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Condition monitoring of reciprocating compressor valves using analytical and data-driven methodologies

Christopher Guerra

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Condition Monitoring of Reciprocating Compressor Valves Using Analytical and Data-Driven Methodologies

by

Christopher J. Guerra

A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Mechanical Engineering

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Christopher J. Guerra

Date
Dedication

To my parents, Mary Kay and Joseph Guerra.
Acknowledgments

This research would not have been possible without Dresser-Rand, who funded this project and provided the necessary equipment to make it possible. Without this funding and compressor this thesis would not have been possible. I would also like to thank Dr. Jason Kolodziej, my thesis advisor, for his support and guidance.
Abstract

Condition Monitoring of Reciprocating Compressor Valves Using Analytical and Data-Driven Methodologies

Christopher J. Guerra

Supervising Professor: Dr. Jason Kolodziej

Condition-based health monitoring systems are a very important addition to machinery to monitor the system and assure it is running at the peak efficiency, to schedule maintenance, and prevent catastrophic failure. Many times these systems are combined with different sensors to predict when service is required for different wear parts and this keeps the machine running optimally. An accurate prediction of health is accomplished by measuring and analyzing different critical parameters and detecting when these parameters deviate from the nominal values. Recently, these systems have started to become more common on industrial compression technology. Typically, reciprocating compressor health monitoring systems only use indirect measurements, P-V diagrams, to monitor the health of the system. This research focuses on improving these monitoring systems.

Specifically this research will focus on three different valve failure modes that are common in reciprocating compressors. They are liquid slugging, valve spring fatigue, and valve seat wear. These faults are investigated first through a system level model to better understand how different subsystem dynamics are related through the compressor. Also an instrument investigation is conducted to determine what types of sensors are the most effective at detecting these faults. The Bayesian classification method is used in conjunction with seeded fault training data to create a classifier that can determine the state of health of the machine. The classification approach can be integrated into health monitoring software to be used in different reciprocating compressors.
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Chapter 1

Introduction

Reciprocating compressors are one of the most common machines used to compress and process gas in industry. Since many of the principles that are used in the design and manufacture of these compressors are tried and true the reliability of them are very high. To increase this reliability, condition monitoring can be used to keep these machines operating at their full potential. Condition monitoring is used to show the important performance factors and how they deviate from the norm. Also condition monitoring can be used to show if it is beneficial to change out the defective part now or wait till the next scheduled maintenance period.

One of the main components inside of the reciprocating compressor is the valve. This includes both the suction and discharge valve. The valves account for 36% of the cases where the compressor needs to be shut down and they account for 50% of the total cost of repair [2]. Both of these facts are the driving reasons to look into improving condition monitoring to better predict when a valve failure will occur and how severe the failure will be.

1.1 Valve Failures in Reciprocating Compressors

Valve failures can happen for a multitude of reasons. Motriuk uses the real case of valve failing in reciprocating compressors at a NOVA Gas Transmission Limited site to list possible reasons. He lists the causes as improper installation of the valve, wide operating conditions, pressure pulsations in the pipe, and valve parameters chosen incorrectly. e was able to rule out improper installation from inspection and wide operating conditions by knowing that the compressor was run at a constant speed [3].
Woollitt explains different factors that result in compressor wear. In his paper he mainly looks into the wear rates of the valve back plate. The actual stopping of the valve on the back plate wears in and removes material. This then causes the valve to lift too high affecting the performance. One of the major factors in the wear rates of the back plate was the hardness of the back plate and the material of the poppet valve. If the back plate was hardened and the material of the poppet valve is plastic this causes the back plate to wear faster. This happens because the back plate material gets stuck in the plastic valve wearing the back plate faster [4].

Matsumra et al. discuss the different types of malfunctions that occur when a valve is failing. The three major effects are delay at opening, fluttering, and delay at closing. Delay at opening causes the pressure differential across the valve to increase to the point where the valve opens violently and slams into the back stop. Fluttering is when the valve oscillates while the fluid entering or leaving causing pressure pulsations through the system. A delay at closing causes the pressure differential across the valve to become strong enough where the valve slams close causing damage on the front stop of the valve [5].

The interested reader can look at two different books by Bloch, *A Practical Guide to Compression Technology* [6] and *Compressors and Modern Process Applications* [7]. Both books have further reading on valve failures.

### 1.2 Condition Monitoring of Reciprocating Compressors

Currently the acceptance of condition monitoring is low for reciprocating compressors. However for both turbo compressors and turbines it is widely used to show when there is an issue with the compressor and when it needs to have maintenance conducted. The amount of people using condition monitoring on reciprocating compressors has been on the rise [2].

To effectively implement condition monitoring into a reciprocating compressor there are important factors that need to be continually observed to prevent damage to both the compressor and the driver. Both the inlet and discharge temperatures and pressures are important to look at to effectively
be able to plot the real time P-V diagram versus an ideal P-V diagram. Also the power draw of the driver can help determine failure onset. If the power draw starts to increase, losses inside of the compressor start to build up and the driver needs to work harder to have similar performance outputs from the compressor [8].

One effective way to implement condition monitoring is to use a probabilistic neural network (PNN). Ahmed et al. was able to use both healthy and unhealthy compressor data to create a PNN of a reciprocating compressor. In their study they were able to predict with accuracy of 100% if a compressor was healthy or unhealthy based on previous tests. In this paper they did not look into real time prediction of the condition of the compressor but rather would take data from a test and determine if the compressor is healthy or unhealthy [9]. Looking at the results from using a PNN it appears to be a possible method of predicting the health of the compressor if it can be implemented in real time applications.

The current and state of the art method of health monitoring is done using a Pressure-Volume diagram that is created in real time as the compressor runs. This is then compared to the theoretical P-V diagram. This comparison allows the operator to determine what component on the compressor has failed. A healthy P-V diagram is shown in Fig. 1.1.

![Figure 1.1: An Ideal Pressure-Volume Diagram](image)

Shown in Fig. 1.1 the Pressure-Volume diagram starting at state 1 the
piston starts to retract until pressure reaches the discharge pressure, $P_d$, at 2 the discharge valve opens and fluid starts to exit the cylinder while the piston is still moving forward maintaining the discharge pressure. At 3 the piston reaches the top dead center position and the discharge valves close and then the piston pulls back until the suction pressure, $P_s$, is reached the suction valve then opens at 4. The piston continues to retract and draw in fluid through the suction valves until the full volume is reached at 1. The process is then repeated [2].

Using the P-V diagram is a very effective way to diagnose faults inside of a reciprocating compressor. By overlaying the real time P-V diagram over the ideal P-V diagram it is easy to see what part of the compressor needs repair [1]. The following figures show different faults and their effect on the P-V diagram, Fig. 1.2 shows a leaking discharge valve and Fig. 1.3 shows a leaking suction valve.

![Figure 1.2: P-V Diagram of a Leaking Discharge Valve](image_url)
On Fig. 1.2 and Fig. 1.3, Pressure is the vertical axis and the volume is on the horizontal axis. In Fig. 1.2 it is clear how the discharge valve affects the process. The cylinder reaches the discharge pressure faster but it takes longer to reach the suction pressure. In Figure 1.3 the suction valve affects the process by causing the cylinder to reach the suction pressure faster than ideal it also causes the cylinder to take longer to reach the discharge pressure. It is also possible to show a leaking piston ring in a P-V diagram. The piston ring leak causes the actual curve to cross the theoretical curve during compression and expansion. All of the deviations from the theoretical curve cause a performance change that can cause damage to the machine [2].

1.3 Computer Modeling

The modeling of the compressor is very important for this research. To completely see how the compressor may act and predict an accurate computer model is needed to show what the compressor would do without running it. This will prevent damage to the compressor and also allow a test to be run anywhere on any computer that has the model. The model will be created in MATLAB with Simulink to allow for the most flexibility.

Manepatil et al. goes through the creation of a compressor model with faults. Their goal is to show the performance effects that leaking suction valves, leaking discharge valves, and a leaking piston ring would have on
the compressor without running the compressor with theses faults. They have a very complete model and also include a flow chart of the checks that are used to allow the program to go to the next step. Also they include cylinder heat transfer in their model to increase the accuracy [10]. Many models assume that there is no heat transfer since the compression process occurs very fast [11].

Elhaj et al. discuss the creation of a computer model of a two stage compressor. In this paper, the compressor is a different configuration then the one that this research is being done on, but they introduce instantaneous angular speed (IAS). They used IAS as the basis for plotting performance data against, but also look at it to determine failures. If the IAS changes it is possible that there is an increase or decrease in resistance in the system that will result in a failure. Also the modeling for the simulation was done in MATLAB. The results from this simulation did match up well with the test data from the compressor that was modeled [12].

Sela briefly mentions computer modeling in his paper. He talks about the correction factors that need to be incorporated into the model to create a more accurate model that can then be used for condition monitoring. To obtain these correction factors a compressor that is known to be at full health has to be run and points have to be collected. These points are then compared to the points that are created by the computer model. Different correction factors are then added into the computer model so the computer model results match up to the known healthy compressor results [8].
Chapter 2

Dresser-Rand Compression Test Cell At RIT

2.1 Background

The ESH-1 reciprocating compressor is Dresser-Rand’s smallest reciprocating compressor. It is currently manufactured in India and is the one of the smallest reciprocating compressors Dresser-Rand manufactures. It has a six inch piston and a five inch stroke and a nominal discharge pressure of 36.5 PSIG. It is run by a 10 hp three-phase electric motor that rotates the compressor’s flywheel at 360 RPM. Figure 2.1 shows a typical cutaway for a reciprocating compressor and a similar view of the ESH-1 at RIT.

Shown in Fig. 2.1 is the location of the inlet and discharge valves that are the focus of this thesis. The four different valves, suction and discharge on both the head and crank cylinder, all are built from the same components. Also shown is where these different components are located in the compressor at RIT. The valve assemblies that are investigated in the research are the suction and discharge valves. These assemblies outside of the compressor are in Fig. 2.2. Figure 2.3 is the cutaway of the valve body, this is the same for the suction and discharge valve.

In Fig. 2.3 the highlighted red area is the poppet, the green is the valve spring, and the blue is the valve seat. All three of these areas will be investigated for three different failure modes. For the suction valve, the high pressure side is to the inlet manifold of the compressor that is at atmospheric pressure. While for the discharge valve the high pressure side is to the cylinder volume. Therefore when the low pressure side is lower then the high
Figure 2.1: Left- Typical Cutaway of a Reciprocating Compressor, Right- Side View of the ESH-1 Compressor at RIT

Figure 2.2: Left- Suction Valve Assembly, Right- Discharge Valve Assembly
pressure side the poppets move open and allow flow through the valve, once this pressure gradient reverses the valve closes.

