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Health Monitoring of Cavitation Erosion on Airframe Fuel Pumps

School of Aerospace, Transport and Manufacturing
Sustainable Materials and Manufacturing

EngD
Academic Year: 2019 - 2023

Supervisor: Craig Lawson
Associate Supervisor: David Judt
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ABSTRACT

Aircraft maintenance is a critical aspect of operations that can lead to substantial financial savings if improved. The fuel pump is a vital component of the entire aircraft, ensuring fuel delivery to the engine. Cavitation is common in these pumps, leading to erosion and reducing the pump's remaining useful life. Therefore, the main objective of this work is to develop a viable health monitoring method to diagnose cavitation erosion, where few solutions exist. Initially, a literature review is conducted to identify knowledge gaps and opportunities for technology transfer related to current Health Monitoring (HM) technologies for airborne pumps. Four sensing methods, pressure, flow, current, and temperature sensing, are shortlisted based on their past applications and suitability for an aircraft fuel system installation. A hybrid health monitoring scheme consists of a Computational Fluid Dynamics (CFD) simulation, a model running on Simscape, and an experimental test rig. Live experiments are conducted to validate the simulation methods, enabling the testing of scenarios on a wide range of boundary conditions. The simulations demonstrate strong alignment with the experimental data and successfully distinguish the different levels of erosion. Three out of the four tested sensing methods are sensitive enough to distinguish the different levels of erosion, but each method has its advantages and limitations. Temperature sensing is not useful for health monitoring as the ambient environment strongly influences its results. Despite the success of the developed health monitoring schemes, there is a need for further research and development into more sophisticated health monitoring algorithms before the technologies can be widely implemented on aircraft.

Keywords

Health Monitoring, Diagnostics, Airframe Fuel Pump, Airframe Fuel System, Computational Fluid Dynamics, Cavitation, Cavitation Erosion.

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This research is being funded jointly by Airbus Operations UK and United Kingdom Research and Innovation (UKRI), with the grant number EP/L016389/1. All the data used in the research are available as part of the article, and no additional source data is required. You can refer to the previous portfolio submissions provided for further reading and supplemental data.

Portfolio submission #1, which focuses on a literature review of the current state of HM technologies for airframe fuel pumps, has been published in the peer-reviewed journal, the International Journal of Prognostics and Health Monitoring [1].

Portfolio submission #2, which focuses on CFD simulations for erosion damage prediction, has been published in a peer-reviewed conference publication for the 2022 ASME Turbomachinery Technical Conference & Exposition in Rotterdam [2].

Portfolio submission #3 has been peer-reviewed by academic and industrial supervisors at Cranfield and Airbus UK. The content is subject to approval from Airbus UK before being sent for wider publication [3].

Portfolio submission #4 has undergone internal review with academic supervisors and is awaiting approval from Airbus UK for further publication [4].

All documents have been referenced using the IEEE standard, except for portfolio submission #1, where APA 6th edition has been used instead to conform to the journal's standards.

SUGGESTED READING ORDER

The innovation report provides an overview of all the portfolio submissions, making it necessary to read it first to get a lateral view of the EngD thesis. The portfolio submissions offer a more detailed understanding of the sub-topics covered in the innovation report. To become familiar with the basic concepts of airframe fuel pumps, fuel systems, and the need for health monitoring, it is recommended to read portfolio submission #1 [1] first among the portfolio submissions. After that, portfolio submission #3 [2] is recommended to be read next so that the reader understands the methods used and their context with the entire project. Portfolio submission #4 [3] is recommended to be read afterwards, as it further builds on the topics and relationships discussed in submission #3 but applies to degraded samples. Finally, portfolio submission #2 [4] could be read last, as it primarily discusses the theory behind erosion damage predictions and compares the CFD predictions against reference experimental data.

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List of Abbreviations

σ	Cavitation number	-
ρ	Density	kg/m ³
ρ_l	Liquid Density	kg/m ³
α	Vapour Fraction	-
P	Pressure	Pa
Q	Flowrate	kg/s
P_v	Saturation Pressure	Pa
v	Velocity	m/s
t	Time	s
Δt	Time-step duration	s
T	Incubation time	s
V_{jet}	Jet velocity	m/s
V_{crit}	Critical velocity	m/s
V_{def}	Deformation Velocity	m/s
A_{pit}	Pit area	mm
A_{ref}	Reference Area	mm
A_{dam}	Damaged Area	%
R_b	Bubble Radius	m
N_b	Bubble Density	m ³
c	Chord/Radial length	mm
GCI	Grid Convergence Index	%
p	Local Order of Accuracy	-
AC	Alternating Current	
AOG	Aircraft on Ground	
BLDC	Brushless Direct Current	
CBM	Condition Based Maintenance	
CFD	Computational Fluid Dynamics	
CFturbo	Pump Design Software Package	
CG	Centre of Gravity	
cP	Centipoise, unit for viscosity	
DBM	Direct Bubble Method	

DC	Direct Current
EPM	Erosion Power Method
ESA	Electrical Signature Analysis
GLM	Gray Level Method
HI	Health Indicator
HM	Health Monitoring
HP	High Pressure
IFM	Intensity Function Method
LE/TE	Leading/Trailing Edge
LP	Low Pressure
PHM	Prognostics Health Monitoring
RMS	Root Mean Square
RUL	Remaining Useful Life
SST	Shear-Stress Transport Turbulence Model
Star-CCM+	CFD Software Package
κ - ϵ	Kappa-Epsilon Turbulence Model
κ - ω	Kappa-Omega Turbulence Model

1. Introduction

1.1 Motivations for Implementing HM

Aircraft maintenance is an essential part of operations, as it not only ensures the safety of flight missions but can also influence the profitability of the airline operator. The reliability of the aircraft fuel system is vitally important, as the fuel system not only ensures fuel delivery to the engine, but also provides the means for fuel transfer between tanks, fuel jettison and refuel/defuel of the aircraft on the ground [5]. Understanding the degradation mechanisms of these fuel pumps is, therefore, highly beneficial. It can be used to predict the failure modes of the fuel pump components as the equipment deteriorates over time. This allows operators to mitigate and take action for these faults before the aircraft is unexpectedly grounded. This prevents the operator from incurring excessive costs resulting from unscheduled maintenance and associated out of service time [6].

Implementing a form of Condition Based Maintenance (CBM) and Prognostics Health Monitoring (PHM) can benefit aircraft operations by reducing costs through minimizing the number of unscheduled breakdowns experienced by the operator [7]. Health Monitoring (HM) consists of a set of functions for estimating the present, and predicting the future, state of health of an asset. It includes anomaly detection, fault identification and isolation, and predicting remaining useful life (RUL) amongst its capabilities. The concept of failure prediction is carried out by continuously monitoring and assessing the present state of the system, to synthesize information used for decision making. This helps maintenance operators decide if any corrective action is needed (diagnosis) and schedule the exact moment to carry out the repair work (prognosis) [6]. The present maintenance strategy for operators relies on time-based methods, where the pumping unit is replaced after a certain number of hours of operation or when the pump reaches failure. The former maintenance strategy is called preventative maintenance, while the latter is called breakdown maintenance. It is assumed that limited corrective actions have been applied by the operator before reaching these maintenance intervals or pump failure scenarios [1].

The operator would have to pay substantial fees and additional costs related to passenger compensation if the aircraft is unexpectedly grounded at a guest

airport, having a large impact on the profits gained passengers. Another negative impact of unscheduled breakdowns is to the reputation of the aircraft manufacturer and its perceived reliability. It is therefore crucial, from a cost-saving perspective, for both the aircraft manufacturer and operators, to anticipate these failures. This reduces the number of times the aircraft needs to suspend operations outside its routine maintenance procedures by either detecting an incipient failure using diagnostics or by predicting the exact moment when the fuel pump needs replacement using prognostics. With the implementation of CBM with diagnostics and PHM with prognostics, the pump, in theory should never fail outside the maintenance interval. One approach is to adapt HM techniques, whether executed through diagnostics, prognostics, or a combination of both.

Both boost and transfer pumps are electrically powered centrifugal pumps but have different operating characteristics. The transfer pumps located at the centre tanks must provide higher feed line pressures compared to the feed tank boost pumps. This serves to overcome the line losses from the longer fuel travel path to the engine-feed interface. For the A320 and B737 aircraft, the pump must supply at significantly higher pressures to close the boost pump outlet check valves by overriding the pump pressures. This allows the fuel from the centre tanks to be depleted first before emptying the feed tank. Once the centre tanks are emptied, the transfer pumps are shut off and the feed tank boost pumps take over to supply fuel to the engine. This ensures that the feed tanks are the last tanks to be emptied during the flight mission. Transfer pumps also provide wing load alleviation and ensure correct airframe CG by moving fuel across the different tanks [5].

The fuel pumps focused in this thesis are coloured in green on **Figure 1**. They are the feed tank boost pumps, which are part of the airframe fuel system. The airframe and engine fuel systems are segregated by the low-pressure (LP) valve located on the airframe, which separates and shut-off flow of fuel in the event of an emergency. The transfer pumps are mounted inside the centre tank and are interfaced with the main feed tank within the airframe fuel system [5].

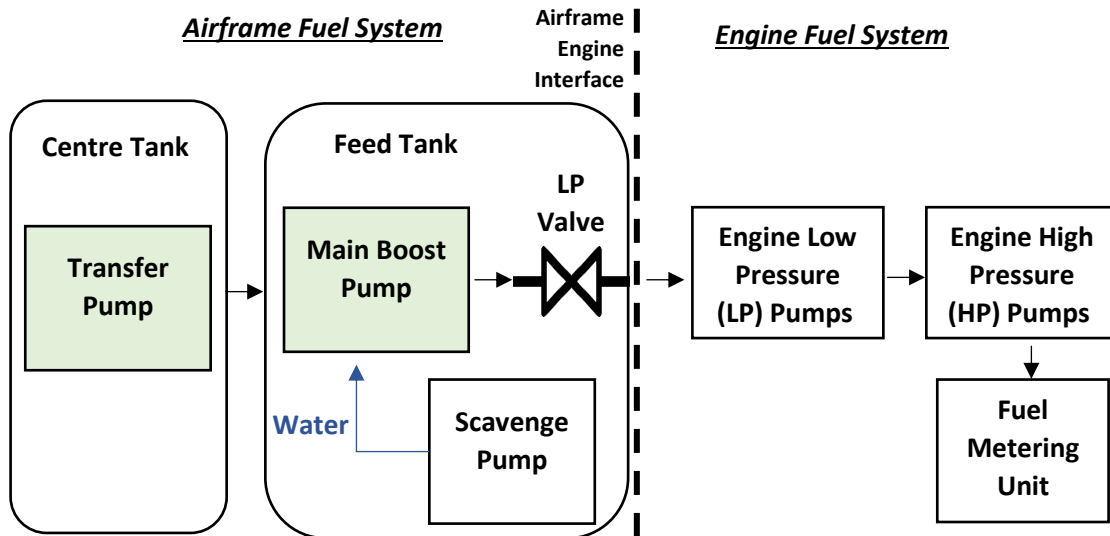


Figure 1. Key elements within the Airframe and Engine Fuel Systems

The feed tank boost pumps serve a crucial role in emergency fuel jettison and de-fueling during ground operations, similar to the transfer pump. **Figure 1** outlines how the low-pressure pumps (LP) interface the engine fuel system with the airframe fuel system. The LP pump provides sufficient fuel to the engine when the airframe fuel pumps are inoperative, allowing the engine fuel system to operate with the same inlet pressure as the aircraft boost pumps. The engine high-pressure (HP) pumps, on the other hand, play a critical role in pressurizing the fuel to the levels required by the engine combustor. They also deliver the fuel at the desired pressure over a broad range of operational speeds [8].

The literature review section focuses on HM technologies that have been used on airframe mounted centrifugal boost pumps; these include not only the diagnostics and prognostics techniques used to perform HM on a specific fault, but also the sensing technologies that have been deployed. As there are few works related to the HM of airframe-mounted fuel pumps, technologies from other industries are referenced so that a comparison can be made for the present capabilities of fuel pumps found in aircraft with pumps from other industries. This section not only highlights the sensing technologies and signal processing techniques that have been used, but also elaborates on capability gaps where airframe fuel pump HM technologies could be developed in the future. The review of airborne fuel pump HM technologies ranges from the year of 1999 up to 2020, as this was the earliest published work found. At the present, few works have

been done for the HM of airborne fuel pumps and there is large scope for development to address this knowledge gap.

1.2 Reasons to Develop Health Monitoring for Cavitation

Cavitation is a common problem found in pumps across different industries [5]. This phenomenon can not only reduce the performance of the pump, but significantly cost the operator financial losses due to premature pump failures and the pump being replaced earlier than intended, as it can no longer produce the required head. Cavitation does not only occur in pump impellers, but also occurs in other blade applications such as hydrofoils and propellers. It is therefore useful to predict for cavitation erosion and to understand how it would damage the pump. Having the ability to predict this fault is useful as it allows pump designers to apply design improvements to prolong its useful life. Operators can also benefit as it gives them the ability to apply corrective action for the pumps and help mitigate the financial penalties associated with unexpected breakdowns.

In order to predict the pump erosion from cavitation, a simulation using a multiphase fluid model of water is used to stimulate cavitation on the pump, executed using Computational Fluid Dynamics (CFD). CFD refers to the branch in fluid mechanics that uses numerical analysis to solve problems that involve fluid flows and its interaction with surfaces. CFD methods are chosen to predict erosion as it is a low-cost, time-efficient alternative over stimulating cavitation naturally with a test rig, and allows the problem to be visualized in software. The results from this simulation can help identify specific areas inside the pump that are most vulnerable to cavitation damage.

Previous works on cavitation simulations on CFD have been focused on the visual study of the vapor fractions and how it influences the pump performance. Very few works have attempted to predict the regions inside the pump that are affected by erosion damage.

Performing diagnostics to detect erosion, creates the capability for fault detection and fault prediction. A difficulty in monitoring incipient cavitation to conduct HM, is that the severity of the problem is only weakly influenced by the present health of the pump and more strongly by its surrounding environment and operating

conditions. Monitoring erosion effects instead, gives the ability to observe changes in behaviour over time, as the permanent change to the impeller geometry is tracked. Incipient cavitation on the other hand, is a transient event over a brief time interval. The amount of material thickness loss (in mm) of the impeller can be correlated to its health; the severity of which can be detected by monitoring motor current, flowrate, and pressure. The changes in those parameters can be linked with a suitable HM technique, to quantify the magnitude of erosion.

This paper describes a hybrid-based HM scheme to detect for cavitation erosion, where a combination of data and model-based HM is conducted to diagnose the current health state of the pump. **Section 2** gives a literature review related to HM theory and current state of HM technologies related to airframe fuel pumps to help identify knowledge gaps. **Section 3** outlines the thesis aims, objectives and statement of innovation. **Section 4** outlines the test-environment and experimental plan; outlining how the test-rig, CFD and Simscape models are used to conduct hybrid-based HM. It also describes the setup for each of those individual elements in detail. The results are divided into two sections, the baseline results under normal operating conditions in **Section 5** and with the eroded impellers included in **Section 6**. **Section 7** discusses the findings from **Section 5** and **6** as well as provide suggestions how the erosion predictions carried out in CFD can be improved. **Section 8** concludes by summarizing the benefits of the research and suggesting future work to build on the project outcomes. It also outlines present challenges and considerations before the developed HM solutions can be widely deployed on aircraft fuel pumps.

2 Literature Review

2.1 Airframe Fuel Pumps

Fuel pumps that are found on the airframe fuel system and the engine fuel system utilize two different types of pumps, respectively. These two fuel systems are separated by an LP shut-off valve mounted in the aircraft fuel system which isolates the engine fuel supply from the airframe when the engine is shut down or for emergency situations [5]. Engine-driven fuel pumps are mounted on the engine to move the fluid directly through physical interaction between the rotor and the fluid, to supply a constant flowrate for varying pump inlet pressures. The centrifugal pumps found on the airframe fuel system move fluid indirectly by boosting the pressure and are powered by an electric motor. For transfer pumps, variations in the pump outlet pressure directly influences the flowrate of the fluid supplied by the fuel pump [8]. The flowrate of the boost pump on the other hand is determined by the engine and its primary aim is to supply fuel under pressure to the engine interface regardless to changes in flow demand [5]. HP positive displacement pumps are used on the engine interface as they can re-prime from a completely dry condition to deliver the required fuel pressure over a changing engine input speed. Excess flow from both the HP pump is bypassed and recirculated back to the inlet of the same pump. The ratio of fuel flow that gets bypassed or fed to the engine is calculated by the Fuel Metering Unit (FMU) More information on the different types of airborne fuel pumps and their operation is found in textbooks that have been compiled by Langton et al. [5] and Messina et al. [8].

2.1.1 Airframe Fuel Pump Motor Types

Centrifugal fuel pumps that have been used in the airframe fuel system uses one of two types of motors: An Alternating Current (AC) induction motor or a Brushless Direct Current (BLDC) motor [5]. Each type of motor has advantages and disadvantages over the other. Both BLDC and induction motors leverage the use of a rotating magnetic field on the stator to generate torque on the rotor. AC Induction motors work by inducing current on the rotor caused by the rotating magnetic field generated by the stator. The induced current in the rotor generates its own magnetic field that reacts with the stator magnetic field to generate torque.

In the BLDC motor, the stator coils generate a magnetic field, and the permanent magnet rotor tries aligning itself to that field. Motion is generated by rotating the stator magnetic field, which is achieved by sequencing the excitation of the stator windings. Another difference between BLDC and an induction motor is the use of permanent magnets on the BLDC rotor [9]. More information on BLDC and AC motors be found from the textbook by [9]. Information related to aircraft fuel system application for both types of motors can be found in the work by [5].

2.2 HM Theory Fundamentals

Health monitoring techniques can be categorized into diagnostics and prognostics. Diagnostics refers to the ability to create an appraisal of the equipment in question using some form of health indicator (HI). Prognostics is concerned with being able to estimate the RUL of that equipment rather than just the appraisal of its present state [10].

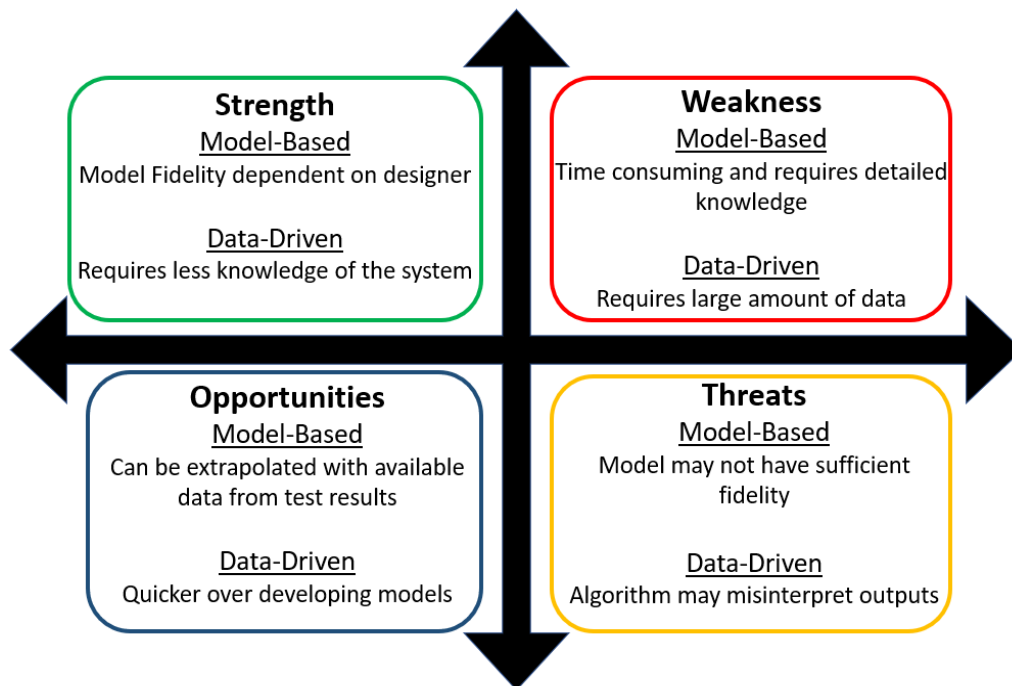


Figure 2. SWOT analyses comparing the merits of model and data-based HM [10].

Within the two basic forms of HM, there are also two main ways for the data to be generated and synthesized. The implementation of HM can either be Model-based, Data driven or a hybrid, where the latter is a combination of both. Model

based HM leverages the understanding of the physical and functional relationships of the system. This method is often used if the user has a deep knowledge of the system in question, so that those relationships can be modelled accurately. Data driven HM utilizes reasoning methods to extract patterns in the datasets, which can be used to build an understanding of the system and make predictions. This requires large quantities of historical data to train the algorithm before it can be used to generate useful results. **Figure 2** depicts a Strength, Weaknesses, Opportunities and Threats (SWOT) analysis to compare model based and data driven techniques for HM. SWOT analysis used to compare the usefulness of the different HM approaches. A detailed explanation of the differences between the different HM methods is found in the works by Ezhilarasu, Jennions, & Skaf [11]. An extensive review for common faults and the state-of-the art of airborne fuel pumps HM can be found in portfolio submission #1 [1].

2.2.1 Model-Based Approaches to HM Pumps

Model-based HM utilizes some form of reference physical model that has been experimentally verified to synthesize the state of health for the system, equipment or small component. The degree of accuracy of the model needs to be understood before it is utilized for HM. The model-generated datasets are used as reference points for a known condition of the equipment, as a baseline to be compared against the sampled data. The correlation or similarity of the sampled data is compared with the baseline data generated by the model before the health state for the equipment is generated.

Kang, Gong & Chen [12] have published a literature review on degradation modelling for various motor-powered equipment across different industries. The authors summaries the algorithms that have been used to model the deterioration of specific equipment and accuracy of estimating a RUL.

Various authors [13, 14, 15] have demonstrated that a model-based approach can be applied to an aircraft pump lip seal, which is a small component that is used to interface between wet-end of a pump with the motor bearing interface. These works have proposed physical modelling techniques focusing on heat

transfer and thermodynamics, to understand the wear processes of mechanical face seals which interface with airborne pumps and optimize their design.

Shi et al., [16] have created a lubrication model for an airborne hydraulic pump and related lubrication changes to changes in the performance characteristics of the pump, such as speed and delivery pressures. These works show that model-based approaches can be applied to analyses specific components of motor-powered equipment within a larger system and yield good results.

An example of model-based health monitoring has been shown by Delaloye [17]. The inventor has developed a patent which is a model-based HM for an airborne lubrication system in a gas turbine, which takes into consideration the lubricant pressure and temperature as well as the rotation speed of the pump-motor. The sampled data from the pump is first compared with the generated data from simulation with the same input parameters, then an assessment of the pump health is determined from the comparison of the sampled against the modelled results.

Fan & Piao [18] have modelled the fuel vapor distribution inside a centrifugal pump for the engine fuel system. It was found that adding a bypass flow inside the pump, significantly reduces the temperature of the fuel but at the cost of a higher fuel vapor distribution at the impeller eye. This made the pump more susceptible to cavitation despite lowering the temperature of the fluid.

There are other works which have characterized cavitation flows with high fidelity computational methods such as the previous example by Fan & Piao [18]. Further examples by various authors [19, 20, 21, 22] are similar but are for non-aircraft applications. These examples do not explicitly use model-based HM for diagnosis but show how a re-occurring fault in a pump can be captured using modelling techniques and the results can be utilized for corrective action.

2.2.2 Data-Based Approaches to HM Pumps

Data-based approaches are often used when the behavioural characteristics of the system or single sub-system in question cannot be fully known, and a model-based technique is not viable. There are few published examples for purely data-based approach for HM of aircraft fuel pumps. Most HM techniques of airborne

fuel pumps that utilize data follow the hybrid approach, where the use of an additional system model can give improved accuracy to the HM diagnosis.

Pandian et al., [23] have investigated various equipment faults on a single type of commercial airliner using data-based methods. This study does not suggest a HM solution but highlights the information collection on certain faults, and how external factors such as logistics, manufacturing and organizational management can influence the aircraft reliability. This report has tried to predict the mean time before unscheduled removals for different aircraft equipment, such as pumps, based on the data sampled on the rate of individual equipment failures during aircraft operations.

Li D. et al., [24] experimented with the frequency of maintenance intervals of water pumps in a closed system, in order find the best combination of scheduled servicing and preventative maintenance. It was found that there is an optimal service interval which reduces the overall life-cycle costs of utilizing the equipment.

Even though these three HM techniques have not been applied explicitly to airborne fuel pumps, the techniques are still useful for this application. The previous methods demonstrate how a purely data-based approach can be used to improve maintenance operations for aircraft systems that rely on multiple pumping equipment.

2.2.3 Hybrid-Based Approaches to HM Pumps

The Hybrid approach utilizes a mixture of HM from both model-based and data-based methods to combine the advantages from each technique.

The work by Niculita, Jennions, & Irving [25] describes the design process of a fuel test rig based on a UAV engine feed system. The entire test set-up compromises of the actual test-rig, but also various other tools which facilitate the use of fault detection and isolation: such as a failure-mode analyses, a model simulator, test-rig controller, fault injection unit and data acquisition. The simulation of the test rig can also inject faults in the virtual domain, so that the expected output could be studied first before executing the actual test on the experimental test-rig. The models are used to create reference points for healthy

cases and hypothesis for fault scenarios. Data-based approaches can be used on model-generated data for algorithm testing, before application with test rig data. Furthermore, the model is continuously updated from the results from the physical test rig to minimize the discrepancies and to adjust for any changes to the physical system.

Another hybrid-based approach has been devised by Al-Tayawe, Ward & Verhulst [26] for the HM of airframe-mounted fuel pumps. The performance parameter of the pump is sampled, then a signal processing algorithm is utilized to generate the RUL. The signal is sampled when the pump reaches a known reference environment for consistent sampling. The sampled data is compared with the reference model at a known health state, representing the different conditions of the pump. A prediction algorithm is continuously updated to generate the RUL based on the previous and present sampled data, with reference to its closeness with the known health states.

Mkadara & Paulmann [27] have concluded that a mixture of modelling and data-based approaches is required for the HM of hydraulic piston pumps. This is because the developed HM solution under laboratory conditions may not be robust as soon as the external environment is introduced. The HM algorithm is thus trained using the developed model initially and before it is supplemented with in-service data to create a robust fault identification algorithm. In this instance, the outlet pressure and leakage flow values are used as the HI to diagnose the health of the pump. Guo et al., [28] have highlighted more HM technologies related to airborne hydraulic piston pumps and gives a general overview of the present state and future development for these types of pumps.

The methods described by Mkadara & Paulmann [27] and Guo et al. [28] have demonstrated general approaches at which HM can be achieved to synthesize the health of the equipment or sub-system. Both model-based and data-based approaches have their own advantages and disadvantages, depending on the application.

Li T. et al., [29] developed a hybrid method using particle-filter-based-prognosis. The particle filters are used to generate the probability density function (PDF) to

express the health of the airborne hydraulic piston pumps based on the sampled return oil flow. The generated of PDFs facilitates the ability to carry out prognosis by comparing the present PDF and future PDF to recursively estimate the RUL. The prognostic algorithm is continuously updated based on the error measured between the sampled data and predicted data. Through observing the two values of the pump return oil flow, the suggested method was able to predict the condition of pump with high accuracy. A similar technique was also devised by Centers and Price [30] where quantity of debris on the lubricant is monitored using ferrography to assess the level of wear on aircraft engines. The sensor is installed at the lubricant pump outlet. Further information on ferrography and how it can be utilized to diagnose aerospace components can be found on the work by Hoffman [31].

Li J. et al., [32] devised another variant but for centrifugal fuel pumps utilizing the outlet pressure as the HI and wiener process algorithm for signal processing. The algorithm developed by these authors are also accurate for predicting RUL of the pump when compared with experimental data.

2.2.4 Limitations to HM Approaches

Model-based health monitoring techniques generally involve analysis of the motor electrical signature, or fluid-mechanical parameters of the pump such as flow and pressure. The data are compared to one or more performance indicators which are an estimation of the pump health. The pump is monitored for changes in its inputs and outputs, or some characteristic related to the performance obtained from sampled data. Examples of these parameters can include the flowrate, pump inlet and outlet pressures, as well as motor current and voltage. The pump model describes the behaviour or input-output relationships related to the operation at known points as reference towards the condition of the pump. The differences between data sampled from operations and data generated from the models are compared to generate the health diagnosis of the pump [26]. A major drawback of existing health monitoring techniques is that in-flight operational pumps may not perform as expected from laboratory testing or as modelled in simulation. This could lead to inaccurate health diagnostics and prognostics where the timing of the next maintenance period is predicted

incorrectly or an inaccurate prediction for the pump Remaining Useful Life (RUL) is generated by the system. This is especially a problem with Aircraft fuel pumps as it would often necessitate taking the aircraft out of service to maintain the equipment [26].

2.2.5 HM Sensing Success Criteria

The minimum level of sensitivity required to detect a fault in an asset can vary. In previous research, a sensitivity range of 5% to 10% has been used to analyse time-domain data. This range is used to determine when a component has entered the next level of degradation, such as differentiating between a 'Healthy' and 'Moderate' or 'Incipient' state of the component. For instance, authors in previous studies [33, 34, 35, 36, 37, 38] observed a 5% change in the measured value before they were confident that a machine component was degrading. However, in other situations, the sensitivity value is set as low as 2%. To detect the next degradation state in such cases, it is necessary to install multiple sensors at different points of the system which must be in agreement. For instance, Skliros, Ali & Jennions [39] placed multiple sensors on an aircraft climate control system to conduct HM. If the sensitivity is set to around 2%, it's required that at least two or three of the other sensors installed on the system must agree. This criterion is chosen because it provides enough differentiation between different health states of a machine component. To estimate the Remaining Useful Life (RUL) of a component, more development can be done to create algorithms.

