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APPLICATIONS OF VIBRATION ANALYSIS AND MACHINE HEALTH MONITORING TO CHAIN MOTOR MAINTENANCE

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ABSTRACT

No matter the type of machine, be it a car, part of a production line, wind turbine, or a chain motor, in order for safe and productive operation, it must be properly inspected and maintained. Chain motors are most commonly used in theaters, arenas, and stadiums to hoist and position sound, lighting, and video equipment over the stage and audience. Chain motors are to be regularly inspected, but the inspection requires nearly complete disassembly of the body of the motor in order to visually inspect the gears, bearings, and lift train, which is a time and labor intensive process. Applying vibration analysis could allow for the inspection process to take place on the outside of the motor, while still providing the same results.

Vibration analysis is the most common form of machine health monitoring, which uses the characteristics and performance of a machine to indicate its condition. In order for vibration analysis to be implemented successfully and accurately, faults and component failures are first introduced experimentally. Vibration signals are recorded with an accelerometer, which are then analyzed for any outstanding features or characteristics in comparison to a signal with no faults. If any of these signals or characteristics are detected during normal operating conditions, targeted maintenance can be performed to correct the problem because its nature and location are known from the vibration signal.

Vibration signals for faults in one bearing were collected, analyzed, and identified in this research. Further testing of the rest of the components and compilation into an algorithm could allow for the mechanical portion of the inspection to be performed from the outside of the motor, and healthy units could be put back in to service without the time and cost involved in the visual inspection. However, this will not completely replace inspections, as there are still components

like the chain, chain guides, suspension hook, and brake that cannot be inspected and analyzed with vibration analysis.

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Chapter 1

Introduction and Literature Review

No matter the type of machine, be it a car, part of a production line, or a wind turbine, in order for productive operation, it must be maintained. Machine maintenance can be broken down into three schools of thought. First is reactive maintenance, where parts are repaired and replaced only after they break. Next is preventative maintenance, which follows a set schedule designed to replace parts before failure occurs. [1,2] Lastly, machine health monitoring, which uses the actual properties of the machine, like vibration, temperature, strain, and lubricant condition for detecting minute changes indicative of a deteriorating, but still functioning component. [3]

Vibration analysis is one of the most common methods employed for machine health monitoring. Signals can be analyzed online, meaning in real time, or offline from a previously recorded signal, depending on how critical detecting faults is. In order for vibration analysis to be implemented successfully and accurately, faults or component failures are first introduced experimentally. Vibration signals are recorded with a sensor, which are then analyzed for any outstanding features or characteristics in comparison to a signal with no faults. If any of these characteristics are detected during normal operating conditions or at an inspection, targeted maintenance can be performed to correct the problem because its nature and location are known from the vibration signal. [4] Vibration analysis is not used exclusively in any one industry or for one type of machinery, but some uses are wind turbines, radar towers, helicopter gearboxes, and plant machinery. [3, 5] For these applications, signals are commonly monitored online to detect faults as soon as possible, well before any failure would occur. In these cases, repairs are difficult and expensive, but letting it go until a catastrophic failure puts productivity, worker safety, and even lives at risk.

These vibrations come largely from the rotating parts of the machine, the gears, bearings, and shafts driven by motors. Gears are designed to transmit mechanical power, and they also have the ability to increase the torque or the speed of the motor as well, depending on their arrangement. They are designed following standards set by the American Gear Manufacturers Association, who also indicate how it can fail. Pitting and scoring are names for the removal of material or deformations of the teeth, either due to fatigue or foreign materials. The teeth can also break off. [6, 7] Vibration analysis is not a new technique, but is under constant research to identify faults sooner and with increased accurately, even with learning algorithms like artificial neural networks and fuzzy logic systems that are constantly monitoring the vibration signal, looking for irregularities and what may have caused them and deciding when to sound the alarm. [8, 9]

The output shafts of motors, as well as shafts carrying gears or other rotating members, need to be supported while still being able to freely rotate. This is accomplished through the use of bearings. Rolling elements, typically balls, rollers, or needles, are sandwiched between the inner and outer ring of the bearing, and allow the two rings to rotate independently of each other with low friction. Races, or grooves on the inside of each ring, keep the elements aligned, and a separator or cage keeps the elements evenly spaced and from rubbing against one another inside the races. Like gears, bearings can experience failures caused by fatigue, known as spalling, or foreign materials in the races that can score, jam, or corrode the elements and races, compromising the functionality of the bearing. [10] Vibration analysis for bearings is attempting to identify the same type of periodic signals that gear analysis is, and therefore uses many of the same methods and techniques. These also include high-frequency resonance technique, wavelet transform, power spectral density, differential evolution, and particle swarm optimization to name a few. [11-13]

Applications

Vibration analysis is a proven and effective way to monitor components such as gears and bearings to determine machine health, but constant, or online, monitoring of machines is often impractical or unnecessary. An example of this would be a chain motor, found most commonly in theaters, arenas, and stadiums. While stadiums and arenas typically host sporting events, they are also able to seat large crowds and often host concerts and performers. However, in order for the act to be seen and heard, sound, lighting, and video equipment weighing hundreds or thousands of pounds needs to be suspended over the stage and the audience. That is accomplished by using chain motors, also referred to as motors or hoists. In this sort of application, chain motors are used in what is known as ‘motor down’ configuration, where the fixed hook is attached to the equipment, and the entire motor climbs the chain. Figure 1 shows a motor down chain motor, and also an arena space that has been changed over to host the NFL Draft, with additional lights, sound, video equipment, and masking in the space. The chain motors can be seen above the lighting trusses, speaker clusters, and shell. This is in contrast to the typical ‘motor up’ configuration of shop hoists and equipment hoists, which are typically fixed to a beam or gantry, and the free end of the chain attaches to the load. When used for entertainment applications, it only takes one or two riggers to pull the free end of the chain up the 60’ or 80’ or 100’ to the structural steel of the building. Pulling up the whole motor safely would require a team of riggers, often just to have to lower it back down in 12 or 18 hours once the show is over. Once all the motors are connected to the steel and the equipment, they are lifted into place with a single controller at the push of a button. In order to do so safely and reliably, the chain motors need to be properly inspected and maintained.

Figure 1: Chain motor and uses in arena rigging [14]

Machine health monitoring could be used as a diagnostic tool in scheduled maintenance by reducing downtime and costs. In chain motors, in order to provide visual inspection of the gears and bearings in the lift train, the motor is partially disassembled to access the components, lubrication is removed, and then the components are individually inspected before reassembly. If baseline vibration readings were collected for the expected range of component failures, and then compiled into an algorithm, healthy units with no faults could be put back in to service without the time and cost involved in the visual inspection.

Chapter 2

Experimental Design

Materials

In order to test bearing faults in a chain motor, multiple copies of a specific bearing and a chain motor are required. Testing also requires a suitable setup to support the motor, multiple weights and a method to attach them to the motor, and sensors and instrumentation to record the vibration signals.

Test Rig

A shop gantry was used as an attachment point for the chain motor. The opening of the hook was not large enough to fit around the pin of the trolley on the gantry, so a suitably rated flat strap was used. This also removed the need to secure the trolley to keep the motor and load from traveling along the beam during testing. A wooden box was built to support and contain the weight bricks that would be used to test the motor under different loads. It was attached to the chain motor using suitably rated flat straps. The complete setup is shown in Figure 2.

Bearing Faults

The bearing used for testing was a single-row radial ball bearing with a 35mm bore, 72 mm outside diameter, and 17 mm width. The bearing supports the motor side of the lift wheel. To introduce controlled faults to the bearings, they were first cleaned and degreased. Using a tungsten carbide rotary tool, faults were created on the inner race, outer race, and ball of three separate bearings, and are shown below in Figures 3, 4, and 5. Each bearing was thoroughly cleaned again to remove any metal shavings or chips, then repacked with grease. An additional bearing was not repacked with grease.

