UTILIZING THE MECHANICAL REDUNDANCY OF PARALLEL SYSTEMS FOR CONDITION MONITORING HYDRAULIC PUMPS IN VARIABLE OPERATION

By

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Abstract

This work investigates and develops an approach to resolve some of the unique challenges associated with condition monitoring variable duty equipment. The proposed solution utilizes the mechanical redundancy of parallel systems to create dynamic criterion for detecting incipient faults. In this context, parallel systems are those which contain multiple subsystems (with similar construction) having synchronized operating conditions. This work evaluates the proposed methodology through its application on parallel hydraulic gear pumps. By comparing the dynamic pressure and vibration signal features, it was found that this approach is capable of distinguishing various incipient failures while the pumps were in both stationary and non-stationary operation.

Keywords: Condition monitoring, fault detection, hydraulic pump, gear pump, non-stationary operation, variable duty, parallel system

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To you, dearest reader,

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Chapter 1

1 Introduction

All mechanical systems have a finite operating life and serious hazards may emerge as they approach the end of their service. Unexpected failures can cause substantial profit losses accrued from down time, and even endanger employees or the environment. These consequences are increasingly unacceptable in today's competitive global economy. In attempt to mitigate these risks, companies have been known to invest between 30-50% of their annual operation expenses in maintenance programs [1]. The ever-present goal of increasing profits while maintaining competitive prices generates a continuous effort to reduce the cost of operation. In economic recessions, this is also a primary method of minimizing a deficit. In either case, maintenance can have a significant effect on a company's profitability.

1.1.1 *Types of Maintenance*

Maintenance programs can be grouped into three general categories: reactive, scheduled and condition-based. These approaches can be distinguished by how and why maintenance is initiated. The reactive approach only initiates maintenance once a machine brakes down. Though this may have the lowest upfront cost, there is an extremely high risk of unexpected machine breakdowns. To reduce the likelihood of an unexpected breakdown, it's become common practice to perform scheduled maintenance, whereby technicians routinely inspect and replace components. This generally requires the machine to be taken out of service several times more often than it would if maintenance were performed upon failure. However, if there are multiple components that are required to operate in unison to perform a larger task, scheduled maintenance allows multiple repairs to be made at the same time. This also reduces the risk of consecutive component failures. Nonetheless, the main drawback of this approach is that premature or unnecessary repairs are continually made to ensure parts are replaced before catastrophic failures occur. This also means it's necessary to carry a surplus of stock components, which increases the cost of inventory.

To strike a balance between running the machine to failure and repairing it prematurely, condition-based maintenance systems monitor the equipment for any signs that a fault is developing. If the system detects a fault early enough, repairs can be scheduled as needed and minimize the amount of unnecessary maintenance. Another benefit is that the machine can be shut down if an imminent catastrophic failure is detected. This also prevents damage to other components in the system and reduces risk to people nearby.

Although condition-based maintenance provides considerable advantages over other forms of maintenance, there remains some applications that are particularly problematic for existing Condition Monitoring (CM) techniques. For instance, when monitoring the vibration of equipment operating under changing speeds and loads, it becomes difficult to detect developing faults using conventional approaches since variable operation has a significant effect on the frequency and amplitude of the systems' vibration. Hence there is a demand for research on CM systems for variable-duty machinery.

1.2 Research Scope

This research investigates the use of parallel systems as a condition monitoring tool to overcome some of the current challenges associated with monitoring variable duty equipment. In this context, parallel systems refer to a class of machinery containing multiple subsystems (with similar construction) operating under the same conditions at any given time. The premise is that the mechanical redundancy in these systems can be utilized to generate a dynamic baseline for detecting incipient faults. This work will extend this concept to hydraulic systems by monitoring the pressure and vibration of gear pumps in various operating conditions.

1.3 Thesis Structure

This thesis is arranged as follows:

Chapter 1: Introduction

- Introduction of the concept of condition monitoring and its importance to industry.
- Establishment of the need for research on variable duty CM systems.
- Definition of the terms and scope of this research on parallel hydraulic pumps.
- Outline of the thesis structure.

Chapter 2: Background and Theory

- Review of the principle theories of condition monitoring and fault detection.
- Outline of relevant gear pump characteristics and failure modes.

Chapter 3: Literature Review

- Discussion on the unique challenges with variable duty equipment.
- Identification of the current solutions for these problems and a discussion on their limitations.

Chapter 4: Experimental Design

- Description of the equipment and systems that were used for collecting data on parallel hydraulic pumps in dynamic operation.
- Explanation of the tests and machining methods that were used to replicate the various failure modes.

Chapter 5: Data Analysis

- Presentation on the analytical methodology used to process the signal data to a point where it's possible to identify faults.

Chapter 6: Results and Discussions

- Illustration of the results obtained from the experiments.
- Discussion of the performance of the purposed methodology.

Chapter 7: Conclusion and Future Work

- Revision of the key findings of this research.
- Discussion of potential developments that can be made based on these results.

Chapter 2

2 Background and Theory

This chapter will describe the generalized approach to developing a condition monitoring system for rotating machinery. This section will also provide the reader with a brief background on the relevant theory and provide references for further reading. The chapter begins by introducing the fundamentals of condition monitoring, such as: the characteristics of incipient faults, feature selection, reduction techniques and classification methods. To conclude, this chapter will investigate hydraulic gear pump characteristics and failure modes to identify the relevant techniques for detecting faults in gear pumps.

2.1 Machinery Condition Monitoring Fundamentals

Condition monitoring systems can be categorised into three classes: fault detection, fault prognosis and fault diagnostics [2]. As the names imply, fault detection systems are designed to detect incipient faults to provide early warnings and prevent equipment from reaching catastrophic failure. In addition to detecting the faults, fault prognosis systems attempt to predict the time remaining until the fault renders the machine inoperable, and fault diagnostic systems attempt to determine the type of failure that the machine is experiencing. Despite their differences, these systems all share the fundamental objective of determining the current condition of the machine through some means of observation.

However, most faults cannot be directly observed without removing the equipment from its normal operation. For example, hydraulic pumps are sealed units and to be visually inspected for damage they must be taken out of service. This can have considerable consequences on critical pieces of industrial equipment, since machine downtime often results in substantial profit losses. This has driven the advancement of “online” condition monitoring systems. These systems generally utilize indirect methods of deducing the machine condition by monitoring the symptoms that faults produce while the machine is in operation.

2.2 Failure Symptoms

Faults produce a variety of characteristic symptoms (such as: changes in vibrations, temperature or reduced efficiency) and the first step in developing a condition monitoring system is to identify the most effective method of sensing the expected failure modes. This can prove to be difficult since different faults manifest in deferent ways from others, not to mention, normal (fault free) operation and wear often produce some background level of these same symptoms. For this reason, it’s critical to select the appropriate sensors that will provide an optimal resolution of the failures specific to the equipment. Table 1 shows a list of common machinery failures and the characteristic symptoms that they generate.

Table 1: Characteristic symptoms of common failure modes (Adapted from ISO 17359 [3]**)**

	Effected Parameters			
Faults	**Vibration**	**Temperature**	**Flow / Pressure**	**Oil Particulates**
Unbalanced Shaft	X			
Damaged Bearing	X	X		X
Damaged Gear	X			X
Lubrication Breakdown	X	X		X
Mechanical Looseness	X			
Damaged Seals		X	X	X

The following will provide a brief description on some common analytical techniques that are available to measure these failure symptoms.

Oil Analysis

Some faults can be detected by analysing samples of oil from the machinery under observation to determine changes in chemical and/or physical composition that may be linked to a failure. This technique is particularly effective at detecting an increase in metal particles in the oil (typically caused by abrasive wear or fractures), as well as oil contamination and degradation of lubricant properties. One of the challenges of this type of monitoring system is that conventional laboratory analysis is not conducive to applications where continuous monitoring is required. This has driven the development of real time monitoring systems, such as the on-line partial debris sensors manufactured by Parker Inc [4]. These systems can measure the size and quantity of particles in the oil using spectrometric analysis and ferrous density. This is a useful method for condition monitoring, although as seen in Table 1, there are some failures which may not have a direct effect on the oil composition.

Thermal Analysis

Several types of faults also cause an increase in the amount of energy that gets converted to thermal energy. These faults can be detected by simply monitoring the changes to the system's baseline temperature or by observing the infrared spectrum emitted from the system. This method is particularly effective on faults that cause an increase in mechanical friction or a sudden drop in hydraulic pressure. A key benefit of thermal monitoring is that it can be non-contact and doesn't interfere with normal machine operation. However, there are also several failure modes that may not produce a noticeable change in temperature. In addition, some systems operate at temperatures that would dwarf the marginal thermal variations generated by the fault.

Vibration Analysis

Vibration is a common indication that a fault is developing, especially in rotating machinery. This is because any unbalance or mechanical defect will typically generate a periodic system disturbance above normal levels. Like any underdamped mechanical system, this causes an oscillating energy conversion between potential and kinetic energy. This can be readily sensed by using commercial piezoelectric accelerometers. Vibration analysis is considered one of the most powerful and widely used tools for condition monitoring because numerous faults not only generate a detectable change in vibration, but also produce unique frequency signatures. Meaning, vibration monitoring not only allows one to detect an imminent failure, it also becomes possible to identify the type of fault [5].

Flow/Pressure Analysis

In many fluid power applications, the system flow and pressure are directly affected by the condition of the equipment [6]. This will be discussed in greater detail in the gear pump section of this chapter. Essentially, the efficiency of a hydraulic system is highly dependent on its capability to seal the high-pressure fluid. Over time, components degrade and can allow some fluid to leak past them, causing a change in the pressure and flow rate. Hence, these parameters can be monitored to gain insight on the condition of the machine. However, the resolution and frequency response of conventional flowmeters are often incapable of distinguishing the marginal flow differences caused by incipient faults. This is not the case for pressure transducers, which can achieve a much greater resolution and frequency response. Like vibration, frequency analysis can enable fault diagnostics in addition to detection. For this reason, pressure is typically a superior monitoring parameter for fault detection in hydraulic systems.

It's often beneficial to utilize a combination of these techniques since a single technique may not detect all potential failure modes in their infancy. From these techniques, it appears most of the expected failure modes of hydraulic gear pumps will affect the system's vibration and/or the flow and pressure.

2.3 Feature Selection

Once the appropriate sensors have been selected, it's necessary to process the signal to extract characteristics (features) that can be used to evaluate the condition of the machine. The most common features for condition monitoring can be categorized into the following domains: time, frequency and time-frequency.

<u>Time Domain Features</u>

One of the most frequently used approaches for extracting signal characteristics, is to use statistical parameters of the raw time-series signal. This is because statistics, such as: root mean square, standard deviation, range, and kurtosis, provide intuitive information on the characteristics of the time series data [7]. In vibration analysis, these values can be used to interpret the relative magnitude or energy of vibration, or the “smoothness” of the signal. These features are particularly useful for capturing transient events in a signal, since frequency-based approaches lose temporal information from the signal. However this approach on its own does have its short comings, especially when the background noise is relatively high compared to the failure signal characteristics. The performance of these features can be improved when used in conjunction with signal processing techniques (discussed in section 2.4).

Frequency Domain Features

Frequency spectrum analysis can also provide useful insight into the condition of the machine since many faults in rotating equipment cause a periotic system response. Several signal processing techniques have been developed to convert time series data to the frequency domain. An excellent review of frequency analysis techniques can be found in [8]. This work will utilize the Fast Fourier Transform (FFT) to examine the frequency spectrum of the signal data. When using the FFT, care must be taken to avoid some issues such as: aliasing, spectral leakage and DC offset. These can be resolved by: using a low pass filter with a cut off frequency set to half of the sampling frequency (Nyquist frequency), windowing, and subtracting the mean of the signal respectively.

The signal amplitudes at known fault frequencies and their harmonics & sidebands or the power spectral density can be used as features for condition monitoring. However, there are some limitations when converting a signal to the frequency domain. In the case where a fault generates an impulse at random, the dominant signal frequencies will often conceal the fault signature. Temporal signal information is also lost, meaning there is ambiguity in determining the time at which failure frequency signatures were excited. For this reason, time-frequency techniques have been developed to retain information from both the time and frequency domains.

<u>Time-Frequency Domain Features</u>

Time-Frequency techniques are those which extract frequency information over the duration of the signal. There are several time-frequency techniques that have been used for condition monitoring, the most fundamental is the Short Time Fourier Transform (STFT). This technique uses a sliding window to segment the signal into a series of slices which are then processed using a FFT to obtain the frequency contents at each slice in time. The frequency and amplitude can then be plotted with respect to time to show how the signal frequencies change with time. This is known as a spectrogram. This technique can be useful for detecting and diagnosing faults in variable duty machinery since the characteristic fault frequencies are often proportional to the speed of the equipment. In which case, the spectrogram would likely show a noticeable trend opposed to the smeared spectrum that would be obtained from the FFT of the whole signal.

However, the spectrogram does share much of the same limitations as the FFT. In the case where the machine speed varies along the window length, “the higher harmonics (in particular) no longer appear as discrete frequencies and are smeared over a number of lines which increases with harmonic order” [8]. In addition, there is a trade-off between the time and frequency resolutions. This is because a narrower window length will increase the time resolution but reduce the frequency resolution. This is referred to as the

Gabor limit. To use this technique successfully, it’s important to find the balance between sufficiently small window lengths (to minimize speed variance over the sample) at the expense of the frequency resolution.

Opposed to the STFT, where the signal is decomposed into its sinusoidal components, Wavelet analysis can be used to decompose the signal by iteratively scaling and shifting a mother wavelet along a signal. A series of localized time-frequency coefficients, representing the correlation between location and scale of the mother wavelet and the signal, can be depicted as a representation of the frequency spectrum over the signal duration. If a proper mother wavelet is chosen, this technique can improve time resolution of high frequency components while maintaining the frequency resolution of low frequency components. Wavelet analysis has been used extensively for signal processing and noise reduction. A more detailed review of the wavelet method can be found in [9].

As was just mentioned, the success of the wavelet technique is highly dependent on the choice of the mother wavelet. In contrast, Empirical Mode Decomposition (EMD) does not rely on the choice of a basis function. Instead EMD decomposes the signal using the oscillatory modes of frequency bands (intrinsic mode functions) and the mean trend of the signal (residue). EMD (and its variants) have proved to be useful tools for analysing non-stationary signals and is described in much greater detail in [10].

Another technique that can also provide useful features is the Autoregressive (AR) model. Essentially, the AR function iteratively determines a set of time-series coefficients that best predict the future signal values based on previous data. AR models have been used for condition monitoring by either using the coefficients themselves as features [11] or the prediction error can be monitored [12]. [13] compared the performance of AR modelling to back propagation neural networks and radial basis function networks and was found to require less vibration data for pattern classification. A detailed review of how AR modeling can be used for CM, can be found in [14].

2.4 Preprocessing and Noise Reduction

When extracting features from the signal, there are several techniques that can be used to improve the signal to noise ratio. The following are a few common methods used in condition monitoring applications.

One approach is to segment the signals to minimize operational variance within the segment (much like the process for the STFT). Another common approach is to utilize filters to reduce the amount of unwanted frequency content from the signal before extracting features. Adaptive noise cancelation can be used to reduce noise by taking a reference signal and continually adapting a filter to remove signal contents that are similar between each signal. An extension of this method, called self adaptive noise cancelation, uses a time delayed version of the original signal. Details on these techniques can be found in [15].

Minimum Entropy Deconvolution (MED) is another method designed to enhance impulsive features in the signal by optimizing a filter to maximize the kurtosis of the signal. A detailed review of this algorithm can be found in [16], the authors of which have also recently proposed an extension of this approach [17]. Their latest paper addresses that MED targets single impulses and proposes a new method (Multipoint Optimal Minimum

Entropy Deconvolution Adjusted) for the deconvolution of an infinite periodic impulse train.

Another signal processing technique that has been used extensively for condition monitoring rotating equipment is called time-synchronous averaging (TSA). In TSA, the signal is resampled a fixed number of times per revolution and averaged over successive revolutions. This results in the filtering of the non-synchronous background noise from the dominant synchronous signal components. An excellent review of this method can be found in [18].

Another well-known preprocessing technique used for condition monitoring is envelope analysis. This technique is useful for extracting the modulation frequencies of cyclical impacts by finding the amplitude modulation (or envelope) of the high frequency signal content, that is excited due to the systems natural resonance, then analysing this envelope in the frequency domain. An excellent review of this method can be found in [8].

2.5 Feature Reduction

Since different faults can be more challenging to detect in different features, it is common practice to monitor several features to ensure a fault is not missed. However, the downfall of this is that the amount of training data required for classification increases exponentially with the number of features being monitored. This is known as “the curse of dimensionality” and there are two general approaches to this problem. The first approach is to select only the features that best correlate with the desired failure. However, in applications where this data is not available, component analysis techniques can be used to transform the feature vector into its principle components.

Principal Component Analysis

In its most general form, Principal Component Analysis (PCA), calculates the orthogonal principal vectors that have the least variance in the sample [19]. Transforming the feature set by these vectors essentially combines any redundant or correlated features, making classification a much simpler task. Variants of PCA, such as, independent component analysis, non-linear PCA and dynamic PCA, have been developed to reduce the feature set to the most statistically independent hyperspace, identify non-linear relationships or those which change over time, respectively. An excellent review of PCA and its variants can be found in [20].

2.6 Classification

After the characteristics of the signal have been extracted, the next objective is to classify them as faulted or healthy. From a machine learning prospective, this is often a very complex task. Numerous algorithms and techniques have been developed to solve these challenges and have proven useful for condition monitoring.

Expert Systems

One of the most commonly employed classification techniques for fault detection is the expert or rule-based approach. These systems are designed by identifying logical relations between the machine condition and the features, typically structured using if-then statements. The most basic rule is where one would set a maximum (or minimum) acceptable value on a feature. If it begins to exceed this threshold level, an alarm is triggered indicating that a fault is present [14]. Additional rules can be added to construct logical relationships or dependencies between features, commonly referred to as decision tables or trees. An excellent review on expert system theory can be found in [21]. Some of these logical relationships can be best described using the principles of *Fuzzy Logic*, whereby a variable can be a represented as some degree between two states. Mechefske provides an excellent review of this methodology in [22].

The simplicity of the expert system approach makes it a very useful tool for CM however, there are a few problems which arise when using this method. Foremost, is how to determine the appropriate value of the threshold. To make this decision, some *a priori* knowledge is required to estimate the variance in the features from normal vs faulted operation. This task is made even more difficult if the machine operates under variable speeds or loads (this topic will be explored further in chapter 3). However, the data required to form these decisions is often limited, so researchers have developed other algorithms to further automate the classification process and more efficiently process available data.

Supervised Classification Systems

Advanced machine learning techniques, such as: Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have proven to be very powerful tools for condition monitoring classification of multivariate systems. This is largely attributed to their ability to process highly dimensional and nonlinear systems.

ANNs were loosely inspired by the biology of cognitive learning. This type of system is trained by sending the features as inputs to a black box neural network layer, which then adjusts the gains between the layers of nodes [23]. During the training phase, it can be forced to output a set of specific values corresponding to the condition of the machine. If healthy and faulted data are available, these can then be tested and refined by inputting new data and validating the outputs are correct.

In contrast, SVMs use statistical based machine learning algorithms. During training this system maps the features into a higher dimensional (kernel) space and determines the hyper-plane that optimally separates the healthy and faulted data. An excellent review of SVM can be found in [24] . This method has been used for diagnosing hydraulic gear pump failures in [25].

Novelty Detection

One of the limitations of these general supervised classification techniques is that they require an ample supply of training data (both healthy and faulted) to classify any new data. For many industrial applications, it's often difficult or impractical to acquire faulted data. This has driven the development of Novelty Detection (aka, one class classification) schemes. These systems are trained using only healthy data, and any novel data that is not identified as healthy is considered faulted. Well known examples of these systems are the autoencoder neural network and support vector data descriptor (SVDD).

The autoencoder neural network, is a type of ANN where the nodes are structured into a bottleneck, forcing the network to compress and decompress the data. When new data doesn't match the training data, the reconstructed output will no longer effectively match the inputs. The fundamentals of this approach are reviewed in [26]. Timusk used this approach for detecting hydraulic system faults in [27].

SVDD is an extension of the SVM classifier. Instead of determining the optimal hyperplane to separate different classification states, SVDD aims to encapsulate the healthy training data in the kernel space. [28], [29] are excellent reviews of this algorithm. Once complete, it’s possible to determine whether new data resides outside the hypersphere to detect faults. A relative distance measure was used with SVDD for classifying gear pump faults in [30].

2.7 Summary of Condition Monitoring Theory

This chapter has described the generalized approach and theory required to develop a condition monitoring system for rotating machinery. Table 2 illustrates the process of developing a condition monitoring system and summarizes the topics that were discussed so far. Since this research is focused on developing a condition monitoring system for hydraulic gear pumps, the following section will introduce some the relevant characteristics of this equipment.

Table 2: Condition Monitoring Development Process

Equipment	Pumps
	Bearings
	Gearboxes
Failure Characteristics	Vibration
	Pressure/Flow
	Temperature
Sensors	Accelerometer
	Pressure Transducer
	Thermocouple
Preprocessing	Segmentation
	Filtering
	Noise Cancelation
	Deconvolution
	Envelope Analysis
Feature Extraction	Time Domain
	Frequency Domain
	Time-Frequency Domain
Feature Reduction	Feature Selection
	Principle Component Analysis
Classification	Expert System
	Supervised Classification
	Novelty Detection

2.8 Hydraulic Gear Pumps

Gear pumps are used in numerous industrial applications because of their simplicity, cost and reliability. However, like all mechanical systems, these pumps eventually wear out and require maintenance. The following section will discuss gear pump characteristics and failure modes to identify relevant features for developing a condition monitoring system.

2.8.1 *Characteristics*

There are several gear pump designs, this work will focus on external gear pumps. However, other designs share much of the same operational theory. As the name suggests, flow is established by the rotating gears, as shown in Figure 1 [31]. As the teeth un-mesh, a low-pressure zone is created at the inlet port causing oil to flow into the voids between the gear teeth. Oil is then circulated around the pump housing in the cavities between teeth. A mechanical seal is created as the teeth come back into mesh, which forces the oil through the outlet port. In one rotation, the volume of oil displaced by the pump is equal to the sum the volume between teeth. Since there are two gears and the void volume is roughly equal to the volume of gear teeth, the total volumetric displacement per revolution is calculated as the cylindrical volume between the root diameter and the crest diameter of the gear. The theoretical flow rate can then be expressed by Eq. (1).

$$Q_T = \frac{\pi}{4}(D_o^2 - D_i^2)w \times N \qquad \textbf{Eq. (1)}$$

Where: Q_T is the theoretical flow rate, D_o and D_i are the outer and inner diameters of the gear respectively, w is the width of the gear teeth and N is the number revolutions per minute.

