DIAGNOSTICS USING MACHINE LEARNING FOR AIR BRAKES IN COMMERCIAL VEHICLES

A Thesis

by

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ABSTRACT

To safely introduce any level of autonomy to trucks, the health of their brake systems needs to be monitored continuously. Out-of-adjustment push rods and leakages in the air brake system are two major reasons for increased braking distances in trucks, and result in safety violations. Air leakages can occur due to small cracks or loose/improperly fit couplings which do not affect the overall braking capacity but contribute greatly to increasing the braking lag and reducing the maximum braking torque at the wheels. Similarly, an increased stroke of push rod leads to a larger delay in brake response and a smaller value of the brake torque at the wheels. Currently, the condition of an air brake system is monitored manually by measuring the push rod offset and by inspecting the couplings and hoses of the system for air leakages. These inspections are highly labor intensive, subjective, time consuming and do not accurately quantify how adversely the braking system is affected. Having an on-board diagnostic device that can monitor the health of air brakes would be crucial in the prevention of road accidents, especially when considering any level of automation and comply with FMSCA safety requirements. The focus of this thesis is to aid the development of such a diagnostic system that facilitates enforcement and pre-trip inspections and continuous on-board monitoring of trucks through the development of a model for its multi-chamber braking system; this model can be used to estimate the severity of leakage and the push rod stroke using real time brake pressure transients. A machine learning model of the air brake system and its experimental corroboration is presented in this thesis.

DEDICATION

To my parents P. S. Ganeshan and Malathy Ganeshan, and my sister Shreethigha for their constant love and support

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I would like to thank the committee chair, Dr. Swaroop Darbha for his inputs throughout this project. It was a privilege to work with a professor of such high academic caliber. I would like to thank him for providing me with the rare opportunity to work on a project such as this. His constant encouragement and words of wisdom and compassion kept me motivated. Not only were the experiences I gained from this work highly valuable, they also helped me realize that I wanted to continue my education and pursue a PhD in Mechanical Engineering.

CONTRIBUTORS AND FUNDING SOURCES

Contributors

This work was supported by a thesis committee consisting of Dr. Swaroop Darbha [advisor], Dr. Sivakumar Rathinam of the Department of Mechanical Engineering and Dr. Shankar P. Bhattacharyya of the Department of Electrical and Computer Engineering

All other work conducted for the thesis was completed by the student independently.

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NOMENCLATURE

IIHS	Insurance Institute for Highway Safety
FMSCA	Federal Motor Carrier Safety Administration
DPS	Department of Public Safety
P_{supply}	Supply Pressure
A_c	Area of the Brake Chamber Diaphragm
k_{spring}	Spring Constant of the Brake Chamber Return Spring
x_d	Displacement of the Brake Chamber Diaphragm
x_0	Effective Pre-load length of the spring
$F_{pushrod}$	Force applied by the pushrod
HP	Horsepower
DAQ	Data Acquisition
FCV	Flow Control Valve
$y_{prediction}$	Output of the model, Leak Velocity Prediction
y_{actual}	Measured Leak Velocity
x_1	Set of all values given to a specific input to the machine learning model
σ_{x_1}	Standard Deviation of all x_1 values
n	Number of Training Data Sets
TTI	Texas Transport Institute

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1. INTRODUCTION

1.1 Background

A study by IIHS indicated that loaded tractors or trailers take 20-40% farther stopping distance than cars [2]. Heavy trucks carry a gross weight of 31,000 lb. or more which bring much larger impact forces into crashes than normal road vehicles. Hence even a 20% change in stopping distance can lead to catastrophic accidents. According to the Federal Motor Carrier Safety Administration (FMCSA), braking problems were an associated cause in the crash in 29% of crashes with large trucks [3]. Given that truck drivers are occasionally fatigued, thus contributing to further delayed response times, it becomes crucial to monitor the state of the pneumatic braking system. The two major factors contributing to failure/ sub-par performance of air brakes are leakage of compressed air from the brake lines, leading to increased response times, and the push rod being out of adjustment [1]. The push rod translates the force from the brake piston to the slack adjuster, which actuates the S-cam of the air drum brakes. The force applied by the push rod to the slack adjuster must be tangential to ensure most efficient braking. Thus, increased delays and reduced braking is observed when the push rod goes out of adjustment. Why then do trucks use such a system? Disk brakes are much more expensive to deploy and are heavier than drum brakes. Freight haulers have a tight budget when it comes to safety systems since they would rather invest the funds in automated transmissions, electronic stability control etc. which would increase their running efficiency. While it is true disk brakes have better stopping potential and do not overheat as much as drum brakes, the cost/ gain in efficiency argument leads to most companies opting to use drum brakes. 23% of the total freight in the United States are carried by buses, trucks and other commercial vehicles [4]. Out of these vehicles, 85% still use drum brakes out of which around 40% were reported to be out of service [4]. Inspections conducted by the DPS [5] take an average of 45 minutes [6]. Inspection of the brake system takes up a major portion of these tests. On the Texas-Mexico border, commercial vehicles are facing delays between 8 hours upto 27 hours [7]. Since these vehicles often carry perishable goods, losses upto 470 million dollars in day are reported [7]. Thus this thesis can help mitigate these losses by reducing the time spent in these inspections.

The focus of this thesis is to develop a machine learning model to aid the development of a diagnostic system for air brakes in trucks; such a system is expected to facilitate the automation of maintenance and pre-trip inspections as well as provide continuous on-board monitoring of air brake system. A disruptive and novel approach is taken by using a machine learning model making this technology versatile and easily scale-able. This model can predict the overall leakage in the system accurately thus allowing us to monitor the health of the brake system. In this thesis, we present a machine learning model of a multi-chamber air brake system, a departure from the single brake chamber model presented in earlier work and provide its experimental corroboration.

1.2 Outline of Thesis

This thesis is organized as follows: In the first section, the layout of an air brake system is presented along with a brief description of key components, followed by the description of the experimental setup. The sections following outline the machine learning model, results from the experimental setup and the implementation of the model using the data.

2. TYPICAL BRAKE SYSTEM

2.1 Pneumatic System

The air brake system on a commercial modern vehicle is a hybrid system of pneumatic and mechanical components. The pneumatic subsystem consists of compressors, air supply reservoirs, foot valve, high pressure withstanding hoses, pneumatic valves such as treadle valve, relay valve and quick release valve. Given below is a simple layout of a truck brake system: The work of [8],

