Proceedings of
ASME TURBO EXPO 2001
June 4-7, 2001, New Orleans, Louisiana, USA

2001-GT-0016

MODEL BASED CONTROL CONCEPTS FOR JET ENGINES

Klaus Lietzau
MTU Aero Engines
Dachauer Str. 665, 80995 Munich, Germany
Email: klaus.lietzau@muc.mtu.de

Andreas Kreiner
Chair of Flight Propulsion
Technische Universität München
Boltzmannstr. 15, 85747 Munich, Germany
Email: kreiner@lfa.mw.tum.de

ABSTRACT

Many jet engine variables cannot be measured in-flight or can only be measured with a complex, and hence unreliable, instrumentation system. This includes variables that are of imminent importance for the safe operation of the engine or for engine life, such as the temperature of the high pressure turbine blades or the surge margins of the turbo compressors, for instance. Current control systems therefore transform limits on these variables into limits on other variables measured by the engine's sensors. This leads to increased safety margins and thus to non-optimal engine performance. An onboard engine model incorporated into the engine control system could provide information about all engine variables. This could enable further control and monitoring system optimisations leading to improved engine performance, reduced fuel consumption, increased safety and engine life.

This paper explains the principle of model based engine control and gives an overview about possible applications for conventional and also thrust vectored jet engines. Modeling methods for real-time simulation as well as methods for online model adaptation are presented. The potential of model based jet engine control is analyzed and fortified by some prototype realizations.

NOMENCLATURE

1 ... 5	Engine stations
A,**B**,**C**,**D**	System matrices
DAE	Differential algebraic equation
EPR	Engine pressure ratio
FANi	Inner fan
FANo	Outer fan
η	Isentropic efficiency
HPC	High pressure compressor
HPT	High pressure turbine
NH	High pressure spool speed
NL	Low pressure spool speed
P	Total pressure
PI	Proportional-integral
PLA	Pilot's lever angle
SM	Surge margin
T	Total temperature
u	Input variable vector
WFF	Weight fuel flow
x	State variable vector
y	Output variable vector
Δ	Deviation

Subscripts:

acc	acceleration
dec	deceleration
max	maximum
min	minimum

Superscripts:

^	estimated variable
·	derivative

1. INTRODUCTION

Demanding requirements concerning component life, reliability and operating efficiency are applied to modern jet engines for aircraft application. Due to component scatter and deterioration during increasing service intervals, large differences within a fleet of engines arise. In current engine controllers, however, these discrepancies are not taken into account directly. This requires increased safety margins within the control and leads to a non optimum use of the engine capabilities.

The development of new, optimized control concepts offers the possibility for improvements concerning the requirements to the whole engine. These concepts require accurate information about engine internal states, which can not be measured in engines during flight or only by means of overly complex instrumentation. Typical examples being compressor surge margins, which being critical for stable engine operation thus necessitating adequate surge margin stack-up to cater for engine scatter, control system scatter and deterioration and the turbine inlet or blade temperature, which have a big impact to the lifetime of the turbine.

A promising approach, which is currently investigated within the Brite/Euram project OBIDICOTE (On Board Identification, Diagnosis and Control of Gas Turbine Engines), is to utilize a real-time engine model running in parallel to the engine, which becomes part of the engine control. This onboard engine model can supply non-measured engine variables to the control and allows to adapt schedules and set-points for optimization of the overall engine capabilities.

Additionally the information provided by the onboard model can be used for monitoring purposes. This is especially true when using a model tracking algorithm (see section 4), that provides information about important engine or component health parameters. Another possibility is to use the "virtual" measurements of the onboard model to improve the validation of the real sensors and for the compensation of faulty sensors [1]. The various possibilities of using an onboard model for diagnosis and monitoring purposes [2], however, will not be shown in detail here. This paper shall give an overview and examples of the use of an onboard model for jet engine control.

2. MODEL BASED CONTROL

2.1 Basics

Many important engine variables cannot be measured directly or can only be measured with a complex, and hence unreliable, instrumentation system. This includes variables that are of imminent importance for the safety and the performance of jet engines, like the compressor surge margins, the turbine inlet temperature or the engine's net thrust. The engine control systems used today circumvent this deficiency by using substitute variables for the generation of demand and limiting values. Thus only measurable variables are used as controlled variables. This approach, however, leads to higher safety margins and thus not all of the engine's performance potential can be used.

A possible solution to improve this situation could be to integrate a simulation model of the engine into the control system (onboard model). This model can provide real-time information about the variables that cannot be measured by the engine's sensors. Figure 1 shows the basic configuration of such a model based control system. The comparison between demanded and actual values can now include so-called "virtual" measurements supplied by the engine simulation model. The real-time engine model is driven by the actuator command signals and also receives information about the actually measured variables. This enables a matching process between the engine and the model. This matching process also yields information about the current engine status, for example with respect to changed component health parameters. This information can be used to optimize the control system for the individual engine and to adapt or trim it to the current engine status.

