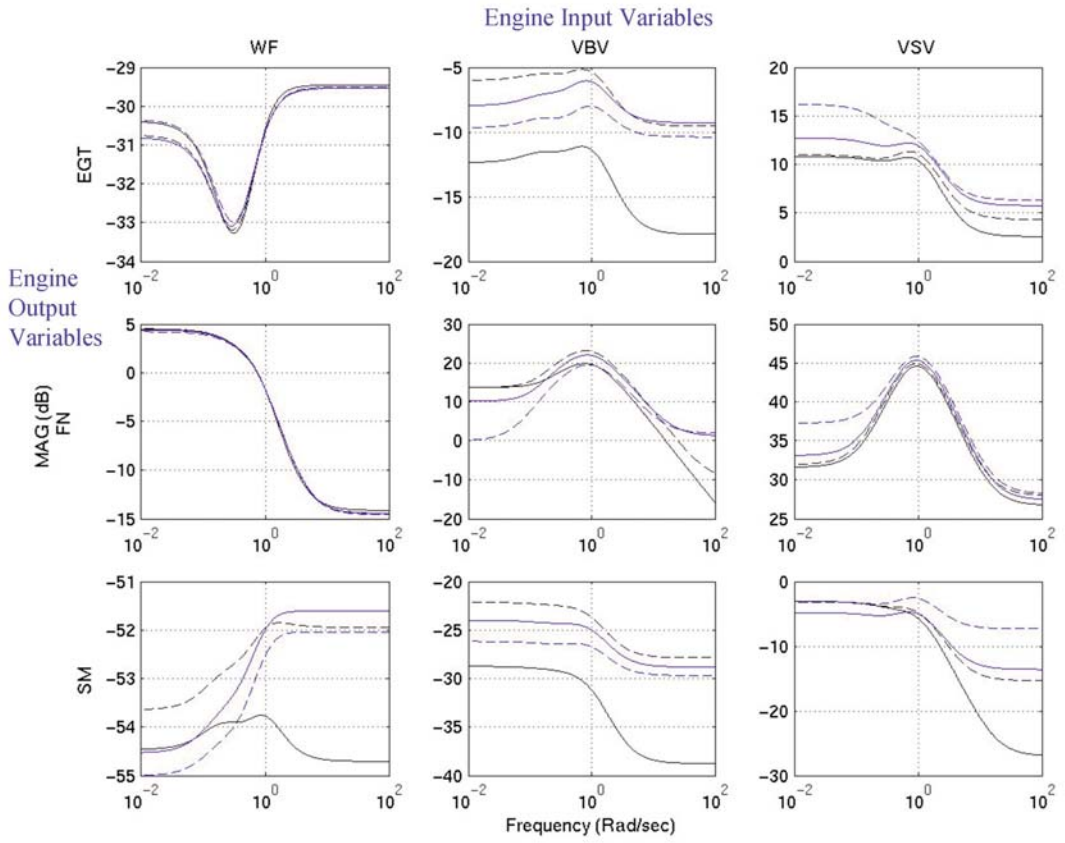


Figure 3. Turbofan engine input-to-output transfer function magnitudes showing the effect of 0%, 25%, 50%, and 75% deterioration (along nominal profile or EDI) on plant dynamics.

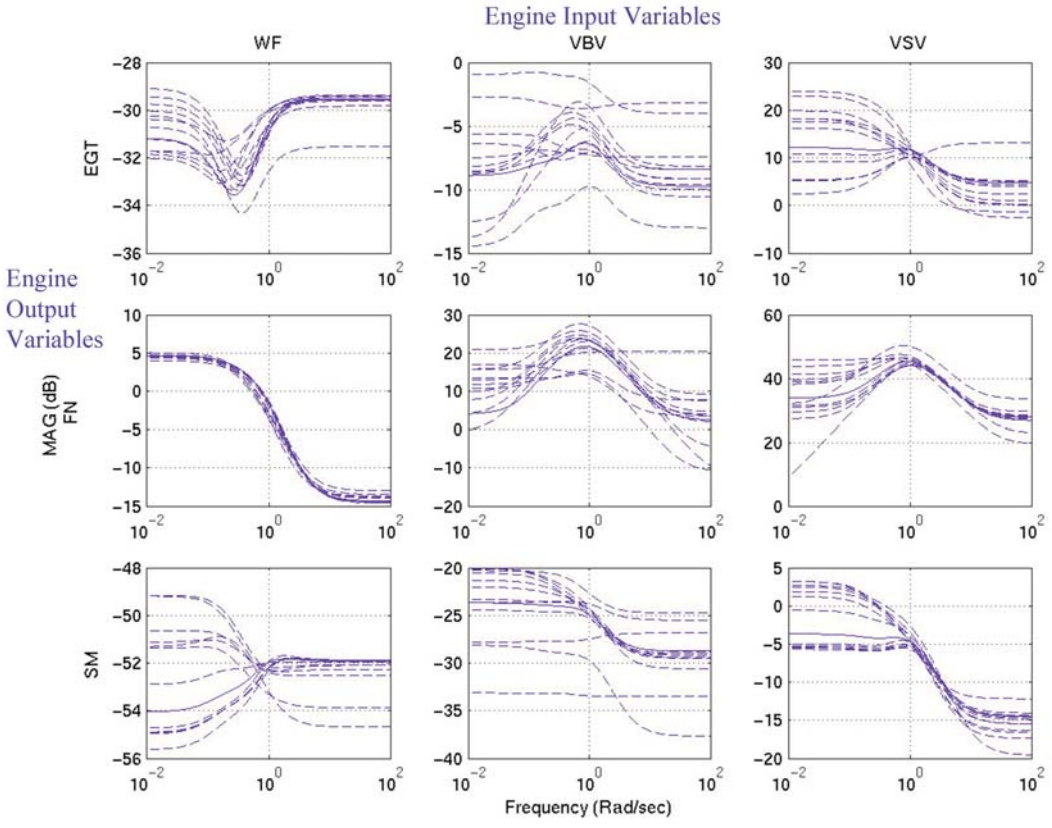


Figure 4. Turbofan engine input-to-output transfer function magnitudes showing the effect of engine-to-engine variation on plant dynamics.