The compressor is fully instrumented and an operational data acquisition system is installed. Figure 2.4 shows what sensors both analog sensors and thermocouples are installed. These sensors provide a good baseline measurement system to measure performance figures for the reciprocating compressor.

### 2.2 Current Use

Currently the compressor at RIT is used for health monitoring research into bearings, valves, and piston rings. Also multiple Multidisciplinary Senior Design projects funded by Dresser-Rand work on the compressor for different 6 month projects. Previous projects were the installation of the compressor into the test cell, installing the RIT Data Acquisition System (DAQ), and reducing the vibration of the compressor. Also there is investigation into the
The RIT compressor was installed by Multidisciplinary Senior Design Team P11452 in October of 2010. They also installed some basic sensors onto the compressor. The following year Multidisciplinary Senior Design Team P12453 installed a functional DAQ onto the compressor with many sensors that have been used in this thesis.

There continue to have senior design projects work on the compressor. The current teams, P13452 and P13453, are installing an accelerometer on the crank shaft for bearing measurements and a rod drop sensor for piston ring measurements. Also in the coming months Dresser-Rand’s Envision system is going to be installed. This system is what Dresser-Rand currently offers for health monitoring. It will be a valuable tool for future research to use as a baseline to later improve the system.
Chapter 3

Compressor Model

3.1 Derivation of Equations

The computer model was based on areas and regions shown on Fig. 3.1. Figure 3.1 was used for both the control volume analysis and also the spring motion analysis. Throughout this derivation the equations are general and can be applied for either cylinder. At the conclusion of this section a summary of the final modelling equations can be found.

Figure 3.1: Control Volume and Basic Valve Representation of the D-R Dual Acting Reciprocating Compressor
3.1.1 Volume of the Cylinder

As shown in Fig. 3.1 the volume changes as the piston moves through the cylinder. Equation (3.2) shows the piston velocity through the cylinder.

\[ \dot{y} = -L_{crank} \omega \sin(\omega t) \]

\[ - \frac{1}{2} \left( L_{con}^2 - L_{crank}^2 \sin(\omega t)^2 \right)^{\frac{1}{2}} L_{crank}^2 \omega \cos(\omega t) \sin(\omega t) \]

In Eqn. (3.2) \( L_{con} \) and \( L_{crank} \) are the connecting rod and crank length respectively. For the motion equation is defined to be zero at top dead center or when there is minimal head cylinder volume and \( y \) is equal to zero at bottom dead center or when there is minimal crank volume. At the minimum volumes the remaining volume is considered the clearance volume.

By multiplying \( \dot{y} \) by the cross-sectional area of the cylinder the change in volume is found, shown in Eqn. (3.2)

\[ \dot{V}_c = A_c \dot{y} \]  

(3.2)

3.1.2 Valve Motion

Discharge Valve

Figure 3.2 shows the free body diagram for the discharge valve. The valve motion can be represented as a simple 1-D spring-mass-damper system.
Starting with Eqn. (3.3) the total forces on the plate can be related to the motion of the plate.

\[ F = m_d \ddot{x}_d \] \hspace{1cm} (3.3)

Equation (3.4) shows the different forces on the discharge valve substituted into Eqn. (3.3).

\[ F_c + N_d - F_d - k_d(x_d + \delta_d) - k_d \delta_d - c_d \dot{x}_d = m_d \ddot{x}_d \] \hspace{1cm} (3.4)

Now relating the cylinder pressure and the discharge manifold pressure forces to the pressures Eqn. (3.5) and Eqn. (3.6) are defined.

\[ F_d = P_d A_{V_d} \] \hspace{1cm} (3.5)

\[ F_c = P_c A_{V_{dc}} \] \hspace{1cm} (3.6)

Substituting Eqn. (3.5) and Eqn. (3.6) into Eqn. (3.4), Eqn. (3.7) is found.

\[ m_d \ddot{x}_d = [P_c A_{V_{dc}} + N_d - P_d A_{V_d} - 2k_d \delta_d] - c_d \dot{x}_d - k_d x_d \] \hspace{1cm} (3.7)

The normal force, \(N_d\), is only present with \(x_d = 0\), \(N_d\) can be solved as shown in Eqn. (3.8).

\[ N_d = \begin{cases} 
-P_c A_{V_{dc}} + P_d A_{V_d} + k_d \delta_d, & \text{if } x_d = 0 \\
0, & \text{if } x_d > 0
\end{cases} \] \hspace{1cm} (3.8)

Equation (3.7) and (3.8) are the final equation of the discharge valve dynamics.

**Inlet Valve**

Similar to the discharge valve the inlet valve can also be modeled as a 1-D spring-mass-damper system from looking at its free body diagram shown in Fig. 3.3.
Equation (3.9) shows the force balance.

\[ m_i \ddot{x}_i = F_i + N_i - k_i (x_i + \delta_i) - F_c - k_i \delta_i - c_i \dot{x}_i \]  \hspace{1cm} (3.9)

Once again relating the cylinder pressure and inlet pressure forces to the pressures Eqn. (3.10) and Eqn. (3.11) are defined.

\[ F_i = P_i A_{Vi} \]  \hspace{1cm} (3.10)

\[ F_c = P_c A_{Vi_c} \]  \hspace{1cm} (3.11)

Next substituting Eqn. (3.10) and Eqn. (3.11) into Eqn. (3.9), Eqn. (3.12) is found.

\[ m_i \ddot{x}_i = [P_i A_{Vi} + N_i - 2k_i \delta_i - P_c A_{Vi_c}] - c_i \dot{x}_i - k_i x_i \]  \hspace{1cm} (3.12)

Like the normal force on the discharge valve the normal force on the inlet valve, \( N_i \), is only present when \( x_i = 0 \), \( N_i \) can be solved as shown in Eqn. (3.13).

\[
N_i = \begin{cases} 
P_c A_{Vi_c} + k_i \delta_i - P_i A_{Vi}, & \text{if } x_i = 0 \\
0, & \text{if } x_i > 0 
\end{cases} \hspace{1cm} (3.13)

Equations (3.12) and (3.13) are the final equations for the inlet valve dynamics.
3.1.3 Mass Flow

The mass flow for this system can be delivered from the control volume analysis in Fig. 3.1.

Equation (3.14) shows the continuity equation.

\[
\dot{m} = \dot{m}_i - \dot{m}_d + \dot{m}_{\text{leak}_i} + \dot{m}_{\text{leak}_d} + \dot{m}_{\text{leak}_{PR}} \tag{3.14}
\]

In Eqn. (3.14) the three leakage terms are the leakage through the inlet valve, discharge valve, and the piston ring. For this preliminary simulation the mass flow through the valves will be represented by a flow through a converging nozzle. A typical representation of flow through a converging nozzle is given by Eqn. (3.15) [13].

\[
\dot{m} = \frac{AP_0}{\sqrt{RspT_0}} \sqrt{\frac{2k}{k-1}} \left[ \left( \frac{P}{P_0} \right)^{\frac{2}{k}} - \left( \frac{P}{P_0} \right)^{1+\frac{1}{k}} \right] \tag{3.15}
\]

For both the inlet and discharge valve flow equations, the area is proportional to the amount the valve is open. Equation (3.16) shows the mass flow though the inlet valve, and Eqn. (3.17) shows the mass flow through the discharge valve.

\[
\dot{m}_i = \frac{x_i}{x_{\text{max}_i}} \frac{A_iP_i}{\sqrt{RspT_i}} \sqrt{\frac{2k}{k-1}} \left[ \left( \frac{P_c}{P_i} \right)^{\frac{2}{k}} - \left( \frac{P_c}{P_i} \right)^{1+\frac{1}{k}} \right] \tag{3.16}
\]

\[
\dot{m}_d = \frac{x_d}{x_{\text{max}_d}} \frac{A_dP_c}{\sqrt{RspT_c}} \sqrt{\frac{2k}{k-1}} \left[ \left( \frac{P_d}{P_c} \right)^{\frac{2}{k}} - \left( \frac{P_d}{P_c} \right)^{1+\frac{1}{k}} \right] \tag{3.17}
\]

The flow area is a function of the valve motion. Equation (3.18) shows this relation for both the inlet and discharge valve.

\[
A_{i,d} = x_{i,d} \pi d_v \text{valve} \tag{3.18}
\]
\[
\dot{m} = \frac{x_i}{x_{\text{max}i}} \frac{A_i P_i}{\sqrt{R_{sp} T_i}} \left[ \frac{2k}{k - 1} \left[ \left( \frac{P_c}{P_i} \right)^{\frac{2}{k}} - \left( \frac{P_c}{P_i} \right)^{1 + \frac{1}{k}} \right] \right] \tag{3.19}
\]

\[
- \frac{x_d}{x_{\text{max}d}} \frac{A_d P_c}{\sqrt{R_{sp} T_c}} \left[ \frac{2k}{k - 1} \left[ \left( \frac{P_d}{P_c} \right)^{\frac{2}{k}} - \left( \frac{P_d}{P_c} \right)^{1 + \frac{1}{k}} \right] \right] + \dot{m}_{\text{leak}_i} + \dot{m}_{\text{leak}_d} + \dot{m}_{\text{leak}_{PR}}
\]

Shown in Eqn. (3.19) the \(\dot{m}_{\text{leak}}\) terms can be set to zero for basic simulations or can be modeled to represent a valve leakage or piston ring leakage. These terms will be modified as different valve failures are modeled.

### 3.1.4 Entropy

#### Inside of the Cylinder

For this model the entropy was chosen as a state variable due to the ease of tracking it through the model. From the entropy the temperature can be found easily. Starting with a control volume entropy rate balance shown in Eqn. (3.20) the entropy rate balance inside of control volume is shown [14].

\[
\frac{dS_c}{dt} = \sum_j \frac{\dot{Q}_j}{T_j} + \sum_i \dot{m}_i s_i - \sum_d \dot{m}_d s_d + \dot{\sigma} \tag{3.20}
\]

Equation (3.20) the rate of entropy change is equated to the rates of entropy transfer plus the rate of entropy production. In this case there are three different types of entropy transfer, and no entropy production. The first term is the entropy transfer of the system from heat transfer, the second is the rate entropy transfer proportional to the mass flow in the system, and the third term is the rate of entropy production.

The first type is the transfer from the air in the cylinder to the cylinder wall. This is shown as Eqn. (3.21).

\[
\frac{\dot{Q}}{T_c} = H \left( \frac{T_w}{T_c} - 1 \right) \tag{3.21}
\]
In Eqn. (3.21) $H$ is the heat transfer coefficient between air and metal.

