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# Gas turbine engine prognostics using Bayesian hierarchical models: A variational approach

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A B S T R A C T

Prognostics is an emerging requirement of modern health monitoring that aims to increase the fidelity of failure-time predictions by the appropriate use of sensory and reliability information. In the aerospace industry it is a key technology to reduce life-cycle costs, improve reliability and asset availability for a diverse fleet of gas turbine engines.

In this work, a Bayesian hierarchical model is selected to utilise fleet data from multiple assets to perform probabilistic estimation of remaining useful life (RUL) for civil aerospace gas turbine engines. The hierarchical formulation allows Bayesian updates of an individual predictive model to be made, based upon data received asynchronously from a fleet of assets with different in-service lives and for the entry of new assets into the fleet.

In this paper, variational inference is applied to the hierarchical formulation to overcome the computational and convergence concerns that are raised by the numerical sampling techniques needed for inference in the original formulation. The algorithm is tested on synthetic data, where the quality of approximation is shown to be satisfactory with respect to prediction performance, computational speed, and ease of use. A case study of in-service gas turbine engine data demonstrates the value of integrating fleet data for accurately predicting degradation trajectories of assets.



## 1. Introduction

Today's complex and advanced systems require costly and sophisticated maintenance strategies. It is estimated that expenditure on maintenance for complex systems amounts to approximately one-half of initial investment before obsolescence forces replacement [55]. Modern industries have adopted cost-effective maintenance strategies that optimise operations, production, and processing equipment up-time. For example, gas turbine engine (GTE) manufacturers, e.g. General Electric, Pratt and Whitney and Rolls-Royce, all have performance-based contracts with commercial airlines in which their compensation is tied to product availability (hours flown) [28,36]. Services, such as TotalCare® and "power by the hour" arrangements, are now regarded as essential to delivering asset operation [29]. The economic impact of such service contracts is significant. According to Dennis and Kambil [11], after-sales services and parts contribute only 25% of revenues across all manufacturing companies but are responsible for 40–50% of profits.

An important aspect of after-sales service is the provision of an effective and efficient maintenance concept and a recent move toward maintenance optimisation is known as Condition-Based Maintenance (CBM). Over the past few decades, CBM

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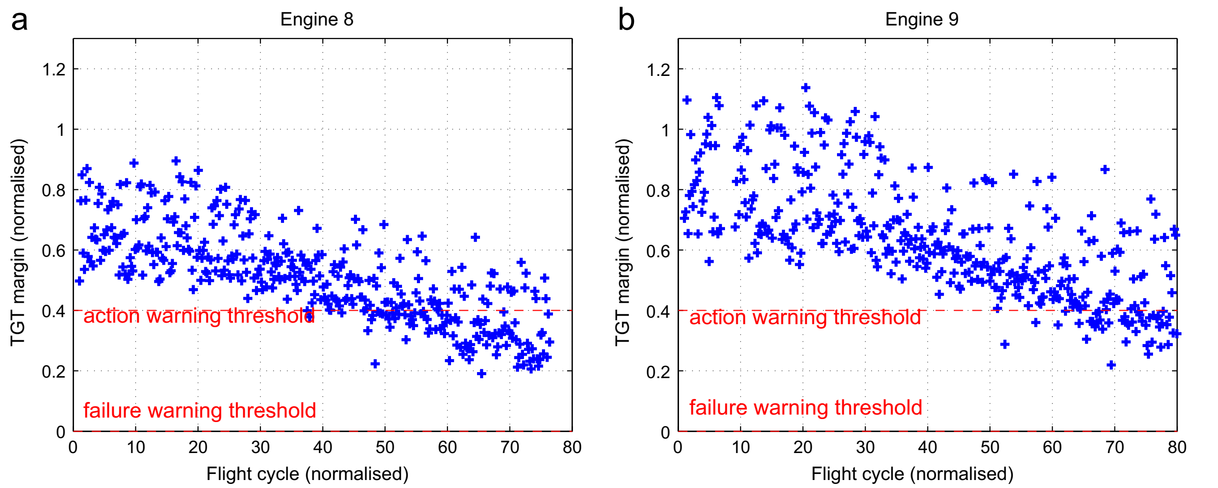


**Fig. 1.** Examples of normalised TGT margin degradation. Engine 8 appears to have a change in degradation slope whereas Engine 9 has very high noise.

technologies in machine condition monitoring and fault diagnostics have become more developed. The state-of-the-art of machine diagnosis consists of the automated detection and classification of faults, whilst prognostics is concerned with trying to predict the damage that is yet to occur. Prognostics promises to significantly reduce operational disruption, spares inventory, maintenance labour costs and hazardous conditions. However, prognostics is a relatively new research area and has yet to receive prominence compared to other areas of CBM [21].

A considerable amount of prognostic research has been conducted to improve the estimation of remaining useful life (RUL) of engineering assets. Examples include automotive [64,1,48], high-value equipment in heavy industries, such as oil and gas production and distribution [50,65] and power generation and distribution [7]. Prognostics has also been widely used in various aerospace domains including avionics [26,60,20,9], unmanned aerial vehicles (UAV) [57], defence, such as the Joint Strike Fighter (JSF) program [8,13] and civil aerospace [34,52].

This paper is focused on civil aerospace GTE prognostics. Aircraft engines are highly valuable assets where large sums are spent in support, maintenance and logistics. The application of prognostic technologies in GTEs can potentially yield profits to engine producers as well as commercial aircraft operators. For instance, Rolls-Royce has more than 14,000 aerospace engines in service, operated by more than 500 airlines and powering more than 5.5 million commercial flights per year [49]. The considerable number of engines to be maintained, in terms of service and provision of spare parts, enables this company to generate revenue about 55% of the more than US$11 billion in total revenues. This evidence also emphasises the significant benefits for commercial airlines in applying GTE prognostics, which is an effective way to reduce life cycle costs and improve engine reliability as well as availability [36,32].

A prognostic technique should take advantage of the fact that a fleet of engines is capable of generating a considerable volume of health signal data and that the similarities between engines at various levels may contain information usable by any or all members of the fleet. Therefore, this paper proposes an algorithm to maximise the value of these data by modelling them with a hierarchical structure that is capable of accommodating multiple degradation signals, one for each engine. In this way, the health information can be shared between the engines to enhance RUL predictions for all assets and particularly where information sharing can compensate for data scarcity e.g. for assets newly entering service.

## 2. Background

### 2.1. GTE degradation

Turbine Gas Temperature (TGT) margin is conventionally used to monitor the gas path degradation of an engine to detect changes in performance and to indicate the need for inspection or maintenance [35,62]. In this paper, TGT margin is used as the main health index to be forecast for RUL estimation of aircraft GTEs [35,37,43]. Fig. 1 shows two examples of normalised TGT margin degradation data for two engines labelled Engines 8 & 9[1] for correspondence with our earlier paper [62]. They have been selected to typify specific challenges in forecasting: apparent change in slope (Engine 8) and poor SNR (Engine 9). The *x*-axis presents the time index which is the normalised number of flight (cycles) whereas the *y*-axis embodies the health index which is the normalised TGT margin.

[1] Eight and nine correspond to their (arbitrary) indexes in the fleet.