Detection of cylinder bore non-cleanup using modeling of piston ring dynamics.

Matthew Bitzer
University of Windsor

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DETECTION OF CYLINDER BORE NON-CLEANUP
USING MODELING OF PISTON RING DYNAMICS

By
Matthew Bitzer

A Thesis
Submitted to the Faculty of Graduate Studies and Research
through the Department of Electrical Engineering
in Partial Fulfillment of the Requirements for
the Degree of Master of Applied Science at the
University of Windsor
Windsor, Ontario, Canada
2003
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ABSTRACT

A study was undertaken to develop a method of detecting an automotive engine manufacturing defect known as cylinder bore non-clean-up. This defect is best described as a rough surface finish inside any cylinder bore of an engine. This defect causes increased piston ring wear and engine noise and vibration. Recently published literature on engine vibration analysis and defect detection is presented. Special emphasis was placed on engine dynamic modeling.

This study examines the effects of cylinder bore non-clean-up on the motion of the piston rings. This is accomplished by modeling the dynamics of the piston and piston rings using a mass-spring-damper model. The equations of motion are derived and the model is presented in state-space form. The input to the model is the force exerted on the piston rings by the cylinder bore surface. The outputs of the model are the piston ring accelerations or vibrations. These vibrations were analyzed in the frequency domain to determine the dominant frequency components. A bank of bandpass filters was designed to filter the measured vibration data from engines with the non-clean-up condition. This was done to increase the signal to noise ratio in narrow bands corresponding to frequency components predicted by the model.

Data collection was carried out using an engine test stand that was capable of measuring cylinder block vibration while the crankshaft is being driven by a motor. Three engines with increasing levels of the non-clean-up defect are tested. The measured vibration signals were filtered through the bandpass filters. The RMS value of the filtered
measured vibration signals were calculated. A threshold level of detection was set based on the comparison of the RMS value for good engines and for engines with the non-cleanup defect.
DEDICATION

This work is dedicated to my wife, Tricia and our daughter, Alyssa.
ACKNOWLEDGEMENTS

The author would like to express his appreciation to Dr. Jimi Tjong and the Ford Motor Company of Canada for providing the equipment and facilities for this research.

Thank you Dr. William Miller, Dr. Majid Ahmadi, Dr. David Ting and Dr. Chunhong Chen for assuming committee roles and for your insight and guidance during this research.

Collection of the data would not have been possible without the continued assistance of Dr. Seog Kim and Tony Fountaine.

Thanks to my wife and family who always gave support and encouragement.
# TABLE OF CONTENTS

ABSTRACT iv
DEDICATION vi
ACKNOWLEDGEMENTS vii
LIST OF TABLES x
LIST OF FIGURES xi
NOMENCLATURE xiii

CHAPTER 1. INTRODUCTION 1

CHAPTER 2. LITERATURE SURVEY 3
2.1 Data Acquisition 3
   2.1.1 Vibration 4
   2.1.2 Pressure 5
   2.1.3 Angular Position Sensor 6
2.2 Data Processing 7
   2.2.1 Statistics 7
   2.2.2 Fourier Transform 8
   2.2.3 Short Time Fourier Transform 9
   2.2.4 Wavelet Transform 10
   2.2.5 Modeling 11
   2.2.6 Neural Networks 13
2.3 Decision-Making Algorithms 14
   2.3.1 Fixed Threshold Levels 14
   2.3.2 Fuzzy Logic 16
   2.3.3 Neuro-fuzzy Systems 18
2.4 Fault Isolation 20

CHAPTER 3. THEORY 23
3.1 Engine Operation 23
3.2 Piston-Crank Assembly 25
3.3 Piston Design 26
3.4 Cylinder Bore Machining 27
   3.4.1 Rough Cut 28
   3.4.2 Finish Cut 28
   3.4.3 Honing 28
   3.4.4 Bore Roughness 28
   3.4.5 Non-cleanup Condition 29
3.5 Mechanical Vibration 29
3.6 Translational Mechanical Systems 30
   3.6.1 Free Damped Motion 31
      3.6.1.1 Overdamped 33
      3.6.1.2 Critically Damped 33
      3.6.1.3 Underdamped 33
3.6.2 Forced Damped Motion 33
3.6.3 Piston-Ring Dynamic Model 34
3.7 Predicted Frequency Characteristics 37
3.8 Bandpass Filters 37
3.9 RMS Threshold 37

CHAPTER 4. EXPERIMENTAL DETAILS 38
4.1 Accelerometers 38
4.2 Torque Transducer 39
4.3 Crankshaft Speed Sensor 39
4.4 Data Acquisition System 39
   4.4.1 Analog-to-Digital Interface Modules 39
   4.4.2 Encoder Input Module 40
   4.4.3 Digital Input/Output Module 40
4.5 Cranking Motor 40
4.6 Test Procedure 40

CHAPTER 5. DATA ANALYSIS 42
5.1 Piston Motion 42
5.2 Piston Ring Model Parameters 44
5.3 Bandpass Filters 45

CHAPTER 6. RESULTS AND DISCUSSION 48
6.1 Measured Vibration Results 48
   6.1.1 Slight Non-cleanup Condition 48
   6.1.2 Medium Non-cleanup Condition 49
   6.1.3 Severe Non-cleanup Condition 49
6.2 RMS Value of Filtered Measured Vibration Signal 53

CHAPTER 7. CONCLUSIONS 55

CHAPTER 8. RECOMMENDATIONS 57

REFERENCES 58

APPENDICES
APPENDIX A: Equipment Specifications 62
APPENDIX B: MATLAB Programming Code 65
APPENDIX C: Piston Ring Model Simulation Plots 72
APPENDIX D: Filter Design Plots 79
APPENDIX E: Photographs of Cylinder Bores 86
APPENDIX F: Measured Vibration Plots 89

VITA AUCTORIS 102
<table>
<thead>
<tr>
<th>Table</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Table 5.1</td>
<td>Piston Position for a Typical Six Cylinder Engine.</td>
<td>42</td>
</tr>
<tr>
<td>Table 6.1</td>
<td>RMS Value of Filtered Measured Vibration Data</td>
<td>53</td>
</tr>
<tr>
<td>Table A.1</td>
<td>Specifications for PCB Piezotronics 308M86 Accelerometer.</td>
<td>63</td>
</tr>
<tr>
<td>Table A.2</td>
<td>Specifications for PCB Piezotronics 482A04 Signal Conditioner.</td>
<td>63</td>
</tr>
<tr>
<td>Table A.3</td>
<td>Specifications for Lebow 1104-200 Torque Sensor.</td>
<td>63</td>
</tr>
<tr>
<td>Table A.4</td>
<td>Specifications for Daytronic 3370 Signal Conditioner.</td>
<td>64</td>
</tr>
<tr>
<td>Table A.5</td>
<td>Specifications for Electro 58426 Digital Magnetic Speed Sensor.</td>
<td>64</td>
</tr>
</tbody>
</table>
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.1</td>
<td>Schematic of Combustion Chamber.</td>
<td>23</td>
</tr>
<tr>
<td>3.2</td>
<td>Piston-Crank Assembly.</td>
<td>26</td>
</tr>
<tr>
<td>3.3</td>
<td>Connecting Rod and Piston with Piston Rings.</td>
<td>27</td>
</tr>
<tr>
<td>3.4</td>
<td>Mass-spring-damper System with Single Degree of Freedom.</td>
<td>30</td>
</tr>
<tr>
<td>3.5</td>
<td>Simplified Piston Profile.</td>
<td>34</td>
</tr>
<tr>
<td>3.6</td>
<td>Mass-spring-damper Model of Piston and Piston Rings.</td>
<td>34</td>
</tr>
<tr>
<td>4.1</td>
<td>Cold Test Stand Set-up.</td>
<td>38</td>
</tr>
<tr>
<td>5.1</td>
<td>Piston Displacement, Velocity and Acceleration Relative to TDC.</td>
<td>43</td>
</tr>
<tr>
<td>5.2</td>
<td>Simulated Force on Piston Rings.</td>
<td>46</td>
</tr>
<tr>
<td>5.3</td>
<td>Simulated Vibration Total.</td>
<td>46</td>
</tr>
<tr>
<td>5.4</td>
<td>Frequency Plot of Simulated Vibration Total.</td>
<td>47</td>
</tr>
<tr>
<td>6.1</td>
<td>NCU Engine # 1 Frequency Plot for Vibration Sensor 1.</td>
<td>50</td>
</tr>
<tr>
<td>6.2</td>
<td>NCU Engine # 1 Frequency Plot for Vibration Sensor 2.</td>
<td>50</td>
</tr>
<tr>
<td>6.3</td>
<td>NCU Engine # 2 Frequency Plot for Vibration Sensor 1.</td>
<td>51</td>
</tr>
<tr>
<td>6.4</td>
<td>NCU Engine # 2 Frequency Plot for Vibration Sensor 2.</td>
<td>51</td>
</tr>
<tr>
<td>6.5</td>
<td>NCU Engine # 3 Frequency Plot for Vibration Sensor 1.</td>
<td>52</td>
</tr>
<tr>
<td>6.6</td>
<td>NCU Engine # 3 Frequency Plot for Vibration Sensor 2.</td>
<td>52</td>
</tr>
<tr>
<td>6.7</td>
<td>Histogram of RMS Value of Filtered Measured Vibration Data.</td>
<td>53</td>
</tr>
<tr>
<td>C.1</td>
<td>Simulated Force on Piston Rings.</td>
<td>73</td>
</tr>
<tr>
<td>C.2</td>
<td>Simulated Vibration of Upper Compression Ring.</td>
<td>74</td>
</tr>
<tr>
<td>C.3</td>
<td>Frequency Plot of Simulated Vibration of Upper Compression Ring.</td>
<td>74</td>
</tr>
<tr>
<td>C.4</td>
<td>Simulated Vibration of Lower Compression Ring.</td>
<td>75</td>
</tr>
<tr>
<td>C.5</td>
<td>Frequency Plot of Simulated Vibration of Lower Compression Ring.</td>
<td>75</td>
</tr>
<tr>
<td>C.6</td>
<td>Simulated Vibration of Oil Control Ring.</td>
<td>76</td>
</tr>
<tr>
<td>C.7</td>
<td>Frequency Plot of Simulated Vibration of Oil Control Ring.</td>
<td>76</td>
</tr>
<tr>
<td>C.8</td>
<td>Simulated Vibration of Piston.</td>
<td>77</td>
</tr>
<tr>
<td>C.9</td>
<td>Frequency Plot of Simulated Vibration of Piston</td>
<td>77</td>
</tr>
<tr>
<td>C.10</td>
<td>Simulated Vibration Total.</td>
<td>78</td>
</tr>
<tr>
<td>C.11</td>
<td>Frequency Plot of Simulated Vibration Total.</td>
<td>78</td>
</tr>
<tr>
<td>D.1</td>
<td>Frequency Response Plot for Filter 1.</td>
<td>80</td>
</tr>
<tr>
<td>D.2</td>
<td>Phase Angle Plot for Filter 1.</td>
<td>80</td>
</tr>
<tr>
<td>D.3</td>
<td>Phase Delay Plot for Filter 1.</td>
<td>81</td>
</tr>
<tr>
<td>D.4</td>
<td>Group Delay Plot for Filter 1.</td>
<td>81</td>
</tr>
<tr>
<td>D.5</td>
<td>Z-Domain Zero-Pole Plot for Filter 1.</td>
<td>82</td>
</tr>
<tr>
<td>D.6</td>
<td>Frequency Response Plot for Filter 2.</td>
<td>83</td>
</tr>
<tr>
<td>D.7</td>
<td>Phase Angle Plot for Filter 2.</td>
<td>83</td>
</tr>
<tr>
<td>Figure D.8</td>
<td>Phase Delay Plot for Filter 2.</td>
<td>84</td>
</tr>
<tr>
<td>Figure D.9</td>
<td>Group Delay Plot for Filter 2.</td>
<td>84</td>
</tr>
<tr>
<td>Figure D.10</td>
<td>Z-Domain Zero-Pole Plot for Filter 2.</td>
<td>85</td>
</tr>
<tr>
<td>Figure E.1</td>
<td>Photograph of a Good Cylinder Bore.</td>
<td>87</td>
</tr>
<tr>
<td>Figure E.2</td>
<td>NCU Engine # 1 with Slight Non-cleanup Condition.</td>
<td>87</td>
</tr>
<tr>
<td>Figure E.3</td>
<td>NCU Engine # 1 with Medium Non-cleanup Condition.</td>
<td>88</td>
</tr>
<tr>
<td>Figure E.4</td>
<td>NCU Engine # 1 with Severe Non-cleanup Condition.</td>
<td>88</td>
</tr>
<tr>
<td>Figure F.1</td>
<td>NCU Engine # 1 Vibration Sensor 1.</td>
<td>90</td>
</tr>
<tr>
<td>Figure F.2</td>
<td>NCU Engine # 1 Vibration Sensor 2.</td>
<td>90</td>
</tr>
<tr>
<td>Figure F.3</td>
<td>NCU Engine # 1 Frequency Plot for Vibration Sensor 1.</td>
<td>91</td>
</tr>
<tr>
<td>Figure F.4</td>
<td>NCU Engine # 1 Frequency Plot for Vibration Sensor 2.</td>
<td>91</td>
</tr>
<tr>
<td>Figure F.5</td>
<td>NCU Engine # 1 Filtered Vibration Sensor 1.</td>
<td>92</td>
</tr>
<tr>
<td>Figure F.6</td>
<td>NCU Engine # 1 Filtered Vibration Sensor 2.</td>
<td>92</td>
</tr>
<tr>
<td>Figure F.7</td>
<td>NCU Engine # 1 Frequency Plot for Filtered Vibration Sensor 1.</td>
<td>93</td>
</tr>
<tr>
<td>Figure F.8</td>
<td>NCU Engine # 1 Frequency Plot for Filtered Vibration Sensor 2.</td>
<td>93</td>
</tr>
<tr>
<td>Figure F.9</td>
<td>NCU Engine # 2 Vibration Sensor 1.</td>
<td>94</td>
</tr>
<tr>
<td>Figure F.10</td>
<td>NCU Engine # 2 Vibration Sensor 2.</td>
<td>94</td>
</tr>
<tr>
<td>Figure F.11</td>
<td>NCU Engine # 2 Frequency Plot for Vibration Sensor 1.</td>
<td>95</td>
</tr>
<tr>
<td>Figure F.12</td>
<td>NCU Engine # 2 Frequency Plot for Vibration Sensor 2.</td>
<td>95</td>
</tr>
<tr>
<td>Figure F.13</td>
<td>NCU Engine # 2 Filtered Vibration Sensor 1.</td>
<td>96</td>
</tr>
<tr>
<td>Figure F.14</td>
<td>NCU Engine # 2 Filtered Vibration Sensor 2.</td>
<td>96</td>
</tr>
<tr>
<td>Figure F.15</td>
<td>NCU Engine # 2 Frequency Plot for Filtered Vibration Sensor 1.</td>
<td>97</td>
</tr>
<tr>
<td>Figure F.16</td>
<td>NCU Engine # 2 Frequency Plot for Filtered Vibration Sensor 2.</td>
<td>97</td>
</tr>
<tr>
<td>Figure F.17</td>
<td>NCU Engine # 3 Vibration Sensor 1.</td>
<td>98</td>
</tr>
<tr>
<td>Figure F.18</td>
<td>NCU Engine # 3 Vibration Sensor 2.</td>
<td>98</td>
</tr>
<tr>
<td>Figure F.19</td>
<td>NCU Engine # 3 Frequency Plot for Vibration Sensor 1.</td>
<td>99</td>
</tr>
<tr>
<td>Figure F.20</td>
<td>NCU Engine # 3 Frequency Plot for Vibration Sensor 2.</td>
<td>99</td>
</tr>
<tr>
<td>Figure F.21</td>
<td>NCU Engine # 3 Filtered Vibration Sensor 1.</td>
<td>100</td>
</tr>
<tr>
<td>Figure F.22</td>
<td>NCU Engine # 3 Filtered Vibration Sensor 2.</td>
<td>100</td>
</tr>
<tr>
<td>Figure F.23</td>
<td>NCU Engine # 3 Frequency Plot for Filtered Vibration Sensor 1.</td>
<td>101</td>
</tr>
<tr>
<td>Figure F.24</td>
<td>NCU Engine # 3 Frequency Plot for Filtered Vibration Sensor 2.</td>
<td>101</td>
</tr>
</tbody>
</table>
NOMENCLATURE