Instrumentation

Three accelerometers were mounted directly outside the bearing housing where neither they nor their cables would interfere with operation of the chain motor. Their locations are shown in Figure 6, with their specifications in Table 1. The accelerometers were connected to a National Instruments BNC-2120 shielded connector block, which interfaced and recorded to the LabView Signal Express software via a National Instruments USB-6251 multifunction I/O device. Data was sampled at 5 kHz.

Table 1: Accelerometer specifications

Accelerometer	Model	Sensitivity	Measurement Range	Broadband Resolution	Frequency Range	Sensing Element
1	PCB 333B30	100 mV/g (±5%)	±50 g pk	0.00015 g rms	0.5 to 3000 Hz (±5%)	Ceramic
2	PCB 353B03	10 mV/g (±5%)	±500 g pk	0.003 g rms	1 to 7000 Hz (±5%)	Quartz
3	PCB 602D91	100 mV/g (±5%)	±50 g pk	0.000350 g rms	0.5 to 8000 Hz (±3 dB)	Ceramic

Test Conditions

Each condition of the chain motor, i.e. healthy, outer race fault, inner race fault, no grease fault, and ball fault, were tested under four loading conditions. First, there was no load attached to the motor, then 290 lbs., 570 lbs., and 850 lbs. These will respectively be referred to as no load, low load, medium load, and high load conditions. Vibration signals were recorded for both directions of travel of the motor, three times each direction for every fault at every load.

Figure 2: Complete test setup with gantry, motor, weight box, and instrumentation

Figure 3: Inner race fault

Figure 4: Outer race fault

Figure 5: Ball fault

Figure 6: Sensor location

Chapter 3

Signal Processing

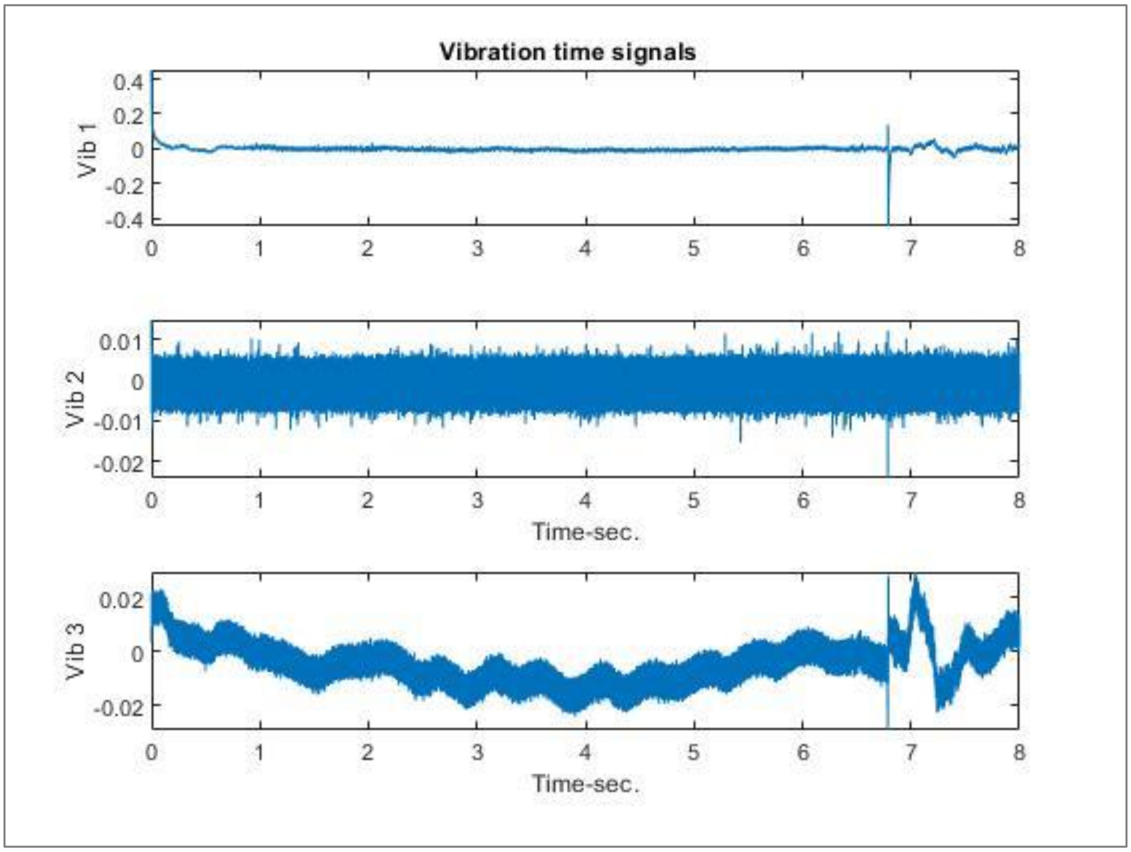
As simple and convenient as it would be to be able to take a vibration signal and hold it up to the light to compare it to a signal from a known fault, it is not that easy. Every rotating part of a machine, the operation it is performing, and even the environment it is in create vibrations that appear as noise in the recorded signal and can mask the fault features. That is one reason why it is important to get the sensors as close to the bearing as possible, to keep the strength of the fault features high and reduce other noise. Statistical parameters including root-mean-square, skewness, kurtosis, and crest factor can help identify faults from the time domain signal, and Fast Fourier Transform, or FFT, of the frequency domain is another useful measure. The values alone may indicate that a fault is present, but is it the comparison and trends of each parameter that are used to detect and diagnose faults.

Parameters

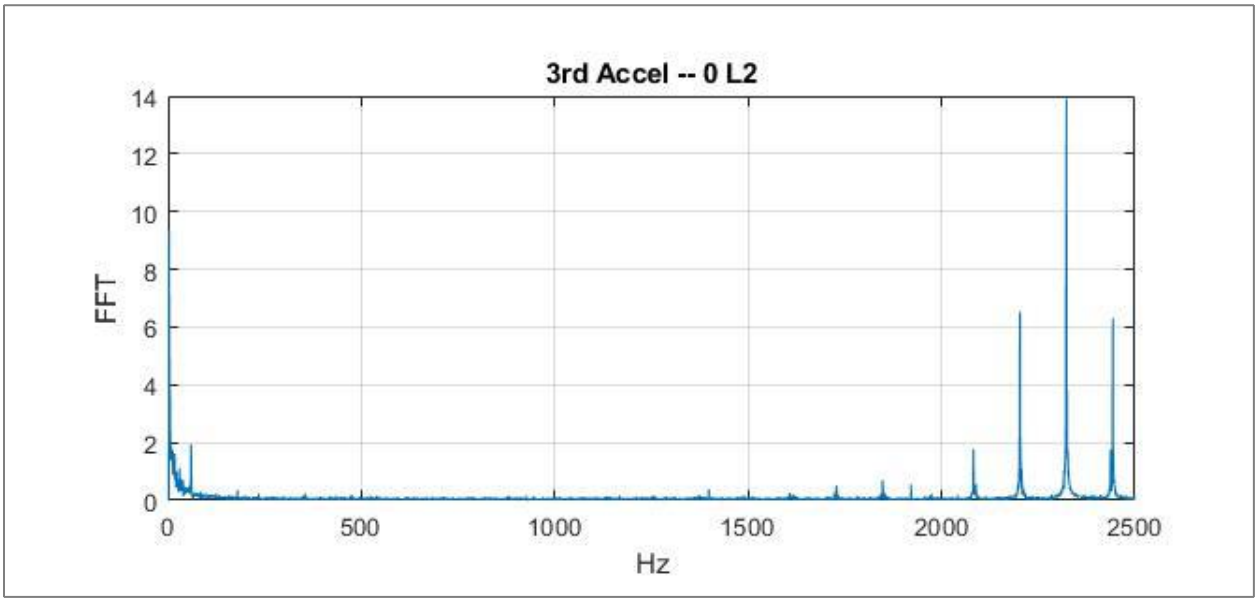
Root-Mean-Square, or RMS, is a common parameter for a distribution of data that is similar to a mean, except that the values are squared before averaging, so that positive and negative numbers do not cancel each other out. In vibration signals, RMS can still be thought of like a mean, where deviation from healthy values indicates that something has changed to create a uniform disturbance in the signal. Skewness and kurtosis are normalized statistical moments of the third and fourth order, respectively. Skewness represents asymmetry in the distribution of the signal, shifted to the left if negative and to the right if positive. Kurtosis is a measure of flatness of the signal around the average, with higher values tending to represent more frequent and larger spikes in the signal. A normal distribution has a kurtosis value of 3. [15] Crest factor is the ratio of peak to RMS values. With higher values, the signal has higher or more frequent peaks in comparison to the RMS. [16] A fast Fourier transform (FFT) is a more efficiently calculated discrete Fourier transform (DFT), but both transforms deconstruct a signal into its component frequencies. These different frequencies can be noise from another part of the machine or different resonances within the machine that are masking each other, all of which were buried in the recorded signal. The FFT output is a graph of frequency, with larger spikes corresponding to a larger presence of that frequency in the original signal. [17] An FFT plot is shown in Figure 7b, with large low frequency components below 50 Hz, and a few high frequency components above 2,000 Hz.