For conducting frequency-domain analysis, Johnston & Todd [38] and Sarma et al. [40] have suggested a sensitivity value of approximately 150%. This chosen threshold value provides a clear distinction between the signal and noise floor. The aim of this study is to evaluate each measurement technique individually and determine the most appropriate operating point for their usage.

2.3 HM Sensing Methods

This section focuses on prevalent detection methods for diagnosis. First, their operating principles is introduced, followed by a discussion of their respective merits and application examples. The state of the art between HM technologies that are used in airframe fuel pumps is compared with other aerospace pumps

used in the engine fuel system. Further examples from relevant industries will be discussed to suggest how HM can be applied to airframe fuel pumps.

2.3.1 Thermal

Thermal monitoring of pumps involves measuring different areas of the pump by using thermocouples. It can be used as an indirect method to detect motor winding and bearing faults on other components of the pump. For example, a fault related to motor winding can lead to a temperature rise in the specific region of the fault. For bearing faults, the increased bearing wear increases the friction and the temperature in that region of the machine. HM that leverages temperature data is often used in conjunction with another measurement source, such as speed or an electrical signal [41].

Emmons [26] has investigated thermal HM for application in aerospace, where an invention related to the fuel delivery system in a gas turbine engine is described. The technique assumes that the HI captured for one equipment are dependent on the condition of a neighbouring element within the system. The position, speed, temperature, and sample time of the second component, such as the adjacent valve, is used to indirectly diagnose the fuel pump.

Emmons & Salminen [42] have devised an application for aerospace fuel pumps, where a HM technique is described also for a gas turbine mounted pump. The life expectancy of the fuel pump is generated based on the position of the fuel-actuated actuator relative to the fuel pump speed value. The temperature of different components in the fuel delivery system are sampled and the RUL of the fuel pump is estimated. A prognostic algorithm is used to generate the RUL based on the time-history trend of health assessments from the collected data.

Li & Jiao [43] have analysed the effects of heat transfer from the pumped fluid, related to the flow-performance of the hydraulic piston pump found on the aircraft. Neither study incorporates HM directly, however, they show how modelling techniques using thermal parameters can be utilized to observe changes in the pump operating characteristics.

Physical thermal modelling is widely used to predict the behaviour of an equipment item with the purpose of HM or performance optimization, as it allows

accurate observations of changes in the behaviour of the equipment due to temperature. Temperature-based HM is commonly used for the diagnosis of pumps, but it is deployed in conjunction with another measurement technique, such as rotational speed to diagnose the present health of the pump. An example of this has been highlighted by the invention previously discussed in this section, by Emmons & Salminen [42]. Temperature samples can provide some indication when the pump is about to fail. The main weakness of utilizing temperature-based monitoring alone is that the location of the temperature rise inside the pump cannot be exactly isolated unless multiple sensors are used [41].

2.3.2 Vibration

Vibration monitoring functions on the principle that mechanical vibrations at various frequencies are related to identifiable sources in the entire pump and can be used to provide an indication of the condition of the machine. The vibration energy of the machine is measured through the parameters such as displacement, velocity, or acceleration.

Further background theory on vibration analyses and a list of pump faults that are detectable using it is given by Sinha & Rao [44]. Retrofitted vibration sensors are common for ground-based pumps, but are not as often used on airborne pumps, where the retrofit of these sensors may not be practicable and lead to re-certification of the equipment due to intrinsic safety requirements. **Figure 3** highlights the vibration signatures from a healthy pump and a faulty pump. In the event of a fault, such as a bearing defect, the amplitude of acceleration increases at a certain frequency value. Each fault for the same machine can have a vibration spike at a different frequency.

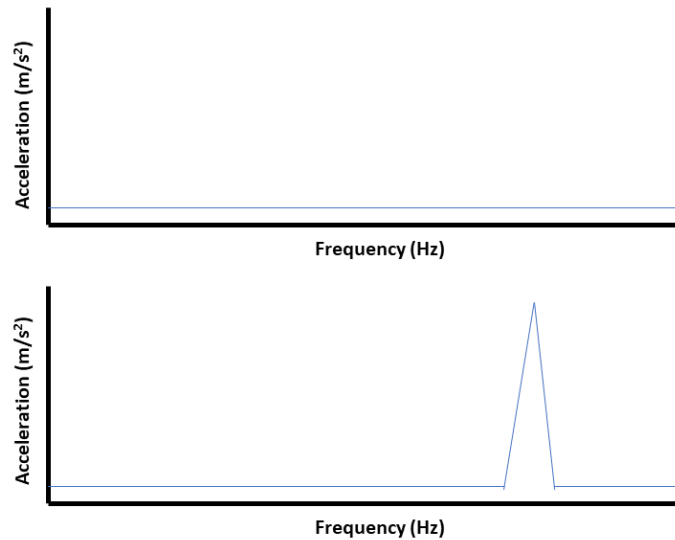


Figure 3. Vibration spectra for a healthy and faulty pump

Vibration monitoring has been applied to airframe-mounted fuel pumps under laboratory conditions. Adamkowski, et al. [45] have highlighted how an already eroded impeller can produce further torsional vibrations on the pump shaft, which in turn can be detected using vibration analyses. Even though this is not an aircraft specific example, cavitation erosion is a common problem on airborne fuel pumps and detection techniques that have been devised in this work are useful for aerospace applications.

Du, Wang, & Zhang [46] have devised a fault classification method utilizing the vibration power signals and a layered clustering algorithm for the diagnosis of airborne hydraulic piston pumps. It was found that this strategy was effective in classifying the different types of faults such as valve abrasion, low inlet pressure, bearing wear, swash plate eccentricities and variations in piston clearances.

Pecho & Bugaj [47] have experimented with a method to diagnose bearing faults and loose pump rotors using vibration monitoring through an auxiliary HM device attached to an aircraft fuel pump when the aircraft is grounded. The Recurrence Quantification Analysis is a less computationally complex technique for carrying out diagnosis under controlled conditions and is an alternative to using the more widely employed time and frequency-based methods.

Jiao et al., [48] have experimented with a method which focuses on recording vibration monitoring on the x, y, z planes and pressure signals from an airframe

fuel pump to detect bearing faults. Both inventions have relied on conducting HM while the aircraft is grounded under controlled conditions.

Overall, vibration methods are an effective tool for diagnosis and fault classification, but its merits are often superseded by electrical signature analyses if the equipment is electrically powered, such as is the case with the airframe-mounted boost pump. The sensors required to perform electrical HM can be placed away from the flammable areas of the fuel tank, therefore bypassing intrinsic safety requirements. This is because modern pumps segregate the control electronics from the pump wet end.

2.3.3 Electrical

Stator current and terminal voltage monitoring fall under the category of electrical signature analyses (ESA). Unlike vibration analysis, the pumps mechanical faults are interrogated indirectly through the measurement of the motor electrical parameters [49]. ESA relies on placing current sensors across the stator or power supply to interrogate the present condition of the motor, which most BLDC motor drives include by design. It has been shown that there is a relationship between the motor vibration and the magnitude of the stator currents or terminal voltages at certain harmonics [50]. This relationship can be proportional to the mechanical vibrations, where the magnitude of the corresponding stator current harmonic components also increases along with it. More information on the basics of ESA for electric motors can be found in the work by Kliman & Stein [49]. Specific information on the relationship between vibration and ESA has been outlined by the work by Riley et al. [50].

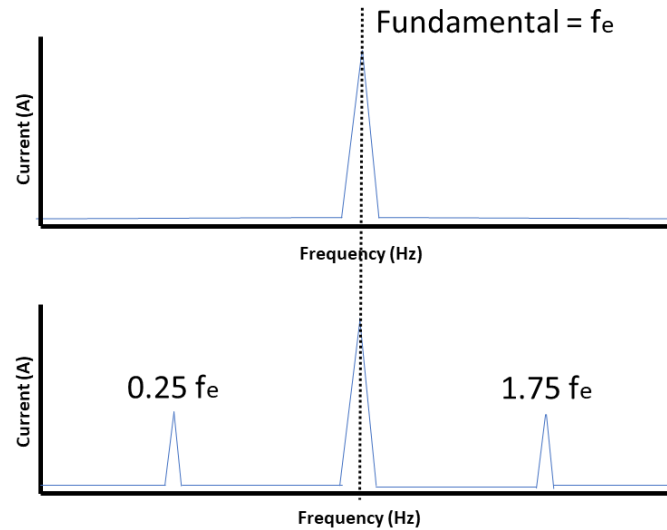


Figure 4. Application of ESA for on electrically powered pumps

Figure 4 highlights how a fault generates current signals at certain frequencies. The spike in the center represents the excitation frequency of the motor, which is known as the fundamental frequency, f_e . After the occurrence of the fault, the sidebands on $0.25 f_e$ and $1.75 f_e$ becomes distinguishable. Note that unlike vibration analyses, faults signatures that are detected by ESA are observed in conjugate pairs such as on the example highlighted by Rajagopalan et al. [41] Like vibration analyses, each fault has a spike in amplitude at different frequencies.

Lu & Kumar [51] have devised a patent for electrically powered traction motor HM. This model-based technique relies on collecting the electrical signal of the traction motor and comparing it with a mathematical model representative of the same system to generate the system RUL. Even though this is applied for traction motors, the same principles could be applied to aircraft fuel pumps, where instead of evaluating tyre traction, the information regarding the flowrate could be interrogated instead. This invention is especially useful as it examines the operating environment before carrying out HM, a feature that can be applied for carrying out a HM for a fuel pump during flight.

Other past work focused on the diagnosis for cavitation on aircraft such as with Schmalz & Schuchmann [52] where the authors have devised a method for cavitation detection on airframe centrifugal fuel pumps using phase voltages and currents. The sampled signal is compared with some known thresholds for the

faulty condition to indicate the working condition of the pump when the aircraft is grounded. Unsworth, Discenzo & Babu [53] as well as Haynes & Eissenberg [54] have devised a similar technique to diagnose cavitation for a non-aircraft pump using ESA. Both works are similar in that their solution is designed to detect cavitation in pumps, but the pump application and utilization of electrical signals are different.

Haylock et al. [55] and Mercrow et al. [56] have discovered methods whereby a shorted stator coil on a permanent magnet-based machine for an airframe fuel pump could be detected by analysing the increased current ripple on the control signal inputs. The information is then used by the motor to switch off the faulty phase winding and operate with a missing phase. This circumvents the motor from operating with a shorted stator coil.

There are few published sources that are related to the ESA for airframe fuel pumps, most published works are for diagnosing electric motors or non-aerospace pumps. ESA holds promise to be used for HM, as it is generally simpler to install the HM equipment compared to vibration sensor counterparts. Furthermore, the sensors tend to be more reliable than vibration sensors as they are not exposed to the stresses that are sourced from the pump. The primary disadvantage of ESA is that the equipment needs to be powered by an electric motor. Another disadvantage of ESA is that this method cannot isolate the vibrations that originate from the motor or the pump. It cannot distinguish faults which have the similar electrical signatures when the origin of the vibrations is unknown. For the few published examples of ESA on airframe fuel pumps, all the existing HM work has been done while the aircraft is grounded under a controlled environment.

2.3.4 Pressure

Pressure based HM is performed by monitoring changes in pressure across the fluid-mechanical network of the system. It can be applied by adding pressure transducers at various points in the flow network to interrogate specific areas of the system. These pressure transducers can be installed at different areas within the fuel system network or on an individual component where there is a likely

pressure change, such as on a pump or a valve [25]. The measured values of the pressure can be observed nominally [38] or with the aid of some signal processing technique [34] to synthesize patterns within the pressure pulsations and gain some form of useful indicator to diagnose and estimate the present state of the equipment.

Niculita, Skaf & Jennions [34] have presented a novel method, where the pressure pattern changes are monitored at the valve inlet. These patterns are recorded and used to anticipate sudden valve shut offs by utilizing a Bayesian change point algorithm. The change in valve pressures is done by throttling direct proportional valves, which in turn mimics different levels of severity from sudden valve blockages. Jung, Niculita, & Skaf (2018) extends this work by comparing different signal processing techniques to evaluate their effectiveness for detecting the same fault.

Skaf, Eker, & Jennions [57] have also used the same test rig devised by Niculita et al. [34] but for RUL estimation of valve filter clogging, which is also simulated through throttling the proportional valve. The devised HM technique leverages resulting pressure differential across the valve and flowrate to train the prognostic algorithm and generate the RUL.

A technique devised by Wang, Dong, & He [58] utilize the suction dynamics of aircraft hydraulic pumps during transient conditions to conduct HM. The scheme uses two models: The first models the pump dynamics and the second are for transient values on the pump inlet line, which are both validated using a test rig. The duration of pressure transient signals is compared with the reference value. The longer the deviation from this baseline value, the more likely the pump is to cavitate.

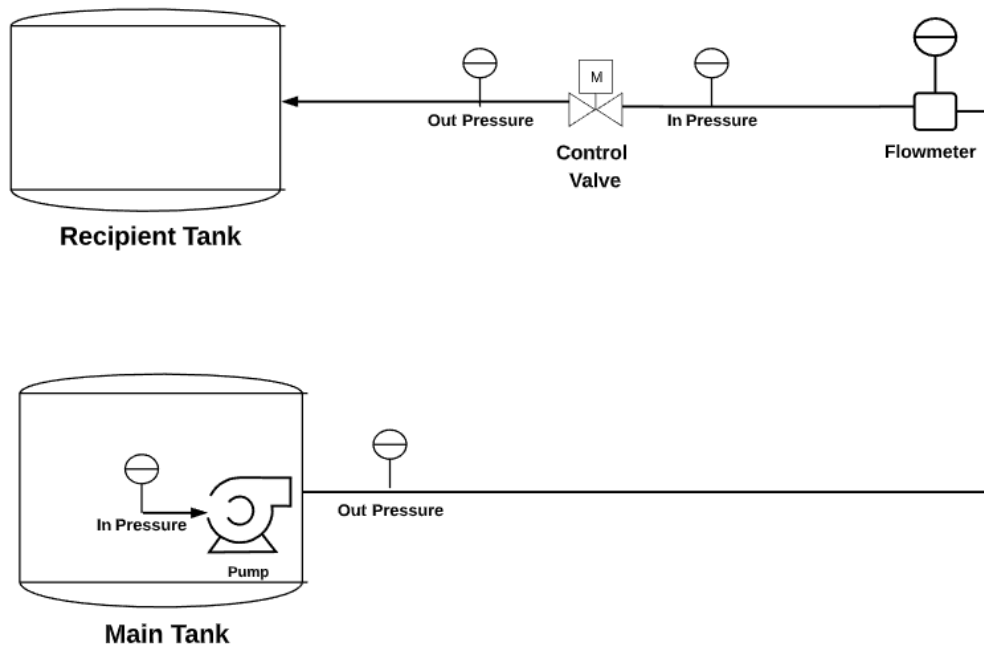


Figure 5. Pressure and flow transducer Layout Inside the test-rig

Figure 5 outlines an example of a simple two-tank system consisting of a centrifugal pump, control valve, four pressure sensors and a flowmeter. The pressure sensors are installed in pairs to monitor pressure changes between the valve and pump. The flowmeter is installed only once as the flow value is the same across the network. There may be multiple flowmeters if there is a junction within the network, as the information related to the ratio of flow between one junction and another may be useful. As highlighted by this diagram alone, pressure sensors are more likely to be sensitive to changes to the condition of an individual component. Therefore, pressure is more often used as a HI performing pump HM, whereas the value of flow is influenced by multiple components that share the same flow network.

Johnston & Todd [38] have utilized pressure sensors placed between LP and HP pumps as well as the valve interface to diagnose bearing faults. Specific flight conditions such as external temperature, and pump pressures dictates how the system performs HM. The measured values are processed with time and frequency domain techniques to evaluate the health of the pump. The external environment is simulated with a rotary valve, generating air ripples to simulate

the environmental disturbance. Full details on the experimental set-up used to simulate the aircraft environment, has been outlined by Johnston & Edge [59].

Flint & Briliat [60] has devised an invention that relies on the use of an electrical solenoid to conduct HM on a gas turbine engine for aircraft. HM is performed by comparing the percentage valve demand against the actual position of the valve-actuator, or by comparing the percentage difference between the servo pressure line and the control value of the pressure line. When the difference reaches a certain value for either of those comparative parameters, an engine warning is given to warn operators.

Lu, Wang, & Wang [61] have devised a method to synthesize the health of airborne hydraulic pistons using three health indicators: pump outlet pressure, system line pressure and the displacement of the recipient actuator. The combination of these sources is not only better to detect and distinguish faults but ensures reliable HM if one of the pressure sensors fail.

Ma et al., [62] have devised a different HM solution for aircraft hydraulic piston pumps. The proposed model-based method attempts to diagnose leakage flows inside the pump by monitoring the output pressure and the swashplate angle. This method is unique as it attempts to incorporate the flight dynamics into the model and the non-linear behaviour caused by it.

Pressure measurements have been widely used for HM of pumps, either by sampling and observing the raw signals nominally or with additional signal processing. Either of these approaches can yield useful outputs for HM. Pressure is often used as it is indicative of the pump performance, and any deterioration in this value can intuitively be linked to pump health. Pressure based HM has been researched for both airframe fuel pumps and engine fuel pumps.

2.3.5 Flow

Flow based monitoring relies on the measurement of the flowrate along a certain path of a fluid-mechanical system. One flow sensor is deployed across a certain network or path, as the flow is likely to be the same for all elements in that flow path. This is unlike pressure-based monitoring, where the transducer is implemented before and after the equipment in question to monitor the pressure

rise or drop [62]. HM approaches using flowrates have been done in conjunction with another parameter. This is because although the flowrate measurement can indicate a clear reduction in flows within the system, it may not be able to detect steady deterioration over time. For example, Johnston & Edge [59] have showed that flow measurements did not detect any noticeable change as the pump deteriorated to a failure condition. Flow is useful when combined with pressure signals to synthesize the health of the pump as supplementary information. The quality of fluid in the flow can also be monitored to assess wear on aircraft engines, such as with Centers & Price [30] where the quantity debris is monitored at its lubricant pump outlet to assess engine health. Hoffmann [31] also mentions a similar technique but carried out under lab conditions.

Griffiths [63] has invented a method which utilizes flow control for HM of leakages for a fuel pump in a gas turbine engine. The leakage flow at a specific speed is established through a calibration and the leakage flow is compared at the same reference speed again. The flow values are adjusted based on the temperature of the fluid for consistency of measurement.

Bergada et al., [64] have outlined the relationship between the flow leakage and output pressure ripples for airborne hydraulic piston pumps. The results are used to assess the present conditions of the components inside the port barrel plates inside the pump. The higher the observed flow leakage, the larger the clearance of the components inside the port barrels, which can be used to diagnose the degree of wear for the pump.

A flowrate signal is a useful indicator for HM; however, it is often used in conjunction with another HI, such as pressure. Flow is mostly used for HM on hydraulic pumps installed on the engine fuel system, as leakage flows captured from the barrel ports are easily measured. For airframe fuel pumps, outlet pressure signals alone are better to interrogate specific points of the fluid network and generally are more responsive to external disturbances.

2.3.6 Rotational Speed

The rotational speed is often employed to aid the execution of HM using the techniques mentioned above for a pump. Like temperature, using this parameter

in isolation may not be useful but can achieve diagnostics when used in conjunction with parameters such as motor current or pressure as shown in the following examples for pumps installed on the engine fuel system [65, 42, 63, 66]. Further details are provided in the relevant sub-section within **Section 5**. In these situations, the primary parameter being monitored has been regulated to a set value by the control system. Once the controlled parameter, such as the pump outlet pressure, reaches the desired value, the motor speed at that moment is analysed and is used as the primary HI. The HM diagnosis begins by assessing the motor speed. The purposes of this initial health check are to justify more detailed HM diagnosis to be performed by the system, such as taking temperature samples across the engine fuel system for the aircraft.

Villeux [67] has devised a HM method for an aircraft gas turbine mounted fuel pump. The speed is reduced from a known value as the fuel flow is initiated by the ignition system. During this process, the outlet of the pump pressure is initiated to the desired pressure and the gas turbine engine is monitored to verify if light-off is successfully achieved, which is when the correct ratio of air-to-fuel mixture is achieved. The pump motor speed at which engine light-off is achieved determines the health status of fuel pump.

Rotational Speed is often used as a secondary HI in addition to a primary parameter such as pressure, temperature, vibration, or ESA. This parameter is often used to diagnose the health of the hydraulic pumps installed on the engine fuel system and is not used for centrifugal pumps installed on the airframe fuel system.

2.4 Cavitation Theory

Cavitation occurs when the pressure observed at the pump inlet is less than the vapor pressure of the liquid. For a pump, the leading edge of the impeller is considered to be the most vulnerable region, as this is the point at which the static pressure is the lowest in the entire pump [8]. This creates bubbles in a trail of vapor which reduces the head output of the pump. Furthermore, these bubbles implode at very high pressures as it travels towards the trailing of the pump impeller which creates an erosive effect on the metal surface. This results to

permanent damage to the pump impeller and reduces its capability to generate head at a given flowrate. If the erosion becomes severe, then the pump can no longer produce the required head to be useful or fail altogether. Cavitation for pumps is a transient behaviour, where the cavitation appears briefly when the boundary conditions are satisfied and eventually disappears when the pump reaches steady state boost pressure [68, 69].

The actual value of this vapor pressure is dependent on the temperature, altitude and the type of fluid being pumped. Water (H₂O) at sea level and room temperature has a vapor pressure of 3170 Pa but this threshold can increase if the ambient temperature or altitude is raised, making the pump more susceptible to cavitation. A non-dimensionless parameter which gives an indication to the severity of cavitation is called the cavitation number. The lower this value, the more severe the cavitation. The cavitation number is defined as follows [70]:

$$\sigma = \frac{P_T - P_v}{\frac{3}{4} \rho_l v^2} \quad (1)$$

Equation 1. Cavitation Number Definition

For Equation 1, σ Refers to the cavitation number, P_T is the total pressure measured at the pump inlet, P_v is the vapour pressure of fluid, ρ_l density of the liquid and v rotation velocity of the pump impeller. For a hydrofoil, the constant on the denominator is $\frac{1}{2}$ instead of $\frac{3}{4}$ [71]. The thresholds for the severity cavitation are dependent on the application of the blade. An example of this with a hydrofoil, where a value of $\sigma < 3$ is considered to be severe whereas for pump impellers this value is $\sigma < 0.5$.

The damage mechanism caused by cavitation erosion creates a sandpaper-like surface on specific regions of the pump such as the impeller. The effects of pump erosion have been known to reduce its capability to boost pressure and compromise operational efficiency, as highlighted by the works by the various authors to evaluate for erosion damage to pumps in [72, 73, 74, 75, 76, 77, 45, 78]. When the erosion becomes severe, the pump can no longer operate effectively or fails completely altogether.

These works discuss the damage mechanism and performance penalties of erosion but the authors do not propose a mathematical model to predict it.

Vapor fraction α , is the most common parameter used to observe for cavitation in CFD and is useful to understanding areas in the pump where the bubbles grow and collapse, but does not highlight the areas that are affected by the subsequent erosion. This dimensionless parameter quantifies the ratio of vapor to liquid that is present in the fluid with a maximum value of 1 and minimum value of 0. An example of how vapor fraction is utilized to study cavitation is available in the works carried out by the authors [79, 80, 81, 82, 83] for two-stage pumps and [84, 85, 86] for single-stage pumps. The simulations carried out in these works focus on the visual study of cavitation for different blade geometries, but they do not give an in-depth explanation on how the erosion will develop as a result of cavitation.

2.5 Erosion Damage Models

There has been past works which have modelled cavitation erosion using CFD for different types of blade applications, such as pump impellers, ship propellers and hydrofoils. These methods work by applying user-defined field functions to predict the areas where the erosion damage is most concentrated. Most of the used-defined field functions described are primarily based on some relationship with the changes in pressure caused by the cavitation process. The models leverage the assertion that the bubble collapse generates a pressure value that is much higher than the ambient pressure and that locations of these bubble implosions in turn are areas in the pump that have highest concentration of erosion [87, 88]. There is no single universal method that is able to predict erosion damage reliably for all applications and its accuracy will depend on the blade geometry. The variables used for the user-defined field functions have been calculated from the running of the cavitation simulation, so no additional model is required to apply them in predicting erosion.

The simplest out of the four erosion models discussed by the authors Schmidt et al [89] as well as Boorsma & Whitworth [90], uses the maximum pressure of the regions where the vapor fractions collapse on the surface, to determine which

parts of the pump are most sensitive to erosion. While this model is simple, it does not give an accurate approximation of the erosion areas.

The Intensity Function Method (IFM) outlined by Equation (3) was devised by Li & Van Terswiga [91] and applied to an aerofoil by Eskilsson & Bensow [92] as well as by Usta et al [93]. This method was devised to improve estimating erosion areas using maximum pressure method and relies on visualizing the pressure gradient on the surface.

The Gray Level Method (GLM) outlined by Equation (2) was devised by Dular et al. [71] and has demonstrated its accuracy in predicting erosion on a single-stage radial pump and a hydrofoil. The more rigorous version of GLM is used in this work. Unlike all of the other methods mentioned, it is able to quantify the amount of erosion, in addition to identifying the areas. The more advanced implementation of GLM involves the calculation of jet velocities and associated deformation pressure on the pump surface as outlined in sub-section 4.3.1.

The Erosive Power Method (EPM) was reported by Usta et al. [93] and has been further tested by Koksai et al. [94]. This method has demonstrated good accuracy in predicting the erosion profile from the former studies but has not been applied to a radial pump. This function builds on the simplified version of the GLM function, by adding the product of vapor fraction and pressure gradient. As a result, there are similarities between the two methods, the erosion areas predicted by these two functions yield similar projections when applied to a propeller [93].

Another erosion model developed by Fukaya et al. [95] known as the Direct Bubble Modelling (DBM), also shows very good accuracy with experimental data but is much more computationally expensive when compared to the other erosion models. DBM requires a separate model and involves modelling the growth and collapse of individual bubbles, which means a very small time-step and fine mesh is required when compared with the previous methods, so that the evolution of these individual particles can be resolved. This method has only been experimentally verified with a Francis turbine, which has a very different geometry compared to the subject pump and most commercial pumps. Due to the lack of

experimental verification and significantly higher computational cost, this method is not selected for the current subject pump.

2.6 HM Test-Rigs

There have been some previous works that have used hybrid-based HM to diagnose cavitation erosion. One example is a test-rig that was created for a UAV fuel system [33]. This test-rig was designed to detect general fuel system faults like clogged valves and leakage flows.

Sarma, Tuohy & Djurovic [96] have developed a test-rig that is tailored to detect stator and rotor-related faults for a generator unit used on a wind turbine. This test-rig aims to replicate a wind turbine configuration but in a lab environment. Similar to the hybrid-HM setup discussed in this paper, the test-rig used in the thesis also utilizes a system model running on MATLAB in addition to the experimental rig, so that hybrid-based HM can be carried out. The subsequent work by the same research group [40, 97] builds on the validated test-environment and describes the results for their HM scheme.

Wang et al. [98] described a test-rig setup to detect wear caused by slurry erosion using data-based HM with vibration sensors. The authors of this work conducted accelerated fault testing by artificially recreating the erosion wear. The damage profiles are approximated using statistical data gathered from the field. No mention has been made about the success of the HM techniques, but the methods have been used across different industries to diagnose the same problem. The work does not outline the success of the devised test set-up, but the methods and materials suggested in this work are based on field experiences.

The method outlined in Section 4 focuses on hybrid-based HM, where model and data-based approaches are combined to provide more advanced detection and prediction algorithms as part of future work [33]. Additionally, for future expandability of HM techniques, the multiple sensing methods used by the test-rig discussed in this paper allows a comparative study to be carried out. The results from this can provide advice on which HM is most practical and reliable to diagnose cavitation erosion. The test environment is designed specifically to

detect cavitation erosion damage on centrifugal pumps and operates at significantly higher pressures and flow rates than the previously referenced work.

2.7 Commercial Benefits of Implementing HM

Incorporating Health Monitoring (HM) for airframe fuel pumps can result in significant cost savings by improving operations in numerous ways. However, since the sponsor has not provided any in-service data, it is not possible to accurately estimate the financial benefits of implementing HM for airframe fuel pumps alone. The discussions and financial projections presented in this section are for generic aircraft components, but they can also be applied to airframe fuel pumps.

One of the main advantages of using HM (Health Monitoring) is its ability to minimize costs associated with unscheduled disruptions. These disruptions could include flight cancellations, turnbacks, delays, and diversions. HM can reduce these events by utilizing fault forwarding and re-prioritization based on the current state of its equipment [99].

Sensors are capable of continuously measuring the performance of various systems, including the motor speeds, current, pump pressure, and flowrate, as demonstrated in **Sections 5** and **6**. When integrated into aircraft, the data collected by these sensors can be streamed on connected aircraft to provide real-time information related to system and equipment performance. This allows maintenance teams to be continuously informed and troubleshoot problems in real-time, which can help mitigate equipment-related problems through workaround actions before they become a failure. Based on this information, missions can be planned to avoid unscheduled Aircraft on Ground (AOG) situations at guest airports. Moreover, HM not only helps reduce costs and improve operational safety, but also allows for the identification of parts inside the fuel system that require immediate attention and appropriate actions to be taken, ultimately saving costs for the airline operator.

