Accommodating Repair Actions into Gas Turbine Prognostics

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ABSTRACT

Elements of gas turbine degradation, such as compressor fouling, are recoverable through maintenance actions like compressor washing. These actions increase the usable engine life and optimise the performance of the gas turbine. However, these maintenance actions are performed by a separate organization to those undertaking fleet management operations, leading to significant uncertainty in the maintenance state of the asset. The uncertainty surrounding maintenance actions impacts prognostic efficacy. In this paper, we adopt Bayesian on-line change point detection to detect the compressor washing events. Then, the event detection information is used as an input to a prognostic algorithm, advising an update to the estimation of remaining useful life. To illustrate the capability of the approach, we demonstrated our on-line Bayesian change detection algorithms on synthetic and real aircraft engine service data, in order to identify the compressor washing events for a gas turbine and thus provide demonstrably improved prognosis.

1. INTRODUCTION

Gas turbine engines are subject to operational degradation which, over time, will reduce their performance. For effective fleet management, the ability to predict this degradation through prognostics is seen as a vital part of modern health monitoring. Prognostics enables forward predictions of the time to failure, thus offering a route to increase time in-service and reduced disruption for improved asset management. For accurate prognosis, knowledge of maintenance actions which affect the rate and state of degradation is of prime importance but is often difficult to obtain and incorporate.

Maintenance actions like compressor washing increase the usable engine life and the performance of the gas turbine. These actions are performed at geographically dispersed locations by organisations independent to those performing fleet management, which lead to uncertainty in the maintenance state of the asset. Organisational barriers do not permit the feedback of whether an advised maintenance action is taken or if maintenance is performed independent from fleet management advice. The uncertainty surrounding maintenance actions impact the ability to accurately trend and extrapolate the health degradation of a unit.

The solution proposed in this paper accurately detects maintenance events directly from the measured service data through a change detection algorithm. The event detection information is subsequently used as an input to a prognostic algorithm (Zaidan et al., 2013), advising the prognostic algorithm to update the estimation of remaining useful life.

2. LITERATURE REVIEW

Prognosis seeks to estimate the future health state of an asset and this problem has been addressed through a number of approaches, such as particle filters (Schwabacher & Goebel, 2007) and hidden Markov models (Tobon-Mejia et al., 2011), which can capture uncertainty in the projection of health state. Our work in Zaidan et al. (2013), provides a deterministic and efficient calculation which are then extended in this paper to accommodate maintenance events.

The problem of change point detection or detecting abrupt changes in time-series data has attracted a lot of research in the statistics and data mining communities over the last three decades (Basseville & Nikiforov, 1993; Brodsky & Darkhovsky, 1993; Gustafsson, 2000; Kawahara & Sugiyama, 2012). Change-point detection has been widely used in a range of real-world problems such as signal segmentation of a data stream (Tobon-Mejia et al., 2011), fraud detection in mobile networks (Bolton & Hand, 2002), climate change detection (Reeves et al., 2007), motion detection in vision systems (Ke et al., 2007), stock market prices (Chen & Gupta, 1997), nuclear engineering (Fearnhead & Clifford, 2003), and the aerospace domain (Fujimaki, 2005). These methods bring to bear a selection of models, statistical techniques and threshold selection policies to identify change events in data. It is proposed in this work that a unified approach can be provided with Bayesian change detection providing a rigorous means to utilise a statistic data model and incorporate expectations about an impending change as a prior belief.

Generally, change-point detection methods can be classified into two categories depending on the time of detection: retrospective detection (batch processing), and on-line detection (sequential processing). A retrospective change point detection method waits until the end of a fixed period of time, and then uses all the data throughout the period of time to locate the change points. For example, if we are going to detect maintenance events with annual updating, we have to wait until the end of the year to collect all the engine service data before doing any analysis to locate temporarily the maintenance actions. Although retrospective change point detection requires longer reaction periods, it tends to give more robust and accurate detection (Kawahara & Sugiyama, 2012). On the other hand, on-line change point detection must detect change points as soon as possible, this inevitably means acting upon less information. To provide the most timely input into the prognostic algorithms, on-line methods are the focus of this paper.

