Aerospace Science and Technology 16 (2012) 70–81

Contents lists available at ScienceDirect

Aerospace Science and Technology

www.elsevier.com/locate/aescte

Aircraft engine health management via stochastic modelling of flight data interrelations

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ARTICLE INFO

Article history:
Received 20 November 2009
Received in revised form 1 February 2011
Accepted 2 March 2011
Available online 5 March 2011

Keywords:
Health management
Fault detection
Fault isolation
Stochastic modelling
Nonlinear models
Engine systems
Decision making
Statistical inference

ABSTRACT

A novel engine health management (EHM) scheme is introduced. It uses flight-level, instead of thermodynamic, data to cost-effectively augment the onboard EHM redundancy. For a nominal healthy aircraft, fault-sensitive interrelations among flight data are globally modelled inside a flight regime via Constant-Coefficient Pooled Nonlinear AutoRegressive with eXogenous (CCP-NARX) excitation representations. Single or sequential engine faults perturb these interrelations. Statistically evaluating the perturbation-induced effects draws reliable conclusions on the engine's health. Validation and comparisons with Kalman filter-based alternatives are made throughout the regime under various operational conditions.

1. Introduction

In modern aircraft, and even more so in future pilot-less versions, high reliability and safety should be cost-effectively obtained. The multiplication of existing critical hardware (the "hardware redundancy" principle), coupled to voting schemes for health management (HM) purposes, has its limits due to added weight and cost [26]. Significant improvements on reliability/safety may, hence, only result from additional *analytical* redundancy based on the smart use of available system-level signals and hardware [18].

Introducing engine HM (EHM) analytical redundancy by modelling part of the healthy engine dynamics using physics-based principles, and then detecting fault-induced trends in model parameters (or specific functions of them) is commonly used in either on-board [6] or on-the-service-bay [34] versions. Other schemes use the gas path analysis (GPA) approach to identify highly accurate models on typical health-state-related data along the gas path (afterfan total temperature and pressure, high pressure compressor temperature and pressure, and so on): In [25] linear stochastic models (AutoRegressive with eXogenous excitation – ARX, Output Error – OE or Prediction Error – PE) are augmented with "model-error" models, designed following the H_∞ principle and aiming at minimizing modelling uncertainties around an envelope location. In [27] the model augmentation uses a neural network-based part. In both schemes fault-induced trends between the model output and that of the actual engine provides HM results.

A majority of approaches rely, however, on models of the healthy engine dynamics identified via GPA measurements and coupled to fuzzy logic rules [19], or Kalman filters (KF) in standard or adaptive form [24] for estimating fault-induced changes on health parameters. An interesting comprehensive study [30] compares schemes using KFs in linear (LKF), extended (EKF) and unscented (UKF) versions. Both EKF- and UKF-based schemes show superior performance at the price of (one and two, respectively, orders of magnitude) higher online computational effort than the LKF. This is due to necessary onboard transformations (which potentially involve badly-conditioned matrices).

Other EHM schemes rely on multiple engine models or observers to describe the engine dynamics in various health states, and compare the output of each model to that of the engine. Then, the "correct" model and the associated health state are deduced based on the model output being close to that currently measured from the engine. Multiple health-state-related models are built using either KFs [21,23], Takagi–Sugeno fuzzy rules [12], or neural networks [11,28]. Multiple health-state-related observers (designed

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1270-9638/$ – see front matter
doi:10.1016/j.ast.2011.03.002

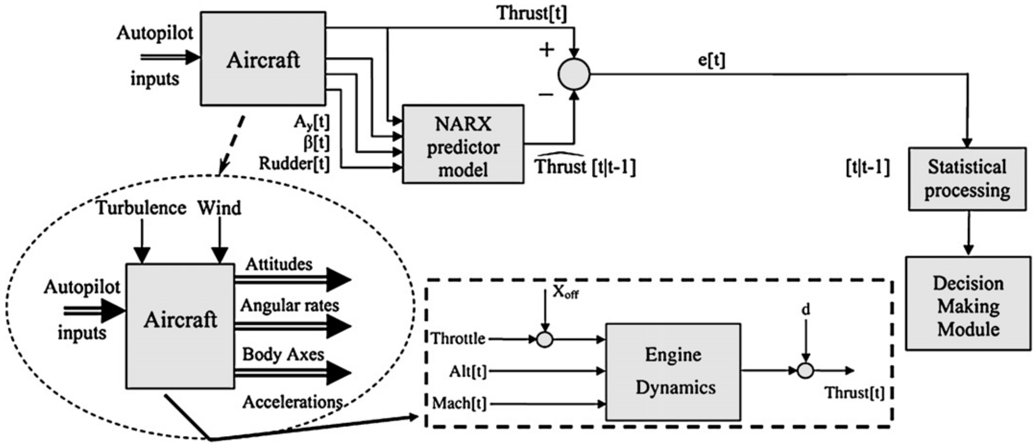

Fig. 1. The engine health management scheme and detail of the aircraft simulator with the engine subsystem.

for enhanced robustness) are reported in [10,29], or, in nonlinear versions in [35].

