A Diagnostic Machine Learning Model for Air Brake Systems in Commercial Vehicles

November 2023 | Final Report

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16. Abstract
Safely introducing autonomy to trucks requires monitoring their brake systems continuously. Out-of-adjustment push rods and leakages in the air brake system are two major reasons for increased braking distances in trucks, resulting in safety violations. Air leakages can occur due to small cracks or loose/improperly fit couplings, which do not affect overall braking capacity but contribute greatly to increased braking lag and reduced maximum braking torque at the wheels. Similarly, an increased stroke of push rod leads to a larger delay in brake response and a smaller brake torque value at the wheels. Currently, an air brake system's condition is monitored manually by measuring the push rod offset and inspecting the system's couplings and hoses for air leakages. These inspections are highly labor intensive, subjective, time consuming, and inaccurate in quantifying adversely affected braking systems. An onboard diagnostic device that can monitor air brake health would be crucial in preventing road accidents. The focus of this report is to help develop a diagnostic system that facilitates enforcement and pre-trip inspections and continuous onboard monitoring of trucks by developing a model for its multi-chamber braking system using machine learning; this model can be used to estimate the severity of leakage and the push rod stroke using real-time brake pressure transients. The novel approach of a gradient descent model that predicts the air brake system air leakage rate using pressure transients at the brake chamber was developed and experimentally corroborated.

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Acknowledgements

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Introduction

A study by the Insurance Institute for Highway Safety indicated that loaded tractors or trailers require a 20% to 40% farther stopping distance than cars [1]. Heavy trucks carry a gross weight of 31,000 lb or more, which brings much larger impact forces into crashes than normal road vehicles do. 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 29% of crashes with large trucks [2]. 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 (a) leakage of compressed air from the brake lines, leading to increased response times, and (b) out-of-adjustment push rods [3]. 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 that the push rod applies to the slack adjuster must be tangential to ensure most efficient braking; when brakes are out of adjustment, this is not the case. Consequently, increased delays and reduced braking are observed when the push rod is out of adjustment.

The question then becomes why trucks would use such a system. Disc 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 because they would rather invest the funds in automated transmissions, electronic stability control, and other areas that would increase their running efficiency. While it is true disc brakes have better stopping potential and do not overheat as much as drum brakes, the argument of cost/gain in efficiency leads most companies to opt to use drum brakes. Twenty-three percent of the total freight in the United States is carried by buses, trucks, and other commercial vehicles [4]. Out of these vehicles, 85% still use drum brakes, around 40% of which were reported to be out of service [4].

The focus of this report is to create a model that will 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 and to provide continuous onboard monitoring of the air brake system. The team has taken a disruptive and novel approach 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. The brake system model helps predict brake pressure in each of the brake chambers based on the brake pedal input, stroke of the push rod, and air leakage rate and location. Based on the measured brake pressure in each of the chambers, one can then estimate the desired quantities (i.e., push rod stroke and air leakage) and appropriately assess the health of the air brake system. In this report, we present a dynamic 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.

Inspections conducted by the Department of Public Safety [5] take an average of 45 minutes [6]. Inspecting the brake system takes up a major portion of these tests. On the Texas-Mexico border, commercial vehicles are facing inspection-related delays of between 8 to 27 hours [7]. Because these vehicles often carry perishable goods, losses up to $470 million per day have been reported [7]. Thus, this report can help mitigate these losses by reducing the time spent on these inspections.

The first section of this report presents the layout of an air brake system along with a brief description of key components of the pneumatic and mechanical systems. The subsequent sections outline the machine learning model, the experimental setup, results from the experiment, and the implementation of the model using the data.

Air Brake System Layout

Pneumatic System Layout

The air brake system on a modern commercial motor vehicle is a hybrid system of pneumatic and mechanical components. The pneumatic subsystem consists of compressors, air supply reservoirs, foot valves, high-pressure withstanding hoses, and pneumatic valves such as the treadle valve, relay valve, and quick release valve. Figure 1 shows a simple layout of a truck brake system:

