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LINEARIZATION AND IDENTIFICATION OF AIRCRAFT TURBOFAN ENGINE MODELS

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Abstract: Experiments are carried out to derive linearized models of aircraft turbofan engine dynamics from standard engine simulators used in industry, the ultimate objective being low complexity gain-scheduled control design. First, standard linearization techniques are applied on the OBIDICOTE model, a commercial aircraft engine model developed within a European project. Second, identification algorithms are applied on the model of a military engine developed by SNECMA Moteurs to power a fighter aircraft. Satisfying low-order linearized models are obtained. The choice of the linearization points (location, density) in the 3D flight envelope (engine power, altitude, Mach number), as well as the nature of the input signals used for identification, turn out to be key features for a sensible control design. *Copyright ©2004 IFAC.*

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1. INTRODUCTION

The introduction of high by-pass turbofan engines in both commercial and military aircraft industries resulted in more complicated control laws and higher expectations on performance. Control laws are designed to provide appropriate fuel flow for rapid yet stall-free acceleration with little or no overshoot, rapid but smooth acceleration without undershoot or flame-out, and a constant steady state operation regardless of aircraft and ambient operating conditions. Control laws are also designed to position bleed valves, variable inlet stator vanes, nozzle and duct area (for military engines) according to the corrected engine speed, see (Spang and Brown, 1999) for an overview.

During normal operation, an aircraft turbofan engine experiences large changes in ambient temperature, pressure, Mach number, and power output level. Consequently, the engine dynamics change in a significant nonlinear manner, and when designing control laws special care must be taken to ensure that the mechanical, aerodynamic, thermal and flow limitations of the turbo machinery are maintained. Current technology in civil and military aircraft engines solves this nonlinear constrained control problem by using many SISO inner-loop (low-level) linear controllers that are gain scheduled and min/max selected by an outer-loop (upper-level) to protect against engine limits (Postlethwaite et al, 1995; Grimble, 2001).

Usually, inner-loop controllers are designed at various engine operation points in the flight envelope, using linearized models of the engine dynamics. Then, these controllers are dynamically scheduled as a function of physical parameters. The use of a collection of linearized models is motivated by the lack of satisfying analytical, or equation-based models for turbofan engines. Consequently, turbofan engine models and simulators used in industry typically contain many lookup tables and empirical data derived from real experiments (Frederick et al, 2000; Bruzelius et al, 2002). In order to ensure a sensible design, it is therefore of paramount importance to have a significant collection of representative linearized models.

It turns out that there is a very few technical references dealing with practical aspects regarding numerical computation of these linearized models. After surveying the recent control literature we only found references (Sugiyama, 2000; Evans et al, 2001) and (Leibov, 2002). (Sugiyama, 2000) describes extended Kalman filter design for recognizing parameter change in engine components and estimating unmeasurable variables over whole flight conditions. In (Evans et al, 2001), three system identification techniques (multisine testing, extended least-squares, nonlinear identification with multiobjective genetic programming) are applied to derive models for the dynamics between the input fuel flow and the high-pressure and low-pressure shaft speeds. Finally, (Leibov, 2002) reports multivariable identification techniques where uncertainty models the difference between nonlinear and linear models.

Motivated by the lack of linearization / identification results for aircraft turbofan engines in the control literature, the objective of this paper is to describe our attempts to derive linearized models of engine dynamics from standard engine simulators used in industry. In Section 2 we report our experiments on the OBIDICOTE model, a commercial aircraft engine model developed within a European project (OBIDICOTE, 2002). The model was implemented in a Matlab/Simulink [1] environment. Thanks to its modular structure, we could use built-in Simulink functions to derive linearized models from various engine dynamics. Section 3 describes our experiments on the model of a military engine developed by SNECMA Moteurs [2] to power a fighter aircraft. In contrast with the OBIDICOTE model, we could not apply the linearization features of Simulink on the military engine model. So we used features of the System Identification Toolbox of Matlab (Ljung, 2002) on input/output data obtained by various simulation benchmarks.