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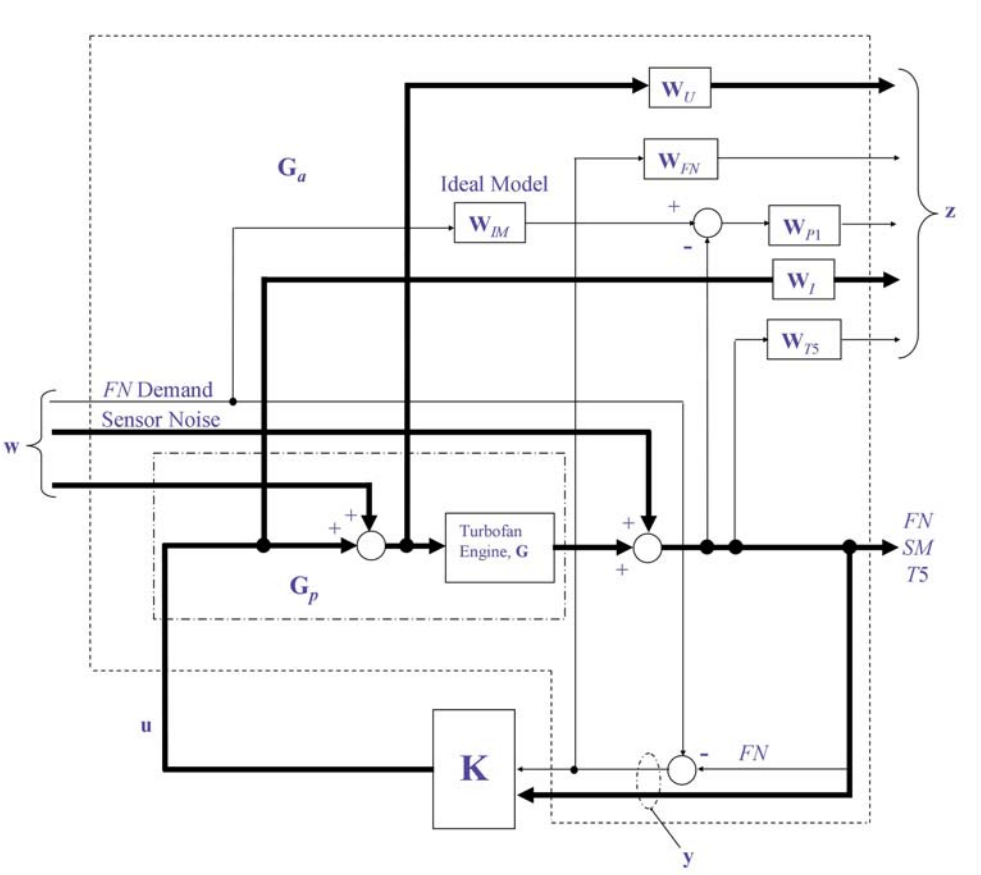


Figure 5. Interconnection diagram for LPVQLF-based turbofan engine thrust/*EGT* controller.

$$\mathbf{B}_{CLP}(\rho)=\begin{bmatrix}\mathbf{B}_w(\rho)+\mathbf{B}(\rho)\mathbf{D}_K(\rho)\mathbf{D}_w(\rho)\\ \mathbf{B}_K(\rho)\mathbf{D}_w(\rho)\end{bmatrix} \quad \ldots (16)$$

$$\mathbf{C}_{CLP}(\rho)=\begin{bmatrix}\mathbf{C}_z(\rho)+\mathbf{D}_z(\rho)\mathbf{D}_K(\rho)\mathbf{C}(\rho) & \mathbf{D}_z(\rho)\mathbf{C}_K(\rho)\end{bmatrix} \quad \ldots (17)$$

$$\mathbf{D}_{CLP}(\rho) = [\mathbf{D}_{ZW}(\rho) + \mathbf{D}_Z(\rho)\mathbf{D}_K(\rho)\mathbf{D}_W(\rho)] \quad \ldots (18)$$

with the time dependence of ρ implied. If the matrix inequality

$$\begin{bmatrix}\mathbf{A}_{CLP}^T(\rho)\mathbf{W}(\rho)+\mathbf{W}(\rho)\mathbf{A}_{CLP}(\rho) & \mathbf{W}(\rho)\mathbf{B}_{CLP}(\rho) & \mathbf{C}_{CLP}^T(\rho)\\ \mathbf{B}_{CLP}^T(\rho)\mathbf{W}(\rho) & -\gamma\mathbf{I} & \mathbf{D}_{CLP}^T(\rho)\\ \mathbf{C}_{CLP}(\rho) & \mathbf{D}_{CLP}(\rho) & -\gamma\mathbf{I}\end{bmatrix}<0 \quad \ldots (19)$$

and its Lyapunov solution matrix

$$\mathbf{W}(\rho) > 0 \quad \ldots (20)$$

for all permissible trajectories of the scheduling parameter $\rho \in \mathbf{P}$, then a family of controllers dependent on ρ (Equation (11)) will provide globally stable, induced L_2 norm performance in terms of γ,[15,16] i.e.,

$$\|z\|_2^2 < \gamma^2 \|w\|_2^2 \quad \ldots (21)$$

Equation (19) is nonlinear and thus, may not be convex. However, with **W** independent of ρ, as well as application of the projection lemma[16], Equation (19) provides a linear matrix inequality (LMI) allowing for numerical solution via state-of-the-art semidefinite programming (SDP) techniques[16]. For an LTI system, this reduces to determining the γ-bounded H_∞ norm. The controller formulas (Equation (12)) are explicit functions of feasible solutions to additional LMI-based constraints[15,16]. For the present study, the parameter space **P** (i.e., the range of EDI under consideration) is discretised with the solution of Equation (19) constrained to be a single Lyapunov matrix solution for all of the corresponding plants.