\[ a \] acceleration (vibration)
\[ BDC \] bottom dead center
\[ c \] damping co-efficient
\[ c_{critical} \] critical damping coefficient
\[ F \] force
\[ F_c \] force due to damper acting on mass
\[ F_k \] force due to spring acting on mass
\[ F_s \] sampling frequency
\[ g \] acceleration due to gravity
\[ k \] spring constant
\[ l \] length of the connecting rod
\[ m \] mass
\[ NCU \] non-cleanup defect
\[ OHV \] overhead valve
\[ r \] radius of the crankshaft journal
\[ RPM \] revolutions per minute
\[ \theta \] angular position
\[ TDC \] top dead center
\[ v \] velocity
\[ W \] force due to gravity or weight
\[ x \] position or displacement
CHAPTER 1
INTRODUCTION

The ability to detect and diagnose automotive engine defects has a significant impact on product quality and therefore consumer experience. Defects will lead to a decrease in consumer confidence and an increase in warranty costs. Consumers continue to be more informed and the automotive market is increasingly competitive. An engine manufacturer must continue to improve quality of the products delivered to the consumer in order to compete.

The quality process begins at the assembly plant. There is a need to ensure that engines with manufacturing and assembly defects do not leave the plant and arrive to the customer. Traditional methods of diagnosing defects include visual or auditory assessment by a human operator. This method can be subjective, inconsistent and sensitive to differences in operator training, experience, physiological conditions and environmental conditions.

Another method of diagnosing engines is by cold test or hot test. During a cold test, the engine crankshaft is rotated to exercise the internal components but there is no combustion occurring in the engine cylinders. Parameters such as mechanical vibration, part displacement or torque required to turn the crankshaft may be measured to detect failure. During a hot test, the engine is started and combustion occurs. Parameters such as flow, pressure, speed and power output may be measured to detect failure. These tests
typically provide the broad conclusion that the engine runs or does not run. Diagnosis is performed after these tests by disassembling the engine in a repair bay to locate the defective component.

The goal of this research is to provide a method of diagnosing a manufacturing defect known as cylinder bore non-cleanup. The method involves the acquisition of cylinder block vibration signals. These signals are analyzed and processed to reveal features that characterize this fault.

This research begins with a review of published literature on engine signal diagnostics.
CHAPTER 2
LITERATURE SURVEY

The area of machine condition monitoring has been the topic of discussion and research for many years. The ability to understand the operating state and diagnose problems has benefits in a number of applications, starting at the initial build and continuing through the life of the equipment. This literature survey explores the different ways that researchers have acquired data from engine signals, processed the data and analyzed the data to diagnose faults in internal combustion engines.

An internal combustion engine is a complex structure. It is comprised of a number of sub-systems that contain not only rotating, but also reciprocating components. Rotating components include shafts, gears and pumps. Edwards et al. [1] provided a good overview of fault diagnosis techniques related to rotating machinery. Reciprocating components include pistons and valves. The combustion process that occurs inside the engine cylinders produces these rotating and reciprocating motions. It is important to have an understanding of the combustion process and the relative movement of components during engine operation. Knowles and Erjavec [2] provided some insight into the operation of internal combustion engines.

2.1 Data Acquisition

The first step in analyzing the state of an engine is to decide what signals provide the most useful information about its operation. The combustion process results in large
pressure waves inside the engine cylinders. This pressure acts on the pistons to rotate the crankshaft, camshaft and interconnected components. These motions cause vibration and noise. Many signals can be acquired using transducers to measure vibration, pressure, temperature, torque and speed to name a few.

2.1.1 Vibration

The use of vibration measurement has great advantages because it is non-destructive and non-invasive. It has been used extensively for condition monitoring of rotating machinery. Alexander et al. [3] were able to detect plain bearing faults using vibration signals from a rotating shaft. In a similar work, Haddad and Chatterji [4] were able to differentiate normal and damaged ball bearings using vibration transducers. Wowk [5] provided a good reference related to the use of vibration measurements to examine the operating state of rotating components.

The most common transducer for obtaining vibration data is the accelerometer. A piezoelectric accelerometer is one type that provides a voltage signal proportional to the acceleration. They are specified by values for sensitivity, accuracy and frequency range. One such sensor might have a 5 mV/g sensitivity with +/- 15% accuracy in the 2 Hz to 20 kHz range.

Other types of sensors are also being developed. The photo-refractive vibration sensor consists of an optical fiber, laser, prism, and photo-detector. Scholl et al. [6] provided a study of this device and a comparison to traditional piezoelectric accelerometers. The
main advantage appears to be its immunity to electromagnetic interference and high bandwidth.

The most common practice is to mount accelerometers on the outside of the engine block, coincident with the location of the cylinder inside, in the horizontal plane and normal to the crankshaft axis. In most studies, only one accelerometer was required to be located in a strategic position for useful data to be collected. By using only one accelerometer located on the engine casing, Antoni et al. [7] were able to observe events in the engine cycle such as combustion start, valve opening and closing and piston slap. In a similar study, deBotton et al. [8] were able to observe the same events and examined the effect of missing spark plugs and spark timing on the vibration signal.

2.1.2 Pressure

Cylinder pressure provides important information about the combustion process because it is the fundamental thermodynamic variable. The pressure in the cylinder changes as the engine proceeds through the four stages of its cycle from intake to compression to combustion to exhaust. Obtaining in-cylinder pressure data is intrusive and is typically obtained by drilling a hole in the cylinder head and inserting the transducer.

Conventional pressure transducers are piezoresistive, piezoelectric or capacitive but other types have been developed. Poorman et al. [9] described a combustion pressure sensor system using fiber optic sensors for the monitoring and control of multi-cylinder engines. In a similar study, Sun et al. [10] studied the signals from two different types of optical probes installed in the combustion chamber. They found that the luminosity measured by
the optical probes correlated well with the signal from a pressure sensor. In a different approach, Zurita et al. [11] presented the idea of reconstructing the cylinder pressure waveform from vibration measurements. By mounting accelerometers on the outside of the cylinder head, they were able to use the vibration measurements to reconstruct a pressure waveform that correlated well with measured pressure waveforms. This was much less intrusive.

2.1.3 Angular Position Sensor

It is useful to know the angular position of rotating components such as the crankshaft and the camshaft. The camshaft sensor helps to determine when the #1 piston is at top-dead center (TDC) on the compression stroke. It is used to synchronize the fuel injection timing. The crankshaft sensor determines the position and speed of the crankshaft and is used to synchronize the firing of the spark plugs. The camshaft and crankshaft produce motion in the valves and pistons respectively and knowing their position in the engine cycle is useful when analyzing the other signals. This is usually accomplished using Hall effect sensors. Bicking et al. [12] discussed the design of one type of these sensors. Other types of sensors include potentiometers and optical encoders. Kato and Nakaho [13] discuss these and the design of an optical encoder that uses a disk with one circular and one spiral slit. They found that there was good linearity between the angular position and the differential distance of the spiral and circular slit.
2.2 Data Processing

There are a number of signals that are available to be acquired from an engine. In general, a signal is a physical quantity that is a function of one or more independent variables. A signal may occur naturally or be artificially synthesized. The goal of signal processing is to exploit inherent information carried in the signal, bring out or find features that are unique to the fault to be diagnosed. The Institute of Electrical and Electronics Engineering (IEEE) Signal Processing Society states that signal processing concerns the

“...theory and application of filtering, coding, transmitting, estimating, detecting, analyzing, recognizing, synthesizing, recording and reproducing signals by digital or analog devices or techniques. The term ‘signal’ includes audio, video, speech, image, communications, geophysical, sonar, radar, medical, musical and other signals” [14]

A number of signal processing techniques employed in the automotive field are described below. These include statistical, time and frequency analysis, modeling and neural networks.