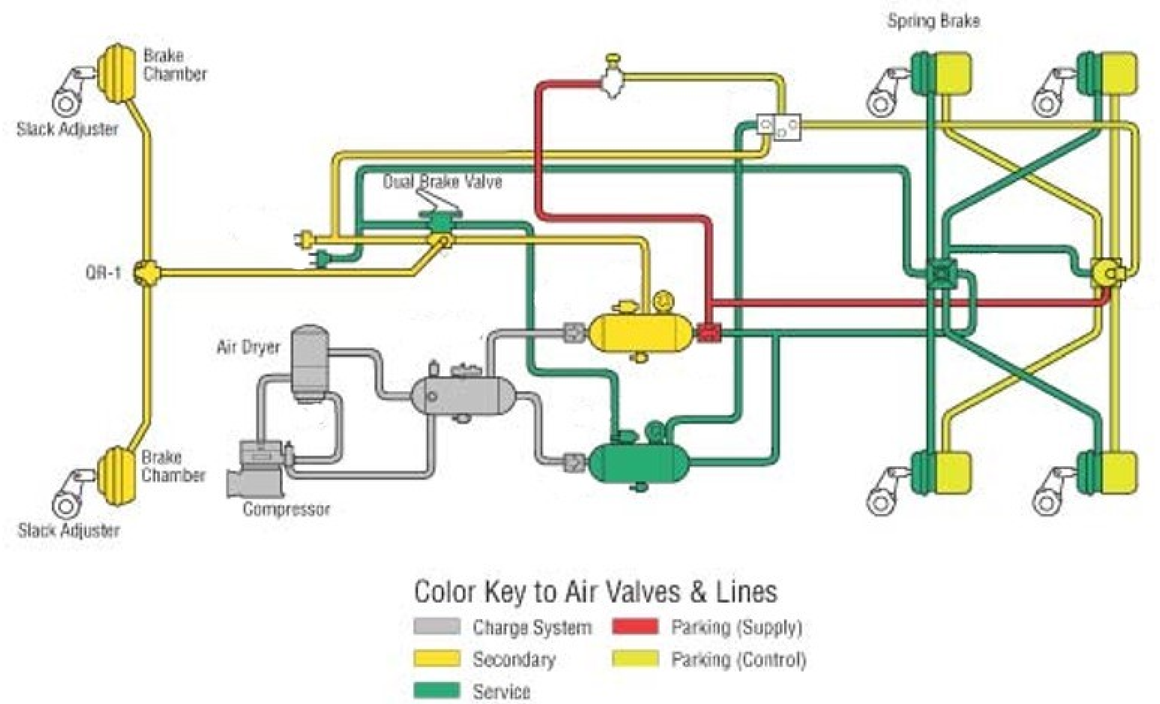


Figure 2.1: A typical truck brake system [Reprinted from [1]]

[9], [10], [11] and [12] allows us to obtain an understanding of these systems and various ways of analysing them. To ensure fail-safe operation, the pneumatic system is split into primary and secondary circuits. The primary circuit is connected to the rear brakes while the secondary circuit is connected to the front brakes. Both circuits have independent reservoirs and are connected to

the same dual brake valve. If a fault occurs either in the primary or secondary circuits, the system can still brake partially, leading to a fail-safe operation.

2.1.1 Treadle Valve

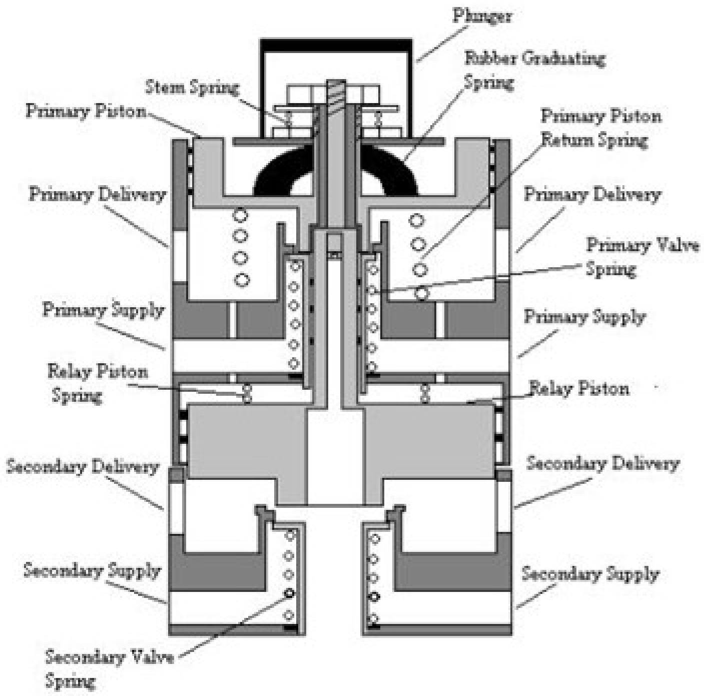


Figure 2.2: Treadle Valve Schematic [Reprinted from [1]]

The treadle valve is connected to the foot pedal (or simply foot) valve that is actuated by the driver. The treadle valve controls the fraction of supply pressure to be sent to the primary circuit, which serves as a relay pressure signal for the relay valve. The relay valve distributes compressed air from the secondary reservoir to the rear brake chambers based on the relay pressure signal. Compressed air delivered through the secondary circuit of treadle valve is connected to the front brakes. The quick release valve splits the incoming compressed air to both the front brake chambers and ensures quick exhaust.

The area of relay valve diaphragm on the primary delivery side is much larger thus allowing the driver's pedal input to act as signal pressure. This overcomes the spring pre-load and opens the supply pressure to the primary circuit. The high pressure from the primary reservoirs acts on the piston, but since a smaller area of the piston is exposed to the high-pressure supply side, the force is proportionally adjusted. Thus, the driver can control the high-pressure brakes with ease. The pressure in the primary circuit acts as a relay signal to move the secondary circuit piston to open the secondary circuit. In the event of a failure in the primary circuit, the foot valve can directly actuate the secondary piston thus providing partial braking.

2.2 Quick Release Valve and Relay Valve

The quick release valve ensures quick exhaust of the front brake chambers and splitting of the air between the two front brake chambers. Similarly, the Relay valve acts as a metering valve and distributes the incoming supply pressure to the four rear brake chambers. Apart from ensuring quick exhaust of the rear brake chambers, the relay valve also ensures that the delay between the actuation of the rear and front brakes is reduced. The quick release valve ensures quick exhaust of

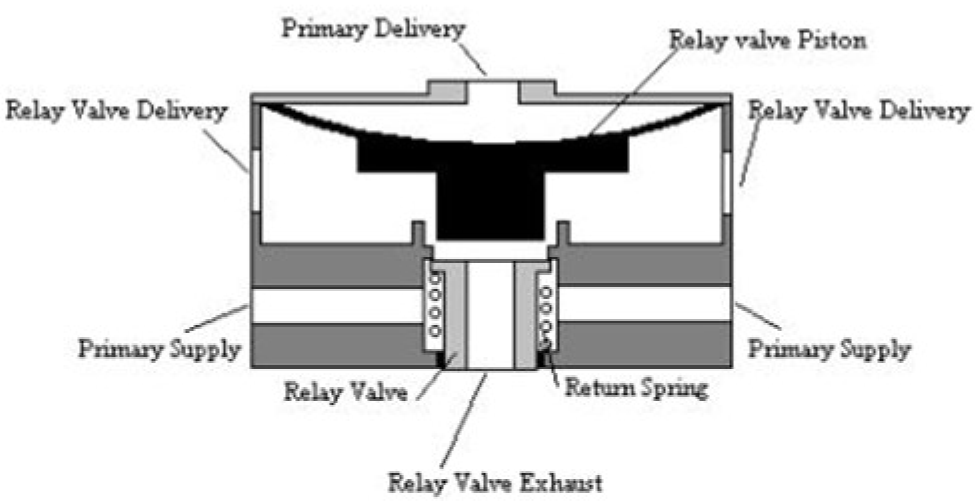


Figure 2.3: Relay Valve Schematic [Reprinted from [1]]

the front brake chambers and splitting of the air between the two front brake chambers. Similarly, the Relay valve acts as a metering valve and distributes the incoming supply pressure to the four rear brake chambers. Apart from ensuring quick exhaust of the rear brake chambers, the relay valve also ensures that the delay between the actuation of the rear and front brakes is reduced.

2.3 Mechanical System Layout

2.3.1 Brake Chamber

Brake chambers are essentially pistons with supply pressure on one side which actuate the linear translation of the push rod. The piston is fitted with a return spring to bring the brake chamber back to its zero-stroke configuration. The force transmitted by the brake chamber is directly proportional to the supply pressure, the spring constant of the return spring and the area of the diaphragm.

$$P_{supply}A_c - k_{spring}\left(x_d + x_0\right) = F_{pushrod} \tag{2.1}$$

here A_c is the area of the chamber, x_d the displacement of the push rod and x_o the effective pre-load length of the spring.

2.3.2 Slack Adjuster

The slack adjuster converts linear motion of the push rod into rotational motion of the S-cam to actuate the brake drum, as given in Fig.5. As discussed earlier, the slack adjuster ensures the force applied by the push rod is tangential so that the maximum torque is transmitted to the S cam. Wear of brake pads can change the clearances between the drum brakes which requires a longer push rod stroke for the brakes to contact the drum. Most modern trucks have automatic slack adjusters which ensure that the push rod stays at 90° with respect to the slack adjuster.