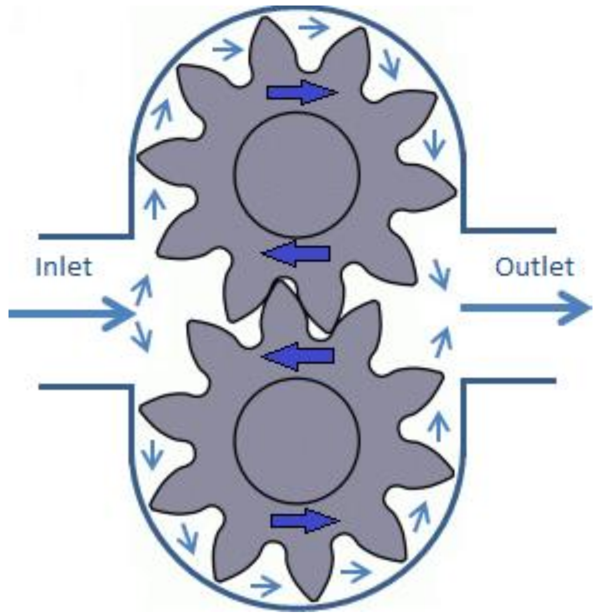


Figure 1: Gear Pump Cross-Section [31]

Leakage is an inherit operating characteristic of gear pumps and is attributed to the slight clearance required between components to operate smoothly. As pressure builds at the outlet port, oil can leak between these clearances in the opposite direction to the intended flow. The velocity profile of the oil leaking between the clearances can be approximated by using Eq. (2) for laminar flow between non-stationary parallel plates with an applied pressure gradient. This is also depicted in Figure 2. However, many assumptions are required to manually integrate this equation over the clearance volumes to determine the net leakage flow rate. Thus making this calculation better suited for approaches that employ numerical tools such, as Computational Fluid Dynamics.

$$u(y) = \frac{1}{2\mu}\frac{\delta P}{\delta x}(y^2 - hy) + \frac{Vy}{h} \qquad \textbf{Eq. (2)}$$

Where: $u(y)$ is the fluid velocity at position y, $\frac{\delta P}{\delta x}$ is the pressure gradient along x, μ is the fluid viscosity, h is the distance between plates and V is the relative velocity of the plate. Note V is positive if moving in the direction of the pressure drop.

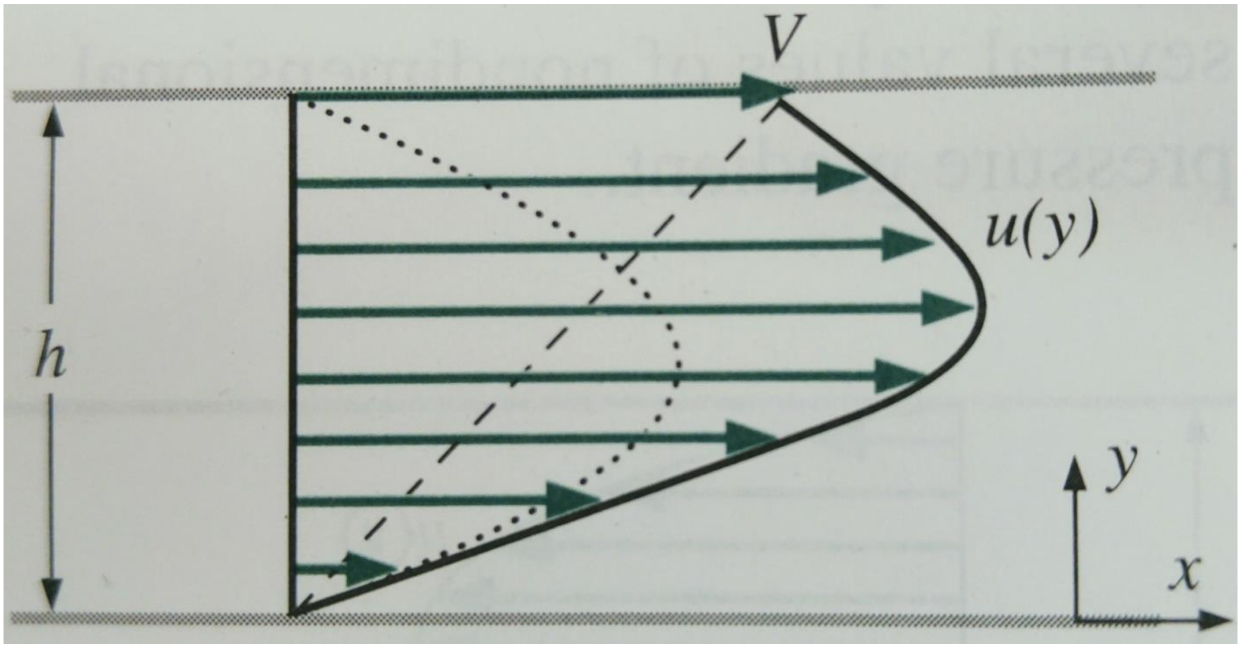


Figure 2: Velocity profile of flow between non-stationary parallel plates with applied pressure gradient, dashed lines indicate the profile for a zero pressure gradient, and dotted lines indicate the profile for a stationary upper plate. [32]

As machinery wears over time, an increase in the clearance between components tends to develop. This clearance can result in a significant effect on the performance of the hydraulic system. Maintenance is required once the pumps ability to generate flow becomes unacceptable. This is often quantified by the volumetric efficiency in Eq. (3).

$$Volumetric\ efficiency = \frac{Actual\ flow\ rate}{Theoretical\ flow\ rate} \quad \textbf{Eq. (3)}$$

Since the total flow is generated by a finite number of gear teeth, the control volume of the outlet port varies slightly as the gears rotate. This makes flow ripple an inherit feature of the gear pump design [33][34]. The fundamental frequency of this ripple is a function of the number of teeth and the angular frequency of the gears, represented in Eq. (4).

Since the gears are out of phase with each other, the harmonics of the fundamental frequency are also prevalent in the system.

$$f_r = \omega \times n \qquad \textbf{Eq. (4)}$$

Where: f_r is the fundamental flow ripple frequency, ω is the gear rotational frequency and n is the number of teeth per gear.

From a condition-monitoring perspective, abnormalities in the flow ripple could be used to identify a developing fault. However, it can be a challenge to directly measure this since these marginal flow fluctuations are too small and occur too fast to be detected by conventional flow meters. Alternatively, it's possible to utilize the relation between flow and pressure to observe this phenomenon using pressure transducers. These offer the advantages of being non-intrusive and having greater resolutions and frequency responses. The Bernoulli equation (Eq. (5)) for an ideal fluid expresses that, in a control volume, the sum of the energy in the system is constant. The intuitive relation that fluctuations in the flow cause proportional fluctuations in the system pressure can be mathematically described by taking the time derivative of this equation, shown in Eq. (6) assuming negligible changes in gravitational potential over time.

$$P + \frac{1}{2}\rho\, v^2 + \rho g h = c \qquad \textbf{Eq. (5)}$$

$$\frac{dP}{dt} + \rho\, v\, \frac{dv}{dt} = 0 \qquad \textbf{Eq. (6)}$$

Where: P is pressure, ρ is the fluid density, v is fluid the velocity, g is the gravitational acceleration constant and h is the height above a reference frame.

2.8.2 *Failure Modes of Hydraulic Gear Pumps*

In hydraulic gear pumps, the most common cause for replacement or repair is mechanical wear [35]. Small abrasions occur as oil contaminants get caught between stationary and rotating components. As these abrasions accumulate, the amount of internal leakage increases and reduces the efficiency of the pump. The softer material components in contact with the rotating gears are the most susceptible to this type of failure. Thrust plates are used to seal the axial face of the gears and are typically made of brass. Hence, they are often the first component to see signs of wear. However, the housing and gear surfaces can also experience this form of failure.

The effects of cavitation or aeration are another common cause of gear pump failure. Cavitation occurs when suction pressure falls below the vaporization pressure of the fluid, causing small vapor bubbles to form in the fluid. As these bubbles reach the high-pressure outlet, they collapse and cause localized high-pressure shocks in the fluid. These repetitive impacts can cause considerable erosion to the pump components, forming pits on the gear teeth, housing and thrust plates. Similar effects are experienced if air becomes entrapped into the fluid.

Gear pumps can also experience several other failure modes analogous to a typical gear box used for power transmission, including: impact or fatigue fracturing, fretting and bending deformation. As well as rolling element bearing failures such as: inner, outer race or rolling element failures. These failure modes are studied extensively in their own domain and were therefore chosen to be exempted from the scope of this work.

Gear pumps are fixed positive displacement pumps, meaning a fixed volume of fluid is discharged per revolution. Recent advancements in variable drive motor technology has sparked interest in using fixed displacement pumps with a variable drive in place of variable displacement pumps [36]. These systems typically require the pumps to operate at changing speeds and pressures, and are an excellent example of where novel CM systems for variable-duty operation would be beneficial.

Chapter 3

3 Literature Review

This chapter will continue exploring principle works concerning fault detection and condition monitoring techniques for rotating machinery, with a focus on equipment in variable operation. This section will describe the current state of this domain and why there is a need to continue advancing CM systems for variable duty equipment.

The chapter begins with a discussion on the unique challenges that arise when attempting to monitor equipment in variable operation, as well as, the current techniques being used for this class of equipment. The subsequent section will then present the emerging solution which utilizes the mechanical redundancy in parallel systems and how the CM discipline benefits from this research.

3.1 Condition Monitoring Equipment in Variable Operation

Most traditional condition monitoring systems perform very well for stationary signals. However, there are some difficulties that arise when analysing signals from equipment in variable operation. In these applications, the machines' operational state can have a significant effect on the signal and its features. This makes it challenging to differentiate between feature variance caused by incipient faults and the variance caused by the change in operation. In the case where a machine is subjected to an extreme operational state, it's possible that a conventional CM system could falsely identify the signal variation as a developing fault.

In the CM discipline, false alarms can often have severe consequences [37]. A major concern is that these cause the technicians to lose faith in the system, meaning next time the alarm is triggered it will not be taken as seriously. Rudimentary CM systems control the threshold levels as a means of reducing the risk of false alarms caused by operational variations. However, this also increases the risk of undetected faults and reduces the amount of lead time available to initiate proactive maintenance. If too many faults are detected late or are not detected at all, the technicians will again lose faith in the CM system and resort to other less efficient maintenance strategies. This is a major challenge that arises when implementing CBM on variable duty equipment. The following will investigate some of the methodologies have been developed in attempt to solve these issues.

Comparison to Historical Samples:

A general approach to this problem has been to collect a complete set of normal and faulted data spanning all possible operational conditions so that new data can be compared to historical samples having similar operational states. State specific classifiers can then be trained to identify the most probable condition of the machine while in a given operational state. This approach has also been extended to novelty detection classifiers where only healthy samples are collected for all possible operational states. In 2001 Timusk utilized this approach for identifying faults in a hydraulic system using state specific autoencoder neural networks [38]. More recently in 2009, McBain built on this methodology using statistical parameterization to reduce the need for training multiple classifiers [39]. In this paper, McBain used a generalized SVDD classifier to detect gearbox faults with marginal effects on classification error.

Though this approach is well suited for a number of applications, the primary challenge with it is in the amount of data that is required for its implementation. In most industrial applications, it is not possible (or feasible) to collect a complete set of historical data that spans all possible operational states that the machine could be subjected to. This task compounds as additional system state parameters (speed, load, temperature etc...) are added to the state definition. It's also necessary to identify how similar a new operational state must be to a historical record before the new data can be compared. To be effective, a balance is needed between the state accuracy and the amount of required training data. Since a larger tolerance correlates to more feature variance per given state, while a smaller tolerance reduces the amount of available data for a given state.

Signal Processing Techniques

Another approach to reducing the influence of variable machine operation has been to process the signal in a way which eliminates signal characteristics that are known to be dependent on the machines operation. One such technique was developed on the premise that many frequency components of rotating systems are highly correlated to the rotational frequency. Thus, by processing the signal to the angular or order domain much of the effects of changing speed can be reduced. Figure 3 depicts the spectral smearing which occurs when directly analysing the frequency spectrum of a signal containing an increase in frequency. It also shows how this effect can be reduced by resampling the signal a set number of times per fundamental cycle. This results in spectral lines correlating to an order of the fundamental resampling frequency. Excellent reviews on this methodology, its implementation and its limitations can be found in [40] and [41].

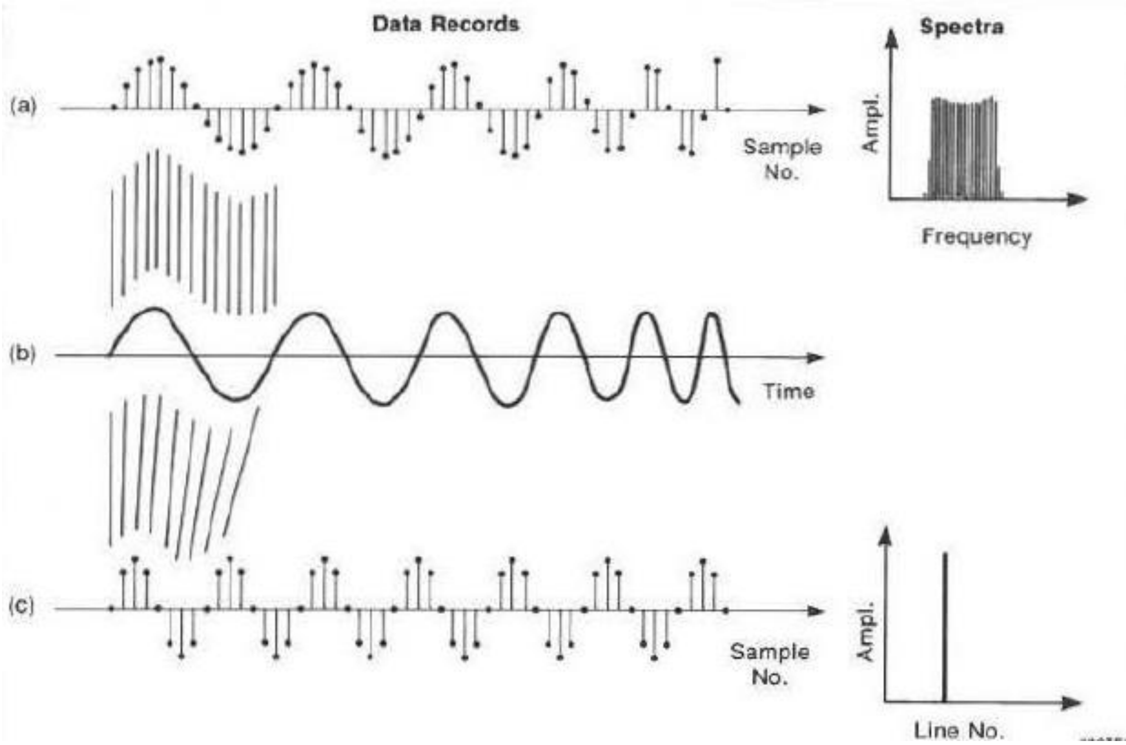


Figure 3: Analysis of a fundamental component which is increasing in frequency [8]

a) Data record resulting from a uniform sampling rate, and its spectrum which spreads over a frequency band corresponding to the speed change;

b) The original time signal;

c) Data record resulting from sampling 8 times per fundamental cycle, and its spectrum which is concentrated in one analysis line.

While this approach can help reduce the effects of the machines changing speed, there are still other operational states (load, temperature etc.) that can have a significant effect on the signal. In addition, the effect of structural resonance can also affect the signal characteristics. In either case, it should be noted that the amplitude of the order spectrum is still highly affected by changes in the machines' operation.

System Modeling Techniques

Another approach, which has seen substantial development over recent years, has been utilizing computational models to determine the theoretical system response to changes in operation. A recent review of over 200 publications focusing on the dynamic modeling of gearbox faults can be found in [42]. In lumped-parameter modeling, systems are approximated by a series of mass, spring and dampening components. By inputting the real-time operating conditions to the numerical model and solving for the systems response, it becomes possible to compare the actual system to the theoretical response. The machine condition can then be deduced by monitoring the residual difference between the theoretical and actual system. It's also possible to simulate known failures into the system model to compare a theoretical failure response to the actual system. This approach was used in [43] where, spur gear dynamics were modeled to estimate the effects of fault growth, illustrated in Figure 4. Similarly, finite element analysis has also been used to simulate the dynamics for condition monitoring purposes.

Though system modeling techniques have been used to increase the performance of condition monitoring systems for variable duty machinery, it too has its limitations. A common shortcoming when applying this approach to industry is the time and technical knowledge required to properly model a complete physical system. Even a simple single stage gear box, can quickly become complex. In addition, each element is only an approximation of the real-world system and therefore there will always be some error between the physical and theoretical systems. In addition, there are often numerous sources of noise and variables which are near impossible to model in most industrial applications. Thus, transferring the challenge to quantifying the tolerable error.

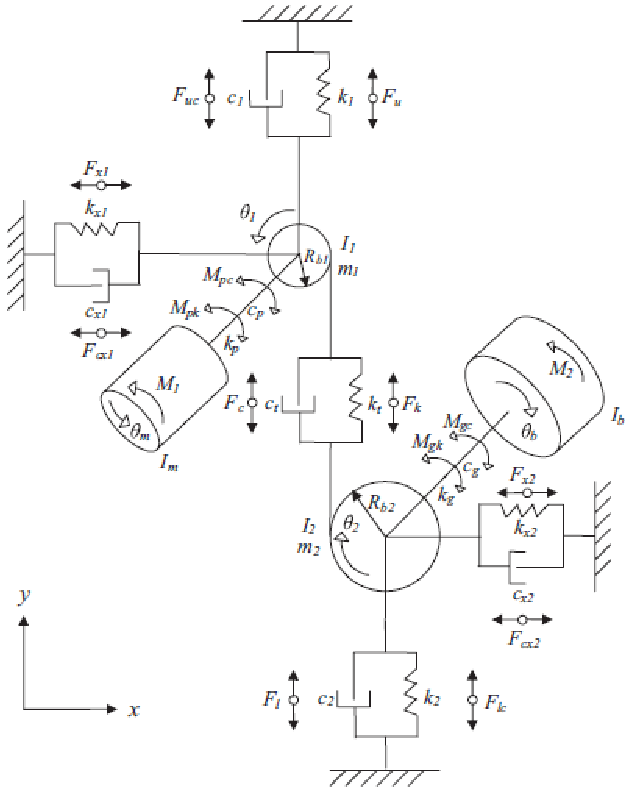


Figure 4: System Modeling Approach for Calculating Theoretical Spur Gear Dynamics and Estimation of Fault Growth [43]

In summary, many techniques have been developed to increase the performance of condition monitoring systems for variable duty equipment. However, there are still some limitations to their implementation on industrial equipment. It's clear that this domain requires a solution with the following criteria:

- Requires a minimal amount of healthy training data.
- Minimizes all effects of variable duty operation (speed, load, temperature resonance, noise, etc.).
- Is simple to understand and can be implemented quickly.

3.2 Mechanical Redundancy in Parallel Machinery

In this work, parallel machinery refers to equipment with multiple similar subsystems in synchronized (or linked) operation. This type of machinery presents a unique opportunity for condition monitoring systems due to the mechanical redundancy that becomes available. Intuitively, healthy subcomponents under the same operating conditions should produce similar feature responses, and as a fault develops in a subsystem, the features should become noticeably different. ElMaghraby [44] explored the concept of exploiting this phenomenon for a condition monitoring system and designed a machine for testing this approach on a variety of parallel mechanisms in non-stationary operation.

This technique would be particularly useful to solve the issues that arise when attempting to detect faults in variable duty machinery. This is because a dynamic baseline becomes available by simply observing and comparing the features from each subcomponent at any time. This would effectively minimize the amount of training data required to detect anomalies during the various operational states.

Two ways in which this approach can be implemented in industry are:

- identifying parallel subsystems that exist in current products, and
- the intentional design of parallel subsystems in critical applications.

Therefore, research in this field benefits the condition monitoring discipline by increasing the scope of machinery that are eligible for CBM and increasing the tools available to overcome CM challenges when variable operation is necessary. The present work aims to expand this area of research into hydraulic systems, in particular hydraulic gear pumps.

3.3 Summary

To conclude, this review has provided an overview on condition monitoring theory for monitoring machinery in variable operation. Upon review of the current solutions, it's clear that additional research is needed to overcome some of the challenges that remain when implementing these systems in the industrial environment. An emerging technique, utilizing the mechanical redundancy of parallel systems, was also identified as a high potential solution to overcome these issues.

Chapter 4

4 Experimental Design

This chapter describes the equipment and systems that were used for testing parallel hydraulic pumps in dynamic operation. Section 3.1 describes the mechanical components that were used for these experiments. Section 3.2 provides details on the sensors, instrumentation and data acquisition equipment. Section 3.3 presents the machine's operation cycle and systems that were implemented to control and vary the speed and load. Section 3.4 explains the various tests and machining methods that were used to replicate the various failure modes.

4.1 Apparatus

The flexible machinery simulator (Figure 5) was principally designed by [45] to test various components in parallel drive systems. The main design criterion for this apparatus was to construct two mechanically identical subsystems that are subjected to synchronized variable operation. It was also designed to easily replace and test components containing seeded faults in numerous types of industrial systems such as: electric motors, gear boxes, bearings, belt drives and hydraulic systems. This design made for an excellent apparatus to collect experimental data for this work. The following describes the various components of this machine.

4.1.1 *Mechanical Design Overview*

Each subsystem is driven by an AC electric motor. Power is transmitted through a reduction gear box and a serpentine belt system to a hydraulic gear pump. The pumps are connected in parallel to a solenoid pressure control valve used to regulate the load on each subsystem.