Many of the previous Bayesian approaches to change point detection have been retrospective (Barry & Hartigan, 1993; Xuan & Murphy, 2007), and have demonstrated strong performance for off-line datasets but are not suitable for making instant decisions. A Bayesian on-line change point detection algorithm was recently introduced by Adams & MacKay (2007), and in an alternative formulation by Fearnhead & Liu (2007). While computational cost can be made to be approximately linear in Fearnhead & Liu (2007) by applying resampling strategies, a preferred recursive formulation by Adams & MacKay (2007) provides a closed form solution that is linear and introduces no approximation errors. This closed-form Bayesian algorithm, estimates the time since the last change point, which is called the run-length. Adams and MacKay used an underlying predictive model of the time series that is updated at each sample point, to estimate the probability of a new sample extending or resetting to zero the run-length. Recently, the algorithm has been implemented to automatic speech recognition systems to work in real-world environments (Chowdhury et al., 2012).

In this paper, we propose the integration of the on-line change point detection algorithm (Adams & MacKay, 2007), with a Bayesian-inference prognostic approach (Zaidan et al., 2013). The prognostic algorithm is updated as new data is received and outputs predictive probability distributions for the expected future health. The predictive distributions can be used in the detection algorithm to incorporate step change discovery into prognostic methodologies. The Bayesian methods employed effectively addresses the problems of novelty threshold selection; the incorporation of prior knowledge; and change detection with uncertain, noisy, and missing data.

To illustrate the capability of the approach, on-line Bayesian change detection algorithm will be implemented on real aircraft engine service data, in order to identify the compressor washing events of a population for gas turbines.

3. Mathematical Model

3.1. Prognostic Model

The true degradation is unknown and we choose to model a related health index of the asset which may be estimated from noisy data collected from the system. The health index estimate may in many systems be described as a probability distribution for a parametrically linear model which is projected forward in time to give an anticipated future health index, shown below in Equation (1):

$$\mathbf{x_{1:t}} = \phi(\mathbf{t})^T \mathbf{w} + \varepsilon \tag{1}$$

where ε is a random error term that follows a normal distribution $\varepsilon \sim \mathcal{N}(0, \sigma_n^2)$. In general, ϕ is a polynomial basis function, $\mathbf{w}$ is a vector of weights and $\mathbf{x_{1:t}}$ is the set of degradation measurements. Here we choose $\phi(\mathbf{t}) = (\mathbf{1}, \mathbf{t})^T$ as an affine function form with $\mathbf{t}$ denoting time, but of course variables other than time may be included such as variables related to usage.

Data measured from the environment is modelled as a normal distribution with mean $\phi(\mathbf{t})^T\mathbf{w}$ and variance σ^2. The likelihood distribution, $p(\mathbf{x_{1:t}}|\mathbf{t}, \mathbf{w}, \sigma^2) \sim \mathcal{N}(\phi(\mathbf{t})^T\mathbf{w}, \sigma^2 I)$, is used with a prior distribution to calculate the parameters of the posterior distribution. It is necessary to select an appropriate prior distribution of our data in order to obtain an analytically tractable posterior distribution, which is desirable for real-time, deterministic computation. We assume the prior distribution is a normal-inverse gamma (NIG) distribution and written as $p(\mathbf{w}, \sigma^2) \sim \text{NIG}(\mathbf{w}, V, a, b)$. The parameters for the prior distribution $(\mathbf{w}, V, a, b)$ can be built from an in-service database by way of ordinary least squares (OLS) estimation.

The posterior distribution for the model parameters, $p(\mathbf{w}, \sigma^2|\mathbf{x_{1:t}}, \mathbf{t}) \propto p(\mathbf{x_{1:t}}|\mathbf{t}, \mathbf{w}, \sigma^2)p(\mathbf{w}|\sigma^2)p(\sigma^2)$, are calculated based on a parametrised NIG distribution $(\text{NIG}(\mathbf{w}^*, V^*, a^*, b^*))$ as detailed in Zaidan et al. (2013).