2.2 Applications

The integration of an onboard model into the engine control system enables the use of virtual measurements in the control system. This can help to increase the engine performance, safety and life and to reduce specific fuel consumption. Apart from the possible use of virtual sensor signals for sensor validation and substitution, new or enhanced control functions will be made possible that shall be explained by the following examples.

2.2.1 Turbine Temperature

The temperature of the high pressure turbine blades is of exorbitant importance to engine life. This temperature, and also the gas temperature at the turbine inlet is usually not retrieved by engine sensors. This holds especially for commercial jet engines. The simulated turbine temperature provided by an onboard engine model can be used by the control system to avoid or limit the temperature peaks that occur during accelerations at high power levels. Depending on the degree of detail of the used simulation model, either the metal temperature of the turbine blades, or the gas temperature at the turbine inlet can be used as virtual measurement.

2.2.2 Surge Margin

The surge margins of the compressors play a vital role for the safe operation of the engine. Especially during transient manoeuvers, such as fast accelerations, a stall of the flow around the compressor blades leading to compressor surge must be avoided. The distance of the current operating point to the surge line (surge margin) usually cannot be measured by sensors. Current engine control systems circumvent this deficiency by using a limit on the spool accelerations or by using fuel schedules to prevent compressor surge. The onboard model can be used to determine the current margin between the operating point and the nominal surge line of the turbo compressors and provide the control system with this information. With the knowledge of the current shift of the operating line the surge margin stack-up could be reduced thus enabling improvements of engine performance, whilst guaranteeing safe operation even of degraded or worn engines. A further amendment to this could be made by taking into account also effects on the surge line itself.

2.2.3 Net Thrust

Another quantity that is not measured in-flight is the engine's net thrust. Current control systems usually translate the thrust command given by the pilot (pilot's lever angle, PLA) into another demand value. This demand value is some measured variable, like the engine pressure ratio (EPR) or the speed of one of the engine's spools. However, this method can get quite complex, since the variations of the ambient conditions and flight envelope must be taken into account. Another disadvantage of this approach is that it leads to unwanted asymmetric thrust distribution when different engines have a different health status.

For the thrust vectoring of future combat aircraft, a detailed knowledge of the current engine thrust is of even higher importance. Here, the flight control system also commands side force components of the engine thrust. These have to be transformed by the engine control system into a corresponding deflection angle of the vectoring nozzle, under high demands on accuracy. For this application the onboard model must also include a model of the complex flow phenomena occurring in deflected nozzles. This model can be derived from CFD calculations and calibrated by test data. Extensive testing will be necessary to cover all non-linear effects occurring within the operating range of the engine and the multiple-degree-of-freedom vectoring nozzle.

2.2.4 Supersonic Inlet

In supersonic flight regimes, the matching between the air intake and the engine itself is of vital importance. If this matching is insufficient, the system of oblique and normal shocks outside and inside the inlet can collapse. This can lead to a detached bow shock outside the inlet, having severe consequences on the absolute value of the net thrust, but above all the direction of the net thrust vector angle. An onboard model integrated into the control system can be used here to gather accurate knowledge about the current positions of the different shock waves. Using this knowledge, the pressure recovery of the inlet can be optimized without compromising on the operational safety.

3. MODELING

This section will describe the methods for modeling and simulation of jet engines that seem most appropriate for the use as onboard model. Aspects of modeling uncertainties and real time aspects will be discussed.

3.1 Physical Modeling

For the physical or performance analysis modeling of jet engines, the engine is first subdivided into its different components, like air inlet, compressors, turbines, combustion chamber, thrust nozzle, and so on. The operating behavior of the single components is either described through physical equations or by using characteristics and maps that can be obtained by rig tests or by CFD calculations. The component models can include energy conserving parts like spools (mechanical), blades, discs and casing (thermal) or gas volumes (thermodynamical). Thus also the transient behavior of the engine can be described.

The different components modeled as described above are coupled via laws of conservation of mass, momentum and energy. This usually leads to a non-linear set of equations, which can be solved by means of appropriate numerical methods. If the engine model includes energy conserving parts (transient model), the resulting set of equations is usually of a differential algebraic type (DAE). This DAE can be solved by special integration algorithms or by using the iterative solution mentioned before to explicitly solve for the vector of state derivatives and to use standard methods of integration to simulate.

3.2 State Space

State space systems originate from linear system theory. These systems are especially suited for real time applications due to the low computational power necessary for simulation. To form a state space system, suitable state variables are chosen for all energy conserving parts of the system. These variables form the state vector **x**. The dynamical behavior of the system can then be described by using the state and output equations

$$\Delta\dot{\mathbf{x}} = \mathbf{A}\Delta\mathbf{x} + \mathbf{B}\Delta\mathbf{u} \quad (1)$$

$$\Delta\mathbf{y} = \mathbf{C}\Delta\mathbf{x} + \mathbf{D}\Delta\mathbf{u} \quad (2)$$

where the vectors $\Delta\mathbf{x}$ (state variables), $\Delta\mathbf{y}$ (output variables) and $\Delta\mathbf{u}$ (input variables) denote deviations from the corresponding values at a specific reference point. The system matrices **A**, **B**, **C** and **D** are usually determined by linearization of a non-linear physical model around an operating point.

