

Towards System Prognostics: Filter Clogging of a UAV Fuel System

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ABSTRACT

Filtration of contaminant is an essential part of engineering processes in industry. Clogging of filtration medium is one of the primary failure modes in many application areas leading to reduced performance and efficiency. Imitation of real life clogging scenarios in laboratory conditions is not an easy task to perform. This paper presents a data collection methodology for filter clogging phenomena in a laboratory based fuel system rig and filter clogging prognostic rig. The fuel system laboratory test-bed represents an Unmanned Aerial Vehicle (UAV) fuel system and its associated electrical power supply, control system and sensing capabilities. It is specifically designed in order to replicate a number of component degradation faults with high degree of accuracy and repeatability. The fuel system rig can produce benchmark datasets to demonstrate and examine the fuel system failures. Filter clogging failure in the fuel system rig is simulated using a direct proportional valve (DPV) within the system. Pressure and flow rate readings are collected continuously throughout the tests as an indicator of filter clogging phenomena. The opening rate of the DPV is automatically adjusted by emulating the pressure drop trajectories which are generated from the filter clogging prognostic rig. The system response to clogging filter failure in the fuel system rig is then compared to the response which is generated from the filter clogging prognostic rig. The results show that the pressure drop signals obtained from the fuel system rig matches closely the pressure drop levels from the filter clogging prognostic rig when the particles' size is small.

1. INTRODUCTION

IVHM is a relatively new comprehensive technology, enabling many disciplines with an integrated framework. Maintenance strategies such as Condition Based Maintenance (CBM) or Reliability Centred Maintenance

(RCM) are enabled using IVHM. Prognostics and diagnostics are integrated into the framework involving the monitoring of sensory information and predicting the future health level of the system, based on the monitored data. IVHM technology has potential applications in many fields such as aerospace, military systems, electronics, machinery, energy, and manufacturing. In IVHM, real-time sensory data obtained from the equipment is analysed continuously to detect and forecast the health states and to plan maintenance based on the forecasted health.

IVHM acts an imperative role in aircraft operation management, and continues to offer the potential for a paradigm shift in the way that aircraft organisations conduct business operations. (Benedettini et al., 2009) postulate that IVHM is also potentially applicable to non-vehicle systems such as industrial process plants and power generation plants. IVHM enables many disciplines with an integrated framework. CBM, Health and Usage Monitoring Systems (HUMS), and RCM are some of the maintenance strategies offered under IVHM where diagnostics and prognostics considered under the analytics category.

Prognostics is the fundamental technology within IVHM, where it requires identification of the current health level and extrapolating it to a predefined failure threshold, concluded with the estimation of remaining useful life (RUL). The output of prognostics (i.e. RUL) is the duration between the current time and the time at which the forecasted health level reaches to a predefined threshold. Benefits of the prognostics motivate researchers and the industry to achieve reduced costs, increased safety and availability via better maintenance planning. In contrast with traditional maintenance philosophies, the IVHM approach enables modelling and tracking of individual equipment deterioration leading to a maintenance action only when it is necessary rather than performing scheduled maintenance.

The failure mechanism of system components often caused due to some sort of degradation process. Therefore, degradation data of system components can sometimes provide more information for assessing the reliability and

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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 length, 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 significantly low that no meaningful and sufficient information can be extracted from the degradation data. In addition, the amount of historical run-to-failure datasets we have and insufficient instrumentation for measuring degradation indicator are other reasons for doing an accelerated test. 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 subjecting a component/system to conditions in excess of its normal service parameters to accelerate the degradation process than that experienced in normal condition, more performance information would be collected in a shorter time.

Filtration phenomenon is interest of several engineering processes including automotive, chemical, reactor, and process engineering applications. Besides, several industrial applications such as food, petroleum, pharmaceuticals, metal production, and minerals embrace filtration process (Sparks, 2011). 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 (Sutherland, 2010).

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 (Wilfong et al., 2010, Jones, 2008). 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. (Jones, 2008) reports that filter clogging indication due to fuel contamination may result in an aircraft having to return to the ground or divert for further fuel filter inspection or replacement. In today's maintenance planning, fuel filters are replaced or cleansed on a regular basis. (Jones, 2008) 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.

Clogging process of different types of filtration mechanisms has been studied in the literature. (Roussel et al., 2007) 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. (Pontikakis et al., 2001) 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. (Roychoudhury et al., 2013) 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. (Baraldi et al., 2013, Baraldi et al., 2015) developed a similarity-based and Gaussian process regression (GPR) prognostic approach to estimate the remaining useful life (RUL) of sea water filters. (Saarela et al., 2014) presented a nuclear research reactor air filter pressure drop modelling scheme which utilises gamma processes.