The predictive distribution $(\pi_t = p(\mathbf{x_{t+1}}|\mathbf{x_t}))$, used to extrapolate for prognosis, can be used to evaluate the belief that a new data point belongs to the learnt mode by evaluating a predictive student-t distribution populated from the posterior updated model parameters. This distribution is constructed as $\text{St}(\phi(\mathbf{t}_*)^T\mathbf{w}^*, b^*(1+\phi(\mathbf{t}_*)^T V^* \phi(\mathbf{t}_*)), a^*)$, and may be used to calculate π_t for data point x_{t+1}.

3.2. Change-point Detection Technique

The detection of step change in engine performance data, is performed to identify the compressor washing events of a gas turbine using a Bayesian on-line change point detection approach. This approach is based on Bayes' theorem which allows us to make some inference for event E from observed data x. In other words, we can calculate the posterior probability $P(E|x)$ of E given x by using the Bayes' theorem:

$$p(E|x) \propto p(x|E)\, p(E) = \text{likelihood} \times \text{prior} \tag{2}$$

In this work, our goal is to partition the engine data into segments, which each show a natural decline in performance, separated by change events, where performance is recovered through a maintenance action. The delineations between segments are called the change points.

To determine these change points, we use the run-length method suggested by Adams & MacKay (2007), which is based on the Bayes' theorem. The data are independent and identically distributed (i.i.d) between change points, and the parameters are independent across the change points. The positions of change-points are not specified in advance but instead must be inferred from the data. The change point has occurred if the run-length, r_t, drops to zero; otherwise, the run-length increases by one ($r_t = r_{t-1} + 1$).

In this method, the predictions of the next data point should consider all possible run-lengths and weigh them by the probability of the run-length given the data. By finding the most probable run-length to be 0, i.e. an end to the current data segment, we find a change point. Notationally, we write x_t as the data at time t and $\mathbf{x_{1:t}}$ for the set of data $\{x_1, x_2, \ldots.., x_t\}$, in addition, $\mathbf{x_t^{(r)}}$ is the set of most recent data corresponding to run-length r_t at time t.

The objective, for each time step t, is to estimate the run-length distribution $p(r_t|\mathbf{x_{1:t}})$ over the collected data. By applying a confidence threshold to the run-length distribution, we can determine that the change point has occurred and then setting $r_t = 0$; or otherwise, conclude that it has not occurred and increment run-length as $r_t = r_{t-1} + 1$. The probability distribution for the run-length $p(r_t|\mathbf{x_{1:t}})$ at time t can be estimated sequentially to predict the change point.

The run-length distribution $p(r_t|\mathbf{x_{1:t}})$ can be computed as

$$p(r_t|\mathbf{x_{1:t}}) = \frac{p(r_t, \mathbf{x_{1:t}})}{p(\mathbf{x_{1:t}})} \tag{3}$$

with the probability of evidence calculable by marginalisation, $p(x_{1:t}) = \sum_{r_t} p(r_t, \mathbf{x_{1:t}})$.

The recursion relation for $p(r_t, \mathbf{x_{1:t}})$ can then be derived by writing as the marginal over r_{t-1}, and noting $\mathbf{x_{1:t}} = \{x_t, \mathbf{x_{1:t-1}}\}$:

$$p(r_t, \mathbf{x_{1:t}}) = \sum_{r_{t-1}} p(r_t, r_{t-1}, x_t, \mathbf{x_{1:t-1}}) \tag{4}$$

$$= \sum_{r_{t-1}} p(r_t, x_t|r_{t-1}, \mathbf{x_{1:t-1}})\, p(r_{t-1}, \mathbf{x_{1:t-1}}) \tag{5}$$

$$= \sum_{r_{t-1}} p(r_t|r_{t-1})\, p\left(x_t|r_{t-1}, \mathbf{x_t^{(r)}}\right) p(r_{t-1}, \mathbf{x_{1:t-1}}) \tag{6}$$

By exposing the previous time-step joint probability $p(r_{t-1}, \mathbf{x_{1:t-1}})$, a sequential estimate is possible.