The second form of entropy transfer comes from the energy balance for the control volume. Equation (3.22) is the 1st Law of Thermodynamics where kinetic and potential energies are assumed zero, this is then reduced to Eqn. (3.23) which relates it to the enthalpies.

$$\frac{\dot{Q}}{\dot{m}} - \frac{\dot{W}}{\dot{m}} = u_c - u_i$$

(3.22)

$$\frac{\dot{Q}}{T_c} = \frac{h_i - h_c}{T_c} \dot{m}_i$$

(3.23)

The final part of Eqn. (3.20) is shown in Eqn. (3.24) as the rate of entropy production.

$$\dot{\sigma} = \dot{m}s_c$$

(3.24)

Finally substituting Eqn. (3.21), Eqn. (3.23), and Eqn. (3.24) into Eqn. (3.20), Eqn. (3.25) is found.

$$\frac{dS_c}{dt} = H \left( \frac{T_w}{T_c} - 1 \right) + \frac{h_i - h_c}{T_c} \dot{m}_i + \dot{m}s_c$$

(3.25)

**Cylinder Wall**

From Eqn. 3.20, the cylinder wall can be modeled as a closed system. Since the wall is solid there is no mass flow and Eqn. 3.26 is the result.

$$\frac{dS_w}{dt} = \sum_i \frac{\dot{Q}_i}{T_i} + \dot{\sigma}$$

(3.26)

In Eqn. (3.26) $\frac{\dot{Q}_i}{T_i}$ is the entropy change that occurs between the boundary of the system and $\dot{\sigma}$ is the entropy that is created within the boundary that is irreversible. In this case $\frac{\dot{Q}_i}{T_i}$ is both the transfer from the air that is being compressed to the cylinder wall and from the cylinder wall to the environment. In this system there are also irreversibilities from the friction between the piston rings and the cylinder wall. Equation (3.27) shows the final equation
for the entropy rate change for the cylinder wall.

\[
\frac{dS_w}{dt} = H \left( \frac{T_c}{T_w} - 1 \right) - H_\infty \left( 1 - \frac{T_\infty}{T_w} \right) + \frac{P_F|\dot{V}_c|}{T_w} \quad (3.27)
\]

In Eqn. (3.27) the first two terms come from the heat transfer between the gas in the cylinder and the cylinder jacket and the heat transfer between the cylinder jacket and the environment respectively. The last term is from the irreversibilities from the piston rings rubbing on the cylinder wall.

### 3.1.5 Manifold Volume

Starting with the conservation of mass in the manifold Eqn. (3.28) shows the conservation of mass inside of the manifold.

\[
\frac{dm}{dt} = \dot{m}_{in} - \dot{m}_{out} \quad (3.28)
\]

From Eqn (3.28) the \( \dot{m}_{in} \) is given by the mass flow from both discharge valves given by Eqn (3.17). For the discharge of the manifold, it is assumed to be a very large orifice with linear resistance as shown by Eqn (3.29).

\[
\dot{m}_{out} = K_{dis} \delta P = K_{dis} (P_d - P_{tank}) \quad (3.29)
\]

For the manifold volume the ideal gas law is used to find the change in mass in the volume related to pressure and volume. Equation 3.30 shows this.

\[
P V = mRT \quad (3.30)
\]

Taking the derivative of Eqn. (3.30) and knowing that the volume does not change and the discharge gas is constant in temperature Eqn. (3.31) is found.

\[
\frac{dm}{dt} = \dot{P}V \quad (3.31)
\]

Substituting Eqn. (3.31) and (3.29) into Eqn. (3.28), results in:
\[
\dot{P}_{\text{man}} = \frac{\dot{m}_{\text{in}}}{V_{\text{man}}} - \frac{K_{\text{dis}} (P_{\text{man}} - P_{\text{tank}})}{V_{\text{man}}}
\]  

Equation (3.32) is the final state equation for the pressure in the manifold volume behind the discharge valves.

### 3.1.6 Given Properties

The following equations are typical thermodynamic equations and are given here for reference [14].

From the Second Law of Thermodynamics, Eqn. (3.33) is given.

\[
s - s_0 = c_v \ln \left( \frac{T}{T_0} \right) - R_{sp} \ln \left( \frac{\rho_0}{\rho} \right)
\]

Equation (3.35) shows the Ideal Gas Law solved for pressure.

\[
P = \rho R_{sp} T
\]

The enthalpy of the system can be solved for in terms of temperature, pressure, and density, by Eqn. (3.36) assuming specific heat.

\[
h = c_v (T - T_0) + \frac{P}{\rho}
\]
\[ \rho = \frac{m}{V} \quad (3.37) \]

Finally the specific entropy can be expressed as:

\[ s = \frac{S}{m} \quad (3.38) \]

### 3.1.7 Final State Equations

Equation (3.2) is the representation of the piston motion through the cylinder.

Equations (3.39) - (3.44) govern mechanical and thermodynamic performance of the head cylinder of the compressor.

\[ \dot{V}_{c,h} = A_{c,h}\dot{y} \quad (3.39) \]

\[ m_{d,h}\ddot{x}_{d,h} = [P_{c,h}A_{Vd,h} + N_{d,h} - P_{d,h}A_{Vd,h} - k_{d,h}\delta_{d,h}] - c_{d,h}\dot{x}_{d,h} - k_{d,h}x_{d,h} \quad (3.40) \]

\[ N_{d,h} = \begin{cases} 
-P_{c,h}A_{Vd,h} + P_{d,h}A_{Vd,h} + k_{d,h}\delta_{d,h}, & \text{if } x_{d,h} = 0 \\
0, & \text{if } x_{d,h} > 0 
\end{cases} \]

\[ m_{i,h}\ddot{x}_{i,h} = [P_{i,h}A_{Vi,h} + N_{i,h} - k_{i,h}\delta_{i,h} - P_{c,h}A_{Vi,h}] - c_{i,h}\dot{x}_{i,h} - k_{i,h}x_{i,h} \quad (3.41) \]

\[ N_{i,h} = \begin{cases} 
P_{c,h}A_{Vi,h} + k_{i,h}\delta_{i,h} - P_{c,h}A_{Vi,h}, & \text{if } x_{i,h} = 0 \\
0, & \text{if } x_{i,h} > 0 
\end{cases} \]
\[ \dot{m}_h = \frac{x_{i,h}}{x_{\text{max},i,h}} \frac{A_{i,h} P_{i,h}}{\sqrt{R_{sp} T_{i,h}}} \sqrt{\frac{2k}{k-1} \left[ \left( \frac{P_{c,h}}{P_{i,h}} \right)^\frac{2}{k} - \left( \frac{P_{c,h}}{P_{i,h}} \right)^{1+\frac{1}{k}} \right]} \]  
(3.42)

\[ -\frac{x_{d,h}}{x_{\text{max},d,h}} \frac{A_{d,h} P_{c,h}}{\sqrt{R_{sp} T_{c,h}}} \sqrt{\frac{2k}{k-1} \left[ \left( \frac{P_{d,h}}{P_{c,h}} \right)^\frac{2}{k} - \left( \frac{P_{d,h}}{P_{c,h}} \right)^{1+\frac{1}{k}} \right]} + \dot{m}_{\text{leak},i,h} + \dot{m}_{\text{leak},d,h} + \dot{m}_{\text{leak},PR} \]

\[ \frac{dS_{c,h}}{dt} = H \left( \frac{T_{w,h}}{T_{c,h}} - 1 \right) + \frac{h_{i,h} - h_{c,h}}{T_{c,h}} \dot{m}_{i,h} + \dot{m}_{S_{c,h}} \]  
(3.43)

\[ \frac{dS_{w,h}}{dt} = H \left( \frac{T_{c,h}}{T_{w,h}} - 1 \right) - H_{\infty} \left( 1 - \frac{T_{\infty}}{T_{w,h}} \right) + \frac{P_F |\dot{V}_{c,h}|}{T_{w,h}} \]  
(3.44)

Equations (3.45) - (3.50) represent the crank cylinder of the compressor.

\[ \dot{V}_{c,c} = A_{c,c} \dot{y} \]  
(3.45)

\[ m_{d,c} \ddot{x}_{d,c} = [P_{c,c} A_{Vd,h} + N_{d,c} - P_{d,c} A_{Vd,h} - k_{d,c} \delta_{d,c}] - c_{d,c} \dot{x}_{d,c} - k_{d,c} x_{d,c} \]  
(3.46)

\[ N_{d,c} = \begin{cases} -P_{c,c} A_{Vd,h} + P_{d,c} A_{Vd,h} + k_{d,c} \delta_{d,c}, & \text{if } x_{d,c} = 0 \\ 0, & \text{if } x_{d,c} > 0 \end{cases} \]

\[ m_{i,c} \ddot{x}_{i,c} = [P_{c,c} A_{Vi,c} + N_{i,c} - k_{i,c} \delta_{c,h} - P_{c,c} A_{Vi,c}] - c_{i,c} \dot{x}_{i,c} - k_{i,c} x_{i,c} \]  
(3.47)

\[ N_{i,c} = \begin{cases} P_{i,c} A_{Vi,c} + k_{i,c} \delta_{i,c} - P_{c,c} A_{Vi,c}, & \text{if } x_{i,c} = 0 \\ 0, & \text{if } x_{i,c} > 0 \end{cases} \]
\( \dot{m}_h = \frac{x_{i,c}}{x_{max,i,c}} \frac{A_{i,c} P_{i,c}}{\sqrt{R_{sp} T_{i,c}}} \left[ \frac{2k}{k-1} \left( \frac{P_{c,c}}{P_{i,c}} \right)^{\frac{2}{k}} - \left( \frac{P_{c,c}}{P_{i,c}} \right)^{1+\frac{1}{k}} \right] \) (3.48)

\( - \frac{x_{d,c}}{x_{max,d,c}} \frac{A_{d,c} P_{c,c}}{\sqrt{R_{sp} T_{c,c}}} \left[ \frac{2k}{k-1} \left( \frac{P_{d,c}}{P_{c,c}} \right)^{\frac{2}{k}} - \left( \frac{P_{d,c}}{P_{c,c}} \right)^{1+\frac{1}{k}} \right] \)

\[ + \dot{m}_{\text{leak}_{i,c}} + \dot{m}_{\text{leak}_{d,c}} + \dot{m}_{\text{leak}_{PR}} \]

\( \frac{dS_{c,c}}{dt} = H \left( \frac{T_{w,c}}{T_{c,c}} - 1 \right) + \frac{h_{i,c} - h_{c,c}}{T_{c,c}} \dot{m}_{i,c} + \dot{m}_{s,c,c} \) (3.49)

\( \frac{dS_{w,c}}{dt} = H \left( \frac{T_{c,c}}{T_{w,c}} - 1 \right) - H_{\infty} \left( 1 - \frac{T_{\infty}}{T_{w,c}} \right) + \frac{P_{F}|V_{c,c}|}{T_{w,c}} \) (3.50)

### 3.1.8 RIT Compressor Values and Model Results

Using Eqns. (3.39) - (3.50) a computer model was created to simulate the compressor’s performance. Table 3.1 is the list of values that is used in the simulation. The parameters that were estimated were done so to first closely match the data from the compressor. After this was matched the parameters were looked at to make sure that they made engineering sense and would be realistic values for the system.