In this paper, the clogging filter phenomena will be emulated in the laboratory using two test rigs. From the first rig (filter clogging prognostic rig), the degradation profile of the filter will be created by running an accelerated test. Then, the degradation profile will be mimicked in the second rig (fuel system rig) throughout the adjustment of DPV.

Following sections present a brief description of the filter clogging prognostic rig as well as the fuel system rig. Then, data collection and results from both test rigs will be presented. Finally, some conclusions and future work are given.

2. FILTER CLOGGING PROGNOSTIC RIG

This section discusses the filter clogging experimental scenario under accelerated aging conditions. An experimental rig to demonstrate filter clogging failure consist of the following major components: Pump, liquid tanks, tank stirrer, pulsation dampener, filter, pressure and flow rate sensors, and data acquisition system connected to a computer. Figure 1 illustrates the design of such experimental rig. Each component is discussed below.

- **Pump:** There are different types of pumps enabling a liquid to flow through a complex system. Since the system will involve contaminants in the fluid, a peristaltic pump has been used as its mechanism is more tolerant to particles in the liquid. A Masterflex® SN-77921-70 (Drive: 07523-80, Two Heads: 77200-62, Tubing: L/S© 24) model

peristaltic pump was installed in the system to maintain the flow of the prepared suspension. The pump is a positive displacement source, providing a flow rate ranging from 0.28 to 1700 ml/min (i.e. from 0.1 to 600 RPM). The peristaltic pumps can confine the fluid to the tubing. In this way, the pump cannot contaminate the fluid and vice versa. Detailed design of the prognostic rig is illustrated in Figure 1. A photograph of the test system including all components is displayed in Figure 2.

- **Dampener:** The aim of using rigid tubing is to prevent the system from the unwanted tubing expansion due to pressure build up which interrupts the actual pressure build up generated from filter clogging. A Masterflex® pulse dampener is installed on the downstream side of pump to eliminate the pulsation in flow, hence pressure drop across the filter. Majority of the system is furnished with a rigid polypropylene tubing whereas the pump side is covered with a flexible Tygon® LFL pump tubing.

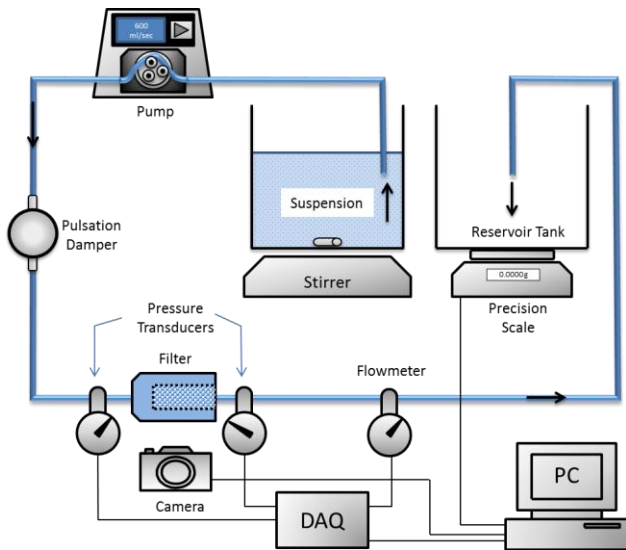


Figure 1. Filter clogging prognostic rig system design

- **Tank:** One half-sphere-shaped main tank and two subsidiary tanks (i.e. reservoir tank and clean water tank) are installed in the system. The sphere shape tank bowl enables the stirrer work efficiently leading to homogeneously distributed slurry in the tank. The prepared suspension is kept in the main tank and pumped through the filter and poured into the reservoir tank. The clean water tank is used to fill-up the system components (e.g. tubing and the filter chamber) with clean water prior to each test. A Kern® 10000-1N type high precision weighing scale (weighing range: 0.1 – 10,000 g.) is placed

under the reservoir tank and connected to the PC with a serial cable to keep track of the amount of filtrated liquid continuously.

- **Particles:** The suspension is composed of Polyetheretherketone (PEEK) particles and water. PEEK particles have a density (1.3g/cm^3) close to that of room temperature water and have significantly low water absorption level (0.1% / 24 hours, ASTM D570). Having a low water absorption level will prevent particles to expand their volume when they mix with water. Subsequently, closer density with water allows particles to suspend longer in water. Therefore, PEEK particles are selected to be used in the accelerated clogging of filter experiments. The particles have a wide distribution as seen in Figure 3. For this reason, narrowing the distribution by sieving is found to be necessary before conducting experiments.

