

A Simple State-Based Prognostic Model for Filter Clogging

Zakwan Skaf *, Omer F. Eker, Ian K. Jennions

IVHM Centre, Cranfield University, MK43 0AL, UK

* Corresponding author. Tel.: +44-1234-75-2324. E-mail address: z.skaf@cranfield.ac.uk

Abstract

In today's maintenance planning, fuel filters are replaced or cleaned on a regular basis. Monitoring and implementation of prognostics on filtration system have the potential to avoid costs and increase safety. Prognostics is a fundamental technology within Integrated Vehicle Health Management (IVHM). Prognostic models can be categorised into three major categories: 1) Physics-based models 2) Data-driven models 3) Experience-based models. One of the challenges in the progression of the clogging filter failure is the inability to observe the natural clogging filter failure due to time constraint. This paper presents a simple solution to collect data for a clogging filter failure. Also, it represents a simple state-based prognostic with duration information (SSPD) method that aims to detect and forecast clogging of filter in a laboratory based fuel rig system. The progression of the clogging filter failure is created unnaturally. The degradation level is divided into several groups. Each group is defined as a state in the failure progression of clogging filter. Then, the data is collected to create the clogging filter progression states unnaturally. The SSPD method consists of three steps: clustering, clustering evaluation, and remaining useful life (RUL) estimation. Prognosis results show that the SSPD method is able to predicate the RUL of the clogging filter accurately.

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1. Introduction

Prognostics is an inherent part of Condition-based maintenance (CBM). Prognostics is the ability to predict the health status of a given component/system, for a predefined time in the future or forecast the failure's time, and its remaining useful life (RUL).

Large amounts of literature focusing on prognostic techniques have been published by researchers [1-12]. Prognostic approaches can be classified into experience-based models, data-driven models, and physics-based models, as shown in Figure 1. Experience-based models correlate knowledge and engineering experience with the observed monitoring data to infer RUL from historical measurements [1]. Data-driven models rely only on learning systems behaviour directly from collected raw monitoring data to predict the projection of a system's state or to match similar patterns in the history to infer RUL. Data-driven models include but are not limited to statistical models, reliability functions, and artificial intelligence models [2]. Physics-based models quantitatively characterize the progression of failures using physical laws to estimate the RUL [3]. More recently, hybrid prognostics

approaches have been presented, attempting to leverage the advantages of combining different prognostics techniques in the aforementioned different classifications for better capability of managing uncertainty related to system complexity and data availability to achieve more accurate RUL. However, hybrid prognostics models can have higher computational cost which leads to more difficulties in some applications. Hybrid prognostics models can be mainly categorised into experience-based model & data-driven model [4], experience-based model & physics-based model [5], data-driven model & data-driven model [6], data-driven model & physics-based model [7], and experience-based model & data-driven model & physics-based model [8]. Moreover, hybrid modelling can be performed in two approaches, namely: series approach and parallel approach [9]. The main challenges of hybrid prognostic approaches are choosing the right category which depends on available data and information, and choosing the appropriate fusion mechanism for developing the hybrid model.

Filtration phenomenon is an interest for several engineering processes including automotive, chemical, nuclear reactor, and process engineering applications. Besides, several

industrial applications such as food, petroleum, pharmaceuticals, metal production, and minerals embrace filtration process [13]. The aim of the filtration systems is to keep the rest of the system running smoothly; moreover, they play a vital role in maintaining the process operating. Modern commercial vehicles and automobiles have numerous types of filters including fuel, lubricant, and intake air [14].