The prior belief of change, $p(r_t|r_{t-1})$, only needs to consider two possible states – the run-length increases or resets to zero. By this binary condition, the method is made tractable. Consequently, the joint distribution of $p(r_t, \mathbf{x_{1:t}})$ is computed for only these two cases: as a growth function when $r_t = r_{t-1} + 1$; or a change point function when $r_t = 0$.

The expression $p\left(x_t|r_{t-1}, \mathbf{x_t^{(r)}}\right)$ is the predictive distribution given the only the previous data points to build models. This is calculated by fitting probabilistic models to all possible r_{t-1} run-lengths of the data ($\mathbf{x_t^{(r)}}$) using the model shown in Equation (1), and assessing the probability of the data point at x_t given the predictive distribution for that model. The calculated predictive distributions, which we label as $\pi^{(\mathbf{r})}$, for the normally distributed data is calculated directly from the student-t distribution, as outlined in Section 3.1. The detection of change point enables the model parameters to be reset to some initial conditions.

Assuming that the prior probability of a change-point is given by the pre-specified hazard rate (H) (which, for simplicity, we assume to be independent of r_t), then

$$p(r_t|r_{t-1}) = \begin{cases} 1-H & if \quad r_t = \quad r_{t-1}+1 \\ H & if \quad r_t = \quad 0 \\ 0 & otherwise \end{cases} \tag{7}$$

In this work we tuned the value of H empirically (to 0.02), however the data could be used to select the value either by a priori learning from fleet data or using on-line techniques such as shown in Wilson et al. (2010), removing need for heuristic tuning.

The proposed on-line change point detection algorithm applied to prognostics is summarised as follows:

1. Learn priors for degradation model parameters (using OLS).
2. Initialise the run-length distribution $p(r_{t-1}) = 1$.
3. Observe new datum x_t.
4. Evaluate predictive probability using student-t distributions for all run-lengths $\pi_{\mathbf{t}}^{(\mathbf{r})}$
5. Evaluate the hazard function $H(r_t)$ (constant in this example)
6. Evaluate the growth probabilities

$p\left(r_t, x_{1:t}\right) = p\left(r_{t-1}, \mathbf{x_{1:t-1}}\right)\pi_{\mathbf{t}}^{(\mathbf{r})}(1-H)$

7. Calculate the change point probabilities
$p\left(r_t = 0, x_{1:t}\right) = \sum_{r_t} p\left(r_{t-1}, \mathbf{x_{1:t-1}}\right)\pi_{\mathbf{t}}^{(\mathbf{r})} H$

8. Calculate the evidence
$p\left(x_{1:t}\right) = \sum_{r_{t-1}} p\left(r_t, \mathbf{x_{1:t}}\right)$

9. Determine the run-length distribution
$p\left(r_t|\mathbf{x_{1:t}}\right) = \frac{p(r_t, \mathbf{x_{1:t}})}{p(\mathbf{x_{1:t}})}$

10. Apply a threshold to the run-length distribution to determine if a change point has been detected. Reset the run-length as $r_t = 0$, and goto step 2; or, increment $r_t = r_{t-1} + 1$

11. Update the degradation model parameters distribution through the steps outlined in Section 3.1 to calculate the predictive $p(\mathbf{x_{t+1}}|r_{t-1}, \mathbf{x_t^{(r)}})$ for all possible run-lengths

12. Estimate the remaining useful life (RUL) by projecting forward the degradation model parameters using the prognostic model (Zaidan et al., 2013)

13. Return to Step 3.

4. Case Study

Gas turbine engines become fouled with airborne contaminants such as unburned fuel, oil, solids and pollen which encrust compressor components. Proper operation and maintenance can be used to minimize the fouling type losses. For example, compressor washing can be used as effective method to maintain the compressor efficiency and prevent significant fouling to occur. The washing of gas turbine compressors maximize the power output, and fuel efficiency, as well as increase the life time of the compressors components (Kurz & Brun, 2001; Malinge & Courtenay, 2007; GE, 2008).