The S-cam on Fig.2.4 turns clockwise to push the brake pads on to the brake drum, initiating the braking sequence. The return spring ensures the brake pads return to a position of no-contact once the braking force has been released. These brakes are also called self-applying, i.e. the direction of rotation of the wheel drum does not matter. However this leads to uneven wear of the brake pads, as one of the brake pads is forced further than the other. Unlike disc brakes, frequent application will lead to overheating of brakes. When the truck has to traverse through mountainous terrain,

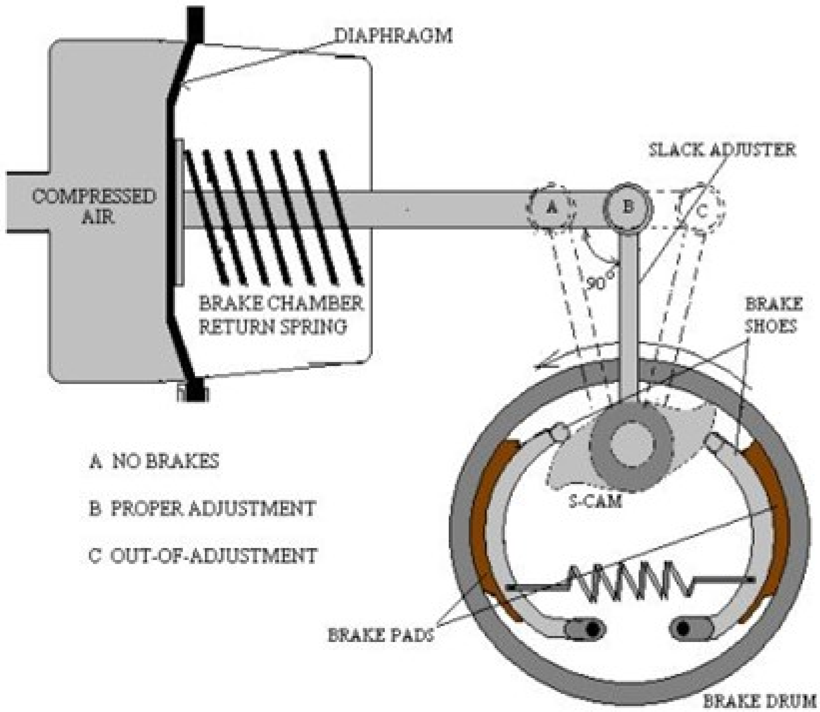


Figure 2.4: Slack Adjuster [Reprinted from [1]]

brakes need to be applied on and off to control the vehicle. However, this leads to brake fade where the pads have overheated and cannot provide the same friction as their cold state.

3. EXPERIMENTAL RESULTS

3.1 Experimental Setup

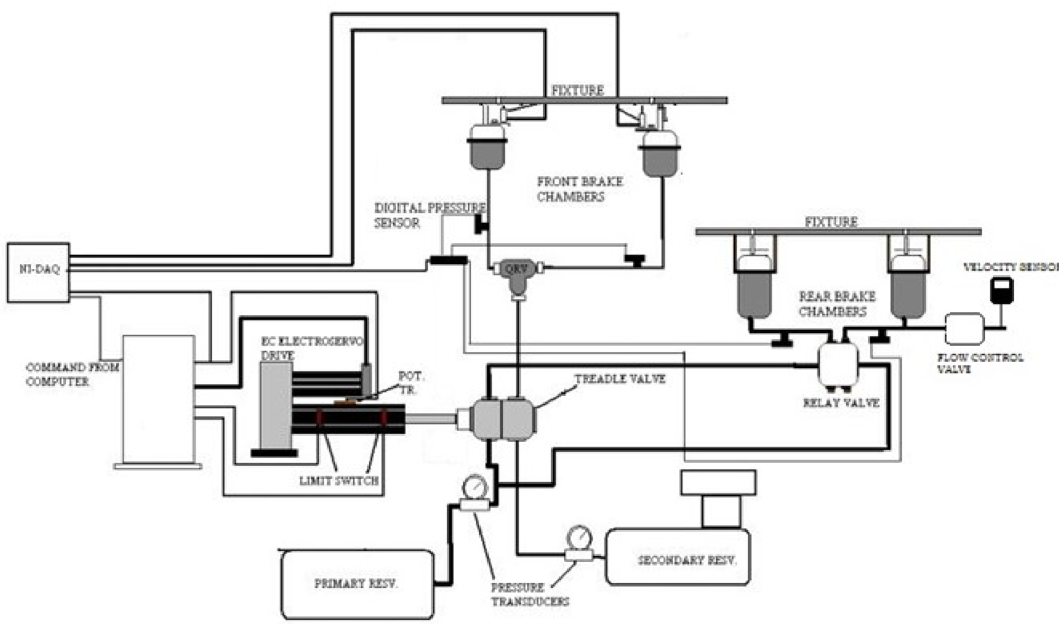


Figure 3.1: Experimental Setup Schematic [Adapted from [1]]

The experimental setup as shown in Figure 3.1 was setup with “type 20” front chamber brakes and “type 30” rear chamber brakes. “Type 20” brakes have 20 in^2 cross sectional area and “Type 30” brakes have 30 in^2 cross sectional area. Air is supplied by a 5 HP air compressor to the primary reservoir and 2 HP compressor for the secondary reservoir. Having separate reservoirs not only ensures a quicker response time but also acts as an added degree of safety/redundancy in the case of failure of any one of the pneumatic circuits.

Each of the brake chambers have pressure sensors fitted on them, and all the sensors are connected to the Data Acquisition (DAQ) unit. The treadle valve is actuated by a servo drive controlled electro-mechanical actuator with position feedback. A motor controller is used to control the actuator, and is interfaced with NI LabView. On one of the rear chambers, A flow control valve (FCV) is used to simulate different degrees of leak in the system.

The FCV opens completely for four turns of the dial, and is completely sealed for 0 turns of the dial. The dial is turned by half, 1 full, 2 full etc. to introduce different degrees of leak in the system. An air velocity sensor is used at the end of the flow control valve. The coupling allows us to adjust the diameter to the minimum requirement of the velocity sensor. This velocity is used to calculate the mass flow rate of the leaking air. The sensor has a sampling rate of 2 readings per sec so the readings were averaged out over 5 secs once the system reached steady state pressure. Table 3.1 provides the specifications of the equipment used.