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2. LINEARIZATION OF THE OBIDICOTE MODEL

The main objective of the European project OBIDICOTE running from 1998 to 2002 (OBIDICOTE, 2002) and involving partners from both industry and academia was to define the principles for a new generation of digital controllers and data management systems in order to increase both reliability and performance of power generation systems. Within the project, a physical model of a gas engine was developed and implemented in Fortran code, and then later on compiled and included in a Matlab/Simulink environment. The resulting model is highly nonlinear, consisting of many lookup tables and empirical data.

The model is a typical high by-pass ratio two-shaft gas turbine civil aircraft engine. It can be used for both steady state and transient operation. The jet engine model is valid for a flight envelope defined by its Mach number and geopotential pressure altitude. A large number of signals can be manipulated in the OBIDICOTE model: control inputs, flight conditions, disturbances and health parameters. The model is built on seven dynamic states: low pressure rotor (fan) speed XNLP, high pressure rotor (compressor) speed XNHP, and five metal temperatures TM3B, TM3C (high pressure compressor), TM4B (combustion chamber), TM42B, TM4C (high pressure turbine), using standard engine station locations. The three input signals that are available for control are: fuel flow (WFE), inlet guide vanes position (ZDANIG) and bleed flow (ZDG26W). Finally, most relevant output signals include the two rotor speeds XNLP, XNHP, pressures P2 (induct), P5 (low pressure turbine) and temperature T41 (gas temperature at high pressure turbine inlet cooling bleed recovery).

In the Matlab/Simulink implementation of the OBIDICOTE engine model the user has access to all the system variables, including the five metal temperatures, which are state variables. As a result, we can use the linearization features of Simulink to derive linearized models around a given equilibrium point, i.e. around a given steady state of the engine. In particular, we used function `linmod` and its variations. This function derives standard linear models $\dot{x} = Ax + Bu$, $y = Cx + Du$ from systems of differential equations described in a Simulink block diagram.

We could not obtain useful results with the latest version of function `linmod`, part of release 13 (Matlab version 6.5 and Simulink version 5.0). As indicated in the documentation it may be due to a bad choice of default parameters in the function. In particular, we suspect that when applied to the OBIDICOTE model, the default tunings of function `linmod` are not appropriate. The `linmod2` function, which uses a slightly different algorithm than `linmod`, tries to balance the trade-off between round-off error (caused by small perturbations due to finite precision mathematics), and truncation error (caused by large perturbation levels, which invalidate the piecewise linear approximation of the Taylor series expansion). Unfortunately, we could not either obtain satisfying results with function `linmod2`.

[1] Matlab and Simulink are trademarks of The MathWorks, Inc.

[2] SNECMA Moteurs is the aerospace engine manufacturer subsidiary of the French national aerospace propulsion and equipment group SNECMA, Société Nationale d'Etudes et de Construction de Moteurs d'Aviation.

We had a better experience with the `linmodv5` function, which is the previous version of `linmod` available with Matlab version 5. This function allows to play manually with the state and input perturbation levels. We could then optimize over these tuning parameters, trying to find the perturbation levels leading to the minimum static error between the original nonlinear time-response and the linearized time-response. Usually, we noticed that the dynamics followed appropriately. The obtained linearized models are of seventh order, but in most of the cases, they could be reduced (either by simple pole-zero cancellations, or by Gramian-based balancing) to first or second-order transfer functions without significant loss. In Figure 6 we report time-responses of signals XNLP, XNHP, TM3B and P3 to a step in input WFE applied at time 1 second. As can be seen, in this case one can hardly distinguish between the original nonlinear OBIDICOTE model and its linearized model.

In order to validate our time-domain results, we carried out a frequency-domain analysis. In particular, for the transfer function WFE to XNLP (fuel flow to fan speed) which is of key relevance in engine control, from the original seventh-order model we could easily derive equivalent first and second-order linearized models from static gains and cutoff frequencies.