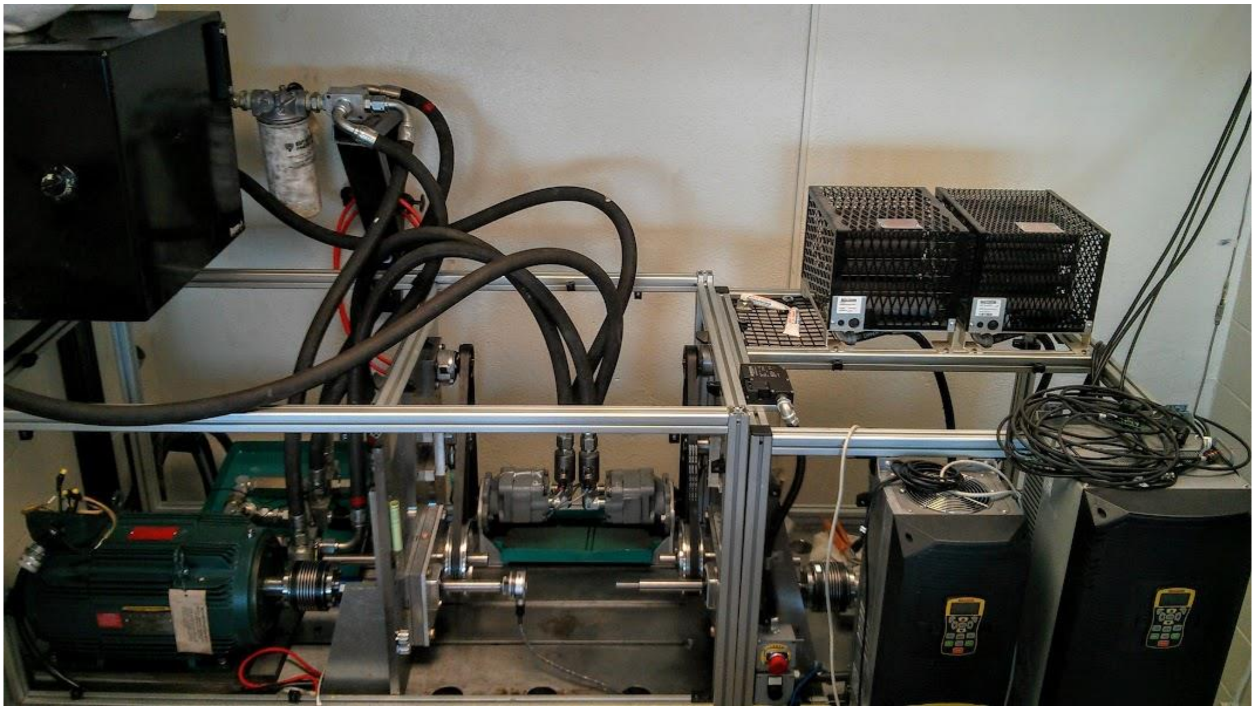


Figure 5: Flexible Machinery Simulator at Laurentian University

4.1.2 *Motor Specifications*

Baldor Reliance® AC induction motors were used as the prime movers in this work. The specifications of these motors are listed:

- Power rating: 10 HP
- Number of poles: 4
- Speed at 60 Hz: 1800 RPM
- Torque Rating: 30 lb·ft at 1800 RPM

4.1.3 *Gearbox Specifications*

A new modular gear box was manufactured for this work. This was done to reduce the amount of space that the previous gear boxes occupied so that torque transducers could be placed between the gearbox and the motors for future work. This design also improved shaft alignment tolerances and increased accessibility to the gears and bearings. The specifications of the gearbox are listed:

- Reduction ratio: 3:1
- Gear face width: 0.5”
- Gear pitch: 15
- Center to center distance: 4”
- Bearings: Rexnord™ ERK-16

4.1.4 *Serpentine Belt Drive Specifications*

An automotive accessory drive system was used to transmit power from the gearbox to the hydraulic pump. Figure 6 shows the geometrical design for the serpentine system. The specifications of the serpentine belt drive are listed:

- Drive pulley diameter: 6.3125”
- Pump pulley diameter: 2.875”
- Number of belt groves: 6
- Static belt tension: 80 Lbs

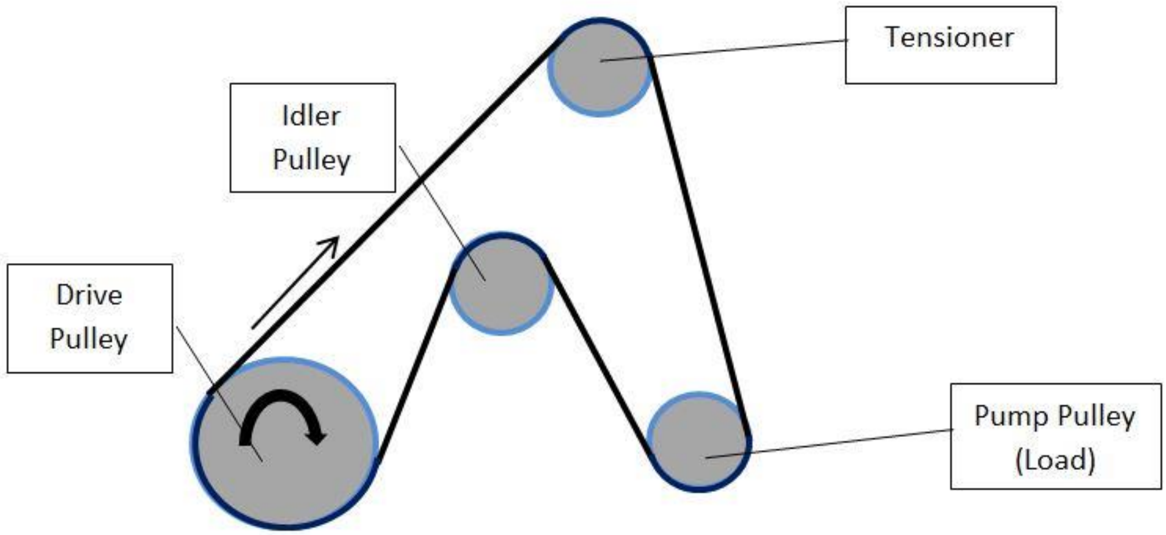


Figure 6: Serpentine Belt Drive Geometry

4.1.5 *Hydraulic Gear Pumps*

Two Metaris™ MHP-20 external gear pumps were used in this work. These pumps are fully serviceable and replacement components can be purchased easily at a relatively low cost. These pumps allowed for relatively easy fault seeding. The specifications of the hydraulic gear pumps are listed:

- Gear width: 1”
- Pump displacement: 1.97 in^3/rev
- Maximum pressure: 3000 psi
- Number of teeth per gear: 10

4.1.6 *Hydraulic Loading Circuit*

Figure 7 depicts the machine schematic diagram which shows the details of the hydraulic circuit used to load the machine in this work. The proportional solenoid pressure relief valve restricts the flow of hydraulic oil, increasing the output pressure at the pumps and the load on the system. The solenoid's electrical current is proportional to the relief pressure and is used to control the system load. Several hydraulic components were also used to ensure the safety of the operator and machine in the case of a potential catastrophic failure. A detailed list of the components used in this circuit is shown in Table 3.

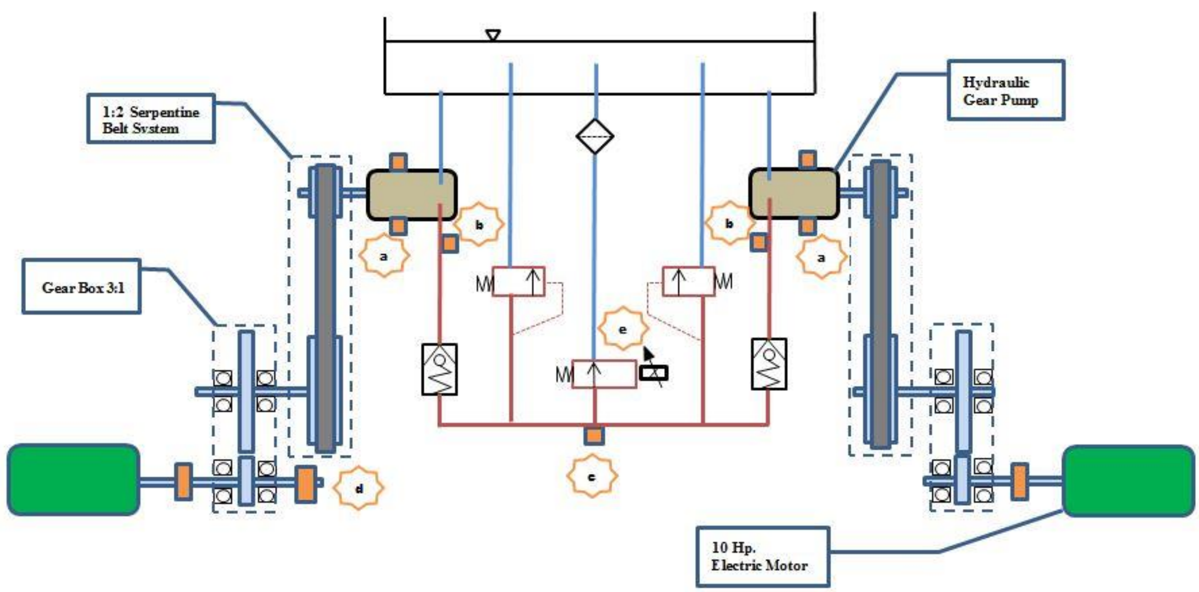
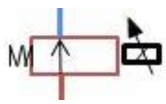
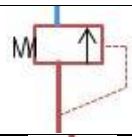
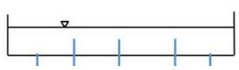


Figure 7: Machine Schematic

a) Pump Piezoelectric Accelerometer b) Pump Pressure Sensor c) Manifold Pressure Sensor d) Encoder e) Solenoid Pressure Relief Valve

Table 3: Hydraulic Component List

Symbol	Component	Manufacture and Model Number	Specifications
	Solenoid proportional pressure relief valve	Hydraforce™ TS12-26	Maximum pressure: 3000psi Rated flow: 50 gpm Voltage: 10 V DC Max current: 1.3 A
	Pressure relief valve	Parker™ RDFA-LAN-CEM	Cracking pressure: 800 psi Rated flow: 25 gpm
	Check valve	Parker™ C-1000-S5-SAE	Cracking pressure: 50 psi Rated flow: 25 gpm
	Hydraulic oil reservoir	Generic	Max volume: 30 gallons
	Filter	Generic	N/A

To prevent over pressurization of the system, a pressure relief valve was used with a cracking pressure set slightly above the intended operation pressure (760 psi). This was done to ensure safety in the event of a line blockage or stuck proportional valve. Check valves were used to prevent flow reversal in the pumps which could cause damage to some of the machine components. The reservoir size was chosen to minimize the possibility of pump cavitation or aeration and to adequately dissipate any heat generated during operation. It is common design practice to size the reservoir at least three times the flow rate of the system [46]. This reduces the possibility of the operator getting burnt when they work on the hydraulic pumps or other components of the machine. Particle contaminants can increase wear on moving components, thus a filter was also used to insure any oil contaminants are removed during the oil circulation.

4.2 Data Acquisition

In order to gather time series data representing the various machine conditions, the apparatus was instrumented with an array of sensors and a data acquisition system. This data could then be used to examine the pressure and vibration of the hydraulic pumps and control the speed and load of the system. This section defines the data acquisition equipment and sensors that were used in this work.

4.2.1 *Sensors and Instrumentation*

The machine schematic (Figure 7) in the previous section illustrates the locations of the sensors that were used in this work. Two IFM™ PU5401 pressure sensors were selected and purchased to gather time series pump pressure data. These sensors were selected for their excellent step response time and relatively low cost. The sensor specifications are listed:

- System pressure measuring range: 0-3625 psi
- Analog output signal: 0-10 V
- Step response time: 1 ms

Two manifolds were machined from 2” OD mild steel bar to place these sensors as close as possible to the outlet ports of the pumps. This was done to capture transient pressure data that could be used for gear pump fault detection. The manifolds were drilled and taped using an SAE-16 O-Ring Boss thread on the ends to connect the manifold to the hydraulic pumps and hoses. A ¼”-19 BSPP thread was drilled and tapped in the radial direction and a 7/8” wide flat section was machined using an end mill to connect and seal the sensors to the manifold.

A Barksdale™ 423X pressure transducer was placed in the hydraulic circuit at the proportional relief valve. This sensor was used to determine the total pressure and load on the system. The sensor specifications are listed:

- System pressure measuring range: 0-3000 psi
- Analog output signal: 0.5-5.5 V

A PCB Piezoelectronics™ 603C01 ceramic shear accelerometer was mounted on each hydraulic pump in the radial direction to capture changes in the machine vibration due to incipient faults. These transducers function due to the piezoelectric effect of certain crystals, where an electric charge is generated proportional to the force applied to the crystal. For these sensors, the sensed force is proportional the acceleration of the sensor. These sensors also contain an integrated circuit that converts the high-impedance charge generated by the piezoelectric to a usable low impedance voltage signal. The accelerometer specifications are listed:

- Sensitivity: (±10%) 100 mV/g
- Frequency Range: (±3 dB) 0.5-10000 Hz
- Measurement Range: ±50 g

A BEI™ XHS25 dual channel incremental optical encoder was used to record and control the rotational speed of the electric motors. Optical encoders work by shining lights through slits on a disk onto photodiodes. As the disk rotates it either blocks or permits the light from reaching the photodiode. The signal that is produced can be used to determine the rotational speed by knowing the angular resolution of the encoder and the time between signal cycles. The encoder resolution used in this work is 360 cycles/turn.

4.2.2 *Data Acquisition Platform and Modules*

A Windows® computer with a Peripheral Component Interconnect Express (PCIe) bus was used as the data acquisition platform for this research. PCI is an international bus standard for personal computers and there is a large selection of hardware modules that can be purchased and easily installed for data acquisition. National Instruments™ (NI) PCI-4472 8-Channel Dynamic Signal Acquisition Board module was used for data acquisition of the pressure transducers and accelerometers. This module has eight simultaneously sampled ±10 V analog inputs and is specifically designed for high-accuracy sound and vibration data acquisition. The NI PCIe-7851R Multi-function reconfigurable input/output (RIO) with an onboard Field-Programmable Gate Array (FPGA) module was used in conjunction with the SCB-68R shielded input/output (I/O) 68 pin connector block to control the speed and load of the system and for encoder speed data acquisition. The FPGA module allows for user-programmable onboard processing which provides enhanced execution speeds. The RIO delivers versatility for additional data acquisition channels and control outputs. NI LabVIEW™ software was installed and used to program the various controls and setup the data acquisition modules. Figure 8 illustrates the connectivity between the various data acquisition and control units. Time series data was collected from the PCI-4472 at a synchronized 10 kHz sampling frequency.

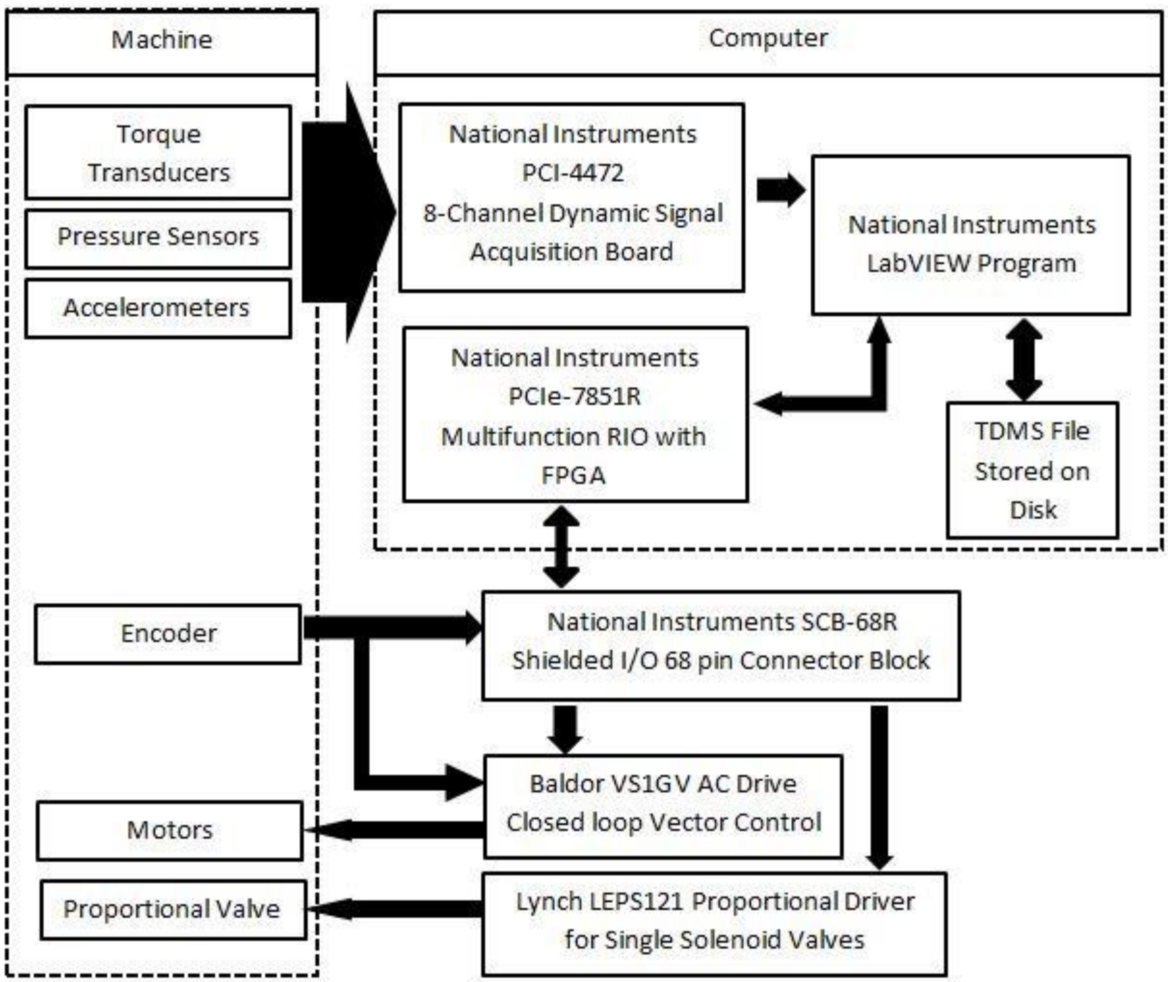


Figure 8: Flow Chart of Data Acquisition Modules and Control Systems

4.3 Duty Cycle and Control

This section will describe the duty cycle and control systems that were designed to simultaneously control the speed and loading conditions.

4.3.1 *Duty Cycle*

The variable duty cycle shown in Figure 9 was designed to examine the machine in various operational states with independently controlled speeds and pressures. This duty cycle tests a variety of ramp up, hold, ramp down combinations between three steady state motor speeds (200, 400, 600 rpm) and pump pressures (17.5, 35, 52.5 bar).

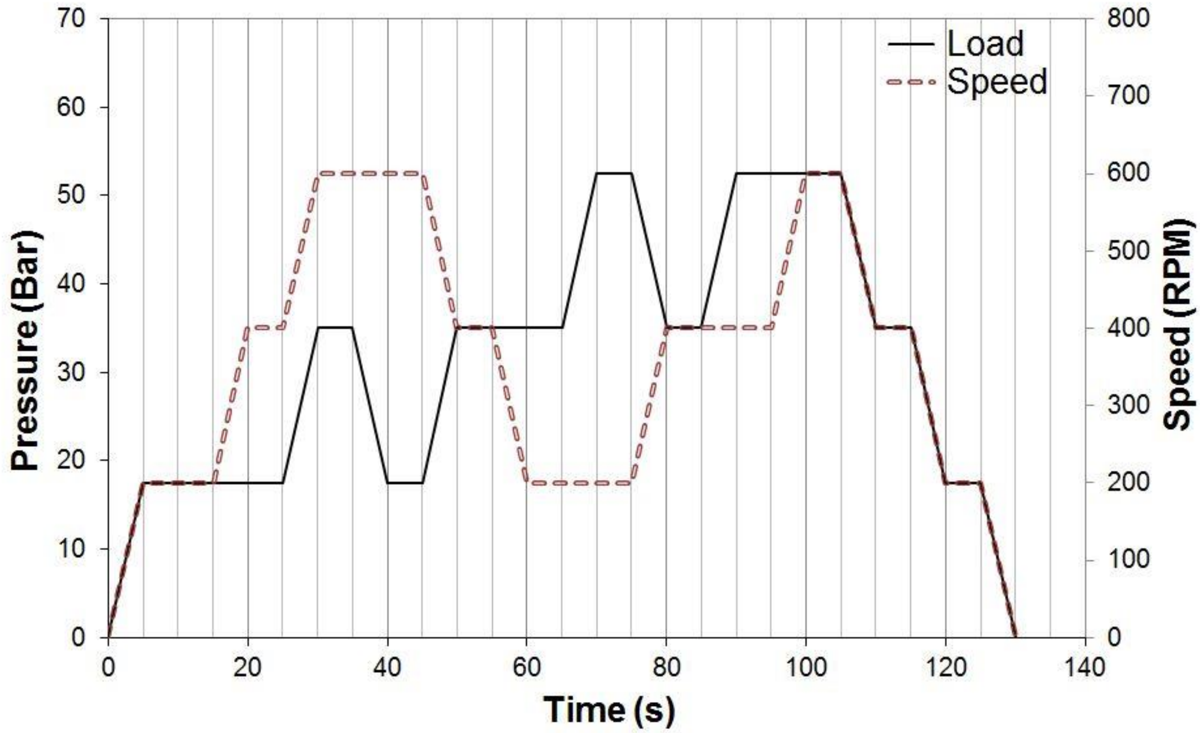


Figure 9: Variable Duty Cycle

4.3.2 *Speed Control System*

The speed profile was programed in the LabVIEW program. When the program was run, it would output a set point to the PCIe-7851R which would then send a 0-10 V signal to the Baldor™ VS1GV Motor Drive. Based on this signal voltage and the encoder shaft speed, an optimized closed-loop Proportional Integral Derivative (PID) controller in the Baldor Drives then applies the appropriate output voltage and current frequency to the motors. The PID gains were optimized using the onboard automated system during the machine setup. Specifications for the Baldor Driver are listed:

- Input voltage: 575 VAC (3-phase)
- Power rating: 30 hp
- Control mode: closed loop vector

4.3.3 *Load Control System*

The system load was independently controlled using an open-loop control by similarly sending a 0-10 V signal from the PCIe-7851R to the Lynch™ proportional driver. This driver then delivers the appropriate solenoid current signal based on the input voltage, thus setting the system pressure. Specifications for the proportional driver are listed:

- Input signal: 0-10 VDC
- Rated output current: 2 A

4.4 Test Matrix and Fault Replication

The main objective of this section is to describe the strategy that was employed to compile a representative set of normal and faulted data. The section also describes the various machining methods that were required to replicate the different faults.

4.4.1 *Test Matrix*

Table 4 shows the various tests that were completed to collect data on the healthy and faulted components. Between each test, the pumps would be disassembled and reassembled with the given components for the next test. The pumps were then primed by running the machine at low speeds and low loads until the air was forced out of the system. Loud noises were audible when air was still trapped in the pumps and valves. Occasionally, the entrapped air could not be forced out and the machine would need to be turned off overnight to let the air settle out of the system. Due to the great deal of time that was required between tests, the number of times that the pumps were required to be disassembled and reassembled was optimized by carefully organizing the test matrix such that only one pump was being opened at a time. The only exception to this was when a faulted component was to be tested in both pumps consecutively.

Control data was collected using eight unique combinations of fault free (healthy or normal) pump gear sets and thrust plates. This was done to gather a comprehensive set of control data and to minimize any experimental bias from specific components being placed in an individual pump.

The three gear pump failure modes (thrust plate wear, gear wear and cavitation damage), were replicated by incrementally damaging a component and replacing it into the pump. Ideally each fault would be tested in each pump however, this was unrealistic due to the amount of time required to complete these tests. It was decided that adequate amounts of data could be collected by testing the first and last three progressions in opposite pumps, as well as, testing the third and sixth progressions in both pumps. Tests six and seven of the gear tooth wear progression had to be removed from the test matrix due to a noticeable change in the system operation during the fifth test.