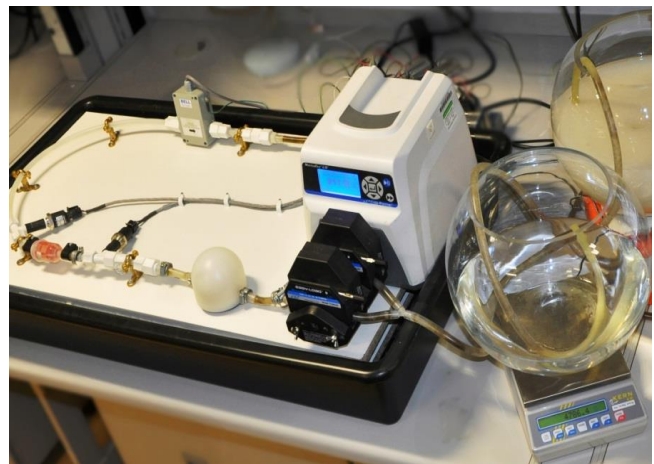


Figure 2. Filter clogging prognostic rig

- **Stirrer:** An adjustable speed ceramic SC-1 type magnetic stirrer was installed in the system to ensure that the particles are distributed uniformly in the tank during the experiments. This is necessary as the particles, even though they are meant to be naturally buoyant, sink after a while leaving the water clean.
- **Pressure Sensors:** Upstream and downstream Ashcroft® G2 pressure transducers (measurement range: 0 - 100 PSI) are installed in the system to capture the pressure drop (i.e. ' ΔP ') across the filter, which is considered as the main indicator of clogging.

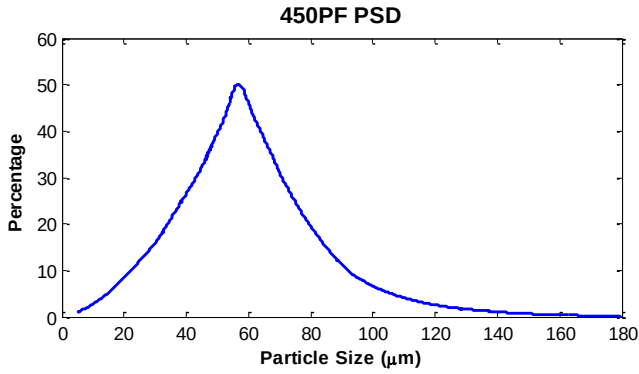


Figure 3. PEEK particle size distribution

- **Flow Rate Sensor:** A GMAG100 series electromagnetic flow meter (measurement range: 3 – 25,000 millilitres per minute) is installed in the system to keep track of the flow rate in the system. The flow meter is also suitable for high pulsation flows. Magnetic flowmeters have no moving parts, which allow measuring the flow rate of slurry by means of the magneto-inductive principle. This type of flow meters has been selected for two reasons: 1) To enable measuring flow rate of water & PEEK suspension with no accuracy degradation; 2) They are reliable and very low unnecessary pressure loss across the flow meter. In addition, a pulse rate to current converter is interfaced with the flow meter for converting frequency to proportional analogue 4-20mA current outputs.
- **Camera:** A high quality macro lens camera is positioned on top the filter chamber, enabling to take macro pictures every two seconds. The mesh inside the filter; hence, the retained particles can clearly be captured and used in an image processing application for determining the ground truth clogging rate or an auxiliary source for modelling of the filter clogging phenomena. To be more precise, pressure and flow rate data can be compared or utilised with the features extracted from the image data.

All components are placed on a grid style dripping tray in order to prevent potential problems due to a potential leakage. The prognostic rig is designed so that no other component will deteriorate other than the filter. This means that, filter clogging is the only failure type to be targeted in the degradation modelling.

3. FUEL SYSTEM TEST RIG

This section discusses the fuel system test-bed with different failure modes. The fuel system test rig is a laboratory test-bed represents an Unmanned Aerial Vehicle (UAV) fuel system and its associated electrical power supply, control system and sensing capabilities. It is specifically designed in

order to replicate a number of component degradation faults with high accuracy and repeatability so that it can produce benchmark datasets to evaluate and assess the developed algorithms. The rig consists of the following representative components: 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 4. The realization of the above system is shown in Figure 5.