As engine degradation happens, the engine efficiency will decrease. Consequently, the fuel consumption will increase to generate the required thrust. As a result the temperature of the engine will increase, and therefore the global health of the engines can be derived from the core flow temperature measured at the turbine exit (Marinai et al., 2003). The temperature is named either Exhaust Gas Temperature (EGT) or Turbine Gas Temperature (TGT). An estimate of the difference between the certified TGT maximum (redline) and a projection of TGT to full-rated take-off at reference conditions is named TGT margin (Malinge & Courtenay, 2007). The TGT margin is usually used to monitor the overall performance of the engine through Engine Health Monitoring (EHM) to detect the shifts performance for each engine, indicating the need for inspection/maintenance, and to forecast the remaining useful life of the engines.

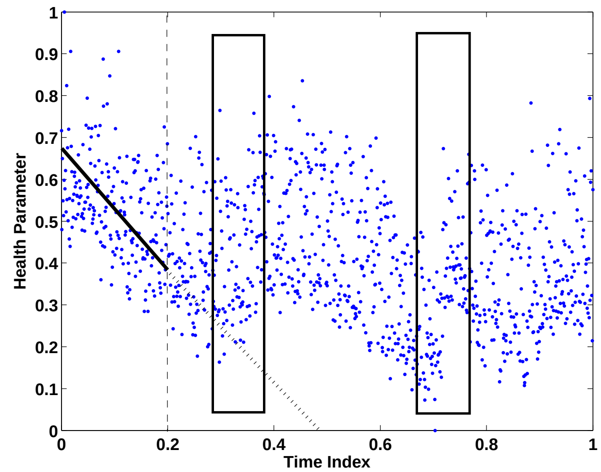

Figure 1. Example data of a single engine's measured value of TGT margin over a number of maintenance events, the time region of which are shown with black rectangles. The solid black line shows a regression fit of the linear model to the data received by time index 0.2, and the dotted line the projection of future values.

In general, the estimation of RUL is at the centre of system prognostics and health management. RUL gives operators estimation for decision making by quantifying how much time is left until functionality of engine is lost. RUL can be defined as the difference between present time and the time when the prediction of TGT margin crosses the zero TGT margin. Figure 1 shows an example of the TGT margin signal with compressor washing events. The measured value of TGT margin is presented as blue dots and suspected maintenance action (detected visually by step changes in the data) are highlighted to occur at some time within the rectangular region. The model presented in Equation 1 is fitted to the data received up until time index 0.2 (black line), from which point a projection is made (the techniques of prognosis are not the focus of this paper but those projections also incorporate uncertainty bounds not shown). It is clear that inclusion of the effects of compressor washing is needed for accurate estimation of RUL.

In the following section, we experimentally investigate the performance of the proposed algorithm using synthetic and real-world datasets.

4.1. Case study 1: Synthetic Dataset

In this first case study, the on-line Bayesian change point detection algorithm will be tested on synthetic data. Technique verification with synthetic data is an important method to evaluate the performance prior to testing to real-world dataset because the ground truth is available, in contrast to the real data which is subject to uncertainty in the true event times and the measured TGT margin. The synthetic data is generated to have similar noise and shape characteristics to the real data in Figure 1, and provides the true health index and change point times corrupted by the artificial noise.

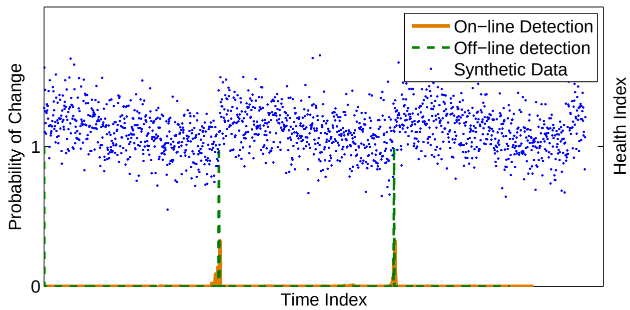

Figure 2. Synthetic Data: The graph represents the degradation signal (blue dots) (segmented by two change events) and the probabilities of zero run-length at each time instant for the on-line technique validated against an off-line technique.