4.0 CONTROLLER DEVELOPMENT

LPVQLF control seeks to provide a globally stable closed-loop system with optimal performance described by Equation (21). This is achieved by accommodating uncertainty in the system via 1) the parameter dependence (deterioration dependence) of the state space system described by Equation (11), and 2) the ability to incorporate model uncertainty at each deterioration point (i.e., engine-to-engine variation). For the large commercial turbofan engine simulation used in this work, the available actuators are fuel flow (*WF*), variable bleed valve position (*VBV*), and variable stator vane (*VSV*) position. An exhaust gas temperature measurement, as well as accurate thrust and stall margin estimates are assumed to be available.

The transfer functions from the three engine inputs, *WF*, *VBV*, *VSV*, to the outputs *EGT*, *FN*, and *SM* (shown in Fig. 3), provide an indication of the effect of engine deterioration on the nominal engine dynamics. Figure 3 presents four plants corresponding to 0%, 25%, 50%, and 75% deterioration (i.e., EDI), illustrating that the ability of the *VBV* and *VSV* actuators to control the plant output is affected by the level of deterioration. Figure 4 presents an example of the effect of engine-to-engine variation on a 25% deteriorated plant, highlighting the need for explicit representation of this source of uncertainty in the controller design as well.

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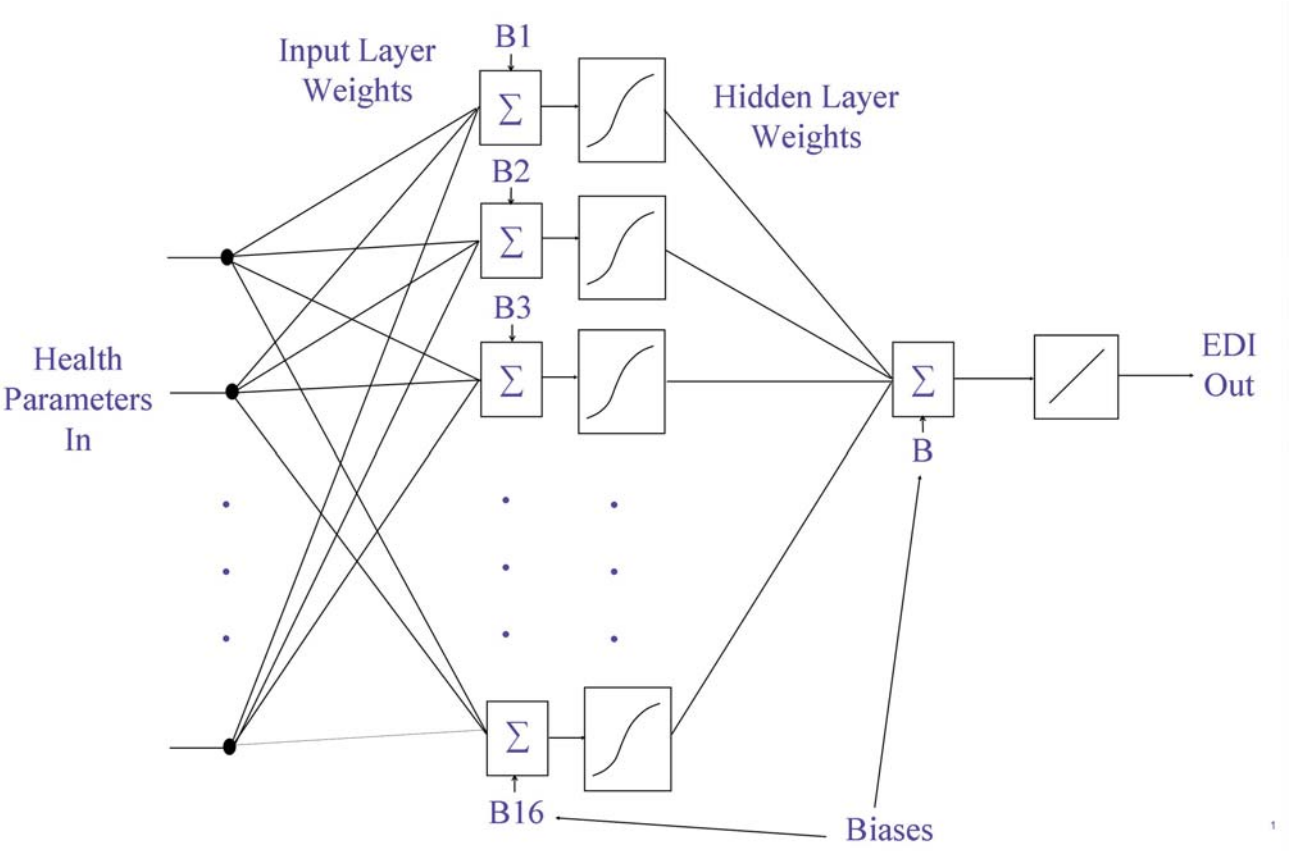


Figure 6. Feedforward neural network used to map engine health parameters to the controller scheduling parameter, EDI.