Table 4: Test Matrix

	Test #	Fault size	Left Gear	Left Plate	Right Gear	Right Plate
Normal Tests	1	N.a.	3	2	4	3
	2	N.a.	**1**	2	4	3
	3	N.a.	1	2	**2**	3
	4	N.a.	**4**	**1**	2	3
	5	N.a.	4	1	**3**	3
	6	N.a.	**2**	1	3	3
	7	N.a.	2	1	**1**	**2**
	8	N.a.	**3**	1	1	2
Thrust Plate Wear	1	0.001	3	**1A10**	1	2
	2	0.002	3	**1A20**	1	2
	3	0.003	3	**1A30**	1	2
	4	0.003	3	**3**	1	**1A30**
	5	0.004	3	3	1	**1A40**
	6	0.005	3	3	1	**1A50**
	7	0.006	3	3	1	**1A60**
	8	0.006	3	**1A60**	1	**2**
Gear Tooth Wear	1	0.001	**2B1**	**3**	1	2
	2	0.002	**2B2**	3	1	2
	3	0.0033	**2B3**	3	1	2
	4	0.0033	**1**	3	**2B3**	2
	5	0.004	1	3	**2B4**	2
	~~6~~	~~0.999~~	~~1~~	~~3~~	~~2B5~~	~~2~~
	~~7~~	~~0.999~~	~~1~~	~~3~~	~~2B6~~	~~2~~
	8	0.004	**2B4**	3	**1**	2
Gear Cavitation Damage	1	1	**4C10**	3	1	2
	2	2	**4C20**	3	1	2
	3	3	**4C30**	3	1	2
	4	4	**1**	3	**4C30**	2
	5	5	1	3	**4C40**	2
	6	6	1	3	**4C50**	2
	7	7	1	3	**4C60**	2
	8	8	**4C60**	3	**1**	2
			Notes:	**Components to Change**		
				~~Removed from Test Matrix~~		

4.4.2 *Thrust Plate Wear Replication*

To accurately reproduce progressive thrust plates wear, a computer numerical control (CNC) milling machine was programed to remove 0.001” from 70% of the sealing face area of the thrust plate. After testing the CNC on some test pieces of aluminium it was realized that a jig would be required to consistently control the depth of cut. Realistically, this wear would likely occur over the entire face, however fasteners were required to secure the plate (Figure 10) and thus only 70% was removed for practicality. The first and last progressions of the thrust plate wear can be seen in Figure 11. A slight score of the coating material can be seen in the first progression, while a deeper groove into the metal can be seen in the last progression.

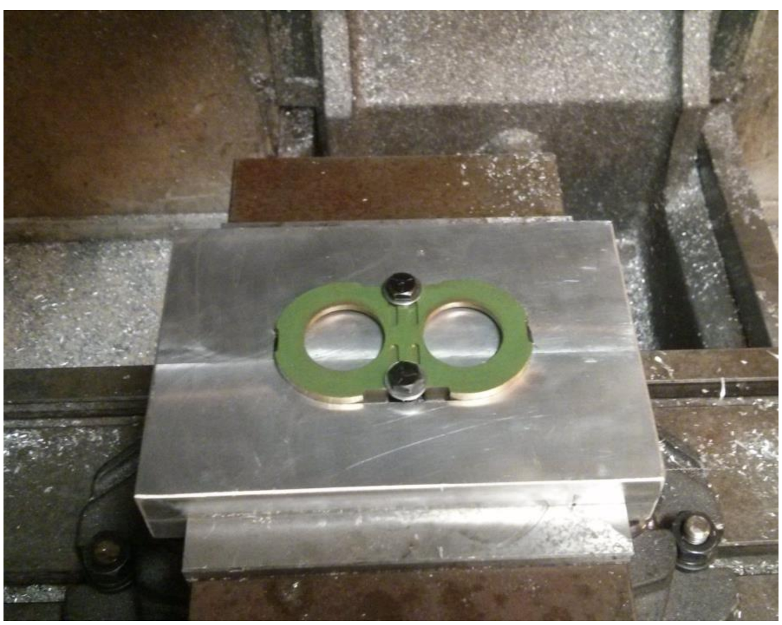
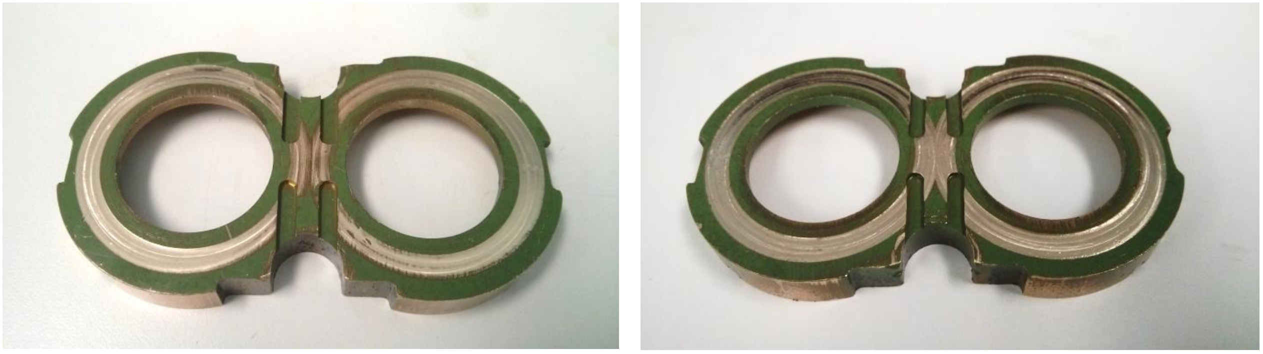


Figure 10: CNC Thrust Plate Machining Setup



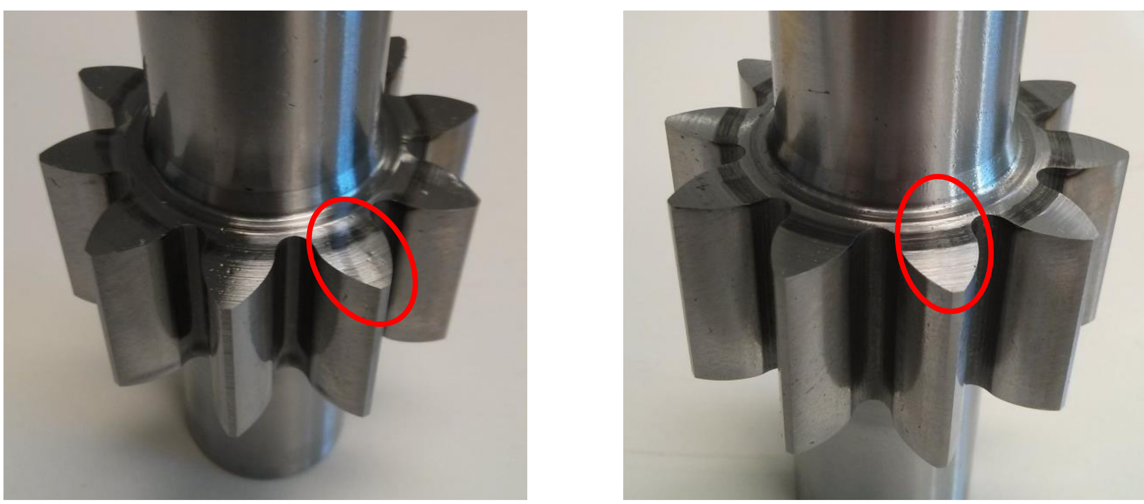
a) 0.001”   b) 0.006”

Figure 11: Thrust Plate Wear Progression

4.4.3 *Gear Wear Replication*

To reproduce the gear wearing from abrasions between the thrust plate and the gear, material was removed from the side face in the radial plane. A lathe was used for the first attempt to replicate gear wear. However, due to the hardness of the material, it proved to be extremely difficult to cut uniformly into the gear surfaces. One reason for this difficulty was because the tool holder deformed slightly during the cut. This would reduce the cutting back pressure, making an uneven cut on the gear teeth. Secondly, the amount of material that was being removed was too little to initiate consistent shearing plastic deformation. This problem was resolved by using a surface grinder to remove material and an indexing chuck to rotate the gear. This setup (Figure 12) allowed for a consistent and uniform removal of material from the gear teeth. Figure 13 shows the first and last progressions of the replicated gear wear.

Figure 12: Surface Grinder Setup for Gear Wear Replication

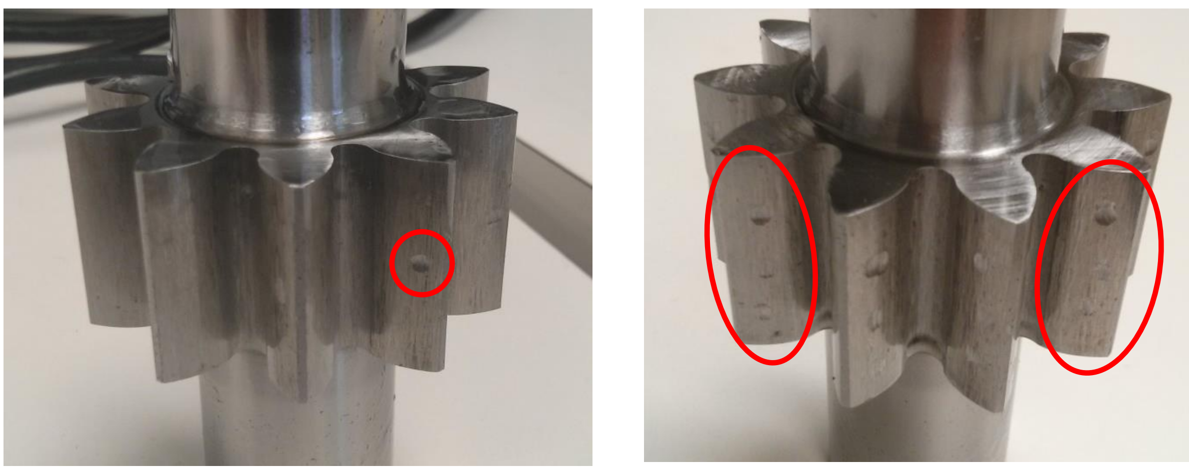


a) 0.001” **b) 0.004”**

Figure 13: Gear Wear Progression

4.4.4 *Gear Cavitation Replication*

A hand-held high speed abrasive tool was used to replicate gear cavitation damage. For each progression of the fault, a pit ~0.125” in dimeter was created using 0.375” diameter spherical abrasion tool to remove material at a single point along the meshing surface of each gear tooth. Figure 14 illustrates the first and last progressions of the replicated gear cavitation damage used in this work.



a) 1 Pit per Tooth **b) 6 Pits per Tooth**

Figure 14: Gear Cavitation Progression

Chapter 5

5 Data Analysis

This chapter presents the analytical methodology that was developed to detect faults in parallel hydraulic gear pumps. Section 5.1 begins by providing a brief overview of the analytical process to give a greater context to the following sections. Section 5.2 explains the time series data segmentation process and section 5.3 describes the preprocessing techniques that were implemented for this work. Following which, section 5.4 presents the various features that were used to detect incipient faults, as well as, the residual calculations that have been designed specifically for CM parallel systems. Section 5.5 then defines the normalization scheme that was implemented to ensure equal comparisons between features. Section 5.6 presents the method that was used to consolidate the features from common domains to values that can be compared and utilized to represent the machine condition. To conclude, section 5.7 will describe the approach that was used to compare the feature domains and their response to various operational states.

5.1 Analytical Methodology Overview

Figure 15 graphically depicts the analytical methodology and how the time series data was manipulated to determine the likelihood that a fault has developed in one of the subsystems. Continuing from the end of Chapter 4, the first process that is depicted is the collection of data from the two subsystems. The nine steady-state acceleration and pressure signals were extracted and segmented from the 130 second duty cycle test.

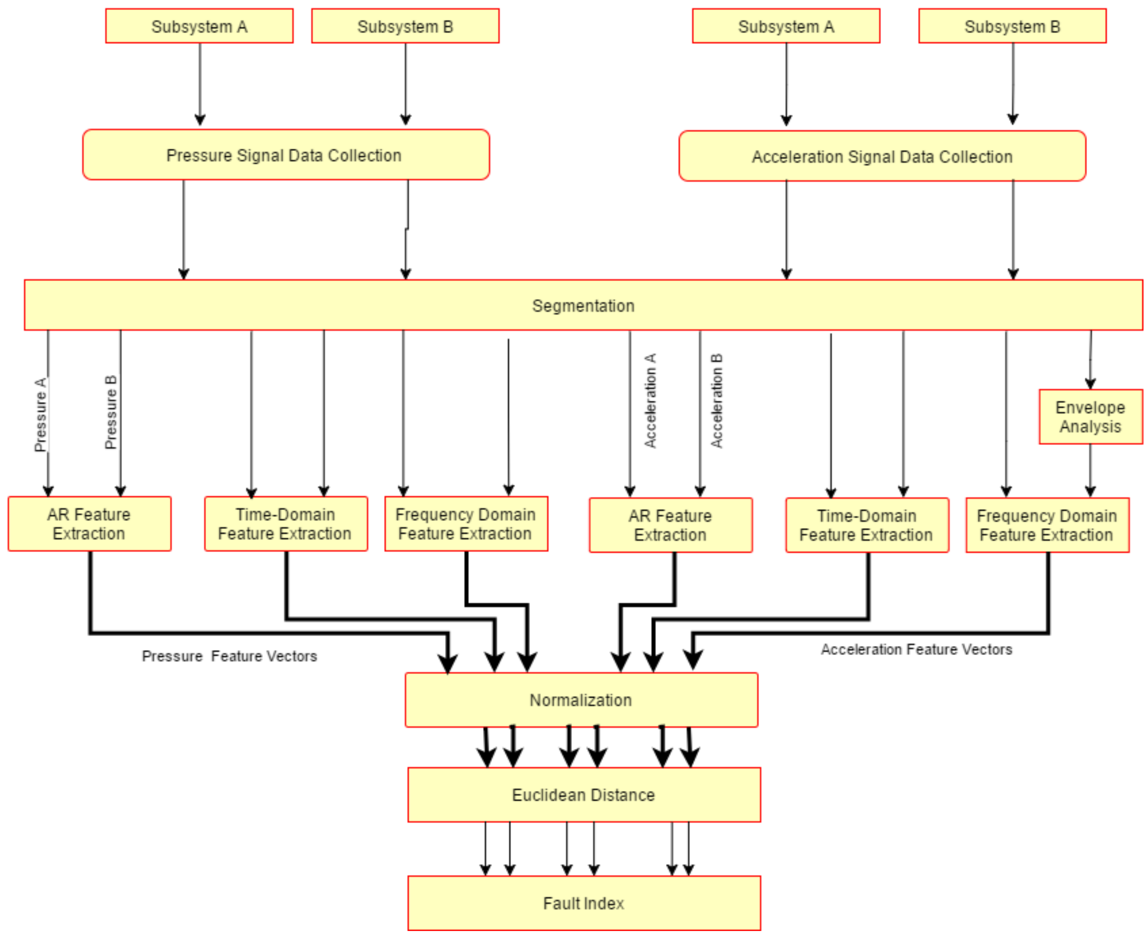


Figure 15: Analytical Methodology Flow Diagram

Envelope analysis was then used as a preprocessing technique to prepare acceleration data segments for frequency domain feature extraction. Feature extraction is the mathematical analysis on the data segments to obtain numerical parameters which are sensitive to developing faults. The features that were examined in this work were broken into three groups: time domain, frequency domain and auto-regressive features. These groups were examined individually to compare the performance of each group for each of the various failure modes.

The feature residuals were then calculated by computing the difference between the features from each subsystem. However, some feature residuals can be orders of magnitude different, making it difficult to compare one feature to another. To solve this problem, each residual was normalized between -1 and 1 with respect to mean and standard deviation of the residuals that were collected using healthy components. The root sum of squared residuals (i.e. Euclidean distance) was then used to obtain a single value that essentially represents the magnitude of similarity between the features from each subsystem. A progressing fault is expected to cause features from each subsystem to become increasingly different. Thus, shifting the normalized feature residuals from the typical -1 to 1 range and yielding a shift in the Euclidean distance distributions. Statistical analysis on these values was then used to compare which feature sets trended best with a given fault.

5.2 Segmentation

In unsteady machinery, variance in speed and load typically cause changes to the time series data signals. If the entire signal is analysed for feature extraction, these normal operational variations can make it difficult to distinguish the slight changes that are caused by incipient faults from the changes caused by variability in machine operation. This effect can be minimized by analysing smaller segments of the signals, since operational changes are negligible over a short time. However, if the segment length is too small, there is a possibility that a fault signature will not be captured in the segment. the signals were segmented every five pump shaft revolutions with 70% overlap. This was selected to ensure that periodic fault phenomena and any irregular signal features, diminished from the Hann window (in Section 5.3.2), were captured. Figure 16 and Figure 17 illustrate the segmentation process of the pressure and acceleration signals. Also, the beginning and end sections of each test were removed at this stage to exclude any interval where the machine was operating at less than 200 rpm and 17.5 bar.

5.3 Preprocessing

5.3.1 *Acceleration Signal*

Several techniques have been developed to refine raw time-series data and enhance the extraction of condition indicating information from the signal. One of the major difficulties in vibration analysis is separating the diagnostic information from a signal which is dominated by noise from normal machine vibration. Envelope analysis [8] is an effective solution to this problem.

Every mechanical system has a natural resonation frequency that is excited when impacted. In a condition monitoring system, envelope analysis can exploit this phenomenon since incipient faults typically produce some form of periodic impulse. The frequency of which (modulation frequency) can be extracted through amplitude demodulation of the high frequency band carrying the resonance signal.

Figure 18 illustrates the steps required to extract the envelope signal for spectral analysis. In step 1, a Fast Fourier Transform (FFT) on the data segment was used to obtain the full frequency spectrum of the signal. During preliminary analysis, a demodulation band was selected using a Fast Kurtogram [14] to find the frequency range with high spectral kurtosis. The 4200-4600 Hz range had consistently high kurtosis over the duty cycle.