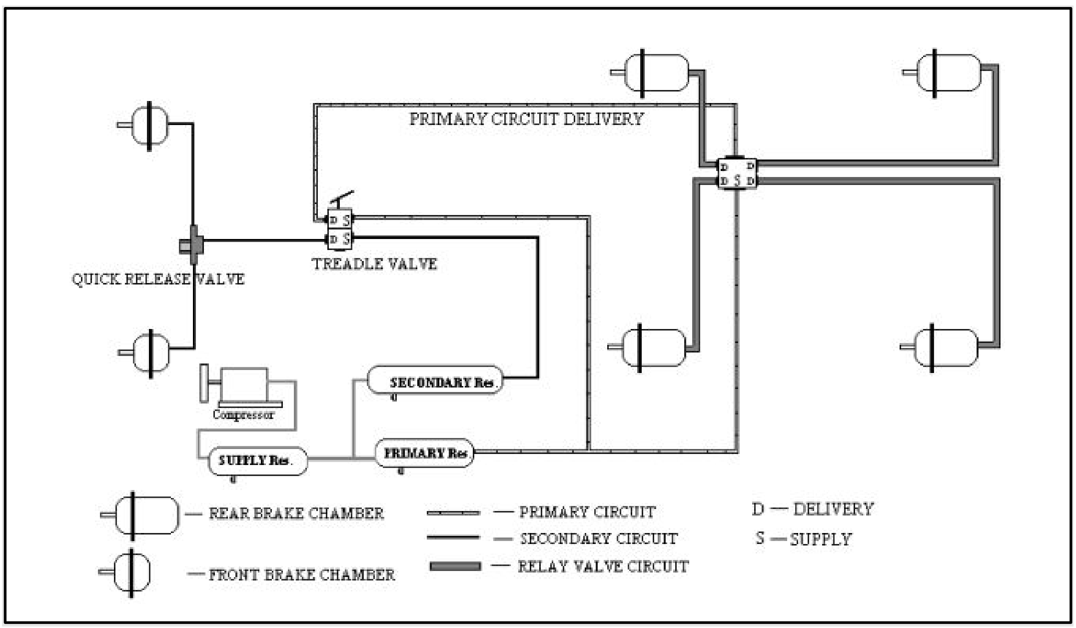

Figure 1. Diagram. Typical truck braking system (reprinted from Dhar [3]).

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.

Treadle Valve

The treadle valve (Figure 2) is connected to the foot pedal (or 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.

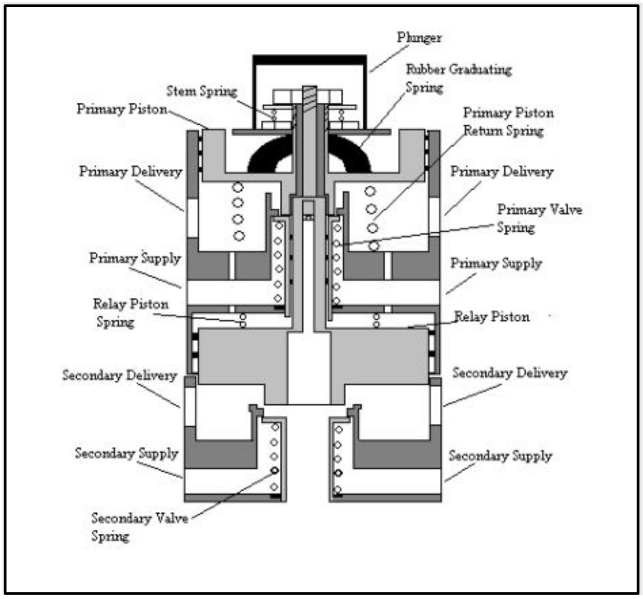

Figure 2. Diagram. Treadle valve (reprinted from Dhar [3]).

The area of relay valve piston 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 because 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.

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 (Figure 3). 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.

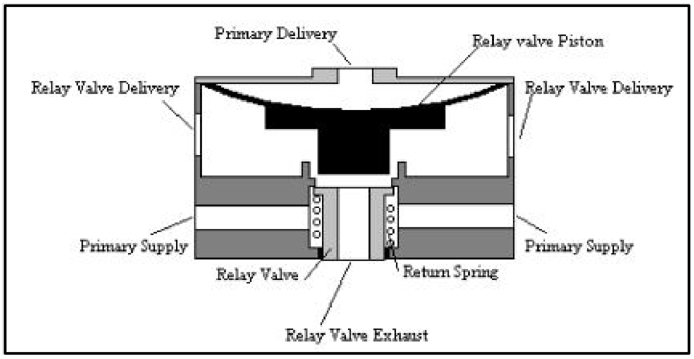

Figure 3. Diagram. Relay valve (reprinted from Dhar [3]).

Mechanical System Layout

Brake Chamber

Brake chambers (Figure 4) are essentially pistons with supply pressure on one side that actuate the linear translation of the push rod.

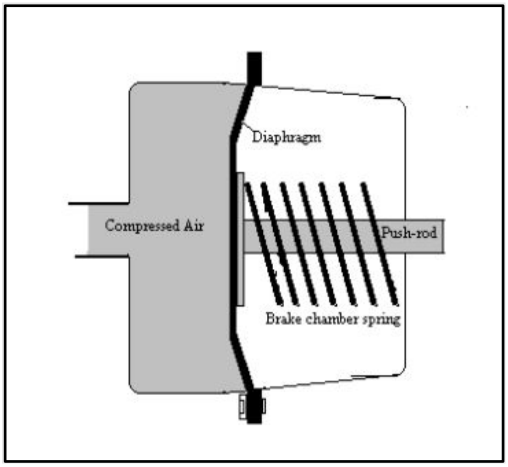

Figure 4. Diagram. Brake chamber (reprinted from Dhar [3]).

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.

$$P_{supply}A - k_{spring}(x_d + x_0) = F_{pushrod}$$

Here, A is the area of the diaphragm, x_d is the displacement of the push rod, and x_0 is the effective pre-load length of the spring.

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 shown in Figure 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. The wear on brake pads can change the clearances between the drum brakes, which requires a longer push rod stroke for the brakes to contact the drum. Although most modern trucks have automatic slack adjusters that ensure the push rod stays at 90° with respect to the slack adjuster, the brake system is still prone to becoming out of adjustment.