The main conclusions that we could draw from our extensive experiments on the OBIDICOTE model are as follows:

- only input WFE has significant impact on the output, the influence of the two remaining inputs ZDANIG and ZDG26W being marginal;
- for most of the transfer functions we obtained a seventh-order model that could be simplified to a first or second-order model without significant loss of accuracy both in time-domain and frequency-domain;
- there is significant influence of the 3D flight envelope (engine power, altitude, Mach number) operating point on the linearized dynamics, which motivates the use of a control law scheduled by the flight parameters. In decreasing order of influence, we find engine power, altitude and Mach number. The choice of the linearization points (location and density) in the flight envelope has significant impact when designing a gain-scheduled control law, but this is out of the scope of this paper.

3. IDENTIFICATION OF THE MILITARY ENGINE MODEL

For analysis and design purposes, SNECMA Moteurs developed a Matlab/Simulink model of a twin-spool turbofan engine powering a fighter aircraft. The main difference with respect to the OBIDICOTE model studied in Section 2 is the lack of access to several physically unmeasurable quantities. More specifically, there is no notion of a state in the model, which must be considered as a black box, so that experiments just provide a set of input and output data. As a result, we could not use the `linmod` features of Simulink, and we opted for a linearization of the model via standard input/output identification techniques.

The main control variables in the military engine are inputs WF32 (fuel flow), A8 (exhaust nozzle area) and output XN2 (fan speed), XN25 (high pressure shaft speed), PS32 (combustion chamber pressure), DPQ23 (high pressure compressor Mach Number, or dynamic to total pressure ratio) and TM49 (turbine metal temperature)

After various attempts, we decided to use the *pem* function of the System Identification Toolbox for Matlab, which computes a discrete-time estimated model together with a prediction error estimate. The function handles state-space models, can identify multivariable systems, and features various useful algorithm tuning parameters.

Our identification experiments were carried out within the Atelier Contrôle Moteur (ACM) object-oriented engine control toolbox developed by SNECMA Moteurs, which incorporates in a modular way all the steps relevant to the design of a control law: modeling, analysis and design.

The contribution described in the paper concerns the modeling step in the ACM environment, and together with SNECMA Moteurs we agreed on the following points:

- identified models must be linear, continuous-time, and of lowest possible order, keeping in mind our ultimate objective which is low complexity gain-scheduled control design;
- models must be representative enough to cover all dynamics, including engine dynamics, but also actuator and sensor dynamics, possibly with delays.

A general identification module has been developed that can be applied to various engine sections. Each section corresponds to a regulation mode, in the spirit of standard multivariable upper-level regulation schemes (Postlethwaite et al, 1995; Grimble, 2001). Each section splits out into various partitions, which are input/output couples associated with SISO or MIMO transfer functions to be identified. Figure 1 gives a partial overview of the directory where identified data are stored, showing three sections (nominal SISO, sensors, actuators) and their respective partitions. In total we consider eight engine sections. For each section in each partition, we must derive an identified model parametrized by the flight parameters over which the control law is scheduled.

First, we identified linear models from output data corresponding to step inputs. We used a sample frequency of 100Hz to derive discrete-time models with function pem. In Figure 2 we represent a comparison of nonlinear military engine model signal XN2 with corresponding linearized third-order model dynamics for a small step of WF32 around 25% maximum throttle and ground-test conditions (zero Mach and altitude). The linearized model cannot be distinguished from the nonlinear model: the fitting estimate returned by function `compare` is greater than 99.5%. This fitting factor degrades significantly if we consider second-order or first-order linearized models. In Figure 3 we represent signal DPQ23 for a small step of A8 at ground-test conditions. We can notice a feedforward term that can be incorporated as fast dynamics in the linearized model if the identification time window is chosen appropriately. Due to this term, the fitting factor degrades to slightly less than 90%.

Second, we considered multisine inputs instead of step inputs and carried out the same identification procedure. As explained in (Evans et al, 2001), multisines, which are arbitrary sums of harmonically related sines, are used to reduce the time spent testing engines. Historically, identification relied on the use of time-consuming "wobble" tests, in which the engine is excited by single sines of different frequencies: gain and phase shifts were then calculated at each frequency, generating Bode plots. In Figure 4 we report original and identified PS32 signals corresponding to multisine input WF32 with spectrum in the band 0.1-50Hz, consistent with the sampling frequency of 100Hz used in the digital engine control setup. In Figure 5 we represent signals DPQ23 and TM49 for a similar multisine input on A8. We can see that if responses of the XN2 and PS32 signals to multisine input WFE32 are correctly identified (fitting factors greater than 99%), this is not the case of responses of the DPQ23 and TM49 signals to multisine input A8 (fitting factors of 61% and 83% respectively), even though fifth-order linearized models were used.