2.2.1 Statistics

Haddad and Chatterji [4] studied the assumption that scalar features of a vibration signal such as the mean, variance, standard deviation, root-mean-square, kurtosis and crest factor captured important properties of the signal. They measured how these values changed with increasing rotational speed of a shaft. Upon examining the relationship they could distinguish between normal and damaged shaft bearings. Tjong [15]
described a time domain averaging method for separating a vibration signal into periodic and transient components, those that occur only at specific positions in an engine cycle. This is accomplished by averaging a number of signals together to obtain the periodic components and then subtracting the periodic components from the original signal to obtain the transient components. The transient components were then exaggerated by squaring the values. This method was used to detect various piston and crankshaft bearing defects.

2.2.2 Fourier Transform

Movement of a periodic nature is best viewed in the frequency domain. The Fourier Transform method has been used extensively in condition monitoring of rotating equipment. It is well known in the practice that certain faults produce measurable characteristics in the frequency domain. A common cause of excessive vibration in machinery is imbalance of rotating components. Imbalance occurs when the center of rotation and the center of mass are not coincident. This causes a dominant vibration at a frequency corresponding to one times the revolutions per minute. This idea can be expanded to internal combustion engines. deBotton at el. [16] discovered that the frequency spectra of a vibration signal showed a peak at a frequency corresponding to twice the running speed of the engine. They attributed this to the combustion process that occurred once in each of the four cylinders every two revolutions of the crankshaft. In other words, there were two cylinders firing every revolution. They also observed a peak at a frequency corresponding to four times the running speed. They attributed this to the closing of the valves that occurred twice in each of the four cylinders every two
revolutions of the crankshaft. In other words, there were four valves closing every revolution. They found that unlike common rotating machines, the angular velocity of a reciprocating engine is not uniform but varies during a revolution. To account for this, the sampling rate for the Fast Fourier Transform analysis was not dictated by an external clock but was synchronized with the position of the crankshaft.

2.2.3 Short Time Fourier Transform

The Fourier Transform reveals the frequency components that are present in a signal. It does not reveal when in time the frequency components are present. This is sufficient if analyzing stationary signals whose frequency content does not change with time. However, the frequency content of a non-stationary signal is changing throughout the length of the signal and this may be of interest when analyzing the signal. The Short Time Fourier Transform is a method that gives a time-frequency representation of the signal. It subdivides the signal into shorter time segments or windows. A Fourier Transform is performed on each segment or time interval during which the signal is assumed to be stationary. The frequency components and amplitudes are determined for each time interval, resulting in a plot of time, frequency and amplitude known as the spectrogram. The disadvantage to this method is that the resolution in time and frequency is fixed because the window width or time interval is fixed. A narrow window results in good resolution in time but poor resolution in frequency. Conversely, a wide window results in poor resolution in time but good resolution in frequency. Furthermore, narrow windows emphasize high frequency components and wide windows emphasize low frequencies.
Kimura et al. [17] used the spectrogram to analyze the vibration signal of a diesel engine to detect excessive metal-to-metal contact in the crankcase.

2.2.4 Wavelet Transform

The Wavelet Transform (WT) is another method that gives a time-frequency representation of the signal. It is similar to the Short Time Fourier Transform in that it is a measure of similarity between basis functions and the analyzed signal. Except in this case the basis functions are not the cosine and sine with different frequencies but a wavelet whose width is scaled in relation to frequency. The advantage of the WT is that the resolution is not fixed. Jiang et al. [18] illustrated the ability of the wavelet transform to overcome the problem of poor frequency resolution in the high band and poor time resolution in the low band.

Scholl [19] examined the ability of the wavelet transform to analyze impulsive and transient sounds such as rattles, clicks and taps buried within background noise. He found that the first and second level scale plots of the wavelet transform showed an increase in amplitude at the time of the impulsive sound.

Ball et al. [20] used the continuous wavelet transform to analyze acoustic data from microphones and diesel engines. They were able to represent the start, strength and duration of combustion events and the uniformity between engine cycles. They examined how the high frequency band CWT plots changed when an incipient fault was
present in the engine. They observed qualitative differences when introducing fuel injection faults.

Zhang and Tomita [21] described a method of using the wavelet transform to detect the combustion anomaly known as knock. Knock is the term used to describe the phenomenon of spontaneous ignition of a portion of end gas before or after normal combustion is to occur. They used the vibration signal obtained from an engine under a knocking condition. Instead of using any of the already developed wavelets to decompose the signal, they suggested creating a mother wavelet from the part of the vibration signal they believed was most characteristic of knock. They performed a wavelet analysis on normal and engine knock vibration signals. By using a value they called instantaneous correlation, they took the sum of the amplitude between the $\frac{1}{2}$ and 2 scale of the transform at each interval in time. By examining this value, they were able to determine the onset and strength of the knock.

2.2.5 Modeling

Many papers have been written using a model-based approach to fault detection. In this process, a mathematical model is constructed by taking into account as many variables as possible and known principles of motion, rotor dynamics and thermodynamics. When the system has been adequately modeled, it should be possible to detect anomalies by comparing the response of the system to that of its model. Numerous texts have been written about rotor dynamics through the years including that of Den Hartog [22], Genta
[23] and Tondl [24]. The principles of thermodynamics are also well understood and explained in a number of texts such as Cengel and Boles [25].

Modeling of an automotive engine is an enormous task and one that has received a lot of attention. In an automotive engine, it all begins with the combustion process that takes place inside each cylinder. Combustion in the cylinder is what creates the reciprocating motion of the pistons and valves, as well as the rotating motion of the crankshaft and camshaft. Many papers have been presented that model the combustion process and the associated motion of the engine components. van Nieuwstadt and Kolmanovsky [26] proposed models for gas flow, combustion, heat transfer and piston-crank dynamics. They used these models to construct various algorithms for correcting cylinder imbalance by adjusting fuel delivery to injectors during operation. Ali and Moskwa [27], Cruz Peragón et al. [28] and Templin [29] presented other combustion or thermodynamic models. Tjong [15] modeled the piston-crank dynamics in order to understand the mechanism of engine vibration caused by impacts between mechanical components. He examined the effect that various piston-crank mechanism defects had on the vibration response of the engine. Haubner [30], Hoffman and Dowling [31] and Rego and Martins [32] presented other valve and crankshaft dynamic models. Diagnosis of a fault is based on differences between actual measurements versus model parameters. The extreme complexity and non-linearity of engine dynamics make it difficult to model the system. Polycarpou [33] provided an overview of non-linear modeling techniques for constructing and analyzing non-linear system models.
2.2.6 Neural Networks

An alternative to complicated mathematical models is a neural network. These are often employed because of their non-linear, pattern recognition and classification qualities. They can provide a non-linear mapping between inputs and outputs. The accuracy of the network typically depends on the type of network, number of inputs and outputs, the quality and quantity of training data and the training method. Hu and Hwang [14] provide a good reference about neural network structure and application.

Haddad and Chatterji [4] used scalar features of a vibration signal such as standard deviation, peak, kurtosis and crest factor to train a neural network to identify normal and damaged bearings. Succi and Chin [34] used frequency characteristics of vibration signals as inputs into a neural network to classify the condition of a hydraulic pump. Scaife et al. [35] proposed a neural network capable of detecting faults in the air manifold system of a diesel engine. The inputs included speed, torque, pressures and temperatures at various operating points of the engine under normal and fault conditions. The network was able to classify the difference between a healthy engine and an engine with air leaks or restrictions in the manifolds. They obtained fair results and stated that additional work was needed to consider more inputs to the system such as additional thermodynamic variables, vibration and noise measurements. Wu and Lee [36] described a system for detecting misfire events. As an alternative to describing the engine combustion and dynamics by a system of non-linear mathematical equations, they inputted engine speed and manifold pressure to a neural network to classify the firing events as normal or misfire. Kolmanovsky [37] developed an admissible engine operating envelope model
based on experimental engine mapping data. The data was used to train a neural network known as the support vector machine or SVM. The 8 inputs used were speed, air-to-fuel ratio, swirl control valve setting, fueling rate, EGR rate, fuel rail pressure, injection timing and spark timing. The network was trained to classify good and bad engines based on engine roughness and misfire. A success rate of greater than 90% was attained for classifying good and bad engines. This SVM model could then be used to decrease engine roughness and misfire by controlling engine operating variables such as spark and ignition timing.

2.3 Decision-Making Algorithms

After collecting, processing and manipulating the data to reveal characteristics of a fault, there has to be an algorithm that decides whether a fault exists. It is desirable to not only detect that there is a fault present, but also be able to identify what fault from a number of possible faults. This is fault isolation. Armstrong [38] described this difference between fault detection and fault isolation.

2.3.1 Fixed Threshold Levels

Many decisions have been based on exceeding fixed threshold levels. Alexander et al. [3] averaged the frequency components of many vibration signals taken from the same machine before a known fault. This became a reference spectrum. After this initial step, they monitored the machine. They found the frequency spectra of the test signal, averaged this with all previous spectra to obtain a mean spectrum and compared it to the reference spectrum. Each time this comparison was performed they calculated a term
they called ‘variation index’. They found that the variation index did not change significantly over time for an undamaged bearing. However, the variation index increased significantly when a damaged bearing was introduced. This value eventually exceeded a fixed threshold value. At this point they considered the machine to have a fault. They set the fixed threshold level low enough to allow for detection of low levels of damage but high enough so that insignificant changes would not indicate a fault.

Tjong [15] designed a test for defects based on exceeding a threshold value for vibration. He obtained the vibration signal over many combustion cycles of an engine with respect to crankshaft angle. He found an average signal by averaging all the cycles at each crankshaft angle value. He then subtracted this average signal from each cycle and squared the difference at each crankshaft angle value. The result was a variance signal for each cycle that he referred to as the running variance. The crankshaft angle datum was divided into 6 equal windows. In each window, the maximum variance values were averaged across the cycles to obtain a value for each window. A fault was determined to be present if each window value exceeded a fixed threshold value. By determining which window values exceeded the threshold, he was able to predict which cylinder had the fault. The threshold value was originally set equal to the average of the window values of 15 known defective engines. The threshold value was then changed using trial and error until the algorithm achieved 100 percent success in rejecting defective engines.

Scholl [19] studied the comparison between a visual threshold of detection for impulsive features on a wavelet scalogram plot versus the audible threshold of detection of humans.
He used a wind tunnel and a hydraulic shaker to simulate wind noise and road noise. He combined this noise with a rattle impulse sound from the vehicle interior and increased the noise until the rattle could not be distinguished over the noise. He found that although the rattle impulse could not be heard or seen in the time domain signal, a noticeable peak was observed on the first level wavelet plot.

Willimowski and Iserman [39] proposed a method of misfire detection based on the analysis of the exhaust gas pressure in the manifold. They recognized that at misfire there is a large pressure drop and then a large pressure increase upon re-instated combustion. Their algorithm involved recognizing the maxima and minima of the pressure signal and comparing them to threshold values.

2.3.2 Fuzzy Logic

This methodology is an alternative to the traditional crisp boundary decision-making. The transition from “belongs to set” to “does not belong to set” is not crisp but gradual based on membership functions. Membership functions or fuzzy sets, map a value to a membership grade that describes the degree to which a value belongs to the sets. There are fuzzy rules that take the form “if x is A then y is B”. A group of these rules is the rule base or knowledge base. A fuzzy inference system contains a rule base, a database of membership functions used in fuzzy rules and a reasoning mechanism that performs an inference procedure upon the rules. The system is given facts to derive a reasonable output or conclusion. Jang et al. [40] provided an excellent resource on the theory of fuzzy logic.
Many studies have explored the use of fuzzy logic for automotive engine faults.
Liu et al. [41] proposed a method of detecting misfire by using a fuzzy pattern recognition system to decide if the engine is healthy or faulty and to specify which cylinders had a misfire. They used the non-linear engine dynamics model based on the torque balance equation. While analyzing the model in the frequency domain, they defined four dimensionless features that they called torque component ratio, torque fluctuation index, acceleration component ratio and acceleration fluctuation index. While analyzing time domain signals for angular velocity and acceleration, they defined six additional features that they called the maximum acceleration index, minimum acceleration index, summed acceleration index, angular variation index, velocity variation index and acceleration variation index. They combined these features into a fuzzy vector and created a number of fuzzy logic rules. The fuzzy inference system was successful in identifying one or more misfiring cylinders up to an engine speed of 1500 revolutions per minute in less than one engine cycle or 80 milliseconds. Testing at higher speeds was left for future work.