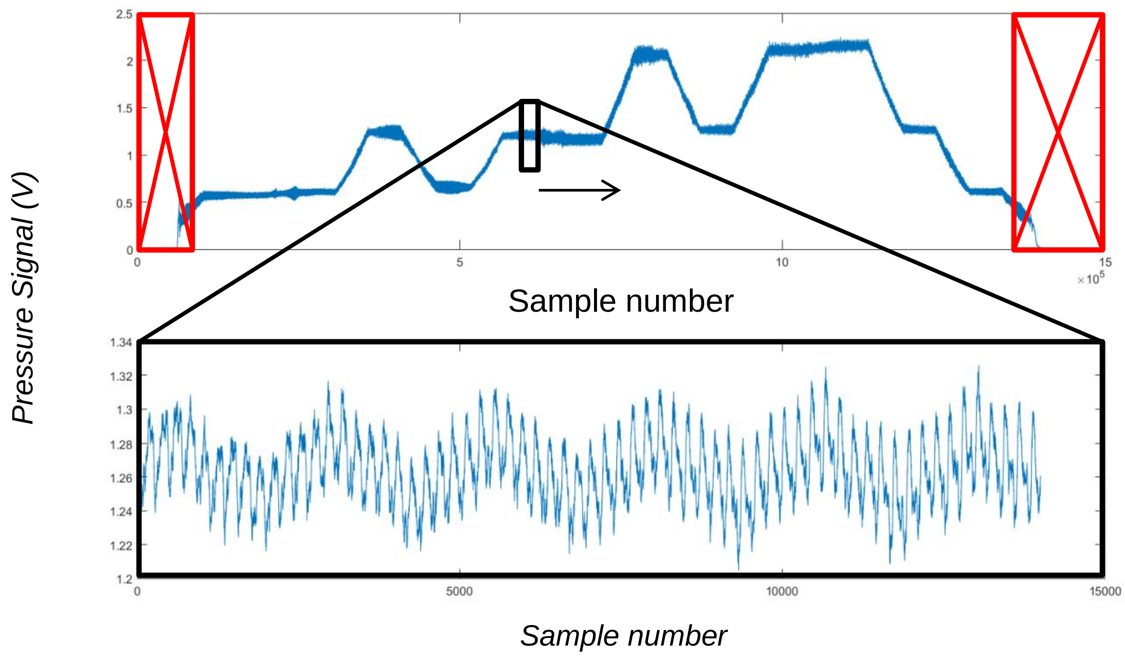


Figure 16: Segmentation of Pressure Time-Series Data

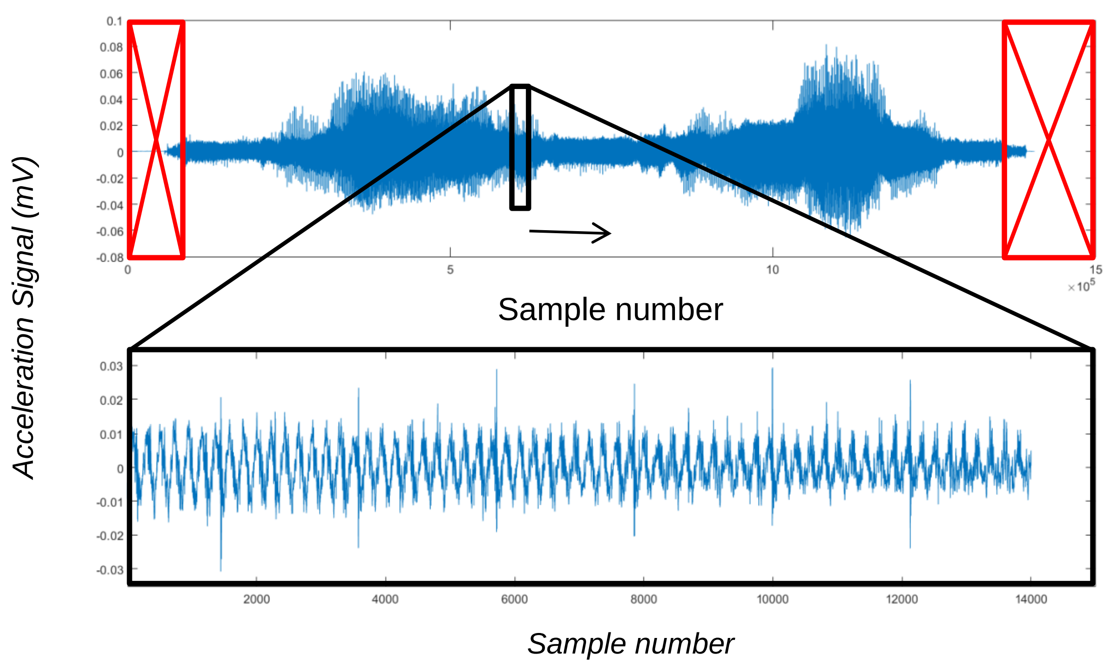


Figure 17: Segmentation of Acceleration Time-Series Data

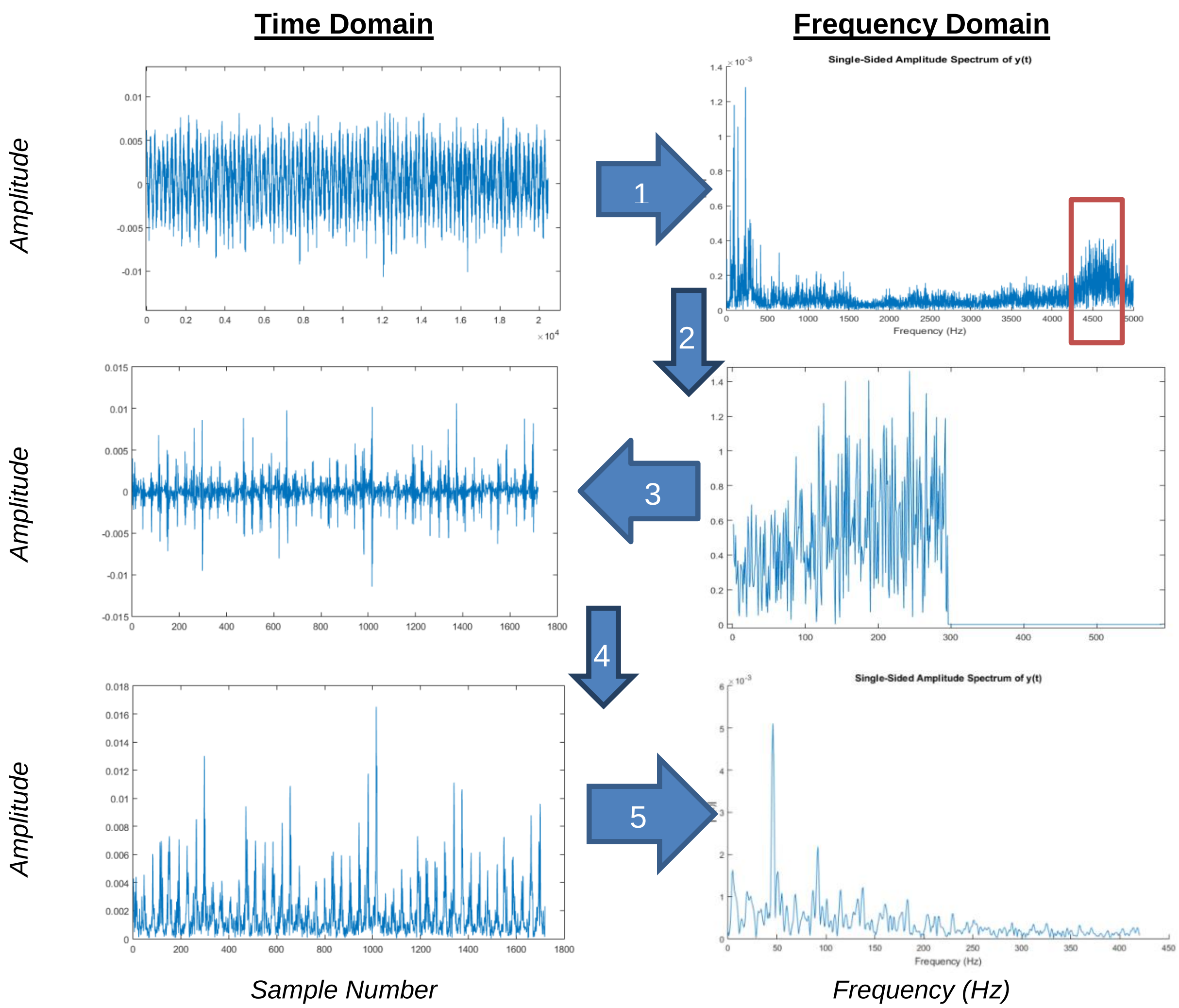


Figure 18: Envelope Analysis Preprocessing

The complex frequency spectrum in this band was then extracted and padded with an equal number of zeros to create a one-sided spectrum for amplitude demodulation (Step 2). The inverse Fourier transform was then used to obtain the demodulated signal containing a series of periodic impulses (Step3). The envelope of this signal was then attained by taking the square root of the squared signal (Step 4). A FFT of the envelope signal was then taken (Step 5) for spectral analysis of the dominant modulation frequencies.

5.3.2 *Pressure Signal*

The examined faults were not observed to exhibit high frequency resonance in the pressure signal that could be used for amplitude demodulation. Therefore, the envelope analysis technique was not used since it did not provide any improvements to the pressure signal frequency features. However, some standard preprocessing was done to the pressure signal to enhance the frequency domain feature extraction. Unlike the acceleration signal, the pressure signal was not centred about zero. Therefore, the DC offset had to be corrected by subtracting the average pressure (effects are shown in Figure 19). A Hann Window was also used to minimize spectral leakage (Figure 20).

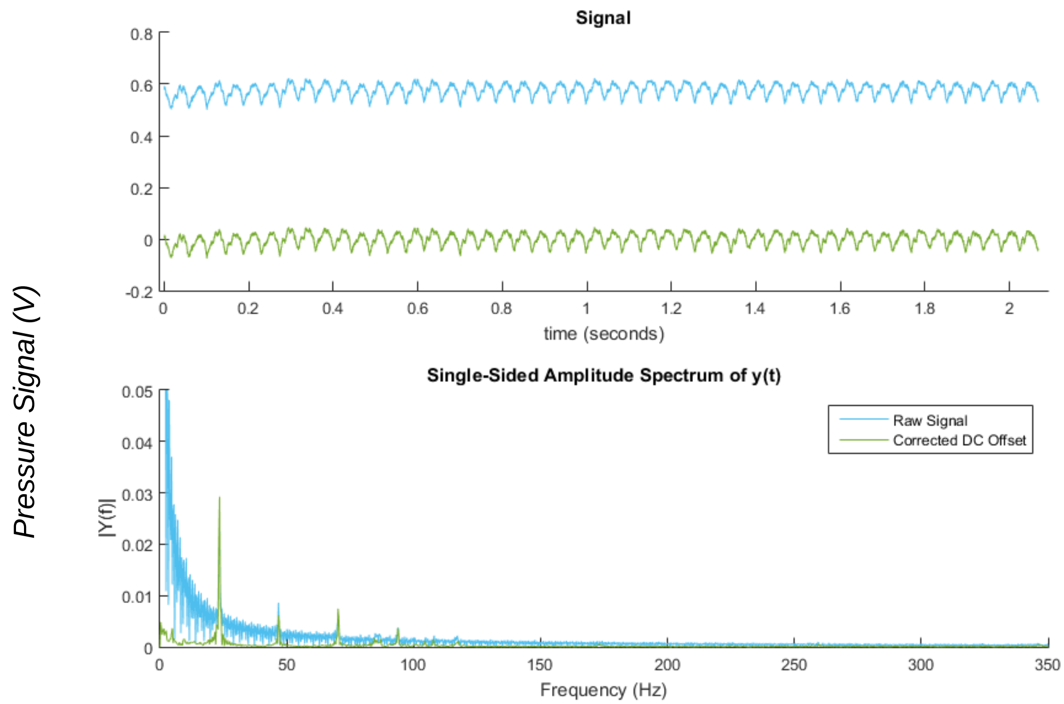


Figure 19: Pressure Signal Preprocessing (Adjusting DC Offset)

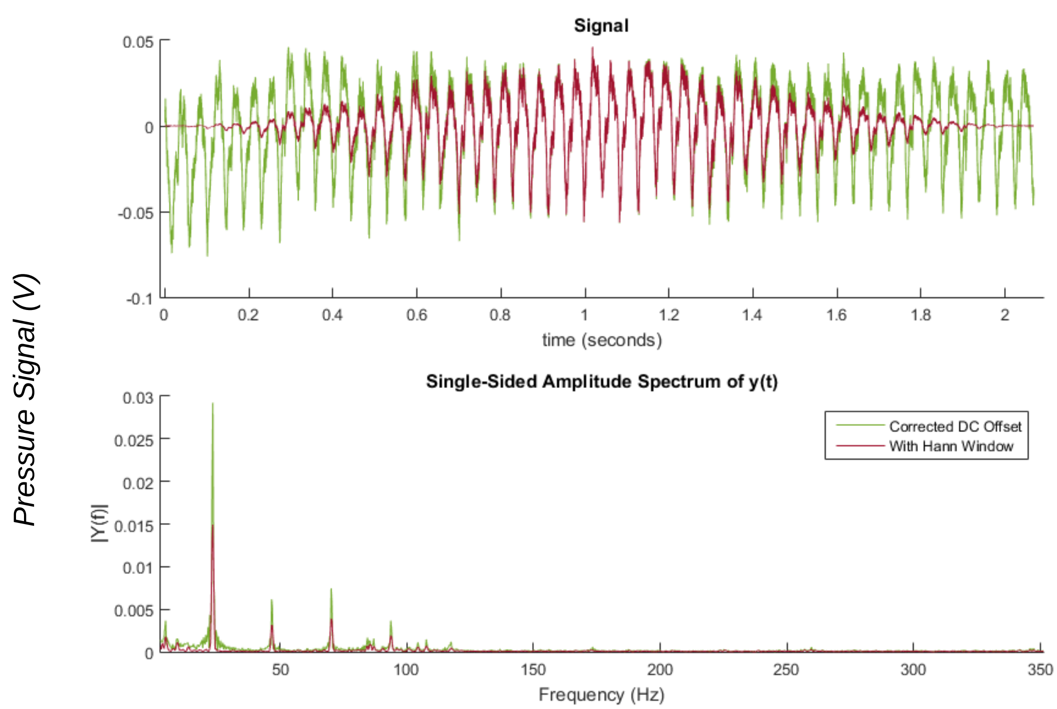


Figure 20: Pressure Signal Preprocessing (Improving Spectral Leakage)

5.4 Feature Extraction

The literature review established three categories of features that would likely reveal faults in this system: time domain features, frequency domain features and auto-regressive (AR) model features. The following sections provide details on the mathematical operations that were utilized for fault detection and comparison of each category's response to the different failure modes. The main objective of this work is to calculate the residual difference between subsystems characteristic parameters. The residuals will then be used as features to assess the response to various failure modes while in both stationary and non-stationary operation.

5.4.1 *Time Domain Features*

Statistical analysis of the time series data segments can provide meaningful parameters that describe characteristics of the signal. An incipient fault would likely cause a change to the signal characteristics of the corresponding subsystem. Equations 7 to 10 show the parameters that were calculated using the time series data segments (with *N* data points) collected from pump A and B (x_A and x_B respectively).

Peak-to-Peak $$f_1 = [\max(x_A) - \min(x_A)] - [\max(x_B) - \min(x_B)]$$ **Eq. (7)**

RMS $$f_2 = \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_{Ai}}^2} - \sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_{Bi}}^2}$$ **Eq. (8)**

Crest Factor $$f_3 = \frac{\max(x_A)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_{Ai}}^2}} - \frac{\max(x_B)}{\sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_{Bi}}^2}}$$ **Eq. (9)**

Shape Factor $$f_4 = \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_{Ai}}^2}}{\frac{1}{N}\sum_{i=1}^{N} |x_{Ai}|} - \frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N} {x_{Bi}}^2}}{\frac{1}{N}\sum_{i=1}^{N} |x_{Bi}|}$$ **Eq. (10)**

5.4.2 *Frequency Domain Features*

As discussed in the literature review, hydraulic gear pumps inherently produce flow ripples that cause periodic fluctuations in the pressure and vibration signals. Changes in the frequency of these oscillations could provide valuable information on the condition of the machine [33], [34]. The dominant pressure excitation frequencies, produced by the flow ripple, are equivalent to the gear mesh frequency and the harmonics (since gears are out of phase). The modulation frequencies, of vibrations induced by gear faults, should also be equal to the gear mesh frequency and the harmonics. Therefore, maximum amplitude of the signals in four harmonic ranges corresponding to ½, 1, 1½ and 2 times the gear mesh frequency (GMF) were used as features in this work, shown in Eq. (11).

$$f_{5-8} = \max(Amp(FreqRange_{\ k})_A) - \max(Amp(FreqRange_{\ k})_B) \qquad \textbf{Eq. (11)}$$

$$Frequency\ Range_1 = (0.25{:}\,0.75) * GMF$$
$$Frequency\ Range_2 = (0.75{:}\,1.25) * GMF$$
$$Frequency\ Range_3 = (1.25{:}\,1.75) * GMF$$
$$Frequency\ Range_4 = (1.75{:}\,2.25) * GMF$$

5.4.3 *Autoregressive Model Features*

The Autoregressive (AR) algorithm computes coefficients (a_i) of an N^{th} order model that provide the least estimated variance *e(t)* based on the prior values of a time series *y(t)*, shown in Eq. (12). A 10^{th} order model using the forward-backward approach was chosen for this work. The model order was arbitrarily selected with the intent of optimizing the model with further analysis. However, for reasons discussed in Section 6.5.2, this was deemed out of the scope of this research. Eq. (13) shows the residual calculations of the model coefficients collected from pump A and B (a_A and a_B respectively) that were used as features in this work.

$$y(t) + a_1 * y(t-1) + a_2 * y(t-2) + \cdots + a_N * y(t-N) = e(t) \qquad \textbf{Eq. (12)}$$

$$f_{9-18} = a_{i\,A} \; - \; a_{i\,B} \qquad \textbf{Eq. (13)}$$

5.5 Normalization

When attempting to compare features to one another, there is a challenge that arises when the feature values differ by orders of magnitudes. To overcome this, Eq. (14) shows how features were normalized with respect to the mean and standard deviation of the features that were collected during the healthy test. By subtracting the mean and dividing by three standard deviations of the healthy features (f_{iH}) each feature becomes normalized between -1 and 1 with a confidence interval of 99.7%. This interval was chosen so that a shift in either direction will have an equal influence on the Euclidean distance (described in the following section). This is beneficial since, a fault in subsystem A is expected to cause a shift in one direction and in the opposite direction if the fault is seeded in subsystem B. A feature before and after normalization is shown in Figure 21 and Figure 22 respectively.

$$F_i = \frac{f_i - mean(f_{iH})}{3 * stdv(f_{iH})} \qquad \textbf{Eq. (14)}$$

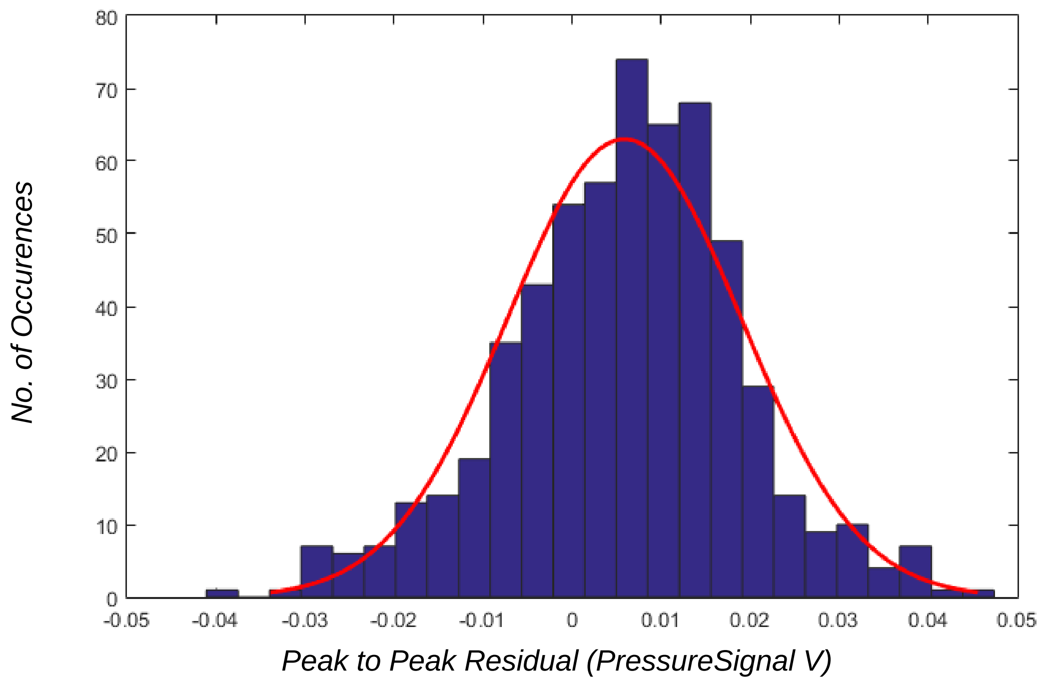


Figure 21: Feature Distribution Before Normalization

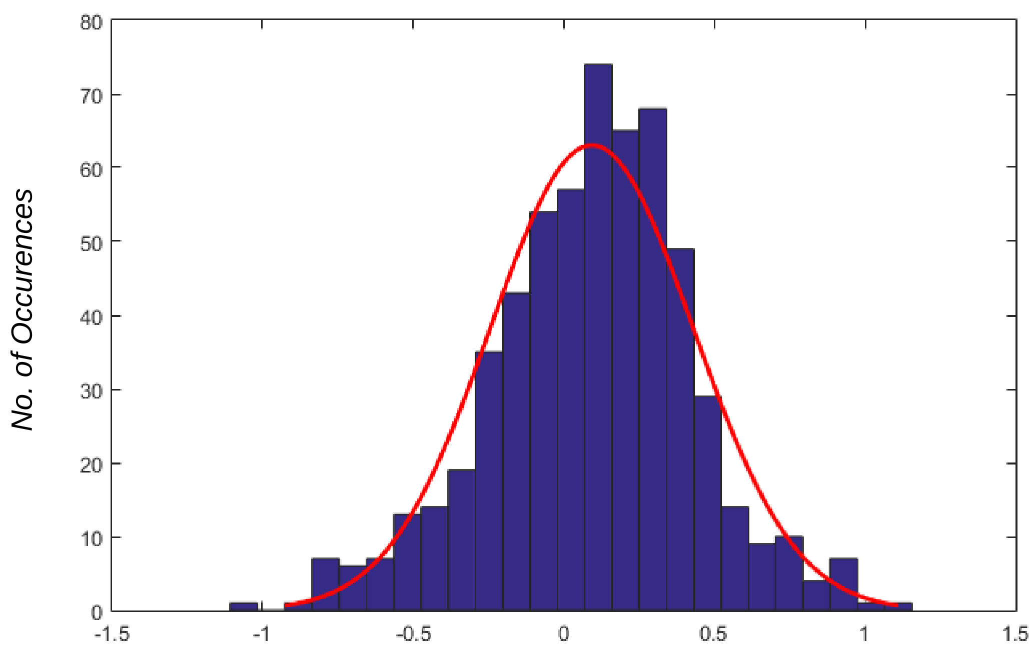


Figure 22:Feature Distribution After Normalization

5.6 Feature Vector Dimension Reduction

Comparing the numerous features individually would be tedious and would require additional training data to avoid the curse of dimensionality (where the amount of data required for classification increases exponentially with the number of features used for classification). Instead, a reduction technique was used to summarize the features from each group into a single parameter. The Euclidean distance of the normalized features (F_i) was chosen to do this because it produces an intuitive value which represents how close the features from each subsystem are, as shown in Eq. (15). This value is useful for condition monitoring since an incipient fault is expected to increase the distance between subsystem feature vectors.

$$E = \sqrt{\sum F_i^{\,2}} \qquad \textbf{Eq. (15)}$$

The resulting values closely resemble a lognormal distribution (Figure 23). Since feature residuals have been normalized between -1 and 1 at this point, healthy Euclidean values will mostly be distributed between 0 and 1. Residuals from the faulted tests were normalized using statistics from the healthy tests, meaning any changes that occur due to the faults will shift their normalized residuals and cause the Euclidean distance to increase. These values could then be analysed to classify the condition of the machine. It should be noted that the number of features can have an influence on the location and scale of this distribution. In future work, this equation should be normalized by dividing by the number of features in the set.

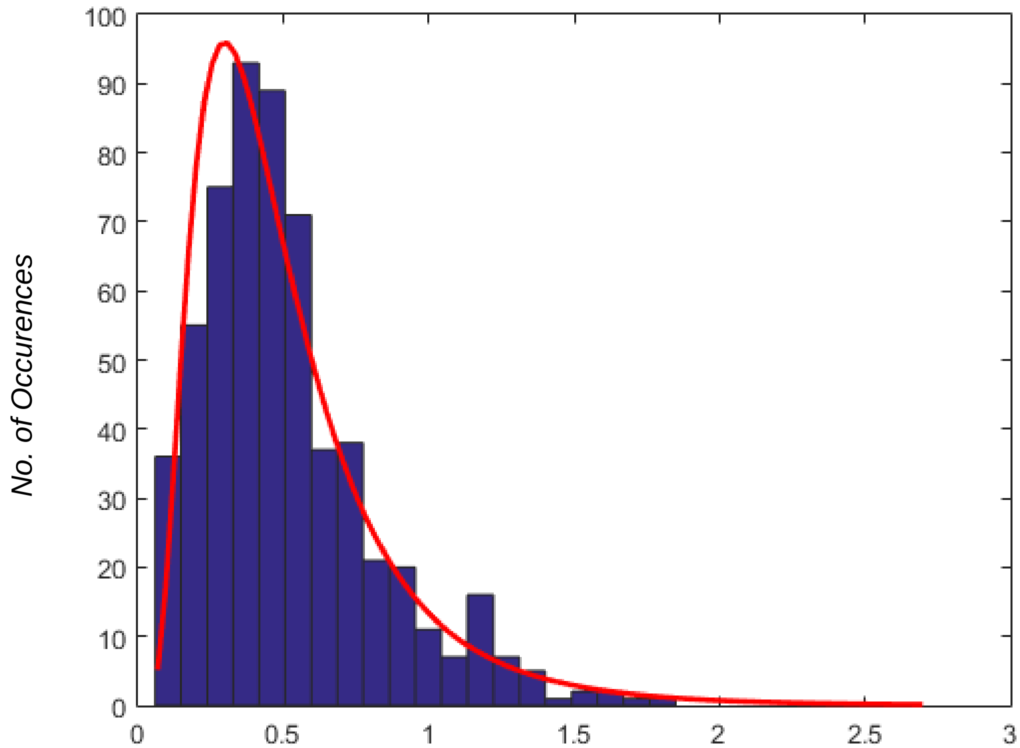


Figure 23: Histogram of Euclidean Distance Values of Pressure Features (Complete Duty Cycle)

5.7 Feature Group Comparison

5.7.1 *Complete Duty-Cycle*

Several techniques were examined to compare which feature sets were best at indicating failures. Visual inspections of the box plots (samples shown in Figure 30 and Figure 31) were conducted to observe the changes in the distance distributions that occur due to the various failures. This preliminary result, discussed in Section 6.4, confirmed that faults have an effect on the distance distributions. The most noticeable being the increase in the number and magnitude of outliers (>95th percentile). Due to the high quantity of samples obtained from the entire duty cycle, the mean of these distributions are only marginally affected by the presence of these outliers. However, a slight increase in the mean (from the presence of outliers) has a much more significant effect on the standard deviation, since it contains the sum of the squared differences from the mean. Therefore, the standard deviation of the Euclidean distributions will be used when comparing the response of each feature domain to each of the failure modes over the entire duty cycle.

5.7.2 *Steady-State Sections*

The samples from the steady-state sections had fewer samples that were closer together, meaning the standard deviation did not show a substantial change even though the mean of the steady-state samples varied with the presence of faults and operating conditions. Therefore, the mean of the Euclidean distance values will be used to compare the response of each feature domain with respect to the different failure modes and operating conditions.