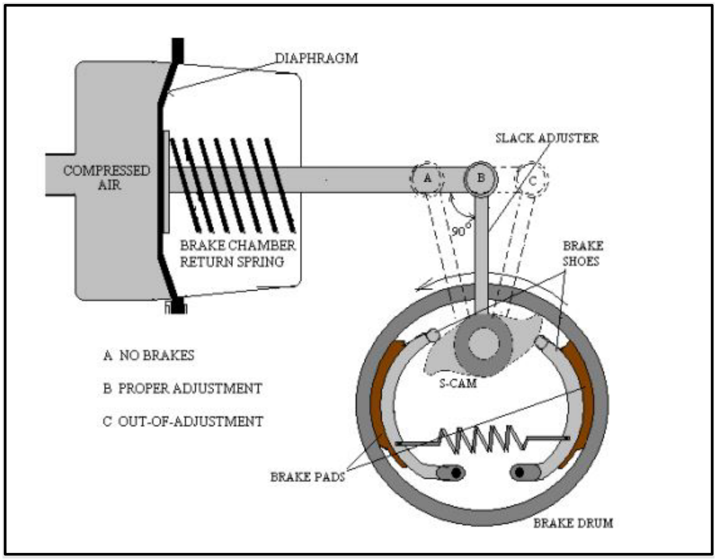

Figure 5. Diagram. Slack adjuster (reprinted from Dhar [3]).

The S-cam in Figure 5 turns clockwise to push the brake pads onto 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 action leads to uneven wear of the brake pads, as one of the brake pads is forced further than the other. Unlike with disc brakes, frequent application will lead to overheating of drum brakes. When the truck must traverse through mountainous terrain, 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 in their cold state.

Leak Model

Several studies [8-12] have dealt with modeling the pressure transients in single-chamber air brake systems without any leaks. The pressure transients of these systems are highly dependent on the mode in which the systems operate. These modes are the pressure rise mode, hold mode, and pressure decay mode, and they are purely dependent on the pressures inside the treadle valve and the movement of the primary and secondary pistons depending on these pressures.

We have modified the leak-free equations as given in Dhar [3]. The air is assumed to leak through a possible fault in the system (e.g., incorrectly fitted tubing, punctures in the hoses). In the experimental setup, we simulated a leak via a flow control valve (FCV); the number of turns of the FCV controls the mass leakage flow rate. It is assumed that leakage behaves like a flow through nozzle that exhausts to atmospheric pressure. The system pressures are high enough to assume that the flow is choked. We employed the following equation for choked flow:

$$\dot{m}_{leak} = C_d A_l \frac{P_{\mathrm{b}}}{\sqrt{RT}} \sqrt{\gamma \left(\frac{2}{\gamma + 1}\right)^{\left(\frac{\gamma+1}{\gamma-1}\right)}}$$

where C_d is the coefficient of discharge of a nozzle, A_l is the area of leak, P_b is the pressure in the brake chamber, R is the gas constant for air, γ is the ratio of specific heats of air, and T is temperature of the surrounding air. The parameter K is defined as

$$K = \frac{C_d A_l}{\sqrt{R}} \sqrt{\gamma \left(\frac{2}{\gamma + 1}\right)^{\left(\frac{\gamma+1}{\gamma-1}\right)}}$$

Identification of the parameter K requires the measurement of different values of steady state pressures and FCV positions corresponding to different leak flow rates. The parameter K can be suitably chosen to minimize the least-square error using the linear equation for $\dot{m}_{leak}$.

The pressure evolution in the brake chamber can be determined through the conservation of mass applied to the brake chamber. If $\dot{m}_{in}$ is the mass flow rate of the air coming from the reservoir, and $\dot{m}_{leak}$ is the mass of air leaking just prior to entering the brake chamber (as is the case in the experimental setup), the rate of change of mass in the brake chamber, $\dot{m}_{BC}$, is the difference between the two quantities and can be expressed as:

$$\dot{m}_{in} - K \frac{P_b}{\sqrt{T}} = \dot{m}_{BC}$$

Figure 6 illustrates the comparison of the values from the leak-free and leak models versus experimental values.