A report by Grouse [100] reveals that airlines spend 10% of their operating expenses on maintenance fees, which might be responsible for the delays that occur. In 2016, operators spent a total of US\$62.1 billion on maintenance repair

operations (MRO) costs, with 40% of these costs being related to engine components like the fuel delivery system. This value is expected to rise to US\$90 billion by 2024.

2.7.1 Fault-Forwarding

By developing the ability for Health Monitoring (HM), component faults can be identified electronically, such as airframe fuel pump reports [99]. This allows the required components for repair to be prepared in advance before the aircraft arrives or at the appropriate maintenance interval. Around 75% of airline managers reported that optimising logistics was important for maintenance operations and to reduce delayed departures [100]. This information can be used for predictive maintenance, technical analysis for ground crew, and to advise flight crew on diversion-related decisions [6]. This is particularly critical for airframe fuel pumps and other components in the fuel systems, where replacing the components takes longer than other parts of the aircraft.

2.7.2 Prioritisation and Improved Supply Chain Efficiencies

Airbus aircraft equipped with Connected technology can collect and transmit data related to 24,000 health parameters to ground operators. This data is then sent to a cloud-based platform that can be used to generate work orders, component data, and plan maintenance operations based on flight schedules. The data can be streamed in real-time or triggered by the installed HM algorithm [100]. Remote HM is especially beneficial for maintenance operations as it improves component availability for fuel system parts. If a fault is reported during a flight, the maintenance team can quickly identify the problematic component and find a suitable replacement [6].

2.7.3 Reduced No-Fault-Found

Streamlining Health Monitoring (HM) data during flight can reduce the occurrence of No Fault Found (NFF) incidents. NFF is a situation when the built-in test equipment (BITE) of an aircraft registers a failure, but no fault is found when the component is brought for repairs. This results in a significant amount of time and labor wasted in making a planned repair action for a component that does not need it [99].

Airlines have identified that NFFs occur for approximately 30% of all avionics removal, costing an average of US\$150,000 per incident and translating to US\$3.3 billion per year. However, HM with a connected aircraft has proven to be the only real long-term solution to reduce NFF. The data streaming from connected aircraft has enabled operators to reduce NFFs by up to 15%, resulting in significant savings [100].

For example, an aircraft Line Replaceable Unit (LRU) from an operator can have a rate of 60% for NFF, costing US\$30,000 annually from wasted labor alone. Visual inspection has only been successful in troubleshooting 25% of the occurrences. It has been projected that if NFFs can be reduced by 40%, a saving of US\$1.3 billion costs can be made from this problem alone.

Moreover, the savings will be much more significant for NFFs in an airframe fuel pump, where the time and labour costs are significantly higher than LRUs. Removing the pump would require a significant amount of time from draining the tank and going inside it, whereas LRUs are largely modular in design. It is estimated that an LRU takes over an hour, whereas replacing an airframe fuel pump may take half a day to do.

2.7.4 Financial Management from Servicing Aircraft

The results obtained from HM analyses can be utilized to forecast the running costs associated with a particular aircraft. Based on the collected data, operators can make financial decisions regarding the performance of the aircraft in its present state and evaluate its profitability. HM can also be used to optimize the scheduling of inspections, minimizing the overall maintenance costs, and increasing the financial efficiency of maintenance operations [101].

2.7.5 Reduced Down-time disruptions

According to Grous [100], Health Monitoring (HM) can be used to determine the probability of unexpected disruptions and calculate associated costs. For instance, HM can help reduce the Aircraft on Ground (AOG) time which could cost up to US\$150,000 per hour. AOG occurs when an aircraft has to be grounded on a guest airport for an unscheduled repair, and during this time, the operator has to pay huge financial penalties for leasing the space until the aircraft is able to fly again. AOGs have a significant impact on the overall operating costs

of airlines, and their rate varies depending on several factors such as the size of the aircraft, airport, and load. In 2018, it was estimated that AOGs cost the airline industry US\$62 billion annually.

Data from HM can help estimate the remaining useful life (RUL) of critical components and alert operators about components that are likely to fail soon. With this information, missions can be planned accordingly, and AOGs can be minimized by replacing the critical components in advance. Operators and other key stakeholders believe that HM data from a connected aircraft could lead to a significant reduction in AOGs. If AOGs could be reduced by 50% through HM, airlines globally could achieve savings of up to US\$15 billion.

AOG reduction is one area where HM could improve, and airline operators have set a target cost reduction of 5%-15%.

Unscheduled maintenance	Reduction	Est. Year	Narrowbody		Widebody	
			Cost (\$)	Saving (\$)	Cost (\$)	Saving (\$)
Cancellations	5%	2025	82m	4.3m	245m	13m
Delays			5414m	285m	8422m	443m
Cancellations	25%		64.7m	21.6m	194m	64.7m
Delays			4274m	1424m	6650m	2216m
Cancellations	5%	2035	118m	6.2m	353m	18.6m
Delays			7792m	410m	12121m	638m
Cancellations	25%		93m	31m	279m	93m
Delays			6151m	2050m	9569m	3189m

Table 1. List of costs from unscheduled maintenance and projected savings from HM implementation [100]

It is important to note that unscheduled maintenance can have a significant impact on airline operations, causing 3.06%–4.76% of delays and 0.085%–0.68% of cancelled flights [100]. **Table 1** provides an estimate of the global cost of flight delays and cancellations due to maintenance-related issues in 2017, 2025, and 2035 if HM (health monitoring) is not implemented.

According to **Table 1**, if HM is implemented as part of predictive maintenance, it can reduce inspection costs by 30% and decrease the number of delays by 25%. It's worth noting that this percentage is based on generic faults across aircraft,

but it can be applied to fuel-system related maintenance costs as well. This is especially important as fuel components are located inside the wing and are submerged in fuel, which can lead to more significant penalties from unscheduled maintenance and sudden breakdowns.

2.8 HM Literature Summary and Knowledge Gaps

Table 2 provides a summary review of different types of HM detection methods and related faults used on either the airframe fuel system or engine fuel system. Note that a distinction has been made between the engine fuel pump and the aircraft hydraulic pump. Engine fuel pump refers to the entire engine fuel pumping sub-system, including the centrifugal pressure backing pumps and the hydraulic pump that is installed in series. Aircraft hydraulic pump refers to that type of pump itself. This same type of pump may be installed individually on other systems such as helicopter hydraulic systems. The airframe fuel pump refers to the centrifugal pump that is installed within the airframe fuel system.

As highlighted by **Table 2**, In total there are 11 publications for the HM of aircraft hydraulic pumps, 10 for airframe fuel pumps and 8 for pumps for the engine fuel pump. There are also a few publications for engine fuel metering pumps, fuel valves and lubrication pumps which constitute part of the engine fuel system. These sources are from a range of publications since the year of 1999 up to 2020. The earliest work was carried out by Haylock et al. [55] which was a method for HM for winding failures using ESA, intended for airframe fuel pumps. Work by Johnston & Edge [59] attempts to simulate the aircraft environment for testing engine fuel pumps, but this work does not have any HM-specific content, and therefore is excluded from **Table 2**. The techniques that have been developed by Johnston & Todd [38] are a continuation of the aforementioned work.

#	Detection	Fault	Method Summary	Equipment Type	Ref.
1.	Thermal	General degradation	Utilized parameters of one equipment to determine the health of another	Aircraft Fuel Pumps and Valves	[65]
2.			Recorded temperature across fuel system to estimate RUL	Engine Fuel System	[42]
3.			Physical modelling techniques used to analyze temperature influences on component performance (used on hydraulic pumps)	Aircraft Mechanical face seals	[13, 14, 15]
4.				Aircraft Hydraulic Pump	[43]
5.	Vibration	Bearing	RQA method on vibration for diagnosis of bearing-related faults on pumps.	Airframe Fuel Pump	[47]
6.		Bearing, abrasion, low pressure, clearances	Experimental methods using frequency domain analyses methods to detect and classify common faults.	Aircraft Hydraulic Pump	[46]
7.		Axial displacement, Impeller erosion, rubbing,		Airframe Fuel Pump	[48]
8.		Cavitation, Blockage			[52]
9.	Electrical	Winding	Leveraged input current ripples to diagnose for shorted coil windings		[55, 56]
10.	Pressure	Bearing	Like the frequency domain methods above, but includes a model to compare the sampled signals for HM	Engine Fuel Pump	[38]
11.		Blockages	Algorithms that utilized pressure points in fuel system to predict sudden blockages and valve shut offs.	Aircraft Fuel System	[34, 10]
12.			Prognostic algorithm based on pump outlet pressure to estimate RUL	Airframe Fuel Pump	[26, 32]
13.				Aircraft Hydraulic Pumps	[27]
14.		General degradation	Adjusts speed of pump to desired output pressure and samples the motor current for HM	Engine Fuel Metering Pump	[102]

15.			Leverages a reference model to compare the sampled signals	Airborne Lubrication Pump	[16, 17]
16.			Records the position of the valves and line pressures then compares it to some reference value	Aircraft Fuel Valve	[60]
17.		Cavitation	Model used to predict cavitation occurring by monitoring transient pressures across system		[58]
18.		System Leaks	Utilized multiple pressures sampled across system and actuator position to classify faults		[61]
19.	Flowrate		Prognostics algorithm based on return oil flow to estimate RUL of equipment.	Aircraft Hydraulic Pump	[62, 64]
20.					[29]
21.		General Degradation	Hybrid approach using a reference model and in-service data.		[27]
22.			Monitors the quantity of debris at pump outlet to assess engine health	Engine Fuel Pump	[103]
23.		System Leaks	Hybrid based approach using a reference model and in-service data.		[63]
24.	Rotation Speed	General Degradation	Utilized rotational speed at which light-off is achieved for diagnosis		[67]

Table 2. Summary of HM detection methods and related faults

Most methods of HM for airframe fuel pumps are pressure based and ESA, with 3 publications for each method. The success of each method is not known, as there are no in-service data to provide evidence for their reliability. Most of the HM works have been tested under lab-conditions and no evidence has been shown for their function during flight conditions. The work by Johnston & Todd [38] for an engine fuel pump, has made some attempt to simulate HM for flight conditions by creating a disturbance using a rotary valve. The work that has been devised by Al-Tayawe et al., [26] gives an indication on how the HM might be executed when there are external disturbances from the aircraft environment, but no working prototype has been demonstrated. This highlights that there is large scope for development for HM of airborne fuel pumps, principally for airframe fuel

pumps, as there are few published works which attempt to diagnose common faults. More value can be added to future findings if these works can not only diagnose faults but also perform HM when exposed to the aircraft environment. This also applies to publications for both engine fuel pumps and aircraft hydraulic pumps, where the HM is carried out under lab conditions.

Flowrate measurement have not been widely used for the HM of airframe fuel pumps as leakage flows are not easily captured on centrifugal pumps and often the flowrate captured is influenced by the behaviour of other equipment in the same flow network. Isolating faults using flowrate quantities alone for an airframe fuel pump is not practical. A similar work was carried out by Hoffman [31] under lab conditions. This not only highlights an alternative method of HM by monitoring flow quality, but also demonstrated how sensors attached to airborne pumps can be used to carry out HM for other components within the system.

Other works concerning predictive maintenance on aircraft have been carried out by Kahlert [6] and Pandian et al. [23] outline the benefits of applying HM to aircraft operations and propose a general strategy on how an HM solution could potentially be implemented with existing aircraft maintenance routines. These works, however, do not provide specific detail on how a test and certification regime could be applied to an already-developed HM solution. There is also no detail on how the HM diagnosis is implemented for fuel pumps.

Past works have been carried out to perform HM on water pumps for cavitation erosion from Adamkowski et al. [45] using vibration sensing only. Wang et al. [98] describes a test-rig used to carry-out HM to detect for wear caused by slurry erosion, but only discusses the setup without the results. Another data-based method for aircraft fuel pumps by Jiao et al. [48] uses vibration monitoring to distinguish different pump faults but does not propose a scheme to detect for an eroded impeller. Previous works by the various authors [72, 73, 74, 76, 77] describe the damage and performance penalties caused by slurry erosion but does not suggest a HM scheme to detect it. Slurry erosion is similar to cavitation erosion but the wear is caused by fine particles present in the fluid.

Previous CFD simulations on cavitation erosion have been focused on the visual study of the vapor fractions and identifying erosion areas. Previous works such as by Dular et al., [71] and Dular & Coutier-Degosha [104], Usta et al. [93] as well as Li and Van Terswiga [91] have respectively developed the field functions to predict erosion and tested it on single-stage pumps, propellers and aerofoils. The works by Dular used an erosion model initially developed by Fortes-Patella, Reboud & Briancon-Marjollet [105] through experiments carried-out on an aerofoil. Portfolio #2 submission [4] extends the previous works by predicting erosion damage on two-stage pumps.

The proposed fault testing scheme uses the erosion wear areas as identified in portfolio submission #2 [4] and artificially creates erosions on the impeller as a means of accelerated fault testing. This work therefore extends the findings from the Gray Level Method (GLM) [71] to project the wear areas, experimentally test artificially eroded impellers, and to then develop a HM scheme. The test-rig system flow and pump head rise data is gathered to determine the appropriate operating points for the pump and later linked to the HM method. Current sensors are used in each of the three phases of the motor terminals to conduct an electrical signature analysis (ESA). These types of sensors are chosen, as they are largely non-intrusive and low-cost when compared to torque, acoustic and vibration techniques [106]. This is highly desirable for simple but also cost-effective implementations of HM.

3. Thesis Aims and Objectives

3.1 Aims

The aim of the thesis is to develop a health monitoring solution that combines different methods, which can be used to detect cavitation erosion in the airframe fuel pump. The proposed solution relies on CFD simulations, system models implemented in Simscape and an experimental test-rig.

3.2 Objectives

1. Investigate factors which affect the fuel pump's performance as a result of cavitation erosion.
2. Review and shortlist the most viable measurement techniques to diagnose cavitation erosion.
3. Build and validate a functioning test rig that executes a fuel transfer tank.
4. Build and validate a simulated system model of the live test rig on Simscape.
5. Build and validate a simulated CFD model of the pump used in the test rig and the model used to estimate erosion damage on the pump.
6. Replicate the erosion damage at various discretized steps throughout its life as a means of accelerated fault-testing, using CFD to project erosion areas.
7. Simulate erosion damage on CFD and highlight erosion-sensitive areas.
8. Capture health indicators from the test rig that are sensitive to different levels of erosion and compare them with CFD.
9. Input differences resulting from erosion damage to the system model on Simscape.
10. Derive conclusions regarding the final chosen measurement points for pump HM.

3.3 Statement of Innovation

The work carried out proposes a new method for health monitoring (HM) of airframe fuel pumps, specifically for diagnosing cavitation erosion. The method developed is a hybrid approach that combines computational fluid dynamics (CFD), a system model running on Simscape, and an experimental test-rig to validate the results. The HM proposed in the thesis is not only useful for diagnosing faults related to cavitation erosion, but can also be extended to detect

other common pump faults, such as axial displacement. This hybrid approach is also applicable for developing HM for other electrically powered devices, such as robotic actuators.

Numerous studies have been conducted to perform HM diagnostics on various types of faults such as bearing, motor winding, and axial displacement defects. However, there have been very few studies done specifically on HM for cavitation erosion. To bridge this knowledge gap, research has been carried out to identify and develop sensing techniques that would be most appropriate for fuel pumps installed in aircraft environments.

The research study showed a new application of a BLDC motor for HM, which offers distinctive features compared to its AC counterpart. Additionally, the CFD methods used demonstrated an accelerated fault testing technique for cavitation erosion, which is a substitute for the natural damage of blade samples.

The thesis discusses a novel study that compares the viability of different sensing methods for diagnosing cavitation erosion. It provides an overview of the advantages and disadvantages of each method, as well as their sensitivity for detecting the fault. The findings of the study, along with knowledge of sensor installations and limitations of the aircraft fuel system environment, can be used to implement HM for airframe fuel pumps in the existing fleet or for next-generation aircraft.

The proposed CFD methods improve the design and prototyping process of pumps by accurately monitoring performance degradation in software. The findings from the model running in Simscape provide evidence that this environment has the required level of fidelity to model cavitation erosion with some additional code and can be useful for HM. These techniques can be extended to similar methods to recreate other equipment faults and help develop HM strategies.

The findings from the pressure sensor outlined in the study prove the viability of pressure-based HM. The sensor used in the test-rig meets the installation requirements of an aircraft fuel system, as it relies on a simple and lightweight device.

Similarly, the flowmeter and current sensing methods developed show positive outcomes for cavitation erosion detection. The primary advantage of these two methods is that the sensors are already installed in existing aircraft. An additional set of logic would only need to be implemented to detect changes to those erosion-sensitive parameters.

4. Materials & Methodology

4.1 Test-Rig Configuration

The primary goal of the HM test-environment is not to stimulate pump cavitation and detect it, but to detect the damage caused by the subsequent erosion and have a diagnostic technique that can differentiate various levels of its severity. The test rig is illustrated in **Figure 6**. Full specifications, calibration and uncertainty analyses of the HM test-environment can be found on portfolio #3 submission [2].

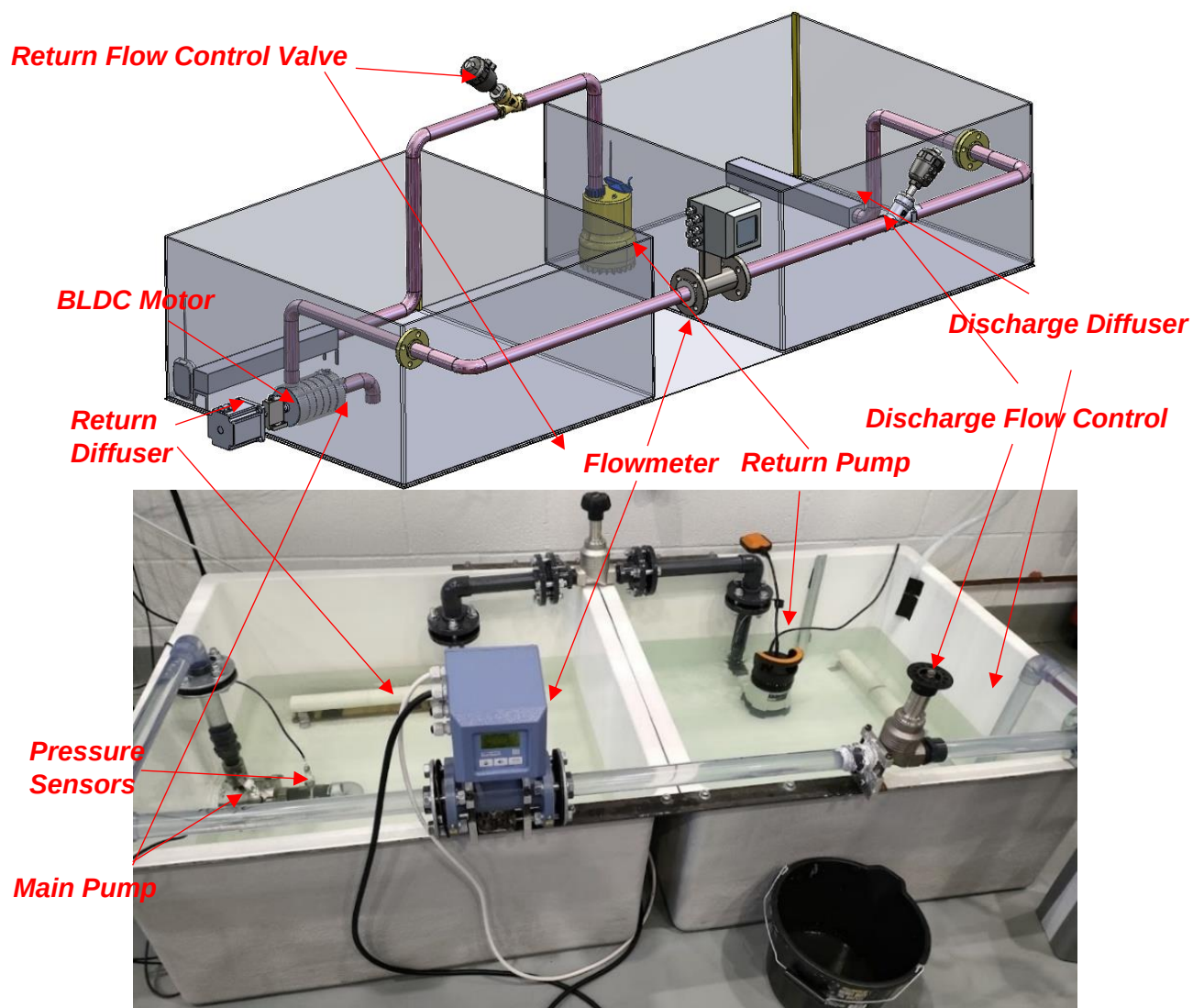


Figure 6. Test-Rig 3D-Render and Actual Installation On-site

4.1.1 Main Pump

The main pump being used in the experiment and modelling activities is a centrifugal pump with a two-stage impeller. It has a 1.25-inch inlet (31.75 mm) and a 1.0-inch (25 mm) outlet, the diameter of the impeller is 95mm and the pump case is 100 mm. The impeller has 5 blades, but its specific speed and blade curvature are not specified by the manufacturer. The head-flow performance curve of the pump is outlined in **Figure 18a**, while blade geometry is depicted in **Figure 16**. In addition to being representative of many pumps in industry, this specific pump model is chosen as spares are widely available in the market, making it practical and cost-effective for carrying out fault-related experiments.

4.1.2 Tank Design and Piping Installation

The test-rig uses a two-tank layout so that the outgoing fluid flow does not create disturbance in the main tank. The tanks have a capacity of 400L. The pump is submerged in water and mounted on the side of the tank as this is the most practical installation of a submersible pump. A snorkel is installed in the inlet to decrease the unusable fluid level. The tank is created out of glass reinforced plastic (GRP) for strength. The pump centre of rotation is placed 110mm above the base of the GRP tank to allow ease of installation with the motor components outside the tank. **Figure 7** depicts the process diagram of the test-rig setup.

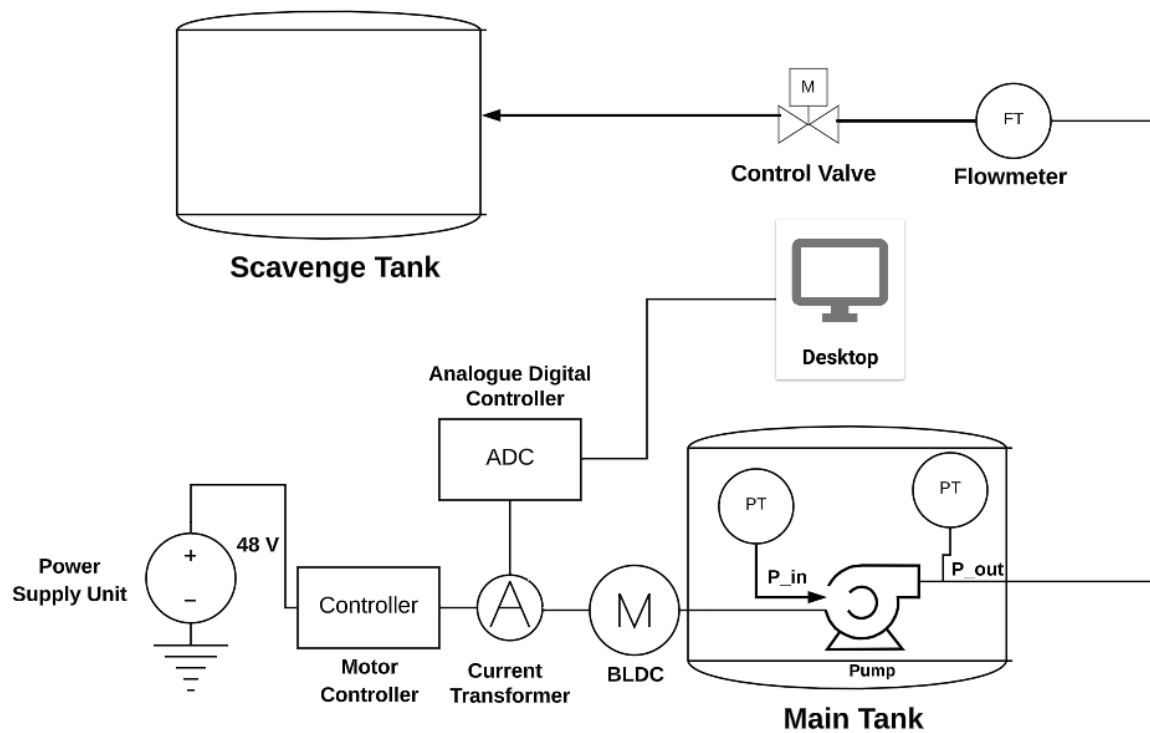


Figure 7. Schematic View of Test-Rig

The pipe material chosen is transparent PVC, as it meets the operating pressures of the pump and allows the flow to be visually monitored for any abnormalities. A pipe with 1.25-Inch (31.75 mm) inner diameter is chosen so that the entire cross section is filled with water under normal operating conditions. This pipe diameter allows a fluid velocity of over 0.5 m/s under the lowest operating flowrate, and near 3 m/s on the highest, which ensures reliable operation of the magnetic flowmeter. The total pipe length is approximately 5m so that other test-rig components such as pipe elbows, flowmeters and valve can have the required pipe distance between each other.

4.1.3 Motor Details and Installation

A 1 kW, 48VDC BLDC motor is used to power the pump. The model of the motor is the D110BLD1000-48A-30S and controller is BLD-50A both by DMKE. The motor supply voltage is connected to the motor controller unit receives the motor hall-effect sensors input and provide the appropriate speed regulation. The motor has an operating speed of 0 to 3500 RPM, which can be modulated via a potentiometer input in the controller interface.

4.1.4 Pump Control Strategy

The pump speed is operated at either 2900 RPM, or 3500 RPM as recommended by the pump manufacturer. Operating the pump above or below these speeds is not recommended, as it is outside the intended operating points by the manufacturer. The impeller may be operated outside the pump rotors' specific speed, and thus the head-flow characteristics may deviate from the known characteristic behaviour. Operating between these mentioned speed boundaries is also possible, but there will be no reference data from the manufacturer datasheet to validate the data with. To modulate the flow a globe valve is used. Throttling the valve moves the operation point of the pump along the head and flow, while varying the motor speed shifts head flow curve diagonally as highlighted in **Figure 18a**. The BLDC motor has its own controller unit that controls the switching electronics for motor speed regulation using Pulse-Width Modulation (PWM) at a switching frequency of 10 kHz. This controller is a Proportional Integral and Derivative (PID) cascade controller with a speed outer-loop and a current inner loop. The values of the gains and stability limits are not specified by the manufacturer and the model running on Simscape was manually calibrated until the performance of the two systems matched.

4.1.5 Data Acquisition Unit

The motor is operated at a maximum of 3500 RPM, which is equivalent to rotation frequency of 116.67 Hz. The fundamental frequency when performing frequency-domain analysis for the current signature is widely accepted to be up to the 10th harmonic (1166.7 Hz), above which one will experience significant attenuation with resulting small signal noise ratios [98]. According to Nyquist Sampling Theorem, the minimum sampling frequency should be at least twice the signal of interest, but a sampling frequency of ten times the signal of interest is recommended for improved signal resolution [107]. Following the latter recommendation, yields a minimum sampling frequency of 11.67 kHz. The Texas Instruments ADS8588SEVM-PDK is used as the data acquisition unit for its high sample rate in each channel. This unit has a dedicated Analogue Digital Controller (ADC) on each of its 8 inputs with a sample rate of up to 200 kHz on

each channel, allowing simultaneous data capture of multiple sensors. A sampling rate of 50 kHz is chosen as this is twice the sensing bandwidth of both the pressure and current sensors at 25 and 23 kHz respectively, and to keep data sizes manageable. The ADC can accept input voltage ranges of $\pm 10\text{V}$ on its analogue inputs with a resolution of 16 bits, so it is compatible with most of the selected sensors.

4.1.6 Sensor Specification and Installation

Current, flow, pressure and temperature sensors are installed on the test rig. The installation points of the sensors on the test rig are defined as follows:

Current Sensor: WCS1800 current transformers (CT) are placed between the motor input terminals and the output of the inverter bridge circuit, so that each of the three motor phase currents can be individually measured. This particular model is connected Integrated Circuit (IC) on a board which amplifies the CT output signal before reaching the ADC. CTs are used for current sensing as it does not make a direct electrical connection with the motor, protecting the ADC from large currents and voltages that the unit is not rated for. CTs measure the current value by measuring the change in magnetic field as a result of the BLDC trapezoidal current profile in each of its three phases. This model sensors are capable of measuring the current up to $\pm 35\text{A}$ and has a bandwidth of 23 kHz. The current output does not exceed 25A peak for each phase, the extra 10A headroom allows sufficient headroom to capture large spurious transients that may appear during the fault-testing phase. The CTs convert the measured current at a rate of 0.08A/V , meaning that the sensors will output 1V to the ADC, for every 0.08A measured. At 0A, the current sensors output a voltage of 3.7V. This is intended the drift voltage from the built-in ICs to indicate that the sensor is functioning as intended. The sensors outputs 1V at 0A when it is faulty.