We then compared in the frequency-domain (pole-zero locations and Bode plots) the various linearized models obtained from input step responses and input multisine responses. We could notice important discrepancies both in the static gains and dynamics.

The main conclusions that we could draw from our experiments on the military engine model are as follows:

- good fitting factors were obtained for linearized models of orders two and three, and it is probably not necessary to resort to higher order models;
- there is a strong influence of the nature of the input signals on the validity of the identified linearized models: we got excellent fitting factors when exciting the fuel flow input WF32 with multisine signals, whereas step signals appeared more appropriate for the nozzle area input A8. Moreover, there are strong discrepancies when identifying the same transfer functions with input data of different nature. These observations lead us to the conclusion that the input signals used for identification must be careful chosen and should be consistent with the physics of the engine;
- as with the OBIDICOTE model, there is a strong influence of the 3D flight envelope parameters on the linearized dynamics. The choice of the linearizing points will be a key ingredient in the derivation of gain-scheduled control laws.

4. CONCLUSION

Following extensive experiments on a commercial aircraft engine model (OBIDICOTE) and a military aircraft engine model, we can observe that standard linearization/identification techniques provide satisfying results. The obtained transfer functions have generally low (first, second or third) order, and seem to be locally representative of the highly nonlinear engine dynamics. However, these transfer functions strongly vary within the 3D flight envelope (engine power, aircraft speed, altitude), which indicates that a significant amount of linearized models must be derived, and that control laws will be scheduled appropriately over these models.

Directions for further research include multivariable (MIMO) identification, especially for military applications where variable geometry inputs can be fully used together with fuel flow to improve engine dynamics. No major difficulty is expected since the pem function of the Matlab System Identification Toolbox is designed to handle multivariable transfer functions.

It is also expected that the design of scheduled control laws will have significant impact on the choice of the linearized / identified models, especially on their location in the flight envelope and on the nature of the input signals used for identification (steps, multisines or others). An iterative design procedure would then consist of the following steps:

(1) derivation of linear models with appropriate choice of the linearization points and identification input signals;
(2) design of a control law scheduled over these models;
(3) analysis of the achieved closed-loop behavior, and return to step (1) if performances are not satisfying.

The ACM toolbox currently developed by SNECMA Moteurs should provide a user-friendly modular environment to perform all these tasks, and should result in significant savings in time and effort for engineers designing control laws for turbofan engines.

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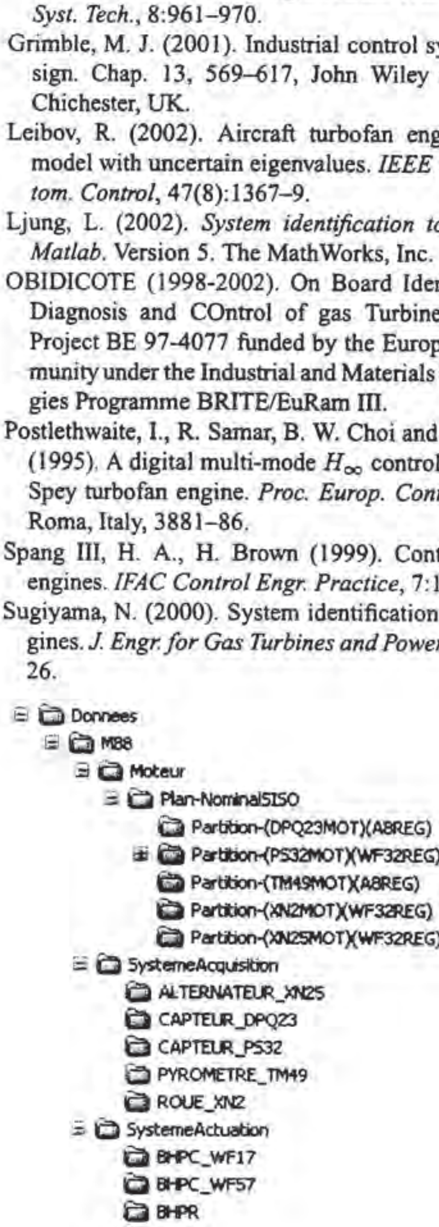

Fig. 1. Partial overview of the engine sections and partitions in the ACM toolbox.