Analysis

The vibration signals were processed using a MATLAB code that then exported the statistics of the signal to an Excel spreadsheet. The code asked for the user to define the interval, chosen as the region while the chain motor was running at a constant velocity, ignoring the high amplitude spikes caused by the brake releasing or engaging when starting or stopping the motor. A sample signal from each accelerometer from one trial is show below in Figure 7a, the interval used for analysis would be from approximately 0.5 to 6.75 seconds. The MATLAB program then removed any DC component of the signal and calculated the statistical parameters from the resulting signal. It also took the FFT of the signal from each accelerometer, and the peaks were recorded. The FFT plot for Accelerometer 1 is shown in Figure 7b.



(a)



(b)

Figure 7: (a) Time domain signals for Accelerometers 1, 2, and 3 and (b) FFT graph of Accelerometer 3

Chapter 4

Results and Trends

Three accelerometers were used for data collection due to their different specifications and therefore responses to each fault. The four statistical parameters, RMS, skewness, kurtosis, and crest factor, were different for each accelerometer, and therefore were analyzed separately. Outliers from each data set were identified and removed using the interquartile range method, then the remaining data points were averaged for each loading condition; no, low, medium, and high. These averages, and the average of the entire data set, were plotted against each other versus the type of fault. The FFT responses from each accelerometer varied slightly in magnitude with nearly identical frequencies, so they were not separated by accelerometer.

RMS

The RMS data from Accelerometer 2 and 3 have a consistent pattern across all faults and distinct values for each fault, except for outer and inner race in Accelerometer 3. Their graphs are shown in Figure 8, and could be very useful in helping to identify faults. The data for Accelerometer 1, also in Figure 8, is less clear, but for a medium or high load could be used for fault identification because those values are distinct for each fault.

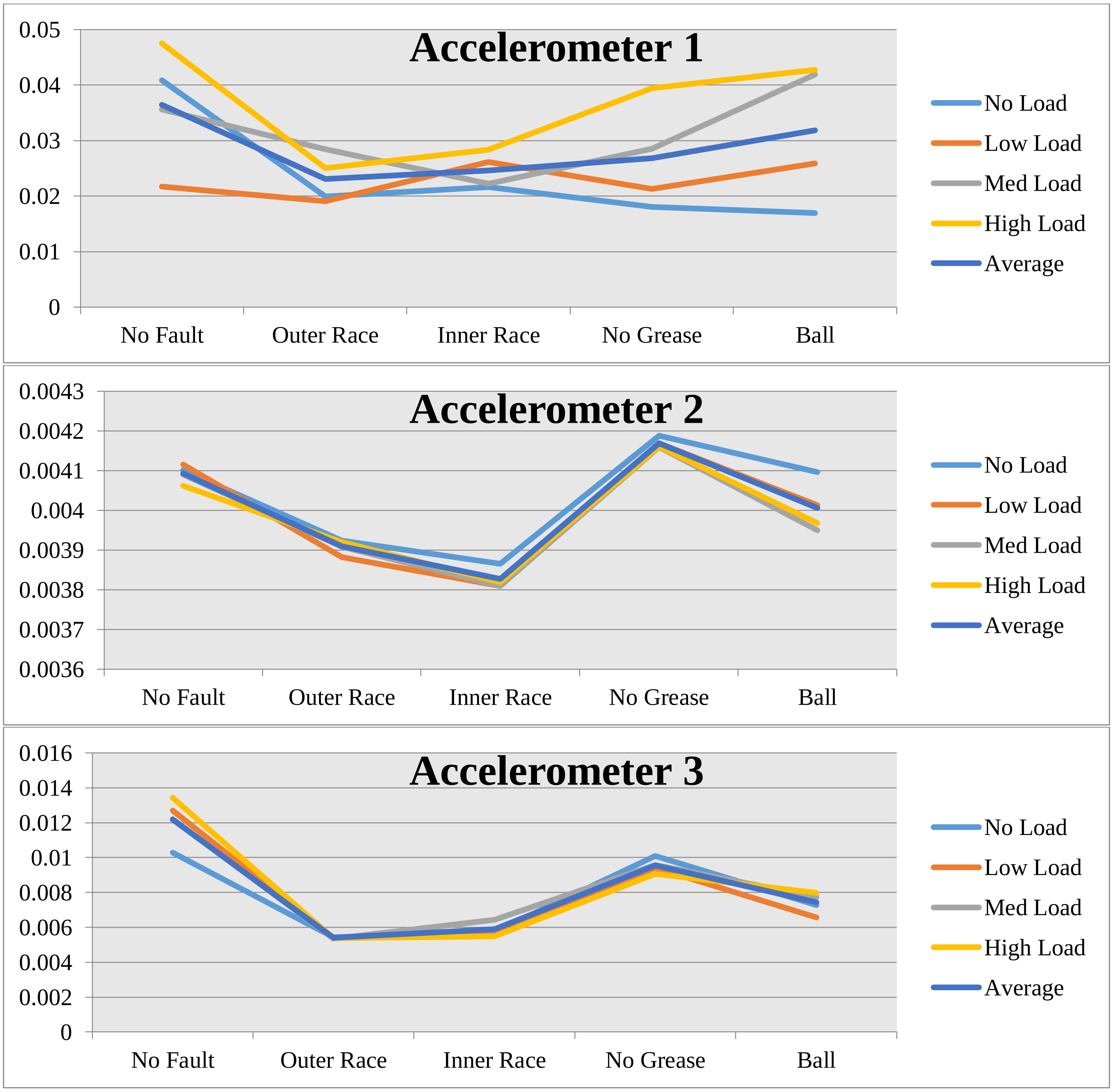


Figure 8: RMS data from all faults and all loads

Skewness

Accelerometer 3 shows the best pattern across all loads, but like for RMS, there is little change between the values for outer and inner race faults. However, for a known load, it could be useful in identifying faults. Accelerometer 1 shows a resemblance of a pattern, but is not as clear, though it still could be used for a known load. Accelerometer 2 has little distinction between the faults, except for no grease, but would generally not be useful. All are shown in Figure 9.