The interconnection block diagram used for LPV control system design is presented in Fig. 5. The nominal plant (i.e., the plant used for controller design) is shown as **G** and is the state-space model of a large turbofan engine. $\mathbf{G}_p$ is the perturbed plant, which includes the effects of uncertainty due to model inaccuracies (e.g., engine-to-engine variation), and $\mathbf{G}_a$ is the augmented plant incorporating performance weights for controller design. Plant inputs are specified by **w** (exogenous) and **u** (control). Plant outputs are specified by **z** (unmeasured performance measures) and **y** (measurements).

Optimal performance is achieved by specifying a set of performance weights included in the augmented plant, $\mathbf{G}_a$, of the system along with the nominal plant **G**. By satisfying Equation (21) for a specified value of γ of the augmented plant, the induced L_2 norm of the disturbance-to-performance measure transfer matrix is maintained below γ for all plants specified by $\rho \in \mathbf{P}$. Robustness to plant uncertainty (i.e., in-band model error or neglected dynamics) and minimisation of input control energy are also addressed by including their effects or allowed limits via suitably designed frequency-dependent weights (e.g., $\mathbf{W}_I$ and $\mathbf{W}_U$). The goals of the controller are to provide acceptable thrust response while minimising the net change in exhaust gas temperature in the presence of engine deterioration and model uncertainty. This is analogous to the so-called mixed sensitivity H_∞-optimal control problem for a linear time invariant system[17].

Shown in Fig. 5 as an exogenous input to the plant, **G**, are norm-bounded perturbations in the plant model, i.e., uncertainty. Since a detailed uncertainty representation may add significantly to the complexity of the controller (i.e., controller order), an unstructured diagonal input uncertainty model is used with the upper bound set as the frequency dependent weight $\mathbf{W}_I(s)$. A simplified transfer function is assigned to envelop the frequency-dependent error between the 'actual' and reduced order plants. $\mathbf{W}_I(s)$ essentially represents the normalised difference between the actual (or perturbed) and the nominal (reduced order) plant, i.e.,

$$\text{Model Error} = \text{Magnitude of}\left[\frac{\mathbf{G}_p(j\omega)-\mathbf{G}(j\omega)}{\mathbf{G}(j\omega)}\right] \quad \ldots (22)$$

To reduce the order of the controller, the frequency-dependent weights were set to constants, effectively representing 30% modeling error across the entire frequency range of interest, providing a conservative upper bound on model uncertainty due to engine-to-engine variation for all levels of deterioration.

Each of the remaining performance weights shown in Fig. 5 are described as follows. Model matching is provided by $\mathbf{W}_{IM}$ (*IM* refers to the *Ideal Model*) corresponding to what would be considered to be the ideal step response for the plant considered. $\mathbf{W}_{IM}$ is simply a second-order transfer function with a natural frequency and damping ratio tuned to provide rapid thrust response with no overshoot. $\mathbf{W}_{FN}$ provides integral action (i.e., high gain at low frequencies) to ensure zero steady-state offset for setpoint tracking of engine thrust. $\mathbf{W}_{TS}$ weights the exhaust gas temperature response so that the deviation of *EGT* from nominal is minimised. $\mathbf{W}_{P1}$ provides a means for a 'trade-off' between thrust response and *EGT* response, i.e., in order to achieve tighter control of *EGT* engine thrust response may have to be sacrificed by decreasing this weight. $\mathbf{W}_{P1}$, as well as $\mathbf{W}_{FN}$ and $\mathbf{W}_{TS}$ were tuned at each EDI to provide adequate thrust response and tight control over *EGT*. Plant interconnection and controller design were performed using the MATHWORKS Mu Analysis and Synthesis and LMI Toolboxes as part of the MATLAB software package[18,19].

The deterioration index, itself being a function of engine health parameters such as component efficiencies and flow capacities,

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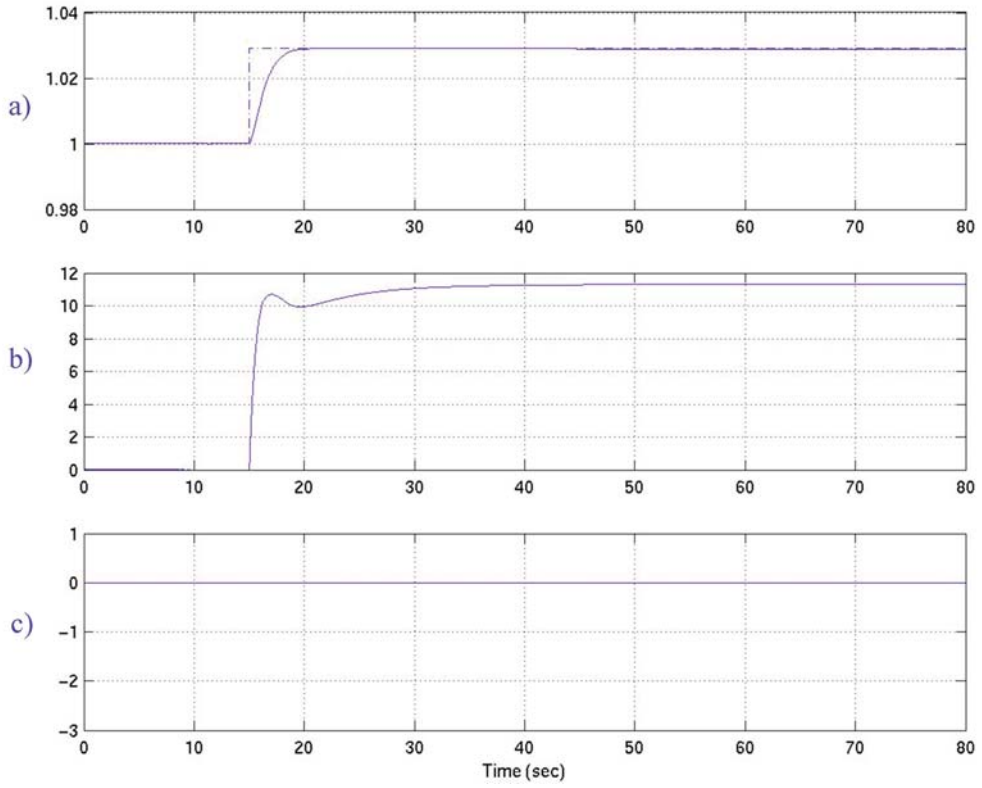


Figure 7. Thrust-only control of 40% deteriorated engine (EDI of 0·4),
(a) Normalised thrust response,
(b) *EGT* deviation from steady state (Deg F),
(c) *VSV* and *VBV* deviations from steady state (Degrees and in^2 respectively).