The graph in Figure 2 shows an artificial time-series signal containing two change points, which can be visually identified at intervals spaced 30% along the time index axis. Superimposed on this figure are the probabilities of zero run-length at each time point calculated from two different change detection approaches. The on-line method described in Section 3.2 is validated against visual inspection and a widely cited off-line (retrospective) technique (Ruggieri, 2013). The on-line technique can clearly be thresholded to provide a change detection indication, however the probabilities of zero-length are lower in magnitude and time resolution compared to the off-line technique, though sufficient for our application this implies lower robustness.

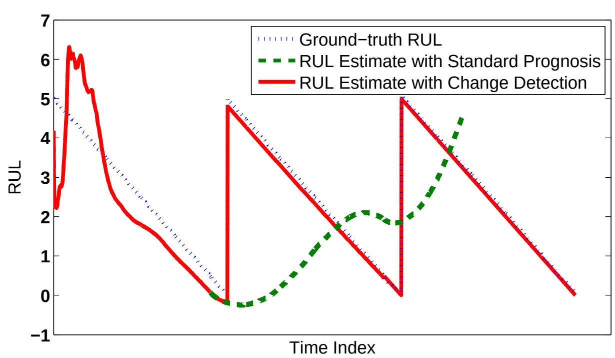

Figure 3. RUL estimation for synthetic data: The true RUL (dotted blue line), the estimated RUL (red line) with change detection, and the estimated RUL without change point detection (dashed green line) are shown.

A possible enhancement to decision making is to exploit the property of this on-line algorithm to calculate the probability of all run-lengths at each time step, not only zero-length. Because the confidence in a change detection increases as n more data points are collected, the most probable run-length after a true change time will occur at run-length n data points after the true change. A simple strategy is thus to observe the probability mass at low run-lengths (empirically it was found 0-5 points were sufficient, see Table **??**) and compare this to the probability of the run length increasing, this change in probability mass around an event is an effective measure of detection robustness. Enhancements can also be made computationally by strategies such as not carrying very low run-length probabilities to the next algorithm iteration, this is discussed in Turner et al. (2009).

Figure 3 shows the mean of the estimated RUL from the prognostic algorithm with (red line) and without (green dashed line) change detection. This estimate is made at every observation time over the asset life and compared against the known true RUL. It is clear how the estimated RUL increased after detecting a change point event through a reset of the prognostic algorithm, whereas with no change detection the estimate of RUL diverges to infinity. Due to the periodic nature of synthetic signal, setting the model priors to the posterior estimate before the change events means that the initial model learning shown at the start of the training period is avoided, this is only appropriate for perfect repair.

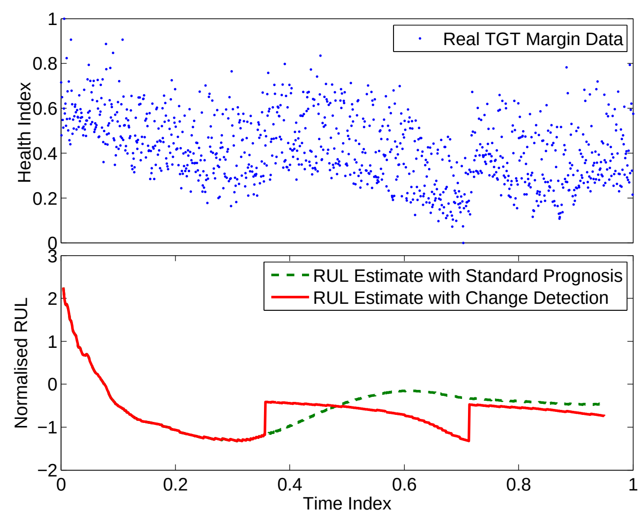

Figure 4. The TGT margin data is shown in the upper plot, with the mean RUL estimate for the prognostic algorithm with and without change detection in the lower plot

4.2. Case study 2: Real-World Dataset

Having validated the effectiveness of change detection and prognostic strategy, we apply the proposed method to real-world datasets, the results are shown in Figure 4. The x-axis is the time index which is the normalised number of flights, and the y-axis embodies the health index which is the normalised TGT margin, this is shown by the blue dots in the upper plot. The lower plot shows the mean RUL estimate for the prognostic algorithm with and without change detection. The step changes in RUL can be shown to visually coincide with significant events in the data at t=0.37 and 0.74, indicative of a compressor wash.