Chapter 6

6 Results and Discussions

This chapter reports on the results that were obtained from the experiments and will discuss the performance of the approach that was developed for condition monitoring parallel hydraulic pumps in dynamic operation. Sections 6.1 to 6.4 will demonstrate the challenges that are encountered when condition monitoring dynamic systems, as well as, confirm preliminary hypotheses that form the foundation of the analytical methodology. Section 6.5 describes the performance of feature vector groups over the entire duty cycle of the machine. Section 6.6 separates the results into 9 unique steady state operating sections and reflects on the findings.

6.1 Effects of Operational Changes on Subsystem Features

Figure 24 and Figure 25 confirm a fundamental problem that arises when attempting to condition monitor equipment in dynamic operation; changes in operation have substantial effects on diagnostic features. In these samples, the peak-to-peak measurement of the pressure signal from each pump is plotted with respect to speed and load. The magnitude of the diagnostic feature increased significantly as pressure increased from 22 bar to 45 bar and decreased as speed increased from 200 rpm to 600 rpm (ANOVA, $p<0.05$). These variations are what make it difficult to determine whether a change in a feature is due to a developing fault or if it is merely due to a change in operation.

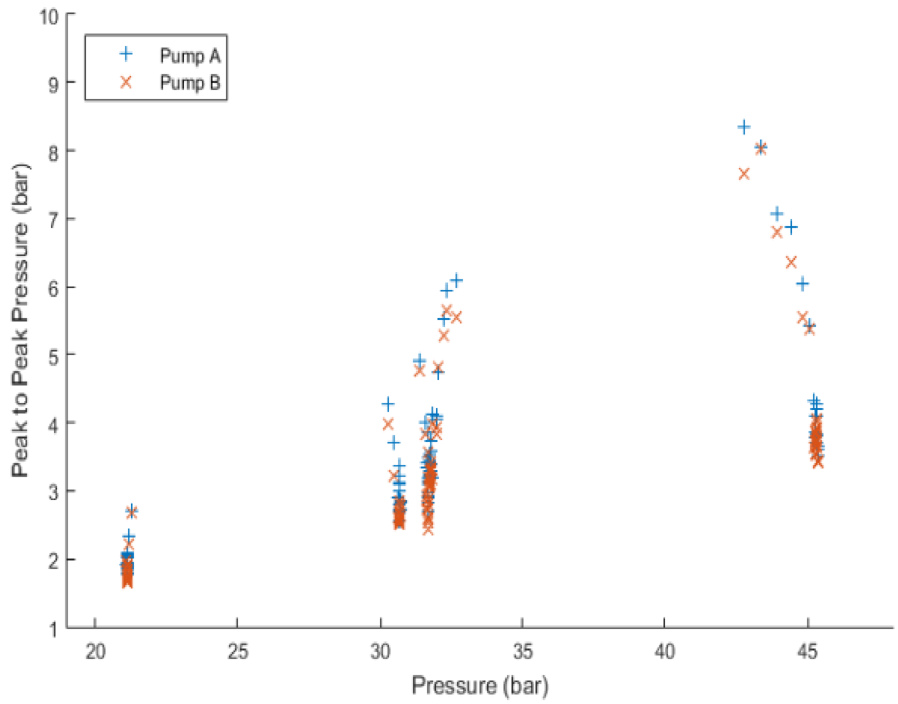


Figure 24: Effects of Changing Load on Diagnostic Feature

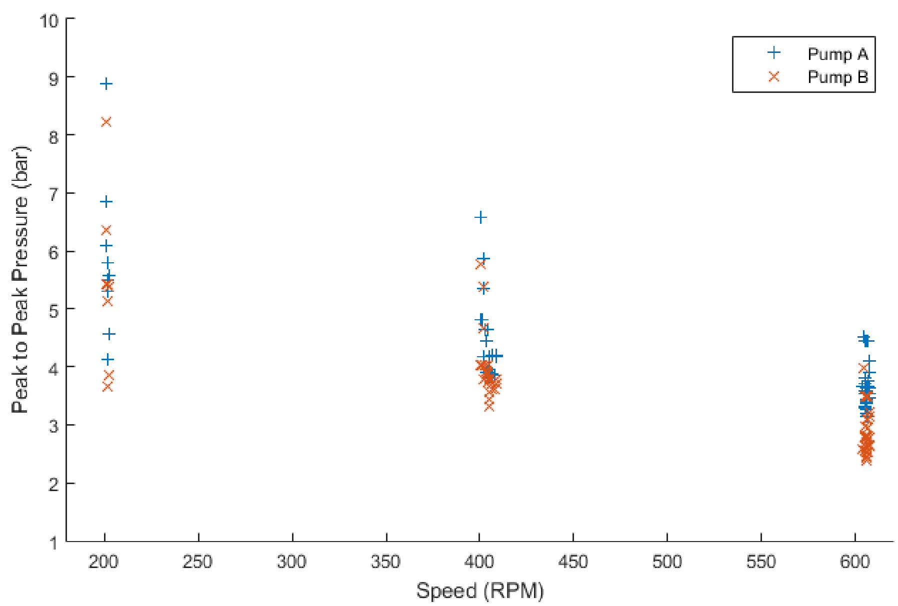


Figure 25: Effects of Changing Speed on Diagnostic Feature

Figure 24 and Figure 25 also illustrate that the features obtained from both sub-systems (pump A & B) are similar while operating in parallel at different speeds or loads. This supports the theory that the mechanical redundancy of parallel systems can be exploited to improve the performance of condition monitoring systems for equipment in variable operation.

6.2 Effects of Operational Changes on Feature Residuals

Figure 26 and Figure 27 validate the notion that the feature residuals that were identified for the parallel system approach are not significantly affected by changes in operation (ANOVA, $p > 0.05$). These examples show the residual between the subsystems' peak-to-peak feature plotted with respect to speed and load. The feature residuals are significantly less affected by the changes in operation. This confirms that the feature residuals from parallel systems have potential to be used as parameters that are less sensitive to variations in the operating state.

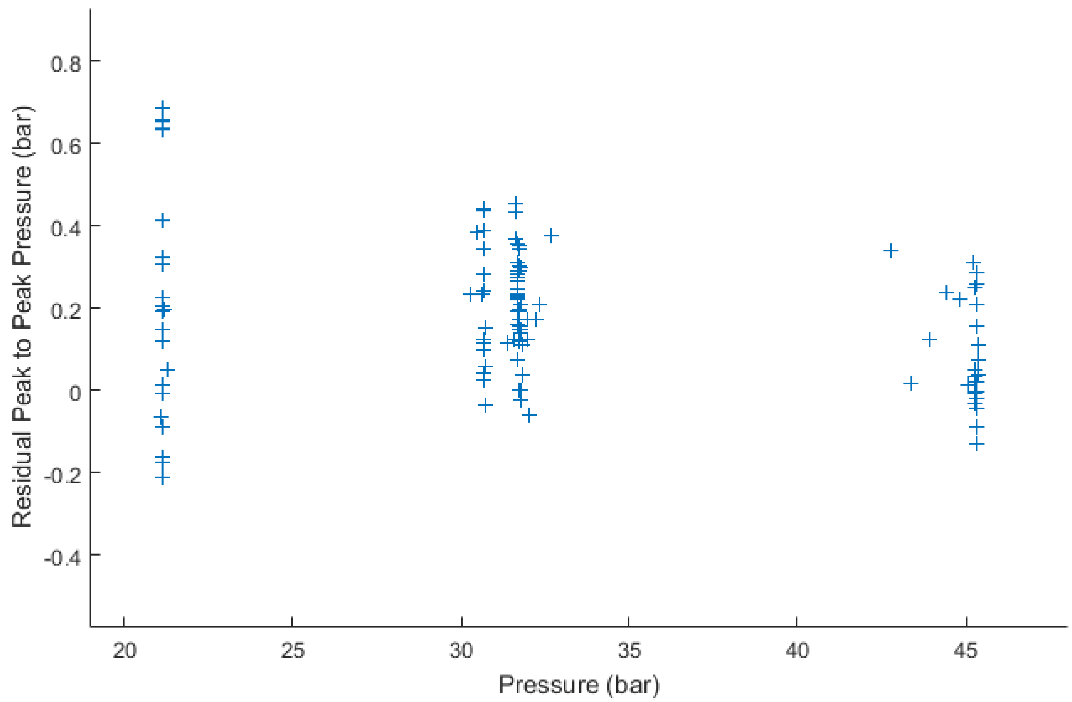


Figure 26: Effects of Changing Load on Feature Residual

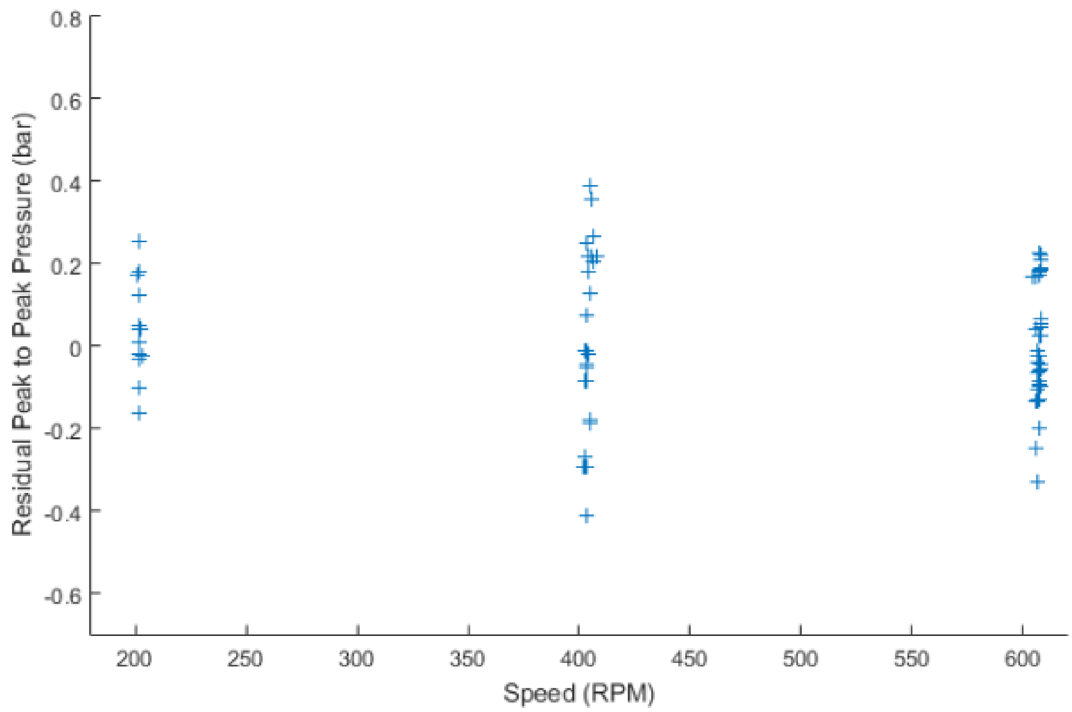


Figure 27: Effects of Changing Speed on Feature Residual

6.3 Effects of Fault Progressions on Normalized Residuals

Figure 28 and Figure 29 illustrate that the developing faults caused a noticeable change in feature residuals. These plots show the distributions of normalized peak-to-peak pressure residuals with respect to healthy and faulted tests. The samples from the healthy tests show negligible variance between the eight tests. In contrast, the quantity and magnitude outliers in the thrust plate wear progression were observed to increase from an average of nine outliers with an average magnitude of 1 to a maximum of 25 outliers with an average magnitude of eight. This is of interest because it supports the initial research question that the feature residuals can be sensitive to developing failures in parallel systems.

Another noteworthy observation is that the sign of the outliers was found to be related to the subsystem that the fault was seeded in. This has potential to be exploited in future work for identifying which subsystem the fault is located in. Figure 29 shows a positive shift when the fault is in the right pump and vice versa. The peak-to-peak residual was calculated by subtracting the right from the left (L-R), suggesting that the fault either causes a decrease in the pressure pulsation amplitude in the faulted pump or an increase in the non-faulted pump. Assuming the incipient faults have minimal effect on the healthy subsystem, the former is likely the case and is probably attributed to the increase in internal leakage that this fault causes.

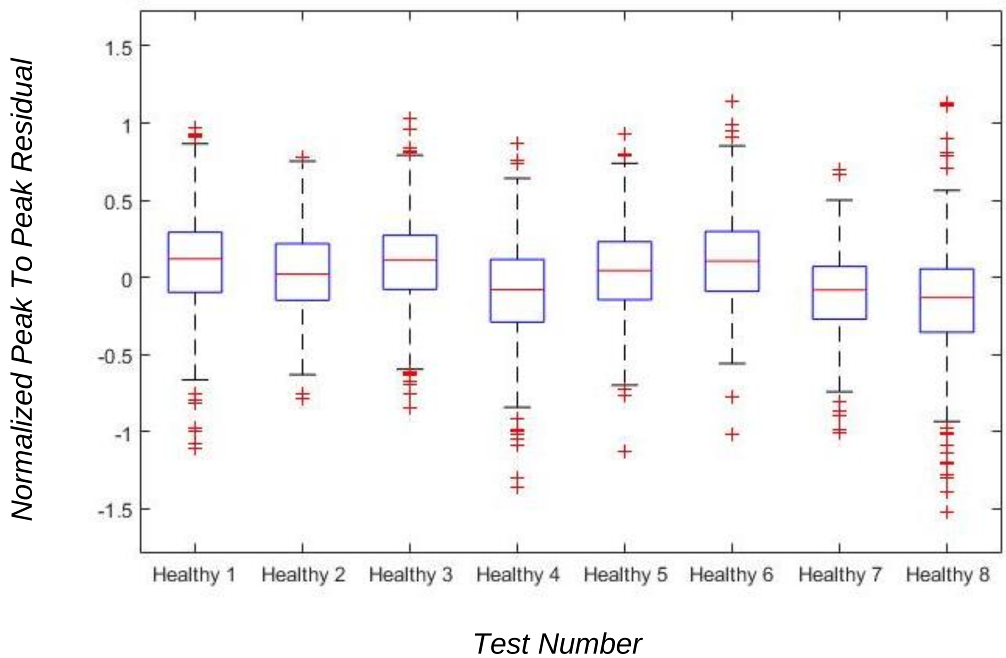


Figure 28: Normalized Feature Residual (Healthy Tests)

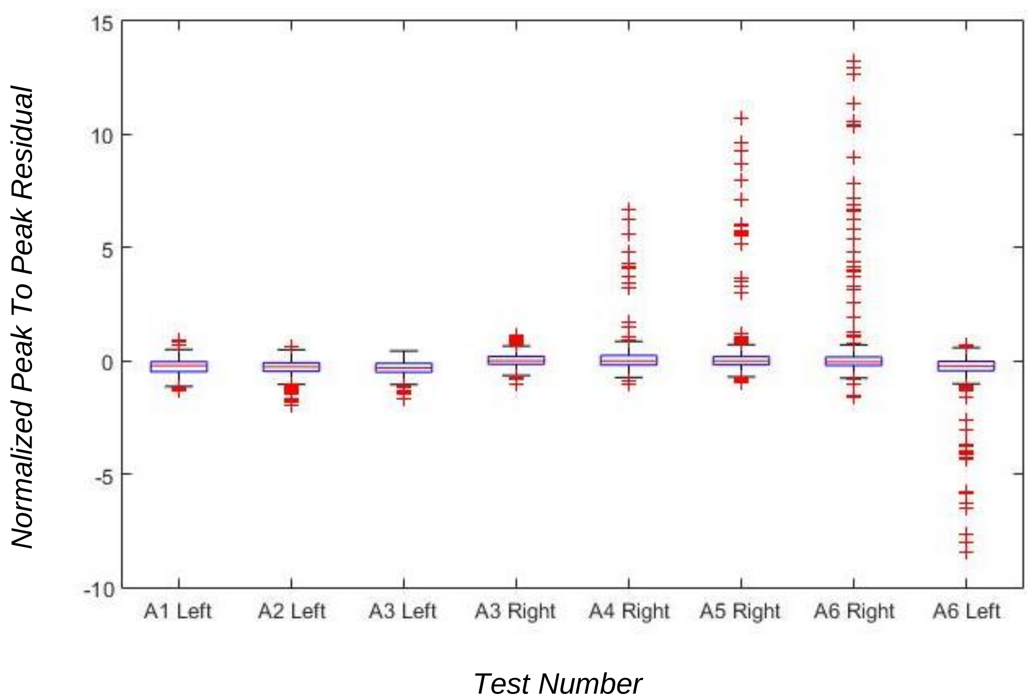
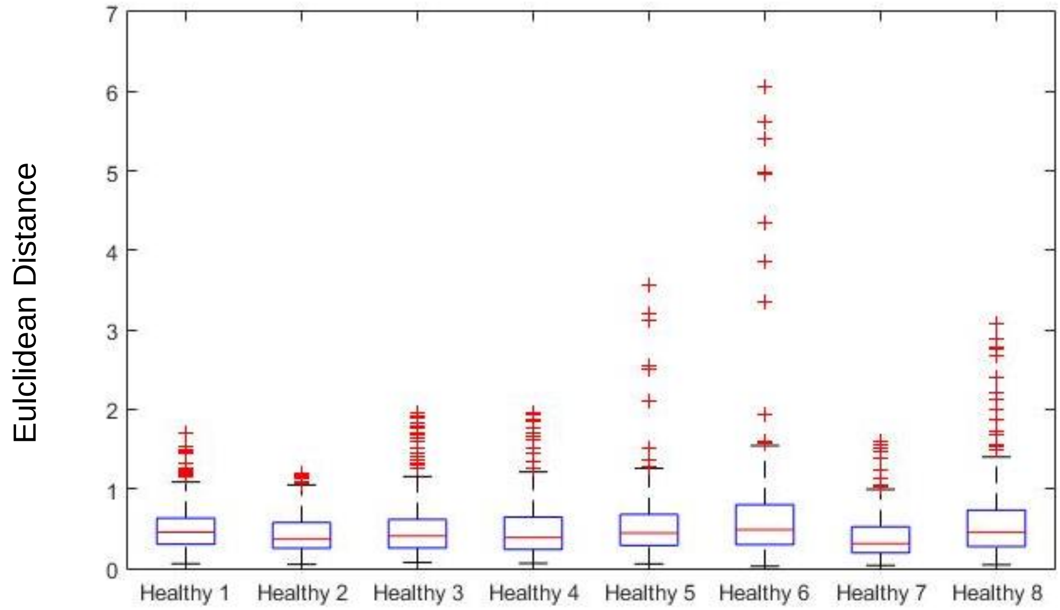


Figure 29: Normalized Feature Residual (Thrust Plate Wear Progression)

6.4 Effects of Fault Progressions on Domain Specific Euclidean Distances

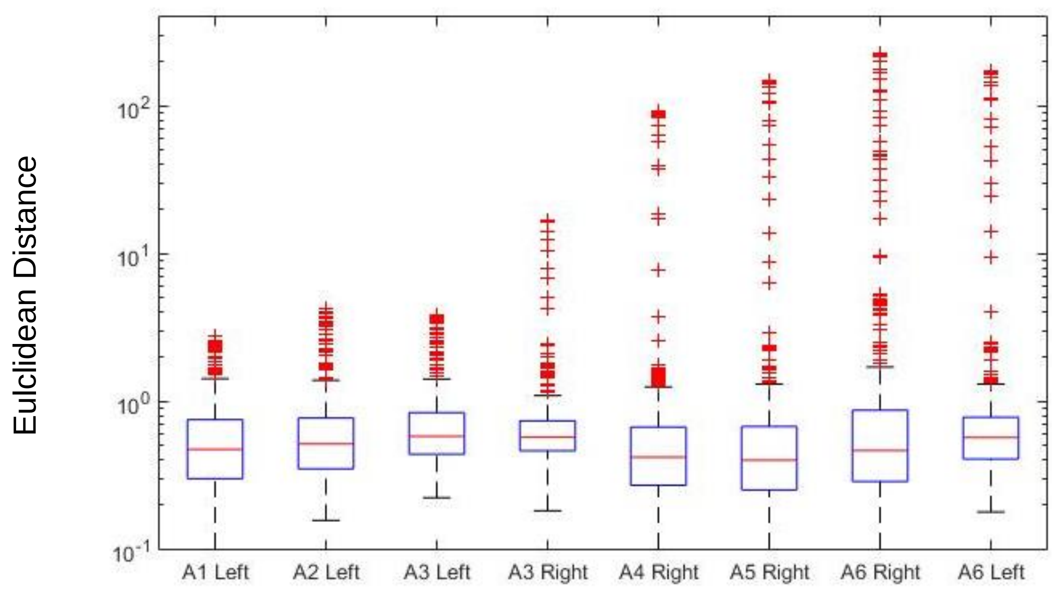
Figure 30 and Figure 31 illustrate the distribution of Euclidean distance values, obtained from the pressure signal time domain features, with respect to healthy and faulted tests. Consistent with the previous section, there is a pronounced increase in the quantity and magnitude of outliers shown in the thrust plate wear progression compared to the healthy tests. This supports that the Euclidean distance of a set of features preserves the sensitivity to developing faults.

Compared to the previous section, the healthy tests show some variance in the outlier magnitude (specifically tests 5, 6 and 8). This is likely attributed to the components having variable run in times. However, the magnitudes of the healthy outliers are marginal when compared to the magnitude of the outliers from the thrust plate wear progression.



Test Number

Figure 30: Euclidean Distance Distributions, Time Domain Features of the Pressure Signal (Healthy Tests)



Test Number

Figure 31: Euclidean Distance Distributions, Time Domain Features of the Pressure Signal (Thrust Plate Wear Progression)

6.5 Feature Group Comparison-Complete Duty Cycle

This section will compare the influences that the various faults had on the three feature groups (Time domain, Frequency Domain and AR) from the pressure and acceleration signals. The objective of analysing these results was to compare the signal source (pressure vs. acceleration) and feature groups that trend best with the different faults.

6.5.1 *Pressure Signal Features*

Figure 32 to Figure 35 show the standard deviations of the pressure signal Euclidean distance distributions over the complete duty cycle. As shown in Figure 33 and Figure 34, the standard deviation of the time and frequency domain Euclidean distance values increased with the thrust plate and gear wear progressions from an average healthy value of 0.3 to a maximum of 2.3 during test 7 of the thrust plate wear progression. However, the pressure features were not noticeably affected by the cavitation damage. AR coefficients showed very little response to any faults and generally had the highest baseline values in the healthy tests.

The trend between the pressure signal time & frequency domain features and the thrust-plate and gear wear faults supports that these failures caused an increase in the amount of internal leakage. Conversely, the lack of trend between the pressure signal features and the cavitation damage likely indicates that this failure did not cause significant internal leakage.