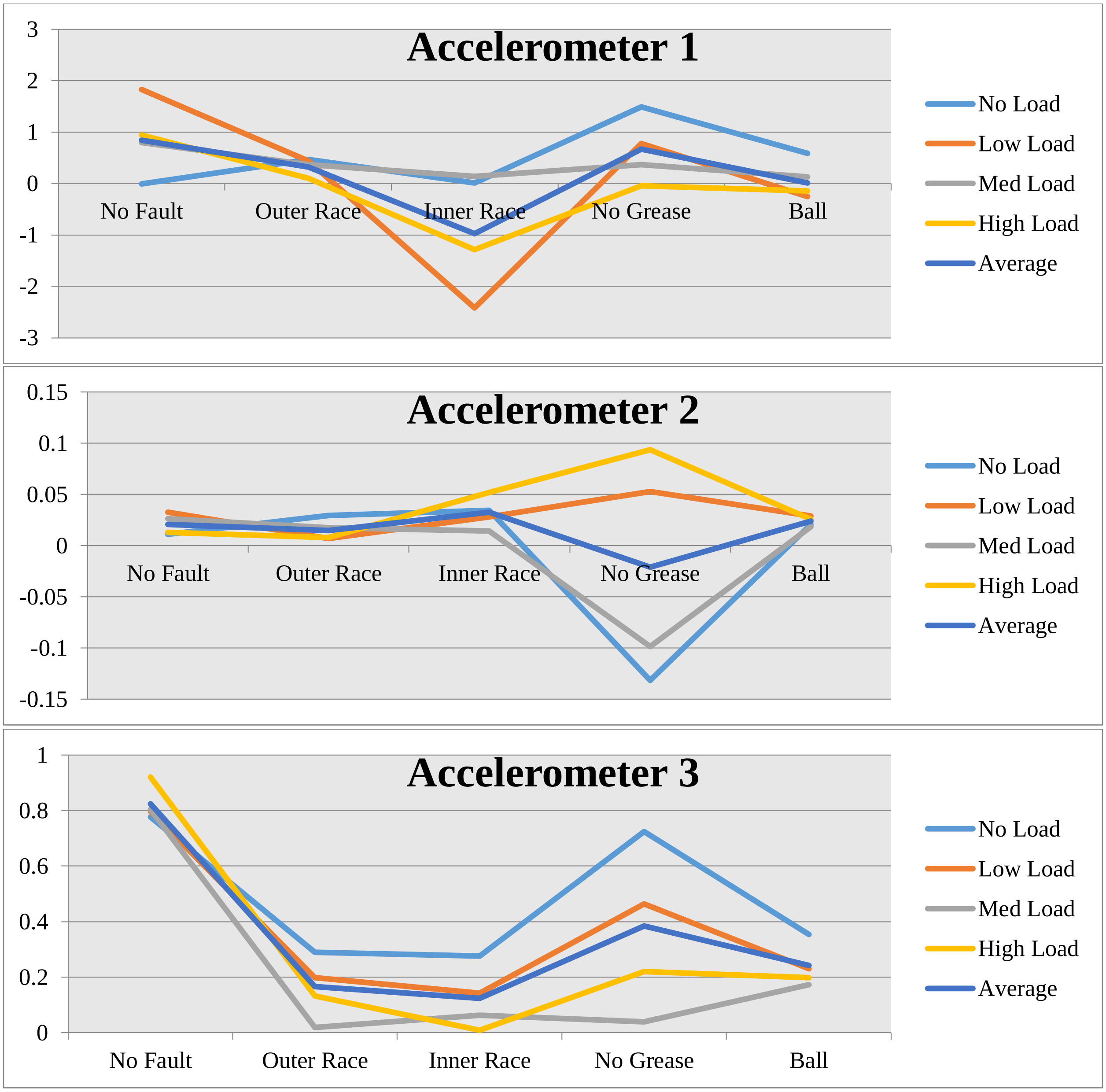


Figure 9: Skewness data from all faults and loads

Kurtosis

Accelerometer 1 shows a fair pattern with enough variation between faults that it could be used to identify all faults. The same is true for Accelerometer 2, but with less distinction between faults. Kurtosis values for Accelerometer 3 are very similar with little distinction between faults and would not be useful. All are shown in Figure 10.

Crest Factor

Accelerometers 1 and 2 show a general trend and there is enough variation between loads that both could be used for fault identification. Accelerometer 3 would be more difficult because there is less difference between faults, but it may be useful. The graphs are shown in Figure 11.