Flow Sensor: The Burkert SE56 magnetic flowmeter as this technology provide the greatest resilience to pipe vibrations and shockwave disturbances from the pump. The distance between the neighbouring pipe bend and the valve is placed 5 pipe diameters (159mm) as this is the distance recommended by the manufacturer to eliminate any flow disturbances caused by the adjacent

components. The output of the flowmeter is set as an impulse and frequency on both of its channels to represent the same flowrate output in different ways. The impulse output signal is a duty cycle between 0 to 100% between the maximum and minimum flowrate of the system specified by the user, which in this case is 0.25 l/s and 2.5 l/s. The frequency output generates a maximum frequency of 100 Hz at the maximum flowrate and 10 Hz at the minimum. Any flow abnormalities such as reverse flows can be detected by visual inspection of the transparent pipe or by alarm outputs of the sensor. For magnetic flowmeters, the pulse and frequency outputs are preferred over 4-20mA signal for HM application, as it is representing the captured signals in its most raw form, ensuring that no information is lost.

Pressure Sensors: Two Burkert 8316 pressure transmitters are installed on the test rig pipes placed two pipe diameters away (63.5mm) on the respective pump inlet and outlets. This model is chosen as it is within the measurement range to capture the pump head rise of 0-40m and has a bandwidth of 25 kHz. The sensor outputs a 4-20mA signal and is interfaced a termination resistor of 250-ohm that converts the output range to 1-5V to represent the pressure range to the ADC. The method of installation and parameter extraction follows the standard outlined by ISO 9906 Annex A [108]. The sensors are installed at two measurement points, so the pump head rise is accurately measured.

Temperature Sensor: A thermal imaging camera is used to monitor the temperature of the motor and record increases as a result of the erosion. This tool is advantageous as multiple areas of the system can be simultaneously monitored. The camera has a resolution of 1°C and saves the output as an image.

4.2 Test-Rig Simulation Model

The simulation model of the test-rig running on Simscape, depicted by **Figure 8**, is used to produce additional model data for the purpose of the HM algorithm development. The model is implemented using the MATLAB/Simscape environment and makes use 'thermal liquid' (TL), mechanical and electrical domain components. This software package is used for the system model as it provided a sufficient level of fidelity to carry out model-based HM, as highlighted

by previous works for diagnosing motor-related faults [96, 97]. It also has the advantage of doing multi-domain physics simulation, so all the parameters of the test-rig can be simulated in a single model. This ensures fluid property variations due to temperature is accounted for.

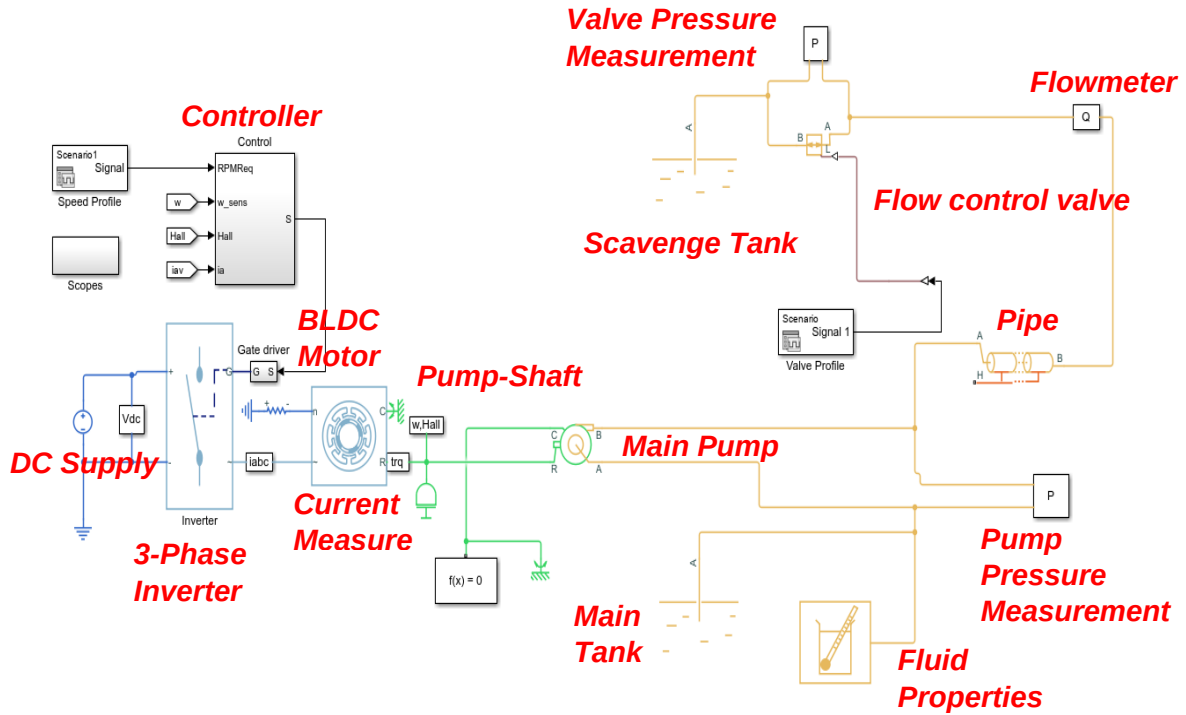


Figure 8. Simscape Simulation set-up

4.2.1 Electromechanical Components

BLDC Motor: The motor is modelled to reflect the component that is installed on the test-rig to power the pump. The phase currents are measured on each phase input of the inverter, in between the controller output. The motor has similar defining parameters as the installed unit. The BLDC model in Simscape models the electrical components as a resistor-inductor component. The user can define the pole number, the value of the resistor, inductor & and mutual inductances, as well as motor inertia. The stator winding architecture and back-EMF profile can also be defined by the user, but this has been defined as wye-wound and trapezoidal to represent the motor.

Pump-Shaft Interface: The pump shaft interface connects the BLDC motor block with the pump and defines the rotational inertia. A torque sensor is connected in

the model but is not installed on the test-rig, mainly used to help tune the controller.

DC Power Supply: An ideal DC supply of 48V DC is used to represent the DC power supply powering the inverter.

Inverter: This element interfaces the 48V DC supply to the BLDC motor. The inverter converts the controller signals into voltages with the appropriate switching sequence to simultaneously power the motor and regulate its speed. The transistors are modelled as ideal components as at a low switching frequency of 10 kHz, the limitations of the transistors used are not apparent.

Current Sensor: An ideal current sensor is connected between 3-element wire outlined as 'iabc' to measure the current signals being output by the inverter going into the BLDC motor. The test-rig results have highlighted that the current ripples in the circuit are a greater source of uncertainty than the accuracy of the sensors themselves.

4.2.2 Fluid Components

Tanks: The two tanks are unsealed and are represented by the reservoir block with unlimited fluid quantity. The level of the fluid can be specified by the user to simulate the static head.

Pipe Segments: The pipe segment block used represents the pipe installation of the test-rig, such as the pipe length, diameter, material & surface roughness, and number of 90° pipe segments on the entire fluid path. The Reynolds number of the flow is also specified in this block and is chosen based on the CFD results.

Valve Block: The valve block is used to modulate the flow and its coefficients are the same as on the valve used on the test-rig. It is modelled to open with an equal percentage, and the valve coefficients at different open % are defined in a look-up table. The parameters inputted to this component are based on the flow coefficients values outlined in the manufacturer datasheet for the valve.

Main Pump: The main pump used on the test-rig is defined based on a look-up table with three elements: Pump rotational speed, and its corresponding head

Return Pump: The return pump and pipes are not simulated as their task in the test-rig is only to refill the main tank and keep water level at the same value during the run of the simulation and is not measured for HM. The tank level and static head can be defined using the reservoir block that simulates the tanks.

Flow Sensor: A single, ideal flowmeter highlighted by the 'Q' block is connected in series between the two tanks in the fluid path. Like the pressure sensor, the flow sensors are ideal as the errors is close to negligible, when compared to error caused by turbulence.

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Figure 9 represents the simulation set-up of the model running on Simscape. The areas highlighted in with the dashed red circles are the components that are modified for each erosion level to recreate its effects, as observed by the test-rig data. This is the same model as **Figure 10**, but an additional block element has been added called 'Erosion Effects'. This particular block is created to represent the pressure and flow fluctuations effects caused by the turbulent flows. This created block component is a necessary addition, as the pump block provided in Simulink does not provide sufficient level of fidelity to recreate those flow disturbances found on the test-rig. The centrifugal pump block simply uses a look-up table based on the assigned values for pressure and flow, then outputs a flat, constant values for pressure and flow based on the corresponding pump operating point. This pump operating point is controlled by the flow control valve, where the valve coefficient is assigned using the 'Valve Profile' signal block. **Figures 10** and **11** portrays each of those highlighted blocks in **Figure 9** when inspected in closer detail.

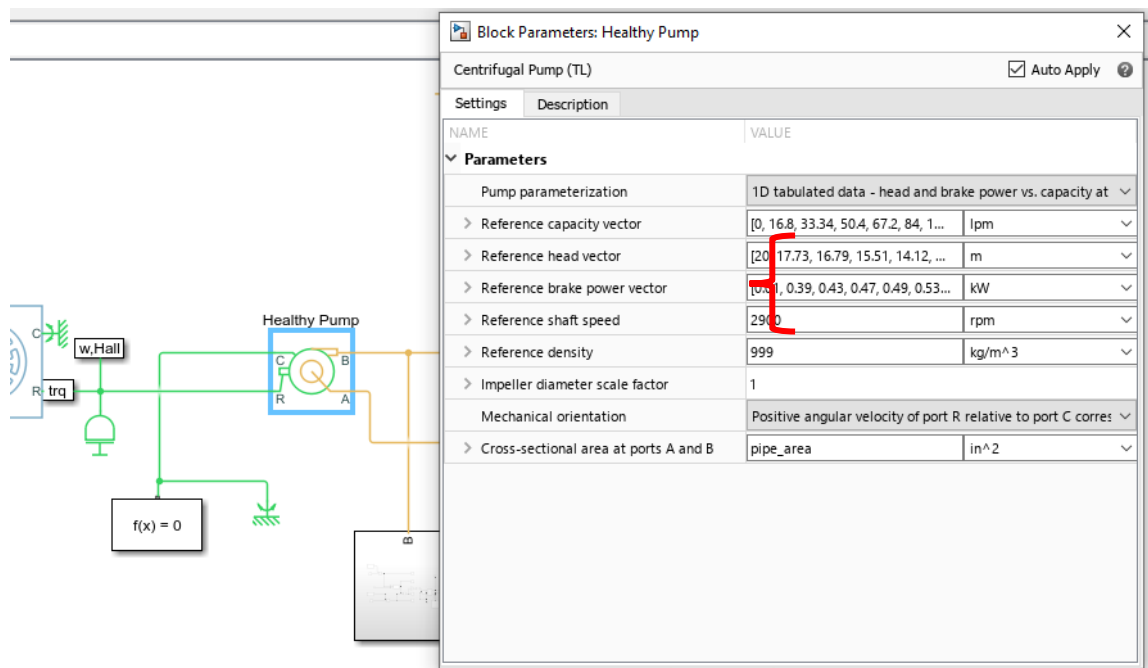


Figure 10. Pump Block Parameters used for Erosion Damage Definition

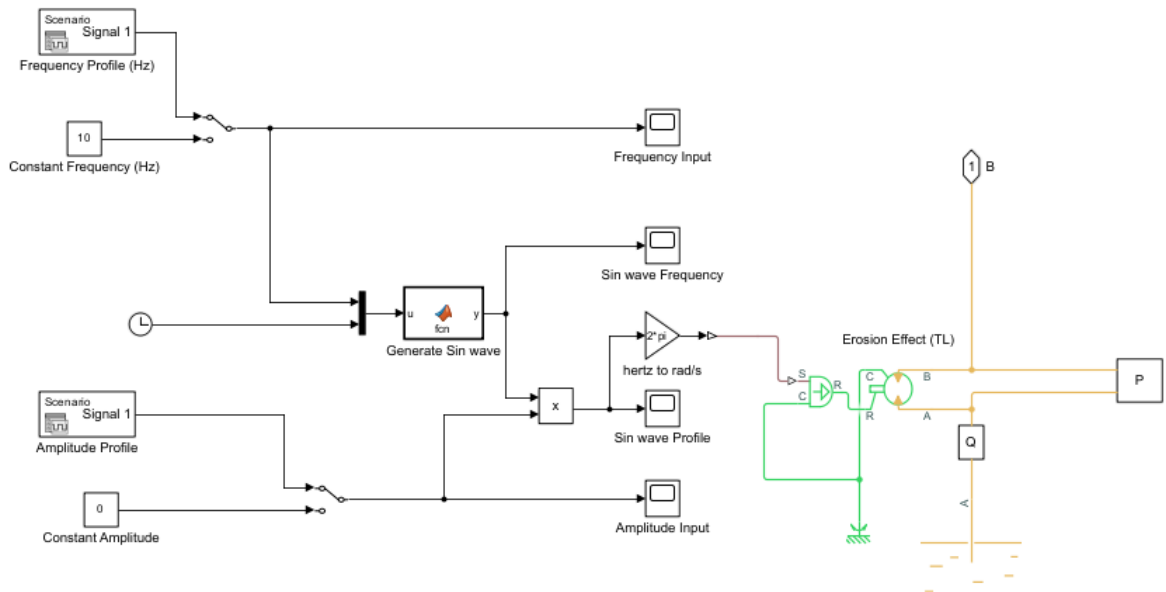


Figure 11. Inside 'Erosion Effect' block

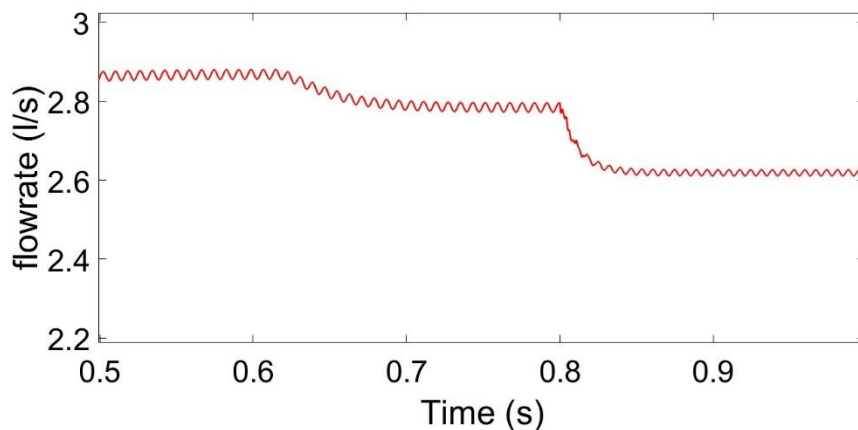


Figure 12. Influence of 'Erosion Effect' block to flowrate

Figures 10 and 11 provides a more detailed view of the components of the highlighted components in **Figure 9**. **Figure 10** examines the pump block parameters, the red parentheses highlight the variables that are modified to recreate the degradation effect caused by each erosion level, which are: 'Reference capacity vector', 'Reference Head Vector' and 'Brake Power Vector'. 'Reference Capacity Vector' refers to the flowrate of the pump, expressed in liters per minute or 'lpm'. Reference head vector refer to the pressure rise induced by the pump expressed in meters or 'm'. The reference brake power vector refers to the input power required to run the pump at a specific operating point within the head and flow curve expressed in 'kW'. Changing the values of the latter does

not affect the fluid-mechanic performance of the pump but affects the current draw of the BLDC motor at a given operating point in the head-flow curve. It is observed that with an eroded impeller, the flowrate stays largely unchanged and that the most noticeable changes are in the pressure output of the pump and the current output of the motor. Significant changes to the output current of the motor however, occurs only on the transition between healthy to severe erosion states, where a 11% sensitivity is outlined. Current-sensing as installed on the test-rig does not have sufficient sensitivity to distinguish between healthy and moderate erosion states. The results highlight that the pressure output of the pump degrade evenly in between the three erosion levels and that there is sufficient sensitivity of approximately 12%.

Figure 12 highlights the components inside the 'Erosion Effect' block. This block was designed based on the works by Gallo [109], where a similar capability of modelling flow ripples accurately was required for a positive-displacement pump. The techniques used in the mentioned work has been adapted to be used with a centrifugal pump. Two signal sources are outlined, 'frequency profile' and 'amplitude profile'. Each of those respective components vary the frequency and amplitude of the ripple waves respectively. Each block has a toggle switch to operate between their respective profiles or a constant value. The respective profile values are assigned to correspond to each amplitude and frequency of the pressure ripples to their respective pump operating points based on the collected test-rig data.

Figure 12 outlines a sample flowrate output with and without the erosion ripple effect activated. The effects are subtle as the oscillations in the flowrate have an order of $1\text{E-}02$ in amplitude. This sample is for a pump with moderate erosion running at 3500 RPM. Without the mechanism **Figure 11**, the sinusoidal ripples would be flat.

To deactivate the effects induced by this block, simply toggle the switch on the amplitude side to activate 'constant amplitude' mode, where the sinewave amplitude is set to 0, thereby nullifying the effects of the entire block. This is useful if the effects from the pump ripples do not wish to be included in simulation.

Constant frequency selects the default value of 10 Hz, as this is sufficiently low in comparison to the order of amplitude of the actual frequency of the ripples observed, which are between 100 to 200 Hz.

The generate sine wave function is a user-created script that generates a sine wave output with the same frequency values as the input. The output of the frequency is multiplied the amplitude profile so that the sine wave generated has the combined properties of the desired frequency and amplitude profile. The output frequency is converted to rad/s from hertz as the rotation block operates in radians. The ideal rotation block provides motive power to the fixed-displacement pump to provide the necessary flow disturbance that corresponds to the operating values found on the test-rig. Using the ideal rotation block is necessary as the test-rig results indicate that no additional harmonics are generated from the different erosion levels. Linking the motive power from the fixed-displacement pump input to the pump would have generated additional harmonics that would not be consistent with the test-rig findings.

4.3 CFD Modelling

The areas mostly affected by cavitation erosion are identified using CFD simulations run with Star-CCM+ as there are previous works that have accurately predicted cavitation using the same software package such as the work by Yilmaz, Atlar & Khorasanchi [110] and Ge, Svenborg & Bensow [111]. The areas most affected by erosion effect are identified by implementing the GLM field function initially developed by Dular [71]. STAR-CCM+ provides variations of the κ - ϵ and κ - ω to allow for the selection of different turbulence models depending on the application. The multiphase fluid model is used for H₂O provided by the fluid database in Star-CCM+.

The κ - ω shear stress transport turbulence (SST) model is used, as it combines the advantages of κ - ϵ , and the κ - ω models. κ - ω SST (Menter) applies the boundary layer estimation using κ - ω formulation which allows the model to accurately estimate the boundary layers from the viscous sub-layer to the surface wall. Through the use of an additional blending function, the κ - ϵ behaviour is

applied in the free-stream and avoids the common problem with $\kappa\text{-}\omega$ in over-estimating boundary layer separation [112].

Compared to other turbulence models, $\kappa\text{-}\omega$ SST provided the relatively superior accuracy for estimating the boundary layers near and far from the wall surfaces for steady-state simulations [113]. Its usefulness for unsteady simulations has also been validated Mao et al. [112], Zhang [114] and Deyou et al. [115]. A high level of alignment with experimental data was achieved in scenarios that have adverse pressure gradients and separating flows.

The eroded component is 3D scanned and re-assembled in software to replace the healthy component, the same as it would be in the test-rig installation. The pump in CFD is run at identical test conditions as the pump on test-rig, which is being submerged underwater. The performance of the impeller is tested, and the HM parameters of interest are monitored, except for motor currents, as this is not possible to be monitored in CFD. After ensuring that the data from the test-rig and CFD are consistent, the differences between the healthy and eroded impeller are analysed. This is to understand whether the erosion causes any noticeable change to the monitored parameters and a HM solution can be developed. The differences as a result of the erosion will create the adjustment factors in the model being run in Simscape.

4.3.1 Implementation of Erosion Model in CFD

The erosion mechanism is explained in the following section using **Figure 13**. The sequence of events starting from cavitation to erosion damage and related equations are summarised in the steps outlined in this section. The diagram has been reproduced from the work of Dular et al. [71]. The events of cavitation erosion are described as follows:

1. The cavitation cloud collapse creates a shockwave that spreads onto the fluid. The magnitude of the emitted pressure wave P_{wave} is closely related to the velocity of the change of the vapour cloud volume ($d\alpha/dt$).
2. The magnitude of the shock wave as it travels towards the solid surface. The mathematical description that highlights events 1. and 2. are summarised by Eq. (2).

3. Single bubbles are present near the solid surface. As the shock wave reaches the single bubbles near the surface, the bubbles begin to oscillate and form a bubble-jet with velocity v_{jet} , that damages the surface. Eq. (3) highlights the relationship governing the bubble jet creation. Eq. (4) and Eq. (5) outlines the criteria these jet bubbles must meet to induce erosion damage onto the surface. The minimum vapor fraction of $\alpha > 0.01$ is needed so that sufficient bubbles are present to cause erosion [116].
4. The high-velocity liquid jet from the bubbles v_{jet} impact the solid surface and erodes the surface creating a pit area A_{pit} . The magnitude of A_{pit} is directly related with the bubble-jet velocity v_{jet} as expressed by Eq. (4) to (9).

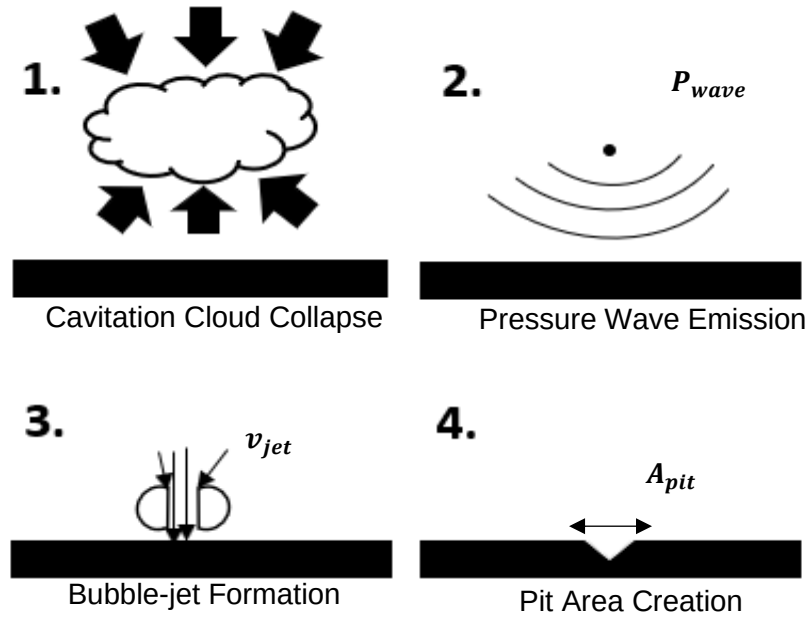


Figure 13. Events related to cavitation damage

The main mechanism responsible for damage on the solid surface is from the water hammer stress that is generated by the velocity of the jet bubbles v_{jet} . The approach to predict erosion is based on when a threshold compressive stress is reached, and that after this point the deformation of the solid is fully plastic. The deformation, and thus pit area creation occurs only if the bubble jet velocity v_{jet} can result in a stress value that is high enough to overcome the yield stress of the material p_y , which is expressed by v_{crit} . As v_{jet} travels through the fluid, some

of the energy is lost within the medium and some absorbed by the body of the material during impact. The excess energy that deforms the surface is highlighted by Eq. (5) velocity of deformation v_{def} . The excess energy from the impact expressed by v_{def} then creates the plastic deformation on the surface with pit area A_{pit} .

The method by which the erosion damage is predicted in CFD is by utilizing field functions. All of the simulations are calculated using variables which have already been generated from the cavitation simulations and thus can be carried out with only a small addition to computational cost. The erosion algorithm is implemented in post-processing and is updated at the end of each time-step of the run.

The simplified Gray Level Method (GLM) works by taking the pressure observed at cell P with the vapor pressure P_v multiplied by the derivative of the vapour fraction α as highlighted by Eq. (2). A more rigorous implementation is highlighted by the subsequent Eq. (3) to (9) and is the focus of this work. The implementation has been verified with a hydrofoil in the works of Dular & Coutier-Degosha [104] and Peters et al [116], but never been implemented on a radial pump. Dular et al. did not use CFD to predict erosion in [71]. The sequence of calculations that have been used to implement the erosion model is outlined below:

$$P_{wave} = (P - P_v) \left(\frac{d\alpha}{dt} \right) \quad (2)$$

Equation 2. Cavitation Pressure Shockwave

Eq. (2) highlights how the magnitude of emitted pressure wave P_{wave} is related to the velocity of the change of the vapour cloud volume from the cavitation cloud collapse. It is a simplified version of GLM implementation than can generate the approximate wear areas, and outlines the general principle of the more rigorous version of the erosion model. Eq. (2) can be implemented by itself without Eq. (3) to (9) to approximate the wear areas but this method will not be able to calculate the quantity of erosion damage.

(3)

$$v_{jet} = 8.97\gamma^2 \sqrt{\frac{P - P_v}{\rho}}$$

Equation 3. Bubble-jet Velocity

v_{jet} is the jet velocity from bubble collapse that damages the metal surface, as portrayed by event 3 in **Figure 13**. As highlighted by Eq. (3), the magnitude of v_{jet} is dependent on the pressure of the surface and inversely proportional to the density. This implies that the erosion model implemented will over-predict the value of v_{jet} when there is large pressure advection, such as sharp LEs along the surface. Transition regions between vapor to liquid has lowest ρ and leads to higher estimated values for v_{jet} .

The observed pressure P and density ρ at the cell represents the combined values of the liquid and vapor mixture in the medium. These variables are extracted from the CFD simulation at the end of each time-step to continuously update v_{jet} and subsequent equations to evaluate the erosion damage. P_v is the saturation pressure of the liquid valued at 3170 Pa. γ is the distance ratio from the center of the bubble to the surface of impact valued at 1.1, and 8.97 is a dimensionless constant. Both of these values are based on the experimental findings by Plesset and Chapman [117].

$$v_{crit} = \sqrt{\frac{p_y}{\rho} \left(1 - \left(1 + \frac{p_y}{B} \right)^{-1/n} \right)} \quad (4)$$

Equation 4. Bubble-jet critical velocity to cause erosion

v_{crit} is the minimum velocity required for the jet bubble to deform the surface of the metal. p_y is the yield stress for the copper sensor used in the reference experiment and the constants n and B are outlined by the experimental work of Lush [118]. The values used in the simulations are 200 Mpa, 300 Mpa, and 7 (dimensionless) for each of those respective variables. v_{crit} in this case is 118.5 m/s, any excess velocity from this value is converted to damage the surface. The

vapor fraction must also be $x > 0.01$ on the surface, so that there are significant enough number of bubbles present to cause erosion [116].

$$v_{def} = v_{jet} - v_{crit} \quad (5)$$

Equation 5. Bubble velocity related to deformation

v_{def} is the excess energy from v_{crit} that quantifies the magnitude of damage to the impeller surface. As a condition, $v_{jet} > v_{crit}$ so that plastic deformation can occur and cause harmful damage to the surface. The excess energy v_{def} represents the magnitude of energy that causes damage on the solid surface. A key assumption of this equation is that the treatment of the surface is fully plastic once this threshold velocity value v_{crit} is met, and therefore all the excess kinetic energy from bubble jet v_{def} is used to deform the surface of the blade.

$$t_{def} = \frac{r_{jet}}{c_l} \quad (6)$$

Equation 6. Bubble-jet Transport Time

t_{def} is the time required for the bubble jet to travel across its radius of travel r_{jet} , while c_l is the bubble sonic velocity. The value of this assumed to fixed on the implementation of this model. Their respective values are set at 10 μ m and 1484 m/s based on the experimental work of Plesset and Chapman [117].

$$d_{pit} = v_{def} t_{def} \quad (7)$$

Equation 7. Pit diameter caused by jet bubbles

d_{pit} is the pit surface diameter from the subsequent bubble jet collapse, which is a product of the deformation velocity v_{def} and the transit time of the bubble jet t_{def} across the surface of the solid body. Since t_{def} is a fixed value from experimental data, the d_{pit} is directly proportional to v_{def} , which in turn is directly related to v_{jet} . Since v_{jet} is directly proportional to pressure and inversely

proportional to the density of the fluid mixture, the erosion model proposed predicts the peak of the erosion values where the pressure gradient is highest. The value of vapour fraction across the area determines the likelihood of erosion.

$$A_{pit} = \pi(26.7d_{pit})^2 \quad (8)$$

Equation 8. Pit area Caused by jet bubbles

A_{pit} is the pit area calculated from the pit diameter d_{pit} and the coefficient 26.7 is based on the experimental results from Fortes-Patella et al [105].

$$A_{dam} = \frac{\sum_{t_{start}}^{t_{end}} A_{pit}}{A_{ref}} \cdot \frac{T}{\Delta t} \quad (9)$$

Equation 9. Accumulated pit area caused by jet bubbles

A_{dam} quantifies the relative erosion damage on the impeller surface, where A_{ref} is the referenced area of the blade in question. T is incubation time from experiments and Δt is the time between each timestep within simulation. This second term provides the scaling factor to scale-up the smaller values of A_{pit} from the shorter simulation time so that it is comparable with experimental data. The experimental data represents the sum of the erosion damage from one hour of cavitation. This approximation is acceptable as erosion wear is linear over time [78, 104, 119]. t_{start} and t_{end} represent the time of start and end of the sampling interval for the summation of the erosion damage area. t_{start} is chosen at the end of the pressure transient in the beginning of simulation and t_{end} the value at the end of the 38ms sampling interval. This time interval is chosen as this value is the interval suggested by the authors in the referenced work [104].

