Expert Systems With Applications xxx (2015) xxx–xxx

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Prognostics of gas turbine engine: An integrated approach☆

Q1 Martha A. Zaidan[a,b,c], Rishi Relan[a,b,c,*], Andrew R. Mills[a,c], Robert F. Harrison[b,c]

[a] Rolls-Royce University Technology Centre, UK
[b] Department of Automatic Control and Systems Engineering, UK
[c] The University of Sheffield, Mappin Street, S1 3JD, UK

ARTICLE INFO

Keywords:
Diagnostics
Prognostics
Bayesian hierarchical model
Information-theoretic change point detection
Irregular events

ABSTRACT

Condition-based maintenance is an emerging paradigm of modern system health monitoring, where maintenance operations are based on diagnostics and prognostics. Condition-based maintenance strategies in the industry benefit from accurate predictions of the remaining useful life (RUL) of an asset in order to optimise maintenance scheduling, resources and supply chain management. Due to the substantial costs involved, small improvements in efficiency, result in the significant cost reductions for overall maintenance services as well as its impact on energy consumption and the environment. In this paper, we present a data-driven methodology combining the hierarchical Bayesian data modelling techniques with an information-theoretic direct density ratio based change point detection algorithm to address two very generic issues namely dealing with irregular events and dealing with recoverable degradation, which are often encountered in the prognosis of complex systems such as the modern gas turbine engines. Its performance is compared with that of an existing Bayesian Hierarchical Model technique and is found to be superior in typical (heterogeneous) and non-typical scenarios. First, the technique is illustrated by an example on the simulation data and later on, it is also validated on the real-world civil aerospace gas turbine fleet data.

1. Introduction

For many of the world's largest manufacturers, aftermarket service and parts operations are essential to their business. For example, Rolls-Royce, one of the world's largest jet engine and gas turbine makers, 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 (CDS, 2014). The company's service and part business revenue is about 55% of the approximately US$11 billion total revenues (Rolls-Royce, 2014). This evidence emphasises the significant benefits of applying prognostics in civil aerospace gas turbine engines, which is one of the effective ways to reduce life cycle costs, improve engine reliability as well as availability (Li & Nilkitsaranont, 2009; Marinai, Probert, & Singh, 2004).

In gas turbine applications, the degradation pattern of a gas turbine engine health over time is unknown. It could be linear, nonlinear or the combination of both (Li & Nilkitsaranont, 2009). The variation in degradation pattern occurs due to fault event or due to the operating condition. Furthermore, the engine health may be recovered significantly after proper maintenance, which in-turn affects the degradation pattern in the next cycle. In order to estimate appropriate remaining useful life (RUL), it is important to accommodate these events into a prognostic algorithm. In this paper, an integrated prognostic algorithm is proposed to estimate RUL of civil aerospace gas turbine engines.

This paper is organised as following: Section 2 provides the background information about the gas turbine engine degradation phenomenon its challenges. Section 3 describes the generic methodology and the practical implementation of integrated prognostic approach. Sections 3.1 and 3.2 discuss briefly the details of the main algorithms namely Bayesian Hierarchical Models and Direct density based change point algorithm respectively . In the Section 4 capabilities of the proposed algorithm are demonstrated on the two different synthetic data sets produced under two different operational scenarios. Results are stated in the Section 5. Conclusions are discussed in the Section 6.

2. Background

2.1. Gas turbine engine degradation

Turbine Gas Temperature (TGT) margin is conventionally used to monitor the gas path degradation of the engine to detect the changes

☆ The corresponding authors have equal authorship and contributions.

* Corresponding author at: The University of Sheffield, Mappin Street, S1 3JD, UK. Tel.: +32483028818.

E-mail addresses: martha.a.zaidan@gmail.com (M.A. Zaidan), rishirelan@yahoo.co.in, rishirelan@gmail.com (R. Relan), a.r.mills@sheffield.ac.uk (A.R. Mills), r.f.harrison@sheffield.ac.uk (R.F. Harrison).

http://dx.doi.org/10.1016/j.eswa.2015.07.003
0957-4174/

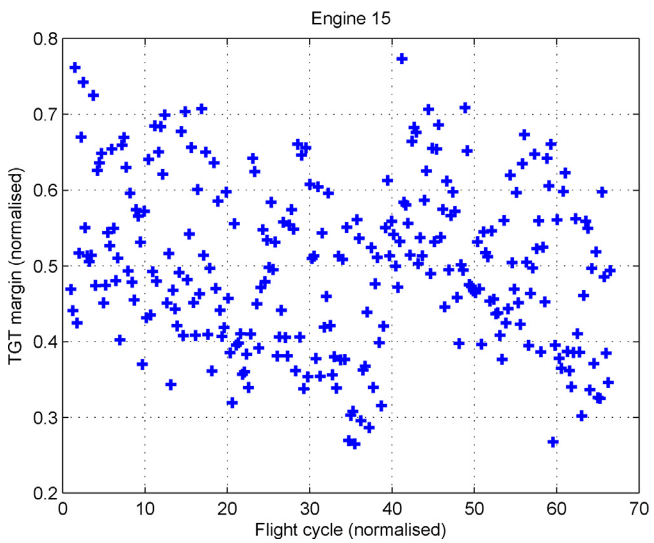

Fig. 1. Example of normalised TGT margin data. The maintenance effect can be seen around flight cycle at 40 where the TGT margin degradation has recovered.