In order to control and acquire data from the fuel system test rig, a system using National Instruments (NI) LabVIEW virtual instrumentation has been utilized: a CDAQ – 9172 device with six compact DAQ modules: NI 9485, NI 9205, NI 9472, NI 9401 and two NI 9263. The National Instruments 9485 is a 8-channel solid-state relay sourcing or sinking digital output module for any CompactDAQ or CompactRIO chassis. One channel was used which provides access to a solid-state relay for switching the 24V voltage applied to the shut-off valve in order to control the open/close position. The NI 9205 module receives the analogue voltage output from the pressure transducers and flow-meters, converts this information using the pre-defined calibration curves into digitized information readable on the GUI. The NI 9472 module is a 8-channel 24V logic, sourcing digital output module which provides the signals to the pump inverter in order to implement the pump controls (Start pump, Stop pump, Increase speed, Decrease speed, Forward/Reverse, Relative Speed). The NI 9401 module counts the rotational speed laser sensor analogue output pulses and converts them into frequency. The NI 9263 module is a 4-channel, 100 kS/s simultaneously updating analogue output module which enables the implementation of the direct proportional valves position control. Valve position is modified by varying the voltage applied to the solenoid.

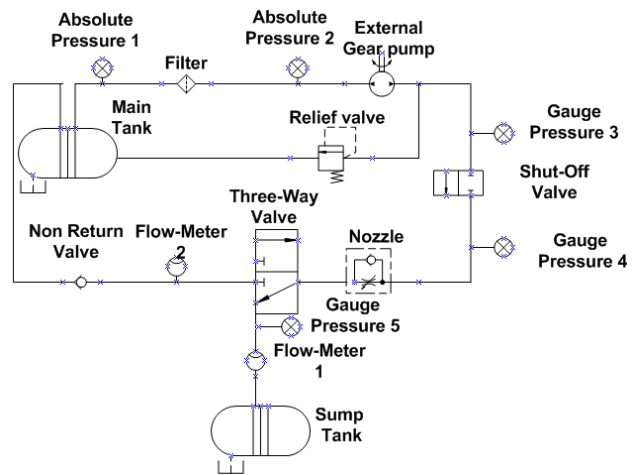


Figure 4. Schematic of the experimental setup

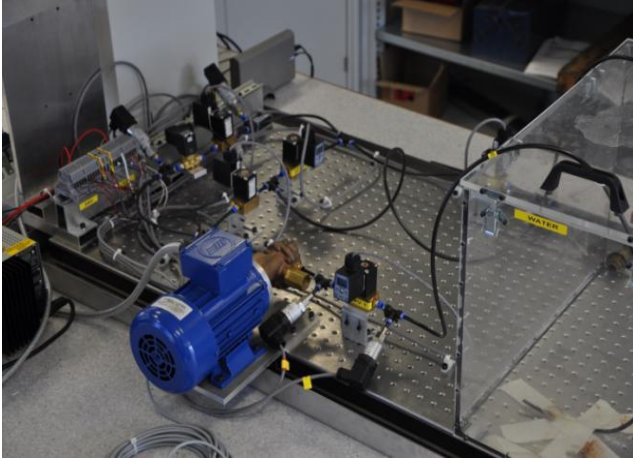


Figure 5. Fuel system test rig

The main GUI is shown in Figure 6. The user has control over shut-off valve position, pump speed in manual or mission profile mode and direct proportional valve position in order to be able to inject faults. These functions can be seen in Figure 6. Within the same GUI the sensor output for rotational speed is displayed as well as pressure in different points of the fuel rig and volumetric flow rate on both recirculation line and engine feed line. The control system of the fault injection module can best be described with reference to the GUI. National Instruments LabVIEW software version 2014 being used to customize the control for the entire system. Referring to Figure 8 the controls are structured in three layers (top three layers) of the GUI:

- The top layer contains Pump Control Unit and Valve Control Unit.
- The second layer enables the control of 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 control of fault injection mechanism at the sensor level.

The data presented to the user in the GUI on the bottom layer:

- Pressures in different points of the system (e.g. before filter, after filter, after pump, after shut-off valve, before sump tank).
- Volumetric flow rate in the main line.

The degradation of five different components is emulated by closing or opening one of the five DPV. From the hardware and software point of view, the control system accommodates five failure modes in a plug and play manner: a clogged filter, a degraded pump, a stuck valve, a leaking pipe and a clogged nozzle. Several failure scenarios including clogged filter and faulty gear pump have been

investigated and mostly diagnostics based studies have been conducted. DPV have the ability to mimic fuel filter blockage has been utilized to imitate the clogging filter scenario.