Above is the abridged version of the calculation of the area of damage A_{dam} starting from the calculation of v_{jet} , which uses variables extracted from CFD. More details on the origins of the equation terms and definition of the constants used can be found in Dular et al [71, 104, 120, 119] as well as Plesset & Chapman [117].

Although this method has demonstrated some agreement with experimental data as highlighted by the calibration results in Portfolio #2 [4] a fundamental drawback of the method is that it assumes that the bubble jet, vapor and subsequently the creation of the pitting areas are in the same location, and that this holds true under all cavitating conditions. The bubbles may differ as they travel across the fluid and may displace some distance in the horizontal direction before colliding onto the surface. The erosion model does not take this into account, which is a contributing factor in the disagreement with experimental data.

4.3.2 Model Assumptions and their Influence on Erosion Estimations

The assumptions made in simulating erosion are based on the work Plesset & Chapman [117] on modelling spherical bubble collapses with water, and are listed as follows:

1. **Liquid simulated is incompressible:** Compressibility is not significant for flows which are much slower than the speed of the sound. This allows vapour pressure P_v to be set at a constant value as the temperature is fixed.
2. **Ambient pressure and vapour pressure is constant:** Similar to the first assumption, this means that the vapour pressure P_v remains constant, and that the calculation of P_{wave} and v_{jet} is influenced by the pressure and density of the fluid.
3. **No permanent gases are inside the bubble:** All portions of the simulated fluid can transition between liquid and gas. The concentration of air molecules (O_2) is negligible.
4. **The effects of surface tension are ignored:** The bubble radius r_{jet} is assumed to be uniform and there are no expansions during its travel [121]. This allows r_{jet} to be set at a fixed value of 10^{-5} m, which is crucial to calculation of pit diameter d_{pit} in Eq (7).
5. **The flow across the pump is non-viscous:** Based on the work by Rattray [122], the effects of viscosity are insignificant for bubbles with radii of 10^{-5} m or greater and collapsing in atmospheric pressures.
6. **Vapour pressure inside the bubble is uniform:** The assumption of uniform bubble interior pressure is valid as long as the bubble velocities are

below the speed of sound. Neglecting other effects mentioned, allows a constant value of P_v is used in the simulation.

Temperature effects are more likely to be included due to the changes to the ambient environment rather than compressibility of the fluid, when considering the boundary conditions of the pump during operation. Deviating from assumptions 1 and 2 means that the saturation pressure P_v will deviate as a result of the temperature and will need to be continuously be updated [8]. The fidelity of the simulations will increase, as it will incorporate environmental effects to the wear estimations, but with significant increase in computational cost. The heat transfer between the ambient environment to the fluid needs to be understood before the saturation pressure P_v is calculated at each timestep. If permanent gases are included, such as air, then its primary influence would be on the temperature of the bubble as outlined Hirschfelder, Curtiss & Bird [123]. this influences the value of P_v similar to assumptions 1 and 2.

If the vapour pressure inside the of the bubble P_v is assumed to not be uniform, then this parameter would need to be updated at each timestep by an additional modifier, and is no longer constant. This vapour pressure P_v would be a function of the pressure inside the bubble to the ratio of the number of molecules found on the fluid, as outlined in the work by Yasui [124].

When carrying out the erosion damage estimations with an alternate fluid such as kerosene, the effects of surface tension and viscosity, as described in assumptions 5 and 6, need to be re-considered. This is because the average bubble radius r_{jet} of the fluid is 4.5×10^{-6} m is less than the minimum threshold for the related physical effects to be omitted. The smaller bubble radii influence the way at which the external pressure of each bubble is estimated as a function of its internal bubble pressure, surface tension and viscosity. The calculation of v_{jet} can no longer be retrieved from the pressure calculated in each cell, but using the mentioned technique that is based on the work of Ye et al. [125].

P_v and r_{jet} are kept constant in this work as a result of the stated assumptions and provided sufficient fidelity when compared to the referenced experimental

work by Dular et al. [71] and Bachert et al. [126]. The treatment of these constants as another variable could potentially improve the fidelity of the erosion estimations but at significant computational cost. The model could potentially become more flexible, as it would have the capability of modelling erosion using different fluids and adapt to the different environmental conditions.

4.3.3 General Configuration for CFD Simulations

All the CFD simulations carried out in this work in Star-CCM+ share many common features in their configuration with each other. All simulations are performed as multiphase calculations with water and water vapor used as the liquid and gas model respectively with initial parameters at 20 °C, using a constant density fluid model, with a Saturation pressure P_v of 3170 Pa. This yields a liquid/vapour density ρ_l and ρ_v of 998.2 kg/m³ and 0.5953 kg/m³ respectively. Prior to the results discussed in **Section 4**, the cavitation models were compared with the reference pump and hydrofoil simulations to see which had better agreement with experimental data from [71, 104]. The Scherr-Sauer cavitation model [127] has been chosen over the Rayleigh-Plesset model [128] as it has been shown to follow the reference experimental data more closely. Likewise, the κ - ω SST turbulence model has been chosen over κ - ϵ as the former shows closer agreement with experimental data. The selection of both cavitation and turbulence has been narrowed down based on a literature survey of previous works for cavitation [79, 80, 81, 82, 83]. The bubble density N_b and radius R_b has been set to 5×10^8 and 1×10^{-5} m based on suggestions by Peters et al. [116]. All simulations use implicit unsteady, segregated fluid and Volume of Fluid models with a second-order solver.

The primary difference between the simulations is the geometry, mesh set-up and simulation time with each timestep Δt . Mesh density is increased significantly near and on the blade surfaces for all simulations, as this is the area that is most affected by erosion. All the simulations reference an incubation time of 3600 seconds to project the erosion wear from one hour of cavitation. The sum of erosion damage is sampled over a time period of 38 ms and scaled to be equivalent to one hour of running as suggested in the work by Dular & Coutier-Degosha [104]. Since the wear progression increases almost linearly over-time,

this method of projection is deemed to be acceptable and still showed close agreement with experimental data [71].

4.3.4 Subject Pump Mesh Configuration

The 3D scanned pump is imported to Star-CCM+ as a .STL file. Surface wrapping is carried out so that any surface anomalies on the 3D geometry are corrected. **Figure 14** shows the mesh set-up of the subject pump at various viewing angles.

Figure 14 (middle-left) shows a cut-away representation of the pump mesh, with the impeller made visible. The rectangular box containing the pump is not shown in the picture, which serves to improve flow continuity of the model. **Figure 14** (top-left) represents the impeller blade when viewed from the top and **Figure 14** (top-right) is a close-up view of the blade mesh. **Figure 14** (right) outlines the pump with its inlet and outlet pipe without the tank. **Figure 14** (bottom-left) outlines the same pump inside the tank. The blade is largely straight at the LE and at a steep curvature section there is a steep increase in the blade angle. The first impeller on the top interfaces with the incoming fluid and provides the initial boost. The second impeller boosts the pressure output into greater levels and interfaces with the pump outlet. A short pipe is created at the inlet and a long pipe section is used to simulate the pipe connection to the rest of the system and to reduce the effects of backflow.



Figure 14. Pump set-up in CFD, clockwise from right: Pump and pipe geometry, Pump set-up inside tank, cross-section of pump model, and pump impeller

A polyhedral mesh is used in consisting of approximately 11M cells. A timestep of $\Delta t = 4.72\text{E-}5$ is chosen when the pump is running at 3500 RPM and a timestep of $\Delta t = 5.75\text{E-}5$ is chosen when the pump is running at 2900 RPM as both of these constitute 1 degree per timestep. It was found that these timesteps provided adequate level of resolution but allowed reaching convergence in a timely manner to compensate for the relatively high cell count. The pump flowrate is fixed at 0.83kg/s as this represents approximately 55% of the maximum pump flowrate, which is a typical operating point of the pump.

Prior to running the cavitation simulations, the pump performance is calibrated for operation under non-cavitating conditions to ensure that the simulated model is representative to how the pump would perform in reality. The pump is validated against the manufacturer datasheet and the pump performs as according to the manual with an error of 3%, which is within the uncertainty of the manufacturer measurements.

The simulation set-up is outlined in **Figure 14**. The subject pump is simulated inside a volume of fluid to represent it being submerged. A short pipe of similar length to the test-rig is connected at the inlet. A long pipe section at the pump outlet is used to simulate the long pipe connection between it and the destination tank. A polyhedral mesh is used for the pump and connecting pipes. A surface trimmer mesh is used for the tank to improve continuity of the simulation but at a small increase of computational cost. Surface and volume controls to selectively refine different areas inside the pump. A systematic mesh sensitivity study is carried out to reduce discretisation errors by following the standard set by the ASME Journal of Fluids. More details related to the grid study for the subject pump in the 3rd portfolio submission [2] and the reference pump used to calibrate the erosion model is found on the 2nd portfolio submission [4]. two grid convergence studies are carried out so that discretisation errors from the reference and subject pump are quantified.

4.4 Experimental Procedure

The main purpose for the methods proposed is to develop a strategy to diagnose for cavitation erosion using a hybrid-based HM. The purpose of the tests carried out in the experimental rig is aimed to verify the accuracy of the CFD simulations and the system model running on Simscape.

Different types of sensors are placed across the test-rig so that the performance penalties and differences caused by cavitation erosion can be captured, and an HM mechanism can be developed to detect for this specific fault. The motor currents, pressure, flow and temperature across the pump are monitored. The test rig sensors have been selected based on a literature review on pump degradation mechanisms [72, 73, 74, 75, 76, 77, 78, 129, 130] and possible

sensing techniques [1, 106]. The test pump is chosen as its design and performance envelope follows the specification of future airframe fuel pumps. The sensors are also chosen based on not only on their success for detecting similar faults, but also their suitability for installation on the aircraft fuel system environment. There is also a knowledge-gap related to erosion HM on two-stage pumps and the findings in this future research attempts to address this lack of knowledge.

In addition to experimental test rig data, results from a test-rig simulation and pump CFD model are coupled to the development of the HM detection mechanism. The CFD simulation is used to predict the areas inside the pump that are most susceptible to cavitation erosion and validate head and flow rate performance of the pump.

The performance degradations caused by the pump erosion provide the adjustment factor to the system model that is being run on Simscape. An example is with the pump outlet pressure loss observed at moderate impeller degradation. The same degree of pressure loss is represented in the Simscape model by modifying it with a suitable block to represent the change. The four sensors are initially chosen to conduct HM are temperature, flowmeter, pressure and current sensors. Temperature sensing is carried out with a thermal imaging camera on the BLDC motor coils. The current sensors are installed in each of the three motor phases as it allows ESA to be conducted for each of them. Compared to other methods, the primary disadvantage of ESA is that it has relatively lower signal-to-noise ratio (SNR) compared to the other methods, but these shortcomings can be remedied by using the appropriate signal condition and processing techniques [106].

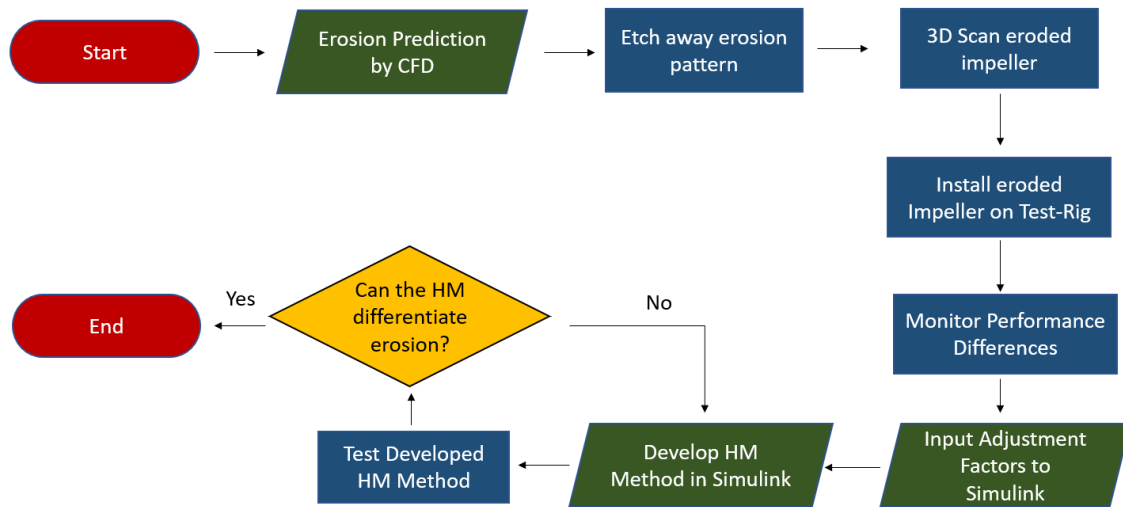


Figure 15. Flowchart outlining use of the HM test-environment

Figure 15 summarizes the sequence of simulations and experiments carried out in this work using the test-rig, CFD and Simscape model. The sequence starts by running the erosion prediction in CFD. First, the boundary conditions are set to replicate the cavitation experimental work by Dular et al. [71] and Bachert et al. [126]. These set of operating conditions are representative of in-service pumps experiencing cavitation.

CFD is used to predict areas inside the pump that are most vulnerable to the cavitation erosion damage. The results inform the areas to remove as a means of accelerated fault testing. The pump impeller blade surfaces are etched away around the leading and trailing edges of the impeller as predicted by the erosion model running on CFD. The 3D scan of the damaged blade is then re-meshed for subsequent CFD analysis so its performance differences can be studied. Once 3D scanning is complete, eroded impeller components are re-installed on the test-rig for the experimental campaign to generate data. **Section 4.5** provides further detail on the operating conditions and impeller combinations used during testing. The pump CFD simulations and the test-rig experimental runs are conducted under equal boundary conditions so that differences between the results are directly comparable. This is repeated for healthy and eroded impellers. Additionally, the test rig will have multiple repeat runs after re-assembly to

quantify to what degree the component installation influences sensors data results.

Once the checks between the CFD and test-rig results are satisfactory, the adjustments are implemented to the validated Simscape model in its healthy state. The changes to the model represent the damage caused by the eroded components and allow modal analysis to the HM parameters of interest: current, pressure and flow signals. The adjustments can be in the form of an additional block component or implementing some form of mathematical function in the existing model blocks that would reflect the performance degradation caused by the fault. A hybrid-based HM algorithm can then be developed to the relevant parameters that have been influenced by the erosion and differentiate between the three levels of erosion.

An additional mechanism that simulates the pump flow ripples, as this parameter has demonstrated a significant amount of sensitivity between the different levels of erosion. The centrifugal pump block in itself does not have sufficient fidelity to depict the flow dynamics that is being measured by the test-rig, so an additional mechanism is created in Simulink to represent this behaviour as detailed in **Section 4.2.3**.

Upon satisfactory completion of the initial validation of the CFD, model running on Simscape and test-rig data with each other and under pump healthy conditions, the erosion testing can commence. More details on the validation exercise from the three methods are highlighted in portfolio submission #3 [2]. The reasoning behind these preliminary experiments is to ascertain the level of accuracy between the three methods and outline any discrepancies.

Based on the current, flowrate and pressure data from the test-rig and combined with simulation model and CFD data, the effectiveness of the HM technique is evaluated. A key evaluation criterion is the ability to distinguish the different levels of erosion, under various pump operating conditions, with different sensors and model data inputs.

4.5 Experiment Test Sequence

Initial baseline tests are carried out using a non-damaged pump to validate the three methods used to conduct hybrid-based HM to ensure that the result is in agreement. Further details of this exercise can be found in the work by portfolio submission #3 [2].

Speed (RPM)	Flowrate (l/s)
2900 RPM	0.28, 0.56, 0.84, 1.12, 1.40, 1.68, 1.96, 2.21, 2.33
3500 RPM	0.56, 0.84, 1.12, 1.40, 1.68, 1.96, 2.24, 2.67, 2.82

Table 3. List of pump operating points

Varied Parameter	Values	Research Question
Tank Head Level	0m, -0.2m, +0.2m	How does the different head level vary the pump performance and HI?
Motor Speed	2900 RPM, 3500 RPM	How does the speed vary the pump performance and HI?
Re-Assembly Count	2	How does the overall pump performance and resulting HI vary at each successive re-assembly?
Erosion Levels	0%, 53%, 80%	Which signals can detect the penalties from erosion?
Valve modulation	6.67% up to 90% open (in increments of 6.67%)	How does erosion influence the flowrate?

Table 4. List of varied parameters

For each cavitation erosion level, the pump is initially run at seven operating points to their corresponding speed highlighted by **Table 3**. These points are selected based on the manufacturer's specified pump performance envelope. The flowrate intervals have a value of 1 m³/h between each flowrate point. The additional data points highlighted in red are additional data-points added for experimentation and simulation for erosion detection. An additional two values highlighted in red are also included in addition for the motor current tests and to monitor the flow oscillations. These values are chosen as they correspond to the

valve being opened at 73.33% and 86.67% in the test rig. The valve is not opened to 100% as this would result in such low head output that any differences caused by the erosion becomes less detectable by the pressure sensors. These flowrates are not included in the results section in the steady-state pressure output tests as they are outside the intended operating point of the pump. Preliminary tests reveal from test-rig data that the head values would converge for the different erosion cases. These very high-flowrates are also in the accuracy limits of the CFD predictions limiting its usefulness for model-based HM.

The goal is to collect baseline data under normal operating conditions before the erosion tests outlined in **Section 4.6** are carried out. The nine data points give the ability for comparison between whether erosion is easier to detect when the pump is operated at a higher flowrate but lower output pressure, or the opposite.

The tests are run at different tank levels and motor speeds, as well as number of assemblies, to see how these independent variables could possibly affect the results. These permutations are summarised by **Table 4**. As highlighted by the previous work in portfolio submission #3 [2], the static head and number of assemblies did not create a significant influence on the results. The lack of change caused by these two parameters eliminated it as a test variable. The captured data from these runs are instead averaged and standard deviations calculated to help quantify the level of error in the measured data. The speed of the pump does influence on the output and as a result a separate dataset is generated for comparison.

Normality of Data: The 6 samples taken for each data point in the test-rig has been run with the Shapiro-Wilk test [131]. This is the most reliable method to test for normality when the sample sizes are less than 50 [132, 133]. Histogram, Q-Q plot and Skewness tests are also reliable test to check for normality, but only when the sample size is at least 50 [132]. Based on the null hypothesis results from the Shapiro-wilk test, the collected datapoints conform to a normal distribution. Further reading on the Shapiro-Wilk test can be found on the work by Shapiro & Wilk [131] and Hanusz & Tarasinska [133].

4.6 Fault Level Definition

The level of pump erosion damage is quantified by the thickness in the impeller remaining, measured in mm. The erosion damage is classified into three levels; 'Healthy', 'Moderate' and 'Severe'. **Figure 16** visually portrays the erosion severity levels, with the following definition:

1. 'Healthy' case is defined when 100% of the blade thickness is remaining. This represents a pump that has no cavitation damage. The pump impeller has 1.5mm of material thickness remaining at the LE/TE
2. 'Moderate' case is defined when 47% of the blade thickness is remaining. This represents a pump that has significant cavitation damage. The pump impeller has 0.7mm of material thickness remaining at the LE/TE
3. 'Severe' case is defined when 20% of the blade thickness is remaining. This represents a pump that has excessive cavitation damage. The pump impeller has 0.3mm of material thickness remaining at the LE/TE.

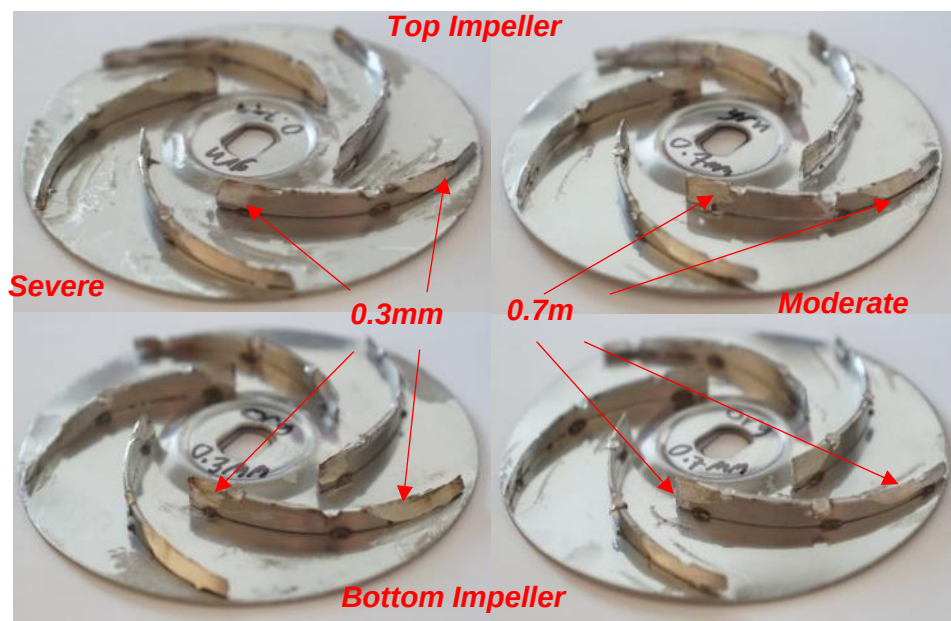


Figure 16. Impeller samples with damage at blade LE and TE. The numbers indicate remaining thickness

5. Baseline Testing Results

5.1 Erosion Algorithm Calibration with Reference Pump

The erosion model calibration can be found in the 2nd portfolio submission [4]. The purpose these simulations are to validate the accuracy of the GLM algorithm used to predict the erosion areas. The estimated damage areas generated in CFD are compared with experimental data from an aerofoil and a pump with similar geometry as the subject pump.

5.2 Erosion Algorithm Application on Subj. Pump

The erosion algorithm is applied to the subject pump at a rotation speed of 2900 RPM as depicted by **Figure 17**. The results from the CFD simulations inform the areas to sand away as outlined in **Section 4.6**. This is a more conservative damage estimate to the 3500 RPM case, and allows a more critical estimation to the sensitivity of the HM techniques used.

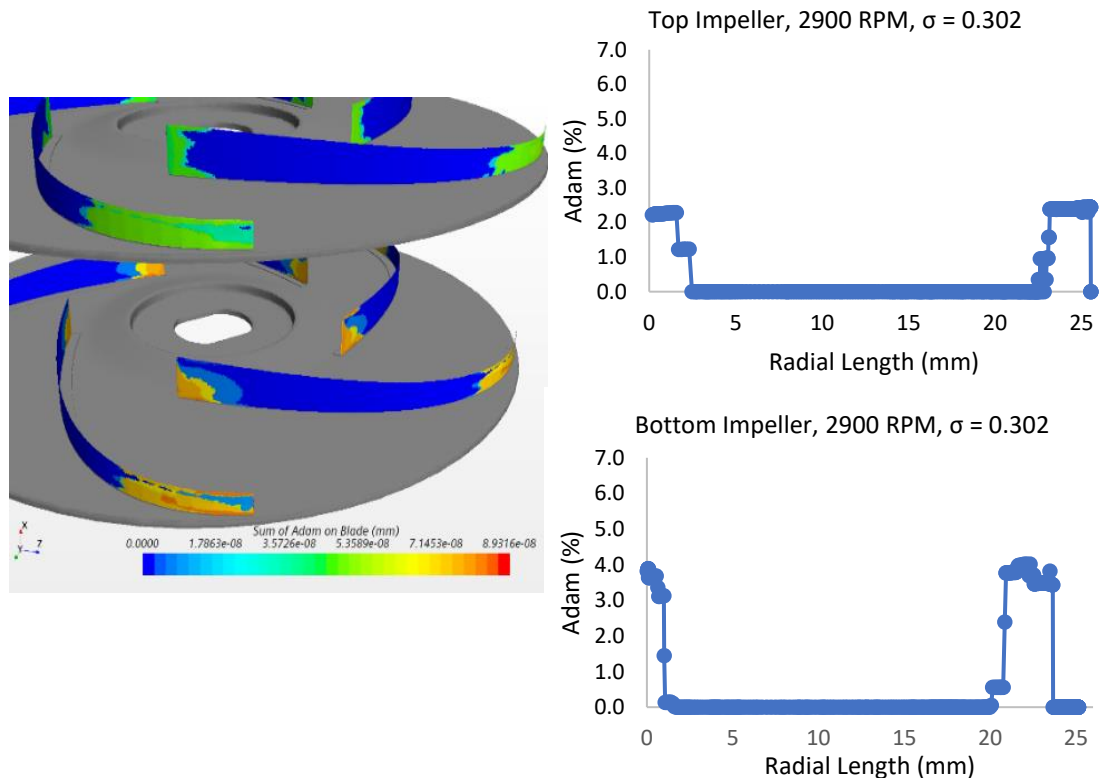


Figure 17. Wear Distribution across subject pump at 2900 RPM

Figure 17 (left) is the 3D iso-surface of the erosion areas whereas **Figure 17** (right) is the 2D representation for the first (top) and second stage (bottom) impellers respectively.

There is increased erosion wear at the blade LE and TE is due to the higher-pressure gradient at these points, where vapor fraction, $\alpha > 0.01$. The cause of the sharp pressure gradient at the blade LE ($x = 0$) is due to the squared shape of the blade. The erosion areas are the highest when the blade curvature is steepest, as this is where the pressure gradient is likely to be the largest hence v_{jet} and subsequently A_{pit} .

For the first stage, vapor $\alpha > 0.01$ across entire surface area of the impeller, but for 2900 RPM case there is insufficient pressure for v_{jet} to exceed v_{crit} of 118.5 m/s. For the second stage impeller, $\alpha > 0.01$ is present at concentrated regions at $x = 22\text{mm}$ and $x = 0$, the blade LE and curvature. This combined with the much higher pressure on the second stage of the impeller permits in higher jet velocities v_{jet} that results in wear.

5.3 Results: Test-Rig Baseline Calibration

This section presents pump performance results from the test rig, simulation models and compares them. Additionally, electrical frequency spectral analysis results for healthy impeller conditions based on experimental and model simulated conditions are presented.

5.3.1 Comparison of Test-Rig, CFD, and Simscape Model

Figure 18a compares the pump flow curve that was generated via the CFD model with experimental data from the test-rig. The results from both methods show good agreement and still within the uncertainty of measurements of the test-rig pressure sensors, with an average uncertainty value of 0.85m of head. The uncertainty of the pressure sensors is due to the turbulent flows of the fluid that cause oscillations in the pressure measurements, which are greater than the quoted accuracy of the sensors of 0.2% of its maximum rated value. Slight discrepancies between the two results are caused by the complex flows and fluid interactions of the inside the pump which are difficult to be fully recreated in simulation.

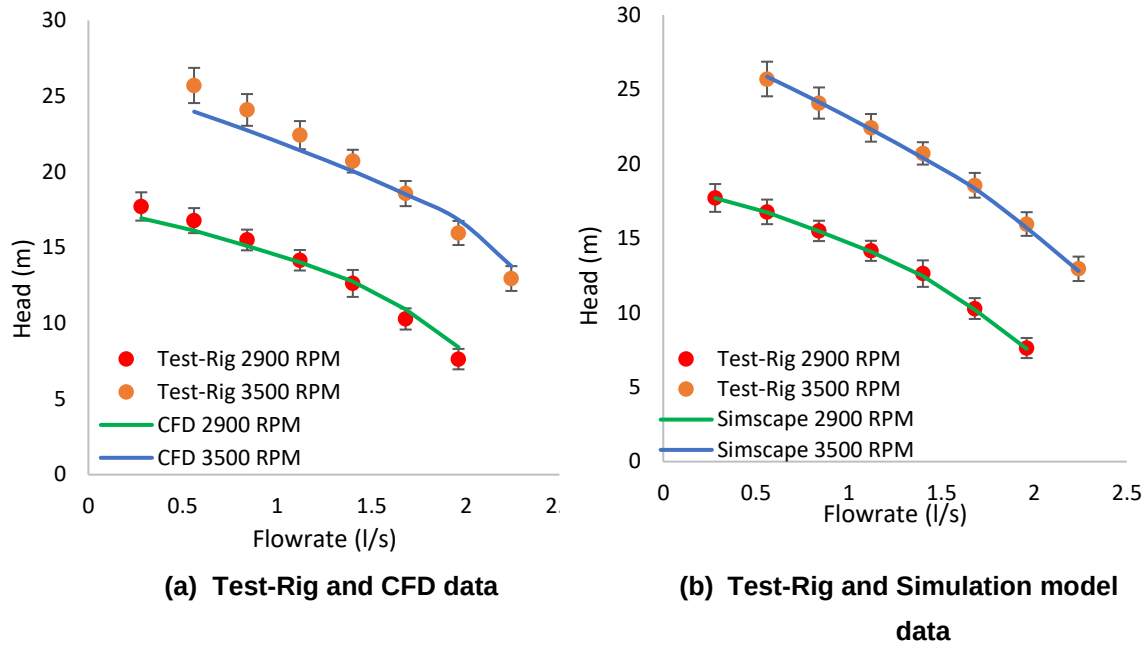


Figure 18. Pump head-flow curve comparing Test-Rig experimental, Simulation and CFD Results

For the test-rig results outlined on **Figures 18a and 18b** varying the head level from 0m, +0.2m and -0.2m static head does not make a significant difference to the pump performance, provided sufficient water level above the snorkel to prevent vortex formation and air entrainment. These values of static head are chosen as the tank height is 0.4 m and the pump is positioned 0.1 m above ground level. Having a change of 0.2 m in water level allows the static head to be varied, prevent overflow and be at the minimum water height above the pump inlet for smooth flow. Changing the static head and re-assembling the pump did not yield a significant difference in the results. The graphs outlined in **Figure 18a and 18b** is an average of those variations in static head and after re-assembly, as outlined in **Table 4**, but with no erosion. The pressure error measurements depicted by **Figure 18b** between the CFD and test-rig results have an average and maximum values of 4.38% and 10.28% respectively.