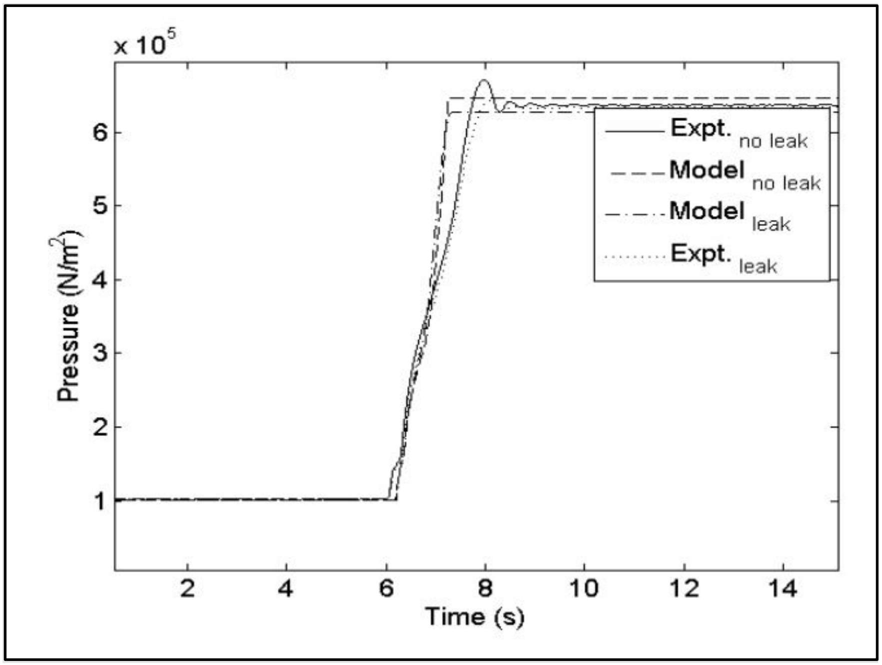

Figure 6. Graph. Pressure traces from model and experiment (single chamber with leak; reprinted from Dhar [3]).

We see that the steady state pressures predicted by both models are accurate, yet the delay times are vastly different. The intention of measuring brake pressure is to accurately estimate these increased delay times in reaching a steady state value, thus estimating the severity of leak in accordance with measured pressures. Additionally, we notice that the leak setup is for a single brake chamber, with the point of leak positioned just outside the brake chamber. The effect of this point of leak on the rest of the system is largely unknown. The implications of these results will be further discussed in the conclusion.

Experimental Setup

The experimental setup as shown in Figure 8 and Figure 9 was created with "Type 20" front chamber brakes and "Type 30" rear chamber brakes. Type 20 brakes have a 20-in^2 cross-sectional area, and Type 30 brakes have a 30-in^2 cross-sectional area. Each of the brake chambers has pressure transducers and linear potentiometers to measure the push rod stroke (Figure 7).

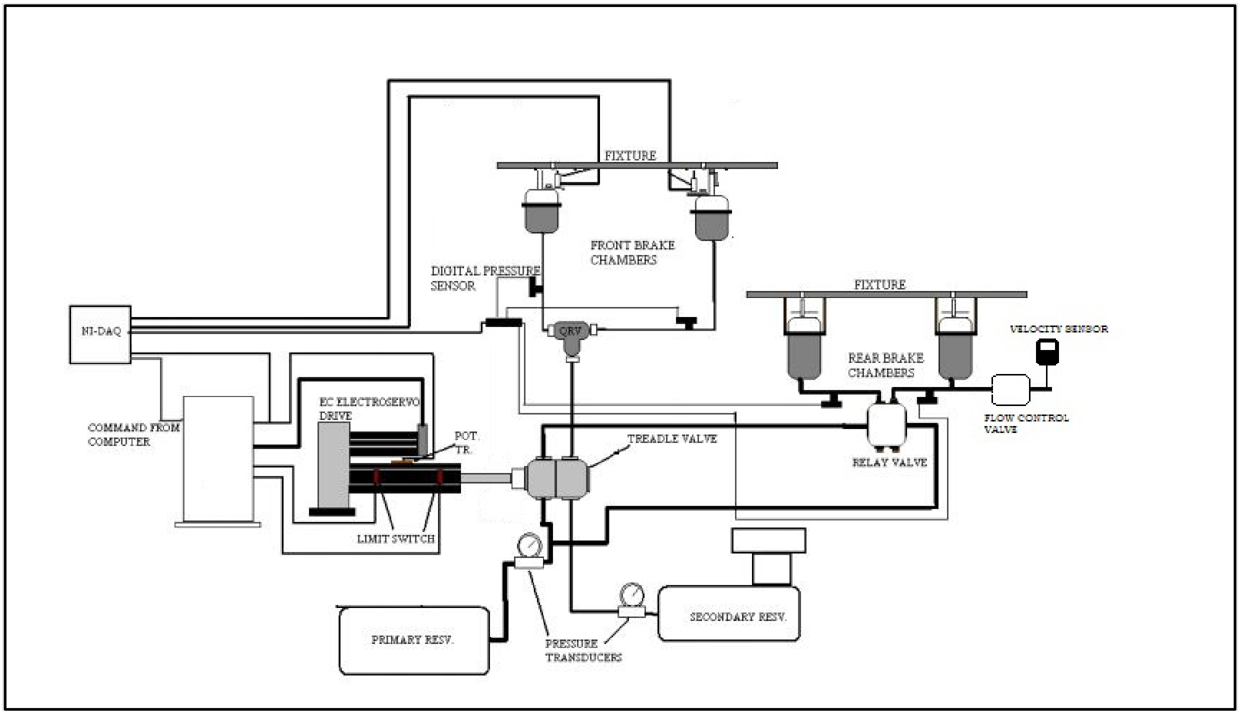

Figure 7. Diagram. Typical brake system (reprinted from Dhar [3]).

Air is supplied by a 5-horsepower (HP) air compressor to the primary reservoir and a 2-HP compressor to the secondary reservoir. Having separate reservoirs not only ensures a quicker response time but also provides an added degree of safety/redundancy in case any one of the pneumatic circuits fails. The treadle valve is actuated by a servo drive-controlled electro-mechanical actuator with position feedback. All the sensors are connected to the data acquisition (DAQ) unit. An FCV is used to simulate different degrees of leak in the system. The FCV opens completely with four turns of the dial. The dial is turned by a half turn, one full turn, two full turns, etc., to simulate different degrees of leak. An air velocity sensor is used at the end of the FCV. This velocity is used to calculate the mass flow rate of the leaking air. Table 1 provides the specifications of the equipment used.