The compressor has a ten horsepower three-phase electric motor that is connected to a flywheel. The operating gas is air, with inlet conditions of 14.7 PSIA and 70 \( ^\circ \)F. The typical discharge pressure at 50\% loading is 32 PSIA and at 100\% loading it is 52 PSIA. The discharge pressures can be manually controlled with a back pressure valve. For consistency the back-pressure valve was always left at the same position.

Figures 3.4 and 3.5 are the resultant plots. These plots are of the state variables that were used in this model: pressure, temperature, volume, and mass flow.
<table>
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<th>Name</th>
<th>Symbol</th>
<th>Value</th>
<th>Known/Estimated</th>
</tr>
</thead>
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<td>Poppet Mass</td>
<td>m</td>
<td>.005 lbs</td>
<td>Known</td>
</tr>
<tr>
<td>Spring Constant</td>
<td>k</td>
<td>6.25 lbs/ft</td>
<td>Modified</td>
</tr>
<tr>
<td>Damping Coefficient</td>
<td>c</td>
<td>0 lbs/ft²</td>
<td>Estimated</td>
</tr>
<tr>
<td>Head Clearance Volume</td>
<td>V_{clear_h}</td>
<td>25.4 in³</td>
<td>Estimated</td>
</tr>
<tr>
<td>Crank Clearance Volume</td>
<td>V_{clear_c}</td>
<td>25.4 in³</td>
<td>Estimated</td>
</tr>
<tr>
<td>Max Valve Motion</td>
<td>x_{max}</td>
<td>.004 in</td>
<td>Known</td>
</tr>
<tr>
<td>Motor Frequency</td>
<td>ω</td>
<td>6.4 Hz</td>
<td>Known</td>
</tr>
</tbody>
</table>

Table 3.1: Parameters Used for Compressor Simulation
Figure 3.4: Pressure, Temperature, Volume, and Mass Flow versus Time for the Head Cylinder Simulation Results

Figure 3.5: Pressure, Temperature, Volume, and Mass Flow versus Time for the Head Cylinder Simulation Results
3.2 Validation

The main purpose of the computer model is to create a simulation that would be realistic to the actual compressor to test different effects of failures on the computer before running them in the compressor. The primary reason for the goal of the model is to simulate seeded fault conditions rapidly. This saves time and money since the compressor does not need to be on-line and operational to run the model. Also this saves time in scheduling the compressor and prevents undo wear and possible damage to the compressor. The goal of the compressor model was to be able to replicate the Pressure-Volume diagram and also the valve motion of the poppets. The PV diagram can already be measured by the current instrumentation installed on the compressor. A method to measure the valve displacement is needed.

3.2.1 Valve Displacement Measurement

The goal of the valve displacement measurement is to capture the opening and closing event of the poppet in the valve. By knowing this the model can be further refined and provides another measurement that can be compared to validate the model. The fiberoptic sensor was selected for its small size, accuracy, and high frequency sensing ability.

It was determined to install a fiberoptic displacement probe behind one of the poppets on the head discharge valve. This valve was chosen because during initial testing it had the most valve chatter. It is expected that this location will give the best validation results of the computer model.

Off Compressor Test

It is necessary to first test the fiberoptic sensor off the compressor to make sure it functioned correctly and gave predictable results. To accomplish this a bench top fixture is fabricated using the actual discharge valve to assure the sensor will read the poppet and also the correct displacement. The probe is placed so the stand off was about 0.06 inches to keep it in the linear range of the sensor. The valve is then pushed up and down to mimic the actual movement of the poppet while in the compressor. Figure 3.6 shows how the
displacement changes as the valve moves.

Figure 3.6: Valve Motion from Test Rig

Initially the valve is 0.062 inches from the end of the probe then it is at 0.032 inches when the valve is opened. This test is determined a success since the probe was measured to move 0.030” using depth micrometers.

Figure 3.7: Model of the Fiberoptic Sensor Under Valve
Figure 3.7 shows how the valve is located under the poppet and where the measurement is taken.

**Design and Installation of Probe**

After meeting with the probe representative it was determined that an off the shelf probe would not fit the application due to the pressures and flow velocities in the manifold. To combat these pressures and velocities, an armored cable is selected. This armored cable behind the probe will also provide protection for the cable during installation and operation since the cable can not be kinked due to the nature of the fiberoptic cable.

First a solid model was drawn in Solidworks to see how much space is open behind the valve assembly where the probe will be installed. Shown in Figure 3.8 is the cutaway of the solid model with the probe at the required stand off distance.

The probe is held at the correct stand off using a compression fitting that is mounted to the pyramid that is attached to the back of the head discharge valve. To go from the manifold volume to atmosphere there is a 2 inch metal sleeve over the PVC coated cable that goes through another compression fitting. Figure 3.9 is the final installation of the probe outside of the compressor.
Figure 3.8: Solid Model of Valve with Fiberoptic Probe

Figure 3.9: View of the Fiberoptic Probe Mounted, Outside of the Compressor
3.2.2 Comparison with Simulated Results

The simulation results of the system model derived in the previous section is compared with data that is collected by a National Instruments Compact DAQ system. For the comparison the PV diagrams for both cylinders and the valve motion on the head discharge valve are investigated. The PV diagrams are the current method in health monitoring of a reciprocating compressor, by matching this there is reasonable confidence that the model is operating correctly. The valve motion is also investigated as a baseline for future work on the model. The main area of the model that is unknown is the valve dynamics. This comparison will help in the future refinement of the model.

Figures 3.10 and 3.11 show the comparison of the PV diagram. The shape of the curve matches the compression and expansion section. Also the time the compressor is at suction and discharge pressure matches well with the model. In regards to the valve dynamics the model does not match the measured data. The simulation shows one peak then the cylinder equalizes to the discharge pressure where as the measured data shows some valve chatter as the discharge pressure fluctuates. This shows that the model still needs work with the valve dynamics.

Figure 3.12 shows that the general shape and time open for the valve motion is very close to the test with the fiberoptic probe. The two signals are not lined up to better show the valve motion. Between the first and second peak for the measured displacement the offset that is observed is assumed to be from the vibration of the compressor influencing the measurement. It is assumed that there are some fluid effects that could not be modelled with this system model that create the extra oscillations.

From the comparison plots (ref. Fig 3.10 - 3.12) it is clear that the model does a good job at showing the general trend for both the P-V diagram and the valve motion. To make the model better there needs to be more work done with the flow through the valve. In this model a basic flow equation was used since the valve was assumed to be a nozzle with subsonic flow. Instead of subsonic flow, supersonic flow equations can be used to possibly improve results. Also some of the modelling parameters were estimated as
shown in Table 3.1. These parameters can be revisited and iterated on more to give more agreeing results. With more model work and more data these areas and volumes could be estimated better.

One assumption that does not need to be changed is the function for the piston motion. From looking at Fig. 3.13 the simulated and test volume match up very well. Initially the volume was assumed to be a direct sine function but later changed to better represent the piston motion.

Clearly the model can be improved by improving, valve dynamics, assumed parameters, and volume shape. Once a more accurate model is created and validated it will become possible to simulate seeded faults and how they effect the outputted parameters without running the compressor. This will also allow for measurement investigation without installing a sensor into the compressor.
Figure 3.10: P-V Diagram Comparison for Head Cylinder

Figure 3.11: P-V Diagram Comparison for Crank Cylinder
Figure 3.12: Head Discharge Valve Motion Comparison

Figure 3.13: Comparison between Simulation Head Volume and Test Head Volume
Chapter 4

Methodology

To walk the reader through the method that will be used in this thesis for classification a teaching example with created data is going to be shown. The data that are used for the teaching example are very similar to the measured results from the compressor. Figure 4.1 shows the basic flow from the inputs to the system then result into an assigned class.

Figure 4.1: Basic Flow Chart for Classification
4.1 Feature Extraction

The goal of feature extraction is to go from the raw signal to two features that can be classified. In this section the reader will be walked through the feature extraction and Bayesian Classification method with an example case that reflects the data taken from the compressor. For this example Eqns. (4.1), (4.2), and (4.3) are the signals that were used. Figure 4.2 shows the three signals plotted against time where \( x \) is the signal.

\[
x_{\text{healthy}} = 0.5\sin(2\pi 6t) + 0.2\sin(2\pi 110t) + 0.2\sin(2\pi 180t) + 0.25\sin(2\pi 270t)
\]

(4.1)

\[
x_{\text{defect1}} = 0.5\sin(2\pi 6t) + 0.1\sin(2\pi 120t) + 0.2\sin(2\pi 180t) + 0.3\sin(2\pi 260t)
\]

(4.2)

\[
x_{\text{defect2}} = 0.5\sin(2\pi 6t) + 0.05\sin(2\pi 100t) + 0.2\sin(2\pi 180t) + 0.1\sin(2\pi 250t)
\]

(4.3)

Figure 4.2: Raw Signals of Example Plotted

Figure 4.2 shows that it is difficult to tell the difference between the three signals. These signals representative with Eqns. (4.1) - (4.3) have two frequencies where different magnitudes exist between the cases, 100Hz-120Hz
and 250Hz-270Hz, and one frequency where the magnitude is the same, 180Hz. This shape is also observed in the data taken from the compressor.

**Windowing the Data for FFT**

The raw signal that is analyzed from the compressor is not periodic. When data is not periodic Fast Fourier Transforms (FFT) do not do as well since it also includes the lower frequencies that come from the nonperiodic nature of the signal. To improve this, a window with overlap is applied to the data. Windowing with remove the nonperiodic nature from the signal by having each data set start and end at zero. Figure 4.1 shows how when a Hanning window is applied the data changes.