Figure 18b compares the results between the calibrated test-rig simulation model running on Simscape and the test-rig experimental data. By using the test-rig data as input parameters to the pump block, leads to a very close agreement between the two methods. The pressure error measurements depicted by **Figure 18b** have an average and maximum values of 0.80% and 1.42% respectively.

5.3.2 Comparison of Test-Rig and Datasheet

Figure 19a outlines the pump head-flow curve comparing the results from the test-rig with the manufacturer's datasheet under two speeds. Very close agreement is achieved between the test-rig and manufacturer datasheet, despite the slight differences in the setup and equipment used. The average error between the test-rig output and manufacturer specification is 3.5% and a maximum value of 7.1%. Disagreement between the datasheet and test-rig results are due to the test-rig being a pump in submerged in a tank, whereas the datasheet values are based on a closed loop pump system setup. The closed loop setup will induce a backpressure at the pump inlet, which is more prevalent at higher operating heads and results in a reduction in the head output.

5.3.3 Current Signature Readings

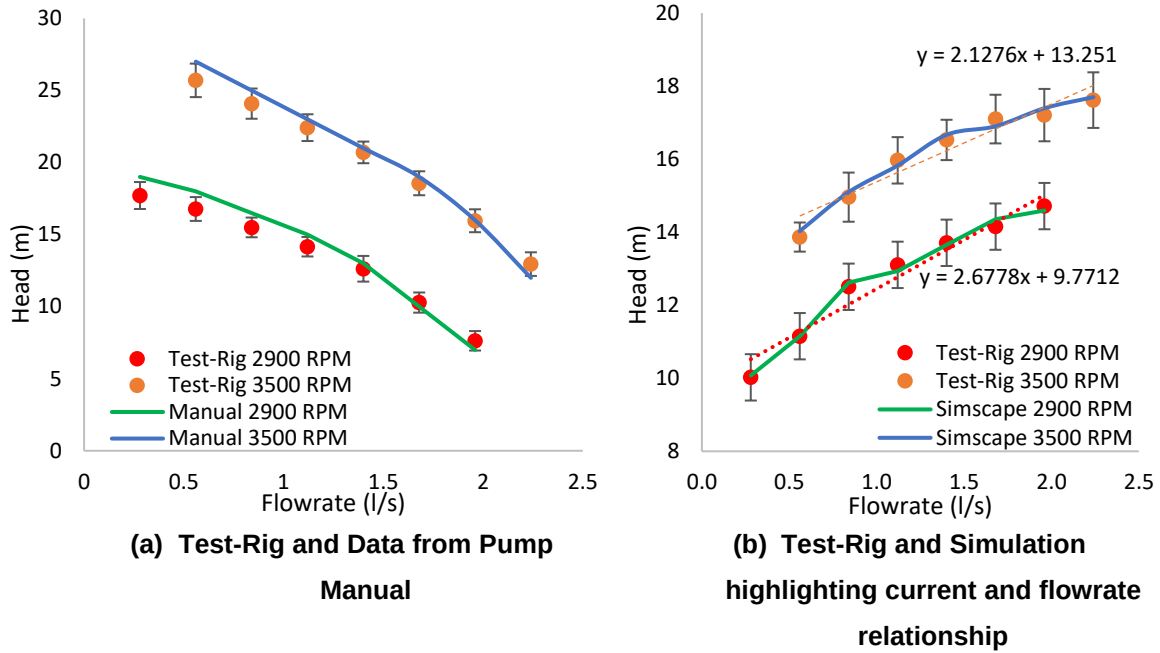


Figure 19. Pump performance comparing results from test-rig and manual as well as pump flowrate plotted against Motor RMS Current

Figure 19b compares the flowrate with the RMS current of a single phase. As highlighted, there is high degree of alignment when observing the RMS current with its corresponding flowrate value. The average current measurement uncertainty value is 0.44A for the 2900RPM case and a value of 0.57A for the 3500 RPM case taking into the errors from the current ripple and standard deviation. The average error between the Simscape and test-rig results is 0.80% and the maximum error is 0.94%. The error for flowrate and pressure measurement is 0.05%. The uncertainty is comparatively lower for the 2900 RPM relative to the 3500 RPM case due to the lower variation from the sampled current values.

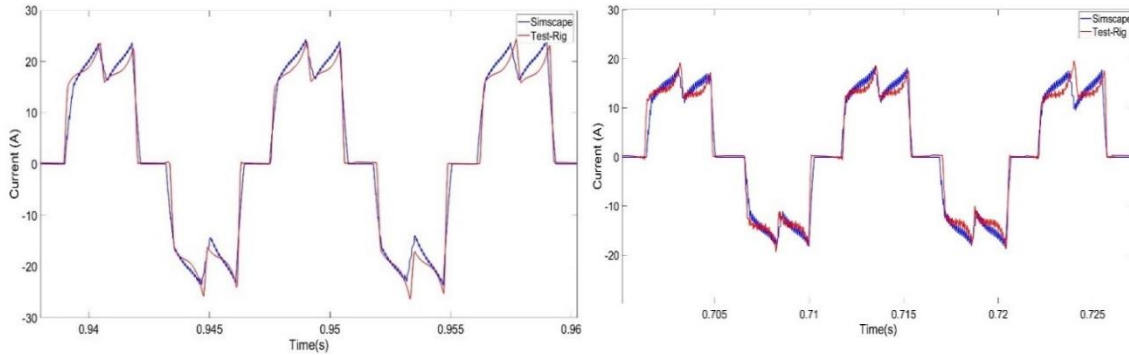


Figure 20. Motor Current Signatures from Test-Rig vs. Simscape

Figure 20 depicts the pump motor signature from a single current phase for 3500 RPM case (left) and 2900 RPM case (right). The current signatures from the experimental data are well-aligned with the results from the Simscape simulation. The speed of the motor can be inferred using the frequency of each current phase and number of poles of the BLDC motor. The pump flowrate can also be inferred from the current waveform RMS values, the higher the flowrate, the larger are the current values. This is due to higher flow resistance at higher flowrates which incites the motor to generate higher torque values to overcome it and regulate the same speed setpoint. Since torque and phase currents are directly proportional in a BLDC motor, the increase in torque leads to an increased current [41].

The motor phase current envelope output in Simscape is influenced by several parameters: controller architecture, pump operating points, PWM switching frequency, as well as motor resistance and inductances. The differences in spurious fluctuations from the current values are due to the PWM switching operating at approximately 50% of its maximum duty cycle at 2900 RPM, and 100% at 3500 RPM. The pump flow operating point determine the overall current draw from the motor. Observing the current ripples on **Figure 20** would imply that conducting ESA at higher RPM speeds should in theory be more reliable as the current measurements has lower noise from the reduced current ripple. This however does not happen in reality, due to the increased variation in sampled current at higher rotation speeds. Since current and flow are linearly tied, the higher flow turbulence observed in the 3500 RPM case lowers the precision from the current samples, resulting in a higher standard deviation. The increased error

caused by this offset the lower errors from the current ripples and yields a higher overall error on all datapoints for the 3500 RPM case.

The Simscape model is capable of representing the changes in current that result from changes in the flow. This means that any current irregularities as a result of the erosion faults, can be captured by the model, and an HM scheme can be developed around it. Providing input data to a HM capability through a simulation model allows the fault and detection schemes to be tested under much wider boundary conditions, including those not possible on the test-rig setup.

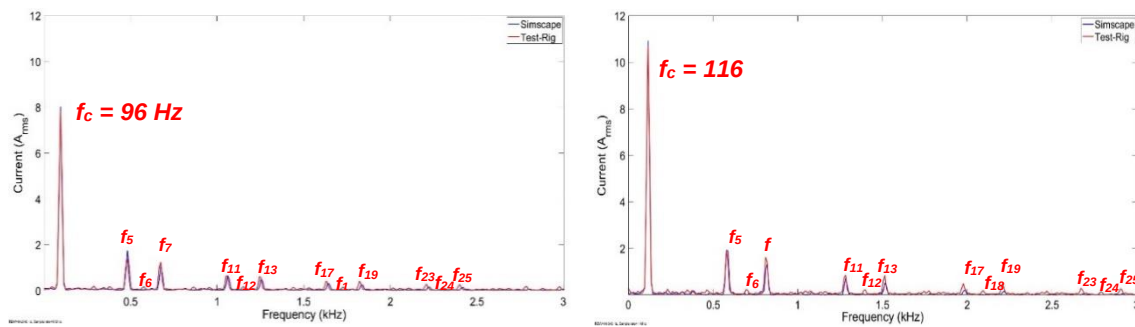


Figure 21. Electrical frequency spectra from Test-Rig vs. Simscape

Figure 21 outlines the frequency spectra from the same signals outlined in **Figure 20** by carrying out Fast Fourier Transform (FFT). The left graph represents the 3500 RPM case and the right represents the 2900 RPM case. This process dissects the time-domain signal into its sinusoidal components and highlights the intensity for each of those constituent signals. This method allows identification of any additional modal signals induced by a fault, as the fault will generate a signal unique at some frequency outside of the baseline spectral pattern. The FFT is carried out using Chebyshev filter due to its low noise at higher frequencies relative to f_c [134]. The range is selected to 3 kHz as according to observation, the signals beyond this frequency would have been significantly attenuated for meaningful analysis. As highlighted by the frequency signature, the signals appear at conjugate patterns and at discrete multiples of the fundamental frequency, f_c . This critical frequency corresponds to the rotational speed of the motor divided by the number of pole pairs, which in this situation is 2. 2900RPM corresponds to a rotational speed of 48Hz, and 3500 RPM to 58Hz. Multiplying with 2 pole pairs yields a value of 96Hz and 116Hz, which is the value

of f_c for their respective RPM cases for the frequency spectra graph on **Figure 21**.

Figure 21 also highlights that the signals appear in conjugate pairs. The model does not show an amplitude at this frequency, whereas the test-rig results express a very small magnitude. The significant amplitudes occur at the odd conjugate frequencies which are located at $+1f_c$ and $-1f_c$, that centres the 6th multiple of f_c such as the 6th, 12th, 18th and 24th harmonic. For each of those respective harmonics, the conjugate pairs appear on the 5th & 7th, 11th & 13th, 17th & 19th and 23rd & 25th harmonic. Since the time-domain signal is trapezoidal, and bears close relation with a square wave, it will have similar constituent signals. The frequency signatures are consistent with square wave theory as it is expressed as the sum of sinusoidal waves at odd frequency integers with attenuating amplitudes, as the harmonic number increases [134]. There are some differences between the simulation model and experimental results even after successful calibration. For the frequency-domain results, there is better agreement than the time domain results, where the values of the signal frequency and amplitude from the model closely follow the test-rig results. The primary difference between the results are the values of the amplitude of the even harmonic components at the 6th, 12th, 18th and 24th harmonic components. The primary difference from this is likely due to the sharp gradation of the slope in the time-domain, which may have increased the amplitude of the signal, even if it is a small value. Another difference is the very slight phase shift between the model and test-rig results, which are more apparent at higher frequency. This is due to the torque ripple caused in the test-rig and the spurious flow which may cause a slightly deviation in the motor speed from its setpoint speed of 3500RPM.

For the time-domain results, a difference between the model and test-data is in the approximation of the current rise from each phase. The shoulder of the waveform peak refers to the 12A point for the 2900 RPM case and 15A point for the 3500 RPM case. Inspecting the peak current values in **Figure 20**, The estimation of current rise (di/dt) from the shoulder of the peak to very tip of the current waveform has a slight discrepancy between the model and test-rig results. In the test rig there is a convex curvature as the current reaches peak values,

whereas for the Simscape model, the curvature is closer to a linear slope. The magnitude of difference is in the order of approximately 2A in this transient region for the time-domain waveform. Inspecting the FFT results in **Figure 21**, the mentioned difference in the current profile only yields small amplitude increase in the even harmonic components, but both waveforms still have the same frequency components and are largely in-phase. This further emphasizes that the slight differences in the waveform envelope will not have a significant impact to the quality of analysis when carrying out HM in the Simscape model.

The mentioned differences in the time-domain waveform are caused by the way the model approximates the motor circuit. The simulation model approximates the BLDC circuit as a Resistance-Inductor (RL) circuit to represent the magnetic components. This approximation, although generally accurate to model the dynamics of the motor, it does not include the magnetic saturation behaviour as the motor reaches its set-point speed [135, 136, 137]. This explains the convex curvature of the current ripple found on the test-rig data. Regardless of this difference, the Simscape model has reached a sufficient level of fidelity, as the comparative differences in the current profile as a result of the erosion damage can still be captured. This is further emphasized in the results outlined in **Figure 19b**, where the RMS output of the current changes depending on the pump flowrate, highlighting how changes in fluid flow can be translated to electrical domain.

5.3.4 Summary of Baseline Results

The presented results in **Section 5** characterize the pump under healthy operating conditions, to establish baseline HM indicators under normal operation. The disagreements between the motor model in Simscape and the unit installed in the test-rig, is due to their full specifications to not being disclosed by the manufacturer, resulting in minor differences. The pump flow characteristics from the test-rig and CFD results showed better agreement than the results between the test-rig and manufacturer datasheet. The flow data outlined in the manual had differences in its test installation, which have contributed to the disagreement between the two results. The pump in the test-rig was submerged, whereas the pump in the test datasheet was not submerged and was directly connected to a

pipe. The experiment and simulation result showed best agreement at median flowrates, which are the operating points between 1.12 l/s to 1.68 l/s.

At high flowrates (>1.68 l/s) the minor discrepancy between the experimental and simulation data is due to the average interpolation method used by CFD to calculate pressure and velocity transitions at the boundary interfaces. As a result, some small-scale vortices and energy transfer that occur in the experiment may have been ignored in the CFD predictions.

At low flowrates (<0.84 l/s), the head prediction shows the highest discrepancy, with a disagreement of 10.28% for 2900 RPM case and 6.74% for the 3500 RPM case. This is because the flow is not completely turbulent, with portions of the flow being laminar, i.e., in the transition region. The moody diagram validates this [138], where the indicated Reynolds number of $Re < 3.0 \times 10^4$ and a relative roughness, (ϵ/d) of 0.0005 from the PVC pipe. The CFD code on the other hand, utilises RANS modelling which assumes that the flow is fully turbulent and cannot predict laminar flows. The boundary layer growth rate caused by laminar flows are different to that of turbulent flows, resulting in different gradients on the surface. This leads to different wall shear stresses and separation that alter the flow [139]. As a result of these differences, CFD cannot predict the flow as accurately in these lower flowrates.

It was found that changing the static head and successive re-assemblies of the pump had minor variations to all the parameters being monitored for HM. The graphs on **Figures 18a, 18b and 19a** represent the average from both re-assemblies and different static head levels being tested. Any differences are more likely to be attributed to the random errors as a result of the turbulent flows across the test-rig. The very minor deviations caused by re-assembly is proven true when pump gasket and annular seals are replaced.

The accuracy advantages of carrying out HM closer to maximum rotation speed is negated because the higher flow turbulence that reduces the precision of the readings. Since current and flow are tied, the flow oscillations create variations in the current readings. These disturbances create random errors that offset the

accuracy gains from the reduced current ripple as highlighted by the 3500 RPM case.

As highlighted by **section 4.5**, the temperature results show high variability in the results even with a healthy impeller. As a result, temperature is not used for HM, and its behaviour is not included in the models used.

The baseline, non-eroded test results have shown conformity between the experimental and simulation methods. It has also demonstrated the novel use of how a BLDC motor can be used to detect changes in flowrate. A high-level of agreement has been achieved between CFD simulations and test-rig results. It was found that the test-rig results show less agreement with the CFD simulation than the flow curve suggested by the manual provided by the manufacturer. The discrepancies between the CFD and test-rig results are due to inherent limitations of CFD in resolving the complex flow interactions in the pump. The discrepancies between the test-rig results and manufacturer data are due to the slightly different test setup used. Other relationships have also been discovered:

- The use of a BLDC motor allows the pump flowrate and RMS current to have a generally linear relationship.
- The dynamics at peak current values differ slightly between simulation and experiment, but RMS values between the two are well-aligned.
- Carrying out ESA at closer to its maximum speed is less reliable as the random errors caused by the increased flow turbulence increases precision errors.
- CFD under-estimates pressure at lower flowrates and overestimates it on higher flowrates relative to rig measurements.

6. Erosion Testing Results

This section compares the results from the three methods used to conduct HM. Not only is the sensitivity of each sensing method is outlined, but the agreement between the test-rig results with the CFD and system model on Simscape is discussed. For the graphs outlined this section, the line represents either the results from CFD model or the system model running on Simscape, and the circles represent points from experimental data. The lines are discrete values corresponding to the same data point from the experiments. The only exception is on **sub-section 6.4.2.**, where the temperature data is discussed, here the experimental data points are represented by lines to improve visual clarity. Unless otherwise stated, the two graphs presented this section represent the 3500 RPM case on the left side and 2900 RPM case on the right for direct comparison.

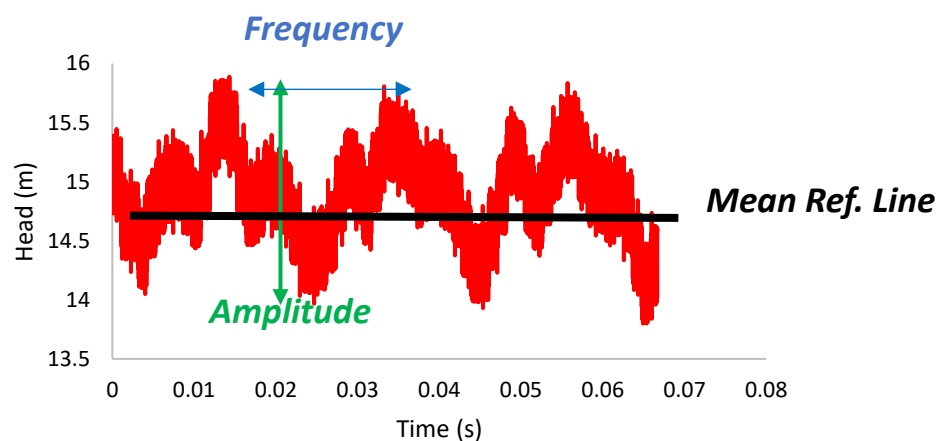


Figure 22. Visual aid to help define parameters fluid-mechanic evaluated

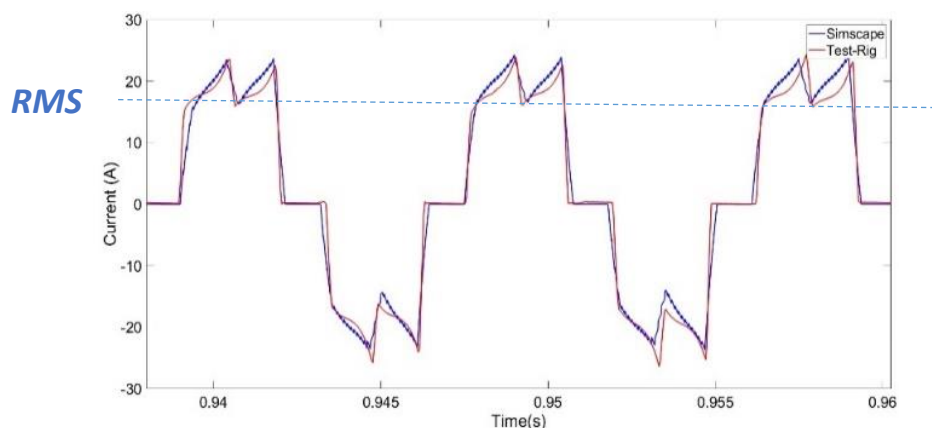


Figure 23. Visual aid to help define how current is evaluated

The test results have shown that the mean, steady-state for measured parameters such as pressure, flow and motor currents could be used as a health

indicator to distinguish the different erosion levels. In addition, it was also found that its transient values could also be leveraged for HM. An example of the latter are the frequency and peak-to-peak amplitude of flowrate oscillations. It was also found that the pressure oscillation frequency is useful for HM, but its peak-to-peak amplitude did not show a high level of sensitivity.

Figure 22 visualizes a sample of the pressure measurement being measured in this section, but it is also applicable for the flowrate measurements. The amplitude for each respective variable refers to the value of the pressure or flow measured from the peak to the trough of the sine wave. In the following graphs included in this section, this is referring to the dQ/dt or dP/dt amplitude for flow and pressure respectively. The mean reference line of the sine wave is the steady state value from the measurements. The frequency is measured as time between successive peaks of the sine wave. The results from the pressure oscillations are the same for flowrate oscillations.

Figure 23 visualizes the definition of the RMS motor current used for HM, measured from one of the phases. It is defined as the peak of the current waveform divided by the $\sqrt{2}$. It was found that this value is a useful HM parameter for gauging the state of the pump. The blue line represents the results from the model running on Simscape data, whereas the red line from the test-rig, and as outlined by the overlay, there is a high level of agreement between the two methods. **Sub-section 7.2.2** provides further details on this as well as discussion on the agreement between the experimental and simulation methods used to conduct HM.

6.1 CFD and Test Rig

6.1.1 Pressure

6.1.1.1 Steady-State Pressures

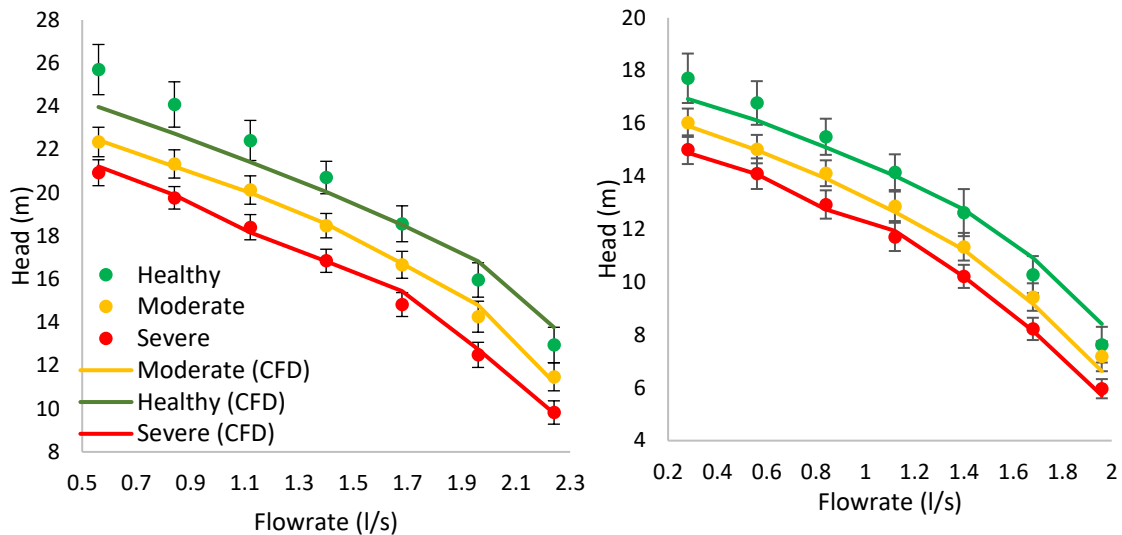


Figure 24. CFD and Test-Rig results highlighting different pump heads at different erosion levels

Figure 24 highlights the steady-state pressure values (head) being induced by the pump for the different erosion levels. There is a sensitivity of more than 6% between the different erosion severities from both test-rig and CFD data for both 3500 RPM and 2900 RPM cases. There is sufficient level of differentiation between the different erosion states that pressure could be used as a reliable indicator for HM. This is according to the description in **section 2.2.5**, where the minimum thresholds for sensitivity are defined for successful HM. The flow and head ranges are selected for this scenario as this is the intended operating range of the pump as specified in the datasheet.

The data outlined also highlights that both test-rig and CFD data are in close agreement, with an overall error average of 2.5% between the two mediums. Worst-case error was found to be a value of 10.28% for the highest flowrate value in the 1.96 l/s, 2900 RPM case and a value of 6.32% for the 2.24 l/s, 3500 RPM case. The low flowrate condition for 3500 RPM case also shows that CFD underestimates the pressure value with a relatively large error value of 6.74%.

6.1.1.2 Pressure Oscillation Frequency

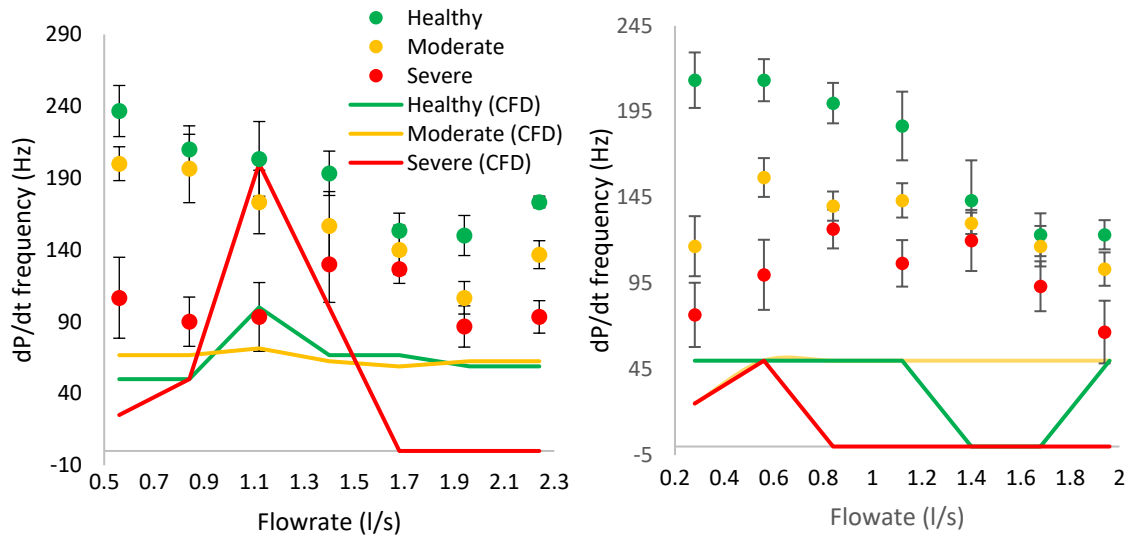


Figure 25. CFD and Test-Rig highlighting fluctuating pressure frequency at different erosion levels

Figure 25 highlights the frequency of the pressure fluctuation being induced by the pump for the different erosion levels, when it reaches its final head value. When it reaches this final pressure value, the centrifugal pump does not generate a straight pressure line, but a fluctuating, sinusoidal wave with a mean at the reference line as depicted by **Figure 22**. This mean value are the values outlined in **Figure 24**.

Observing test-rig results at low flowrates 0.56 l/s, there is appreciable sensitivity between the different erosion levels. This is highlighted by the fact that the data point belonging to each erosion level for the same operating point are outside the error bar of the other. This is further emphasized by the fact that the different data points are integer multiples of the fundamental frequency and have no overlapping error bars. This frequency is defined as the two-rotating speeds of the impeller in Hz, which are 48.33 Hz and 58.33 Hz respectively. Good sensitivity is also shown at the highest flowrates as highlighted by the data points at maximum flowrate **Figure 25** also shows that agreement between the CFD and test-rig results for this parameter is very poor. CFD is not able to resolve all the complex flow interactions to accurately replicated the frequency of the shockwaves from the pump flow. This highlights that pressure frequency is only useful for data-based HM.

6.1.1.3 Pressure Oscillation Amplitude

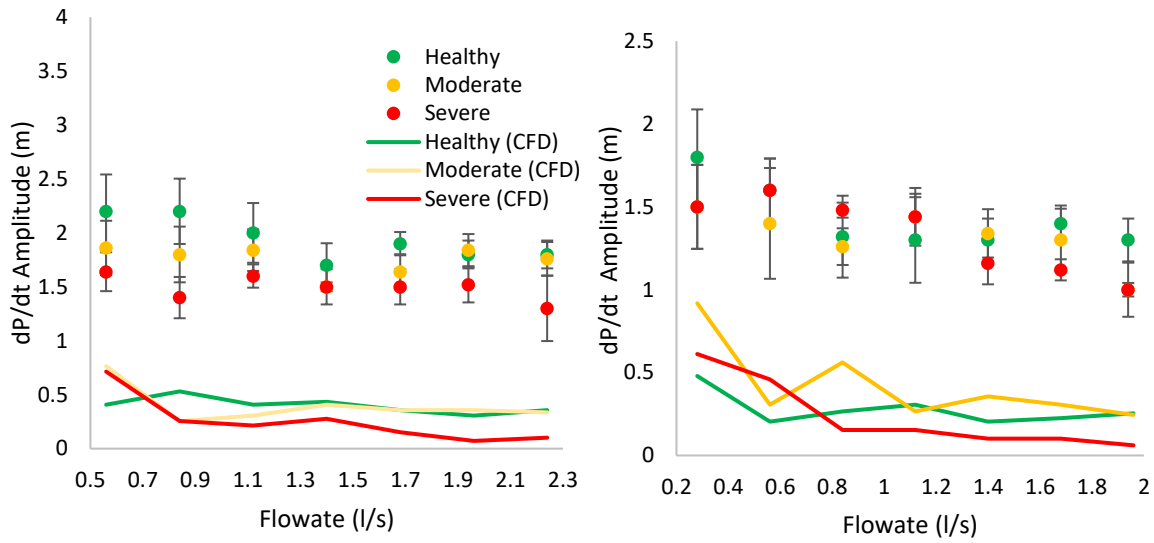


Figure 26. CFD and Test-Rig highlighting fluctuating pressure amplitude at different erosion levels

Figure 26 highlights the amplitude pressure fluctuation is measured from the crest to the trough of the sine wave. This outlines the maximum pressure swing that centre on the reference line of the sine wave, which is the mean value in represented by the points depicted in **Figure 24**. As highlighted in **Figure 26**, there is a large disagreement between the two methods. The CFD underestimates the results of these pressure fluctuations when compared to the test-rig data, by an order of approximately 6 to 8 times for both the 3500 RPM and 2900 RPM cases. This reveals a weakness of the CFD simulations, where it cannot accurately resolve the pressure shockwaves as observed on the experimental rig. A possible solution would be to reduce the timestep of the simulation, where the flow the dynamics from each small movement of the pump impeller could be carried out with more iterative steps and improve its accuracy for this parameter.