Table 1. Setup Specifications

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	MSC #03578382
Velocity Transducer	Alnor	AVM 430-A
Linear Potentiometer	Omega Engg.	LP802-75 LP802-100
Pressure Transducer	Omega Engg.	100G5V
Data Acquisition Board	National Instruments	PCI-MIO-16E-4
Electro-mechanical Actuator	Progressive Automation	PA-14-P-4-50
Motor Controller	Polulu	G2

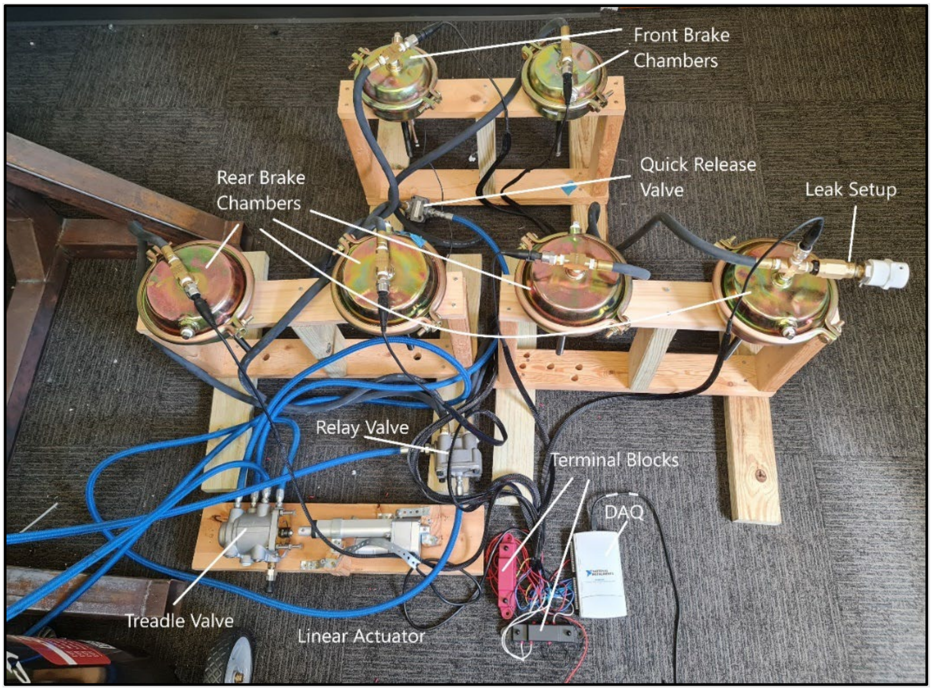

Figure 8. Photo. Experimental brake system setup.

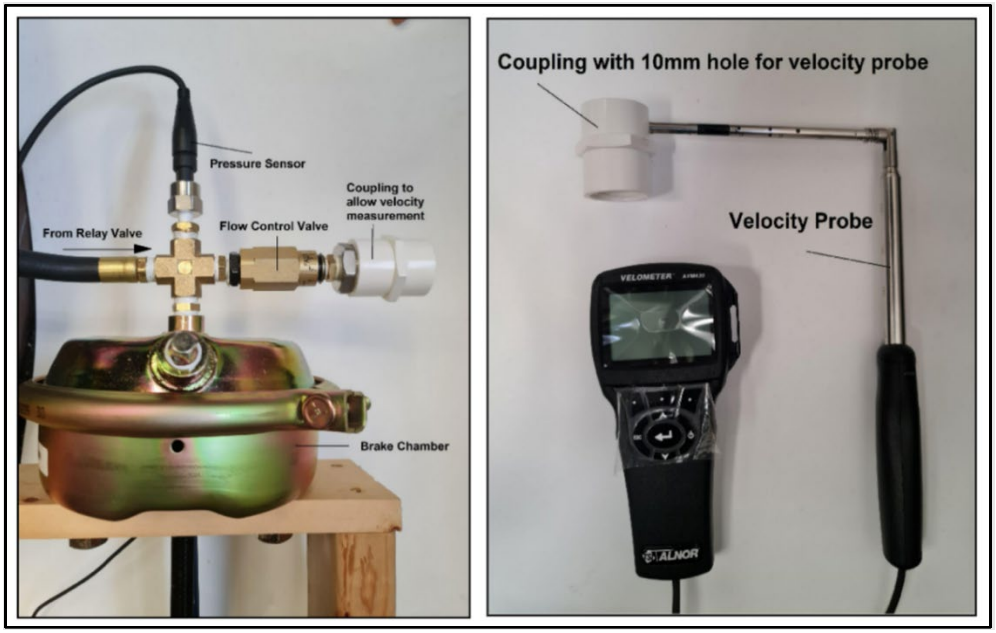

Figure 9. Photos. Experimental leak setup.