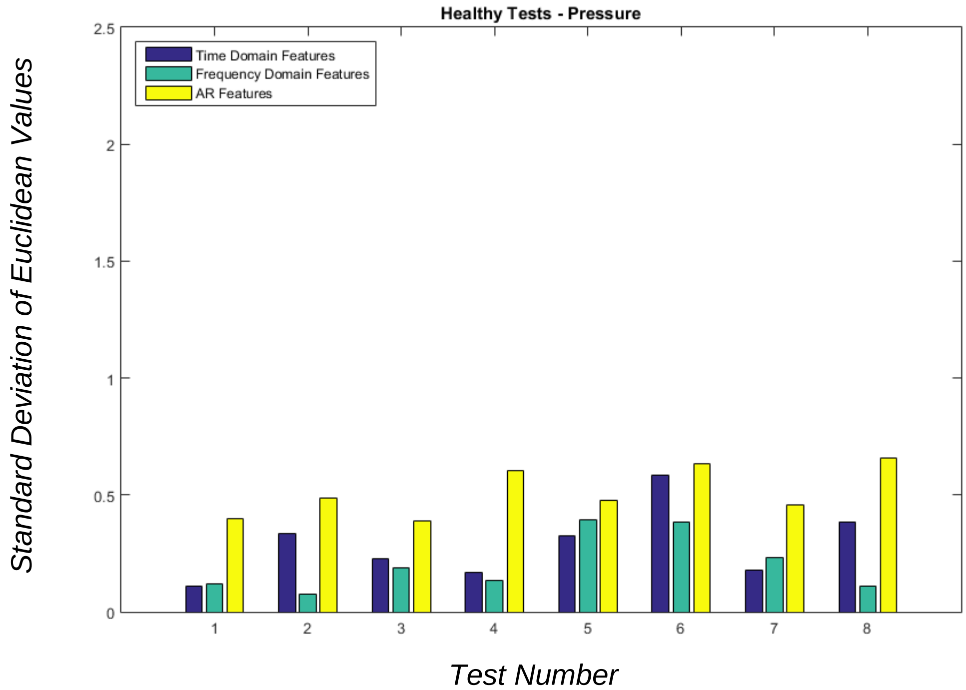


Figure 32: Pressure Signal Feature Comparison (Healthy Tests)

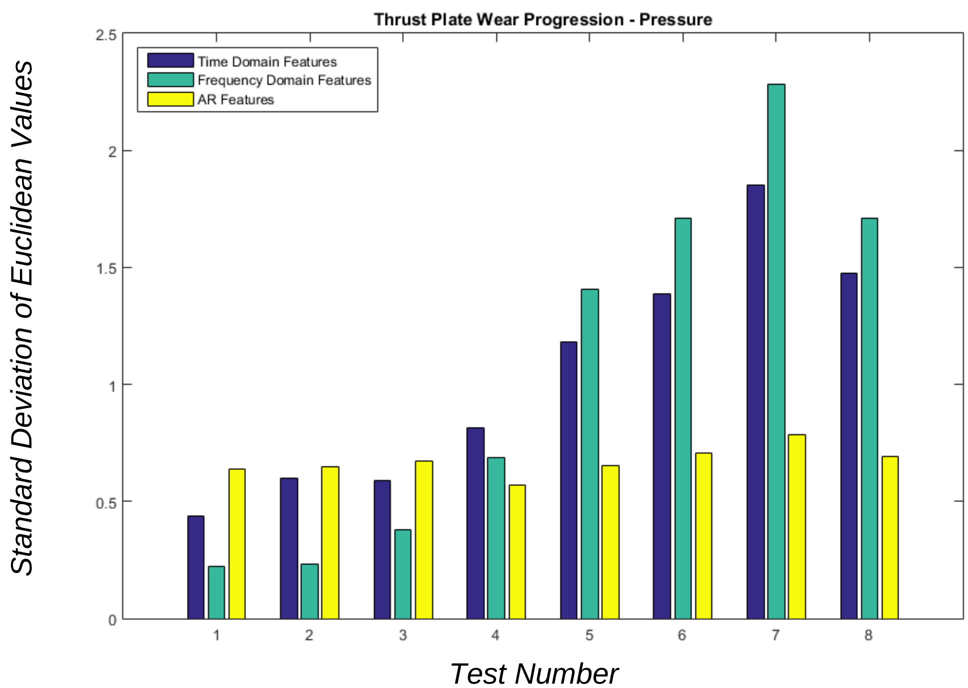


Figure 33: Pressure Signal Feature Comparison (Thrust Plate Progression)

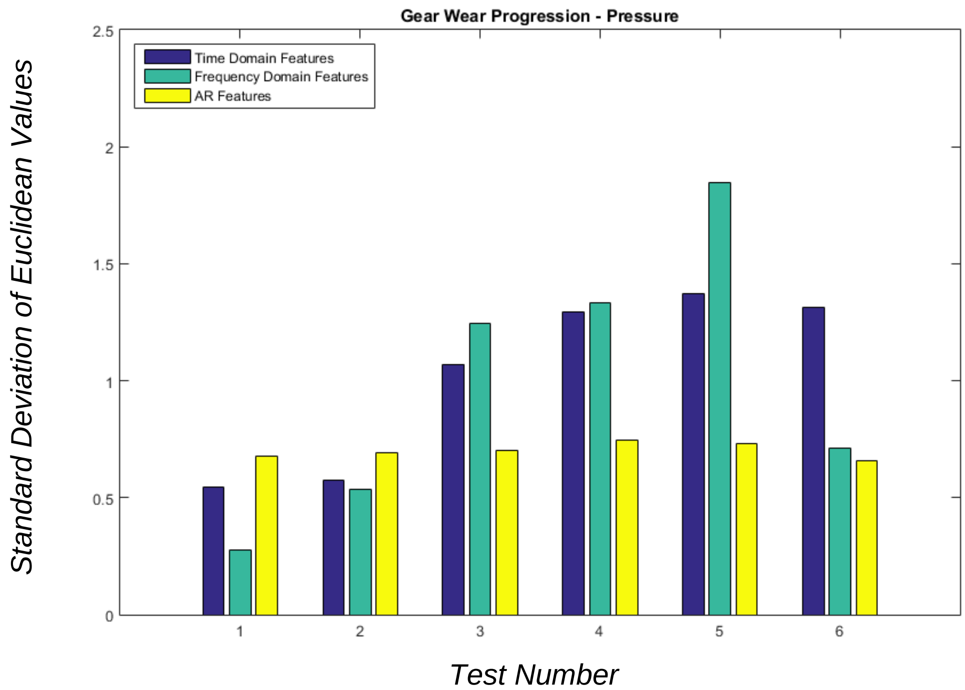


Figure 34: Pressure Signal Feature Comparison (Gear Wear Progression)

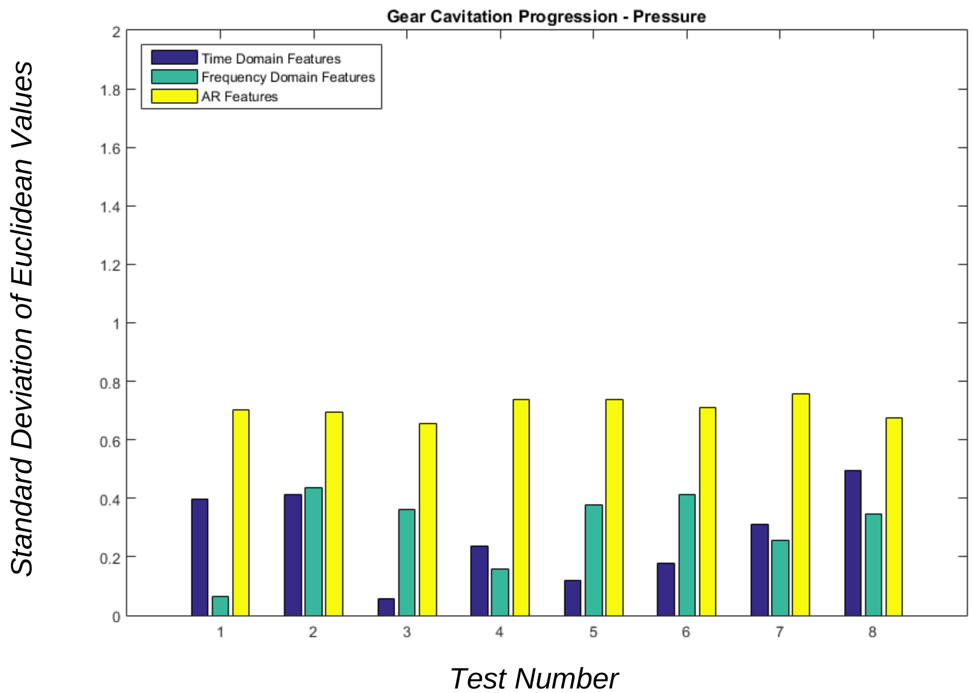


Figure 35: Pressure Signal Feature Comparison (Cavitation Damage Progression)

Acceleration Signal Features

Figure 36 to Figure 39 show the standard deviations of the acceleration signal Euclidean distance distributions over the complete duty cycle. As shown in Figure 39, the standard deviation of the acceleration signal time and frequency domain Euclidean distance distributions increased with the cavitation damage progression from an average healthy value of 0.3 to a maximum of 1.6 in tests 4, 5 and 7. However, acceleration features were not noticeably affected by the thrust plate and gear wear progressions. AR coefficients showed very little response to any faults.

The trend between the cavitation damage progression and the acceleration signal time and frequency domain features indicates that this failure influenced the system vibration response, likely due to the irregularities in the meshing surface. Conversely, the lack of trend between the thrust-plate and gear wear faults likely indicates that these faults did not cause a significant excitation to the vibration of the system.

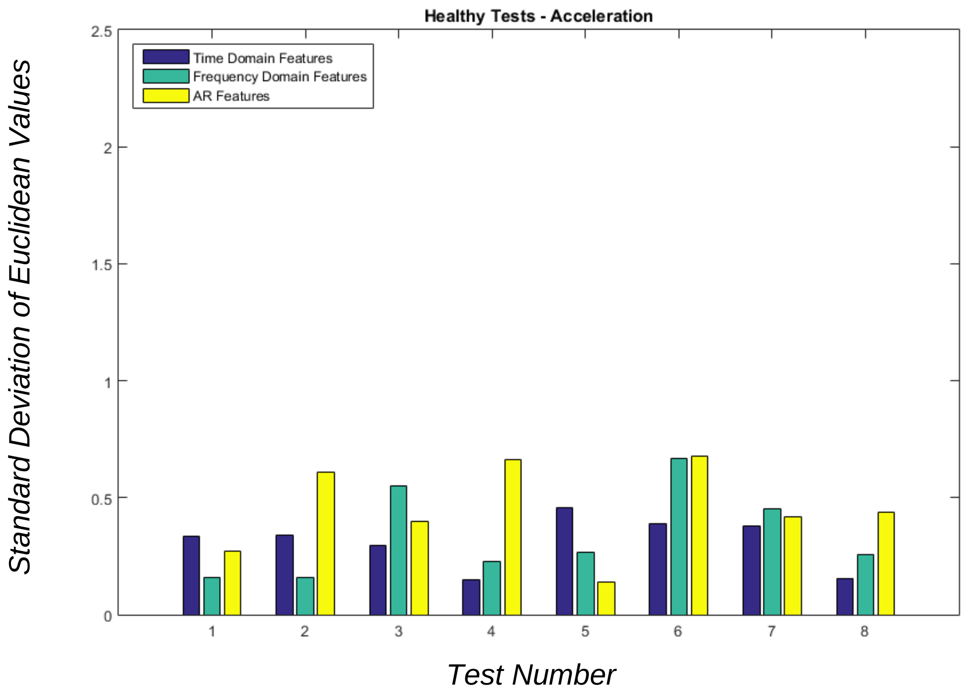


Figure 36: Acceleration Signal Feature Comparison (Healthy Tests)

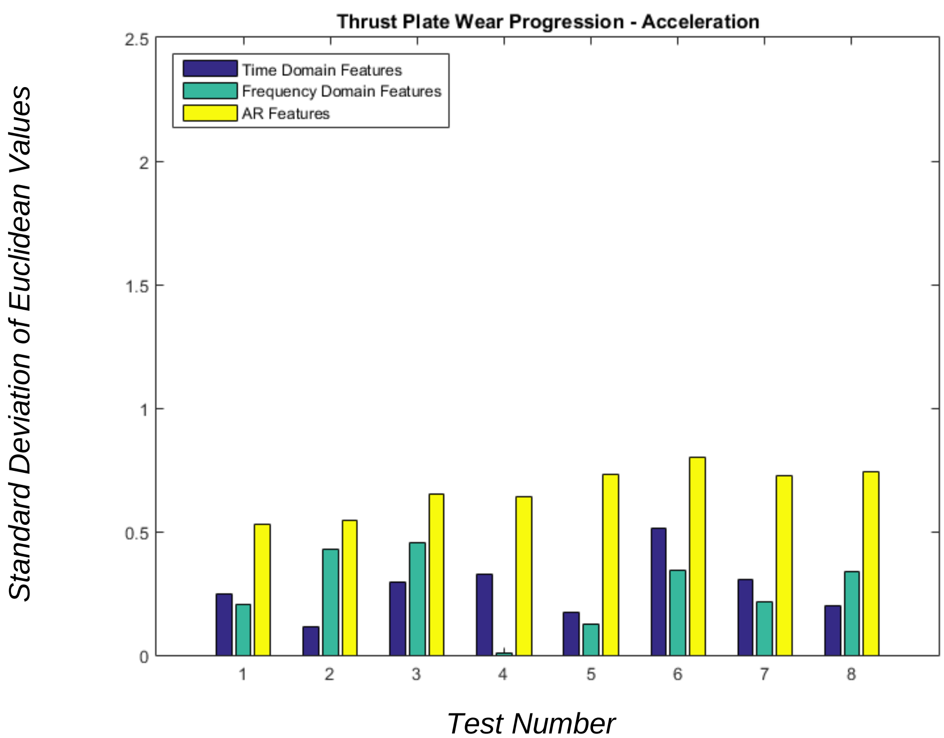


Figure 37: Acceleration Signal Feature Comparison (Thrust Plate Wear Progression)

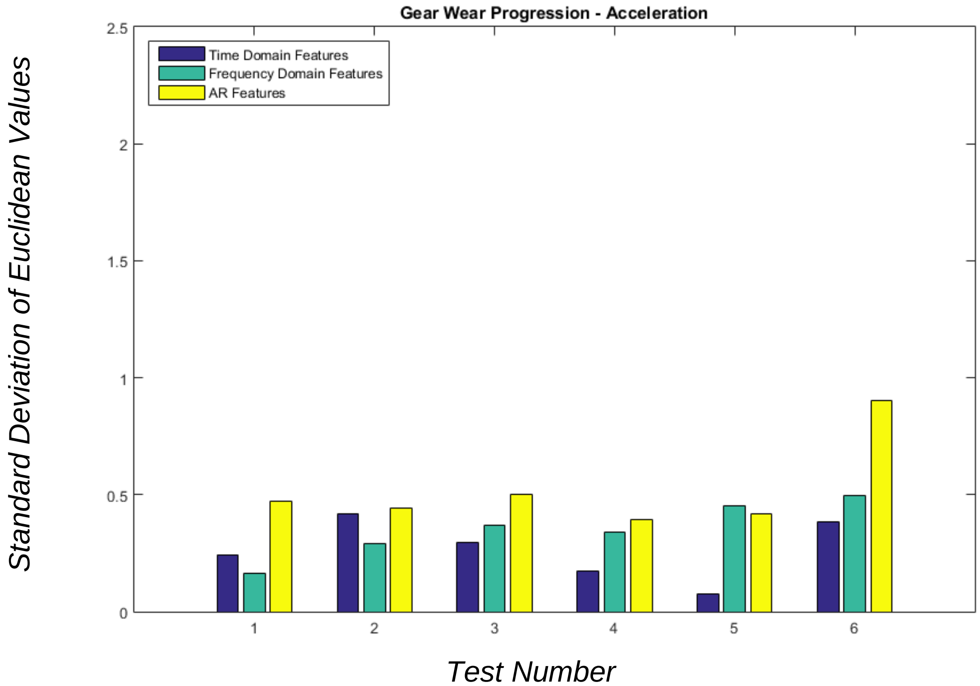


Figure 38: Acceleration Signal Feature Comparison (Gear Wear Progression)

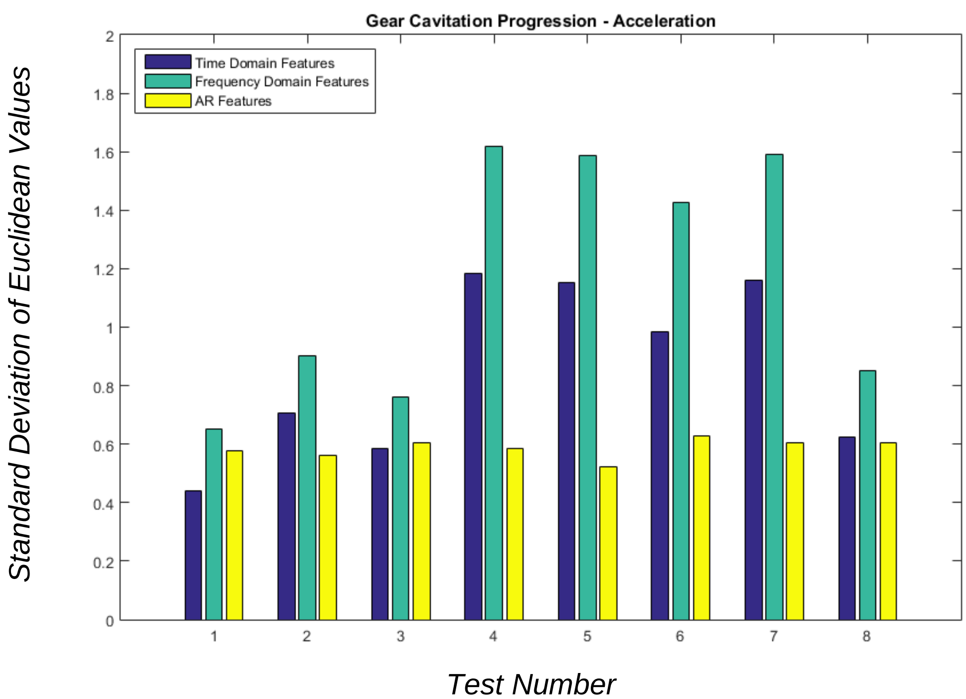


Figure 39: Acceleration Signal Feature Comparison (Cavitation Damage Progression)

6.5.2 *AR Feature Discussions*

The AR features did not show a clear response to any of the failure modes that were tested in this work. During initial data collection and analysis, optimization of the model order was proposed to ensure the order selected is was robust and relatively noise immune. However, the intent of this work matured to solving the existing challenges by: minimizing the amount of healthy training data required, keeping it simple to understand and quick to implement. Therefore, it was decided that the optimization of the AR features no longer fit within the scope and was not examined further.

6.6 Feature Group Comparison - Steady State Sections

The Euclidean distance values were sampled from the nine-unique steady state operating conditions to compare the effects of different speeds and loads. In the following section (Figure 40 to Figure 47): low, medium and high speeds correspond to 200, 400 and 600 RPM and low, medium and high loads correspond to 17.5, 35 52.5 bar respectively. In this section, the feature groups are compared by assessing the mean of the Euclidean distance samples as discussed in Section 5.7.2.

6.6.1 *Pressure Signal Features*

The low speed, high load condition yielded the greatest changes in the pressure signal features particularly in the thrust plate and gear wear progressions (Figure 41 and Figure 42). This result is likely attributed to high pressures resulting in increased internal leakage due to the increased pressure differential and low speeds (i.e. low flow rates) resulting in a greater ratio of leakage to total flow. This could explain why the high pressures and low speeds produced greater feature differences between the subsystems for these faults.

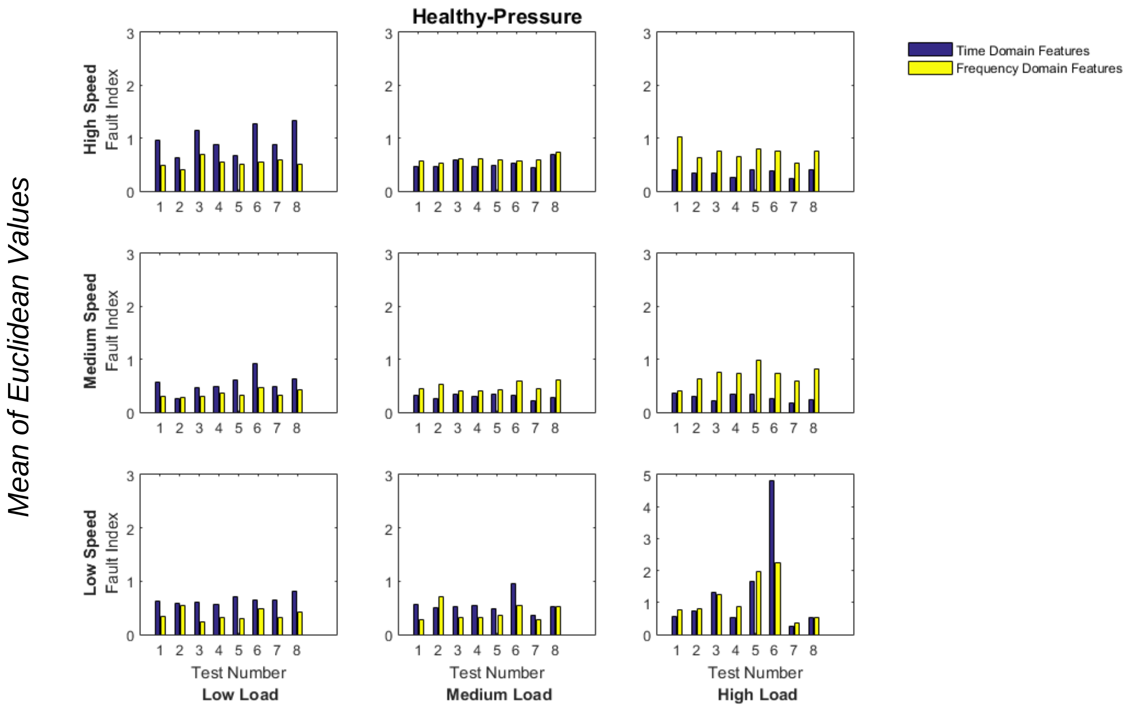


Figure 40: Steady State Pressure Feature Group Comparison (Healthy Tests)