![Figure 4.1: How Windowing Changes the Signal](image1)

To create this windowed signal the window is multiplied by the original signal. One of the disadvantages of the windowing process is the loss of the beginning and end of the signal. To combat this overlapping is done. Overlapping is done to make sure that the ends of the signal are not lost and to give better results. Figure ?? shows how the signal is broken up and overlapped.
Also with the nature of the overlap, the 5 seconds of data instead of having five 1 second segments can now have nine data segments. This allows for the 50 seconds of data to have ninety data sets instead of the original fifty. Typically these different windowed segments would be averaged together after the FFT is taken of each one to get the overall FFT for the signal.

The main effort in applying windowing is selecting a window that will be suited for the application. Figure 4.5 shows how four different windows change the FFT of the inputed signal.
Figure 4.5: Effects of Different Windows on the FFT

Figure 4.5 shows four different windows, from top to bottom: Rectangular, Hanning, Hamming, and Flat Top. In this figure the same 1 second of data is windowed then the FFT is taken. At the lower frequencies, \( \leq 20 \text{Hz} \), the window does remove some of the noise frequencies from the results. The final windowed FFT data is shown in Fig. 4.6.

Figure 4.6: Hamming Windowed FFT’s
Binning of the FFT

After the FFT of the windowed data is created it is broken up into “n” bins. For this research a bin size of 6Hz was taken to assure that any multiples of the operating frequency were in different bins to not skew one bin over another. Range of the FFT that was selected is 20Hz to 350Hz. The lower bound is selected to take the primary operating frequency and the first three harmonics of the operating frequency from skewing the data. While the upper bound is selected since from looking at the results from the FFT there was not much contributions after 350Hz.

The basic principle behind binning is to assign a range of frequencies a value based on the magnitude of the FFT over that range this breaks up the data into specific bins that can then go through a coordinate transformation to reduce the number to a number that can be classified. To calculate the value of the bin the area of the FFT in that range is calculated using the trapezoid rule over that range. Figure 4.7 shows how the FFT is broken up into different bins and how these bins values are related to the FFT.

![Figure 4.7: FFT Showing Bin Ranges and Bin Values](image)

After using the trapezoid rule to compute the area over each bound the bin value is found. Figure 4.8 shows the binning output for the three different example cases.
Figure 4.8 shows how the FFT was brought from a continuous plot into a bar plot that only has a handful of measurements. This binning process makes it easier to look at the FFT and compare it to different cases.

**Principle Component Analysis of the Binned FFT**

If we were to classify the binning results as they were after binning the windowed FFT it would create a classification that could not be visualized. To reduce the number of features from the number of bins to a number of features that can be visualized a coordinate transformation needs to be applied. Principle Component Analysis, PCA, is a popular method to reduce the number of features.

The first step is to create the initial Feature Vector. This is a $m \times n$ matrix where $m$ is the number of data points and $n$ is the number of features. In this case $m$ is the total number of data sets from all three classes and $n$ is the number of bins. The next step is to center each data set around zero.

This PCA matrix is still a matrix the size of $m \times n$. To transform the coordinates the eigenvectors and eigenvalues need to be found. The PCA matrix needs to be square to find the eigenvectors and values, therefore the covariance matrix of the PCA matrix is found. The covariance matrix is a $nxn$ matrix. The covariance matrix related all $n$ features to each other. Next the eigenvectors and eigenvalues are taken of the covariance matrix. The
eigenvalues relate to the percent of the variance each feature accounts for. Table 4.1 shows how the percent variance is found.

<table>
<thead>
<tr>
<th>Feature</th>
<th>Eigenvalue</th>
<th>Percent</th>
</tr>
</thead>
<tbody>
<tr>
<td>z1</td>
<td>0.0083</td>
<td>39%</td>
</tr>
<tr>
<td>z2</td>
<td>0.0033</td>
<td>16%</td>
</tr>
<tr>
<td>z3</td>
<td>0.0004</td>
<td>1.9%</td>
</tr>
<tr>
<td>z4</td>
<td>0.0004</td>
<td>1.7%</td>
</tr>
<tr>
<td>z5-z55</td>
<td>0.0004 - 2E-19</td>
<td>1.6% - 1.3E-15%</td>
</tr>
<tr>
<td>Total</td>
<td>0.0212</td>
<td>100%</td>
</tr>
</tbody>
</table>

Table 4.1: Features from PCA Related to Percent Variance

The eigenvectors are then ordered by eigenvalue from highest to lowest. Depending on how many features are desired those highest eigenvectors are chosen. In this case the final vector needs to have two features for classification therefore a $n \times 2$ vector is created with the eigenvectors, where the 2 can be changed to any amount of features that are desired. This new feature vector made up of the eigenvectors is multiplied with the original PCA vector with the dimensions of $m \times n$ this gives a final resultant vector of $m \times 2$.

The PCA results from the teaching example and the percent variance plot are shown in Fig. 4.1.

![Figure 4.9: PCA Results for Teaching Example](image-url)
4.2 Bayesian Classification

After feature extraction the next step is to classify the results into different classes. To accomplish this a Bayesian Classification method with both quadratic and linear classification types is used.

First the classes need to be decided on. They are assumed to be mutually exclusive. This assumption makes it possible to clearly classify each data set. \( \Omega = (\omega_1 \ldots \omega_K) \) is the set of K mutually exclusive classes. For the teaching example, there are three classes, Nominal, Degraded 1, and Degraded 2. These classes are the levels of degradation for the different failure modes.

Typically there is some knowledge about the system and one class is more likely than the others. The Prior Probability adds weight to the more likely class and penalizes the less likely classes. If there is no knowledge of the system each of the classes are weighted the same. Equation 4.4 shows the properties of the Prior Probability that it needs to add up to 1.

\[
\sum_{i=1}^{K} P(\omega_i) = 1 \quad (4.4)
\]

The input to the classifier is a measurement vector \( z \). It is assumed that there is some noise that occurs when the measurements are taken. This noise is covered from the probability density function of \( z \). Since both the training data that created the bounds and the new measurements were taken on the same machine with the same sensor it is assumed that all of the measurements are effected the same. For this research a Normal Gaussian distribution is assumed. Equation (4.5) is the Normal Gaussian Distribution.

\[
p(z|\omega_k) = \frac{1}{\sqrt{(2\pi)^N |C_k|}} e^{xp} \left(-\frac{(z - \mu_k)^T C_k^{-1} (z - \mu_k)}{2}\right) \quad (4.5)
\]

In Eqn (4.5), \( \mu_k \) is the mean and \( C_k \) is the covariance matrix for each class. These are calculated from the training data set for each class. Equation (4.5) is also known as the conditional probability function where the
result is the probability that an element from \( z \) is apart of class \( \omega_k \).

To get the final classification both Eqn. (4.4) and (4.5) are multiplied together, and the maximum over the different classes is found.

\[
\hat{\omega}_{MAP}(z) = \arg \max_{\omega \in \Omega} \{ p(z|\omega) P(\omega) \} \tag{4.6}
\]

Equation (4.6) is also known as the MAP classifier, or the maximum a posteriori probability classifier. Since it is assumed that it is equal prior probability, Eqn (4.6) reduces to:

\[
\hat{\omega}_{MAP}(z) = \arg \max_{\omega \in \Omega} \left\{ \frac{1}{\sqrt{(2\pi)^N|C_k|}} \exp \left( -\frac{(z - \mu_k)^T C_k^{-1} (z - \mu_k)}{2} \right) \right\} \tag{4.7}
\]

Equation (4.7) is also known as the Quadratic Classifier. This is because the bounds for the classes are quadratic surfaces in the \( z \)-direction when looking at the x-y plane. If in Eqn (4.7) the covariance matrix, \( C_k \) was assumed constant over the classes the Linear Classifier is found.

\[
\hat{\omega}_{MAP}(z) = \arg \max_{\omega \in \Omega} \left\{ \frac{1}{\sqrt{(2\pi)^N|C_k|}} \exp \left( -\frac{(z - \mu_k)^T C_k^{-1} (z - \mu_k)}{2} \right) \right\} \tag{4.8}
\]

Equation (4.8) is the Linear Classifier. Like the Quadratic Classifier it is named for the planar surfaces in the \( z \)-direction that are used as the bounds for the classes.

Figure 4.10 is the result from the quadratic classifier and Fig. 4.11 is the result from the linear classifier.
Figure 4.10: Quadratic Classification for the Teaching Example

Figure 4.11: Linear Classification for the Teaching Example
Chapter 5

Seeded Fault Testing and Classification

5.1 Seeded Fault Testing

The main idea of seeded fault testing is where a fault or failure is introduced into the environment and the change from healthy is observed, by introducing the same failure but at different degrees of failure. The different degrees of failures are all observed with the same instrumentation set to assure the different sets of data can be compared. These failures are introduced in a controlled environment to ensure that the machine is not damaged any further. The main goal of this thesis is to use the results from the seeded fault tests to then classify if the compressor is healthy or not.

5.1.1 Types of Faults and Testing Methodology

For this seeded fault testing there are three different faults that will be investigated. The first failure is liquid slugging. Liquid slugging occurs when a liquid gets into the cylinder and during the compression cycle the force of the liquid trying to compress destroys poppets in a localized area. The second failure mode is valve springs wear. This gives the poppet a weaker spring behind it allowing for slower closing and faster opening. The third is the valve seat wearing down from repeated impact and free rotation from the poppet. This then creates more lift, in turn greater flow area, for the poppet.

For the failure mode related to spring fatigue there are three different conditions that are being investigated, nominal, degraded, and missing or
Table 5.1: List of Springs for Seeded Fault Testing

<table>
<thead>
<tr>
<th>Spring</th>
<th>k-value</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stiff</td>
<td>2.5 lb/in</td>
<td>Red</td>
</tr>
<tr>
<td>Nominal</td>
<td>1.25 lb/in</td>
<td>White</td>
</tr>
<tr>
<td>Missing/Destroyed</td>
<td>0 lb/in</td>
<td>N/A</td>
</tr>
</tbody>
</table>

destroyed springs. Over a spring’s life of repeated compression and expansion the spring wears out and provides less resistance for the poppet as it moves. Also due to some of the environments that the springs are in they can corrode and eventually break completely. Table 5.1 shows the different types of springs that will be used for the seeded fault testing. Where the k-value is the linear spring constant, and the color is the color that they are painted when shipped from Dresser-Rand to keep the different springs easily identifiable.

For seeded fault testing to keep everything consistent the spring failures were run with healthy poppets. Also it was assumed that all sixteen springs in the valve would degrade at the same rate therefore there were only tests run with the same spring in the valve.