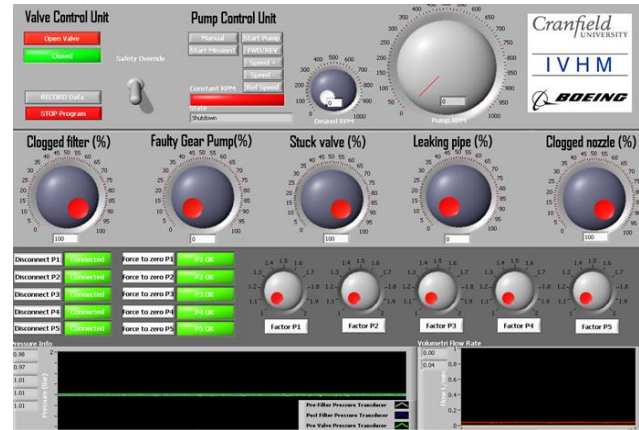


Fig.6. Fuel system – GUI for controls

In this work, we focus on clogging filter failure mode. The filter was replaced by a DPV and set to be initially fully open (this setup captures the healthy scenario as the pressure drop across the valve was identical to the pressure drop across the filter). By gradually closing this valve, the system replicates a behavior of a clogged filter (Figure 7).

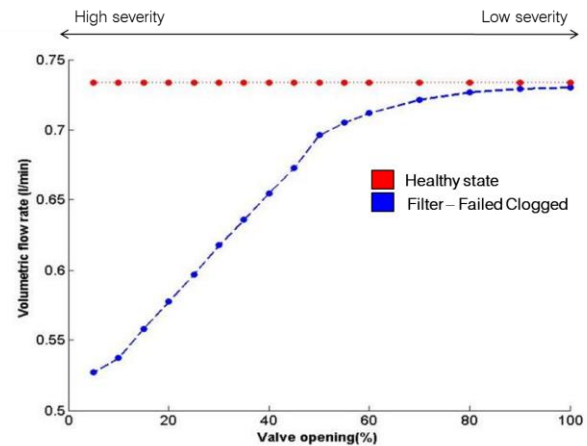


Fig. 7. Physical behaviour – Clogged filter scenario

4. EXPERIMENT AND RESULTS

This section presents the data collection details of results of the accelerated clogging experiments from the filter clogging prognostic rig. Also, it presents the obtained results from injecting the degradation profile of clogging filter from filter clogging prognostic rig into the fuel system rig.

4.1 Data collection from the filter clogging prognostic rig

This section provides the data collection details of the accelerated clogging experiments from the filter clogging prognostic rig.

The PEEK particles for the filter clogging prognostic rig are ordered in the powder form. Particle size distribution of the powder is in range between approximately 5 to 180 microns. In order to see the particle size effect on data collection, the particle size distribution is narrowed into smaller distributions by means of wet sieving. On the other hand, the original sized (i.e. non-sieved) particles are also used shown under the last four operational profiles.

It is crucial to maintain the operational and environmental conditions consistent for the subset of data under the same operational profile. Hence, predefined operating conditions is kept as much as the same for sixteen different operational profiles each of which have four samples. Each operational profile is an outcome of a predefined combination of particle size distribution and solid ratio of the suspension. The entire dataset is comprised of fifty six run-to-failure accelerated aging experiments. Operational profile details are shown in Table 1.

Table 1. Operational profiles

Profile No.	Particle Size (μm)	Solid Ratio (%)	Sample Size
1	45-53	0.4	4
2		0.425	4
3		0.45	4
4		0.475	4
5	53-63	0.4	4
6		0.425	4
7		0.45	4
8		0.475	4
9	63-75	0.4	4
10		0.425	4
11		0.45	4
12		0.475	4
13	Non-sieved	0.4	2
14		0.425	2
15		0.45	2
16		0.475	2

125 micron pore sized Baldwin® BF7725 type of fuel filters is used for clogging experiments in the laboratory environment, shown in Figure 8.

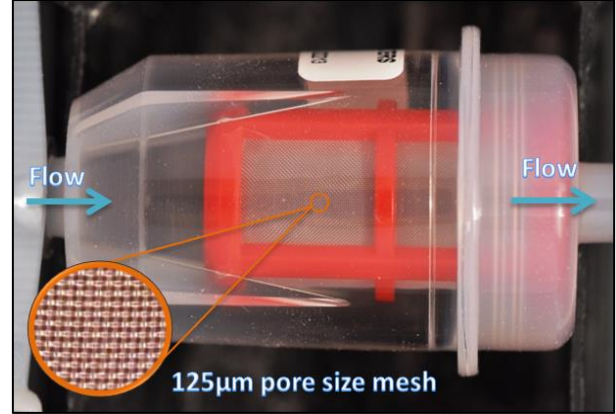


Figure 8. Baldwin fuel filter

Pressure and flow rate readings have been collected continuously which are the main indicators of clogging. Each clogging experiment has been run and monitored until the filter has clogged where the pressure drop has reached its peak and entered into a stable pressure region.