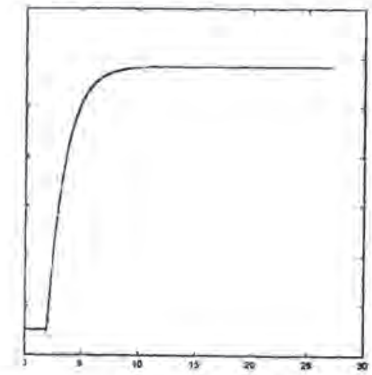

Fig. 2. Time-response of signal XN2 to a step input WF32. Comparison between nonlinear engine model (black) and linearized model (red). Plots cannot be distinguished. Fitting = 99.7%.

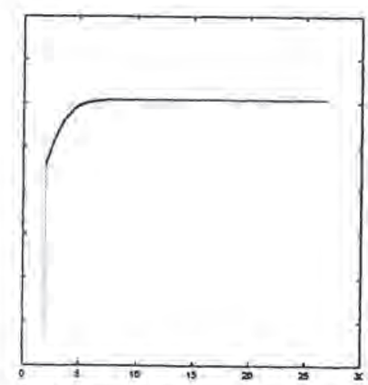

Fig. 3. Time-response of signal DPQ23 to a step input A8. Comparison between nonlinear engine model (black) and linearized model (red). Plots cannot be distinguished. Fitting = 89.3%.

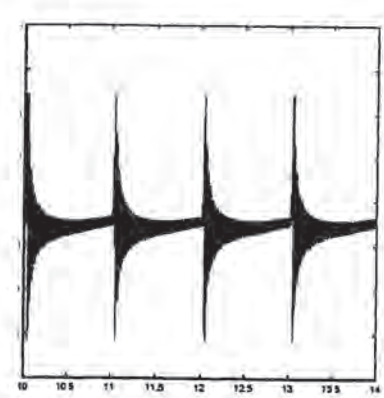

Fig. 4. Time-response of signal PS32 to a multisine input WF32. Comparison between nonlinear engine model (black) and linearized model (red). Plots cannot be distinguished. Fitting = 99.5%.

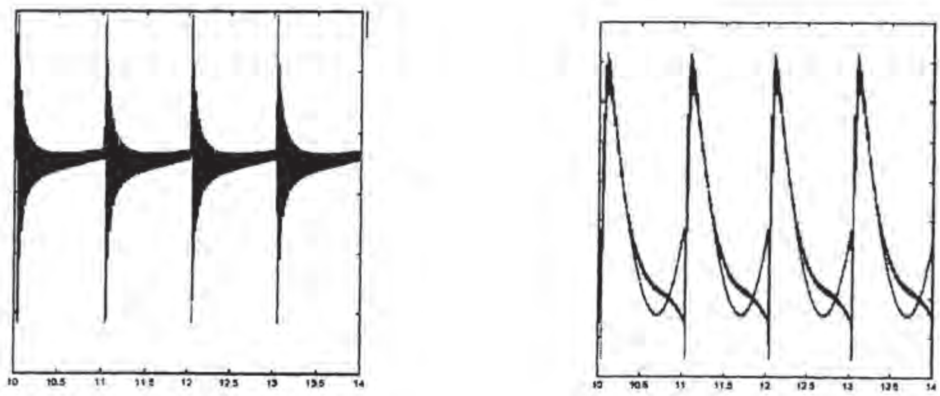

Fig. 5. Time-response of signal DPQ23 (left) and TM49 (right) to a multisine input A8. Comparison between nonlinear engine model (black) and linearized model (red). Fitting = 82.5% (DPQ23) and 60.7% (TM49).