Sharing an important role with pumps, fuel filters filtrate dirt and other contaminants in the fuel system such as sulphates, polymers, paint chips, dust, and rust particulate which are released from a fuel tank due to moisture or other numerous types of dirt have been uplifted via supply tanker [15, 16]. Consequences like engine and pump performance degradation due to increased abrasion and inefficient burning in the engine are the main motivators for fuel filtration leading to a purified fuel. However, filtering the fuel associates with some complications (e.g. clogging of filter) as well. System flow rate and engine performance declines once a fuel filter is clogged where it does not function well in its desired operation ranges. [16] reports that filter clogging indication due to fuel contamination may result in an aircraft having to return to the ground for further fuel filter inspection or replacement. In today's maintenance planning, fuel filters are replaced or cleansed on a regular basis. [16] reports that Boeing 777 fuel filter inspections are performed at every 2000 flight hours. Monitoring and implementation of prognostics on filtration system have the potential to avoid costs and increase safety.

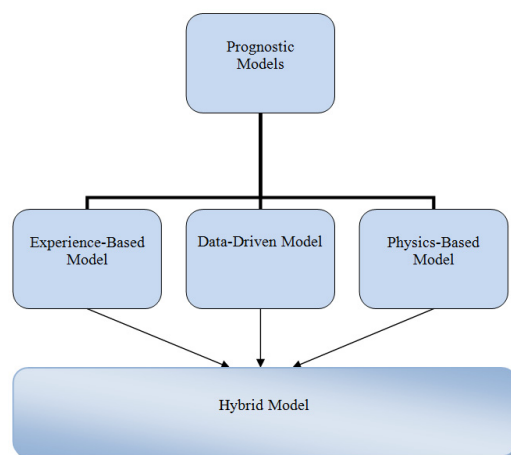


Figure 1. Classification of prognostics models

Clogging process of different types of filtration mechanisms has been studied in the literature. [17] presented a particle level filtration case study; stating that the general clogging process can be considered as a function of: ratio of particle to mesh pore size, solid fraction, and the number of grains arriving at each mesh hole during one test. [18] developed a mathematical model for dynamic behaviour of filtering process for ceramic foam filters. The model is capable of estimation of the filtration efficiency, accumulation of particle mass in the filter, and the pressure drop throughout the filter. [19] presented a diagnostic and prognostic solution for water

recycling system for next generation spacecraft. They simulated several failure scenarios including clogging of membranes and filters. [20-21] developed a similarity-based and Gaussian process regression (GPR) prognostic approach to estimate the remaining useful life (RUL) of sea water filters. [22] presented a nuclear research reactor air filter pressure drop modelling scheme which utilises gamma processes.

The failure mechanism of system components are often caused due to a degradation process. Therefore, degradation data of system components can sometimes provide more information for assessing the reliability and estimating the RUL of system components. In some cases, actual degradation can be observed with time. An example of this would be a crack growing with time on a component. As the crack grows to a certain width, the component will fail. On the other hand, some actual degradation process cannot be observed, but measuring the component's performance is sufficient to be an indicator for component's degradation. Moreover, for some components, the degradation rates at nominal operations are considerably low that no meaningful and sufficient information can be extracted from the degradation data. Thus there is a need to use accelerating methods to increase the degradation rate to collect useful data for prognosis. The implementation of accelerated degradation testing is an appropriate choice to overcome obstacles of developing prognostics techniques in engineering, such as insufficient data, time and cost constraints. For accelerated degradation testing, by using more severe testing conditions to accelerate performance degradation process than that experienced in normal condition, more performance information would be collected in a shorter time.

Organization of the paper is as follows. Section two represents a simple state-based prognostic method. Section three discusses thoroughly the fuel system experimental scenario and the obtained results. Section four concludes the article and future research direction is pointed out.

2. Simple State-Based Prognostics with Duration Information (SBPD)

This section summarises the main steps of SBPD approach in (see [23] for more details), which implemented to predict the RUL. The implementation of SBPD approach has three stages, as shown in Figure 2: the first stage is clustering the health state of the system. k-means clustering technique is used in this work for its simplicity and effectiveness. The k-means clustering method aims to group the samples of the dataset into clusters by optimizing the dispersion between the samples of the datasets and the centre of the identified cluster [24].