To produce a state space model of a jet engine that can be used to simulate the engine at all power settings and within the whole flight envelope, numerical linearizations have to be carried out at many operating points. The **A**, **B**, **C** and **D** matrices obtained then must be interpolated using appropriate parameters [3]. The biggest advantage of state space models compared to physical models is the low computational demand. This, however, is no longer a significant issue due to the constantly increasing computing power available. The biggest disadvantage of state space models is that the complexity of the model increases rapidly with the non-linearity of the system. Another disadvantage is that state space models are less flexible as physical models, especially with respect to the incorporation of changed engine health parameters.

3.3 Modeling Accuracy

When variables obtained by simulations shall be used in the engine control system, the question of modeling accuracy arises. Different aspects during steady state and transient engine operation have to be taken into account.

3.3.1 Steady State

The simplified assumptions used for modeling of the components as well as component tolerances and component ageing lead to deviations between the real engine and the simulation model. This may not be as crucial for monitoring purposes, such as sensor validation, for example. For control purposes, however, the necessary accuracy can only be achieved by implementing some kind of tracking algorithm. The purpose of this model tracking is to detect changed engine health parameters and to adapt the engine model accordingly.

3.3.2 Transient

The accurate modeling of the transient engine behavior is very complex because of the large number of effects that have to be taken into account. The high frequency gas volume dynamics can usually be neglected for control purposes. The low frequency dynamics associated with heat transfer effects, however, are crucial for the dynamical behavior of engine and control system. A precise modeling of the heat transfer between the fluid and the components including heat expansion and the associated tip clearance effects is very costly with respect to modeling and necessary validation work. This leads to a somewhat degraded accuracy of the model during engine transients that has to be taken into account for the control design. Transient model accuracy could be improved by a state matching or model tracking algorithm. The problem using tracking algorithms during transients could be, however, that the algorithm cannot map the modeling errors correctly to the changed state variables or parameters. This could compromise the physical integrity of the engine model.

3.4 Real Time Aspects

Using the computational power available today, physical models of jet engines can be run in real time. The fastest achievable sampling rate depends on the complexity of the engine, the degree of detail of the modeling and, of course, on the available computing power.

A problem that arises when using physical performance models instead of state space models for real time purposes is that the computational time varies at each time step due to the necessary iterations. To enable calculations on real time hardware, the maximum number of iterations must be fixed to limit the computing time for each time step.

4. MODEL TRACKING

4.1 Theory

Methods for parameter identification and state observation are known from linear system theory. The idea of both is to minimize the deviations or modeling errors of a model that runs in parallel to a process. This reduces the impact of disturbances, unknown initial conditions, errors due to modeling uncertainties or changed process behavior. These methods in the following will be titled as "model tracking".

Various engine component characteristics change during the life of a jet engine. This holds especially for the efficiencies of the turbo components. However the onboard model integrated into the control system only resembles a "nominal" engine's behavior. Thus an increasing deviation of the actual engine's parameters to those of a nominal engine leads to increased deviations between the engine variables and the simulated model variables. Since it is these simulated variables that shall be used by the engine control system, some kind of tracking algorithm must be implemented to minimize the deviations between engine and onboard model. The methods suitable here usually are based on the errors between the measured engine variables and the corresponding simulated variables. These errors then are transformed into changes of the engine component parameters. A variety of methods could be implemented [8,9,10]. The following section describes the implementation of the onboard model as a non-linear observer.

4.2 Observers

An observer matches the states of a process (here: the engine) with those of a process model (here: the onboard model). The jet engine observer can be based on a state space model, but it is also possible to use a physical engine model. The overall structure is depicted in Fig. 2. The measured variables $\mathbf{y}$ are compared with the simulated variables $\hat{\mathbf{y}}$. The corresponding simulation error vector is multiplied by a matrix gain $\mathbf{L}$ and the resulting vector is then used to correct the model's state variables $\hat{\mathbf{x}}$. This leads to a dynamic matching process between the actual engine states $\mathbf{x}$ and the estimated states $\hat{\mathbf{x}}$. Using the linear state space model of equations (1) and (2), the resulting observer's equations would be

$$\Delta\dot{\hat{\mathbf{x}}} = \mathbf{A}\Delta\hat{\mathbf{x}} + \mathbf{B}\Delta\mathbf{u} + \mathbf{L}\left(\Delta\mathbf{y} - \Delta\hat{\mathbf{y}}\right) \tag{3}$$

$$\Delta\hat{\mathbf{y}} = \mathbf{C}\Delta\hat{\mathbf{x}} + \mathbf{D}\Delta\mathbf{u}\ . \tag{4}$$