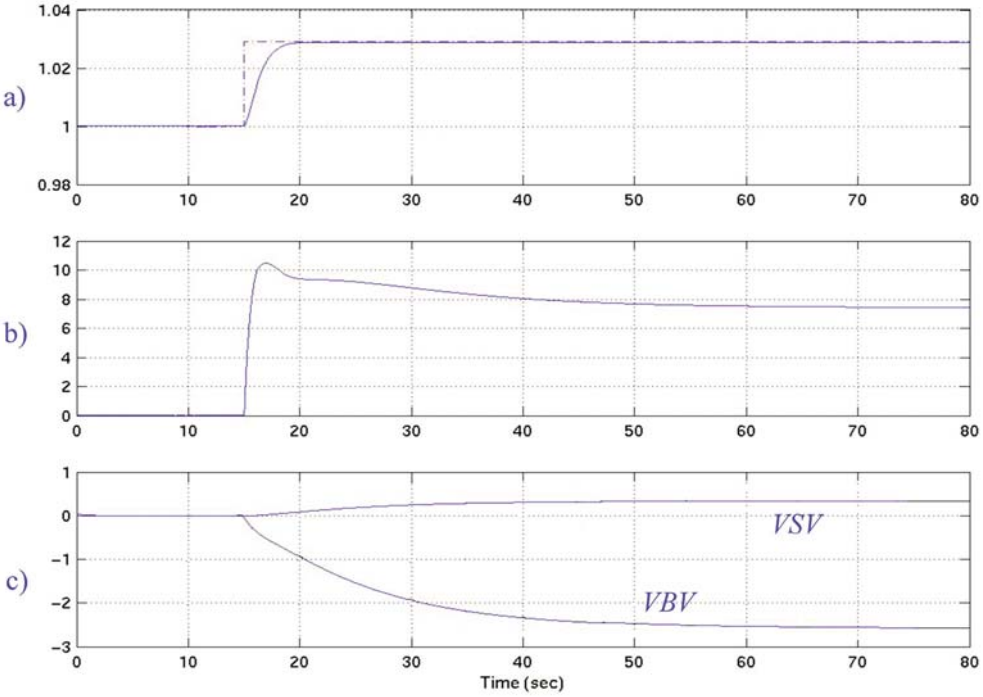


Figure 8. Thrust and *EGT* control of 40% deteriorated engine (EDI of 0·4),
(a) Normalised thrust response,
(b) *EGT* deviation from steady state (Deg. F),
(c) *VSV* and *VBV* deviations from steady state (Degrees and in^2 respectively).

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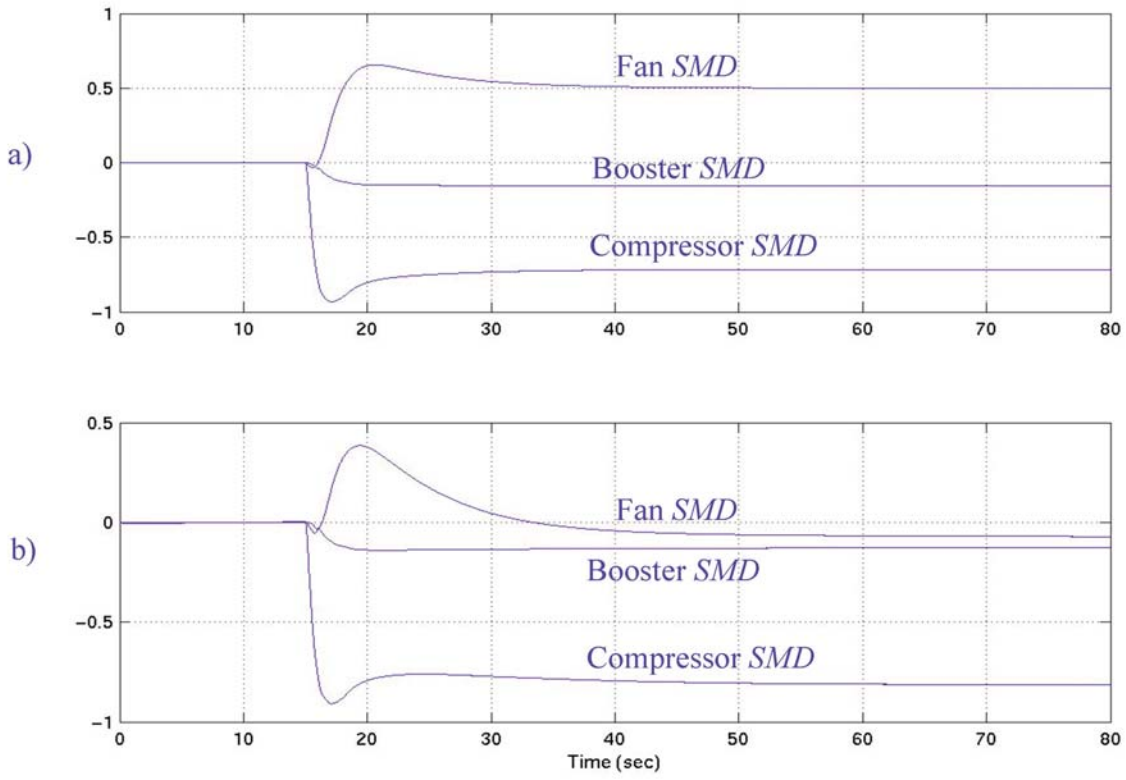


Figure 9. Stall Margin Deviation (*SMD*) response of thrust and *EGT* control of 40% deteriorated engine (EDI of 0·4),
(a) Thrust-only control,
(b) Thrust and *EGT* control.