The failure of wearing the valve seat occurs when the poppets that are made out of plastic get metal fragments on the bottom of them. Then as the poppets open they twist slightly due to the spring compression and over time wear out the valve seat. Since machining the valve seat is not possible it was decided to instead machine the poppets down. Figure 5.1 shows how by machining the poppets does not change any of the dynamics of the valve and simulates valve seat wear.

Figure 5.1: Comparison of Machining the Valve Seat versus the Poppet
For the valve seat wear there were three degrees of failure that were investigated. First was the healthy poppet at full size of 0.700 inches in height, the second case was 1/32” shorter then the healthy, and the third case was 1/16” shorter then the healthy poppet. These values were selected due to typical wear over the life of the valve. Figure 5.2 shows how the flow area changes from the healthy to the 1/32” short to the 1/16” short. In all seeded fault testing with the short poppets it was assumed that all of the poppets would wear the valve seat at the same rate. This means that the valves were always run with either all healthy, all 1/32” short, or all 1/16” short poppets.

![Image](image.png)

Figure 5.2: Comparison of Valve Wear and Flow Area

The testing was conducted on three different valves on the compressor. The temperature data was taken on the head discharge valve. The vibration testing was done on the head suction valve due to ease of access, and since it was not necessary to then seal how the signal wire is leaving the compressor since the suction side is at atmospheric pressure. Finally the dynamic pressure data was taken on the crank discharge valve to allow isolation of the measurement from the other discharge valve. While running at half load the crank cylinder is the active cylinder, by putting the dynamic pressure probe on the crank discharge valve we were able to eliminate the influence that the head discharge valve might give.

For the thermocouple testing data was taken for about two hours at 2Hz. This allowed for a good amount of data point where we could not miss any spikes in temperature but not so much that we were left with massive data files. For both the vibration and dynamic pressure testing data was taken at 10kHz for 50 seconds. The 50 seconds of data was then broken down into 50 separate 1 second data files allowing 50 data points. This allowed to have 50 separate data sets that could then be used for classification. The
<table>
<thead>
<tr>
<th>Sensor</th>
<th>Location</th>
<th>Frequency</th>
<th>Time</th>
<th>Faults Tested</th>
</tr>
</thead>
<tbody>
<tr>
<td>Thermocouple (4x)</td>
<td>H. Discharge</td>
<td>2 Hz</td>
<td>2 hr</td>
<td>Liquid Slugging</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>H. Suction</td>
<td>10 kHz</td>
<td>50s</td>
<td>Springs and Valve Seat Wear</td>
</tr>
<tr>
<td>Dynamic Pressure</td>
<td>C. Discharge</td>
<td>10 kHz</td>
<td>50s</td>
<td>Springs and Valve Seat Wear</td>
</tr>
</tbody>
</table>

Table 5.2: List of Sensors with Location and Data Collection Information

Sampling rates were chosen based on the ability of the sensor but also they were chosen high enough so a FFT of the data could be done and have reasonable resolution. Table 5.1.1 shows the different sensors, what frequency they were sampled, and time of the test.

5.1.2 Thermocouple Testing

One major failure of the poppet valves is liquid slugging. The goal of installing thermocouples behind the discharge of the valve was to measure the temperature difference between the leakage flow through the missing/destroyed poppets and the manifold’s ambient pressure. Figure 5.3 shows the location of the thermocouples behind on the pyramid.

The goal of installing the thermocouples in the four corners it is thought that a temperature distribution could be identified. With the highest temperature where the missing poppets are. The higher temperature is leaked from the cylinder through the missing poppet and into the cooler manifold volume behind the valve.

For the thermocouple testing there were three separate cases run. First all healthy poppets were installed into the head discharge valve. Second, four poppets were removed from the head discharge valve in one corner to represent a serious liquid slugging failure. Finally, only one poppet was removed from the valve representing a minor liquid slugging failure.

For the first two cases the compressor is run at full load until the four thermocouple temperatures reached steady state. This takes about two hours to reach. For the single missing poppet case the compressor is run for an hour at full load then is turned to half load for a half an hour then turned back to full load for another hour. This special case was created to investigate the start up that is observed in the four poppet missing case. The goal is to see
if after the four thermocouples reach steady state to cool the compressor
down slightly by running at 50% load and see if the same start up trend is
observed when the compressor is turned to 100% load.

Figures 5.4, 5.5, and 5.6 show the full run trends for the three different
cases. From Figs. 5.4 - 5.6 it is evident that the final steady state temperature
for the thermocouples is different in all three cases. For the three cases the
steady state temperatures is 210 °F, 130 °F, and 195 °F respectively. This
happens because by adding in this discharge valve leakage the compressor
is unable to reach the same pressure as if there were no poppets missing
with not adding any additional back pressure.

The most interesting trend is witnessed in Fig. 5.6 at both start up and
the transition between half loading to full loading. It is evident that thermo-
couple 1 reads higher then the other three thermocouples. This shows that
there is leakage from the cylinder into the discharge volume through the
discharge valve. A zoomed view of the transition and the load change are
shown in Fig. 5.7. The initial divergence of the thermocouples is observed
on start-up. It was then investigated if there would still have a similar effect

Figure 5.3: Thermocouple Locations on Pyramid
when the compressor was at operating temperature. The missing poppet was directly above thermocouple 1 showing that leakage does indeed have a temperature effect on the discharge temperature.

The major issue with this failure modes that were tested with the thermocouples was that the discharge tank never is able to reach operating pressure of 37 PSIG. This not only contributed to a lower discharge temperature but also a more visual reasoning for the failure that the tank did not pressurize fully. Also, with this monitoring method was after about five minutes all of the thermocouples came to about the same temperature reading likely due to the slow response of the thermocouples and the eventual warming of the surrounding metal. Therefore if the event was not captured most likely the temperature divergence would not be witnessed.

One issue with this testing was the poppet would not be missing before the compressor started. Liquid slugging occurs during operation. This leads to some questions on would the tank stay pressurized or if the temperature divergence be witnessed? It is assumed that there would be a temperature spike on the thermocouple closest to the leak. This is shown from the load change for the one missing poppet test shown in Fig. 5.7. That shows that even when the compressor is at operating temperature there is still a temperature divergence similar to the one that is shown at start up.

Regarding the pressure in the tank that could possibly stay the same in a larger setting. Many times these compressors run in series with multiple cylinders getting to a final pressure. Therefore depending on how much instrumentation is on the compressor a small pressure change from one cylinder may not effect the entire compressor substantively.
Figure 5.4: Temperature Trend Behind a Healthy Discharge Valve

Figure 5.5: Temperature Trend Behind a Discharge Valve Missing Four Poppets
Figure 5.6: Temperature Trend Behind a Discharge Valve Missing One Poppet

Figure 5.7: A Zoomed View of the Temperature Profile for the Discharge Valve with One Poppit Missing
5.1.3 Vibration Testing

For the vibration testing the head suction valve of the compressor is selected since the signal wires leaving through the compressor inlet would not have to be sealed. The accelerometer is selected because of its size and also the ability to be stud mounted. Figure 5.8 shows how the accelerometer is mounted to the valve with and without the unloader fingers.

![Accelerometer Mounted on the Head Suction Valve, Left - With Fingers, Right - Without Fingers](image)

The accelerometer is mounted using a stud mount that attaches to the top of a modified center bolt that holds the valve assembly together. It is mounted such that up is positive and down is negative. Overall the installation takes about twenty minutes and the accelerometer is small enough that it does not impede flow into the suction valve. For the vibration test the compressor had to be run at 100% loading due to the fact that when running at 50% loading the head cylinder is unloaded.

The goal for the accelerometer is to be able to measure the difference poppet impact forces. Changing the spring constant on the valve spring it is expected that the stiffer the spring the slower it would impact the valve seat, while giving the poppet more distance to travel to the valve seat it was expected that the force would be higher since it would impact the valve seat at a higher speed. For failure modes there are three degrees of failures. For spring fatigue healthy springs, stiff springs with twice the spring constant, and no springs are used. For valve seat wear healthy, 1/32” wear and 1/16” wear conditions are used. There is no combination of failures since the end
goal was to see if it is possible to pick up the difference with the accelerometer even though the compressor vibrates violently.

Figures 5.9 and 5.10 show the raw accelerometer signal for both the spring fatigue and the valve seat wear failure.

Figure 5.9 the expected outcome agrees with the actual results. The stiffer springs have the lowest impact force, while the nominal springs are next and then no springs show the highest force. Similar to the spring fatigue case looking at Fig. 5.10 also agrees with the predicted results. The 1/16” wear shows the highest force then the 1/32” wear then the nominal case having the smallest force. Observing the magnitudes of the raw signal it is also easy to see that both the opening event and closing event is captured.

One of the main effects other than the force the poppet impacts the valve seat is the effect that different springs and travel distance have on the P-V diagram. Figure 5.11 and 5.12 show the P-V diagram for the spring fatigue and valve seat wear failures respectively.

Figure 5.11 shows how the P-V Diagram changes drastically between something as small as a different spring constant. With the higher spring constant it requires a greater differential pressure on the suction valve to keep the poppets open. This greater suction pressure then also changes the entire P-V diagram. Where on the other hand the P-V diagram (ref. Fig. 5.12) for the different valve seat wear conditions does not show a large change between the different wear conditions.

Figure 5.13 and 5.14 show the FFT of the data. The FFT’s were taken to look at the frequency spectrum and if there are any differences between the cases that is not observable from the raw signal.

From looking at Fig. 5.13 and 5.14 there are no decipherable frequencies or magnitudes that are different between the different conditions. There needs to be more work done for the accelerometer to make it a viable sensor to pick up the different failures.
Figure 5.9: Raw Accelerometer Signal on Head Suction Valve For Spring Fatigue

Figure 5.10: Raw Accelerometer Signal on Head Suction Valve For Valve Seat Wear
Figure 5.11: P-V Diagram showing Different Spring Conditions on Head Suction Valve

Figure 5.12: P-V Diagram showing Different Valve Seat Wearing Conditions on Head Suction Valve
Figure 5.13: FFT of the Accelerometer Signal for Different Spring Conditions from the Head Suction Valve

Figure 5.14: FFT of the Accelerometer Signal for Different Valve Seat Conditions from the Head Suction Valve
5.1.4 Dynamic Pressure Testing

The dynamic pressure probe is mounted behind the crank discharge valve. This allowed running at both 50% and 100% loading, allowing comparison between the different loading conditions. The dynamic pressure probe used is a PCB 113B28 that has a dynamic pressure range up to 50PSI and a max operating pressure of 200 PSIG. Figure 5.15 shows how the dynamic pressure probe is located behind the crank discharge valve on the pyramid that supports the valve in the compressor.