For a non-linear engine model, for example a physical model as described by section 3.1, the observer becomes

$$\dot{\hat{\mathbf{x}}} = \mathbf{f}\left(\hat{\mathbf{x}},\mathbf{u}\right) + \mathbf{L}\left(\mathbf{y} - \hat{\mathbf{y}}\right) \tag{5}$$

$$\hat{\mathbf{y}} = \mathbf{g}(\hat{\mathbf{x}},\mathbf{u})\ . \tag{6}$$

The matrix gain $\mathbf{L}$ determines the dynamics of the observer and also its sensitivity to measurement or process noise. The higher this amplification, the faster the observer can react to deviations between the onboard model and the engine, e.g. caused by engine incidents. On the other hand, higher gains lead to a increased sensitivity of the observer to measurement or process noise, so a trade-off between fast reaction and noise rejection has to be made when choosing the gain matrix $\mathbf{L}$. One method suitable for gain matrix design is using a pole placement technique. If information about process and measurement noise is available, $\mathbf{L}$ can also be designed using LQE (linear quadratic estimator) theory to form a Kalman filter gain matrix. The resulting non-linear system as described by equations (5) and (6) would then be called an "extended kalman filter". Both methods need linearizations of the model to calculate the gain matrix. In [5] it is suggested to use the gain matrix obtained by a linearized model at one operating point for the whole non-linear process without any matrix gain interpolation.

The usual purpose of an observer is to estimate the states of the process. For the applications described here, the observer should also detect changes in engine health parameters. To achieve this, the parameters to be identified can be treated as a kind of "artificial" state variables and included in the observer design [5,6]. The states of the resulting "extended" system have to be observable using the available measurements [7].

5. APPLICATION EXAMPLE SURGE MARGIN CONTROL

For an illustration of the methods described above, a model based surge margin control of a jet engine will be simulated. The engine is a two spool bypass engine with mixer.

The simulations shown here are carried out using a MATLAB/Simulink environment. The engine model used is a physical model programmed in FORTRAN. This model is coupled with MATLAB/Simulink using a specifically designed interface. For the simulations, sea level static conditions are assumed, i.e. the flight mach number and the flight altitude are both equal to zero.

5.1 "Engine" and Onboard Model

For the simulation of a model based engine control, two different engine models have to be implemented, one representing the actual engine and one representing the onboard engine model. The usage of two identical physical models would mean a perfect matching between the engine and the onboard model and would thus not lead to realistic results. To produce some degree of mismatch between the models the complete transient behavior including spool inertia and heat transfer effects is used for the model representing the real engine. The model representing the onboard model only includes spool inertia and no heat transfer modeling. Thus it is taken into account that the transient modeling of a jet engine cannot perfectly represent the behavior of a real engine (see section 3.3.2). Another difference between the models is that the transient behavior of the actuators and sensors is not included in the onboard version.

5.2 Base Control

The base control for the simulated engine resembles the structure of the control systems widely used today. To demonstrate the benefits of the model based surge margin control, however, the control system tuning is sharpened from the conservative values that would be used for an actual engine control system. This is especially true for the acceleration schedule, which is not able to provide sufficient surge margin anymore.

The basic control is structured as follows: The pilot's PLA command is transformed into a demand value for the EPR. This value is set by the control system via a PI control loop. To improve the control behavior, a pre-steering function for the fuel flow is incorporated that delivers the fuel flow necessary for keeping the current low pressure rotor speed NL. Another PI loop calculates the fuel flow to control the maximum NL permitted (NLmax). Further loops are implemented for the maximum permitted acceleration (NHacc) and deceleration (NHdec) of the high pressure spools. The actual control signal for the fuel flow (WF) is calculated using the following minimum / maximum selection logic:

$$WF_{Base}=\min(WF_{NLmax},\min(WF_{NHacc},\max(WF_{EPR},WF_{NHdec}))) \quad (7)$$

The limit values for the limiting PI loops are set as follows:

$$NLmax=105\% \quad (8)$$

$$NHacc=0.08/s \quad (9)$$

$$NHdec=-0.08/s \quad (10)$$

The other control variables of the engine, like handling bleed and compressor guide vane angles, are open loop controlled by schedules.

To investigate the behavior of the controlled engine, an acceleration from a steady state idle thrust point to maximum thrust is simulated. To take the differences between engines of the same type into account, the isentropic efficiency of the high pressure compressor is step-wise degraded to -3%. Figure 5 shows how the basic control holds the spool acceleration under the limit of 8% per second (red line) during the engine acceleration. In Fig. 6, the surge margin of the high pressure compressor is depicted. It can be seen how, for a nominal engine (black line), the constant acceleration limit leads to a minimum in surge margin at the beginning of the acceleration. When looking at engines with a degraded high pressure compressor (gray lines), it can be observed that the surge margin is smaller compared to the nominal engine at the same acceleration.