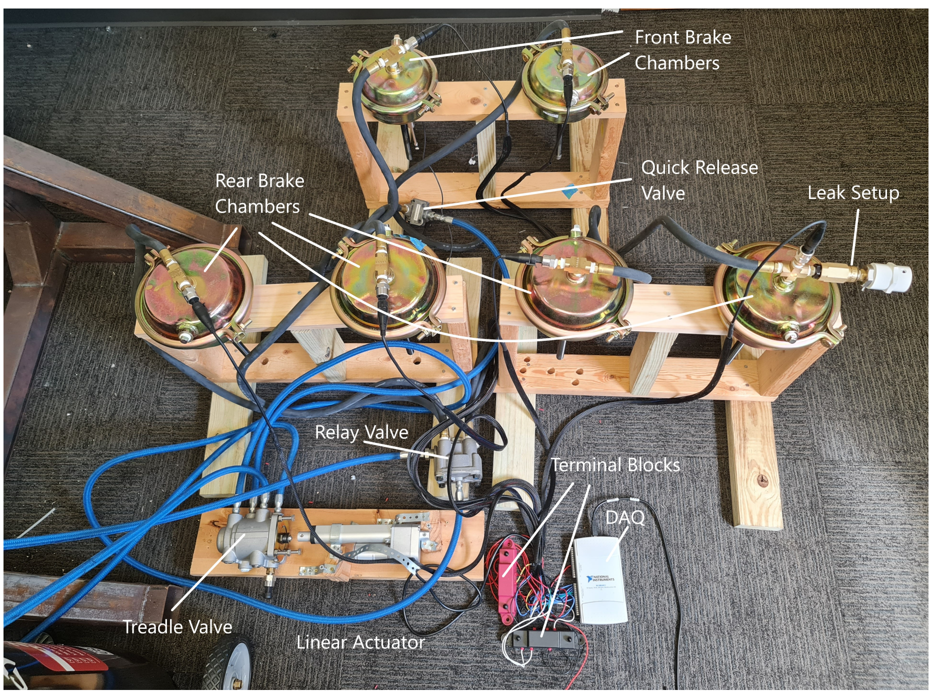


Figure 3.2: Experimental Setup

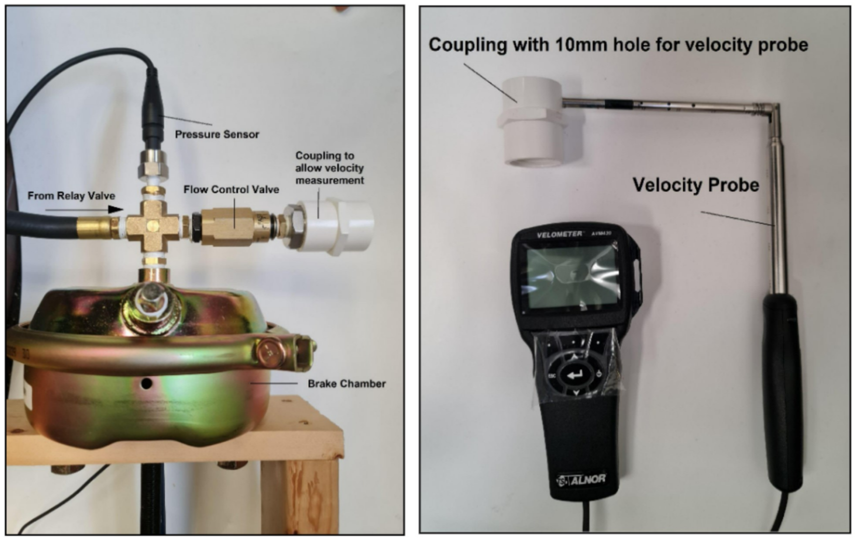
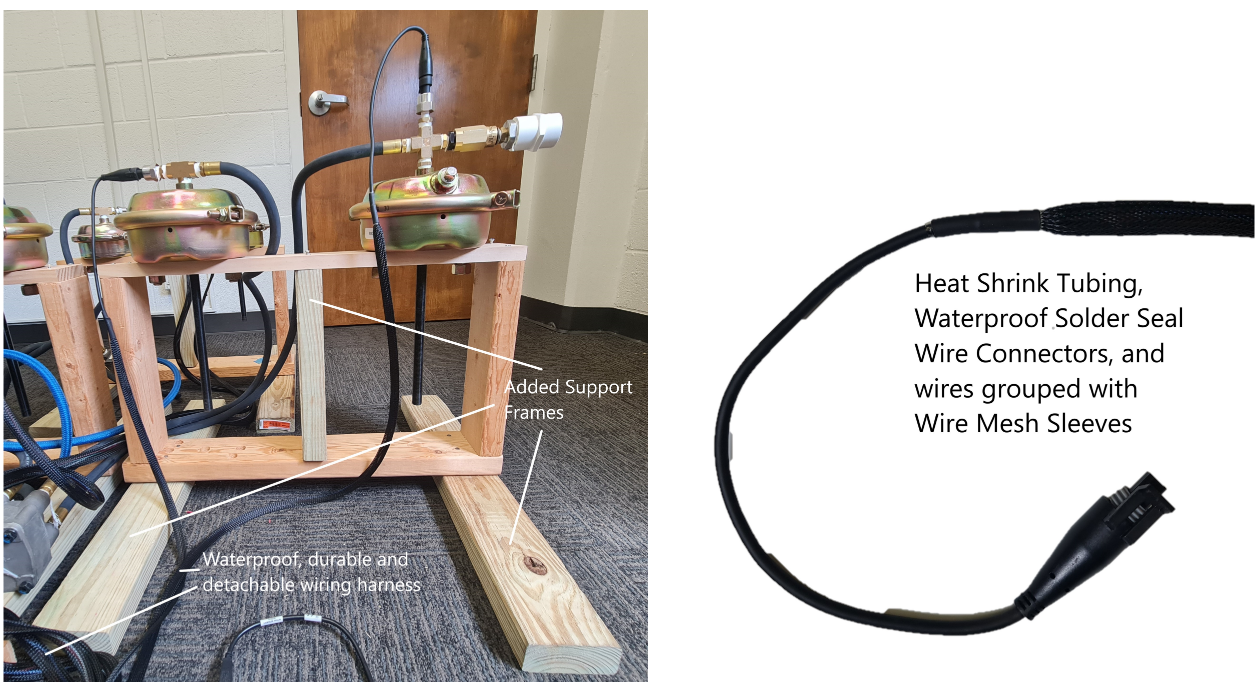


Figure 3.3: Leak Setup



(a) Support Frames

(b) Wiring Harness Improvements

Figure 3.4: Experimental Setup Improvements

Component	Manufacturer	Model no.
Primary compressor/ reservoir	Campbell Hausfeld	WL651300AJ
Secondary compressor/ reservoir	Campbell Hausfeld	FP20002000AV
Pressure Regulator	Omega Engg.	PRG50120
Treadle Valve	Bendix	E-7
Quick Release Valve	Bendix	QR-1
Relay Valve	Bendix	R-12
Brake Chambers	Bendix	Type-20 and Type-30
Flow Control Valve	Mead Fluid Dynamics	
Velocity Transducer	Alnor	AVM 430-A
Linear Potentiometer	Omega Engg.	LP802-75 LP802-100
Pressure Transducer	Omega Engg.	PX181-100G5V
Data Acquisition Board	National Instruments	PCI-MIO -16E-4
Electro-mechanical actuator	Progressive Automation	EC2-B23-20-05B-50-MSI/ MS6E-MT1E-L
Servo drive controller	IDC	B8501

Table 3.1: Specifications

3.1.1 Setup Improvements

Initially, the existing setup had rectangular frames that moved around when the brakes were actuated. Frames were added to increase the strength and rigidity of the setup, as if in an actual vehicle. The wiring harness previously featured plug and play wires. Due to pressurized air constantly being exhausted from the valves during tests, along with movement of the brake chambers due to lack of support frames, it would often lead to connections being cut off or loosening, leading to unreliable data. Thus insulated copper wires were used, with waterproof solder seal connectors. Additionally, Wires going to/from a particular sensor were grouped using a wire mesh and held together with heat shrinks. Connectors were added for all wires to ensure the harness is detachable, in case repairs needed to be made to the setup. Finally, due to compliance of the wooden panel on

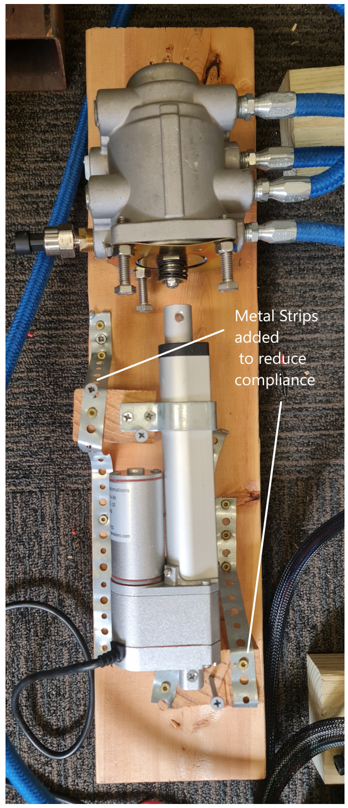


Figure 3.5: Actuator Compliance Improvements

which the treadle valve was mounted, the linear actuator was not co-axial to the treadle valve and thus unable to actuate it fully. Hence metal strips were added to counteract the issue.