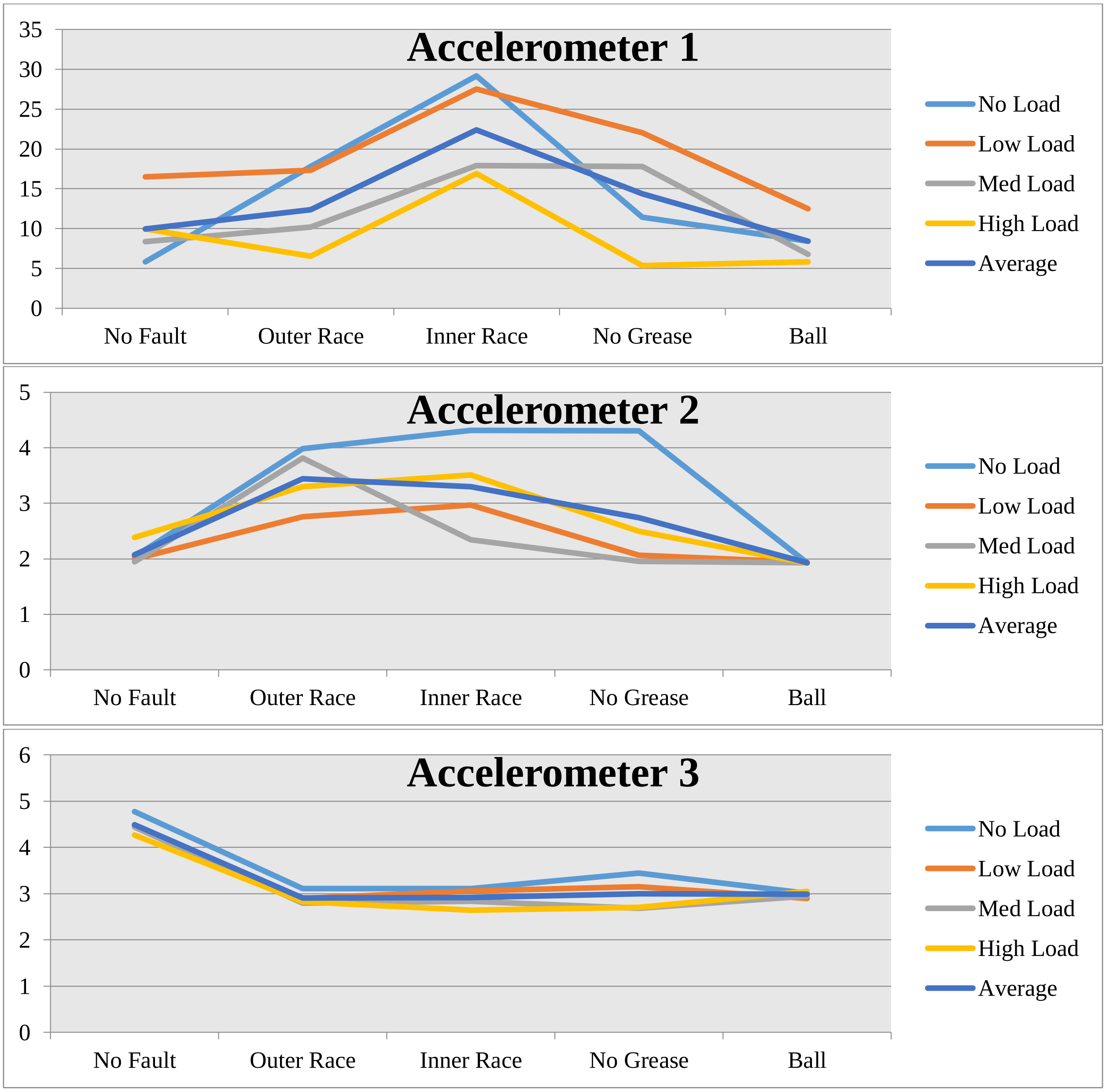


Figure 10: Kurtosis data from all faults and loads

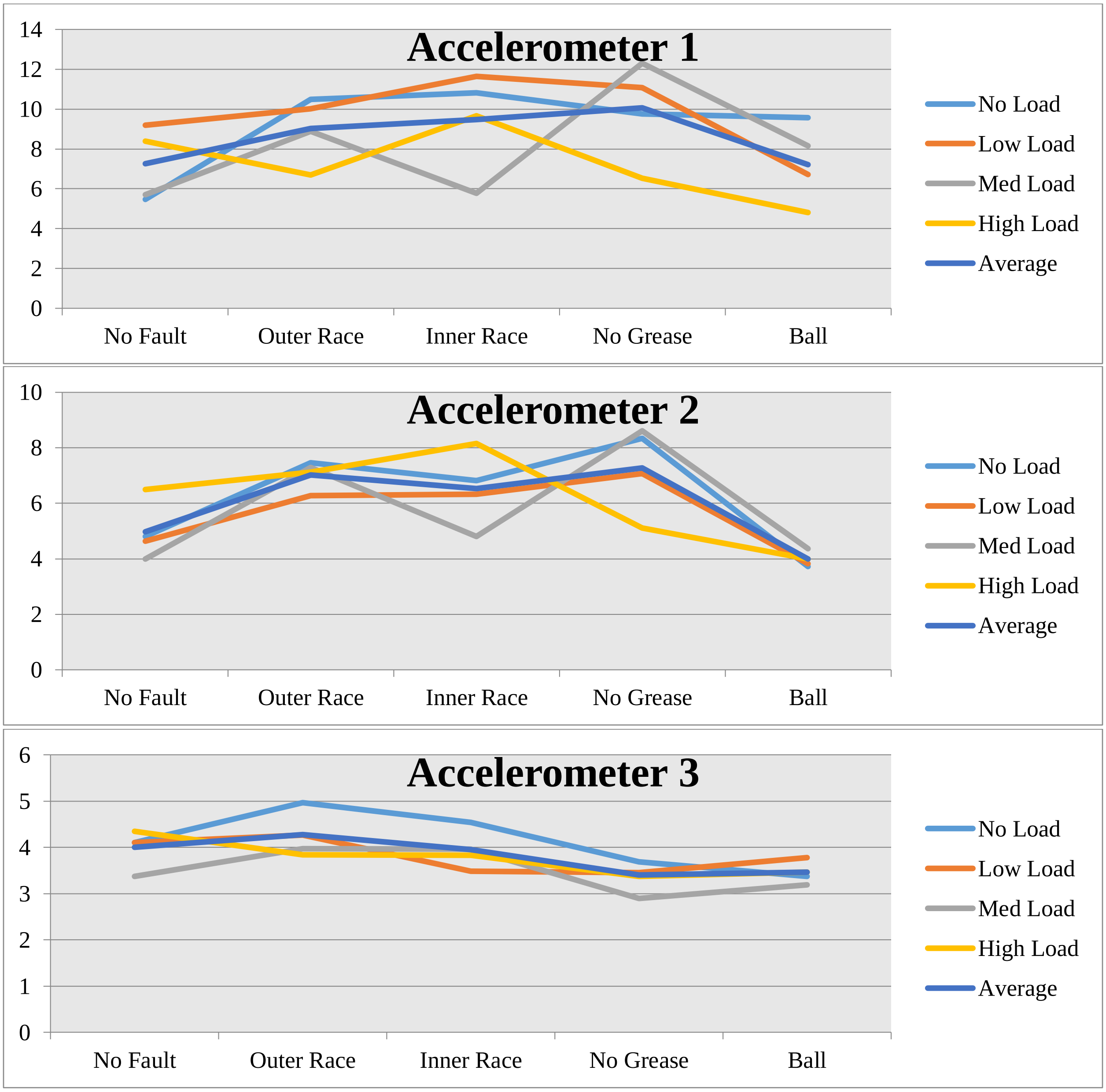


Figure 11: Crest factor data from all faults and loads

FFT

The bearing pass or characteristic frequencies, calculated from the bearing geometry and shaft speed, were not included in this analysis. The expected frequencies are all less than 10 Hz and were not clear in the FFT graphs due to the large quantity of low frequency noise in the signals. The higher frequencies are due to the resonance of the bearing itself or its natural frequency. The FFT data from all faults is shown graphically in Figure 13 and analytically in Table 2. Figure 13 also shows the average value of each band for increased clarity between faults. Each fault generally has distinct frequencies, though there is some overlap between no fault, no grease, and ball, and while inner race is less defined, it does overlap some of the same frequencies as the outer race. It is important to note that each trial typically had FFT spikes at all of the frequency ranges for that fault. This means that fault detection would rely on multiple frequencies, and not just on matching a single data point to a range of expected values.

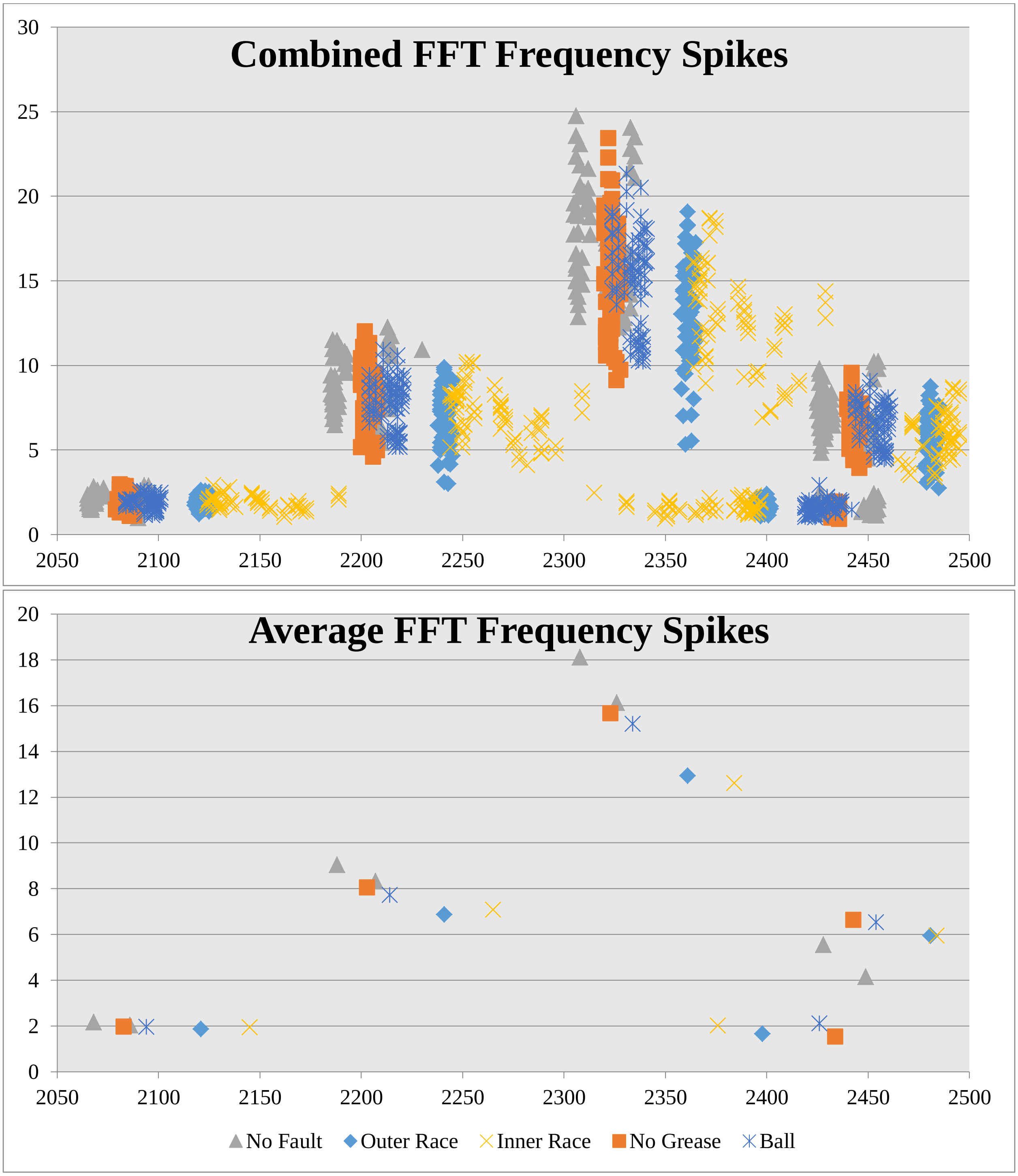


Figure 12: Combined and average FFT data from all faults and loads

Table 2: FFT frequency bands for all faults

Fault	Frequency Range (Hz)	Amplitude Range
No Fault	2065-2073	1.2-2.5
	2081-2095	1.2-2.5
	2185-2193	6.5-11.5
	2201-2230	5.5-12.3
	2305-2313	12.8-24.8
	2321-2335	12.2-24.0
	2425-2433	1.1-9.8
	2441-2455	1.1-10.3
Outer Race	2118-2125	1.2-2.1
	2238-2245	3.1-9.5
	2358-2365	5.3-19.0
	2395-2402	1.1-2.0
	2478-2485	2.7-8.7
Inner Race	2124-2189	1.0-2.9
	2244-2315	4.1-10.2
	2331-2397	0.9-2.3
	2364-2429	6.9-18.7
	2451-2496	3.5-8.6
No Grease	2079-2088	1.1-3.0
	2200-2208	4.5-12.0
	2320-2328	9.1-23.5
	2432-2436	0.9-2.0
	2440-2448	3.9-9.6
Ball	2084-2101	1.1-2.6
	2204-2221	5.1-10.6
	2324-2341	10.2-21.4
	2419-2442	1.0-2.9
	2444-2461	4.5-8.7