Lu et al. [42] designed a vacuum leak detection algorithm using a fuzzy inference system. The fuzzy variables used were throttle position, idle speed and mass air flow. These were determined to be the most important variables according to expert knowledge of the engine to be studied. The fuzzy terms used were low, medium and high for each fuzzy variable. There was one solution variable to describe vacuum leak. The rules and membership functions that made up the knowledge base were generated using expert
knowledge and linguistics. Their algorithm was also capable of generating fuzzy rules and fuzzy membership functions automatically from training data from the engine. The fuzzy rule generation algorithm used a number of iterations of clustering-extracting and re-clustering. The membership functions were optimized using training data and a stochastic annealing process. Kang [43], Lu and Chen [44] and Rhee and Krishnapuram [45] wrote some of the many papers on fuzzy rule generation methods and membership function optimization. Lu et al. [42] tested their system on two different engine types and found that the system had a success rate of 87% for recognizing good and bad engines. The system was suitable for running on a PC platform and fast enough to be implemented as an in-line test in an engine assembly plant.

2.3.3 Neuro-fuzzy Systems

These systems combine the ability of neural networks to recognize patterns and adapt to changing environments, with fuzzy inference systems that incorporate human knowledge and perform decision-making.

Roemer and Pomfret [46] used a combination of neural networks and fuzzy logic as part of an engine health and monitoring system for gas turbine engines. They described a sensor validation scheme capable of detecting failed sensor hardware. Neural networks were used to recognize the non-linear inter-relationships between the different types of sensors such as fuel flow, pressure and temperature. The output of the networks yielded a confidence factor associated with the probability of a failed sensor. The networks were trained using five sensor input signals and four output sensor confidence values. Fuzzy
logic was used before the neural network to decide if the sensor input for speed was increasing, decreasing or in a steady state. The output of this fuzzy decision was used to trigger the particular neural network that was specifically trained to know the sensor relationship for increasing, decreasing or steady state speed. Fuzzy logic was also used after the neural network to decide whether the sensor confidence level outputs of the neural network indicated a good, bad or marginal sensor condition.

Shirkhodaie et al. [47] designed a hybrid neuro-fuzzy based system for detecting bearing failures. They recognized that analyzing the vibration signal in the frequency domain could identify bearing faults. The type and severity of the fault was related to the magnitudes and frequencies of the vibration. They sent the spectrum of the vibration signal through a fuzzy rule-base defined by seven membership functions. This reduced spectrum was then passed through a fuzzy C-means clustering algorithm so that each data belonged to a cluster to a degree specified by its membership grade. Each set of signal clusters uniquely characterized a certain bearing fault. An adaptive neuro-fuzzy inference system (ANFIS) was trained to recognize the signal cluster patterns for different faults. The fuzzy membership functions were tuned using back-propagation and a set of input-output data. The system was then tested using incipient faults. The pattern of the test signal was compared to trained patterns and the closest pattern was selected. They discovered that the system performance was satisfactory but that it degraded as the number of simultaneous faults increased.
2.4 Fault Isolation

The engine structure is very complex and many different faults can exist as well as any combination of faults simultaneously. It is the goal of the data acquisition, data processing and decision-making algorithm to specify the fault or faults.

The goal of the data acquisition stage is to measure the phenomena that are indicative of each failure mode. Vibration can be used to detect mechanical defects. Pressure tells a lot about the combustion process. Torque and speed may be useful in other applications.

The goal of the data processing stage is to reveal what features are created when we have certain failures. Features may be present in the time domain, the frequency domain or both. A failure may cause the presence or the absence of a feature. Actual measurements are often compared to models of the system under study. Neural networks are often trained with actual data to learn how a system operates. These networks are desirable because of their ability to model non-linear systems such as automotive engines.

The last stage is the decision-making stage. Many decisions are based on exceeding a fixed threshold value. Other algorithms use fuzzy logic systems because of their ability to incorporate linguistic terms and reasoning similar to human experts. Fuzzy systems can be combined with neural networks. These hybrid systems use adaptive algorithms and optimization methods for adjusting system parameters and have been useful for detecting automotive engine manufacturing and assembly defects.
In this research, a machining defect known as cylinder bore non-cleanup was investigated. The defect is best described as a roughness inside the cylinder bore along the surface where the piston rings move. The vibration of the piston rings was investigated under this condition in order to devise a method of detecting this defect using vibration measurements. The research and testing had to be carried out using an existing engine test stand located on the engine assembly production line. Therefore, any detection algorithm would have to satisfy the following constraints imposed by the existing test stand. The test stand was originally designed to use vibration measurements to detect loose or missing parts in the engine and it continues to successfully perform this function. For this reason, the physical set-up of the existing test stand could not be modified. Therefore, the position of the vibration sensors was pre-determined and fixed at a point external to the engine cylinder block on the oil pan rail. Attempting to detect the small phenomena of piston ring vibration by measuring vibration outside the engine at this location, introduces a significant signal to noise ratio problem.

The first objective of this research is to create a dynamic model of the piston and piston rings. The input to this model will be the force on the piston rings. The output of the model is the vibration of the piston rings. The model starts as a mass-spring-damper mechanical model. This results in a set of second order differential equations that are transformed into a simpler first order state-space equation model. The input force to this model is simulated using a signal that is developed by considering the cylinder bore surface profile when the non-cleanup defect is present. The output of this model is analyzed in the frequency domain to predict the significant frequency components of the
piston ring vibrations. These components will be used to characterize the non-cleanup defect.

The second objective is to design a bank of bandpass filters that are centered at the frequency components that characterize the non-cleanup condition. This will be used to filter the measured vibration data in an attempt to reduce the signal to noise ratio.

The third objective is to devise a metric based on the RMS value of the filtered measured vibration signal. By comparing this value for engines with and without the non-cleanup condition, a suitable threshold level of detection will be devised. If the RMS value of a test engine exceeds this threshold level then it will be considered a defect.
CHAPTER 3

THEORY

3.1 Engine Operation

An understanding of engine operation is an important basis for comprehensive analysis and modeling of this complicated structure. The modern internal combustion engine used is this study was a four-stroke spark ignition engine. The four strokes are known as intake, compression, power and exhaust. A simple schematic of the cylinder bore, piston and valves is illustrated in Figure 3.1.

![Diagram of Combustion Chamber](image)

**Figure 3.1. Schematic of Combustion Chamber.**
A stroke is defined as the full travel of the piston either up or down in the cylinder bore. During the intake stroke, the exhaust valve is closed, the intake valve is open and the piston moves down the cylinder bore as it draws air and fuel into the cylinder. During the compression stroke, both valves are closed and the piston moves up the cylinder bore as it compresses the air and fuel mixture. During the power stroke, both valves are still closed as the spark plug ignites the compressed air and fuel mixture to cause a rapid increase in temperature and pressure. This pushes the piston down the cylinder bore and delivers power to the crankshaft. During the exhaust stroke, the intake valve is closed, the exhaust valve opens and the piston moves up the cylinder bore as it pushes the exhaust gases out of the cylinder. The engine cycle then repeats itself by starting at the intake stroke. The piston is at top dead center (TDC) at the beginning of the intake and power strokes. It is at bottom dead center (BDC) at the beginning of the compression and exhaust strokes. The up and down movement of the piston on all four strokes is converted to rotary motion by the crankshaft. It takes two full revolutions of the crankshaft to complete the four-stroke cycle. The pressure produced by combustion moves the piston only about half a stroke or one-quarter of a crankshaft rotation. For this reason a flywheel is attached to the crankshaft axis to store some of the power produced by the engine. This stored power is needed to keep the pistons in motion during the remainder of the four-stroke cycle and to compress the air and fuel mixture. The crankshaft also drives the camshaft by using gears or sprockets and a cogged belt or timing chain. The camshaft has raised sections or lobes that push the intake and exhaust valves open at appropriate intervals. The camshaft turns at half the speed of the
crankshaft and rotates one complete turn every two rotations of the crankshaft during each complete four-stroke cycle.

3.2 Piston-Crank Assembly

The displacement of the piston from TDC can be found from elementary geometry. Consider the piston-crank assembly shown in Figure 3.2. The equation of motion is given by the following,

\[ x = l + r(1 - \cos \theta) - \sqrt{l^2 - r^2 \sin^2 \theta} \] \hspace{1cm} (3-1)

where,

\[ \theta = \text{crankshaft angular position}, \]
\[ r = \text{radius of the crankshaft journal}, \]
\[ l = \text{length of the connecting rod} \]
\[ x = \text{position of the piston from TDC}. \]

The piston velocity \( v \), and acceleration \( a \), are found by taking the first and second derivative of the position,

\[ v = \frac{dx}{d\theta} = r \sin \theta + \frac{r^2 \sin \theta \cos \theta}{\sqrt{l^2 - r^2 \sin^2 \theta}} \] \hspace{1cm} (3-2)

\[ a = \frac{dv}{d\theta} = r \cos \theta + \frac{r^2 \cos 2\theta}{\sqrt{l^2 - r^2 \sin^2 \theta}} - \frac{r^4 \sin^2 \theta \cos^2 \theta}{(\sqrt{l^2 - r^2 \sin^2 \theta})^3} \] \hspace{1cm} (3-3)
3.3 Piston Design

The piston is designed to accommodate the requirements of the engine cycle. The piston has to transfer gas forces to the connecting rod and the crankshaft. It also has to seal the combustion chamber from the crankcase. To accomplish this, a typical piston has two compression rings at the top as seen in Figure 3.3. The piston and piston rings move on the surface of the cylinder bore liner. To avoid wear, the piston group is separated from the liner by a lubricating oil film. The film thickness is controlled by another type of piston ring called the oil control ring.
Figure 3.3. Connecting Rod and Piston with Piston Rings.

To improve the sealing ability of the compression rings and to reduce oil consumption, both the compression rings and oil control ring are pre-loaded during assembly. As a result, the piston rings are pressed against the cylinder bore liner. The surface roughness of the cylinder bore liner is an important factor in the interaction with the piston profile.

3.4 Cylinder Bore Machining

The objective of the cylinder bore machining process is to make the walls as straight as possible with no taper, the bores as round as possible with minimal distortion and to provide the right amount of cross-hatch and valley depth for oil retention while also providing a relatively flat, smooth area to support the piston rings. To achieve these objectives, the cylinder bore is typically machined in three stages known as rough cut, finish cut and honing.
3.4.1 Rough Cut

During the rough cut operation, the cylinder bore is machined to remove bulk material from the surface of the bore. It is during this operation that the most material is removed to bring the cylinder bore close to the final diameter specification.

3.4.2 Finish Cut

The finish cut operation uses similar tooling to precisely cut the cylinder bore to the final bore diameter specification. The bore also receives a somewhat improved surface finish.

3.4.3 Honing

A honing tool is used to create a surface finish that resembles a crosshatch pattern that is necessary for oil retention and oil distribution in the cylinder. This is important to reduce friction between the cylinder bore surface and the piston rings. The cutting abrasive in a honing tool might be either diamond stones or vitrified stones such as silicon carbide and aluminum oxide. There are advantages and disadvantages for both types. Vitrified stones are less expensive and produce a cleaner cut but they wear faster and require mineral based honing oils. Diamond stones are more expensive but they wear slower, produce better overall bore geometry and use water based synthetic lubricants.

3.4.4 Bore Roughness

If the bore finish is too rough it will lead to increased piston ring friction and wear as described by Haubner [30]. The quality of the cylinder bore finish also has an effect on engine oil consumption as described by Hill [48]. The bore finish depends on a number
of factors including the type of cutting tool or abrasive stones as well as the number and size of abrasive stones. The finish depends on process parameters such as tool spindle speed, feed rate and stroke speed as well as the tool pressure and cutting lubricant used. The finish also depends on geometric parameters such as the location of the tool spindle centerline with respect to the cylinder bore centerline.

3.4.5 Non-cleanup Condition

The manufacturing defect known as cylinder bore non-cleanup occurs when the previous cutting operation removes more material than the subsequent operation can clean. For example, when too much material is removed during the rough or finish cut, then the honing tool cannot maintain contact with the cylinder walls because the bore is oversized. The surface may not be smoothed to the final specification for roughness. Some potential causes for this include misalignment of the tool spindle with respect to the cylinder bore axis. The effect of cylinder bore non-cleanup and the mechanical vibration response of the piston rings to this defect was the main focus of this research.