In the second stage, the number of clusters will be evaluated because the real number of clusters are not known. In this work, Calinski-Harabasz (CH) index is chosen for its robustness. Calinski-Harabasz (CH) index gives the optimal number of clusters and health states in our problem. CH index is calculated using the formula in Eq. (1) [23]

$$CH = \left[\frac{\sum_{c=1}^k n_c \|z_c - z\|^2}{k-1} \right] / \left[\frac{\sum_{c=1}^k \sum_{i=1}^{n_c} \|x_i - z_c\|^2}{n-k} \right] \quad (1)$$

where

k is defined as the number of clusters

n_c presents how many samples of data in cluster c

n represents the number of all samples in the dataset

z_c is defined the centre of the cluster c

z represents the center of the all samples in the dataset

x_i represents the i^{th} data sample.

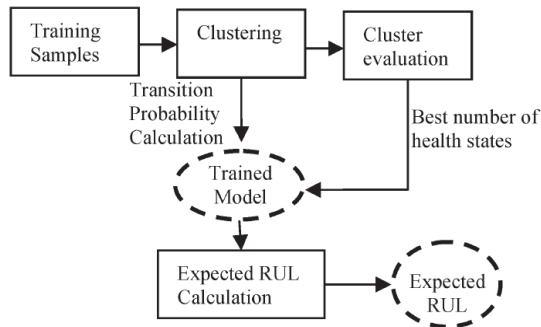


Figure 2. Main steps of Prognostic [23]

In the last stage, the RUL can be calculated as the sum of the total expected time in current health state of the system and each future health states until the system loses its functionality, as shown in (2).

$$E[RUL] = E[T_c^d] + \sum_{s=c+1}^f E[T_s] \quad (2)$$

where

T_s is defined as the time to be spent in the health state s

T_c^d represents the time to be spent in the current health state

d is the time that has been spent in the current health state

c represents the current state

f represents the last health state before fault occurs

E represents the expected value

Several measures have been proposed in the literature to evaluate the performance of a prognostic method, [25, 26]. In this work we used $\alpha - \lambda$ accuracy, prognostic horizon, Root Mean Square Error (RMSE), and Cumulative Relative Accuracy (CRA) as measures of evaluation. The prognostic horizon is defined as the difference between the time when the estimation of the RUL is within the desired error margins and the failure time. The $\alpha - \lambda$ accuracy metric evaluates the prediction accuracy in estimating the RUL within the desired error margins at any given time instances. α indicates the desired accuracy and λ is the time instance. The CRA is defined as the normalized sum of the relative accuracies at given time instances.

3. UAV Fuel System Test Rig

This section describes briefly the fuel system test-bed with different failure modes [27, 28]. The fuel system test rig has the capability to replicate a number of component degradation faults with high accuracy and repeatability. It produces benchmark datasets to evaluate and assess the developed algorithms. It contains the following parts: Main and sump tanks, external gear pump, filter, polyurethane tubing, solenoid shut off valve, direct proportional valves (DPV), non-return valve, control modules for pump, shut-off valve, and instrumentation, as shown in Figure 3. A photograph of the test system including all components is displayed in Figure 4.