Results

Format of the Experiment

The following procedure was used to test the brake system with different degrees of simulated leaks and to capture the velocities and mass flow rates:

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

The average human can exert a maximum of 70 lb of force. The actuator can apply a maximum of 50 lb, thus making a hard braking a reasonable assumption. We performed these tests for the supply pressures of 60 psi, 70 psi, and 80 psi. Generally, supply tanks on trucks are massive, and the pressure they supply can be considered constant for our application. While trucks generally work with pressures of 80 to 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 FCV was set at zero turns (no leak), increasing in steps of half turns up to three turns for these three 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, we found that for two 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, yielding 21 data sets for different conditions. Looking at the experimental data allowed us to get insights into the nature of the system and make observations that would determine the parameters of the machine learning model.

Experimental Results for Multi-chamber Braking System

The experimental setup illustrated in Figure 7 was constructed as shown in Figure 8 and Figure 9. The input to the foot valve was standardized for every test as given in (Figure 10). We assumed that the supply tanks were large enough such that P_{sup} would remain constant. Hence, leak was considered only downstream of the treadle valve. We chose a point of leak such that the highest pressure difference exists among brake chambers, which we later found to be insignificantly small, as discussed later in this report.

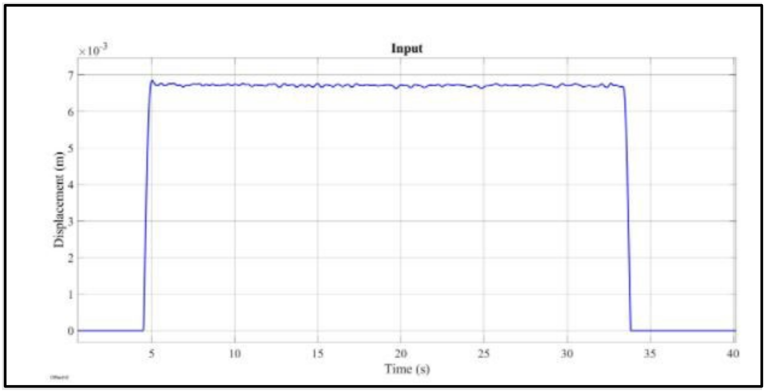

Figure 10. Graph. Input to foot valve.

For the same given input shown in Figure 10, experiments involved introducing different degrees of leak into the system to examine the behavior of the individual chambers and the whole system. The results in Figure 11 clearly show that the front chambers build pressure much faster than the rear chambers because they are smaller, and all the pressures saturate at around the supply pressure at steady state, as expected.

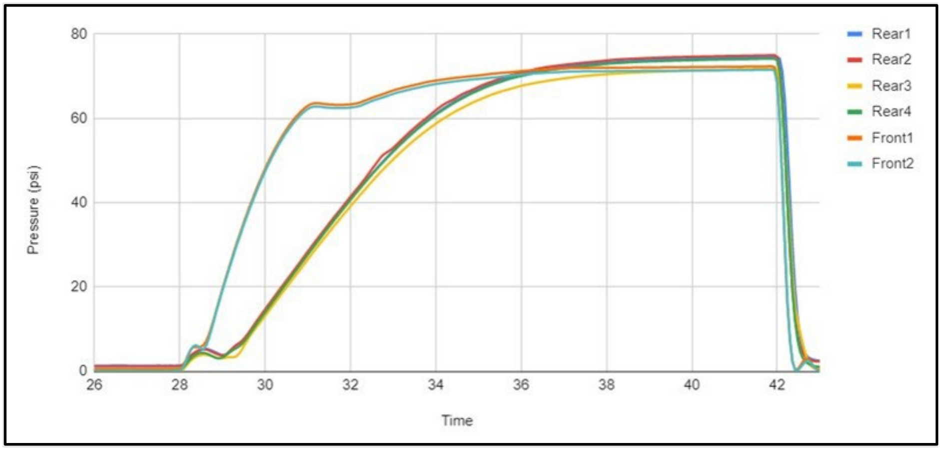

Figure 11. Graph. 80 psi, zero turn leak (max pressure delta: 3.31 psi).

Data was acquired for supply pressures 60 psi, 70 psi, and 80 psi. The FCV was set from zero, and the leak was changed by half-turn increments up to two turns (Figure 12 and Figure 13). The corresponding flow velocity was recorded when the pressures reached steady state just before the foot valve was released.

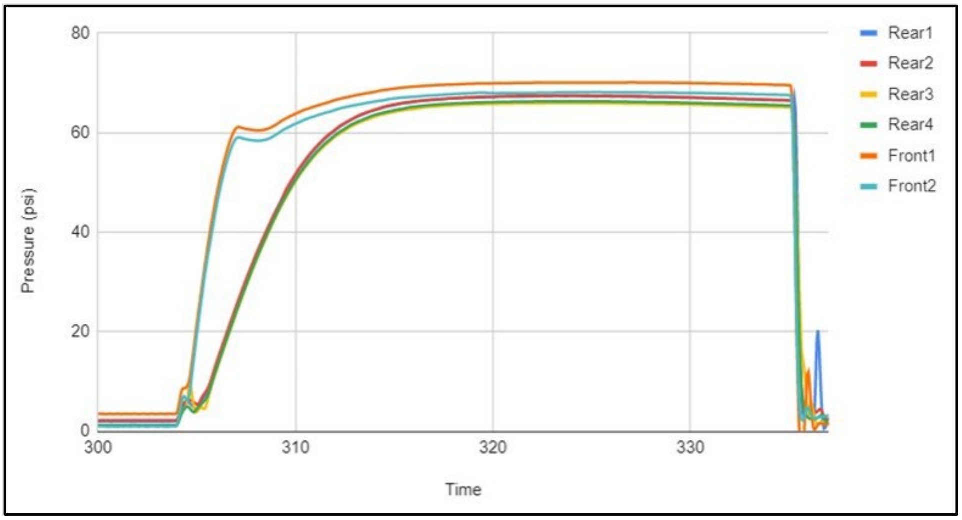

Figure 12. Graph. 80 psi, one turn leak (max pressure delta: 1.29 psi).