Even though there is large disagreement between CFD and test-rig data, both methods agree that there is poor sensitivity in observing the pressure fluctuation amplitude. There is less than 5% differentiation from one erosion state from another. For the test-rig data, confidence in its use for HM is worsened by the fact that the measurements points are within error bars of the other erosion levels.

6.2 Simscape and Test-Rig

6.2.1 Pressure

6.2.1.1 Steady-State Pressure

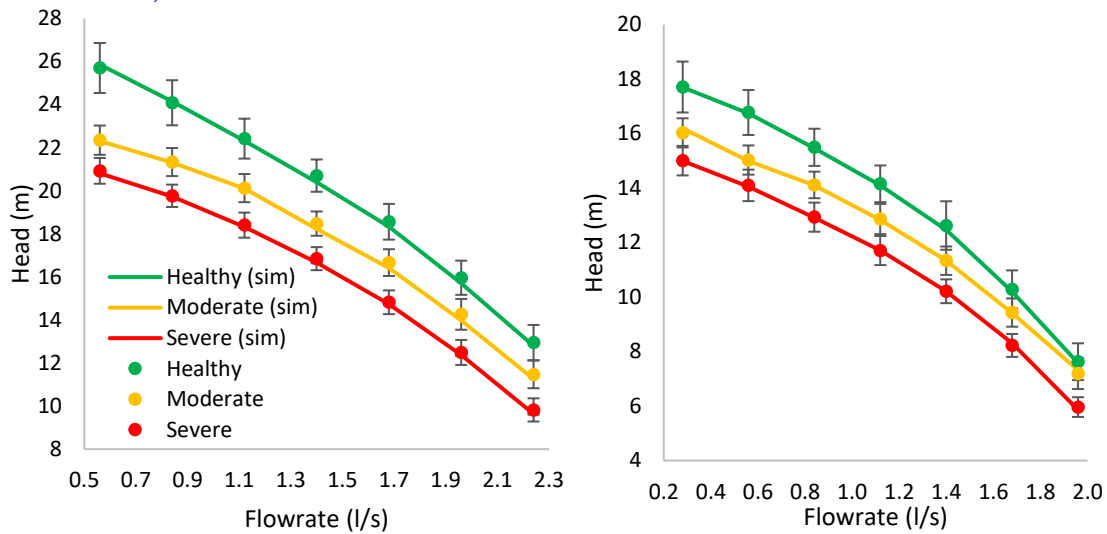


Figure 27. Simscape and Test-Rig results highlighting different pump heads at different erosion levels

The effect of decreased pressure head is implemented by updating the pump block pressure parameter values as described in **sub-section 4.2.3**. The flow values are maintained as it was observed that nominal flowrate for a given erosion level did not yield an appreciable sensitivity to be used for HM, with a change of approximately 2%.

Figure 27 highlights the steady-state pressure values (head) being induced by the pump for the different erosion levels and compares the test-rig results with the Simscape simulation. The simulation is directly calibrated against the test-rig data, as a result can reach an error within less than 1% after fine-tuning for both rotation speeds.

6.2.1.2 Pressure Oscillation Frequency

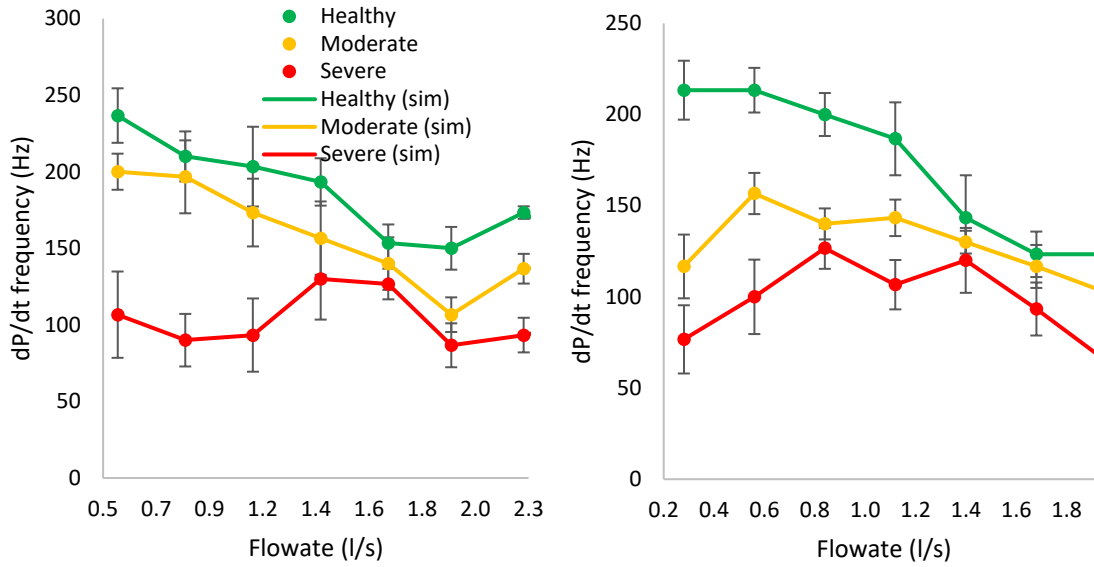


Figure 28. Simscape and Test-Rig highlighting fluctuating pressure frequency at different erosion levels

Figure 28 highlights the frequency of the pressure fluctuations being induced by the pump for the different erosion levels, similar to that of **Figure 25**. The ripple effect is generated by the same mechanism described in **sub-section 4.2.3**.

The mentioned component used to create the ripple effect is successful in replicating the frequency oscillations for each erosion level, achieving an error of less than 1%. The primary compromise comes in **Figure 29**, where it fails to replicate the amplitude of the pressure oscillations, even though it is successful with the flowrate amplitude as highlighted in **Figure 30**. Further description of its sensitivity and usefulness for HM has been provided in **sub-section 6.1.1.2**. This leaves an opportunity for improvement for the ripple mechanism as part of future work.

6.2.1.3 Pressure Oscillation Amplitude

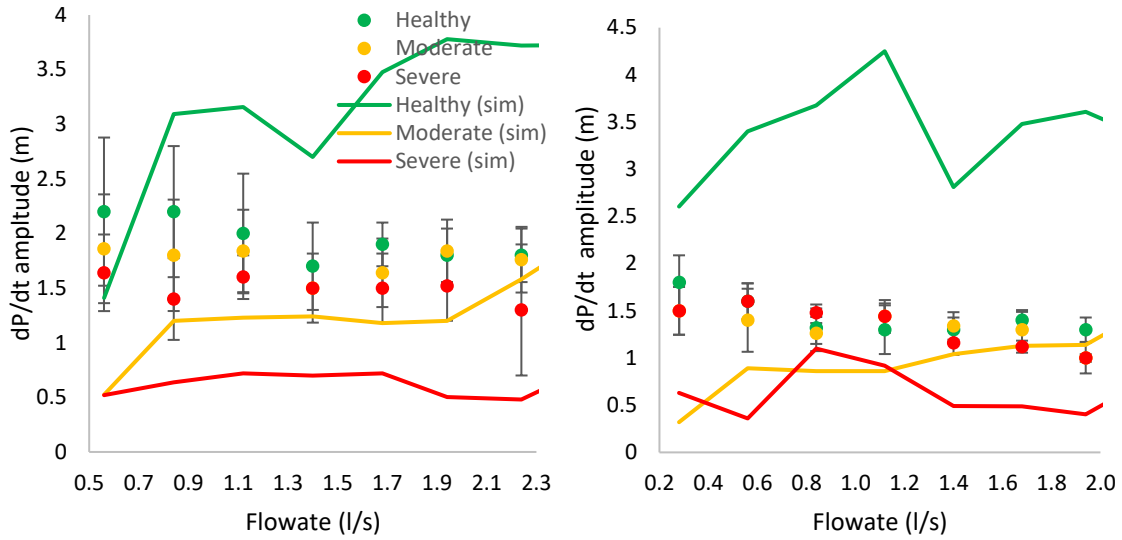


Figure 29. Simscape and Test-Rig highlighting fluctuating pressure amplitude at different erosion levels

Figure 29 highlights the pressure fluctuation amplitude similar to that of **Figure 26** but compares the Simscape data instead with the test-rig. The disagreement between the Simscape and test-rig data highlights a weakness of the mechanism outlined in **sub-section 4.2.3** to replicate the pressure ripples generated by the different erosion levels.

This is as an accepted compromise for the current state of the model. The low sensitivity between the different erosion levels as depicted by the test-rig data points, signified that it is not a reliable health indicator to be used for HM. This low sensitivity is outlined by the overlap in the error bars between the different erosion states, and therefore measurements from this parameter may not be sufficiently reliable and repeatable to be used to conduct erosion HM. As a result of this finding, the ripple generating mechanism was not optimised to replicate this parameter, so that the mechanism can be optimized in replicating the other fault signatures such as the flow ripple amplitude and pressure fluctuation frequency.

6.2.2 Flowrate

6.2.2.1 Flow Oscillation Amplitude

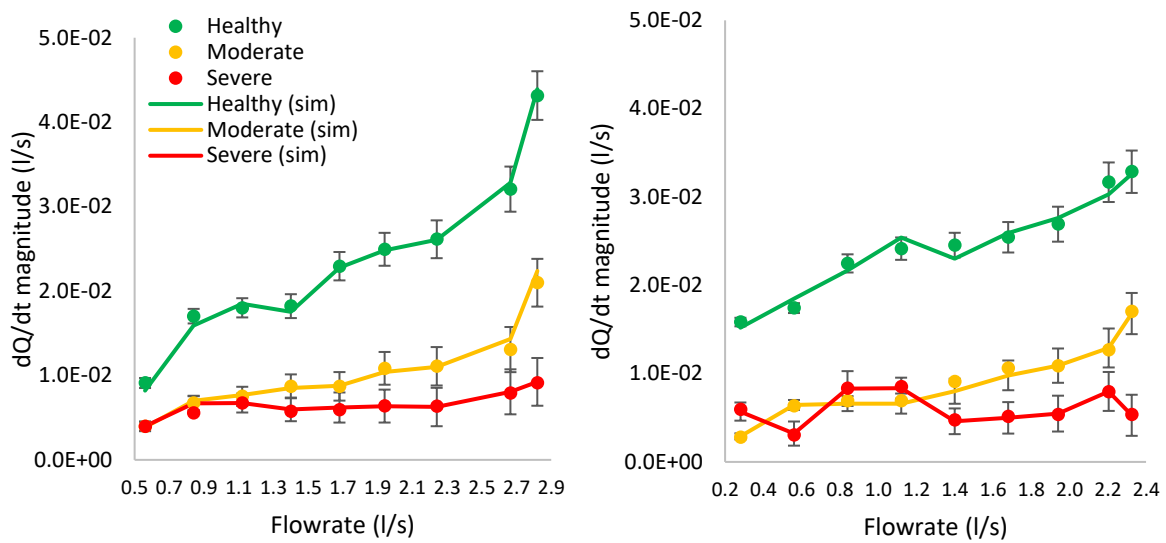


Figure 30. Simscape and Test-Rig highlighting fluctuating pressure frequency at different erosion levels

Figure 30 highlights the flow oscillation amplitude resulting from the Simscape simulations. These flow oscillations are measured similarly to the pressure fluctuation amplitude. The frequency of these flow oscillation is similar to that of pressure and the frequency values can be re-used for the same parameter.

As highlighted by the result, the more severe the erosion, the amplitude of the flow-fluctuations is reduced. The system experiences less flow turbulence as the erosion worsens. This parameter also shows a very high sensitivity between the three erosion levels for both 3500 RPM and 2900 RPM cases. This is particularly true at the highest flowrates where it shows the largest sensitivity valued at approximately 200% on average for both cases. Measuring the three next highest flowrates is also viable where a sensitivity of approximately over 100% can be observed. The sensitivity is reduced at lower flowrates, where moderate and severe erosion cases cannot be distinguished. Measuring flow ripples at this operating point may still be useful as it is still able to distinguish between healthy and moderate or severe cases.

Figure 30 also highlight the success of using the ripple generating mechanism outlined in **sub-section 4.2.3**. The code is able to replicate the ripples generated by the pump in the test-rig for each datapoint within the margins of the error bars.

6.2.3 Current

6.2.3.1 Motor RMS Currents

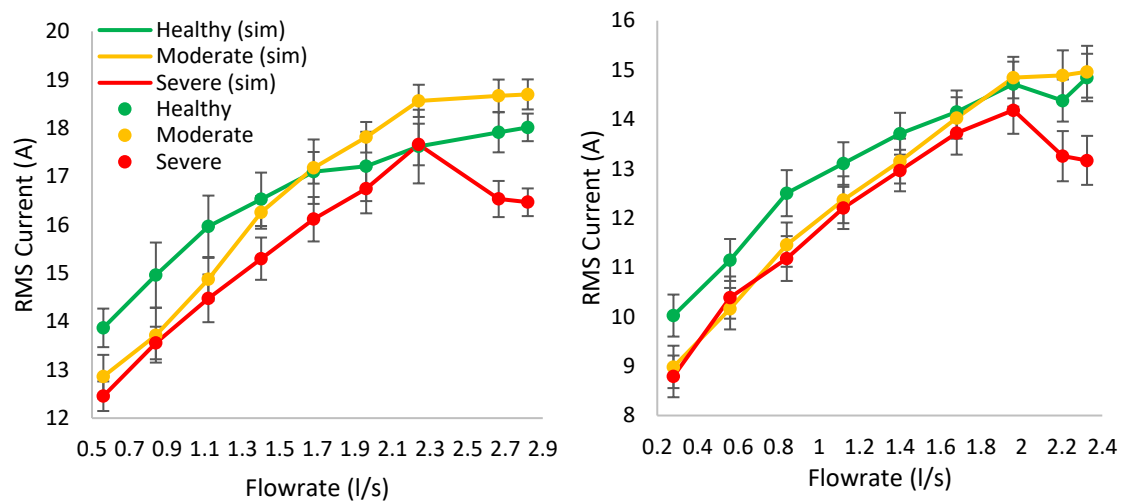


Figure 31. Simscape and Test-Rig highlighting RMS motor current at different erosion levels

Figure 31 outlines RMS motor current when plotted against the flowrate. There is a linear relationship between the pump flowrate and the current generated by the motor. For the 3500 RPM case, the RMS current stops rising after 2.24 l/s of flow, whereas for the 2900 RPM, it stops rising after the 1.96 l/s. The data points after these values shows a sharp decrease rate in the motor current rise for an increase in the flowrate, as these values are outside the intended operating point of the pump used.

A notable observation is the sharp decrease in the current value for the severe erosion case. The amount of material loss of the impeller means that the blade is allowed to slip through the fluid, so even though the flowrate still increases, there will be substantial drop in torque felt by the motor. This leads to a reduction in the current generated by the motor.

The data also shows that the sensitivity between the healthy and moderate erosion case is poor, as there is overlap in the motor current values generated. As a result, distinguishing between the two erosion states will be difficult. There is however a good sensitivity level of approximately 11% for the two RPM cases at the maximum flowrate for distinguishing between the healthy and severe erosion cases.

After calibration, the model running in Simscape shows close agreement with the test-rig data, with an error of approximately 1%. This is done by updating the input power required in the pump parameters block using data acquired from the test-rig.

6.2.3.2 Motor RMS Currents FFT

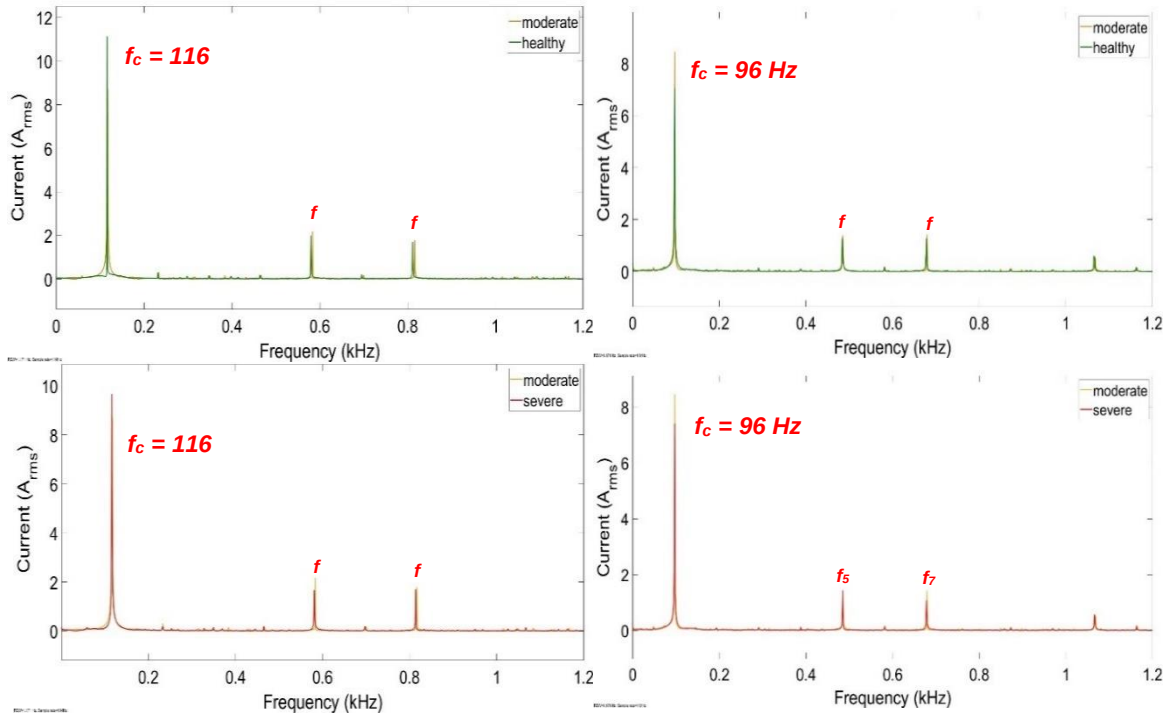


Figure 32. Test-Rig Results outlining the FFT of the RMS motor current at different erosion levels

Figure 32 highlights the FFT results from the current waveform from the BLDC motor currents. The results between the different erosion cases are overlaid so that a comparison could be made between the successive health states. A window of approximately of 10 times the fundamental frequency is shown, as this is the most likely location where a fault could be detected [98, 140]. The top row outlines an overlay of the results for healthy and moderate erosion cases. The bottom row outlines the results for moderate and severe erosion cases.

Analysing the fundamental frequency, the sensitivity between the health states is very low and generally inconsistent. For 3500 RPM case, the peak current values for severe and moderate cases are very close. The healthy and moderate overlay shows higher peak current for healthy case, but for the 2900 RPM case, the peak of the healthy case is less than the moderate case. It is also shown that for the

same case, severe and healthy cases have about the same current value. The moderate values show the highest peak value, which is in contradiction to the 3500 RPM case. Furthermore, in addition to signal not having a consistent pattern of change from the different erosion levels, the quantity of change in the signal peaks are low.

Analysing the further down the frequency spectrum also reveal no additional harmonics are generated from the different erosion levels. There are also no significant changes in the peak values from successive harmonic contents that are present in all erosion levels, such as the 5th and 7th harmonics for both 3500 RPM and 2900 RPM cases.

According to the previous works by previous authors in [38, 40] for FFT to be viable for HM, at least a sensitivity of 150% is required for any signal growth or decay, as significant changes in the frequency domain tend to occur in logarithmic increments. Signal changes in the order of 10% would be acceptable for time-domain measurements, but in the frequency domain, this may be caused by variations on the signal noise floor.

6.3 Jet-Fuel Simulations

The following results are extrapolated data for Jet-A simulation using the validated results with water. No test-rig data is available from Jet-Fuel as adding this element would stretch beyond the available resources allocated in this project in terms of time and budget. Since CFD has shown a high level of conformity with the test-rig results with water, the simulations are then repeated with Jet-A to generate the required data related to its fluid-mechanic performance. The fluid model for Jet-A in Star-CCM+ has been used in previous works and has been deemed a as a reliable reference [141, 142]. The fluid-mechanic performance of the model running in Simscape is then calibrated to the results generated by the CFD simulation result.

The motor currents are generated by updating the input power values based on the results of the CFD simulations. The decrease in output head is used to represent the changes of using a different fluid that has lower density and higher viscosity.

Further discussion on the advantages and limitations of the CFD methods used to generate data with Jet-A, and further description on how testing with Jet-A can be done to improve its results is found in **sub-section 7.2.3** and **sub-section 6.1.2** respectively.

6.3.1 Pressure

6.3.1.1 Steady-State Pressure

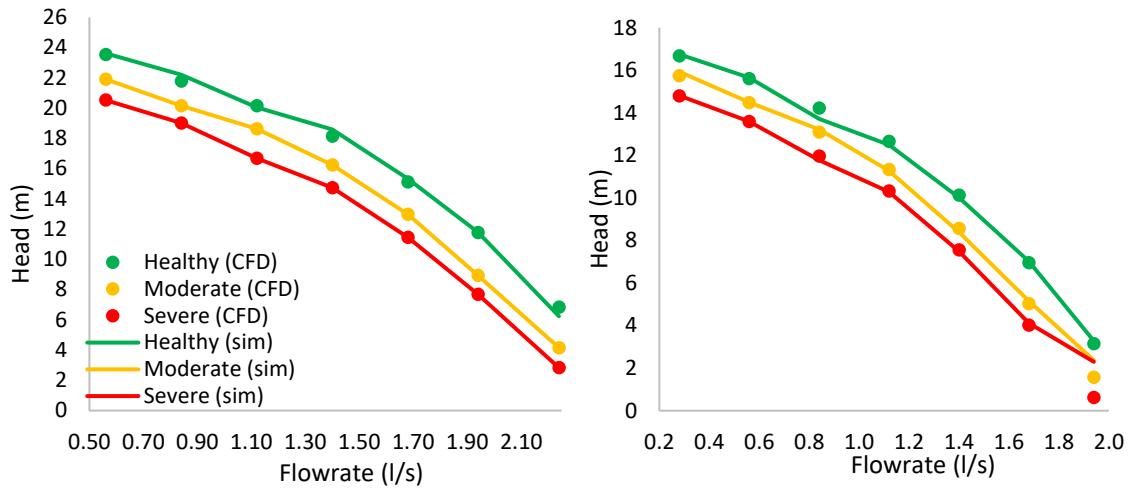


Figure 33. Simscape and test-rig results highlighting different pump heads at different erosion levels

Figure 33 compares the results from CFD simulation and the model running on Simscape using Jet-A as the fluid. A high level of agreement is achieved between the two methods, with an average error of 2%. The largest discrepancy is found for the highest flowrate datapoint for the 2900 RPM case, where CFD predicts a head value of 1.57m and 0.63m for moderate and severe erosion cases respectively and the Simscape data converges at 2.30m of head.

In addition to the disagreement with the last datapoint, according to the CFD results, further increases in the flowrate beyond the normal operating points outlined in **Table 3** will lead to pump generating negative pressure and cease to function properly. This is due to the higher viscosity of the fluid when compared to water at 1.27 cP, as opposed to 0.89 cP [143]. This means it requires greater energy to overcome the internal friction of the fluid. At these higher flowrates, with the same input power fed, the pump could not overcome the internal friction of the fluid at these higher flow velocities and net positive head could not be generated by the component.

6.3.1.2 Pressure Oscillation Frequency

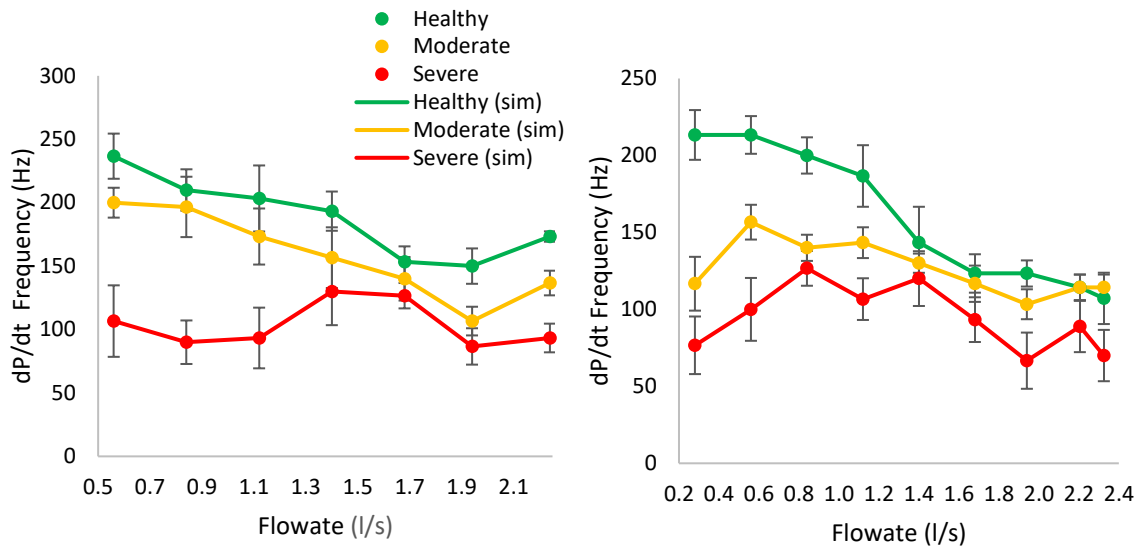


Figure 34. Simscape and test-rig results highlighting different pump heads at different erosion levels

Figure 34 outlines the pressure oscillation frequency when compared with test-rig data. As summarized by the previous results using water, CFD was not a reliable in predicting this parameter accurately. the effect of increased viscosity, as projected by Simscape, does not influence the frequency of these pressure oscillations. It is therefore still viable to conduct HM by monitoring this parameter when running jet-fuel in the pump.

6.3.2 Flowrate

6.3.2.1 Flow Oscillation Amplitude

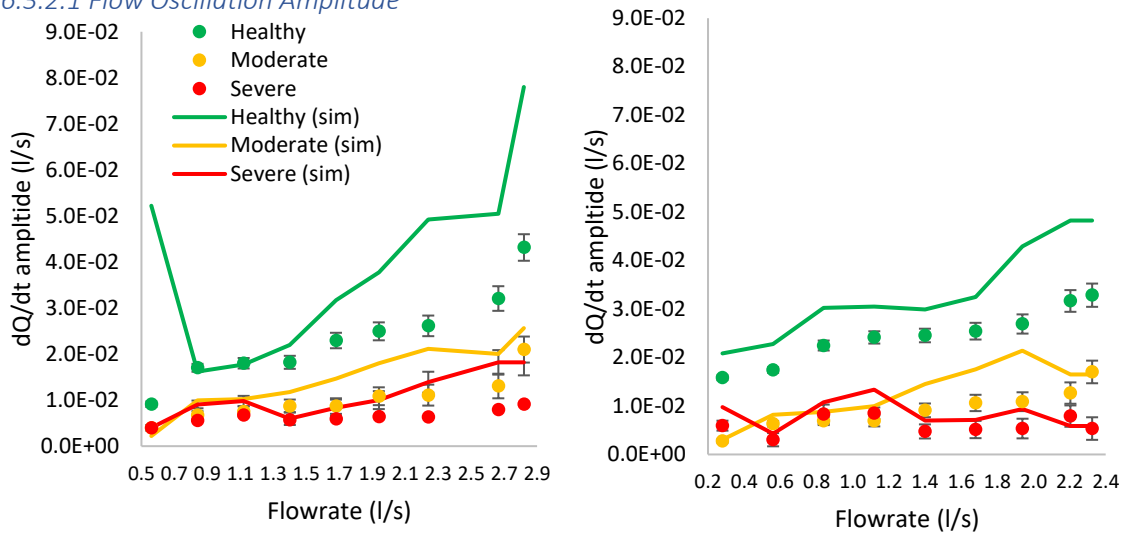


Figure 35. Simscape and Test-Rig highlighting fluctuating pressure frequency at different erosion levels

Figure 35 highlight the flow oscillation amplitude when comparing the test-rig data with water against the projected values generated by Simscape using Jet-A. It is predicted that the flow oscillation amplitude will increase as a result of the more viscous fluid, but as outlined in **sub-section 6.3.1.2** has minimal effect to the frequency of the oscillations.

Based on the Simscape projections, the sensitivity for HM when using Jet fuel will increase when trying to detect a healthy to moderate impeller for both 2900 RPM and 3500 RPM at value of 280%. The sensitivity will decrease when detecting a moderate to severe impeller at a value of 28% for the 3500 RPM case, which is much less sensitivity than when the fluid is water valued at 200%.