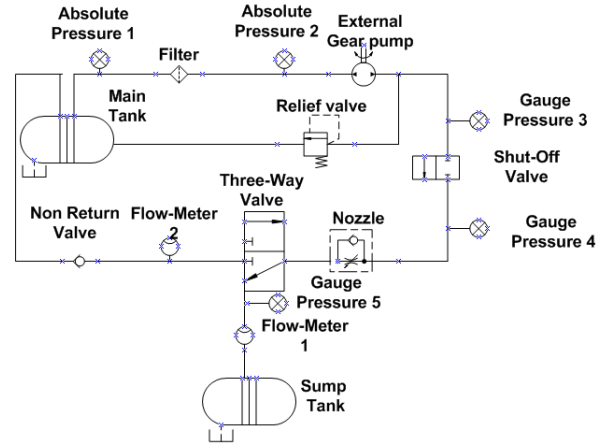


Figure 3. Schematic of the experimental setup

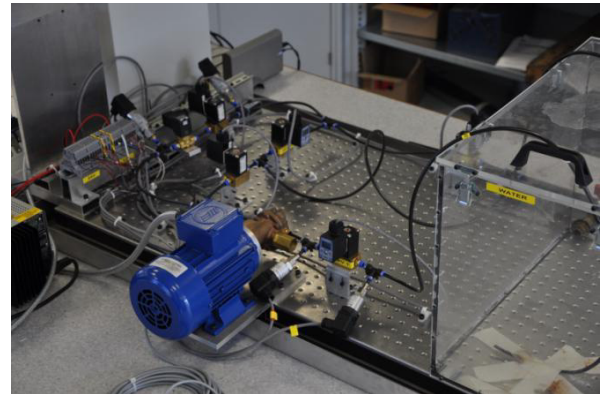


Figure 4. Fuel system test rig

National Instruments (NI) LabVIEW virtual instrumentation has been utilized to control the fuel system test rig. The main GUI for controlling the fuel rig has three layers, as shown in Figure 5. The user has control over valve position, pump speed in the first top layer. The second layer enables the user to control the fault injection mechanisms at the component level. This is done via knobs that are setting the position of five DPV. The third layer allows the user to control the fault injection mechanism at the sensor level.

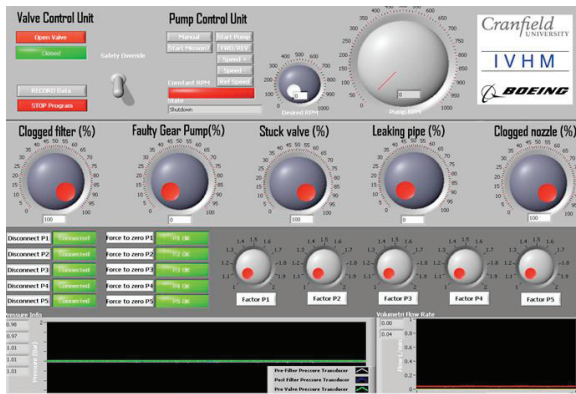


Fig.5. Fuel system – GUI for controls

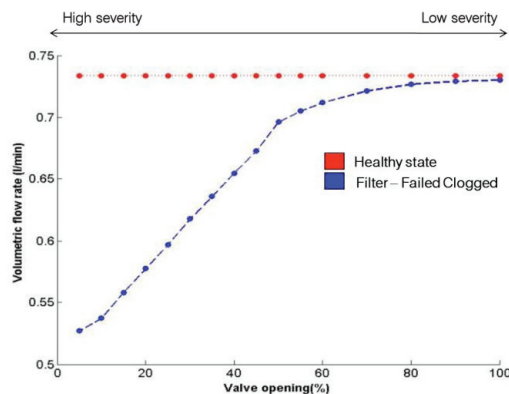


Figure 6. Physical behaviour – Clogged filter scenario

The following failure modes have been emulated in the test rig by changing the DPV opening rate: clogged filter, degraded pump, stuck valve, leaking pipe and clogged nozzle. Several failure scenarios including clogged filter and faulty gear pump has been investigated and mostly diagnostics based studies have been conducted. DPV that have the ability to

mimic fuel filter blockage have been utilized to imitate the clogging filter scenario.

In this work, we focus on clogging filter failure mode. The filter was replaced by a DPV and set to be initially fully open, which presents the healthy condition of the filter. By gradually closing this valve, the system replicates a behavior of a clogged filter (Figure 6).