Chapter 5

Inspection Test and Analysis

It is unnecessary and impractical for vibration signals to be constantly monitored or recorded, even mounted, for a chain motor. If vibration analysis were to be used to with motor inspection, the sensors would need to be mounted on the outer frame of the motor, not the inside, with tapped holes so they could be easily installed and removed. Once the data was collected from the inboard sensors, they were removed and remounted on the top of the frame, still as close to the bearing as possible, shown in Figure 13. This location was chosen over mounting on the side because that is where the loose end of the chain travels and where the chain bag would be mounted. In order to make inspections as efficient as possible, signals were recorded for no load conditions. However, in hopes to bring out the fault features, signals were also recorded under high load. The signals were collected, processed, and analyzed in the same manner as the initial tests, then compared to those values and parameters.

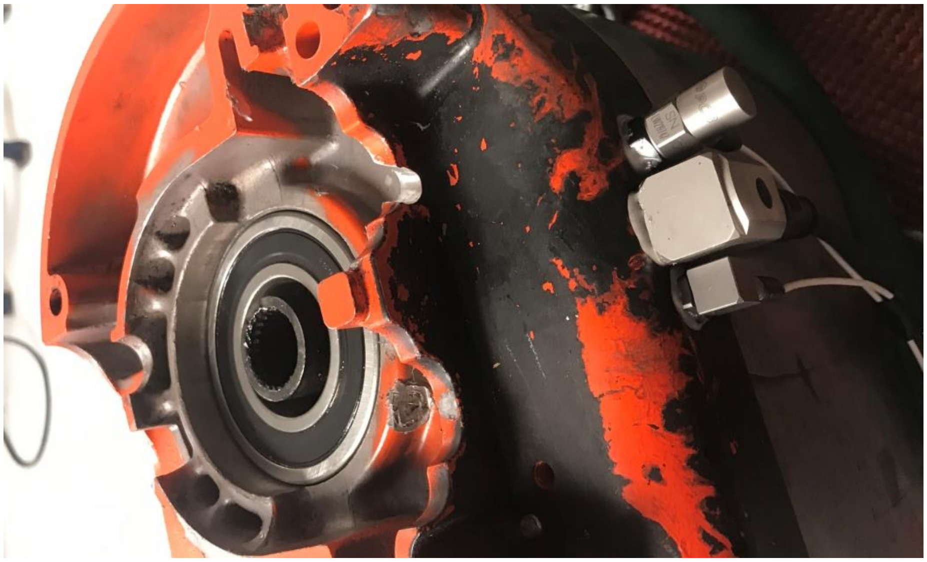


Figure 13: From top to bottom, Accelerometer 2, 3, and 1 in outboard location

Accelerometer 1

The resulting data from the two outboard load trials generally do not follow the trends of the inboard data, except for kurtosis at no load. The outboard values are graphed against the corresponding inboard values below in Figure 14. The no load statistics for all parameters have more distinction between faults than the high load, and with further testing, could all potentially be used for fault identification.

Accelerometer 2

As with Accelerometer 1, there is little relation to the inboard trends, except for RMS at no load, which is shifted upward by about 0.0005 for all faults. Crest factor is the only other factor that is showing enough distinction between faults that would be worth pursuing for fault identification. The inboard and outboard values are shown in Figure 15.

Accelerometer 3

Again, the trends of the statistical parameters do not match the inboard values, except for RMS at no load. For Accelerometer 3, the values are shifted upwards by around 0.01. Kurtosis and crest factor may be useful for fault identification, skewness would depend on further testing. Values are shown in Figure 16.