6.3.3 Current

6.3.3.1 Motor RMS Currents

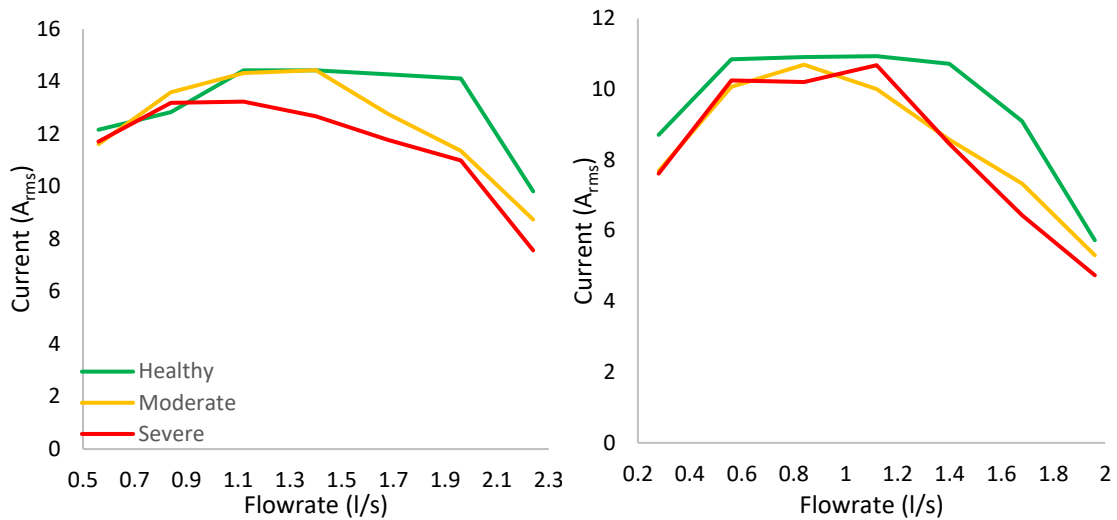


Figure 36. Simscape highlighting RMS motor current at different erosion levels

Figure 36 outlines the projected motor current output with jet-fuel as the fluid. The profile of the motor current when plotted against flowrate is different to that of the graph portrayed by **Figure 31**. Even though Jet-A has 81% the density of water, it also has 42% more viscosity [143]. The latter property of the fluid is the primary differentiating factor when comparing with Jet-A with water. This means that the different to the performance parameters of the pump is more than just a linear scaling. The effects of viscosity become more significant at higher flowrates, as it significantly reduces the head that could be generated by the pump as highlighted in **sub-section 6.3.1.1**. Since the head generated by the pump affects the input power, the significant drop in head generated affects the current draw by the motor and alters its performance envelope. Since CFD cannot generate electrical data, and there is no test-rig data with Jet-A, the RMS current data is not compared with the other methods.

In-spite of the different performance envelope, the sensitivity at maximum flowrates still remains roughly the same, at approximately 15% for 3500 RPM case, and 12% for 2900 RPM. The Jet-A simulation also provide the ability to distinguish between all three erosion levels, instead of just healthy to severe as with water.

6.4 Test Rig

6.4.1 Flowrate

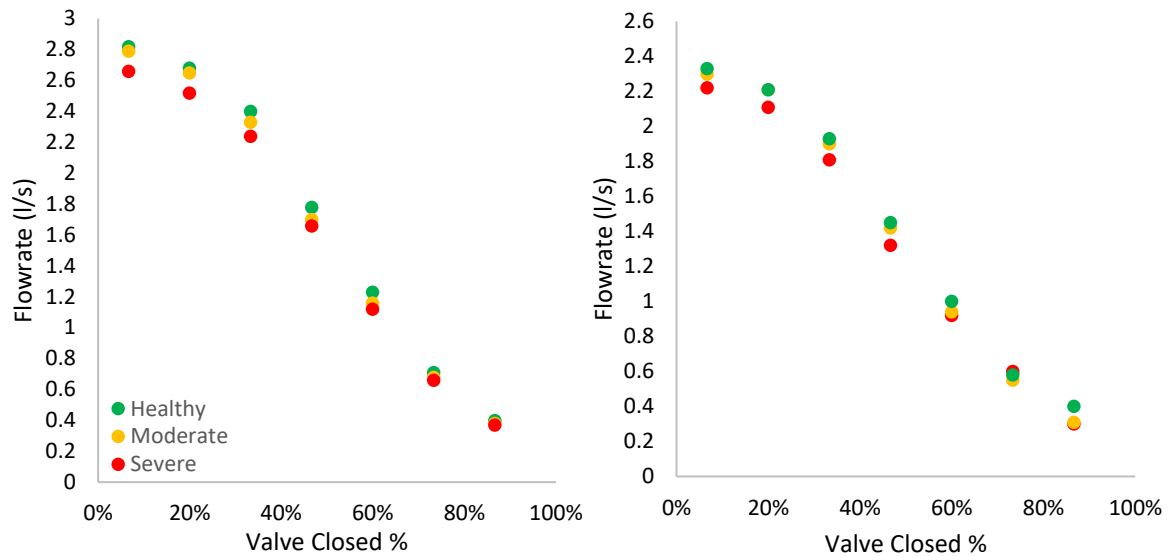


Figure 37. Test-Rig flowrate steady-state at different erosion levels

Figure 37 highlights the test-rig steady state flowrate. As highlighted by the data-points the close proximity of the flowrates at different valve levels demonstrates the low sensitivity of this parameter of approximately 2% at maximum flowrate, which is below than the minimum acceptable value of 5% as highlighted in **Section 2.2.5**. For this reason, using the flow oscillation amplitude in **sub-section 6.2.2.1** is preferred over measuring the average steady-state flowrate values outlined in **sub-section 6.4.1**. The estimated error values from the flow are so small that the error bars are not visible.

6.4.2 Temperature

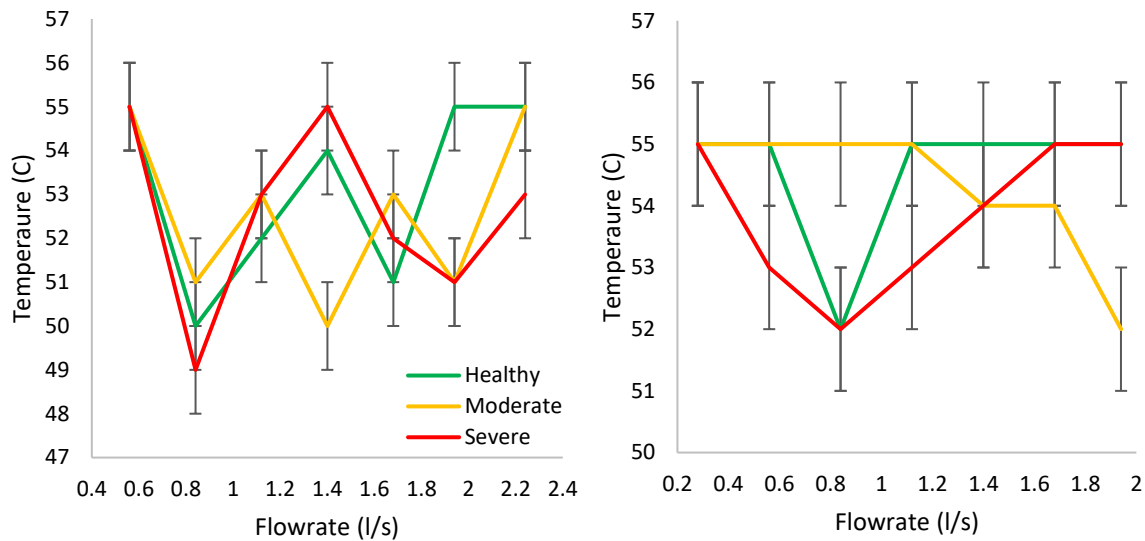


Figure 38. Test-Rig motor temperature at different erosion levels

Figure 38 outlines the motor temperature at different temperatures across different flowrates. As highlighted by the overlapping error bars and graphs, there is no sensitivity between the different erosion levels across all flowrates. These temperature fluctuations are mainly caused by the changing ambient temperature and not from any changes to the pump performance as a result of the erosion. As a result of these experimental findings, temperature is not modelled in simulation.

6.4.3 Summary of HM Testing

The results outlined in **Section 6** compares the data from each of the respective modelling methods against the test-rig results, with the effects of different erosion levels included. The test results in **Section 5** are baseline results carried out under healthy conditions to introduce the relationships between the parameters. The CFD results are used in direct comparison against the test-rig to observe its alignment. The accuracy of its estimations can be further improved by refining the mesh so that its steady-state values conform with the test-rig results. The model running on Simscape was initially developed to design the test-rig but as the system is commissioned, it was found that its accuracy could be improved by adjusting key parameters such as flow, pressure and current, against the test results. Adding additional block elements such as 'Erosion Effect' is necessary to faithfully portray the flow and pressure ripples caused by the turbulence observed on the test-rig.

Even though no sensitivity was observed with the FFT ESA results, carrying out ESA was still possible by means of monitoring the RMS current values within the time domain. The 'Erosion Effect' mechanism implemented was able to mostly replicate the transient behaviour of the pressure and flow-ripples different degrees of erosion, but struggled to replicate the pressure amplitude. This is an accepted compromise as this parameter showed poor sensitivity between the erosion levels. Monitoring the amplitude of the flow-ripple amplitude had much higher sensitivity than monitoring its mean flow values.

This work has described a technique to replicate cavitation erosion damage and conduct hybrid-based HM by using an experimental test-rig, CFD and a model running on Simscape in concert. The following key findings have been discovered in course of the experiments and simulations:

- CFD can provide accurate predictions for degraded impellers on steady-state pressures, but struggles to predict transients with durations that are close to its timestep value.
- Carrying out ESA at close to maximum flowrate significantly improves its sensitivity. Time-domain analysis of the RMS current value is sufficient for HM diagnosis.

- The frequency of pressure ripples can be used to infer the severity of the erosion. The sensitivity is at a maximum when operated at the pump minimum flowrate.
- The amplitude of flow ripples can be used to infer the severity of the erosion. The sensitivity is at a maximum when operated at the pump maximum flowrate.
- The sensitivity from monitoring steady-state flowrate is low at a value of 2% between successive erosion states.

7. Discussion

7.1 Advantages and Limitations to Erosion Predictions

The work has demonstrated how to implement the GLM function to predict cavitation erosion on a radial pump by using a commercial CFD package. The erosion prediction algorithm is also implemented for a two-stage pump for the first time. The limitations of methods are summarised in the following section. Further details of the erosion model calibration with reference experiment could be found on the portfolio submission #2 [4].

7.1.1 Bubble Displacement

For different cases of cavitation, the bubbles may travel a distance of a few millimetres. The erosion model implemented does not take into account the different cavitation conditions and differences in bubble collapse. It applies the same equation for all cavitating conditions, which is one of the weaknesses of using the model.

7.1.2 Compatibility with Commercial CFD

Previous implementations of the erosion model have been carried out with open-source CFD packages, which are less easy to implement. Previous implementation of GLM with commercial CFD software by authors [93, 92] used a simplified model by using Eq. (2) only. This older version is able to highlight the areas vulnerable to erosion but does not show the magnitude of volume loss and is less accurate.

7.1.3 Dependency on Impeller

For a pump, the erosion areas are dependent on the impeller design, specifically in areas with steep curves or sharp angles where there is a large gradient in pressure. The model predicts the peak erosion damage at approximately the same areas on the blade surface. This is due to the inherent weakness of the algorithm as stated in Eq (3) where v_{jet} and hence A_{pit} is directly proportional to the pressure value on the blade surface.

7.2 Test-Environment and HM Results

7.2.1 CFD and Test Rig

The CFD and test-rig results show high-level of agreement with the steady-state pressure values, with an average error of 2.5% for both 3500 RPM and 2900 RPM cases. This highlights the usefulness of CFD for monitoring this parameter to conduct model-based HM. The results from this, in addition to success of previous CFD simulations using Jet-A in Star-CCM+ [141, 142]. give confidence that the results from running CFD simulations with water could be extended to Jet-Fuel by using the provided fluid model.

CFD is successful in predicting the pressure rise of the pump, however, it unfortunately was not able to predict the pressure fluctuation amplitude and frequency. test-rig results highlighted that the profile of the globe valve had some influence in inducing the flow turbulence, and as a result frequency of the generated pressure and flow ripples. Another possible reason is that the current state of the mesh and the timesteps used did not provide sufficient resolution to model all the transient behaviours and complex flow interactions inside the pump.

The flow fluctuations could not be monitored in CFD with the set-up, as the flow is the independent variable and is preset by the user for each pump operating point to observe the resulting pressure output of the pump. As a result of this, the flow being monitored in CFD stays at a largely constant at whatever value is set for that simulation run.

Overall, the usefulness of CFD has been demonstrated in conducting model-based HM and it is reliable for monitoring parameters which rely on steady-state values, such as the pump pressure rise. Its shortcomings are for monitoring transients which have time periods that are close to the timesteps of the CFD

simulation, where events related to the pressure rise and fall could not be resolved accurately.

A possible improvement to increase the required fidelity is to include the valve model into the CFD simulation as detailed in **sub-section 8.2.1.1**. This section discusses this issue in more depth and other elements to improve the results.

7.2.2 Simscape and Test Rig

The Simscape model is particularly useful as it allowed multiple parameters to be simultaneously monitored, whereas the CFD model could only provide information for parameters related to the fluid flow. It is a low-cost alternative to the test-rig where collecting data is more time and labour intensive. Changes could be implemented quickly and its effects understood. The primary drawback of this method that it required data from either the test-rig or higher-fidelity simulation methods to calibrate it. The CFD simulations on the other hand was able to provide an accurate prediction of the steady-state pressure values with the appropriate mesh configuration.

The blocks provided by the various Simscape libraries was able to replicate the test-rig to a sufficiently high fidelity. The base model of the test-rig and basic effect of the impeller erosion was created using those standard blocks. This is specifically referring to the changes to the steady-state current and pressure changes as a result of the erosion.

The other drawback of the Simscape model is that, even with the user-created 'Erosion Effect' block, it fails to replicate the amplitude of pressure ripple. This is in spite of the fact it being able to replicate the pressure frequency, as well as the amplitude of the flow ripples. This was deemed to be acceptable compromise as highlighted in **sub-section 6.1.1.3**, where the test-rig results highlighted that there is not sufficient sensitivity for pressure amplitude to be useful for HM. As a result, the calibration for the 'Erosion Effect' block was prioritized to maximize the fidelity of the pressure ripple frequency and amplitude for the flow oscillation, in expense of being able to not being able to model the amplitude of the pressure oscillations accurately.

7.2.3 Jet-Fuel Simulations

The Jet-Fuel (Jet-A) results used in this project is generated using the validated CFD model, which has been validated with test-rig data using water (H₂O) as the fluid. It has been shown in **sub-section 6.1.1.1** that a high-level of agreement has been achieved between the CFD and test-rig data when monitoring the steady-state pressure values. This provides a sufficient level of confidence to extrapolate the results with Jet-Fuel. This is done by using the validated results from the CFD and re-running the simulations with Jet-A as the fluid. The results from this simulation in turn is used to calibrate the Jet-A version of the model running in Simscape, to provide the data in place of test-rig results with the fluid.

It was found that the higher viscosity of fluid yields in a significant decrease the head generated by the pump, specifically at higher flowrates, which is exacerbated even further with higher erosion levels. According to the CFD results with Jet-A, the pump will generate negative flow at flowrates beyond 2.11 l/s for 2900 RPM case and 2.67 l/s for the 3500 RPM case. As a result, the maximum flowrate is limited to 1.96 l/s and 2.24 l/s for the respective pump rotation speeds.

Jet-A is 42% more viscous than water [143]. This means that at higher flow speeds, it will require much more power provided by a higher rotation speed, in order to be able to generate positive head. This is demonstrated by the 3500 RPM and 2900 RPM cases, where the maximum flowrate before negative pressure is increased to 2.24 l/s from 1.96 l/s. The higher rotation speed provides the required energy for the fluid to overcome the internal friction and allow it to continue it to generate positive head at higher flowrates [8].

Furthermore, since the pressure amplitude results cannot be relied upon as outlined in **sub-section 6.1.1.3**, it is ignored as a HM variable. The results for the pressure and flow fluctuations provide a useful projection to how the parameter is changes when this fuel is used in place of water. The only way to be fully confident with the results is to validate it with test-rig data with Jet-A. In-spite of not having test-rig data, a high level of confidence could still be had with the CFD results related to steady-state pressures, as the water simulations have demonstrated that it had an average error of 2.5% for all the data points when compared to the test-rig.

8. Conclusion

Four possible sensing methods most viable for HM was initially shortlisted. These evaluations are made based on a literature survey of existing HM solutions and examining its suitability for installation in an aircraft fuel system. Three out of four of the proposed HM measurement methods has been identified to be successful for the HM of cavitation erosion, as highlighted by their ability to distinguish the different levels of erosion. Not only the sensing methods have been identified, but its strengths and weaknesses, as well as how to best use that particular sensing technique has been studied. The knowledge found from the results from this part of the study can help operators formulate viable strategies on how to deploy these sensors in aircraft. In addition to successful developing a HM scheme, there are other benefits from this research and opportunities for future work

8.1 Benefits of Research

8.1.1 CFD Erosion Modelling

GLM is practical as it uses field variables already computed by the cavitation simulation. The results can be used as part of accelerated fault testing to create some form of condition monitoring solution. Pump designers could significantly decrease the duration of the design process in testing for cavitation resistance by having the erosion model predict the potential damage areas. The ability to predict long-term cavitation erosion in the early stage of the design allows more opportunities to optimise the blade design and mitigate erosion.

8.1.2 Development of HM Test Environment

The developed test-environment ability to distinguish different levels of erosion damage in different way. The test-rig functionality and performance has been validated. The CFD model is able to predict the impact of the erosion damage based on pump pressure output. The developed system model on Simscape has shown its conformity with the test-rig for all erosion levels. All of the assets developed in the exercise can be extended to other pump faults and initiate new thrusts of research for other issues related to fuel pump operations. Similarly, the techniques and methods developed could be used as an example to create another test-environment for other faults beyond airframe fuel pump.

8.2 Future Work

The results from the HM experiments highlight there is a large room for extension in improving the results. This paper has provided a comprehensive overview for the HM of aircraft fuel pumps and incorporates consideration of other pump HM technologies used in that could be used for the fuel system. Below outlines the future work that could be done to improve the results of the experiments and simulations carried out. In addition to this, further suggestions are created to outline how these HM technologies could be incorporated in the future.

8.2.1 Improvements to HM Testing

8.2.1.1 Improved CFD Model

A possible room for future work would be to do a dedicated study to improve the CFD model, where not only pump mesh and timesteps are refined, but also the implementation of the flow-control valve into the CFD model. This would be done instead of simulating the pump inside the tank, and extending the simulation to include both components.

The CFD model had a significant difference from the test-rig in that the flow is limited by adjusting the mass-flow value at the pump outlet face, whereas in the test-rig the flow was limited by the globe valve. Including the globe valve would improve the fidelity of the simulation, where the dynamics of the flow resulting by the globe valve profile could be monitored. It is clear from the test-rig result that the profile of the globe valve had some influence in the turbulence of the flow and thus affected the generated frequency of the pressure and flow ripples. In this method, the mass-flow value will be fixed to a single value, representing the absolute maximum flowrate of the pump. The flow will then be modulated by adjusting the position of the globe valve relative to its seat. The closer it is to its seat, the lower the flowrate and opposite is true when increasing the flowrate, as this is how the flow is modulated in the actual test-rig. Another room for improvement to increase the fidelity would be to include the effects of the pipe-bending found at the outlet.

The CFD model in STAR-CCM+ has been validated against test-rig results using water. Further improvement would be to validate the CFD model with test results using Jet-A fuel. Implementing all the suggested improvements may

have a strong chance in improving the results related to the prediction of pressure oscillations, however these will come at a significantly high computational cost.

8.2.1.2 Testing with Jet-Fuel

Due to limited resources of the project, the test-rig was not able to run using Jet-Fuel. Implementing this would have translated to a significant increase in cost of not just paying for the fuel, but also components associated that would go far beyond the allocated budget. An additional layer of health, safety and contingency plans would have been required for testing that will push the project before the prescribed deadline.

Validating the test-rig with water is a necessary as a first step, as the task could be achieved with significantly lower cost and with less stringent safety margins. The results provided a proof of concept and a comparison study that hybrid-based HM for cavitation erosion could be carried out using the three HM methods used.

Generating test results with Jet-A will be a very useful next-step for this project to supplement the findings with water. This will be useful to validate the findings in **Section 6.3**, in particular in areas where CFD cannot be depended on, such as predicting the transient behaviour from the pump pressure and flows.

8.2.1.3 Algorithm Development

The captured test results can be improved by using Machine Learning (ML) to automate the process of carrying out diagnostics using the health indicators identified. Having ML can also provide the capability to develop prognostics, as the data collected could be used to project the RUL of the pump.

ML can be categorised to four distinct categories: classification, clustering, regression and ensemble. Classification uses prior observation to predict values from the fed data by categorising them into discrete classes. Clustering is similar to classification but achieves its goal differently by grouping similar datasets together. Regression methods use continuous values instead of discrete levels to indicate the condition [144]. Ensemble fuses several classifier outputs to reduce variance on the results. With ensemble ML, the classifier outputs that have lower confidence can be compensated through several techniques such as averaging, boosting or voting [145].

These ML techniques each use their own classifiers to categorise data into a subset of classes. Examples of these are Bayesian network (BN), Support Vector Machine (SVM) and Fuzzy Logic. Another example is deep learning, which consists of employing neural networks (NN) that replicate human brain function. Neurons form the processing elements using weights, biases and co-relations in hidden layers to classify faults. A comprehensive review of ML methods and classifiers can be found on the work by Sarker [146].

In the case of the thesis, a supervised ensemble model may outperform deep learning in terms of cost-to-performance for diagnosing simpler data, especially if a physics-based model is available [144]. Health indicators such as pressure, current, and flow can be categorized using statistical separation and classification by Support Vector Machine (SVM) to differentiate the input data between known severity levels. In cases where there is a lack of understanding about the system, the use of deep learning may be justified. However, it should be noted that the training of Neural Network (NN) classifiers with additional hidden layers can be computationally intensive and require a significantly larger amount of data [147].

It is not possible to declare one ML technique as the best overall. The selection depends on various factors such as the specific application, availability of data, and computational resources. Therefore, it is important to have a clear understanding of the problem constraints before implementing the most accurate and cost-effective machine learning strategy [148].

The amount of data needed to train the ML algorithm is uncertain, but estimates can be made by analysing past projects. Guo et al. [149] used 18 sensors with 2205 samples each to implement an ensemble method for fault detection and achieved 88.6% accuracy in diagnosing a hydraulic system. Shao, Wang & Wang [150] was able to attain an accuracy of 96.15% through the use of 15 signals, each consisting of 100 samples, to diagnose a diesel engine. In contrast, the thesis relied on 6 sensors, each with 348 samples. As evidenced by the examples cited, the optimal amount of data for training machine learning models can vary and a surplus of data does not necessarily equate to higher accuracy. The number of datasets required for effective ML training is influenced by numerous

factors, including but not limited to the application, data quality, and feature extraction approach. [144, 148]. If ML is to be applied to the thesis data, an initial effort should be made to develop a baseline ML algorithm before proceeding with additional data collection. The amount of data that would need to be collected is justified based on the achieved results compared with the required accuracy of the diagnosis/prognosis algorithm.

The thesis findings suggest initial sensing methods with sufficient sensitivity for detecting the presence of erosion in aircraft fuel pumps. However, acquiring flight data for in-service aircraft and training the chosen algorithm is the biggest challenge when applying machine learning. The sensing techniques used in the thesis can be implemented on a ground test-rig of the aircraft fuel system in question. This approach allows data collection and development of basic machine learning capabilities without the logistic hurdles of acquiring flight data, thus reducing the initial cost of development.

It would be a challenge to link the three erosion states with the number of flight hours and the environmental conditions. For instance, an aircraft that mostly flies in a tropical environment will be more prone to cavitation due to higher vapor pressure compared to those flying in colder environments [8]. For example, if an aircraft with 5000 hours of flying time is mostly used in tropical regions, it may experience moderate erosion in the fuel pumps. However, if the same aircraft is flown for the same number of hours in arctic regions, the erosion will be significantly lower. Therefore, continuous inspection and data analysis of the pump throughout its service life is essential. By correlating the severity of erosion with the number of flight hours, environmental conditions, health indicators, and other factors, it is possible to estimate the Remaining Useful Life (RUL) of the pump. The development of a Health Monitoring (HM) strategy can be co-developed with the airline as part of its planned maintenance activities to make the costs of developing an HM solution more manageable. Instead of just replacing the pump during the maintenance intervals, the operator can work alongside the aircraft manufacturer to provide the required data in developing a HM scheme.

8.2.1.4 Extension of Boundary Conditions and Other Scenarios

The validated model-based methods are useful to simulate the aircraft environment. This is particularly useful when replicating the environment during high-altitude flight, which would not be possible with the test-rig. The results from the simulation could supplement the test-rig results or be used as a preliminary study before carrying out testing with actual aircraft under flight conditions, which are very costly.

The model could also provide testing with scenarios which would require significant change to the test-rig, carrying out the test with simulations first could be used as a feasibility study for adding future upgrades to the test-rig. such as observing how a new valve or a new route in the test-rig system could affect the pump performance.

8.2.2 Improvements to Erosion Predictions in CFD

This work has demonstrated how to implement the GLM function to predict cavitation erosion on a pump using commercial CFD software. GLM is also implemented for a two-stage pump for the first time. The results are still useful not just for this HM work, but also to pump designers and operators. In spite of this, there are still further opportunities to which the erosion predictions can be improved:

1. **Further Testing of GLM:** The research demonstrated in this paper can be improved by further testing of GLM using different pump designs. The extent at which the pump volute influences the erosion areas could be better understood. Further testing of GLM with different blade geometries can also be beneficial to understand how well it estimates erosion. Additional experimental data would need to be generated to support the findings from these studies, as at the moment experimental data only exists for hydrofoils, single-stage radial pumps and propellers.
2. **Comparison with other Erosion Models:** A feasibility study can also be done to examine which applications of GLM excels and further investigate its accuracy and limitations. Comparison of different erosion models such as DBM, IFM and EPM methods can be done to examine its accuracy when compared with experimental data.

3. **Improvement to Estimation of *Apit*:** The erosion algorithm assumes that v_{jet} behaves uniformly for all cavitating conditions, when in reality the different severities of cavitation influence the mechanism that the bubble travels and collapses on the surface. An improvement can be made to the erosion model where some conditional modifier exists for v_{jet} to adjust according to the cavitation severity. This correction factor would adjust for how the bubble travels at different cavitation conditions.

8.2.3 HM Integration on Aircraft

Developing novel HM technologies with prognostics gives operators forewarning of pump failure and enable implementation of preventative repairs. HM of airborne pumps thus far has only been implemented under laboratory conditions, such as the test-rig used in the thesis. Despite the ongoing work in the HM of airborne fuel pumps, there are still open questions that need to be addressed if HM technologies are to be realised. Through this research, the following opportunities related to the HM of airframe fuel pumps for the benefit of industry and academia have been identified:

1. **Sensing Technologies:** Further research is required to establish which sensing technologies are most appropriate to be adapted for the hostile working environment inside the fuel system. Deploying multiple types of sensors may be a solution, however the reliability and integrity of these individual sensors is yet to be determined and a linked HM approach developed.
2. **Pump Control Integration:** At the present, no HM solutions have been implemented on in-service airframe fuel pumps and future HM solutions are proposed as an add-on feature. Future research is required to understand the benefits and limitations of applying HM as an auxiliary solution to the pump, or if the HM technologies could be better implemented as part of the innate design of the fuel pump motor controller.
3. **System Integration:** Hardware integration and fusion of HM-related data across the aircraft fuel system requires further study. The HM solution sensors and their data will need to be combined with the existing Fuel Control System and the Flight Warning System. This synthesis of data on the flight

atmospheric and fuel system conditions will also need to be understood to enable HM approaches for the fuel pumps.

4. **Baseline Information:** There is a lack of operational and sensor information of aircraft fuel pumps under environmental conditions, which are representative of flight conditions. Simulated faults, accelerated life and performance tracking experiments, as well as capturing the fuel system environmental data during flight will require verification of the appropriate baseline and threshold values, for a HM implementation of aircraft fuel pumps. The design of an experimental program to generate such data, or data processing and mining methods of published operational data.
5. **Prediction Models:** More prediction models are needed which can generate the RUL from existing sensing technologies. How far in advance the warning information can or should be provided, as well as how to adjust the maintenance strategy based on the outputs of these predictive models, are open research questions. Present health monitoring solutions have not been fully optimised, and the effects of system performance deterioration are unclear, and require further study.
6. **Cost Evaluations:** Financial assessments related to the deployment of novel HM technologies for aircraft fuel pumps have not been studied in depth. The implementation costs compared to the return on investment from the improved prediction accuracy will need to be examined. The financial study in **section 2.7** relies on general maintenance data and can be supplemented using in-service data specific to airborne fuel pumps.

Despite the differences in operations with pumps used in aircraft fuel systems, there is large possibility for HM technology transfer from other industries. Operators would benefit if these existing HM solutions could be integrated with aircraft fuel pumps in the future. The next step for implementing HM to airborne fuel pumps would be to investigate the six considerations outlined in this section as a first step towards entry into service.

9. References

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