4. Implementation and Results

Our aim in this work is to predict the RUL of a filter in the UAV fuel system from the pressure and flow value by implementing SBPD method. The propagation of the clogging filter is implemented for different degrees of severity using the DPV. Position 100% valve open corresponds to a healthy filter, 10% valve opening corresponds to an almost clogged filter. The fault is injected gradually with different degree of severity.

Pressure and flow rate readings have been collected continuously which are the main indicators of clogging. Each clogging experiment has been run and monitored by changing the valve opening rate until the filter has clogged (valve is closed) where the pressure drop (i.e. differential pressure, ΔP = pressure value after valve – pressure value before valve) has reached its peak region as shown in Figure 7.

Total of 10 samples of filter clogging are used in this paper. Eight of the samples are used for training, and the rest one dataset is used for testing the algorithm. The pressure drop and flow rate data is visualised in Figure 7.

This dataset comprises of ten run-to-failure samples representative of different operational profiles of clogging. Therefore the variance at the times reaching the lowest valve opening level is adjusted to another clogging test rig dataset

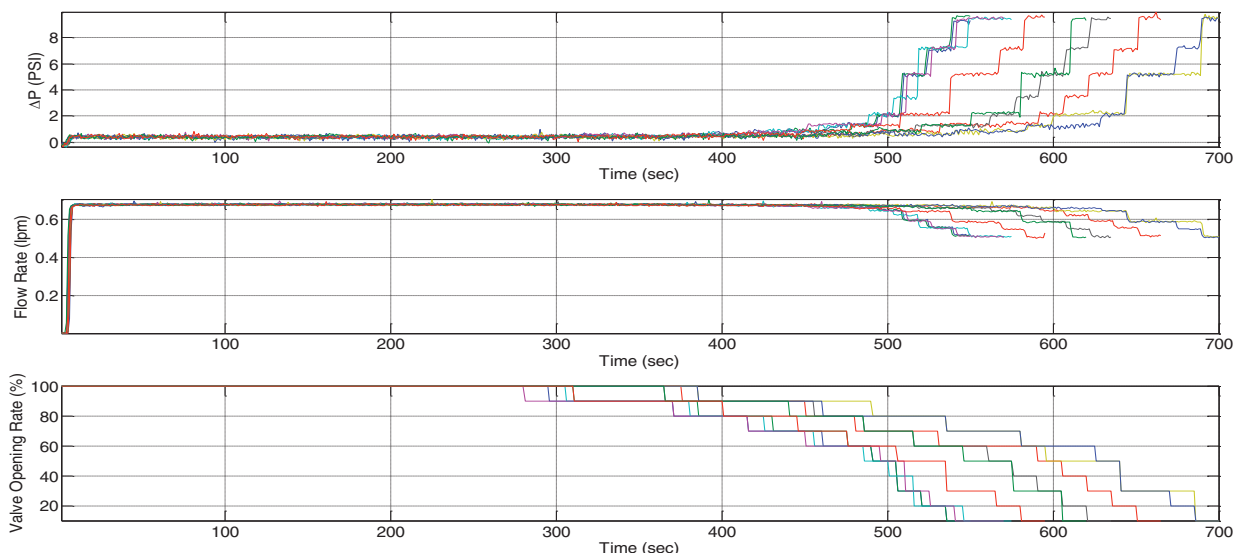


Figure 7. Filter clogging propagation samples. The different coloured trajectories exemplify the data from a single operational profile where the life