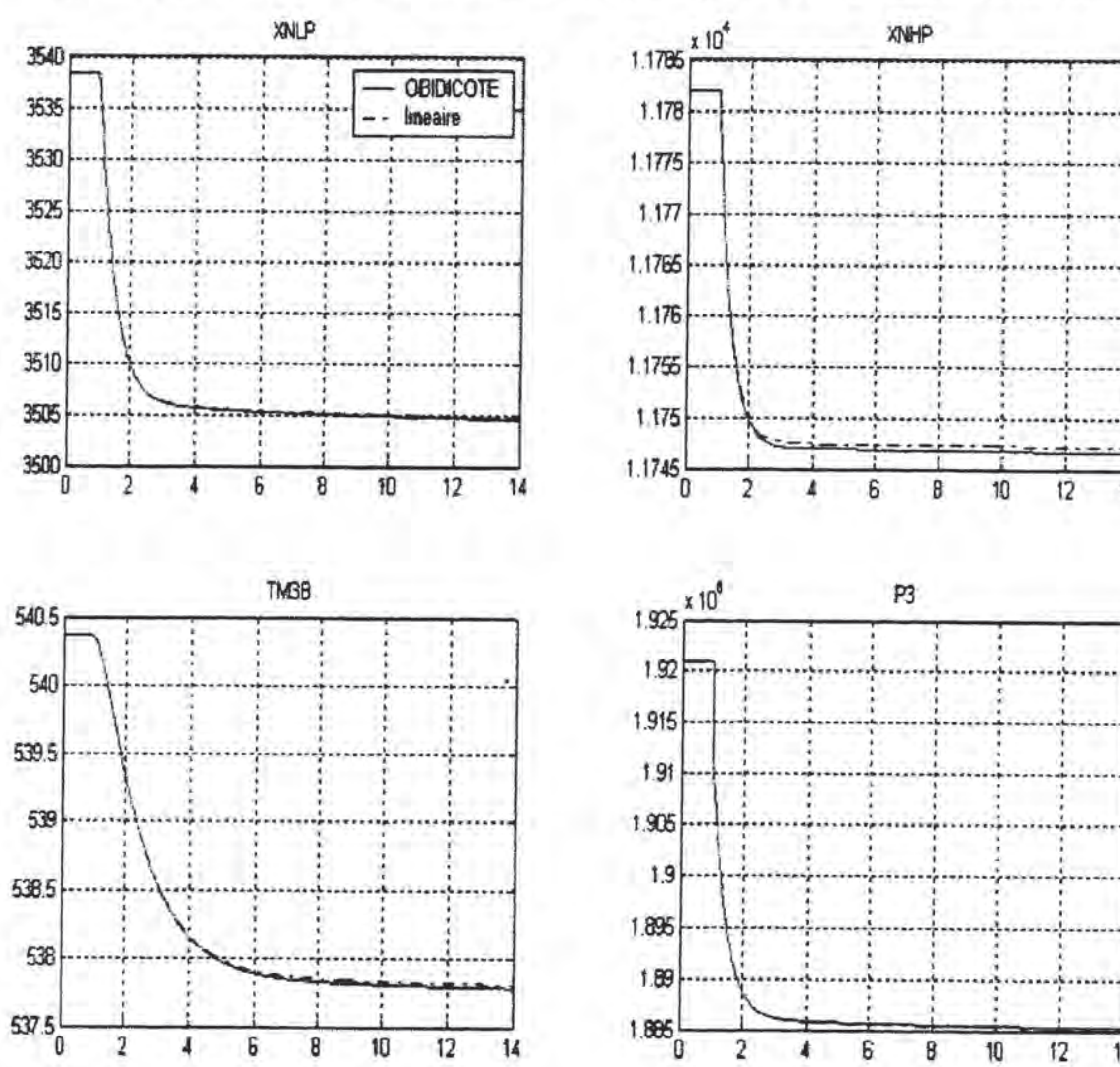

Fig. 6. Time-responses of various output signals to a step input WFE. Comparison between nonlinear OBIDICOTE model (solid lines) and linearized models (dotted lines).