Finally, non-model based schemes use thresholds on engine health state parameters [32], pattern recognition techniques [3], or even fuzzy inference [2] on groups of engine parameters to detect fault-induced trends. These works are comprehensively reviewed in [33].

The proposed onboard EHM scheme innovates by operating on *flight-level*, rather than engine thermodynamic, data. Since available data are used, the expensive/complex development of new physical sensors or hardware is avoided. The resulting (unrelated to GPA) EHM redundancy is intended to complement the existing GPA-related one, in order to enhance the available decision-making capabilities. The approach extends the generic ideas of relevant work in [13], and relies on stochastic nonlinear modelling of the interrelations among flight data such as acceleration, thrust and so on. Hence, the use of (often unavailable) physics-based or empirical models, as in [6], is no longer needed. These interrelations are *fault-sensitive*, that is, valid exclusively for a nominal healthy aircraft, and are modelled via Constant-Coefficient Pooled Nonlinear AutoRegressive with eXogenous (CCP-NARX) excitation representations. Potential single or sequentially occurring engine faults perturb these nominal (CCP-NARX modelled) interrelations. Then, custom-built statistical hypothesis tests evaluate the perturbation-induced effects in order to detect abnormal engine operation, and (when possible) isolate causes of engine malfunctions. Hence, additional ability to judge the GPA-based internal engine diagnosis is provided.

The paper is organized as follows: Section 2 presents the aircraft (a nonlinear simulator) and the considered engine faults. Section 3 describes the CCP-NARX modelling procedure and the design of the statistical tests. Section 4 shows some modelling and HM results, along with brief comparisons with LKF-based schemes. Finally, Section 5 presents some concluding remarks.

2. The aircraft and the faults

A simulator of an autonomous twin-engined small passenger aircraft is used in this study. It is a 6 degree-of-freedom nonlinear aircraft model, with the inputs (stick, wheel, pedal, throttle) provided from a specifically designed autopilot block according to a predetermined flight trajectory (Fig. 1). The input and the resulting attitude signals (including the angle-of-attack α, the sideslip angle β, surface moments, accelerations and angular rates) are available. The wind and turbulence effects (conforming to MIL-F-8785C) are considered as system disturbances. The considered faults affect the left engine, and are simulated by acting on selected signals fed into the engine subsystem, as shown in Fig. 1.

Table 1
The faults considered.

Type	Description	Magnitude
F_k^A	Part of throttle input (k% of total) fed to engine	$k = 25$
F_k^B	Unstable thrust & flameout	$k = 550$
F_k^C	Recurrent engine thrust reduction (k% of nominal)	$k = 30$
$F_{k_1,k_2,t}^D$	$F_{k_1}^A$ fault shortly followed (in t s) by $F_{k_2}^B$ fault	$k_1 = 25$, $k_2 = 550$, $t = 10$, 20 s

The HM scheme monitors the engine operational level, rather than any internal components (fans, compressors and so on) as in GPA-based schemes. Thus, a relatively simple engine model is considered, since no GPA signals (other than the total thrust) have to be used. The simulated faults involve:

a) Partial reduction of the throttle input signal fed into the left engine control module, with the measurements of altitude and Mach signals (designated as $Alt[t]$ and $Mach[t]$, respectively) being unaffected. The engine operation is substantially altered, as if the link from throttle to engine suffered a severe, but not fatal, failure (see Fig. 2(a) from instant 150 s onwards). This fault is referred to as F_k^A with A indicating the fault type and k its considered magnitude (k% of the throttle input normally entering the engine control module, see Table 1).
b) Unstable left engine thrust output simulating inconsistent compressor airflow before flameout (see Fig. 2(b)), that is, engine shutdown. This situation may be due to severe successive internal incidents (such as blade loss) causing fast deterioration. This fault is referred to as F_k^B with B indicating the fault type, and k its magnitude, corresponding to the colored noise's standard deviation $\sigma = k$ added to the thrust output to simulate the fault.
c) Recurrent left engine thrust reduction (see Fig. 2(c)). The left engine thrust repeatedly drops to lower values for short time intervals, possibly due to unstable compressor airflow. This situation may be due to either physical damage, or control software issues. The fault is referred to as F_k^C, with C indicating the fault type and k the % periodic reduction of the current left engine thrust nominal value.
d) Multiple sequentially occurring faults affecting the left engine. The occurrence of F_k^A faults is followed some seconds later by F_k^B faults affecting the already "faulty" engine. Clearly, this sequential occurrence is not equivalent to superposing the effects of *single* F_k^A and *single* F_k^B faults, meaning that a separate $F_{k_1,k_2,t}^D$ class is necessary. These sequential faults are referred to as $F_{k_1,k_2,t}^D$, with D indicating the fault type and