3.2 Results and Observations

3.2.1 Format of the Experiment

- Brake is applied such that it simulates hard braking.
- The pedal is held at the fully applied position until the chamber pressures reach steady state
- Once the system reaches steady state, leak velocity measurements are taken
- Pedal is released

The average human can exert a maximum of 70 lbs of force. The actuator can apply a maximum of 50lbs, thus making a hard braking a reasonable assumption. These tests are performed For the supply pressures of 60 psi, 70 psi and 80 psi. Generally, supply tanks on trucks are massive and the pressure supplied by them can be considered constant for our application. While generally trucks work with pressures of 80-100 psi, the reservoirs available in the lab were not large enough to support such high pressures without noticeable variations in the supply tank pressure, thus lower supply pressures were chosen for the experiment. The flow control valve was set at 0 turns, increasing in steps of 0.5 turns up to 3 turns for these 3 supply pressures. To ensure that the amount of air leaking from the system would be consequential to the system's performance, the pressure rise times were examined. Through trial and error, it was found that for 2 turns of leak, the pressure rise times were about a second longer. Hence a truck moving at 60 mph would have an increased stopping distance of about 90 ft, which is clearly unacceptable due to reasons discussed earlier. Thus the experiments were conducted for the mentioned conditions, thus yielding 21 data sets for different conditions. Looking at the experimental data allowed us to get insights on the nature of the system and make observations that would determine the parameters of the machine learning model.

3.2.2 Experimental Results

The experimental setup described in Figure 3.1 was constructed as given in Figure 3.5 and Figure 3.3. We assume that the supply tanks are large enough such that P_{sup} remains constant. Fig. 3.6 is for the 70 psi no leak case, and Fig.3.7 is for the 70 psi and 2 turn leak case. The following observations can be made from these figures:

- The time taken for the pressure to rise to the steady state value is around 9-10 secs
- The front chambers build pressure much faster than the rear chambers since they are smaller and all the pressures saturate at around the supply pressure at steady state.
- The steady state pressures for the front and rear chambers are different.
- In the two cases in Fig. 3.6 and Fig. 3.7, the pressures amongst the 4 rear chambers and the 2 front chambers are almost invariant.

The actual numerical difference between these pressures are within 1 psi of each other. Leak is introduced in the system asymmetrically, in a manner that would cause pressure variations amongst the rear chambers. However we learn that this is inconsequential and the leak affects the system uniformly. It is also important to note that the front chambers are also affected by a leaking rear chamber. Thus we hypothesize that the pressures in the rear chambers are about the same for any leak introduced in the system. Hence it is difficult to isolate the point of leak by measuring the pressures in each of the different chambers. On the contrary, two pressure sensors, one for the rear chambers and another one for the front chambers will be enough to determine the leak in the system. Hence leak is being considered only downstream of the treadle valve. For the same given input as in Figures 3.6 and 3.7, different degrees of leak were introduced into the system to examine the behavior of the individual chambers and the whole system.

The following observations were made regarding the data:

1) The pressures do not vary significantly amongst the front chambers and the rear chambers:

It is clear from inspecting Fig.3.7 that the pressures in each of the chambers do not vary significantly even when there is significant leak from an asymmetric point in the system (extremely close to chamber "Rear2" in this case). This leads us to hypothesize that irrespective of the point of leak in the system, the pressures within the chambers do not vary significantly. Hence it is difficult to isolate the point of leak by measuring the pressures in each of the different chambers. On the contrary, two pressure sensors, one for the rear chambers and another one for the front chambers will be enough to quantify the state of the entire system.

2) Pressure rise times increase with increasing leakage in the system

We observe an increasing trend in pressure rise times with increasing leakage in the system, as given in Fig.3.8. For the supply pressure of 70psi , Fig. 3.8 shows the variation in rise times for different degrees of leak. Hence we establish that the rise time is an important parameter to be considered. The rise time here is defined as time taken for the pressure to reach 90% of the steady state value starting from time of brake application. The exact method in which the rise times were processed are discussed in the upcoming sections. The rise times are here 7.262, 7.79, 8.09 secs

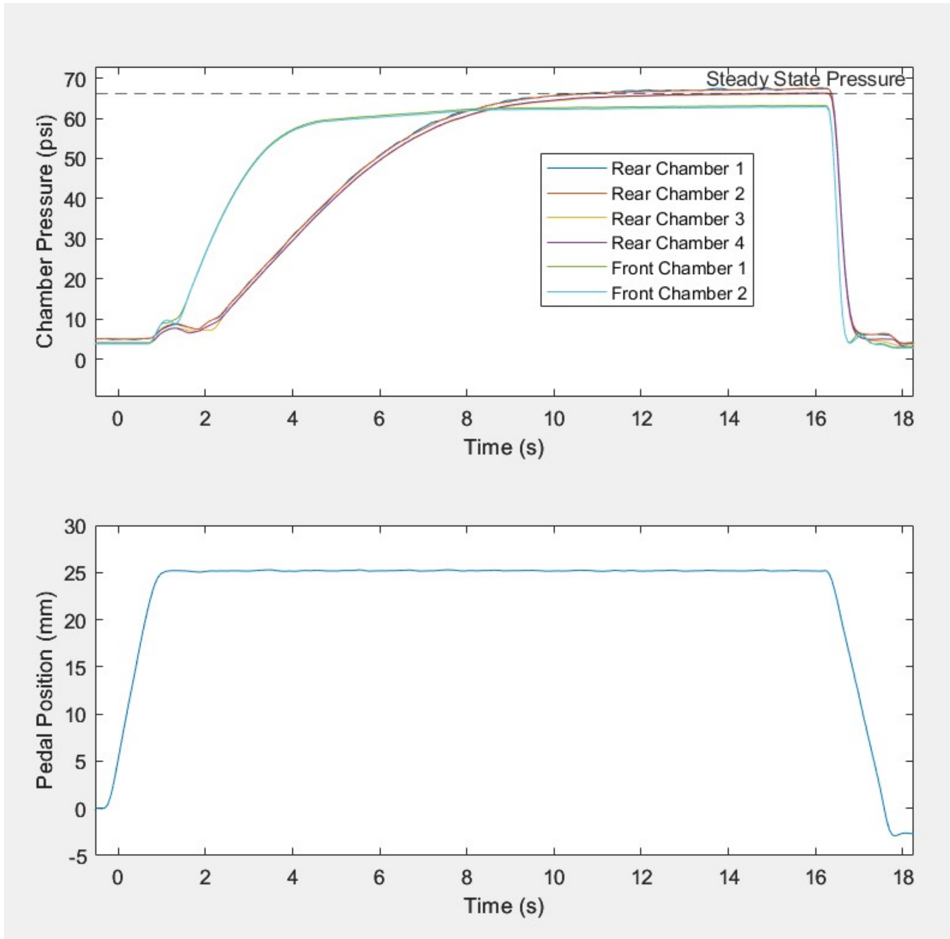


Figure 3.6: 70 psi supply pressure, 0 turn FCV

respectively.

3) Steady state pressures: The steady state pressures reached in the 0, 1 and 2 turn cases for the 70psi supply pressure case are 66.1 psi, 64.6 psi, 59.7 psi,as shown in Fig.3.9. Hence we can observe a decreasing trend in the steady state pressures with increasing leak. This establishes that the steady state pressure can also be an important parameter that is affected by the amount of leak in the system. The corresponding mass flow rates for the given cases above according to the velocity sensor measurements are 0.238g/s, 0.557g/s and 0.621g/s. Similar trends were also observed with other supply pressures as well. The results obtained are intuitive to what can be expected when a system is leaking. Thus we have established that the parameters of pressure rise time, steady state pressure and supply pressure are related to the amount of leak present in the system.