![Dynamic Pressure Probe](image1)

Figure 5.15: Installation Location of Dynamic Pressure Probe Behind Crank Discharge Valve

The dynamic pressure probe measures the pressure wave that occurs during valve opening event. It is measured as a plus or minus on the ambient pressure around the probe. For this research all of the dynamic pressure readings were centred around zero and only the magnitudes were of interest. Figure 5.16 and 5.17 are the raw data for one second from the dynamic pressure probe for spring fatigue and valve seat wear respectively.
There is no visual queues while looking at the raw data that show a difference between the different failure conditions. Currently for health monitoring in a reciprocating compressor the P-V Diagram is looked at and compared to one that is known to be healthy. This comparison is the determining factor if the compressor is healthy or not. Figure 5.18 and 5.19 show the P-V diagram for the five different cases.

From the P-V diagrams for both failures there is no major difference between the different failure conditions. For the spring conditions there is a slight difference between discharge pressure due to the fact that the stiffer springs require a greater differential pressure to stay open. In industry this discharge pressure is controlled by a back pressure valve, in that case there would not be as large of a difference in the discharge pressures. Also the discharge pressure is about the same for the different valve seat wear conditions but there is a different valve dynamics due to the extra valve travel.

As shown in the previous chapter the data is analysed using a frequency response technique. Figures 5.20 and 5.21 show this result using the Hannning window to obtain better results. This frequency response result allows the data to be better understood in the frequency domain.

In Figs. 5.20 and 5.21 there are different frequency magnitudes around 100Hz and 280Hz for all cases. Between the difference in the FFT as a whole and those two frequencies there is a way that the signals can be categorized into different conditions.
Figure 5.16: Raw Data for Dynamic Pressure of Different Spring Conditions, Left - 50% Loading, Right - 100% Loading

Figure 5.17: Raw Data for Dynamic Pressure of Different Valve Seat Wear Conditions, Left - 50% Loading, Right - 100% Loading
Figure 5.18: P-V Diagram Different Spring Conditions in Head Discharge Valve, Left - 50% Loading, Right - 100% Loading

Figure 5.19: P-V Diagram of Different Valve Seat Wear Conditions in Head Discharge Valve, Left - 50% Loading, Right - 100% Loading
Figure 5.20: FFT of Dynamic Pressure For Different Spring Conditions in Head Discharge Valve, Left - 50% Loading, Right - 100% Loading

Figure 5.21: FFT of Dynamic Pressure For Different Valve Seat Wear Conditions in Head Discharge Valve, Left - 50% Loading, Right - 100% Loading
5.2 Results

For the following cases the same process in classification that is outlined earlier is followed. For each case both 50% loading and 100% loading is investigated. For the classification 45 data points are used to create the training data then another 45 data points are used to validate the classification.

5.2.1 FFT Windowing Investigation

Before any data is processed a FFT windowing investigation is conducted to decide the best resolution for the FFT, and what window should be applied to the data to provide the best results. The four windows that are investigated are Rectangular, Hanning, Hamming, and Flat Top.

Figure 5.22: Raw Signal Data Used for FFT Investigation, From Top to Bottom Nominal, Degraded 1, Degraded 2
Figure 5.23: Comparison of Signals with Different Windows Applied, Top to Bottom: Rectangular, Hanning, Hamming, and Flat Top, Left to Right: Windows, Nominal, Degraded 1, and Degraded 2.

Figure 5.24: FFT with Higher Resolution and with Different Windows Results, Top to Bottom: Rectangular, Hanning, Hamming, and Flat Top, Left to Right: Windows, Nominal, Degraded 1, and Degraded 2.
The FFT windowing investigation is conducted to find the best resolution for the FFT and what window is the best for the data. This decision is made based off of the percent variance covered by the first two features from PCA the title about each plot shows this percentage, in Fig. 5.26 and 5.27. Figure 5.26 shows the classification results from the FFT with higher resolution and Fig. 5.27 shows the classification results from the FFT with lower resolution. This data is not classified in this investigation because the classification step does not have any influence on data processing to obtain the best results. The percent variance from the PCA is the main contributor to a successful classification while the classification can be successful for many reasons.

For this research the FFT with higher resolution and the Hanning window is used. It is used for the remaining cases unless otherwise specified.
Figure 5.26: Quadric Classification with the Different Windowed FFT with Higher Resolution, From Left to Right, Top To Bottom, Rectangular Window, Hanning Window, Hamming Window, Flat Top Window

Figure 5.27: Quadric Classification with the Different Windowed FFT with Lower Resolution, From Left to Right, Top To Bottom, Rectangular Window, Hanning Window, Hamming Window, Flat Top Window
5.2.2 Case 1: Spring Fatigue

The first failure mode being investigated is spring fatigue. The first set is run at 50% loading where only the crank cylinder is active. The dynamic pressure sensor that is analyzed in these cases is located behind this valve. Figure 5.28 is the scaled dynamic pressure sensor results from the first run. This is only a 1 second segment of the data to show the basic trend.

![Figure 5.28: Raw Signal for 50% Loading, Dynamic Pressure, Top to Bottom: Nominal, Degraded, and No Springs](image)

Figure 5.28: Raw Signal for **50% Loading**, Dynamic Pressure, Top to Bottom: Nominal, Degraded, and No Springs

Figure 5.29 is the FFT of the raw data shown in Fig. 5.28. The FFT is cut off at 350Hz because there is no meaningful frequencies past 350Hz. The left plots show the FFT without windowing and the right shows the FFT with windowing.
Figure 5.29: The Effect of the Hanning Window has on the FFT at 50% Loading. Left- FFT Before Windowing, Right- FFT After Windowing, Top to Bottom Nominal, Degraded, and No Springs

For binning the frequencies from 20Hz to 350Hz were distributed into 6Hz bins. The lower bound was chosen such that the PCA would not be influenced by the operating frequency and the first harmonics. Figure 5.30 also shows 3 bins of particular interest, Bin 14 (98Hz-104Hz), Bin 27 (176Hz-184Hz), and Bin 42 (266Hz-272Hz). It is assumed that Bin 14 and 42 are from flow dynamics that are not fully understood and Bin 27 captures the third harmonic of 60Hz that comes from electrical noise. That is why Bin 14 and 42 have different magnitudes between the different conditions where as Bin 27 has the same.
Figure 5.30: Binning Results of the FFT with Hanning Window at **50% Loading**, Bin Range From 20Hz to 350Hz with 6Hz Bin Size, Top to Bottom: Nominal, Degraded, No Springs

Figure 5.31: PCA Results from the Hanning Window Data at **50% Loading**, Top: Results from the PCA, Bottom: Percent Variance from the PCA

The bottom plot of Fig. 5.31 shows the contribution to the variance of principle component. In the case of 50% loading for spring fatigue 86% of
the variance is covered by the first two components.

Figures 5.32 - 5.35 show the classification results for spring fatigue at 50% loading. For both the linear and quadratic classification the prior probability, \( P(\omega) \) was equal for each of the three classes. Although both classifications do well if the no spring condition was removed from the data set it could be possible to show better separation of the nominal and degraded spring conditions.
Training (45 pts.)

<table>
<thead>
<tr>
<th>Actual</th>
<th>Nom.</th>
<th>Degrd.</th>
<th>None</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nom.</td>
<td>45/45</td>
<td>1/45</td>
<td>0/45</td>
</tr>
<tr>
<td>Degrd.</td>
<td>0/45</td>
<td>44/45</td>
<td>0/45</td>
</tr>
<tr>
<td>None</td>
<td>0/45</td>
<td>0/45</td>
<td>45/45</td>
</tr>
</tbody>
</table>

Validation (45 pts.)

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Table 5.3: Quadratic Classification Results for Different Spring Conditions at 50% Loading

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Table 5.4: Linear Classification Results for Different Spring Conditions at 50% Loading

Two Bin Classification

From Fig. 5.30 Bin 14 (98Hz-104Hz) and Bin 42 (266Hz-272Hz) show the greatest magnitude difference between the three different degrees of spring failures. The goal of the following plots is to investigate if by only using these two bin values in the classification method will create an as accurate classification as the method with the PCA. For this investigation the 50% loading condition for the spring fatigue failure mode is investigated.

The results below show that the two bin classification method is not as effective as the full method outlined earlier. The two bin method classified the correct condition 67.4% of the time, while the PCA method classified the correct condition 97.8% for the validation data sets for both quadratic and linear classifiers. Although the 2 bin method is simpler than the PCA method the results do not make up for this. The 2 bin classification is much worse than the PCA method. Clearly the PCA method effectively accounts for all bins to increase percent classification correct.
Figure 5.36: Quadratic Classification of 2 Bin Dataset for Different Spring Conditions at 50% Loading, Training Data, 8.89% Misclassification

Figure 5.37: Quadratic Classification of 2 Bin Dataset for Different Spring Conditions at 50% Loading, Validation Data, 29.63% Misclassification

Figure 5.38: Linear Classification of 2 Bin Dataset for Different Spring Conditions at 50% Loading, Training Data, 5.93% Misclassification

Figure 5.39: Linear Classification of 2 Bin Dataset for Different Spring Conditions at 50% Loading, Validation Data, 35.56% Misclassification
Table 5.5: Quadratic Classification Only 2 Bins Results for Different Spring Conditions at 50% Loading

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Table 5.6: Linear Classification Only 2 Bins Results for Different Spring Conditions at 50% Loading

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Next the 100% loading condition for the spring fatigue failure is investigated. Figure 5.40 is the raw data for the dynamic pressure sensor. This is only 1 second of the 50 seconds of data taken for this case. In this case five seconds of the data was corrupted during the run, this is why there are only 40 data points for the Training and Validation sets.
Figure 5.40: Raw Signal for **100% Loading** Dynamic Pressure behind Crank Discharge Valve, Top to Bottom- Nominal, Degraded, and No Springs

Figure 5.41: The Effect of the Hanning Window has on the FFT at **100% Loading**, Left- FFT Before Windowing, Right- FFT after Windowing, Top to Bottom- Nominal, Degraded, and No Springs
Figure 5.42: Binning Results of the FFT with Hanning Window at **100% Loading**, Bin Range From 20Hz to 350Hz with 6Hz Bin Size, Top to Bottom- Nominal, Degraded, No Springs

The FFT of the data shown in Fig. 5.41 is binned into 6Hz bins from 20Hz to 350Hz. Similarly to the 50% loading condition there are bins that are of interest shown in Fig. 5.42. Bin 15 (104Hz - 110Hz) and Bin 44 (278Hz - 284Hz) are assumed to be from the flow dynamics, and Bin 27 (178Hz - 184Hz) contains 180Hz which is the third harmonic of electrical noise.
For spring fatigue at 100% loading the PCA was able to cover 84% of the variance with the first two features. The third feature has a contribution of 10%, this could improve the classification but it will also make it more complex to understand. It is not necessary after calculating the classification bounds since the highest misclassification percentage is 2.5%, (ref. Figures 5.44 - 5.47)
Figure 5.46: Linear Classification for Different Spring Conditions at **100% Loading**, *Training Data*, 2.5% Misclassification

Figure 5.47: Linear Classification for Different Spring Conditions at **100% Loading**, *Validation Data*, 1.67% Misclassification

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Table 5.7: Quadratic Classification Results for Different Spring Conditions at **100% Loading**

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Table 5.8: Linear Classification Results for Different Spring Conditions at **100% Loading**
5.2.3 Case 2: Valve Seat Wear

The second failure mode to be investigated is valve seat wear. Figure 5.48 shows the dynamic pressure signal for the 50\% loading condition, this only shows 1 second of the 50 seconds of data that was captured for this loading condition.