As with many prognostic applications with real data, the lack of ground true degradation for the real data makes an estimate of performance problematic. In addition, there is right censoring (asset removal) of the data before the crossing of the functional failure TGT margin threshold of zero degrees. To obtain an approximation of ground truth, the linear model was first trained on all available data and the zero margin crossing of this model used to generate the approximation to true RUL. The lack of ground truth also extends to the unavailability of true cause for the shift in TGT margin and the exact time.

Notwithstanding the difficulties in obtaining ground truth, some confidence can be developed by testing the change detection performance on synthetic data. Visual inspection of 50 sets of engine data were used to estimate the log ratio of step change magnitude (the signal of interest) to noise (SNR) for various suspected events. This ratio was found to be greater than one for the events in the data. By generating synthetic data with a set of noise characteristics and applying the change detection, Table **??** was created. As SNR decreases the change in probability mass for run-length around the change event decreased, the time accuracy can be measured by the sample interval width. For the highest SNR example, the probability mass shifted by 85 percent from growth to run-length reset over 2 samples (0.85 detection probability within 1 data point), whereas for at SNR of -0.2 only 5 percent change in probability occurred over ±3 samples. These quantified results, and observations from the real data, motivated the application to the full set of real engine data. In these tests, observed suspected changes were detected within a 5 observation interval at greater than 90% probability mass change, but the accuracy is difficult to quantify with precision since the ground truth information is not available.

Table 1. Change Detection Performance

	Probability Mass Change in sample interval		
SNR	±1	±3	±5
5.1	0.85	1.00	1.00
2.8	0.80	1.00	1.00
1.2	0.40	0.95	1.00
0.5	0.20	0.95	1.00
-0.2	0.00	0.05	0.40
-0.9	0.00	0.01	0.05

Despite this unavoidable limitation of the data, the application to the service data validates the principle of the approach, with its performance verified with synthetic data.

5. Conclusions and Future Prospects

Compressor washing increases the usable engine life and optimises the performance of the gas turbine. However, there are uncertainties about the timing and true effect of maintenance actions. These uncertainties surrounding maintenance actions impact prognostic efficacy because there is no information when the prognostic algorithm should be adjusted to accommodate performance changes arising from maintenance action. A Bayesian change point detection method was developed, to be illustrative of the possible prognostics fusion approach, in this paper to detect these maintenance events from the data.

The proposed method of on-line change point detection algorithm was implemented on an example of real aircraft engine service data, in order to identify the compressor washing events of a gas turbine and thus demonstrate the possibility of improved prognosis. Using synthetic data, the robustness of the approach was evaluated for both the detection and impact on underlying ground-truth prognosis. The event detection information was used as an input to a prognostic algorithm, advising the prognostic algorithm to update the estimation of remaining useful life.

In future research work, the following areas could be considered: the hazard rate for maintenance events could be learnt in advance from fleet datasets based on time and degradation, and exploiting this prior parameter to improve sensitivity; and issues regarding the computational efficiency of the change detection approach should be studied. In addition, while the change detection is effective at locating in time the change, there is further analysis needed to incorporate how to handle this event. The performance recovery is not perfect after each event and events later in the life of the turbine recover less performance, the data is to be mined to determine a distribution for expected recovery and this can be used to intelligently inform the reset of the prognostic estimation. The algorithms arising from this work are planned for integration into fleet management software to allow access to a vast array of data and thus facilitate robust testing.

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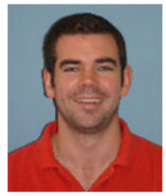

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