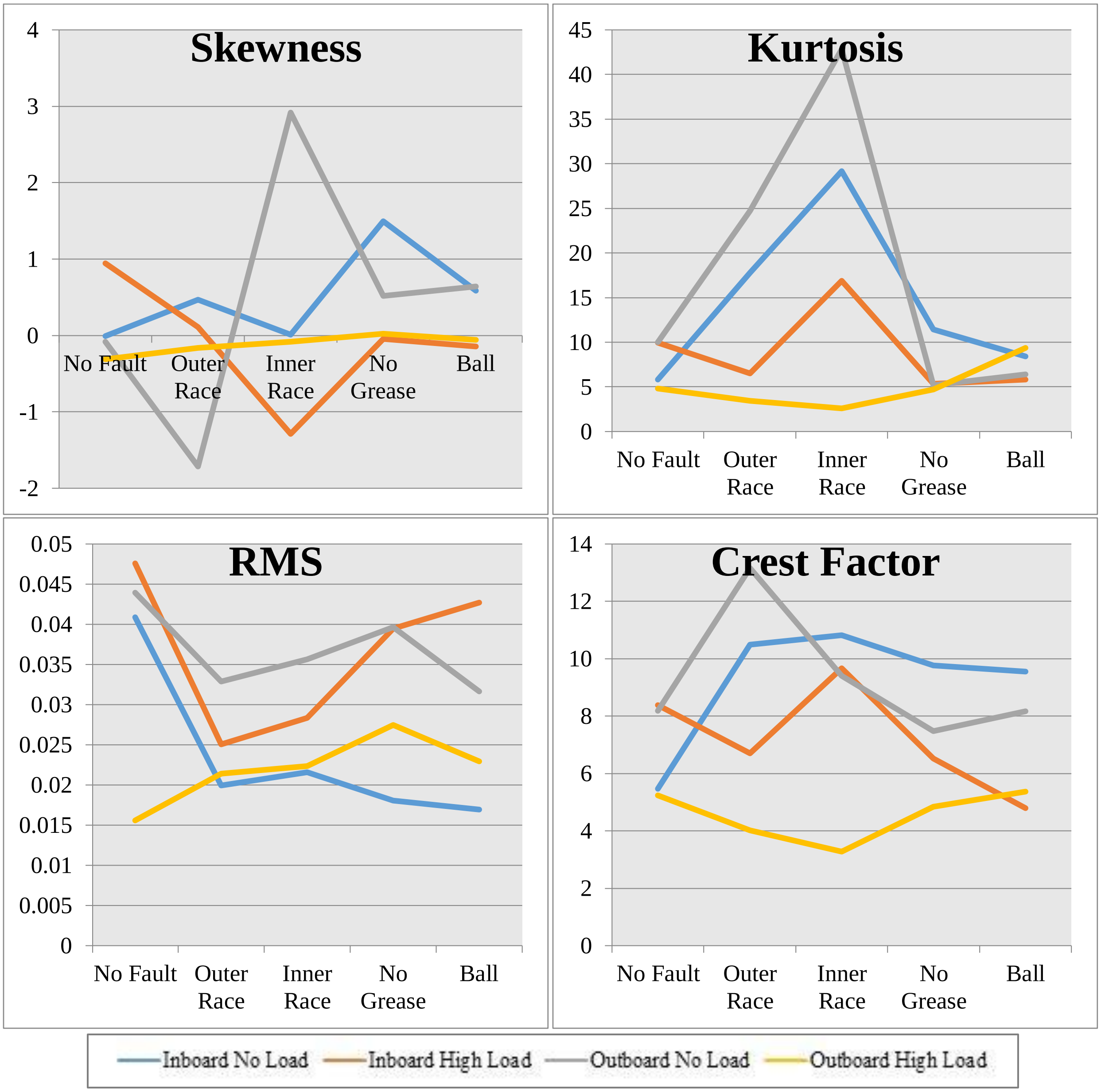


Figure 14: Outboard Accelerometer 1 parameters compared with inboard

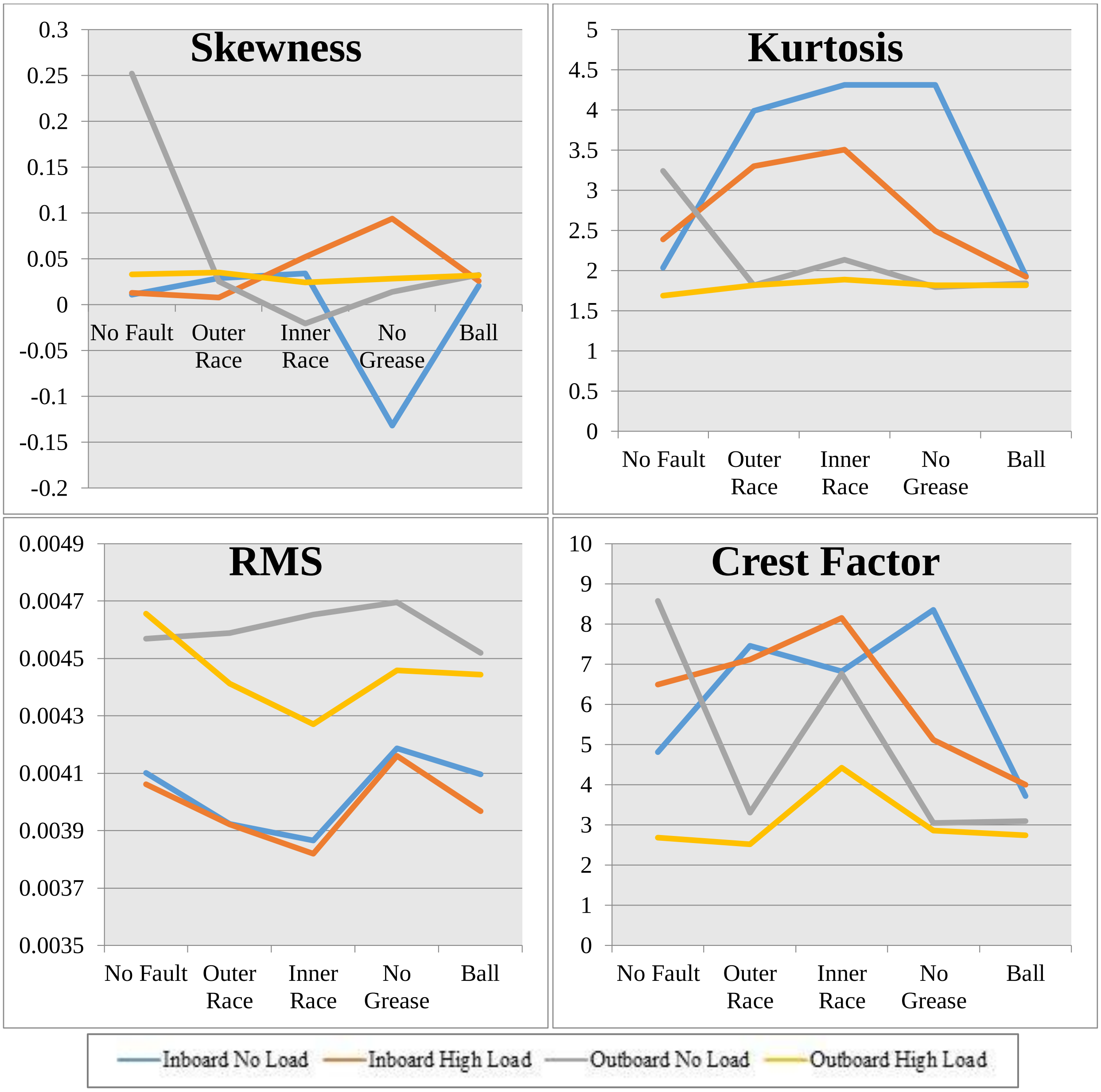


Figure 15: Outboard Accelerometer 2 parameters compared with inboard

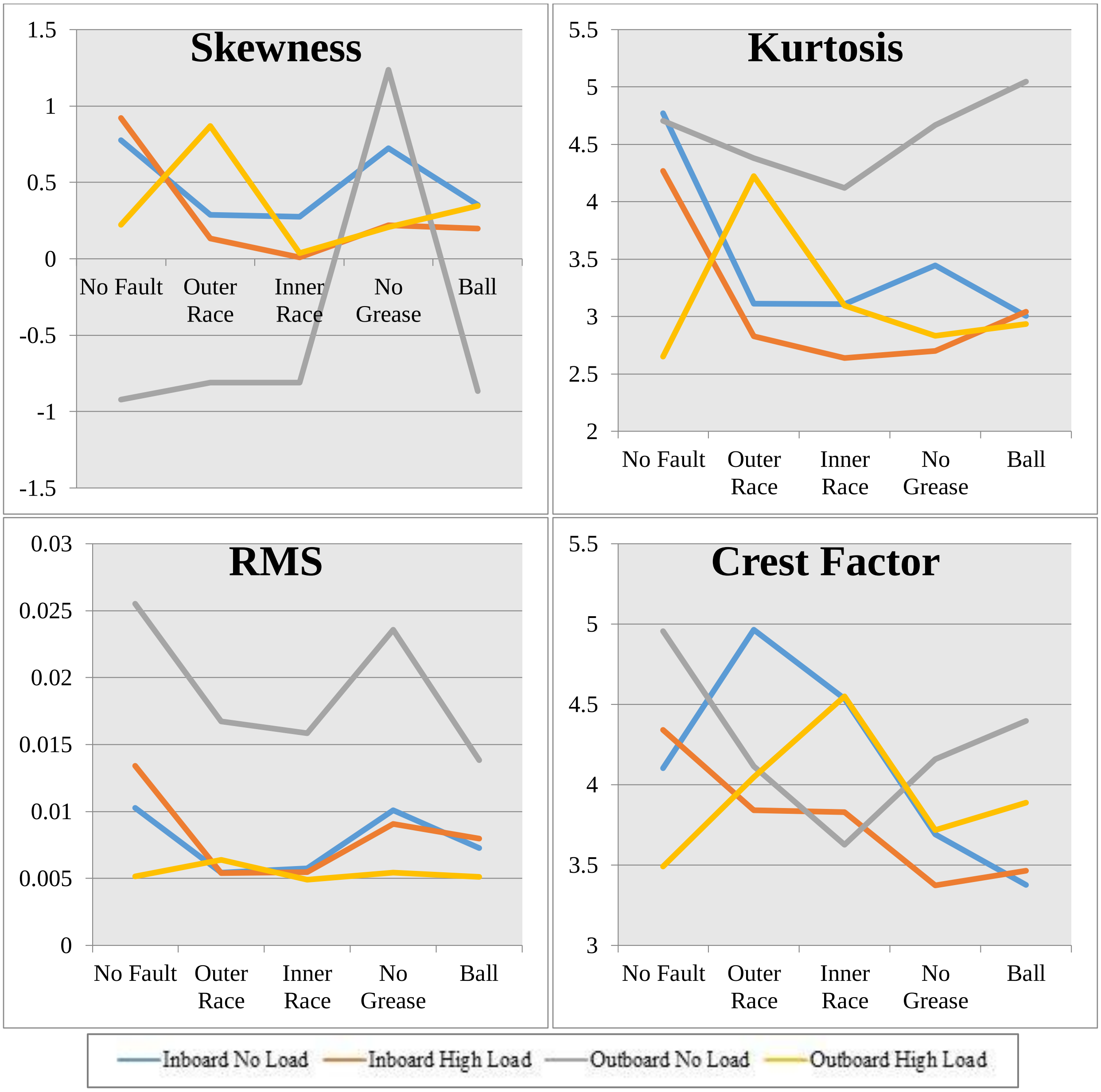


Figure 16: Outboard Accelerometer 3 parameters compared with inboard

FFT

As with the inboard data, the FFT frequencies are identical across each accelerometer, so they were combined. Unlike the inboard data though, the frequencies are different between the no load and high load tests, so they were kept separate. Both are graphed in Figure 17. For no load, no grease is the only fault that has its own frequency band, the rest are clustered close enough together that an accurate fault determination could not be made by FFT frequencies alone. For the high load data, the frequencies are still close together, but with enough separation that it could be used to identify all faults, except possibly ball and no fault. In comparison to the inboard data, inner race shared some of the same frequencies for both loads, largely due to the wide range in the inboard data. For the no load tests, some of the no grease and some of the ball faults overlapped with the inboard frequencies, but for the rest of the faults, the inboard data was not similar.