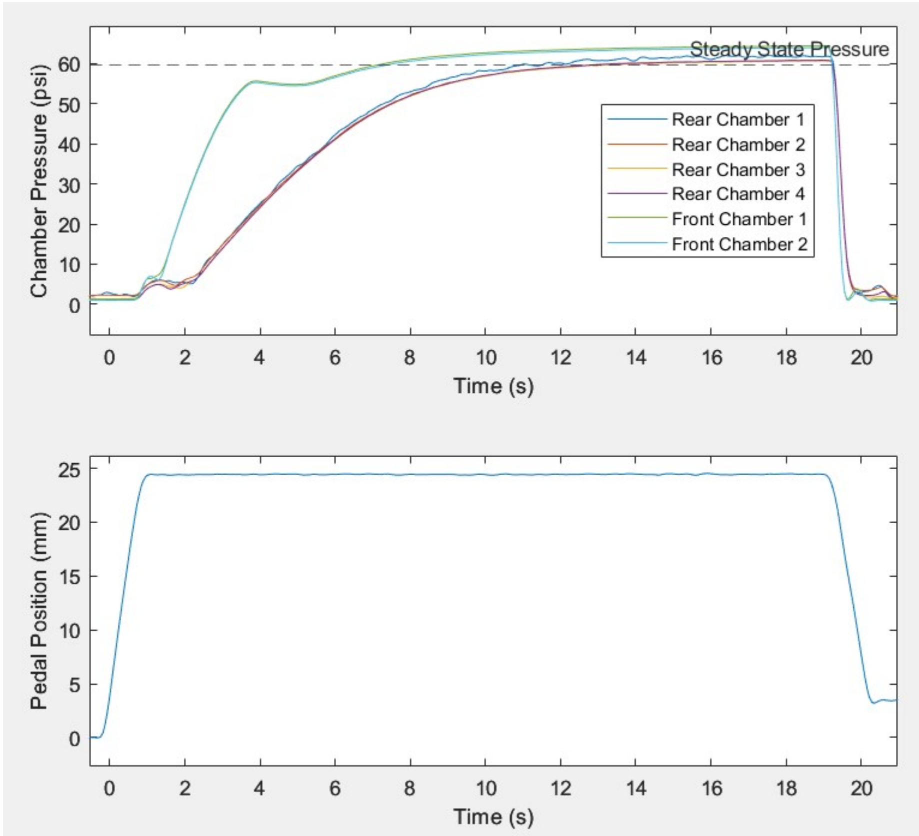


Figure 3.7: 70 psi supply pressure, 2 turn FCV

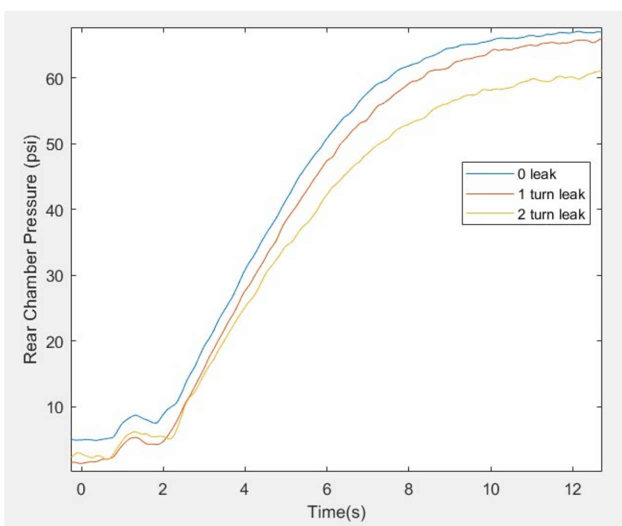


Figure 3.8: 70 psi supply pressure, rise time comparison

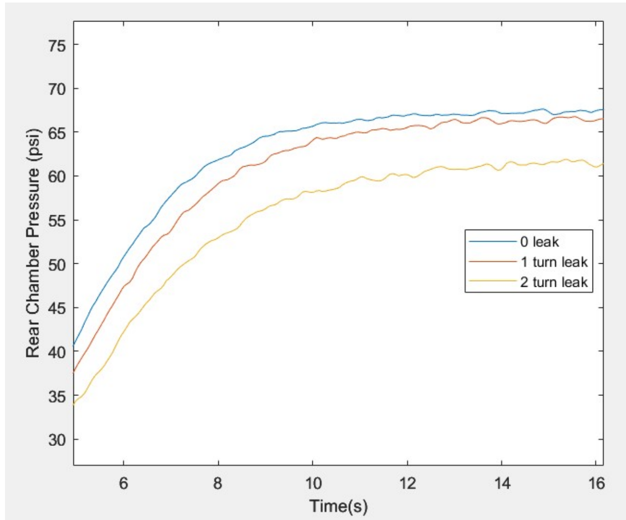


Figure 3.9: 70 psi supply pressure, Steady State comparison

Using the listed parameters (pressure rise time, supply pressure and steady state pressure), a machine learning model can be made with all the data collected for different degrees of leak. The parameters above can be identified from the two pressure sensors, one for the rear and the other for the front. These parameters can be fed to the machine learning model. Given a threshold leakage mass flow rate beyond which operation of the vehicle will be deemed dangerous for a given supply pressure, the health of the brake system can be monitored.

3.3 Machine Learning Model

3.3.1 Mathematical Model vs Machine Learning Model

Contrary to the mathematical model approach by previous authors [1], [13], [14], [15] and [16] a disruptive novel approach of using a machine learning model to predict the leakage in the system is used in this thesis. As shown previously in Fig 2.2, making a mathematical model involves a large number of parameters that describe the various components in the brake system such as springs and valves. The variability of these parameters over sustained usage, including other external factors based on the environmental conditions the vehicle is subject to, is quite significant. Additionally, commercial vehicles on the market could have a plethora of different components, thus advocating the impracticality of a mathematical model. Thus a gradient descent machine learning model is implemented to predict the leaks in the system.

3.3.2 Gradient Descent Model

This model is a linear regression model that works by optimising a cost function using the slope and intercept parameters of a line passing through various points in the system

$$y_{prediction} = \begin{bmatrix} m_1 & m_2 & m_3 \end{bmatrix} \cdot \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} + c \tag{3.1}$$

Where x_1,x_2 and x_3 are the input parameters to the model, and m_1,m_2,m_3 and c are the model parameters tuned to optimise the cost function value. The "features" or inputs to the model are feature normalized using the equation

$$x^i_{1norm} = \frac{x^i_1 - m_{x_1}}{\sigma_{x_1}} \tag{3.2}$$

$$C = \frac{1}{2n} \sum_{i=1}^{n} (y_{prediction} - y_{actual})^2 \tag{3.3}$$

Where σ_{x_1} is the standard deviation of all x_1 values, m_{x_1} is the mean of all x_1 values, x^i_{1norm} is the norm of the i^{th} value in set of all x_1 values and x^i_1 is the i^{th} value in set of all x_1 values. C is the cost function value and n is the total number of training data sets. A learning rate is chosen and the model parameters are edited such that the cost function as given in equation 3.3 converges to a minimum value. Thus the most optimal m_1,m_2,m_3 and c are found, and the leakages in the system can be predicted.