3.5 Mechanical Vibration

A mechanical vibration is the motion of a particle or a body that oscillates about a position of equilibrium. Vibration results when a system is displaced from a position of equilibrium. The system returns to this position under the action of restoring forces, such as the elastic force acting on a mass connected to a stretched spring or the gravitational force acting on a swinging pendulum. All vibrations are damped to some degree by friction forces. The term free vibration is used when only the restoring forces maintain
the motion. The term forced vibration is used if an external force is applied to the system.

3.6 Translational Mechanical Systems

Some mechanical systems can be modeled using variations of a mass-spring-damper system. Consider the system shown in Figure 3.4.

![Diagram of mass-spring-damper system with single degree of freedom](image)

**Figure 3.4. Mass-spring-damper System with Single Degree of Freedom.**

The force exerted on the mass by the spring is given by Hooke's Law which states that the spring exerts a restoring force $F_k$ opposite to the direction of elongation and proportional to the distance $x$ from the equilibrium position. Therefore,

$$F_k = -kx(t)$$  \(3-4\)

The negative sign is used to imply that the force acts in a direction opposite to the motion. The variable $k$ is known as the "spring constant". The restoring force of the
spring from the unstretched position to the equilibrium position is equal to \( ks \) and is equal but opposite to the force due to gravity \( W=mg \).

In the study of mechanics, damping forces acting on a body are considered to be proportional to the instantaneous velocity. Therefore,

\[
F_c = -c \frac{dx(t)}{dt} \quad (3-5)
\]

The negative sign is used to imply that the force acts in a direction opposite to the motion. The variable \( c \) is known as the "damping constant". The general equation of motion is obtained by using Newton's second law to sum the forces acting on the mass.

\[
\sum F = ma(t) = m \frac{d^2 x(t)}{dt^2} \quad (3-6)
\]

\[
F_k + F_c + F = m \frac{d^2 x(t)}{dt^2} \quad (3-6a)
\]

Substituting equations (3-4) and (3-5) into (3-6a) and re-arranging gives,

\[
m \frac{d^2 x(t)}{dt^2} + c \frac{dx(t)}{dt} + kx(t) = F \quad (3-7)
\]

\[
m \ddot{x}(t) + c \dot{x}(t) + kx(t) = F \quad (3-7a)
\]

The linear second-order differential equation shown in equation 3-7 can be used as a mathematical model of the simple mass-spring-damper system. The solution to this equation depends on the input \( F \) and the initial conditions of the system.

### 3.6.1 Free Damped Motion

Consider the simple case where there is no forcing function, so \( F \) is zero. Assume that the solution takes the form,
\[ x(t) = e^{rt} \]  

so,

\[ \dot{x}(t) = re^{rt} \]  

and,

\[ \ddot{x}(t) = r^2 e^{rt} \]  

Inserting these into equation 3-7a gives,

\[ mr^2 e^{rt} + cre^{rt} + ke^{rt} = 0 \]  

or,

\[ e^{rt} (mr^2 + cr + k) = 0 \]  

Since the term \( e^{rt} \) is never equal to zero for real values of \( t \), then the quadratic term in brackets must be equated to zero. The roots of the quadratic term in equation 3-10 are given by,

\[ r_{1,2} = \frac{-c \pm \sqrt{c^2 - 4km}}{2m} \]  

For algebraic convenience, define the following,

\[ \alpha = \frac{c}{2m}, \omega = \sqrt{\frac{k}{m}} \]  

So the roots in Equation (3-11) now become,

\[ r_{1,2} = -\alpha \pm \sqrt{\alpha^2 - \omega^2} \]  

There are three possible cases depending on the algebraic sign of the discriminant in Equation 3-13.
3.6.1.1 Overdamped

In this case the damping coefficient \( c \) is large compared to the spring constant \( k \). The resulting general solution is,

\[
x(t) = e^{-at} \left( Ae^{\sqrt{a^2 - \omega^2}t} + Be^{-\sqrt{a^2 - \omega^2}t} \right)
\]

This equation represents a smooth and non-oscillatory motion.

3.6.1.2 Critically Damped

This is the case when the discriminant in Equation 3-11 or 3-13 is equal to zero. It is convenient to define the critical damping coefficient \( c_{critical} \), which makes the discriminant equal to zero. In this case, any slight decrease in damping would result in oscillatory motion.

\[
c_{critical} = 2\sqrt{km}
\]

The general solution now becomes,

\[
x(t) = e^{-at} (A + Bt)
\]

3.6.1.3 Underdamped

In this case, the damping coefficient \( c \) is small compared to the spring constant \( k \). The roots are now complex values. The resulting general solution is,

\[
x(t) = e^{-at} \left( A \cos \sqrt{\omega^2 - \alpha^2} t + B \sin \sqrt{\omega^2 - \alpha^2} t \right)
\]

This motion is oscillatory but the amplitude approaches zero as time approaches infinity.

3.6.2 Forced Damped Motion

The solution is more difficult to find for the case where the forcing function is a sinusoidal or some other input. The solution becomes even more difficult for a system of
more than one linear differential equation. Consider the following system model for a piston with three piston rings described in the next section.

3.6.3 Piston-Ring Dynamic Model

A simplified profile of a piston with piston rings is shown in Figure 3.5.

![Figure 3.5. Simplified Piston Profile.](image)

![Figure 3.6. Mass-spring-damper Model of Piston and Piston Rings.](image)
The mass-spring-damper model for the piston and piston rings is shown in Figure 3.6.

The equations of motion are given by,

\[ m_i \ddot{x}_i + c_{id}(\dot{x}_i - \dot{x}_d) + k_{id}(x_i - x_d) = F_i \]  
\[ (3-18a) \]

\[ m_2 \ddot{x}_2 + c_{2d}(\dot{x}_2 - \dot{x}_d) + k_{2d}(x_2 - x_d) = F_2 \]  
\[ (3-18b) \]

\[ m_3 \ddot{x}_3 + c_{3d}(\dot{x}_3 - \dot{x}_d) + k_{3d}(x_3 - x_d) = F_3 \]  
\[ (3-18c) \]

\[ m_4 \ddot{x}_4 + c_{1d}(\dot{x}_4 - \dot{x}_1) + c_{2d}(\dot{x}_4 - \dot{x}_2) + c_{3d}(\dot{x}_4 - \dot{x}_3) + k_{4d}(x_4 - x_1) + k_{2d}(x_4 - x_2) + k_{3d}(x_4 - x_3) = 0 \]  
\[ (3-18d) \]

The equations written above represent a second order linear differential equations model.

It would be more difficult to solve using the traditional methods such as the one described in the single degree of freedom model studied earlier. It could be analyzed using the Laplace Transform Method to obtain a transfer function or frequency domain model. There are also a number of numerical methods that could be used. A time-domain state-space model description was used in this research. The state variables are chosen to be the position and velocity of each mass in the system and are represented by \( x_i, v_i, x_2, v_2, x_3, v_3, x_4 \) and \( v_4 \). By using the state variables, the following state equations are derived from the previous equations of motion. There are eight equations in total. This is now a system of first order linear differential equations. This model will depend on choosing accurate values for \( m_i, c \) and \( k \). The model will also depend on how well the piston ring and cylinder bore liner contact forces are simulated. The computer simulation code is written in the MATLAB language and is located in Appendix B.
\[
\begin{align*}
\dot{x}_1 &= v_1 \\
\dot{v}_1 &= -\frac{k_{14}}{m_1} x_1 - \frac{c_{14}}{m_1} v_1 + \frac{k_{14}}{m_1} x_4 + \frac{c_{14}}{m_1} v_4 + \frac{1}{m_1} F_1 \\
\dot{x}_2 &= v_2 \\
\dot{v}_2 &= -\frac{k_{24}}{m_2} x_2 - \frac{c_{24}}{m_2} v_2 + \frac{k_{24}}{m_2} x_4 + \frac{c_{24}}{m_2} v_4 + \frac{1}{m_2} F_2 \\
\dot{x}_3 &= v_3 \\
\dot{v}_3 &= -\frac{k_{34}}{m_3} x_3 - \frac{c_{34}}{m_3} v_3 + \frac{k_{34}}{m_3} x_4 + \frac{c_{34}}{m_3} v_4 + \frac{1}{m_3} F_3 \\
\dot{x}_4 &= v_4 \\
\dot{v}_4 &= \frac{k_{14}}{m_4} x_1 + \frac{c_{14}}{m_4} v_1 + \frac{k_{24}}{m_4} x_2 + \frac{c_{24}}{m_4} v_2 + \frac{k_{34}}{m_4} x_3 + \frac{c_{34}}{m_4} v_3 \\
&\quad - \frac{(k_{14} + k_{24} + k_{34})}{m_4} x_4 - \frac{(c_{14} + c_{24} + c_{34})}{m_4} v_4
\end{align*}
\]

The vector-matrix form of this state-space model is represented as follows,
3.7 Predicted Frequency Characteristics

It would be useful to know what frequency components are present in the vibration output of the model above. This is accomplished by calculating the Discrete Fourier Transform of the vibration. Once the components are predicted by the vibration model, these components could be used to characterize the non-cleanup defect. However, if the vibration test data has a low signal to noise ratio and it may be difficult to find the existence of the predicted frequency components in the measured test data.

3.8 Bandpass Filters

A bank of bandpass filters or a multi-band filter could be used to filter the measured vibration data to increase the signal to noise ratio. The filter bands should be centered at frequencies that correspond to the frequency components that characterize the non-cleanup condition. All measured vibration data would be filtered before being analyzed in the frequency domain.

3.9 RMS Threshold

A metric must be used to decide if a test engine has the non-cleanup condition. The metric can be based on the root-mean-square (RMS) value of the filtered measured vibration data. The decision threshold can be determined by testing a number of engines with and without the non-cleanup defect. When a test engine exceeds the threshold, it will be considered a defect.
CHAPTER 4
EXPERIMENTAL DETAILS

The engine type used in this study was a four stroke, spark-ignition, overhead valve (OHV), 3.8-liter V6 engine. The engine was only partially assembled before testing and was referred to as a "short" block assembly. A "short" block assembly consists of a cylinder block, camshaft, crankshaft, connecting rods and pistons. The test stand set-up is depicted in Figure 4.1.

![Figure 4.1. Cold Test Stand Set-up](image)

4.1 Accelerometers

Two PCB #308M86 accelerometers were attached to the test engine on the oil pan rail to measure vibration. These devices produce a charge proportional to the vibration. To convert the sensor output to a measurable voltage signal, the accelerometers were
connected to an ICP #482A04 charge amplifier. See Appendix A for device specifications.

4.2 Torque Transducer

A rotating shaft torque sensor was used to measure crankshaft torque. The model used was a Lebow #1104-200. The transducer was connected to a Daytronic #3370 signal conditioner. See Appendix A for device specifications.

4.3 Crankshaft Speed Sensor

A digital magnetic speed sensor was used to measure the crankshaft angular speed. The type used was an Electro #58426. See Appendix A for device specifications.

4.4 Data Acquisition System

The data was collected using a Sciemetrics Model 280 Integrated Test System. This system included an 800 MHz Intel Pentium 3 computer with 128 MB of RAM memory, a 15 GB hard drive and a 3.5-inch, 1.44 MB floppy drive. A Sciemetrics Model 808 PCI interface was used to provide communication between the computer and the data collection and input/output modules.

4.4.1 Analog-to-Digital Interface Modules

Data was collected from the crankshaft speed sensor, torque transducer and accelerometers through the Sciemetrics Model 251B 16-channel analog transducer input
expansion module. This module was used with the Model 237 high speed 16-bit analog-to-digital converter module.

4.4.2 Encoder Input Module

The Sciemetrics Model 202 2-channel encoder module allows the data acquisition from the crankshaft encoder. This is important for indicating the angular position of the crankshaft.

4.4.3 Digital Input/Output Module

The Sciemetrics Model 224 and 225 digital I/O modules allowed an interface between the data acquisition system and the programmable logic controller that was used to control the test sequence.

4.5 Cranking Motor

The engine crankshaft was coupled to a servo motor with an integrated resolver. The servo motor was an Allen-Bradley #1326AB-B2E-11. The motor was controlled using an Allen-Bradley #1391-DES servo drive and #IMC-121 servo drive controller.