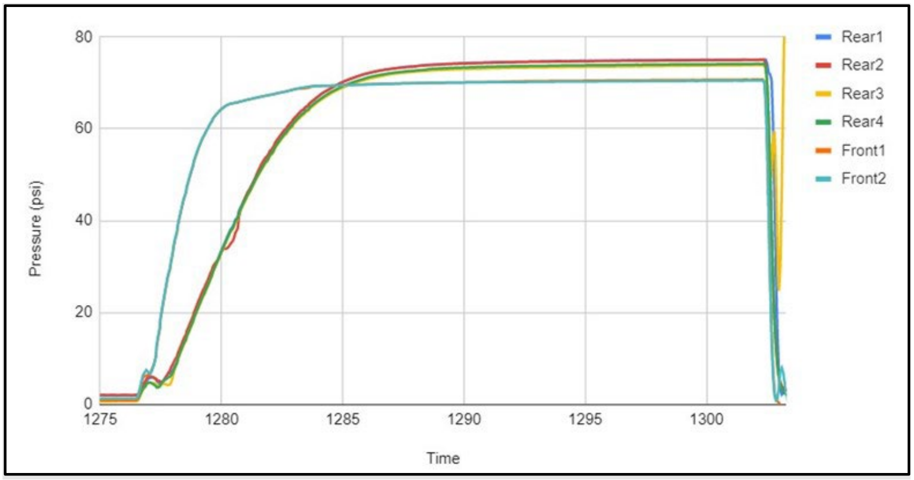

Figure 13. Graph. 80 psi, two turn leak (max pressure delta: 1.39 psi).

A MATLAB Simulink was used to simulate the pressure transients in the chambers using the dynamic model presented earlier (Figure 14). However, only the steady state pressures were modeled accurately, and the pressure transients could not be predicted with great accuracy.

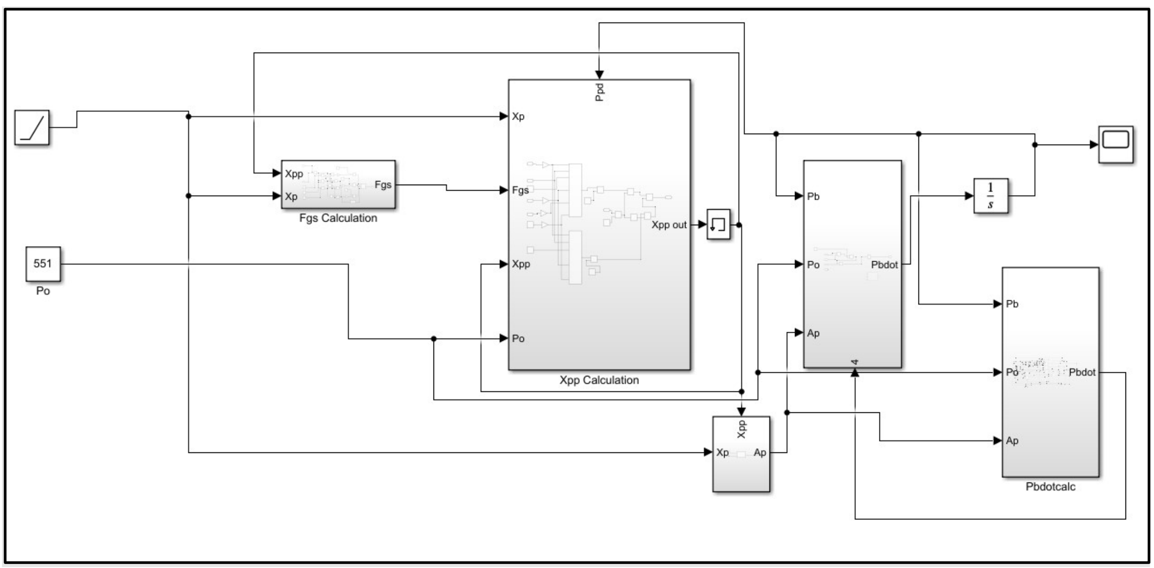

Figure 14. Diagram. MATLAB Simulink model.

This Simulink simulation requires intricate characterization of every component such as valves and springs on the truck braking system. The variability of such factors over sustained usage and the plethora of different models of trucks available on the market demonstrate the impracticality of a mathematical model. Hence, utilizing machine learning to develop models for specific truck types is desired. Given that extensive data can be collected to predict the three parameters discussed later in this report, which are supply pressures, rise times, and steady state pressures, the model parameters may be tuned to suit any truck of choice. While the Simulink model fails to capture the behavior of the multi-chamber brake system, further investigation and development into the machine learning model allows us to exploit the results obtained from experimentation.