in performance for each engine and to indicate the need for inspection/maintenance. In this paper, TGT margin is used to be forecast for RUL estimation of the engines (Malinge & Courtenay, 2007; Marinai, Singh, Curnock, & Probert, 2003; Müller, Staudacher, Friedl, Köhler, & Weißschuh, 2010). Fig. 1 shows an example of normalised TGT margin degradation data. The TGT margin data is normalised to have maximum points of 1 (i.e. the healthiest TGT margin is equal to 1) and flight cycle is the number of flight experience by an aircraft.[1]

An aircraft engine can be considered as a complex system comprising multiple interacting subsystems (Jamshidi, 2010). This system comprises hundreds or thousands of components. Intermediate groupings, or various levels of subsystems, are necessary to describe or depict these systems correctly. Degradation health index measurement, normally takes place at the system level (e.g. TGT margin), may also be influenced by the changes occurring in sub-system level or even component level. In Fig. 2, an aircraft engine is presented as an example of a complex system, which comprises of subsystems (e.g. Lower Pressure Compressor (LPC), High Pressure Turbine (HPT)). Further down the hierarchy, the subsystems are composed of components (e.g. HPT blades, etc.).

A model-based prognostic approach for this type of system is complex to be constructed. However, modern gas turbine engines already have been fitted by numerous sensors for control and monitoring purposes (Waters, 2009). This motivates the direct use of in-flight data to achieve the prognostic goal. Therefore, data-driven approach is promising to estimate RUL of civil aerospace gas turbine engine degradation.

As shown in Fig. 1, there is a large uncertainty associated with TGT margin data as it gets corrupted with noise owing to gas turbine design, manufacturing, ambient and environmental condition, operating condition, mission, maintenance action, etc. (Li & Nilkitsaranont, 2009). Large uncertainty in the data may cause inconsistency in prognostic prediction, especially when there is less data available. In other words, an irrational prediction may arise, e.g. the prediction may show improving health. To overcome this issue, some researchs have been focused on Bayesian approaches, such as (Gebraeel, 2006; Gebraeel, Lawley, Li, & Ryan, 2005; Guo, Li, & Pecht, 2015; He, Williard, Osterman, & Pecht, 2011). In gas turbine engine prognostics, Bayesian approaches have been adopted in Lipowsky, Staudacher, Bauer, and Schmidt (2010) Zaidan, Mills, and Harrison (2013). Bayesian approaches are promising method to deal with large uncertainty in degradation data. This method enables variation and uncertainty to be quantified, mainly by using distributions instead of fixed values in risk assessment.

However, most developed prognostic Bayesian approaches are based on single-level Bayesian non-Hierarchical Models (BnHMs). In gas turbine engine cases, the fleet of engines, shown in Fig. 3, is capable of generating a considerable volume of health signal data. Therefore, a prognostic algorithm should utilise, optimally, data available from multiple fleets of engines (Fig. 3) for estimating the RUL of a specific engine. The solution is to use Bayesian Hierarchical Models (BHMs) which was recently developed by (Zaidan, Harrison, Mills, & Fleming, 2015). In this paper, a Bayesian Hierarchical Model will be used as a main prognostic algorithm. The brief concept of BHM for prognostics will be discussed briefly in Section 3.1, whereas the details of this algorithm can be found in Zaidan et al. (2015).

2.2. Some challenges in Gas turbine engine prognostics

Zaidan et al. (2015) described the use of BHM to deal with prognostics of gas turbine engine degradation. The results revealed that this method is a promising concept in dealing with high uncertainty, but linear degradation data. However, there are some issues in gas turbine engine degradation that need to be considered further. This paper is a continuation of our previous paper (Zaidan et al., 2015) that aims to address some unsolved problems in gas turbine engine prognostics. Several events may affect health index and the degradation pattern of a complex system such as a gas turbine engine. Two main situations which can be considered important in context with a gas turbine engine are: 1. Another situation occurs when the slope in health index changes[2] which may take place owing to a fault or a step change in covariates. 2. First situation is when health index recovers due to maintenance action. For example, if a fault[3] has occurred in an engine, the engine performance may deteriorate faster than non-faulty engine. These issues are described in bit more detail in the following subsections.

2.2.1. Handling multiple degradation patterns

In practice, research reveals that there are many patterns of failure which actually occur in engineering assets (Moubray, 1997). In gas turbine engine degradation, most of the observed patterns of degradation are nearly linear (Puggina & Venturini, 2012), however there are cases where the rates of degradation may be non-linear (Saravanamuttoo, Rogers, Cohen, & Straznicky, 2009). The latter is caused by various factors, including a step change in covariates[4] and fault modes.[5]

To capture non-linear degradation behaviour, several researchers have used dynamic models, such as autoregressive-integrated-moving-average (ARIMA) (Marinai et al., 2003) and DLMs (Lipowsky et al., 2010). However, these models are only effective for short-term predictions, but less reliable when it is used for long-term predictions due to dynamic noise, their sensitivity to initial system conditions and an accumulation of systematic errors in the predictor (Sikorska, Hodkiewicz, & Ma, 2011). Alternatively, detecting the sources of rapid change would support a prognostic algorithm in capturing degradation's non-linearity. For examples, Li and Nilkitsaranont (2009) dealt with two patterns in gas turbine engine's degradation by transiting between linear and quadratic regression models. However, this

[1] This was normalised to maximum of 100, for protecting airline company's sensitive information.

[2] It may deteriorate faster or slower.

[3] Here, this fault does not mean a catastrophic failure where there is a sudden and total failure in the system from which recovery is impossible.

[4] Covariates are any factors which affect degradation, such as operating conditions and environmental effects.

[5] Fault modes are specific types of fault. Creep, fatigue, corrosion, and wear are examples of mechanical fault modes.