5.3 Model Based Control

A model based control loop is now added to the basic control structure described in section 5.2. This PI-type loop uses information about the surge margin provided by the onboard model as virtual measurement. The surge margin is defined as follows:

$$SM_{HPC} = \left(\Pi_{HPC,SM} - \Pi_{HPC}\right)/\Pi_{HPC,SM} \quad (11)$$

With the incorporation of the model based surge margin control loop, the commanded fuel flow becomes

$$WF=\min(WF_{SMHPC}, WF_{Base}) \quad (12)$$

with the limit value for the high pressure compressor surge margin set to

$$SM_{min}=12\%. \quad (13)$$

Figure 4 depicts the overall control law structure and the selection of the active control loop.

The simulation of the controlled engine with the model based surge margin control loop is shown in figures 7 and 8. It can be clearly observed that the control system now lowers the acceleration at the beginning for the surge margin to remain under the demanded limit (figure 8, red line). If the high pressure compressor efficiency is degraded, however, the model based control is no longer able to hold the surge margin above 12%.

5.4 Model Based Control with Model Tracking

For the tracking of the onboard model and for identification of changed engine health parameters, the onboard model is implemented as a non-linear observer as described in section 4.2. To design a kalman filter gain matrix, the model is linearized at an operating point. The onboard model only has two physical states, the spool speeds NL and NH. To be able to cope with changed engine health parameters, "artificial" states are added for changed isentropic efficiencies of outer fan ($\Delta\eta_{FANo}$), inner fan ($\Delta\eta_{FANi}$), high pressure compressor ($\Delta\eta_{HPC}$), high pressure turbine ($\Delta\eta_{HPT}$) and low pressure turbine ($\Delta\eta_{LPT}$). The extended system is observable using the measurements NL, NH, T3, T5 and P5.

As described in section 4.2, the choice of the observer gain matrix determines the dynamic behavior of the observer. A fast reaction to changed engine parameters would be desirable for this application, but leads to a high sensitivity to measurement and process noise. However the biggest problem when choosing a high gain matrix here is the large deviations between "engine" and onboard model that result from the structural differences between the engine model and the onboard model. This leads to a wrong estimation during transients and thus the gain matrix is chosen small enough to track only near steady state changes. Figure 3 shows the reaction of the observer model to a step change of -2% in HPC isentropic efficiency at Time=1s. The changed health parameter is correctly identified after approximately 200 seconds simulation time.

The simulation with model based surge margin control and tracked model (Fig. 9 and 10) shows that the surge margin now can be kept above the limit of 12% both for nominal and degraded engines. This can only be achieved, however, by lowering the acceleration of degraded engines at the beginning of the acceleration phase.

6. CONCLUSIONS

An onboard model integrated into a jet engine control system can provide different engine variables that are usually not measured by engine sensors, for instance:

- Turbine blade or inlet gas temperature
- Surge margins of the turbo compressors
- Net thrust and side forces with thrust vectoring nozzles
- Position of oblique and normal shocks in engine intake

The use of these virtual measurements could improve safety, engine life, specific fuel consumption and engine performance. This especially holds when the onboard model is tracked to represent the actual engine state with an appropriate algorithm. If such a tracking algorithm is used, the model based control with model tracking becomes adaptive, i.e. the control system can adapt to changes in engine health.

Using the simulation example of a model based surge margin control, the structure and behavior of model based control systems with and without model tracking was shown. The advantages of such a model based system, especially in conjunction with model tracking, was outlined.

To be able to determine the usability of such a system for real-world applications, it is now necessary to test the different simulation and tracking methods with test rig engine data. With this testing, statements about the accuracy of the modeled variables can be made. Then it will be possible to quantify the expected improvements using extensive simulations.

ACKNOLEDGEMENTS

Part of the work presented has been conducted within the Brite/Euram Project OBIDICOTE (On Board Identification, Diagnosis and Control of Gas Turbine Engines). The authors would like to thank the involved partners (SNECMA, Rolls-Royce plc, MTU Aero Engines, Volvo Aero Corporation, Fiat Avio, Techspace Aero S.A., Lufthansa Technik AG, Aerospatiale, Chalmers University of Technology AB, National Technical University of Athens, Technische Universität München, Universität Stuttgart, Université Catholique de Louvain), for their contributions to the work.

REFERENCES

[1] Healy T.A., Kerr L.J., Larkin L.J. Model Based Fuzzy Logic Sensor Fault Accomodation. ASME Journal of Engineering for Gas Turbines and Power, Vol. 120, 1998.

[2] Kerr L.J., Nemec T.S., Gallops G.W. Real-Time Estimation of Gas Turbine Engine Damage Using a Control-Based Kalman Filter Algorithm. ASME Journal of Engineering for Gas Turbines and Power, Vol. 114, 1992.