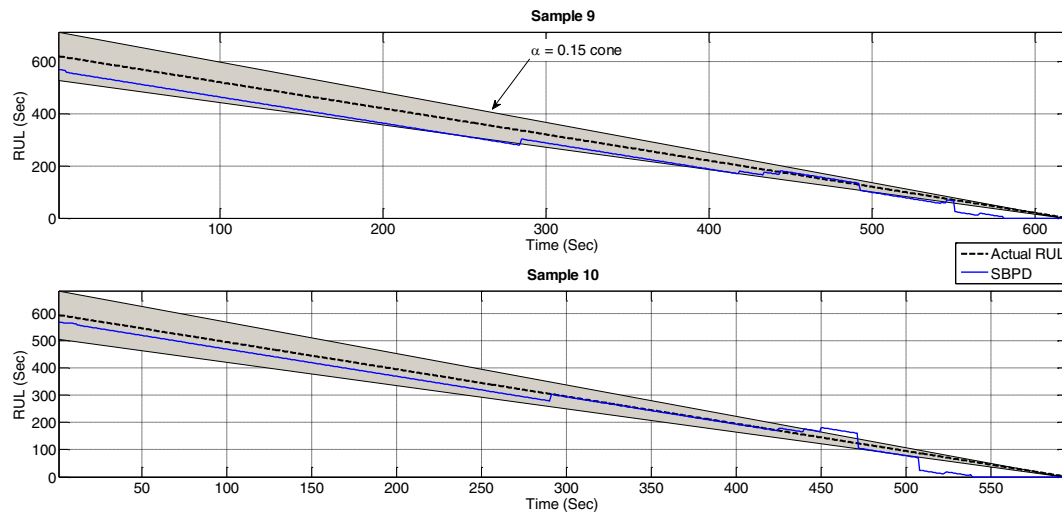


Figure 8. RUL results for test specimens spread is varied

Figure 8 shows the predicted RUL values of the implemented prognostics method in case of two training datasets. The x-axis and y-axis in the Figure 8 are defined as the current life of each test specimen and the RUL for the corresponding to each value of current life, respectively.

In Figure 8, the real values of RUL are presented as black dashed line while the SBPD predictions are in blue lines. As seen in the RUL graphs (see Figure 8), when the system is nearer to its end of life, the algorithm tends to display precautions signals in terms of RUL of the filter. The estimated values of the RUL are within the desired error bounds specified by the $\alpha = 15\%$ cone.

In addition, Table 1 shows the mean values of the evaluation metric for the SBPD approach (prognostic horizon, $\alpha - \lambda$ accuracy, and CRA), as well as RMSE metrics. Higher values or percentages indicate better prognostic results whereas lower RMSE values indicate more accurate predictions. Prognostic-Horizon (PH) metric provides binary results by answering if the algorithm predict within desired accuracy around end-of-life (EoL) and sufficiently in advance. ‘True’ means that the SBPD predictions fall in the desired accuracy bounds half way through the failure. ‘ α ’ and ‘ λ ’ values are selected as 0.15 and 0 respectively. RMSE values have shown in the table fall fewer than 5% error levels. Unlike other metrics, lower convergence distances signify improved prognostics.

Table 1. Prognostic performance evaluation

Model/Metric	PH	$\alpha - \lambda$ (%)	CRA (%)	nRMSE (%)	Convergence
SBPD	True	74.05	80.17	4.96	0.50

5. Conclusion & Future Work

This paper presents an implementation of a data-driven prognostic approach on filter clogging datasets collected from an UAV fuel system test rig. The progression of the clogging of the filter failure is created unnaturally. The degradation level is divided into several groups. Each group is defined as a state in the failure progression of clogging filter. Then, the data is collected to create the clogging filter progression states unnaturally. The propagation of the clogging filter is implemented for different degrees of severity using the DPV. Prediction results are validated by employing several performance evaluation metrics. SBPD method is a well-structured prognostic approach delivering improved performance in five different performance metrics, but the predictions are consistently distant from the actual RUL values.

Although the SBPD approach was applied to the filter clogging problem in the fuel system test rig with success, it is important to apply it to other components in the test rig to verify its effectiveness.

Furthermore, some future work can be expected to apply Hidden-Markov-Models (HHM)-based prognostic method to filter clogging datasets and compare it with SBPD method, which has been used as state-based prognostics with different applications.

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Skaf, Zakwan; Eker, Ömer Faruk; Jennions, Ian K.

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