Figure 5.48: Raw Signal for **50\% Loading** Dynamic Pressure behind Crank Discharge Valve, Top to Bottom - Nominal Poppets, Degraded 1 (1/32\”), and Degraded 2 (1/16\”)

Figure 5.49: The Effect of the Hanning Window has on the FFT at 50% Loading, Left-FFT before Windowing, Right- FFT after Windowing, Top to Bottom- Nominal Poppets, Degraded 1, and Degraded 2

Figure 5.50: Binning Results of the FFT with Hanning Window at 50% Loading, Bin Range From 20Hz to 350Hz with 6Hz Bin Size, Top to Bottom - Nominal Poppets, Degraded 1, Degraded 2

After the FFT is taken, Fig. 5.49, the data is binned. Similarly to the
spring fatigue failure mode the bins were 6Hz in size and ranged from 20Hz to 350Hz. Unlike the spring fatigue case there ranges of bins that show interest they are Bins 8 - 21 (62Hz - 146Hz) and Bins 40 - 45 (254Hz - 290Hz). Both of the ranges of bins are believed to originate from flow dynamics.

![PCA Results from the Hanning Window Data at 50% Loading](image)

Figure 5.51: PCA Results from the Hanning Window Data at **50% Loading**, Top Results from PCA, Bottom- Variance from PCA

The results from the PCA show that 88% of the variance is covered by the first two features. From Fig. 5.51 it is not beneficial to add in the third feature since it would have less then 5% addition.
Figures 5.52 - 5.55 show the classification results for both the quadratic and linear classifier. The quadratic classifier in Figs. 5.52 and 5.53 appear to be linear classifiers but they appear this way because the bounds have a large curvature.

For the 50% loading condition for valve seat wear the two classification methods have a 100% correct classification. This is the highest percentage correct classification over the two failure modes. Clearly the dynamic pressure probe is an effective sensor for detecting valve seat wear at 50%
loading.

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Table 5.9: Quadratic Classification Results for Different Valve Seat Conditions at 50% Loading

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Table 5.10: Linear Classification Results for Different Valve Seat Conditions at 50% Loading

The final condition that is investigated is 100% loading for the valve seat wear failure mode. Figure 5.56 is the raw dynamic pressure signals for this case. This figure only shows 1 second of data as a representation of the 50 seconds of data that make up this full data set.
Figure 5.56: Raw Signal for **100% Loading** Dynamic Pressure behind Crank Discharge Valve, From Top to Bottom Nominal, Degraded 1(1/32”), and Degraded 2(1/16”)

Figure 5.57: The Effect of the Hanning Window has on the FFT at **100% Loading**, Left FFT before Windowing, Right- FFT after Windowing, Top to Bottom- Nominal, Degraded 1, and Degraded 2
Figure 5.58: Binning Results of the FFT with Hanning Window Valve Seat Wear at 100% Loading, Bin Range From 20Hz to 350Hz with 6Hz Bin Size, Top to Bottom- Nominal Poppets, Degraded 1, Degraded 2

Figure 5.57 shows the FFT results, these results are then binned in 6Hz bins from 20Hz to 350Hz. The result from the binning process is shown in Fig. 5.58. Similar to the 50% loading condition for valve seat wear, there are two ranges of bins that are of interest, Bins 10 - 21 (74Hz - 146Hz) and Bins 41 - 46 (260Hz - 296Hz). It is assumed these frequencies arise from flow dynamics through the valves.
Figure 5.59: PCA Results from the Hanning Window Valve Seat Wear Data at 100% Loading. Top- Results from PCA, Bottom- Variance from PCA

After binning coordinate transformation occurs with PCA. Shown in Fig. 5.59 only 77% of the variance is covered by the first two features. If this was increased to three features the percent variance would increase to 93%.

Figure 5.60: Quadratic Classification for Different Valve Seat Wear Conditions at 100% Loading, Training Data, 17.04% Misclassification

Figure 5.61: Quadratic Classification for Different Valve Seat Wear Conditions at 100% Loading, Validation Data, 19.26% Misclassification
As shown in Figs. 5.60 - 5.63 the classification suffers due to the low percentage of variance covered by the two features. For this condition the misclassification ranges from 17% to 31%. These results conclude that the head cylinder influences the measurement. It would be possible to install another dynamic pressure sensor on the head discharge valve and by using the two sensors in conjunction improve the overall result. This is an area that should be investigated more.

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Table 5.11: Quadratic Classification Results for Different Valve Seat Conditions at 100% Loading
Table 5.12: Linear Classification Results for Different Valve Seat Conditions at 100% Loading

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5.3 Summary

Overall the dynamic pressure sensor does a good job at classification for both failure modes at 50% and 100% loading. The correct class was identified 93.2% in the validation data sets. By removing the valve seat wear at 100% loading case this percentage increases to 98.7%. These results show that the dynamic pressure sensor is a viable sensor to install onto a reciprocating compressor to monitor valve health.

In both loading conditions for both failure modes the FFT highlights two frequencies of interest, 110Hz and 280Hz. Both of the frequencies are not multiples of the operating frequency of 6Hz, it is assumed that these frequencies are from the valve flow dynamics. Future work on the compressor model and valve flow can use these frequencies for an investigation to improve both the model and valve flow equations.
Chapter 6

Conclusion

This research based on health monitoring of valve failures in a reciprocating compressor was based on both a computer model and a data driven methodology with the end goal of creating a method that can identify a valve’s health with different defects. Specifically to valve failure modes both spring fatigue and valve seat wear were investigated. There is promise with the computer model and more work needs to be done on it to better understand valve motion and flow through valves better. On the other hand, through seeded fault testing it is possible to determine the different types of failures that valves commonly see.

The computer model did show promise with modeling valve dynamics. Valve dynamics are partially validated and overall the computer model needs more refinement. The current model is able to match the general valve motion shape that is measured by the fiberoptic displacement sensor. The valve dynamics in the current model do create pressure dynamics in the cylinder. Future refinement of the model can be done by incorporating the ability to simulate different failure modes with the ability to output measurements that would be taken by sensors installed on the compressor. This would reduce running time on the compressor that is becoming more difficult to schedule. Also this will allow future research to prove out a sensor before purchasing and installing it. To accomplish this the model needs to leave the systems level and needs to incorporate more complex methods. For example, a CFD investigation will be beneficial to better understand the valve flow.

In this research there are four different sensors that showed promise in the detection of valve health. They are the following:
1. Fiberoptic Displacement Sensor: This sensor is expensive, only able to monitor one valve, and is hard to install. Even with all these negatives against the fiberoptic sensor it is precise and measures the valve’s position directly, which can lead to a measure of valve health. In the future it would be worthwhile to investigate these types of sensors more if the negatives listed previously can be addressed.

2. Thermocouple Array: The array is mounted under the head discharge support pyramid equally distributed circumferentially. Thermocouples are a inexpensive sensor that can have a high level of accuracy if set up correctly. This research showed promise with the temperature measurement except it would only show the failure for a short period of time before all the thermocouples reached the same reading. Like the fiberoptic sensor the thermocouples should be investigated further after the flow characteristics through the different poppets is better understood.

3. Accelerometer: The accelerometer is located on the centerline on the top of the head suction valve. Accelerometers are moderately priced, require extra equipment to run, and are influenced greatly by the motion of the compressor. The accelerometer showed different frequency peaks for the different states of health but it was incredibly noisy from the motion of the compressor. The accelerometer would likely do well on a machine that did not move as severely as the one in this research, since there would be no other shock then the poppet making contact with the valve seat and valve face.

4. Dynamic Pressure Sensor: This sensor is located on the centerline behind the crank discharge valve. The dynamic pressure sensor is moderately priced and like the accelerometer needs a signal conditioner to run. The dynamic pressure was the best out of the four sensors in detecting the differences between the different health cases. It was able to classify correctly 93.2% for the two different failure modes. The dynamic sensor that was used in this research could be used in different sizes of reciprocating compressors. There are also different models
of the sensor that have harsh environment ratings and higher pressure capabilities.

The method used to take the raw signal from the dynamic pressure sensor is not very complex which helps with the ability for it to run in as the compressor is running. The raw dynamic pressure data is first transformed into the frequency domain and a Hanning window is applied to increase the accuracy. The frequencies are then binned from 20Hz to 350Hz. A coordinate transformation takes place that takes the 40 plus bins and transforms them into two features, \( z_1 \) and \( z_2 \). After the training data is taking it is run through the algorithm the bounds of the classes are then set using both quadratic and linear Bayesian Classifiers. The training data only needs to be taken once for each condition. Once the training data is taken the classification bounds that are created by it can be used as long as the conditions that were present at the time of taking the data remains constant. After that it is possible to take data from the compressor and run it through the algorithm and determine the state of health of the valves.

Condition monitoring is becoming a highly recommended addition to different types of machinery. In regards to reciprocating compressors it is a relativity new addition. With the addition of the method outlined in this research, the health of valves can now be incorporated into a health monitoring software package with the appropriate sensor installed on the reciprocating compressor. Previously there were only limited methods that could accurately determine the health of the valves on a compressor.

Going forward a better understanding of the valve flow and continued investigation in sensing techniques should be investigated to bring health monitoring of reciprocating compressor valves to the next level of development. Overall this research was a success in two parts. First a system level model with valve dynamics that showed similar pressure dynamics and valve motion as the actual compressor was created. Secondly, a first algorithm was created using seeded fault testing that can identify different reciprocating valve failures.
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