[3] Sugiyama N. Derivation of ABCD System Matrices from Nonlinear Dynamic Simulation of Jet Engines. AIAA/ASME/ASEE 28th Joint Propulsion Conference and Exhibit, Nashville, USA, AIAA92-3319, 1992.

[4] Hollmeier S. Simulation des Betriebsverhaltens von Antrieben für Raumtransporter / Hyperschallflugzeuge. Dissertation, TU München, 1997.

[5] Sugiyama N. On Line System Identification of Jet Engine. 32nd AIAA/ASME/ASEE Joint Propulsion Conference, Lake Buena Vista, USA, AIAA96-2590, 1996.

[6] Hörl F. Systemtheoretische Methode zur dynamischen Zustandsüberwachung von Gasturbinen. Dissertation, TU München, 1987.

[7] Brown R.G. Not Just Observable but How Observable? Proceedings of the National Electronics Conference, Chicago, USA, Vol. 22, 1966.

[8] Gómez G., Campion G., Gevers M., Willems P. A Case Study of Physical Diagnosis for Aircraft Engines, American Control Conference, 2000.

[9] Volponi A., DePold H., Ganguli R., Daguang C. The Use of Kalman Filter and Neural Network Methodologies in Gas Turbine Performance Diagnostics: A Comparative Study, Proceedings of ASME TURBOEXPO 2000, Munich, Germany, 2000-GT-547, 2000.

[10] Lambiris, B., Mathioudakis K. Adaptive Modeling of Jet Engine Performance with Application to Condition Monitoring, Journal of Propulsion and Power, Vol. 10, 1994.

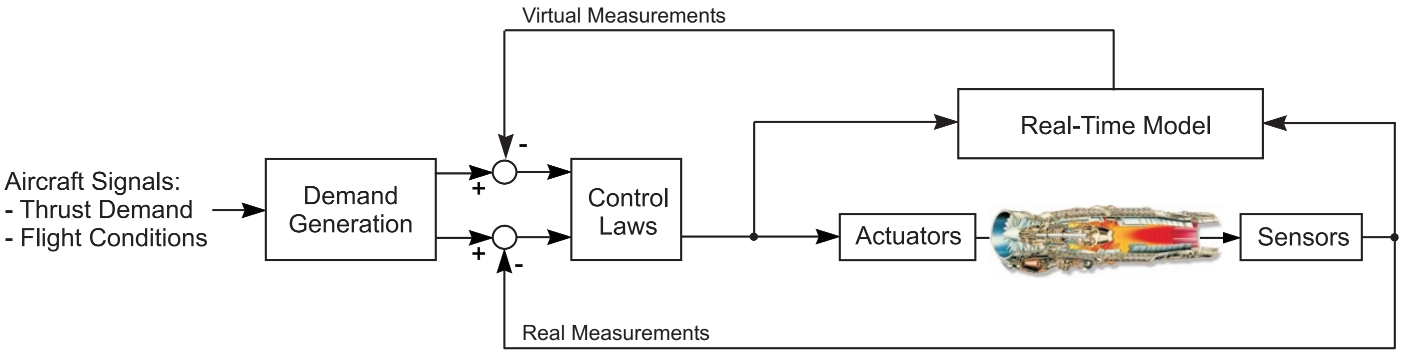

Figure 1: Integration of engine, control system and onboard model

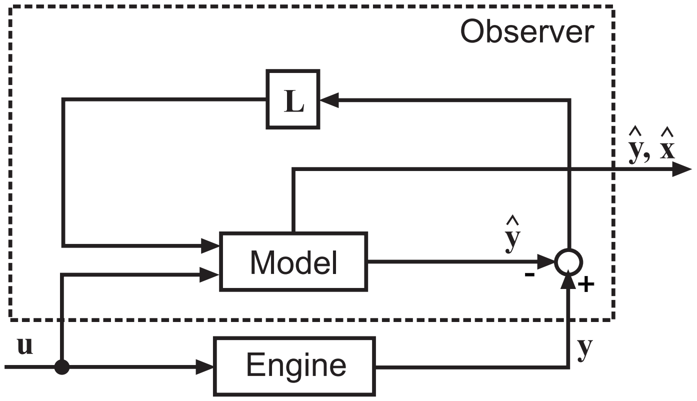

Figure 2: Onboard model as non-linear observer

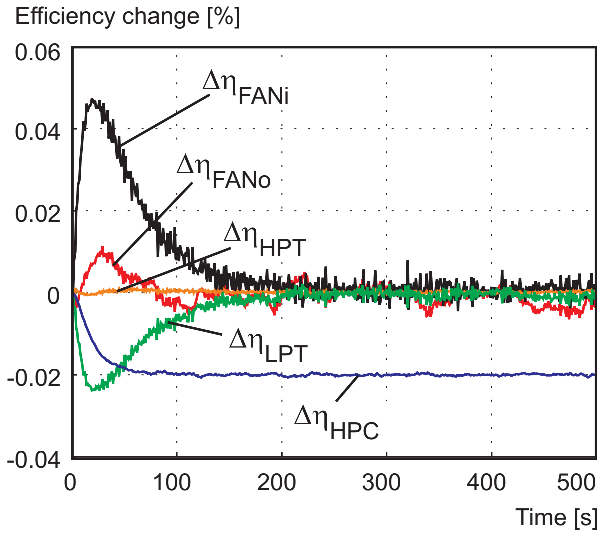

Figure 3: Reaction of observer model to a step-wise change in HPC isentropic efficiency