The data collection is conducted with an NI DAQ-9203 16 bit analogue current output module, which is connected to an NI cDAQ-9174 4-slot USB chassis. Sampling rate is adjusted as 100Hz within the LabVIEW environment which is eligible for capturing the pulses generated by the pump. For visualisation purposes, data is low pass filtered and down-sampled to 1Hz as displayed in Figure 9. Each trajectory in the figure represents differential pressure values for each distinct run-to-failure experiment. As seen from the figure, variation in the beginning is significantly lower than the critical clogging regime. However, the spread in the dataset increases as the experiment nears to the end of life. Variation in the experiments reflects the variation in sixteen different operational profiles.

Figure 9 associates the entire dataset to different particle size distributions. Lightened colour scales represent different distribution of particles used in experiments, where the lighter colours correspond to lower solid ratios. As seen in the figure, the experiments conducted with lower solid ratios takes longer to time reach higher pressure drop levels comparatively to the higher solid ratio experiments. In the figure, red scale trajectories represent the experiments under the first four operational profiles where particle size varies from 45 to 53 microns. This distribution is marked with a red band on top left hand side of the figure. Similarly, green and cyan coloured curves pertain to the 53-63 and 63-75 micron band of the distribution. Finally, the blue line trajectories obtained with non-sieved (i.e. original) particles. The distribution of particles is shown with a blue line.

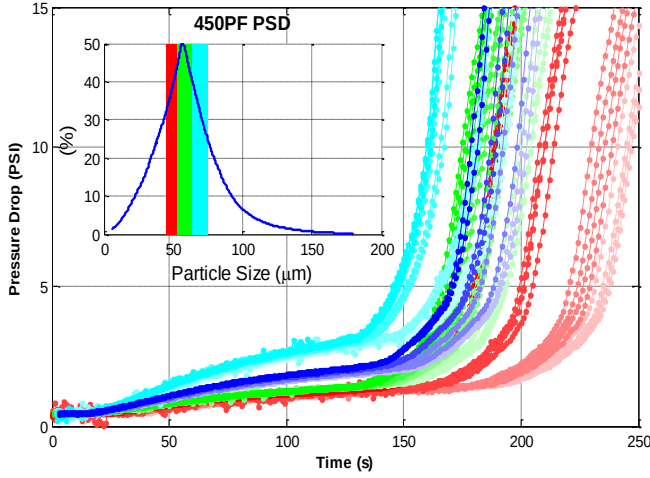


Figure 9. The dataset and sieved particle relation

4.2 Data collection from the fuel system rig

As the degradation phenomena of the filter in the fuel system is emulated by closing the DPV, there is a need to convert the pressure drop (i.e. ' ΔP ') across the filter from the filter clogging prognostic rig, which is considered as the main indicator of filter clogging, into valve opening rate as a function of time. In the fuel system rig, the valve is completely opened when there is no clogging in the filter and completely closed when the filter is clogged. Using this method, we can map the degradation profile of the filter from the filter clogging prognostic rig into the opening profile of the DPV in the fuel system rig.

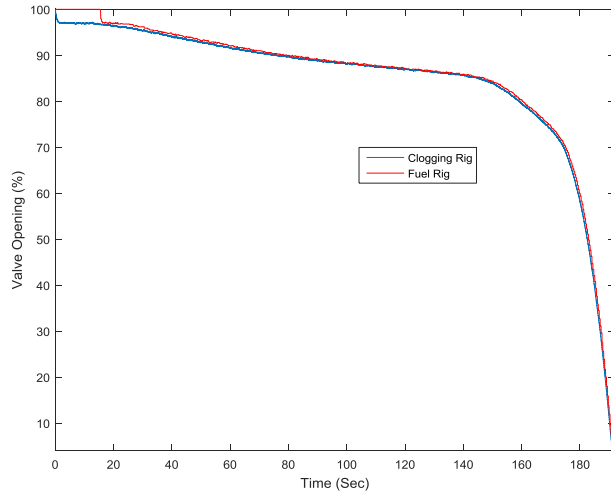


Figure 10. The input signal for the fuel rig

The whole entire datasets in Figure 9 are selected and the pressure drop data of each dataset is used in conversion to valve opening rate values which are used on controlling the opening rate of the DPV. The conversion of pressure drop values into valve opening rate is given in Eq. (1).

$$VOR_t = VOR_{max}(1 - \Delta P_t / \Delta P_{max}) \quad (1)$$

Where:

VOR_t : Valve opening rate at time instance 't'

VOR_{max} : Maximum valve opening rate

ΔP_t : Pressure drop value at time instance 't'

ΔP_{max} : Pressure drop value threshold

Specifically for this experiment VOR_{max} and ΔP_{max} are selected 100% and 15 (psi) respectively. Figure depicts the inputted valve opening signals into the fuel system rig. Smoother blue lines represent the valve opening rates converted directly from the pressure drop data of the filter clogging rig using Eq. (1). The red curve represents the implementation profile of valve opening rate in the fuel system rig.