4.6 Test Procedure

The following describes the test procedure used to collect data. The "short" block engine assembly sits on a pallet and enters the test stand on conveyors. When the engine is in position it is raised off the pallet and clamped. The cranking motor engages the engine crankshaft and slowly turns the crankshaft until a sensor detects the timing mark. This
timing mark represents the position when cylinder number one is at top-dead-center. This provides a reference or starting point. The cranking motor then begins to turn the crankshaft as the data acquisition system measures the torque that is required to start turning the crankshaft from the rest position. This is known as break-away torque. A sample is taken every 0.005 seconds for a length of 5.08 seconds. This represents a sampling frequency of 200 Hz and a total of 1017 samples. At the conclusion of the break-away torque test, the cranking motor turns the crankshaft at a constant 250 RPM as measured by the crankshaft speed sensor. The data acquisition system measures the running torque and the vibration at each accelerometer as the engine is turning at 250 RPM. Data is sampled at a frequency of 750 Hz.
CHAPTER 5
DATA ANALYSIS

The first goal of the data analysis stage of this study was to find the vibration output of the piston ring model. The vibration output is analyzed in the frequency domain to determine the predicted frequency components that could be used to characterize the non-cleanup condition. The second goal was to design a multi-band filter with bands centered at these frequency components. This filter was used to reduce the signal to noise ratio of the measured vibration. The third goal was to calculate the RMS value of the filtered measured vibration data for engines with and without the non-cleanup condition.

5.1 Piston Motion

The following table shows the position of the piston in the cylinder bore for some important values of crankshaft angle for the 6-cylinder engine in this study.

<table>
<thead>
<tr>
<th>Cyl</th>
<th>0</th>
<th>60</th>
<th>120</th>
<th>180</th>
<th>240</th>
<th>300</th>
<th>360</th>
<th>420</th>
<th>480</th>
<th>540</th>
<th>600</th>
<th>660</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>TDC Power</td>
<td>↑</td>
<td>↑</td>
<td>TDC Power</td>
<td>↑</td>
<td>↑</td>
<td>TDC Intake</td>
<td>↓</td>
<td>↓</td>
<td>BDC Comp</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>2</td>
<td>↓</td>
<td>BDC Comp</td>
<td>↑</td>
<td>↑</td>
<td>TDC Intake</td>
<td>↓</td>
<td>↓</td>
<td>BDC Comp</td>
<td>↑</td>
<td>↑</td>
<td>TDC Intake</td>
<td>↓</td>
</tr>
<tr>
<td>3</td>
<td>↑</td>
<td>↑</td>
<td>TDC Intake</td>
<td>↓</td>
<td>↓</td>
<td>BDC Comp</td>
<td>↑</td>
<td>↑</td>
<td>TDC Power</td>
<td>↓</td>
<td>↓</td>
<td>BDC Exhaust</td>
</tr>
<tr>
<td>4</td>
<td>↑</td>
<td>↑</td>
<td>TDC Power</td>
<td>↓</td>
<td>↓</td>
<td>BDC Exhaust</td>
<td>↑</td>
<td>↑</td>
<td>TDC Intake</td>
<td>↓</td>
<td>↓</td>
<td>BDC Comp</td>
</tr>
<tr>
<td>5</td>
<td>TDC Intake</td>
<td>↓</td>
<td>↓</td>
<td>BDC Comp</td>
<td>↑</td>
<td>↑</td>
<td>TDC Power</td>
<td>↓</td>
<td>↓</td>
<td>BDC Exhaust</td>
<td>↑</td>
<td>↑</td>
</tr>
<tr>
<td>6</td>
<td>↓</td>
<td>BDC Exhaust</td>
<td>↑</td>
<td>↑</td>
<td>TDC Intake</td>
<td>↓</td>
<td>↓</td>
<td>BDC Comp</td>
<td>↑</td>
<td>↑</td>
<td>TDC Power</td>
<td>↓</td>
</tr>
</tbody>
</table>

Table 5.1. Piston Position for a Typical Six Cylinder Engine.
The convention is to set the crankshaft position to zero at the point where cylinder 1 is at TDC. All other pistons exhibit the same movement but with an appropriate shift with respect to crankshaft angular position. Combustion occurs at TDC and every 720 degrees in a single cylinder. For the 6-cylinder engine in this study, combustion occurs in a subsequent cylinder every 120 degrees and the firing order was cylinder 1, 4, 2, 5, 3, 6. The term "cylinder pair" is used to describe the cylinders that are at TDC and BDC simultaneously, but combustion in each cylinder occurs 360 degrees apart. The cylinder pairs were 1 and 5 then 4 and 3 then 2 and 6. The motion of the piston in cylinder 1 is depicted in Figure 5.1.

![Figure 5.1. Piston Displacement, Velocity and Acceleration Relative to TDC.](image)
5.2 Piston Ring Model Parameters

The values for the piston and piston ring mass $m$, spring constant $k$ and damping constant $c$ were inputted into the piston ring model. The values were calculated from piston and piston ring manufacturers specifications.

In practice, it would be difficult to measure the force exerted on the piston rings by the cylinder wall. It was mentioned before that the piston rings are compressed before the piston is installed in the cylinder bore. When the compressed piston ring is at rest, it is pushing against the cylinder wall with a certain force and the cylinder wall is pushing back with an equal but opposite force. Therefore, the net force on the ring is zero, the piston is at rest and this satisfies Newton's Law. If the cylinder wall was perfectly smooth, the net force on the rings would be zero and the rings would never move. However, this is never the case in practice since the cylinder wall has a certain roughness.

In the case of the non-clean up defect, the cylinder bore is more rough than normal. For this reason, a small net force was simulated and inputted into the piston ring model. This force was simulated by considering the nominal roughness of a cylinder bore and the spring constant of a typical piston ring. The nominal roughness for a good cylinder bore might be in the range of $5 - 10 \, \mu m$. A cylinder bore with non-clean up might have a roughness of $25 \, \mu m$. For example, the upper compression ring with a spring constant of $0.02 \, N/\mu m$, would compress by $25 \, \mu m$ under a force of $0.5 \, N$. To simulate the non-clean up condition, the input force was constructed using a normally distributed random signal generator with zero mean and a standard deviation of $0.5$. This force is shown in Figure 5.2. The vibration output is shown in Figure 5.3. This vibration represents the
sum of the individual vibrations of the upper compression ring, the lower compression ring, the oil control ring and the piston. The individual vibrations of each mass are shown in Appendix C. The simulated vibrations were analyzed in the frequency domain using the Fast Fourier Transform method of calculating the Discrete Fourier Transform. The frequency plot for the vibration total is shown in Figure 5.4. The plot shows pronounced frequency components in the bands between 200 – 210 Hz and 250 – 260 Hz. These will be used to characterize the non-cleanup condition. The existence of the non-cleanup condition in test engines will be determined by the existence of these frequency components in the measured vibration signals after being filtered by a bank of bandpass filters.

5.3 Bandpass Filters

The filters were designed using two 3rd-order Chebyshev Type 2 IIR filters. The first filter had a stopband between 0 – 245 Hz, a passband between 250 – 260 Hz and a beginning at 265 Hz. The filter had a maximum passband ripple of 3 dB and a minimum stopband attenuation of 20 dB. The second filter had a stopband between 0 – 195 Hz, a passband between 200 – 210 Hz and a beginning at 215 Hz. The filter had a maximum passband ripple of 3 dB and a minimum stopband attenuation of 20 dB. The plots for the frequency response, phase angle, phase delay and group delay for both filters are shown in Appendix D.
Figure 5.2. Simulated Force on Piston Rings.

Figure 5.3. Simulated Vibration Total.
Figure 5.4. Frequency Plot of Simulated Vibration Total.
CHAPTER 6
RESULTS AND DISCUSSION

The measured vibration results are presented in this chapter. Three engines were analyzed with increasing levels of the non-cleanup defect. Photographs of these conditions are shown in Appendix E. Each measured vibration signal was filtered with the passband filters that were designed before. The output signals from each filter were added to produce a filtered measured vibration signal.

6.1 Measured Vibration Results

Each engine is measured with two vibration sensors on the oil pan rail. The time domain and frequency domain plots for both measured vibration sensors for each engine are shown in Appendix F. The time domain and frequency domain plots for the filtered measured vibrations are also shown. The three engines tested had increasing levels of the non-cleanup defect and the levels were described as "slight", "medium" and "severe".

6.1.1 Slight Non-cleanup Condition

The first engine studied had a slight amount of roughness in one cylinder bore. The surface profile had a peak to valley difference of 10 μm. The frequency plots of the filtered measured vibration signals for both sensors are shown in Figure 6.1 and Figure 6.2.
6.1.2 Medium Non-clean up Condition

The second engine studied had a medium amount of roughness in one cylinder bore. The surface profile had a peak to valley difference of 25 μm. The results were similar to the case of a slight non-clean up condition, however the frequency components present in the filtered measured vibrations had higher magnitudes. This is shown in Figure 6.3 and Figure 6.4.

6.1.3 Severe Non-clean up Condition

The third engine in this study had a severe non-clean up condition. The cylinder had concentric circles that were about 1 mm wide, 1 mm deep and equally spaced about 20 mm apart from the top of the cylinder to the bottom. The results were similar to the cases of slight and medium non-clean up condition, however the frequency components present in the filtered measured vibrations had much higher magnitudes. This is shown in Figure 6.5 and Figure 6.6.
Figure 6.1. NCU Engine #1 Frequency Plot for Vibration Sensor 1.

Figure 6.2. NCU Engine #1 Frequency Plot for Vibration Sensor 2.
Figure 6.3. NCU Engine #2 Frequency Plot for Vibration Sensor 1.

Figure 6.4. NCU Engine #2 Frequency Plot for Vibration Sensor 2.
Figure 6.5. NCU Engine # 3 Frequency Plot for Vibration Sensor 1.

Figure 6.6. NCU Engine # 3 Frequency Plot for Vibration Sensor 2.
6.2 RMS Value of Filtered Measured Vibration Signal

It is evident from the previous graphs that the frequency components in the 200 – 210 Hz and 250 – 260 Hz range increase in amplitude as the severity of the non-cleanup condition increases. This is a qualitative observation. As a means of quantifying the comparison, the RMS value was calculated for each filtered measured vibration signal. The results are shown in Table 6.1 for the three engines with non-cleanup.

<table>
<thead>
<tr>
<th>Test</th>
<th>Vibration Sensor 1</th>
<th>Vibration Sensor 2</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCU Engine # 1</td>
<td>0.7754</td>
<td>0.6558</td>
<td>0.7156</td>
</tr>
<tr>
<td>NCU Engine # 2</td>
<td>0.9549</td>
<td>1.0881</td>
<td>1.0215</td>
</tr>
<tr>
<td>NCU Engine # 3</td>
<td>1.6904</td>
<td>0.9420</td>
<td>1.3162</td>
</tr>
</tbody>
</table>

Table 6.1. RMS Value of Filtered Measured Vibration Data.

Figure 6.7. Histogram of RMS Value of Filtered Measured Vibration Data.
The sample of 1000 good engines produced a histogram that is shown in Figure 6.7. The sample population had a mean value of 0.7274 and a standard deviation $\sigma = 0.0658$. The vertical lines show the $\pm 1\sigma$, $\pm 2\sigma$ and $\pm 3\sigma$ boundaries. If the threshold of detection were set at the $+3\sigma$ boundary, then only the severe non-clean up engine and the medium non-clean up engine would be detected. However, the number of false rejects would be low at 3 out of 1000. If the threshold of detection were set at the $+2\sigma$ boundary, the engine with slight non-clean up would still not be detected and the number of false rejects would be higher at 46 out of 1000. If the threshold of detection were set at the $+1\sigma$ boundary, the engine with slight non-clean up would still not be detected and the number of false rejects would be even higher at 318 out of 1000.
CHAPTER 7
CONCLUSIONS

The ability to detect the small phenomena of piston ring vibration among all the engine component movement introduced a significant signal to noise ratio problem. To narrow the search, a piston ring model was developed in this research to model the movement of the piston and piston rings in the direction normal to the cylinder bore surface. By analyzing the simulated vibration from the model in the frequency domain, the non-cleanup defect could be characterized by the predicted frequency components that were present in the signal.