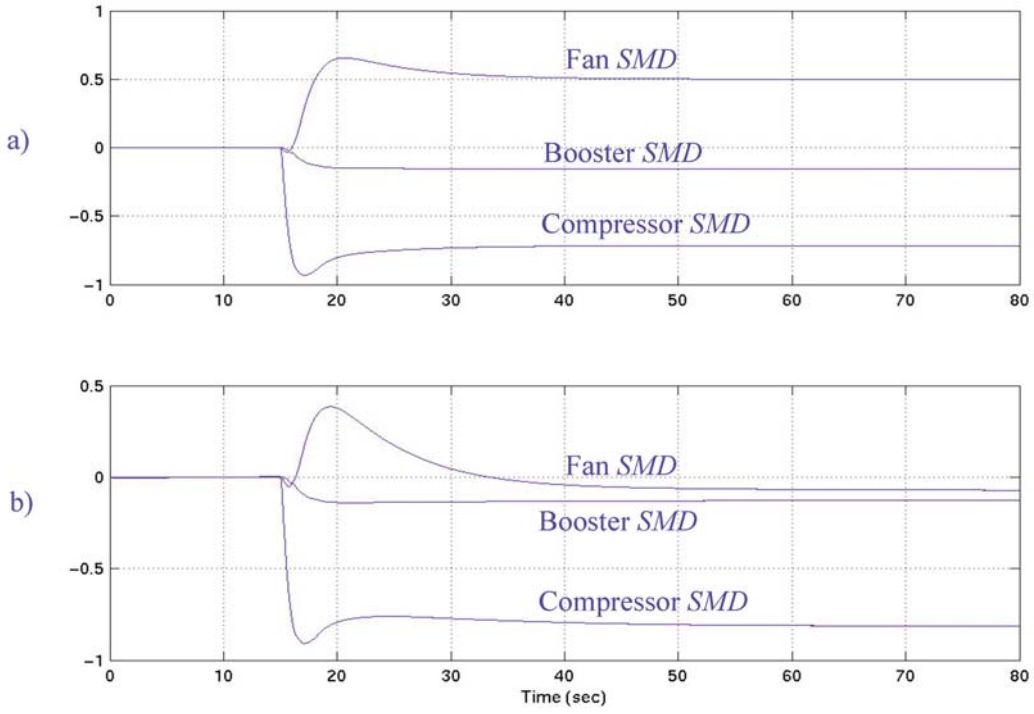


Figure 10. Nominal (undeteriorated) engine response with *LPV* controller scheduling parameter (EDI) equal to 0·0,
(a) Normalised thrust response,
(b) *EGT* deviation response (Deg F),
(c) *VSV* and *VBV* response (Degrees and in^2 respectively).

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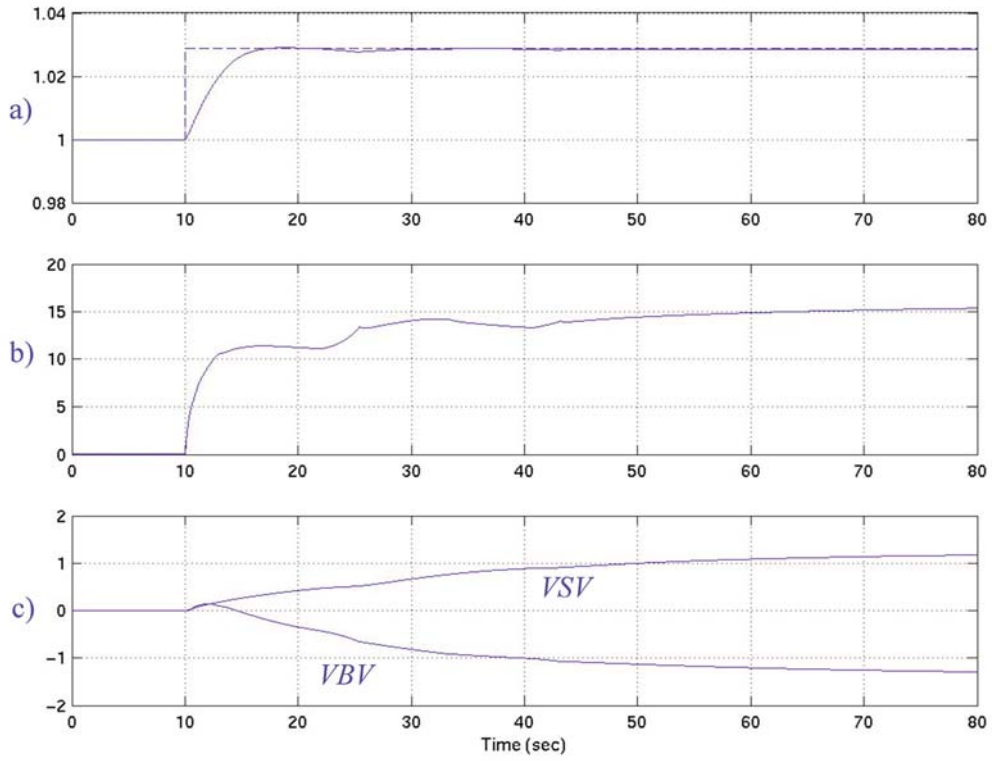