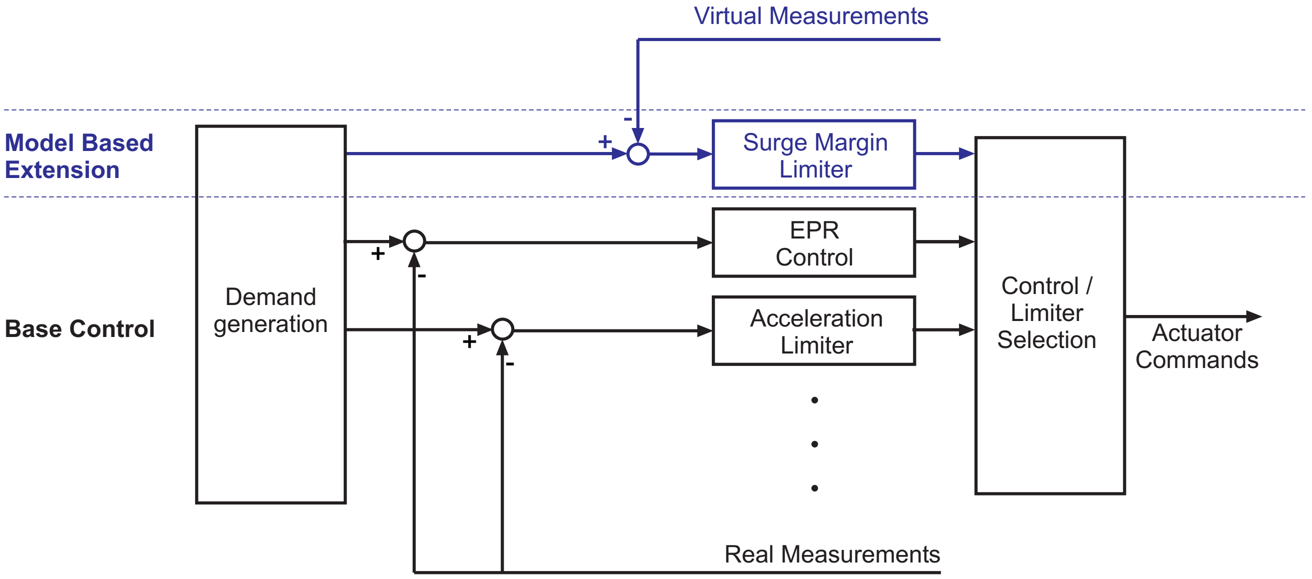

Figure 4: Controller structure of the model based surge margin limitation

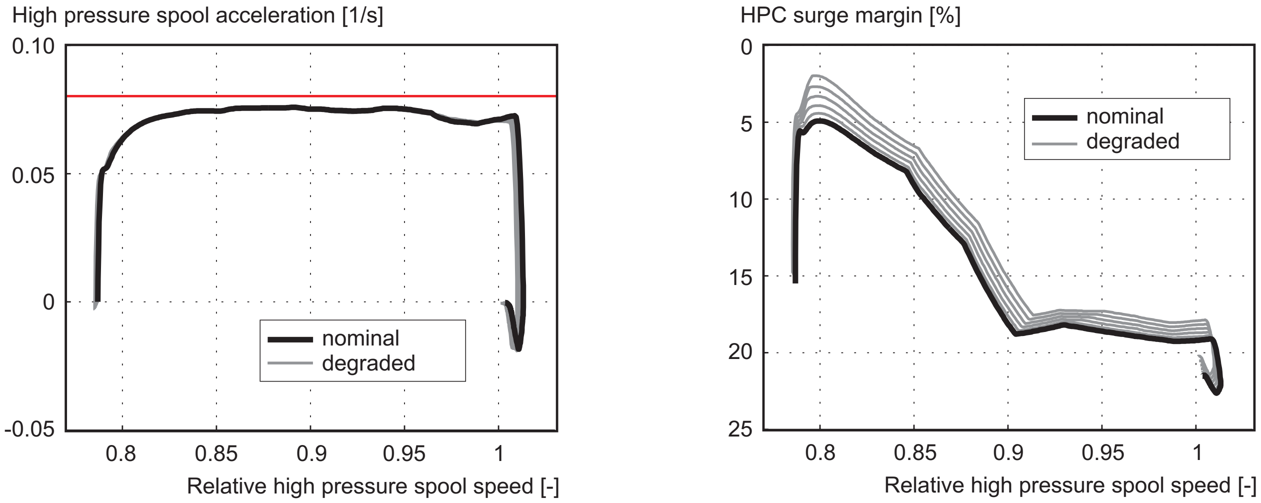

Figure 5 and 6: Acceleration without surge margin control