Based on these findings, two bandpass filters were successfully realized with very low order Chebyshev Type 2 IIR filters. When applied to the measured vibration signals from externally mounted sensors, the filter was able to increase the signal to noise ratio of the measured signals in the frequency bands of interest. By viewing these filtered measured vibration signals for engines with non-cleanup, it was possible to verify the existence of the frequency components that were predicted by the model. The existence of these frequency components was not enough to quantify the existence of the non-cleanup condition since they were also evident in the measured vibration data from good engines. Therefore, a metric was created based on the RMS value of the filtered measured vibration data. This value was somewhat higher for the three engines with the non-cleanup condition compared to the good engines. Setting the threshold of detection became a trade-off between the ability to successfully detect all three levels of non-
cleanup and the number of false rejects that would be produced from good engines. The threshold of detection was finally set at 3 standard deviations from the mean of a population of 1000 good engines. This allowed the severe and medium non-cleanup conditions to be detected and still provided a low probability for false rejects.
CHAPTER 8

RECOMMENDATIONS

The following recommendations are possible improvements to the present work and also future research interests of the author.

The constraints of the existing test stand led to a placement of sensors that was not optimal for detecting the phenomena of piston ring vibration. A more optimal position for the sensors would be outside the cylinder bore wall. It is also advisable to have one vibration sensor for each cylinder bore to determine which one has the non-cleanup defect. This could significantly increase the signal to noise ratio. A number of other measurement techniques should be investigated including laser velocimeters.

Once the physical test set-up has been optimized to reduce the signal to ratio as much as possible, the algorithm in this research could be used to calculate the RMS value of the filtered measured vibration data for engines with non-cleanup and good engines. It could then be determined if there is a more significant difference in this value when the non-cleanup condition is present. The threshold of detection could then be modified to a more optimal value.
REFERENCES


APPENDIX A

Equipment Specifications
<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weight</td>
<td>32 grams</td>
</tr>
<tr>
<td>Sensitivity (+/- 5%)</td>
<td>10.19 mV/(m/s²)</td>
</tr>
<tr>
<td>Measurement Range</td>
<td>+/- 491 m/s² peak</td>
</tr>
<tr>
<td>Frequency Range +/- 5%</td>
<td>1 Hz to 4000 Hz</td>
</tr>
<tr>
<td>Non-linearity</td>
<td>&lt; 1%</td>
</tr>
<tr>
<td>Temperature Range</td>
<td>-54 to +121 °C</td>
</tr>
<tr>
<td>Supply Current Range</td>
<td>2 to 20 mA</td>
</tr>
<tr>
<td>Supply Voltage Range</td>
<td>18 to 30 VDC</td>
</tr>
<tr>
<td>Discharge Time Constant</td>
<td>0.5 to 2.0 sec</td>
</tr>
</tbody>
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Table A.1: Specifications for PCB Piezotronics 308M86 Accelerometer.

<table>
<thead>
<tr>
<th>Specification</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Channels</td>
<td>4</td>
</tr>
<tr>
<td>Sensor Excitation Voltage</td>
<td>26 VDC +/- 1 VDC</td>
</tr>
<tr>
<td>Sensor Excitation Current</td>
<td>2 to 20 mA</td>
</tr>
<tr>
<td>Time Constant</td>
<td>10 to 15 seconds</td>
</tr>
<tr>
<td>Low Frequency Response</td>
<td>&lt; 0.1 Hz</td>
</tr>
<tr>
<td>High Frequency Response</td>
<td>&gt; 1.0 MHz</td>
</tr>
<tr>
<td>DC Offset Maximum</td>
<td>&lt; 20 mV</td>
</tr>
<tr>
<td>Broadband Noise (1 Hz to 10 kHz)</td>
<td>&lt; 3.25 µV (-110 dB)</td>
</tr>
<tr>
<td>Voltage Gain</td>
<td>1.0 (+/- 1%)</td>
</tr>
<tr>
<td>Weight</td>
<td>756 g</td>
</tr>
</tbody>
</table>

Table A.2: Specifications for PCB Piezotronics 482A04 Signal Conditioner.

<table>
<thead>
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<th>Specification</th>
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</thead>
<tbody>
<tr>
<td>Number of Bridges</td>
<td>1</td>
</tr>
<tr>
<td>Bridge Resistance</td>
<td>350 Ω</td>
</tr>
<tr>
<td>Insulation Resistance</td>
<td>&gt; 5,000 Ω</td>
</tr>
<tr>
<td>Excitation Voltage</td>
<td>20 VDC or VAC rms</td>
</tr>
<tr>
<td>Temperature Range</td>
<td>-29 to 93 °C</td>
</tr>
<tr>
<td>Non-linearity, Hysteresis</td>
<td>+/- 0.1 %, +/- 0.1 %</td>
</tr>
<tr>
<td>Output</td>
<td>2 mV/V</td>
</tr>
<tr>
<td>Capacity</td>
<td>20 N-m</td>
</tr>
<tr>
<td>Torsional Stiffness</td>
<td>726 N-m / rad</td>
</tr>
<tr>
<td>Rotating Inertia</td>
<td>4.50 x 10¹⁴ N-m sec²</td>
</tr>
</tbody>
</table>

Table A.3: Specifications for Lebow 1104-200 Torque Sensor.
<table>
<thead>
<tr>
<th>Specification</th>
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</tr>
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<tr>
<td>Input Type</td>
<td>4-arm bridge, 90 to 2000 Ω</td>
</tr>
<tr>
<td>Input Range</td>
<td>1 to 8 mV/V</td>
</tr>
<tr>
<td>Excitation Voltage</td>
<td>5 or 10 VDC regulated</td>
</tr>
<tr>
<td>Analog Outputs</td>
<td>+/- 5 V and 4-20 mA</td>
</tr>
<tr>
<td>Common Mode Rejection</td>
<td>&gt; 80 dB</td>
</tr>
<tr>
<td>Input Impedance</td>
<td>&gt; 100 MΩ</td>
</tr>
<tr>
<td>Output Ripple</td>
<td>0.15 %</td>
</tr>
<tr>
<td>Accuracy</td>
<td>0.05 %</td>
</tr>
</tbody>
</table>

Table A.4: Specifications for Daytronic 3370 Signal Conditioner.

<table>
<thead>
<tr>
<th>Specification</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Supply Voltage</td>
<td>5 to 15 VDC @ 15 mA</td>
</tr>
<tr>
<td>Temperature Range</td>
<td>-40 to 107 °C</td>
</tr>
<tr>
<td>Output Signal</td>
<td>0 to 5 VDC Square Wave</td>
</tr>
<tr>
<td>Weight</td>
<td>142 g</td>
</tr>
<tr>
<td>Time Constant</td>
<td>1 μs</td>
</tr>
<tr>
<td>Housing</td>
<td>400 Stainless Steel</td>
</tr>
</tbody>
</table>

Table A.5: Specifications for Electro 58426 Digital Magnetic Speed Sensor.
APPENDIX B

MATLAB Programming Code
%ringmodel.m
%Matthew Bitzer
%Written 7/30/2003
%This program uses a state-space model for the piston ring
dynamics. The input is the force on the piston rings. This force is
simulated because it is difficult to measure in the real-world. It is
simulated by considering the cylinder bore wall profile with and
without the non-cleanup condition. The output is simulated using the
user-defined state-space model description discussed in the Theory of
this research.

tic;
global Force Tstep

%----Simulate Force on Piston Rings-----------------------------
Tstep=0.0013125;
Tfinal=1.3335;
Tspan=[0:Tstep:Tfinal];

Force=zeros(1,1017);  % input of zero to simulate a smooth bore
%Force=0.1*randn(1,1017); engine=1;  % random input for slight NCU
%Force=0.5*randn(1,1017); engine=2;  % random input for medium NCU
for i=1:20:1000
    Force(1,i)=10;         % engine=3;  % impulses for severe non-cleanup
end

figure
plot(Tspan,Force)
title(['Engine # ',num2str(engine),' Simulated Force on Piston
Rings'],['FontSize',12])
xlabel('Time [s]',['FontSize',12])
ylabel('Force [N]',['FontSize',12])
set(gca,['FontSize',12],['XLim',[0 1.3335],'YLim',[-5 5]])

%----Calculate Model Response-----------------------------------
x0=[0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0]; % initial conditions
[t,x]=ode23('ringmodelsu',Tspan,x0);

accel_ucr=diff(x(:,2));
accel_lcr=diff(x(:,4));
accelOCR=diff(x(:,6));
accel_piston=diff(x(:,8));
accel_total=accel_ucr + accel_lcr + accelOCR + accel_piston;

%----Time Domain Plot of Upper Compression Ring------------------
figure
plot(Tspan(1:1016),accel_ucr)
title(['Engine # ',num2str(engine),' Simulated Vibration of Upper
Compression Ring'],['FontSize',12])
xlabel('Time [s]',['FontSize',12])
ylabel('Vibration [m/s^2]',['FontSize',12])
set(gca,['FontSize',12],['XLim',[0 1.3335],'YLim',[-5 5]])

%----Time Domain Plot of Lower Compression Ring------------------
figure
plot(Tspan(1:1016),accel_lcr)
title(['Engine 
',num2str(engine),
', 'Simulated Vibration of Lower
Compression Ring'], 'FontSize',12)
xlabel('Time [s]', 'FontSize',12)
ylabel('Vibration [m/s^2]', 'FontSize',12)
set(gca, 'FontSize',12, 'XLim',[0 1.3335], 'YLim',[-5 5])

%---Time Domain Plot of Oil Control Ring-----------------------------------
figure
plot(Tspan(1:1016),accelocr)
title(['Engine 
',num2str(engine),
', 'Simulated Vibration of Oil Control
Ring'], 'FontSize',12)
xlabel('Time [s]', 'FontSize',12)
ylabel('Vibration [m/s^2]', 'FontSize',12)
set(gca, 'FontSize',12, 'XLim',[0 1.3335], 'YLim',[-5 5])

%---Time Domain Plot of Piston---------------------------------------------
figure
plot(Tspan(1:1016),accelpiston)
title(['Engine 
',num2str(engine),
', 'Simulated Vibration of
Piston'], 'FontSize',12)
xlabel('Time [s]', 'FontSize',12)
ylabel('Vibration [m/s^2]', 'FontSize',12)
set(gca, 'FontSize',12, 'XLim',[0 1.3335], 'YLim',[-5 5])

%---Time Domain Plot of Total---------------------------------------------
figure
plot(Tspan(1:1016),acceltotal)
title(['Engine 
',num2str(engine),
', 'Simulated Vibration
Total'], 'FontSize',12)
xlabel('Time [s]', 'FontSize',12)
ylabel('Vibration [m/s^2]', 'FontSize',12)
set(gca, 'FontSize',12, 'XLim',[0 1.3335], 'YLim',[-5 5])

%---Frequency Domain Plot-----------------------------------------------
N=1024;
Fs=750; % Resolution in frequency domain will
be df=Fs/N=750/1024=0.7324Hz
(N/2)+1 FFT values
f=(0:N/2)*Fs/N; % Compute frequency values and plot
are (0:Fs/2)
Xocr=fft(accelocr,N); % index for f is 0 to N/2 and values
Xlcr=fft(accellcr,N); % are (0:Fs/2)
Xocr=fft(accelocr,N); % Upper Compression Ring
Xlcr=fft(accelocr,N); % Lower Compression Ring
Xpiston=fft(accelpiston,N); % Oil Control Ring
Xtotal=fft(acceltotal,N); % Piston
Xtotal=fft(acceltotal,N); % Total

figure
plot(f,abs(Xocr(1:N/2+1)), 'black') % index for X is 1 to N/2+1
hold on
plot(f,abs(Xlcr(1:N/2+1)), 'black')
hold on
plot(f,abs(Xocr(1:N/2+1)), 'black')
hold on
plot(f,abs(Xpiston(1:N/2+1)), 'black')
hold on
plot(f,abs(Xtotal(1:N/2+1)), 'black')
hold off

title(['Engine # ',num2str(engine),' Frequency Plot of Simulated Vibration'], 'FontSize', 12)
ylabel('Magnitude of DFT', 'FontSize', 12)
xlabel('Frequency in Hertz', 'FontSize', 12)
set(gca, 'FontSize', 12, 'XLim', [0 Fs/2], 'YLim', [0 750])