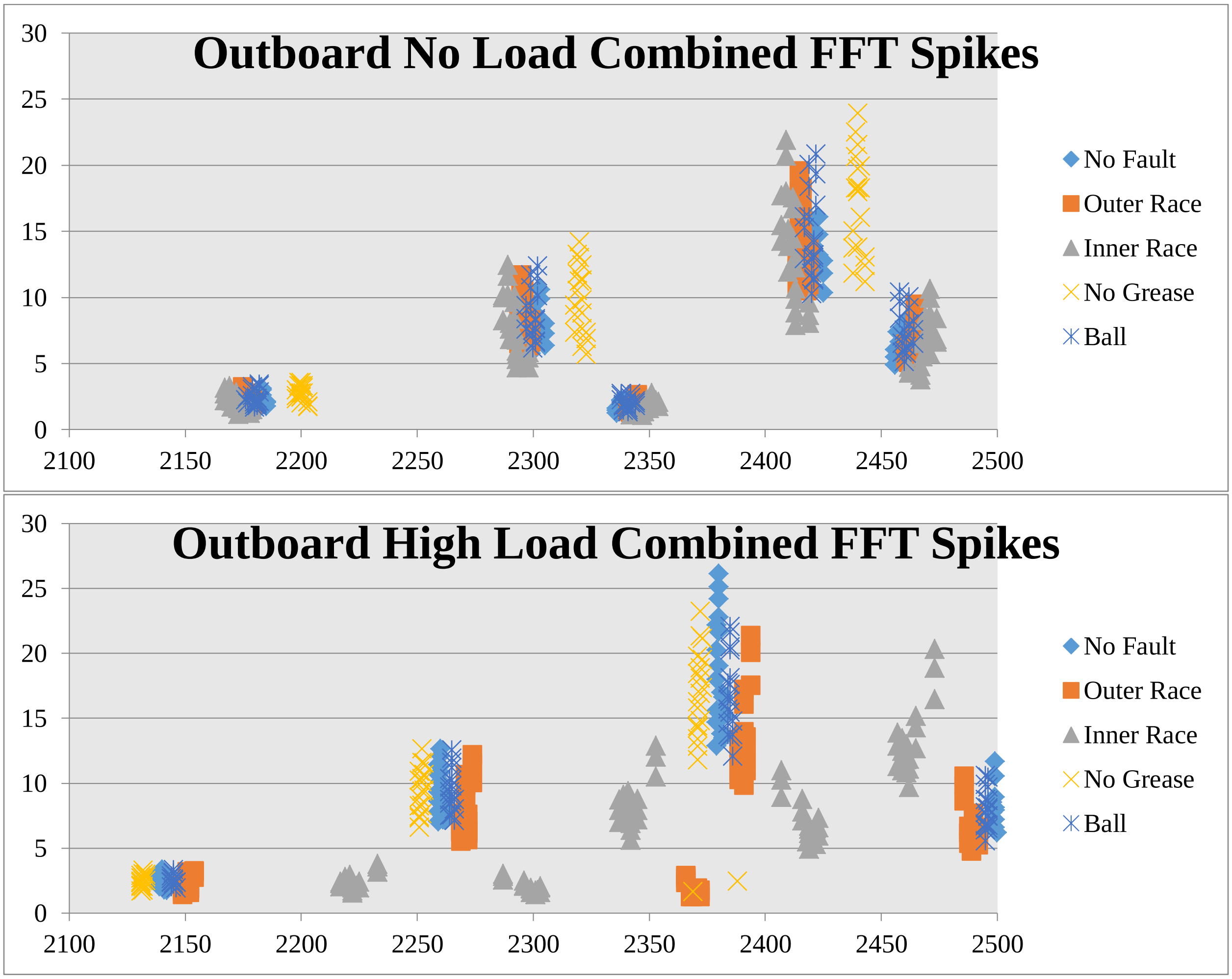


Figure 17: Outboard combined FFT spikes

Chapter 6

Conclusion

This thesis set out to determine the viability of vibration analysis to be used in chain motor maintenance. One bearing was selected for monitoring and analysis, with artificial faults introduced separately in the inner race, outer race, and ball, and one with no grease. Three PCB accelerometers were mounted as close as possible to the bearing to record the vibration signal as each fault underwent testing in four loading conditions. The signals were analyzed to extract the RMS, kurtosis, skewness, and crest factor from the time domain signal and the FFT from the frequency domain.

Accelerometers 2 and 3 could be used to determine the type of fault from the RMS data, while the skewness, kurtosis, and crest factor data were clearest in Accelerometer 1, followed by Accelerometer 2. All accelerometers showed the same frequency bands for the FFT data, which could potentially be used to identify all faults. The mounting points for the accelerometers were impractical for actual use in an inspection, so they were remounted on the outside of the frame and tested again at no load and high load. Of the outboard parameters, only RMS from Accelerometers 2 and 3 had a similar trend to the inboard data, but further testing with each accelerometer could form new trends for fault identification. The FFT frequency bands were different at each outboard load, but at high load they could be used to detect all faults.

Realistically, chain motors may not be suitable candidates for vibration analysis. They are designed for high torque in a small size, resulting in components passing through one another and a very compact layout that make single identification of a component difficult. The high torque also means that many of the components run at low speeds through each reduction of the gear train. Vibration analysis is more difficult at low speeds because the signals often lack the energy to overcome the other noise from the machine.

However, from the inboard sensor locations, bearing faults could be identified from a vibration signal, which would allow for the replacement of the bearing before it caused a larger or catastrophic failure in the motor, gears, or lift train. From further testing and analysis from the outboard sensors, it is believed that the same faults would be able to be identified. Other methods of signal analysis and processing may be more effective, but were outside the scope of this thesis

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ACADEMIC VITA

Christopher Arney

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EDUCATION

- Pennsylvania State University, Capital College, Middletown, PA
- Bachelor of Science in Mechanical Engineering
- Member of both Schreyer Honors College and Capital College Honors Program
- Dean’s List all semesters

COURSEWORK

- Microcomputer Interfacing
- Automatic Control Systems
- Engineering for Manufacturing
- Heat Transfer
- Machine Design
- Machine Dynamics
- Instrumentation, Measurement, and Statistics
- Engineering Materials
- Fluid Flow
- System Dynamics
- Thermodynamics
- Intermediate Mechanics of Materials
- Strength of Materials
- Basic Machining

PROJECTS

Climate Battery Capstone Project Fall 2018 to Present

- Working to analyze, quantify, and improve air-to-soil geothermal heating system used in greenhouses on a small farm

Vibration Analysis Honors Thesis Spring 2018 to Present

- Analyzing vibration signals of a chain motor to determine faults in gears and bearings
- Potential to perform targeted maintenance and decrease periodic inspection downtime

ENGINEERING EXPERIENCE

Henry Molded Products Inc. **Lebanon, Pennsylvania**

Mechanical Engineering Intern May to August 2018

- Designed custom molded pulp packaging solutions for customer parts in SOLIDWORKS
- Created preliminary layout and cost estimates for new pulp system
- Collected machine data around plant to quantify and increase efficiencies
- Worked with maintenance on machine improvement projects and small repairs
- Assisted in mold shop to make master mold for a new part