From the previous result analysis, we know that a pressure trace from any one of the chambers can be used to determine the overall leak in the system. To characterize the pressure trace, we use three parameters, namely, supply pressure, pressure rise time, steady state pressure. Pressure rise time is measured from the starting point of brake pedal input to the time taken for the pressure to reach 90% of the steady state value. The steady state is determined by computing the moving variance for all the points of the pressure trace and setting an upper limit for the same. The first point for which the moving variance falls within the threshold is chosen as the steady state value. The start time of the pedal input is also determined in similar fashion but using a lower limit. The first point for which the threshold is exceeded is chosen as the start point for pressure rise measurements. Due to small drifts in the sensor value and fluctuations in the supply voltage, the data is processes in the method mentioned above. The supply pressure is known and can easily be found from the pressure gauge of the supply tank. The parameter we would like to determine is the amount of leak in the system. This is characterized by the leak velocity in ft/min. This is proportional to the leaking mass flow rate and can be used to determine the leak in a given system. We use the gradient descent machine learning model for a 3 input 1 output case to predict the leak in the system. The model is made using data from a rear brake chamber. The data is processed using MATLAB (code attached in appendix) and the following parameters are obtained:

Using these input parameters, we train the gradient descent model. Fig. 3.10 shows the cost function for the model to show convergence:

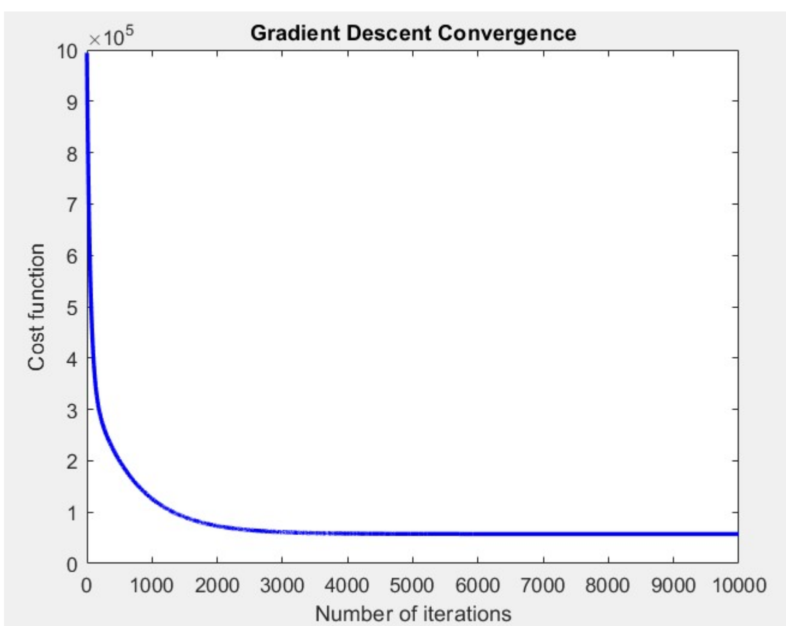


Figure 3.10: Model Convergence

Steady State Pressure (psi)	Rise Time (s)	Supply Pressure (psi)	Leak Velocity (ft/min)	Turns
56.136	8.4523	60	0	0
54.899	8.5184	60	544	1
52.787	8.4593	60	1154	1.5
50.307	8.699	60	1168	2
42.305	7.1409	60	1317	2.5
41.73	7.4963	60	1522	3
57.029	8.4646	60	178	0.5
65.71	7.262	70	0	0
64.595	7.7998	70	644	1
60.833	8.0404	70	1172	1.5
59.23	8.0985	70	1824	2
57.007	8.1015	70	2313	2.5
54.275	8.1005	70	2276	3
66.172	7.6201	70	184	0.5
74.608	7.0191	80	0	0
72.514	7.2594	80	823	1
71.829	7.4992	80	1417	1.5
75.648	7.9217	80	2132	2
72.545	7.9216	80	2391	2.5
70.808	8.0376	80	2566	3
78.218	7.86	80	172	0.5

Table 3.2: Training Data Set

3.3.3 Results

The value to which the cost function converges is 57475.7, thus indicating a standard deviation in prediction of 339.04 ft/min. The average error percentage is 13.3% .Two random tests were conducted which were not included in the training data set to validate the model. The first test was conducted at 65 psi supply pressure and 1.5 turns of the flow control valve. The second test was conducted at 70 psi and 1.2 turns of the flow control valve. The % error in prediction were 14% and 7.9% respectively. The predicted and actual leak velocities were 624 ft/min and 726 ft/min, 1300 ft/min and 1412 ft/min respectively. Hence the total leak in the system can be determined to a reasonable amount of accuracy.

Figure 3.11 shows the error distribution across the training data set. The highest observed is

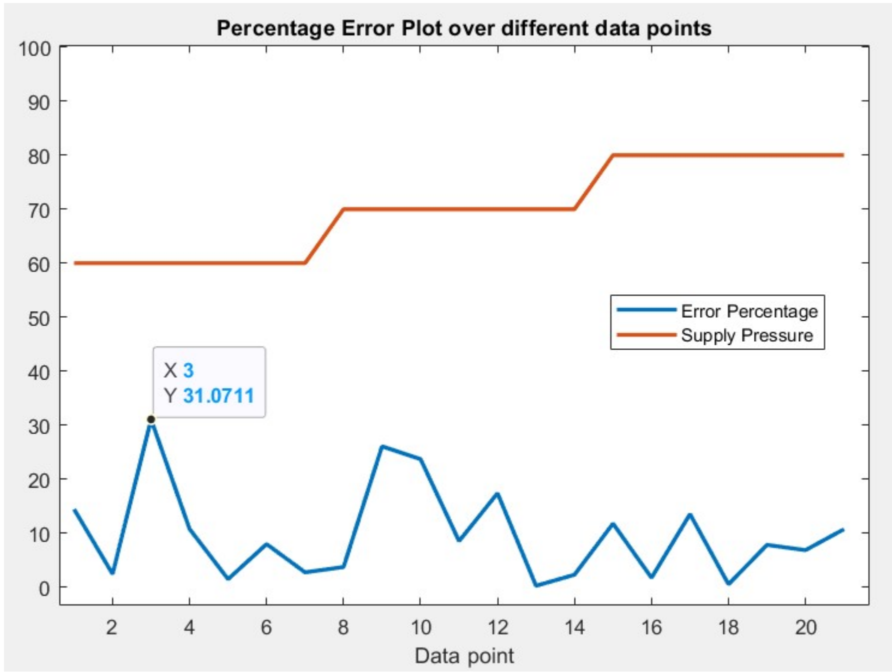


Figure 3.11: Error Distribution over the training dataset

31.07%, however most points are well under 15% error. Models made with front brake chambers also yielded similar errors. Thus the overall leak in the system can be estimated accurately using the model demonstrated in this thesis.

4. SUMMARY AND CONCLUSIONS

Diagnostics of the brake system is necessary from an evolutionary standpoint in terms of truck autonomy. The diagnostic tool described in this paper addresses such concerns for autonomous trucks and truck platooning. We have built a model that can identify the parameters in the pressure traces of the brake chambers accurately and use that to predict leaks in the system as a replacement to standard inspection. The model described in this report achieves standstill testing, requiring the driver to hold the pedal down for a few seconds.A continuous diagnostic tool must be built based on this model thus completely eliminating the requirement for separate tests.

The same experiments may be repeated on actual trucks to obtain pressure transient data which can be compared with the existing machine learning model made from the experimental setup. Introduction of a sensor inserted strategically into the system can help track the health of brake systems real time. Having a separate diagnostic tool which can be fed these raw pressure values to analyze the health of the brake system can help save time during inspections. It also eliminates human error and negligence during inspections.

Going forward, monitoring the push rod stroke and its alignment can allow us to exactly determine the torque transmitted to the S cam, since the force acting on the pushrod can be calculated from the brake chamber pressure, as given in Eq.2.1. Using the stroke data, it is possible to identify the time when the brake pads contact the drum, thus allowing us to determine the exact braking effort. This can be continuously monitored to ensure that the brake system's performance is evaluated accurately.

A comparatively rigid test procedure is described for this machine learning model. However, if the driver's pedal input can also be incorporated in these models, they can be used as continuous monitoring tools that provide real time diagnostics throughout a trip. This would not only improve the robustness of the diagnostics, but would also allow us to use data logged from previous trips to compare and provide predictive diagnostics as to when the truck might go out of service.

The machine learning model implemented works for solving non linear regression problems as long as the features or inputs are roughly linear and lie within a particular delta. However a model using non linear regression or perhaps decision tree or random forest models might work better. Additionally, combined parameters from both front and rear chambers can be input to the model to improve the accuracy of predictions.