%%%---Compute and Plot the Power Spectral Density using Welch's Method---
nfft=1024;
window=hanning(256);
noverlap=128;
[Pxx_u-cr,f]=pwelch(accel_u-cr,window,noverlap,nfft,Fs); \%Welch's method
[Pxx_lcr,f]=pwelch(accel_lcr,window,noverlap,nfft,Fs); \%Welch's method
[Pxx_ocr,f]=pwelch(accel_ocr,window,noverlap,nfft,Fs); \%Welch's method
[Pxx_piston,f]=pwelch(accel_piston,window,noverlap,nfft,Fs); \%Welch's method
[Pxx_total,f]=pwelch(accel_total,window,noverlap,nfft,Fs); \%Welch's method

figure
plot(f,10*log10(Pxx_u-cr),'black')
hold on
plot(f,10*log10(Pxx_lcr),'black')
hold on
plot(f,10*log10(Pxx_ocr),'black')
hold on
plot(f,10*log10(Pxx_piston),'black')
hold on
plot(f,10*log10(Pxx_total),'black')
hold off

title(['Engine # ',num2str(engine),' Welch\'s Power Spectral Density Estimate of Simulated Vibration'], 'FontSize', 12)
xlabel('Frequency in Hertz', 'FontSize', 12)
ylabel('Power Spectral Density (dB)', 'FontSize', 12)
set(gca, 'FontSize', 12, 'XLim', [0 375])

toc;
function xdot=ringmodelsub(t,x);
global Force Tstep

%Initialize variables as per manufacturer's specifications
m1=0.01173; %nominal mass in kilograms of upper compression ring UCR
m2=0.01213; %nominal mass in kilograms of lower compression ring LCR
m3=0.01050; %nominal mass in kilograms of oil control ring OCR
m4=0.56800; %nominal mass in kilograms of piston 0.448 and pin 0.120
k14=20000; %spring constant in N/m=Newton/meter (spec 0.0200 N/um) for UCR ring
k24=31500; %spring constant in N/m=Newton/meter (spec 0.0315 N/um) for LCR ring
k34=420000; %spring constant in N/m=Newton/meter (spec 0.4200 N/um) for OCR ring
c14=0.0; %damping coefficient in N-s/m=Newton-second/meter for UCR ring
c24=0.0; %damping coefficient in N-s/m=Newton-second/meter for LCR ring
c34=0.0; %damping coefficient in N-s/m=Newton-second/meter for OCR ring

index=floor(t/Tstep)+1;
P1=Force(1,index);
P2=Force(1,index);
P3=Force(1,index);

%state equations
xdot(1)=x(2);
xdot(2)=(1/m1)*[-(k14)*x(1)-(c14)*x(2)+k14*x(7)+c14*x(8)+P1];
xdot(3)=x(4);
xdot(4)=(1/m2)*[-(k24)*x(3)-(c24)*x(4)+k24*x(7)+c24*x(8)+P2];
xdot(5)=x(6);
xdot(6)=(1/m3)*[-(k34)*x(5)-(c34)*x(6)+k34*x(7)+c34*x(8)+P3];
xdot(7)=x(8);
xdot(8)=(1/m4)*[k14*x(1)+c14*x(2)+k24*x(3)+c24*x(4)+k34*x(5)+c34*x(6)-
(k14+k24+k34)*x(7)-(c14+c24+c34)*x(8)];
xdot=[xdot(1);xdot(2);xdot(3);xdot(4);xdot(5);xdot(6);xdot(7);xdot(8)];
load ncu.mat

%---Choose which file to view------------------------------------------
viewfile=engine=1; strl='NCU';
viewfile=engine=2; strl='NCU';
viewfile=engine=3; strl='NCU';

viewchan12=9.8*viewfile(1:1017,12); %data is in [g's] so multiply by
% 9.8 to get to m/s^2
viewchan13=9.8*viewfile(1:1017,13); %data is in [g's] so multiply by
% 9.8 to get to m/s^2
viewchan14=viewfile(1:1017,14); %data is in [N-m]
time=0.0013125*(0:1016);

%---Time Domain Plot Sensor 1 and Sensor 2-------------------------------
figure
subplot(2,1,1)
plot(time,viewchan12,'red')
xlabel('Time [s]', 'FontSize',12)
ylabel('Vibration [m/s^2]', 'FontSize',12)
axis([0 1.3335 -30 30])
title(['Engine # ',num2str(engine),' Vibration Sensor 1'], 'FontSize',12)

figure
subplot(2,1,2)
plot(time,viewchan13,'red')
xlabel('Time [s]', 'FontSize',12)
ylabel('Vibration [m/s^2]', 'FontSize',12)
axis([0 1.3335 -30 30])
title(['Engine # ',num2str(engine),' Vibration Sensor 2'], 'FontSize',12)

%---Frequency Domain Plot for Sensor 1 and Sensor 2----------------------
N=1024;
Fs=750; % Resolution in frequency domain will be
df=Fs/N=750/1024=0.7324Hz
f=(0:N/2)*Fs/N; % index for f is 0 to N/2 and values are
(0:F)/2)
figure
subplot(2,1,1)
X=fft(viewchan12,N); % Compute frequency values and plot (N/2)+1 FFT values
plot(f,abs(X(1:N/2+1)),'r-') % index for X is 1 to N/2+1
title(['Engine # ',num2str(engine),' Frequency Plot for Vibration
Sensor 1'], 'FontSize',12)
ylabel('Magnitude of DFT', 'FontSize',12)
xlabel('Frequency in Hertz', 'FontSize',12)
set(gca, 'FontSize',12,'XLim',[0 Fs/2],'YLim',[0 750])

subplot(2,1,2)
hold on
% Compute frequency values and plot (N/2)+1 FFT values
plot(f,abs(X(1:N2+1)),'r-') title(['Engine # ',num2str(engine),' Frequency Plot for Vibration Sensor 2','FontSize',12])
ylabel('Magnitude of DFT','FontSize',12)
xlabel('Frequency in Hertz','FontSize',12)
set(gca,'FontSize',12,'XLim',[0 Fs/2], 'YLim', [0 750])

% Compute and Plot the Power Spectral Density Using Welch's Method
nfft=1024;
window=hanning(256);
noverlap=128;
[Pxx_12,f]=pwelch(viewchan12,window,noverlap,nfft,Fs); % Welch's method
[Pxx_13,f]=pwelch(viewchan13,window,noverlap,nfft,Fs); % Welch's method
[Pxx,f]=pmtm(viewchan12,4,nfft,Fs); % Multitaper Method
figure
plot(f,10*log10(Pxx_12),'r-') hold on
plot(f,10*log10(Pxx_13),'r:')
title(['Engine # ',num2str(engine),' Welch\prime s Power Spectral Density Estimate for Vibration Sensor 1 and 2','FontSize',12])
xlabel('Frequency in Hertz','FontSize',12)
ylabel('Power Spectral Density (dB)','FontSize',12)
set(gca,'XLim',[0 375])

% Compute and Plot the Cross-Spectral Density
[Cxy,f]=cscd(viewchan12(1:1016),accel_total,nfft,Fs,window,noverlap);
figure
set(gcf,'NumberTitle','off','Name','University of Windsor Engine Monitoring - Matthew Bitzer')
plot(f,10*log10(Cxy),'red') grid on
zoom on
set(gca,'XLim',[0 375])
title('Cross Spectral Density Estimate')
xlabel('Frequency in Hertz')
ylabel('Cross Spectrum Density Magnitude (dB)')

% Compute and Plot the Coherence Function Estimate
[Cxy,f] =
cohere(viewchan12(1:1016),accel_total,nfft,Fs,window,noverlap);
figure
set(gcf,'NumberTitle','off','Name','University of Windsor Engine Monitoring - Matthew Bitzer')
plot(f,Cxy,'red') grid on
zoom on
set(gca,'XLim',[0 375])
title('Coherence Estimate')
xlabel('Frequency Estimate')
ylabel('Coherence Function Estimate')
APPENDIX C

Piston Ring Model Simulation Plots
Figure C.1. Simulated Force on Piston Rings.
Figure C.2. Simulated Vibration of Upper Compression Ring.

Figure C.3. Frequency Plot of Simulated Vibration of Upper Compression Ring.
Figure C.4. Simulated Vibration of Lower Compression Ring.

Figure C.5. Frequency Plot of Simulated Vibration of Lower Compression Ring.
Figure C.6. Simulated Vibration of Oil Control Ring.

Figure C.7. Frequency Plot of Simulated Vibration of Oil Control Ring.
Figure C.8. Simulated Vibration of Piston.

Figure C.9. Frequency Plot of Simulated Vibration of Piston.
Figure C.10. Simulated Vibration Total.

Figure C.11. Frequency Plot of Simulated Vibration Total.
APPENDIX D

Filter Design Plots
Figure D.1. Frequency Response Plot for Filter 1.

Figure D.2. Phase Angle Plot for Filter 1.
Figure D.3. Phase Delay Plot for Filter 1.

Figure D.4. Group Delay Plot for Filter 1.
Figure D.5. Z-Domain Zero-Pole Plot for Filter 1.
Figure D.6. Frequency Response Plot for Filter 2.

Figure D.7. Phase Angle Plot for Filter 2.
Figure D.8. Phase Delay Plot for Filter 2.

Figure D.9. Group Delay Plot for Filter 2.
Figure D.10. Z-Domain Zero-Pole Plot for Filter 2.
APPENDIX E

Photographs of Cylinder Bores
Figure E.1. Photograph of a Good Cylinder Bore.

Figure E.2. NCU Engine #1 with Slight Non-cleanup Condition.
Figure E.3. NCU Engine # 2 with Medium Non-cleanup Condition.

Figure E.4. NCU Engine # 3 with Severe Non-cleanup Condition.
APPENDIX F

Measured Vibration Plots
Figure F.1. NCU Engine #1 Vibration Sensor 1.

Figure F.2. NCU Engine #1 Vibration Sensor 2.
Figure F.3. NCU Engine #1 Frequency Plot for Vibration Sensor 1.

Figure F.4. NCU Engine #1 Frequency Plot for Vibration Sensor 2.
Figure F.5. NCU Engine #1 Filtered Vibration Sensor 1.

Figure F.6. NCU Engine #1 Filtered Vibration Sensor 2.
Figure F.7. NCU Engine #1 Frequency Plot for Filtered Vibration Sensor 1.

Figure F.8. NCU Engine #1 Frequency Plot for Filtered Vibration Sensor 2.
Figure F.9. NCU Engine #2 Vibration Sensor 1.

Figure F.10. NCU Engine #2 Vibration Sensor 2.
Figure F.11. NCU Engine # 2 Frequency Plot for Vibration Sensor 1.

Figure F.12. NCU Engine # 2 Frequency Plot for Vibration Sensor 2.
Figure F.13. NCU Engine # 2 Filtered Vibration Sensor 1.

Figure F.14. NCU Engine # 2 Filtered Vibration Sensor 2.
Figure F.15. NCU Engine # 2 Frequency Plot for Filtered Vibration Sensor 1.

Figure F.16. NCU Engine # 2 Frequency Plot for Filtered Vibration Sensor 2.
Figure F.17. NCU Engine #3 Vibration Sensor 1.

Figure F.18. NCU Engine #3 Vibration Sensor 2.
Figure F.19. NCU Engine # 3 Frequency Plot for Vibration Sensor 1.

Figure F.20. NCU Engine # 3 Frequency Plot for Vibration Sensor 2.
Figure F.21. NCU Engine # 3 Filtered Vibration Sensor 1.

Figure F.22. NCU Engine # 3 Filtered Vibration Sensor 2.
Figure F.23. NCU Engine # 3 Frequency Plot for Filtered Vibration Sensor 1.

Figure F.24. NCU Engine # 3 Frequency Plot for Filtered Vibration Sensor 2.
VITA AUCTORIS

Matthew Bitzer was born on July 21, 1976 in Windsor, Ontario, Canada. He graduated from Walkerville Secondary School, Windsor, Ontario in 1995. He enrolled in the Faculty of Engineering at the University of Windsor, Windsor, Ontario and received his Bachelor of Applied Science Degree in Electrical Engineering in 1999. Matthew is currently a candidate for the Masters of Applied Science Degree in Electrical Engineering at the University of Windsor.