Figure 11. 70% degraded engine response with LPV nominal engine controller,
a) Normalised thrust response,
b) *EGT* deviation response (Deg. F),
c) *VSV* and *VBV* response (Degrees and in^2 respectively)

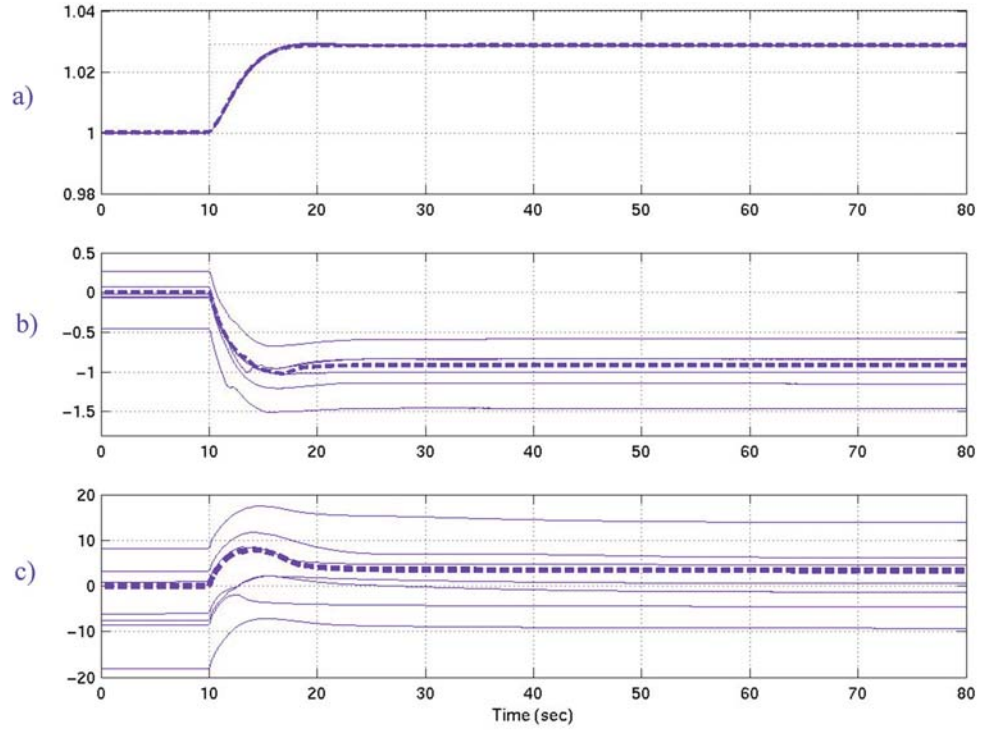


Figure 12. Deteriorated engine response with LPV controller showing robustness to engine-to-engine variation about an EDI of 0.7 (dashed line),
a) Normalised thrust response,
b) compressor *SMD* response,
c) *EGT* deviation response (Deg. F)

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provides the controller scheduling parameter ρ. The uncertainty associated with the deterioration index is primarily due to the estimation of the health parameters, i.e., each deterioration index is associated with a specific set of health parameters. However, in service the likelihood of a specific set of health parameters corresponding to one of the parameter-dependent plants used in the controller design may be extremely low. Thus, a mapping from health parameters to deterioration index, capable of accommodating slight variations in health parameters from the values specifically used in the controller design, is required for calculation of the scheduling parameter ρ. The engine deterioration considered here is limited to relatively predictable, normal component wear-and-tear. As an initial approach, the simple feedforward neural network shown in Fig. 6 was chosen to map the estimated (uncertain) health parameter set to the scheduling parameter, EDI.

The set of sixteen health parameters, known to vary with engine deterioration and engine-to-engine variation (Table 1), is fed through input layer weights to 16 hidden layer neurons, which provide an output based on the degree of activation of Sigmoidal transfer functions. The neurons' weighted outputs are added and fed to the single output layer neuron, whose linear activation function determines the network's final output, i.e., the EDI. A training set consists of an expected set of health parameters corresponding to a specified level of deterioration, which assumes an overall correspondence among the health parameters with respect to engine deterioration. The network was trained on health parameter sets corresponding to 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, and 80% levels of deterioration using the MATHWORKS Neural Network Toolbox as part of the MATLAB software package[20]. The maximum error for the 100 test cases (excluding the aforementioned training sets) presented to the network, neglecting the effect of engine-to-engine variation about a given deterioration level, was 6 per cent. Test cases including the effects of engine-to-engine deterioration resulted in percent errors of up to 40 per cent. Thus, for the present study, an attempt was made to compensate for this by incorporating greater uncertainty in the controller design due to model error. Refinement of the training sets (e.g., additional training sets containing engine-to-engine variation) may be accomplished in the future to enhance the functionality of the network. Additionally, further development of the network may reveal that a subset of the 16 health parameters (each with possibly less engine-to-engine variation) is necessary to provide an accurate calculation of the EDI. As well, potential confounding scenarios and their effect on the calculation of the EDI and the performance of the controller, i.e., engine damage that could result in similar shifts in the health parameters, may be investigated.