The pressure drop responses of each test rig are plotted in Figure 11. The blue lines represent the reference rig signal from the filter clogging prognostic rig whereas the red curve is obtained from the fuel system rig.

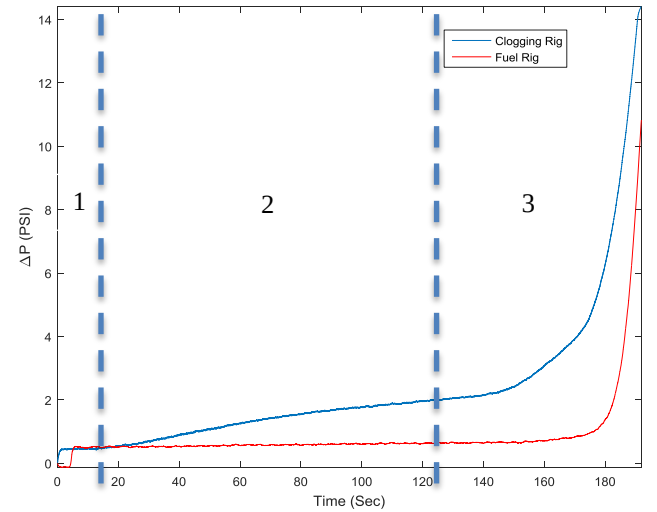


Figure 11. Pressure drop data comparison

Pressure drop across the filter from filter clogging prognostic rig can be divided into three stages, as shown in Figure 11. In the first stage, pressure rate values remain relatively constant. In the second stage, the pressure drop increases steadily. In the final stage, the pressure drop values enter to an exponentially growing region. While, the pressure drop across the valve from the fuel system rig have two stages. During the first stage, pressure rate values remain relatively constant. In the second stage, the pressure drop values are exponential. The reason for having different number of stages of pressure drop from both test rigs is fact that we are unable to emulate the actual cake filtration (Endo et al., 1998) by closing the DPV in the fuel system rig. This fact explains the difference in pressure drop values from both rigs.

By varying the particle size we can generate different degradation profile for the clogging filter. Figure 12 represents the valve opening rate as a function of time in the filter clogging prognostic rig (top plot) and the injected profile of the DPV opening rate in the fuel system rig (bottom plot) for different operational profiles. The comparison of the clogging indicator (pressure drop) dataset collected from both test rigs for different operational profiles is depicted in Figure 13. In Figure 13, the top plot represents the pressure drop data across the filter from the filter clogging prognostic rig and the bottom plot represents the pressure drop data across the DPV from the fuel system rig.

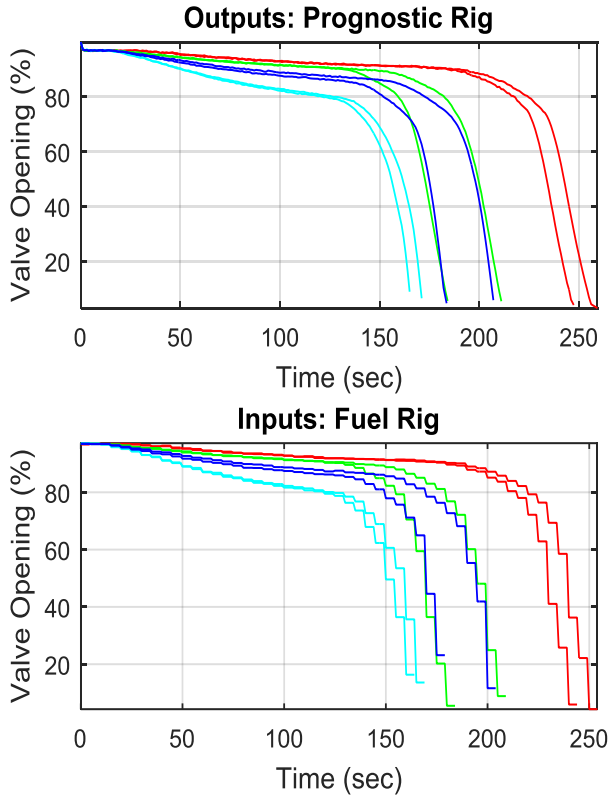


Figure 12. Valve opening rates at different operational profiles

Each trajectory in the figure represents differential pressure values for each distinct run-to-failure experiment. The four different colours represent four different operational profiles which are obtained by using particles with different size distribution. Red, green, cyan and blue colours represent 45-53, 53-63, 63-75 and non-sieved original particle size distribution (i.e. approximately 5-180 micron range). From each profile, two samples are randomly selected and converted to opening rate values. As seen from the plot on top in Figure 13, variation in the beginning is significantly lower than the critical clogging regime. However, the spread in the dataset increases as the experiment nears to the end of life. Variation in the experiments reflects the variation in