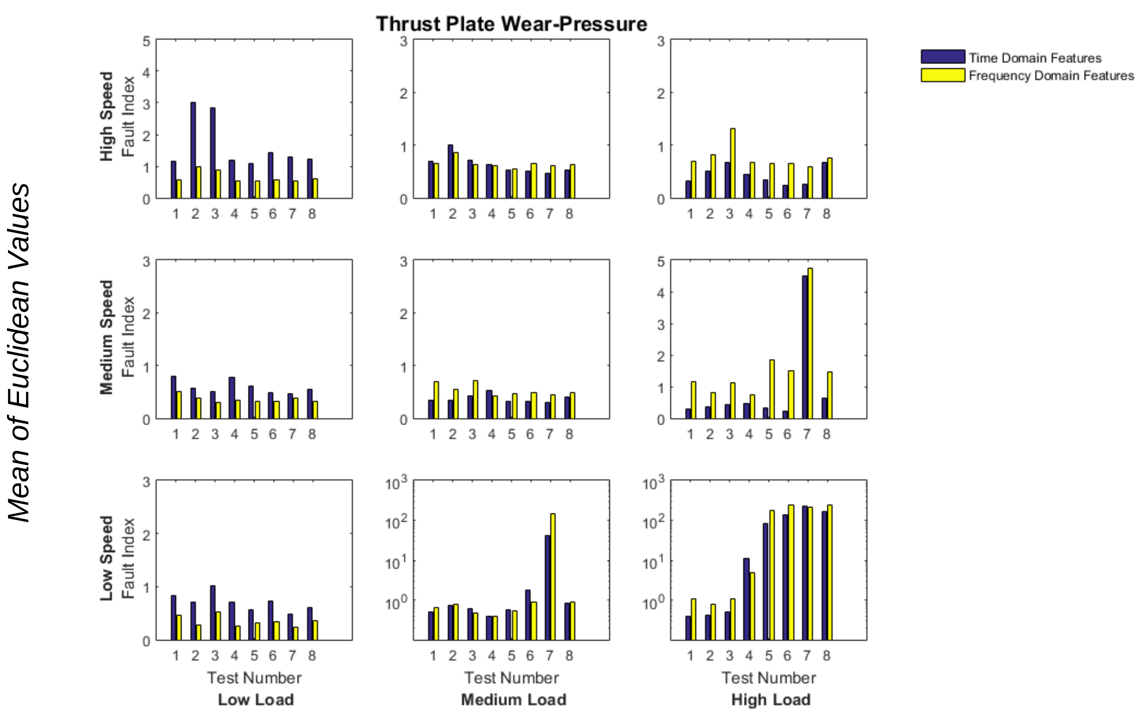


Figure 41: Steady State Pressure Feature Group Comparison (Thrust Plate Wear Progression)

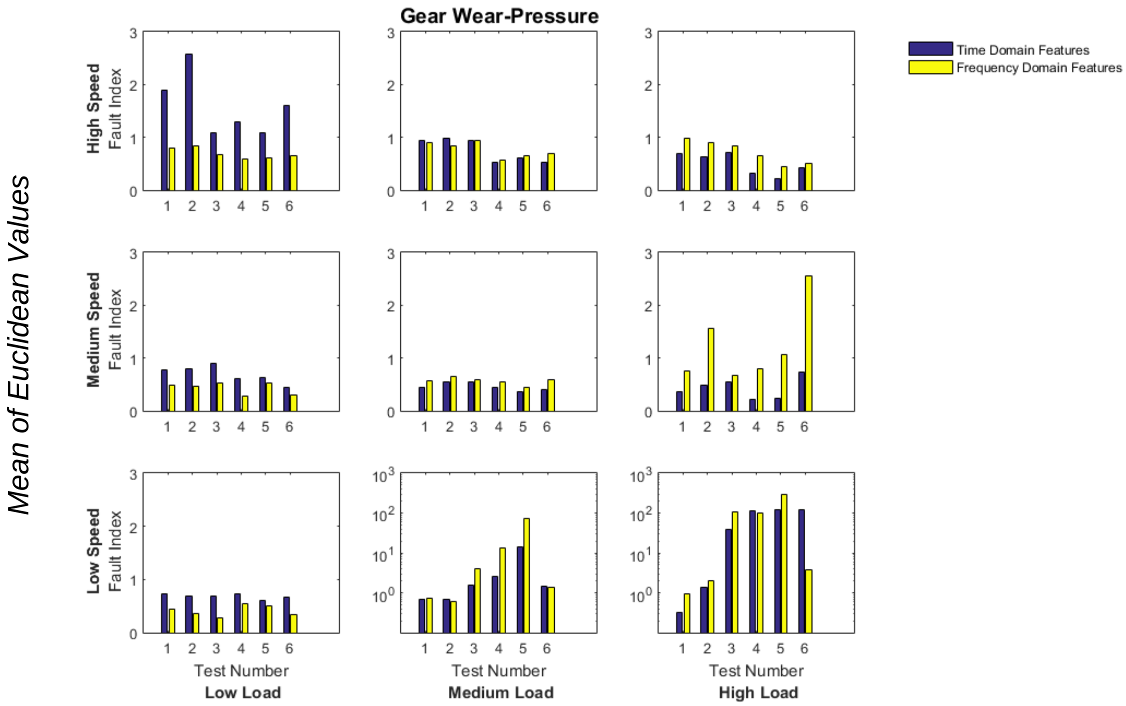


Figure 42: Steady State Pressure Feature Group Comparison (Gear Wear Progression)

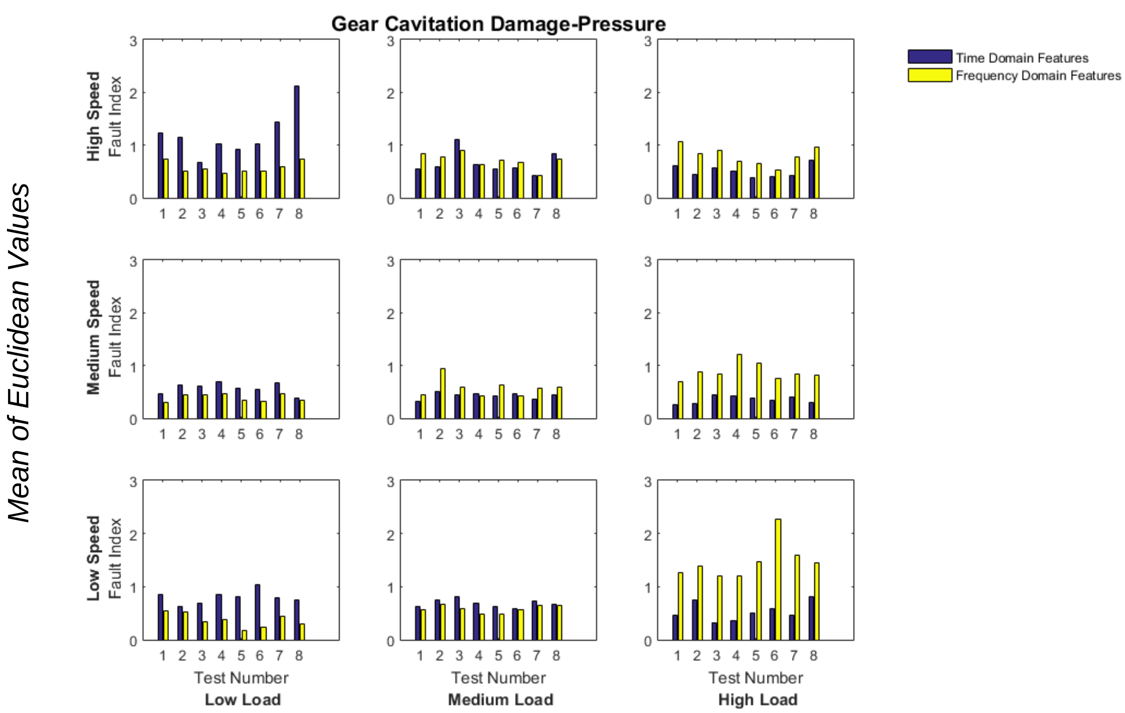


Figure 43: Steady State Pressure Feature Group Comparison (Cavitation Damage Progression)

Acceleration Signal Features

The high-speed conditions yielded the greatest changes in the acceleration signal features specifically in the cavitation damage progression (Figure 47). This is likely attributed to the vibration transmissibility characteristics of the system. Essentially, the amplitude of a system's vibration increases with respect to the excitation frequency (if it's below the systems resonance frequency). This means that the vibration amplitude of the faulted pump is expected to increase with the speed of the system, thus creating greater differences between subsystems at higher speeds. This effect can especially be seen in the frequency features since each feature was related to the amplitude differences in various frequency ranges. Although this effect is also seen in the healthy tests, the variance is marginal when compared to the results from the cavitation damage progression.

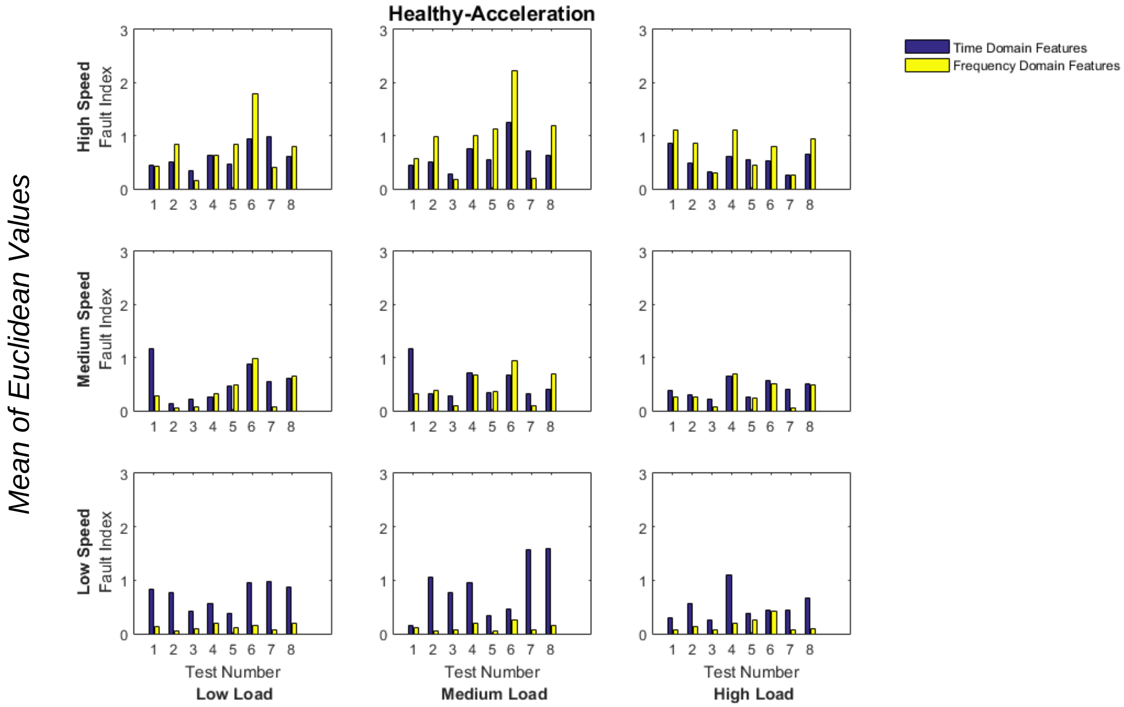


Figure 44: Steady State Acceleration Feature Group Comparison (Healthy Tests)

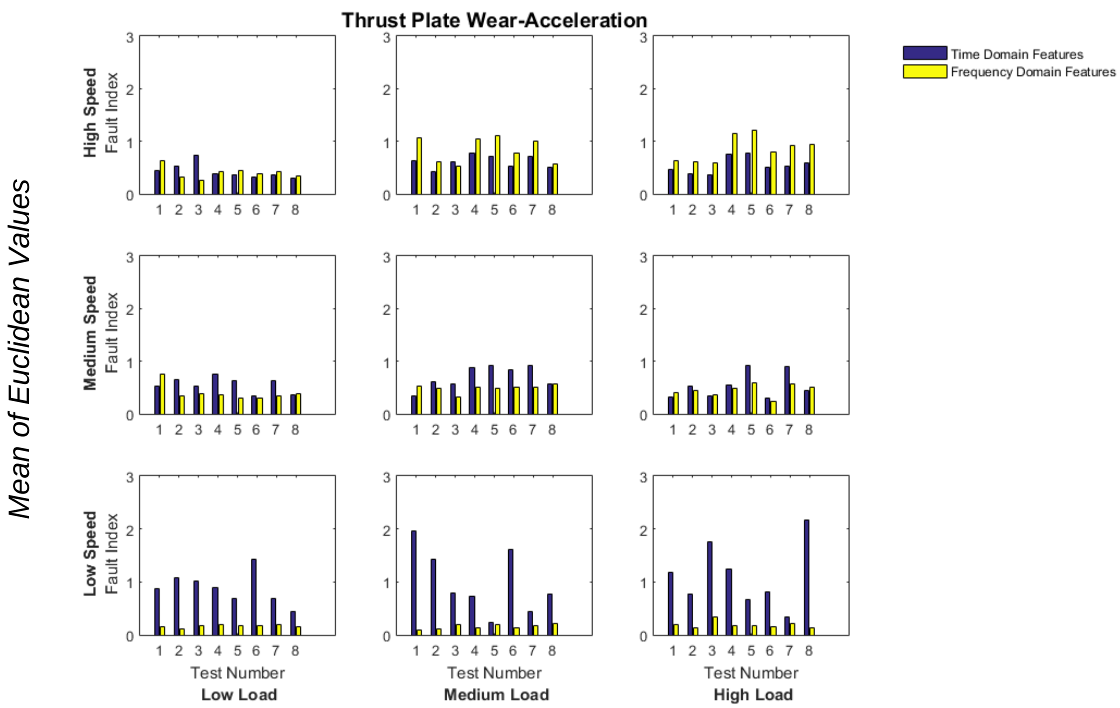


Figure 45: Steady State Acceleration Feature Group Comparison (Thrust Plate Wear Progression)

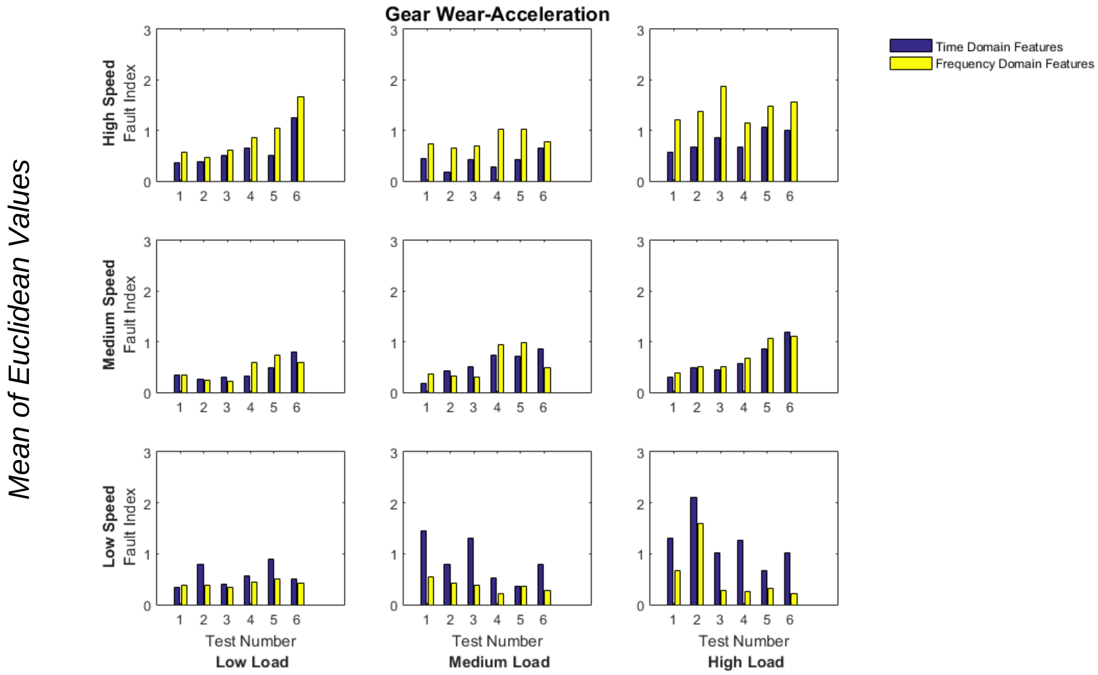


Figure 46: Steady State Acceleration Feature Group Comparison (Gear Wear Progression)

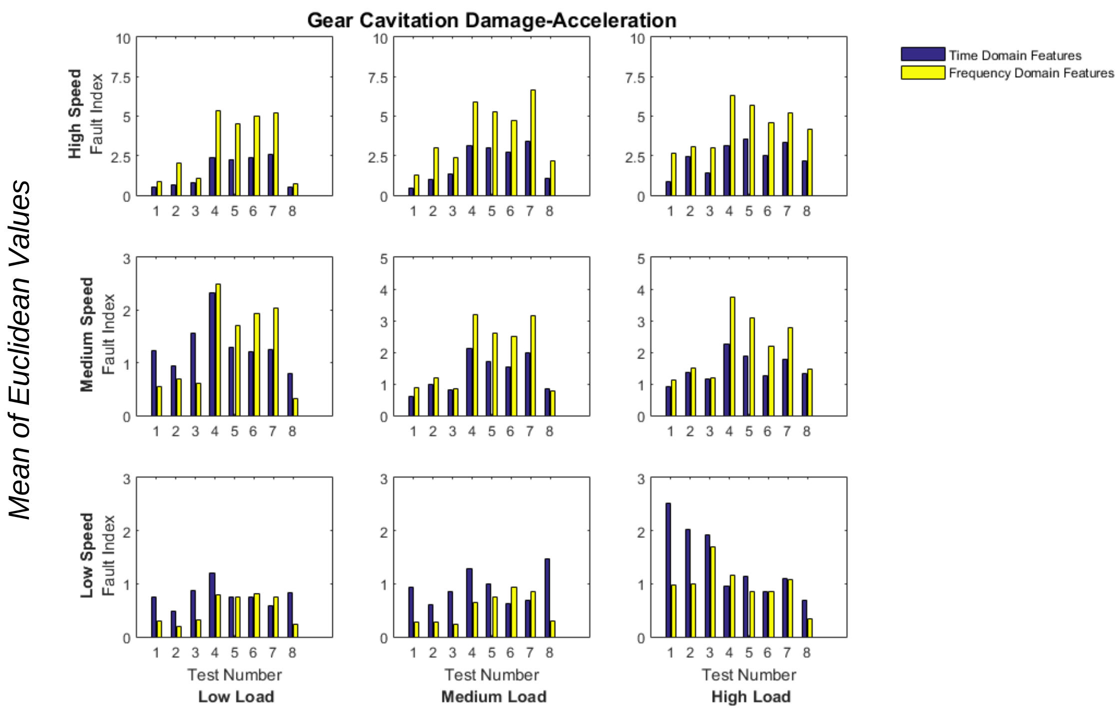


Figure 47: Steady State Acceleration Feature Group Comparison (Cavitation Damage Progression)

6.6.2 *General Discussions*

From what has been discussed so far, these results provide substantial insight into the nature of these faults and how they propagate. However, the most significant observation is that the healthy tests are only marginally affected by the operational state. This is important because it supports that this approach could help reduce the number of false alarms that would typically be triggered during variable operation of healthy equipment, while also maintaining sensitivity to incipient faults with minimal analysis.

Admittedly, these results only show marginal differences for many of the other operating states that have not already been discussed. However, this could likely be improved using other analytical techniques such as: investigating other statistical parameters (other than the mean values that were used in this section), additional data collection to improve the distribution sample size of the steady state sections, and by using machine learning classification algorithms like SVDD or ANN.

Chapter 7

7 Conclusions and Future Work

7.1 Summary of the Problem and Proposed Solution

From a review of the relevant literature, this work identified a need to continue developing condition monitoring techniques for applications where equipment is operating under variable duty. Although solutions exist for this class of machinery, their industrial implementation is mostly limited to due to: the amount of required training data, their ability to minimize all effects of variable operation, or their complexity.

The review also identified an emerging solution that improves on these limitations by utilizing the mechanical redundancy of parallel systems as a dynamic baseline source. It was determined that this concept warrants further investigation into its application for other mechanical components.

Due to the growing interest in using variable drives with fixed displacement pumps as an alternative to variable displacement pumps, hydraulic gear pumps were chosen as the novel components to which to apply this methodology. The review then identified three common failure modes (thrust plate wear, gear tooth wear and cavitation damage) that were selected to be studied in this work.

7.2 Experimental Methodology Summary

The flexible machinery simulator was utilized to collect the experimental data for this work. Hydraulic gear pumps were instrumented with accelerometers and pressure sensors, while a closed loop control program was developed to vary the system speed and load cycles for testing. After developing a test matrix, pumps were seeded with faults by incrementally damaging a component and replacing it into the pumps.

7.3 Analytical Methodology Summary

Pressure and acceleration signals were then collected from each subsystem and the signals from the (nine) unique steady-state machine operations were segmented for analysis. Features from these segments were then extracted and separated into three categories (time, frequency and AR features). The residual difference between subsystem features were then calculated and normalized with respect to the average healthy training data to ensure features are reconditioned to the same order of magnitude. The Euclidean distance was then calculated to measure the magnitude of similarity between subsystem feature groups.

7.4 Summary of Results

Changing speeds and loads were verified to have a profound effect on diagnostic features. This variance is what makes condition monitoring variable duty equipment so challenging, since it becomes difficult to differentiate between a developing fault and changes due to the operational state. Features from parallel subsystems were also observed to be closely related in any operational state. Furthermore, the residual difference between subsystems' features were shown to be independent of the changes in operation. Normalized feature residuals where then shown to be sensitive to developing faults and the Euclidean distance of a set of features was shown to preserve this trend.

Statistical analysis of the Euclidean distance values obtained over the complete variable duty test show:

- Consistent results were obtained using 8 unique sets of healthy components from both pressure and acceleration signal features.
- Pressure signal, time and frequency domain features were shown to trend well with thrust plate and gear wear fault progressions.
- Acceleration signal, time and frequency domain features were shown to trend well with the cavitation damage fault progression.

Logical relationships between these trends were discussed and support that, although the machine was operating under changing loads and speeds, this approach maintained a sensitivity to incipient faults.

Similar results were shown when taking a closer look at the nine unique steady state sections of the duty cycle. However, some interesting observations were also made, such as:

- The low-speed, high-load condition yielded the greatest changes in the pressure signal features during the thrust plate and gear wear progressions.
- The high-speed conditions yielded the greatest changes in the acceleration signal features during the cavitation damage progression.

- The healthy tests showed that both pressure and acceleration features exhibited only marginal variance during any operational state.

The observed relationships were also discussed and were also found to have logical explanations. However, most importantly, the residual results were not significantly affected by changing speeds and loads while healthy subcomponents were installed. Meaning, this research successfully validates that this approach can be used to improve the performance of condition monitoring systems for variable duty equipment.

7.5 Future Work

A potential development on this work that would be highly favorable to industry is the ability to identify which subsystem the fault is located in. A phenomenon that could be exploited to accomplish this was identified in section 6.3, where it was observed that the value of a normalized feature was highly correlated to the subsystem in which the fault was seeded in. In this work, this information was lost during the Euclidean distance calculation when the normalized residuals were squared. Perhaps there is a different distance metric that could preserve this information successfully.

Another avenue that would be worth exploring further is whether this approach can identify similar failures occurring simultaneously in multiple subsystems. The opposing argument is that similar failures occurring at the same time would produce similar signal responses and thus decrease the residual that this approach utilized to detect the fault. This could be particularly problematic for hydraulic systems where oil contaminants could potentially compromise multiple subsystems. However, it may be worth investigating phase coherence to distinguish the failure transients.

It would also be critical to investigate how this approach is recommissioned after a component has been replaced in one subsystem. The foreseen problem being that the new component may need an adequate run-in period before the fault detection system can reliably compare the two systems. Although this concern is somewhat addressed by using 8 healthy tests with unique combinations of sub-components, it would be interesting to study this aspect in an industrial application. In this study, it may be beneficial to save some historical data for intermittent comparison.

Direct comparisons to other methods of detecting faults in variable duty equipment would also be beneficial to this domain of research.

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