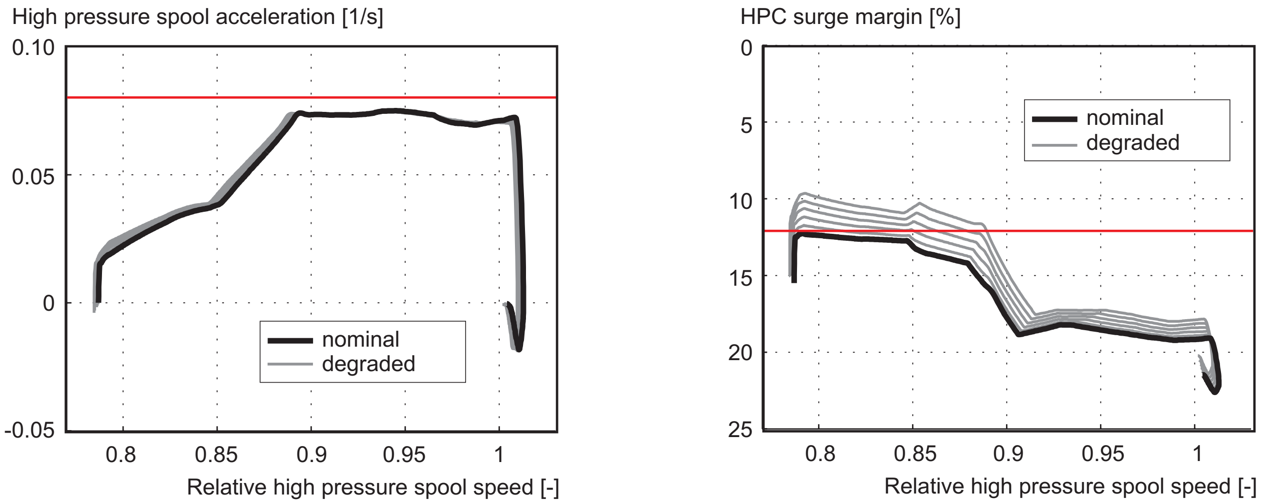

Figure 7 and 8: Acceleration with surge margin control

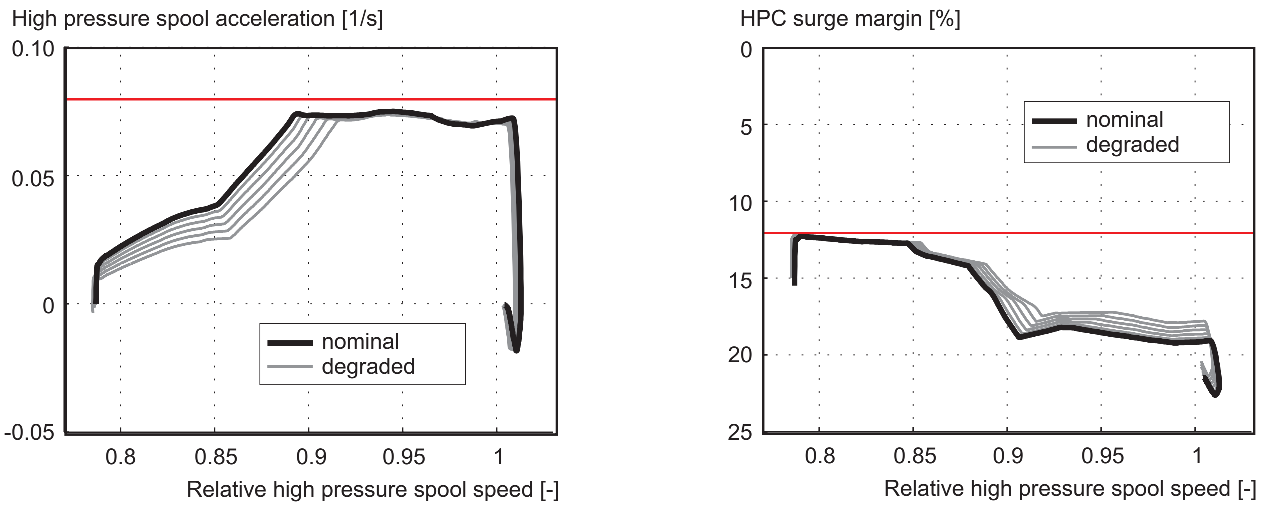

Figure 9 and 10: Acceleration with surge margin control and model tracking