different operational profiles. Fuel rig clogging progression plots (bottom plot) show that the pressure drop response of the fuel system matches closely the pressure drop response from the clogging. In other words, the variation within the time at filter clogging rig samples reaches the threshold (i.e. 15 PSI) is also represented at fuel system's samples.

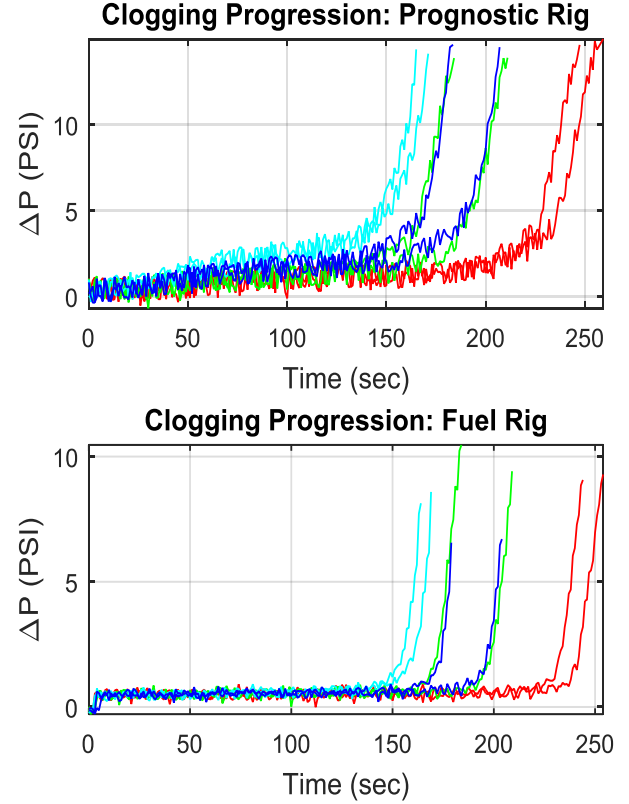


Figure 13. Pressure drops comparison at different operational profiles

Root mean squared error (RMSE) is one of the most commonly used accuracy metric for time series analysis. The RMSE values between the pressure drops from both test rigs are used as measure to evaluate the effectiveness of our work. RMSE calculation equation is given below:

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (y_i - f_i)^2}{n}} \quad (2)$$

Where:

y_i : Prognostic rig pressure drop at time point 'i'
 f_i : Fuel system pressure drop at time point 'i'
 n : Signal length

For quantification, RMSE of both pressure drops from filter clogging prognostic rig and fuel system rig are given in the table below:

Table 2. Accuracy measure for samples

Sample	RMSE
1	1.7164
2	1.6522
3	1.8216
4	1.8367
5	2.2888
6	2.3674
7	1.9289
8	1.8669

From Table 2 we can summaries that RMSE increases when the size of the particle increase, and vice versa. Also, the values of RMSE for 45-53, 53-63 are very close. While the values of RMSE for 63-75 particle size are relatively larger comparing with other values of different particle's size distributions. One can conclude that the pressure drops across the valve in the fuel system rig is closely matches the pressure drops across the filter in the filter clogging rig when the particles' size is small because RMSE is increased by the increment of particles' size, , and vice versa.

5. CONCLUSION AND FUTURE WORK

In this work, an accelerated degradation testing of clogging filter using clogging filter rig is introduced for creating the degradation profile of long-life filter. An accelerated degradation testing is used for creating degradation profile of clogging filter in a shorter time than that experienced in normal condition. Then, the fuel system rig for emulating the filter clogging phenomena via DPV valve is described.

The pressure drop across the valve in the filter clogging prognostic rig is emulated by controlling the opening rate of the DPV as a function of time. The results from filter degradation profile in both test rigs were discussed. The introduced index RMSE verifies the effectiveness of the proposed method for different operational profile.

This work will continue by looking at system level prognostics by emulating different degradation profiles of different fuel system's components and predicting the lifetimes of the system in which these components reside.

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