Finally, the equipment used to measure leak velocity can be improved. The leak velocity is measured over 5 seconds by the velocity sensor and the average is found. The response time of the velocity sensor is about 0.5 second, and thus is not suitable for transient leak detection. Usage of an air flow meter can provide better accuracy, which will be required for pedal input dependent models.

REFERENCES

[1] S. Dhar, *Development of Diagnostic Algorithms for Air Brakes in Trucks*. PhD thesis, Texas A&M University, 2010.

[2] "Fatality facts 2019: Large trucks." https://www.iihs.org/topics/fatalitystatistics/detail/large-trucks.

[3] "The large truck crash causation study - analysis brief." https://www.fmcsa.dot.gov/safety/research-and-analysis/large-truck-crash-causation-studyanalysis-brief.

[4] U. D. of Transportation Research and D. Innovative Technology Administration Bureau of Transportation Statistics, Washington, "National transportation statistics," 2008.

[5] D. of Public Safety, "Commercial motor vehicles." https://www.dps.texas.gov/sites/default/files/documents/rsd/vi/publications/rules/safety_manual/chapter6.pdf.

[6] T. T. Tribune, "Greg abbott's call for more vehicle inspections at the border is causing delays and supply chain issues." https://www.texastribune.org/2022/04/08/texas-border-operation-inspections-delays/.

[7] Landline, "Mexico urges texas to stop border truck inspections; delays up to 27 hours." https://landline.media/mexico-urges-texas-to-stop-border-truck-inspections-delays-up-to-27-hours/.

[8] J. Gerdes and J. Hedrick, "Brake system modeling for simulation and control," 1999.

[9] P. Y.Khan and K.Youcef-Toumi, "Modeling, experimentation and simulation of a brake apply system," *ASME Journal of Dynamics, Systems, Measurement and Control, vol. 116, pp. 111-122*, 1994.

[10] S. D. C.L. Bowlin, S.C. Subramanian and K. Rajagopal, “A pressure control scheme for air brakes in commercial vehicle,” *IEE Journal of Intelligent Transportation Systems, vol. 153, no. 1, pp. 21-32*, 2006.

[11] C. H. T. Acarman, U. Ozguner and A. Igusky, “Pneumatic brake system modeling for system analysis,” *Transactions of Society of Automobile Engineers, Paper no. 2000-01-3414, pp. 1-7*, 2000.

[12] P. R. L.D. Kandt and R. Scheibe, “Determination of air brake adjustment from air pressure data,” *Proc. Instn. Mech. Engrs., vol. 215, part D, pp. 21-29*, 2001.

[13] S. D. S.C. Subramanian and K. Rajagopal, “Modeling the pneumatic subsystem of an s-cam air brake system,” *ASME Journal of Dynamics, Systems, Measurement, and Control, vol. 126, pp. 36-46*, 2004.

[14] R. Foster, “Modelling the pressure transients and push rod extension of a multi-chamber pneumatic braking system,” Master’s thesis, Texas A&M University, 2020.

[15] S. Vilayannur Natarajan, “Modeling the pneumatic relay valve of an s-cam airbrake,” Master’s thesis, Texas A&M University, 2006.

[16] S. R. Coimbatore Subramanian, . *A diagnostic system for air brakes in commercial vehicles*. PhD thesis, Texas A&M University, 2003.

APPENDIX

MATLAB CODE

A.1 MATLAB Code used for Data Processing and Training Set Creation

```
%Get information about what's inside your folder.
myfiles = dir('C:\Brakes Project\Datafinal');
%Get the filenames and folders of all files and folders inside
   the folder
%of your choice.
filenames={myfiles(:).name}';
filefolders={myfiles(:).folder}';
%Get only those files that have a csv extension and their
   corresponding
%folders.
csvfiles=filenames(endsWith(filenames,'.csv'));
csvfolders=filefolders(endsWith(filenames,'.csv'));
%Make a cell array of strings containing the full file locations
   of the
%files.
files=fullfile(csvfolders,csvfiles);
parametermatrix=zeros(length(files),4); % null array to store
   parameters

for i=1:length(files)
```

```
    [a,b,c,d]=data_processor(string(files(i)));
    parametermatrix(i,:)=[a, b, c,d]; %assigning parameters
       obtained from data processor

end
csvwrite("dataset.csv",parametermatrix);%writing it into a csv
   file

function [P1ss  P1rt  supply LeakVel]=data_processor(name)
C=readmatrix(name); %Read the csv file to which the path is given
T= C(:,1); % Time in s
P1=25*((C(:,2))-0.5); % Pressure in psi
P2=25*((C(:,3))-0.5);
P3=25*((C(:,4))-0.5);
P4=25*((C(:,5))-0.5);
P5=25*((C(:,6))-0.5);
P6=25*((C(:,7))-0.5);
Pedal=(60*((C(:,8))))-75.6;% Pedal travel in mm
LeakVel=C(:,15);
LeakVel=LeakVel(1);% Leak Velocity in ft/min
supply=C(:,16);
supply=supply(1);% supply pressure
P1h=P1(P1>40);% Choosing values after pressure rise
V=movvar(P1h,100); % Finding the moving variance over 100
   elements
M=movmean(P1h,50); % Finding the sliding mean over 50 elements
P1hss=M(find(V<5)); % Picking the mean points with variance less
```

```
   than 5
P1ss=P1hss(1); % Picking the 1st mean with variance less than 5
Pedal1 = [Pedal(25:end)]; % Ignoring first 25 values due to
   errors during bootup
PedalV=movvar(Pedal1,10);
time1=find(PedalV>10)+25;% Finding the 1st moving variance
   greater than 10
time2=find(P1>0.9*P1ss);% Finding time at which pressure reaches
   90% of steady state
P1rt=T(time2(1))-T(time1(1));
T=T-T(time1(1));% subtracting the offset such that 0 is aligned
   with start of rise time measurement
```

A.2 MATLAB Code of the Gradient Descent Model

```
% Step 1: Load the dataset
data = table2array(readtable('dataset.csv','NumHeaderLines',0));
X = data(1:21, 1:3);  % Input features
y = data(1:21, 4);    % Output variable
x1=data(23,1);
x2=data(23,2);
x3=data(23,3);
y1=data(23,4);
% Step 2: Normalize the input features
[X, mu, sigma] = featureNormalize(X);

% Step 3: Add bias term to the input features
X = [ones(size(X, 1), 1) X];
```

```
% Step 4: Initialize the parameters
theta = zeros(size(X, 2), 1);
alpha = 0.01;  % Learning rate
num_iters = 10000;  % Number of iterations

% Step 5: Perform gradient descent to minimize the cost function
[theta, J_history] = gradientDescent(X, y, theta, alpha,
   num_iters);

% Step 6: Make predictions using the learned parameters
input = [1, (x1 - mu(1)) / sigma(1), (x2 - mu(2)) / sigma(2), (x3
    - mu(3)) / sigma(3)];
prediction = input * theta;

% Step 7: Display the learned parameters and plot the cost
   function
fprintf('Learned parameters:\n');
disp(theta);
figure;
plot(1:num_iters, J_history, '-b', 'LineWidth', 2);
xlabel('Number of iterations');
ylabel('Cost function');
title('Gradient Descent Convergence');


% Function to perform feature normalization
```

```
function [X_norm, mu, sigma] = featureNormalize(X)
    mu = mean(X);
    sigma = std(X);
    X_norm = (X - mu) ./ sigma;
end

% Function to perform gradient descent
function [theta, J_history] = gradientDescent(X, y, theta, alpha,
    num_iters)
    m = length(y);
    J_history = zeros(num_iters, 1);

    for iter = 1:num_iters
        h = X * theta;
        theta = theta - (alpha / m) * X' * (h - y);
        J_history(iter) = computeCost(X, y, theta);
    end
end

% Function to compute the cost function
function J = computeCost(X, y, theta)
    m = length(y);
    J = (1 / (2 * m)) * sum((X * theta - y) .^ 2);
end
```