Table 1
Health parameter input to the neural network

Fuel flow deterioration (multiplier)
Inlet pressure measurement deterioration (multiplier)
Fan efficiency (adder)
Fan flow capacity (multiplier)
Low pressure compressor efficiency (adder)
Low pressure compressor flow capacity (multiplier)
High pressure compressor efficiency (adder)
High pressure compressor flow capacity (multiplier)
High pressure turbine efficiency (adder)
High pressure turbine flow capacity (multiplier)
Low pressure turbine efficiency (adder)
Low pressure turbine flow capacity (multiplier)
High pressure turbine clearance deterioration (adder)
Compressor discharge seal leakage (adder)
Low pressure turbine aft seal leakage (adder)
Combustor front seal leakage (adder)

5.0 NONLINEAR SIMULATION TESTING

The following presents the results of testing the LPV controller on a nonlinear simulation of a large turbofan engine. Nine interconnected plants, corresponding to 0%, 10%, 20%, 30%, 40%, 50%, 60%, 70%, and 80% levels of deterioration, were provided to an LMI-based convex optimisation algorithm[14] which searches for a feasible solution to Equation (19) through (21) – the output being the Lyapunov function matrix of Equation (20). Additional LMI constraints incorporated into the optimisation provide the controller state-space matrices $\mathbf{A}_K$, $\mathbf{B}_K$, $\mathbf{C}_K$, and $\mathbf{D}_K$[16].

Figures 7, 8, and 9 present a comparison of a thrust-only controller, (*EGT* varying uncontrolled) and a controller incorporating *EGT* control as well as thrust control. The nonlinear engine model is 40% deteriorated (deterioration index of 0·4) at standard day cruise conditions, with the expected set of health parameters corresponding to this level of deterioration. Thrust is controlled primarily via the fuel flow, *WF*, while tight control of *EGT* requires manipulation of *VBV* and *VSV* as well. For the non-*EGT* controlled case (Fig. 7), a 3% increase in thrust demand results in an 11·5 degree increase in *EGT* (Fig. 7(b)). Note that *VSV* and *VBV* are unactuated for this situation (Fig. 7(c)). In contrast, for the same thrust demand input, the *EGT*-controlled engine (Fig. 8) attains an increase in *EGT* of 7·6 degrees in steady state – a net reduction of 3·9 degrees in *EGT* relative to the uncontrolled case. Figure 8(c) presents the corresponding changes in *VSV* and *VBV* for the transient, illustrating the effectiveness of these actuators in *EGT* control. The positions of these actuators are typically scheduled on engine operating parameters to maintain stall margin, thus relatively minor changes in the scheduled positions may provide the additional benefit of decreasing *EGT* and extending on-wing engine life. Figure 9 presents the corresponding component stall margin deviations (*SMD*) for the non-*EGT* controlled and *EGT* controlled cases. As shown in the figure, the *SMD* show no significant change – all values are well above the stall limits for each component.

As mentioned previously, the parameter-dependent controllers are designed to accommodate plant uncertainty due to engine deterioration (i.e., controller scheduled on EDI), with considerable uncertainty incorporated into the design due to engine-to-engine variation. Other control methods, e.g., H_∞ control[17], while accommodating plant uncertainty at a specific operating point in a similar fashion, are intended for LTI systems and fail to adequately accommodate modeling errors due to significant plant nonlinearities across an operational envelope. Consider the LPV-controlled engine response shown in Fig. 10. For the nominal engine, the corresponding LPV controller, robust to engine-to-engine variations, achieves the thrust/*EGT* response objectives.

Figure 11 presents a 70% degraded engine controlled by the nominal engine controller (thrust and *EGT* controlled). Although the thrust response is acceptable, *EGT* appears to be uncontrolled. The need for gain scheduling of robust controllers is clearly evident due to the nonlinear effects of engine deterioration.

An example of controller robustness to engine-to-engine variation is shown in Fig. 12. The base values of the health parameters correspond to 70% engine deterioration – which are taken to be fleet averages. A Monte Carlo approach, using standard deviations calculated from fleet data, is used to determine a health parameter set for each specific engine. As with the example presented in Figs 7 and 8 (the 40% deteriorated case), the net effect is a steady-state reduction in *EGT*. For the engines considered, *EGT* steady-state reductions range from 2 to 4 degrees, with the corresponding thrust response virtually identical for each engine. Compressor stall margin deviation is also shown to illustrate that component margins remain well above their critical values for the engines considered.

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6.0 CONCLUSIONS

An initial study, performed via testing with a nonlinear engine simulation, has demonstrated the ability of linear parameter varying quadratic Lyapunov function (LPVQLF)-based control to simultaneously control engine thrust and exhaust gas temperature while being robust to engine deterioration and engine-to-engine variation. By reducing engine exhaust gas temperature for a given thrust level, it might be possible to reduce thermomechanical fatigue damage and thus extend the on-wing life of the engine. A linear matrix inequality-based optimisation, searching for feasible solutions to quadratic Lyapunov functions based on engine state space dynamics, provides a means for designing unconditionally stable gain scheduled controllers across a full range of deteriorated engines. The quadratic Lyapunov function approach also guarantees stability for instantaneous scheduling parameter variations. Controller gain scheduling is traditionally based on an ad hoc approach, requiring multiple pre-designed linear time-invariant controllers with no stability guarantee for closed-loop plants in between those where an explicit controller design was performed.

With the LPVQLF approach, system (i.e., engine-to-engine) uncertainty is handled by operating condition dependent weights while other, more significant uncertainties due to the highly nonlinear nature of the plant, are addressed by use of the gain scheduled LPV controller. The control system in the study was designed for cruise conditions, using a feedforward neural network to reduce the set of estimated health parameters to a single parameter for gain scheduling, the engine deterioration index (EDI).

Theoretically, the LPV controller is stable for all scheduling parameter trajectories, but the trajectories are still based on a nominal degradation profile. Although the controller is robust to wide health parameter variation around the nominal trajectory, it does not take into account large off-nominal deviations of individual health parameters. Likewise, the health-parameter-to-EDI mapping employed (i.e., a feedforward neural network) was developed using the nominal degradation profile. Values of EDI produced by the neural network as a result of off-nominal health parameter input will be invalid, potentially leading to the scheduling of an inappropriate controller. Prior to controller implementation, the robustness of the EDI mapping to off-nominal health parameter variation and potential confounding scenarios such as engine damage should be assessed.

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