The following observations were made regarding the data:

1) The pressures do not vary significantly between the front chambers and the rear chambers.

It is clear (see Figure 11, Figure 12, and Figure 13) 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) Rise times are significantly different between the three setups.

In Figure 15, the corresponding rise times for zero leak, one turn leak, and two turn leak cases increased with increasing leak levels. Hence, pressure rise times play a significant role in determining the degree of leak present in the system. The pressures described in this graph are for the rear chamber pressures. Hence, as concluded from the previous observation, two pressure sensors can not only quantify the state of the entire system but can also predict the overall leak in the system using the pressure rise times.

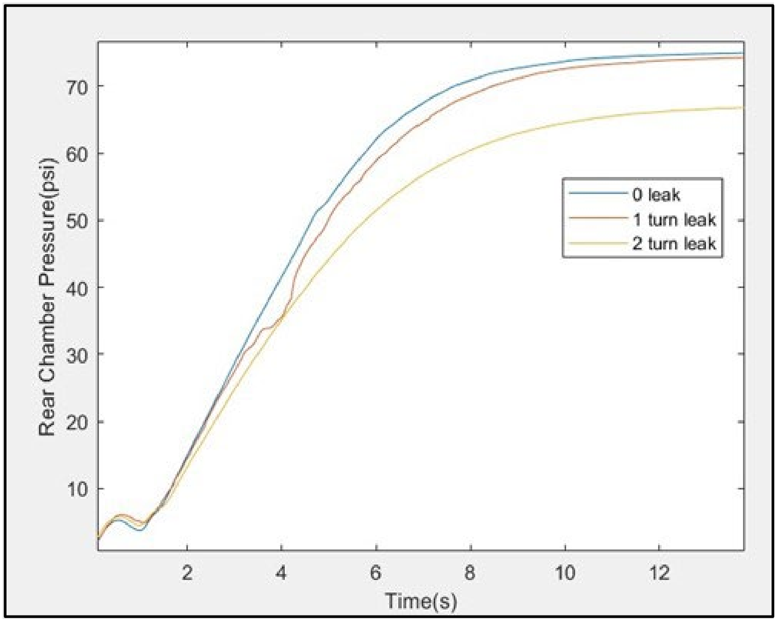

Figure 15. Graph. Pressure rise comparison at 80 psi.

3) Steady state pressures:

The steady pressures reached under different leak conditions for the same supply pressure follow a predictable trend (Figure 16). The higher the degree of leak, the lower the steady state pressure.

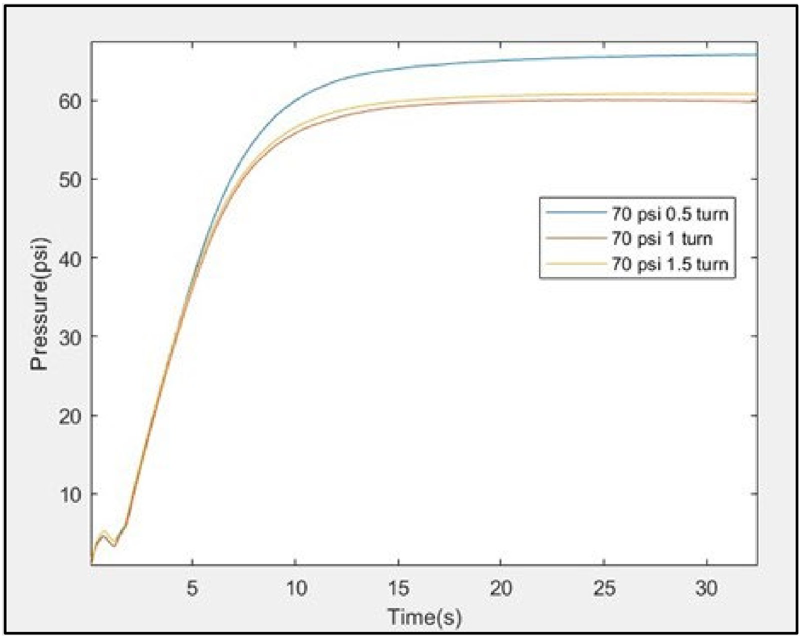

Figure 16. Graph. Steady state pressure comparison at 70 psi.

The steady state pressures reached in the half turn, one turn, and one and a half turn cases are 66.1 psi, 64.6 psi, and 60.8 psi, respectively. Hence, for a given pressure, the steady state pressure can also be used to determine the degree of leak. The corresponding mass flow rates for the given cases above, according to the velocity sensor measurements, are 0.238 g/s, 0.557 g/s, and 0.621 g/s.

Using the given parameters above (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.

Machine Learning Model Results

The training data set for the machine learning model was obtained by setting the FCV from the zero turn setting (completely sealed, no leak), increasing by half turns, up to three turns. This is essentially incrementally increasing the leak orifice diameter. The brake pedal input is set such that it resembles hard braking, and the pedal is held down until the pressure reaches steady state. This routine is repeated for supply pressures of 60 psi, 70 psi (Figure 17), and 80 psi.

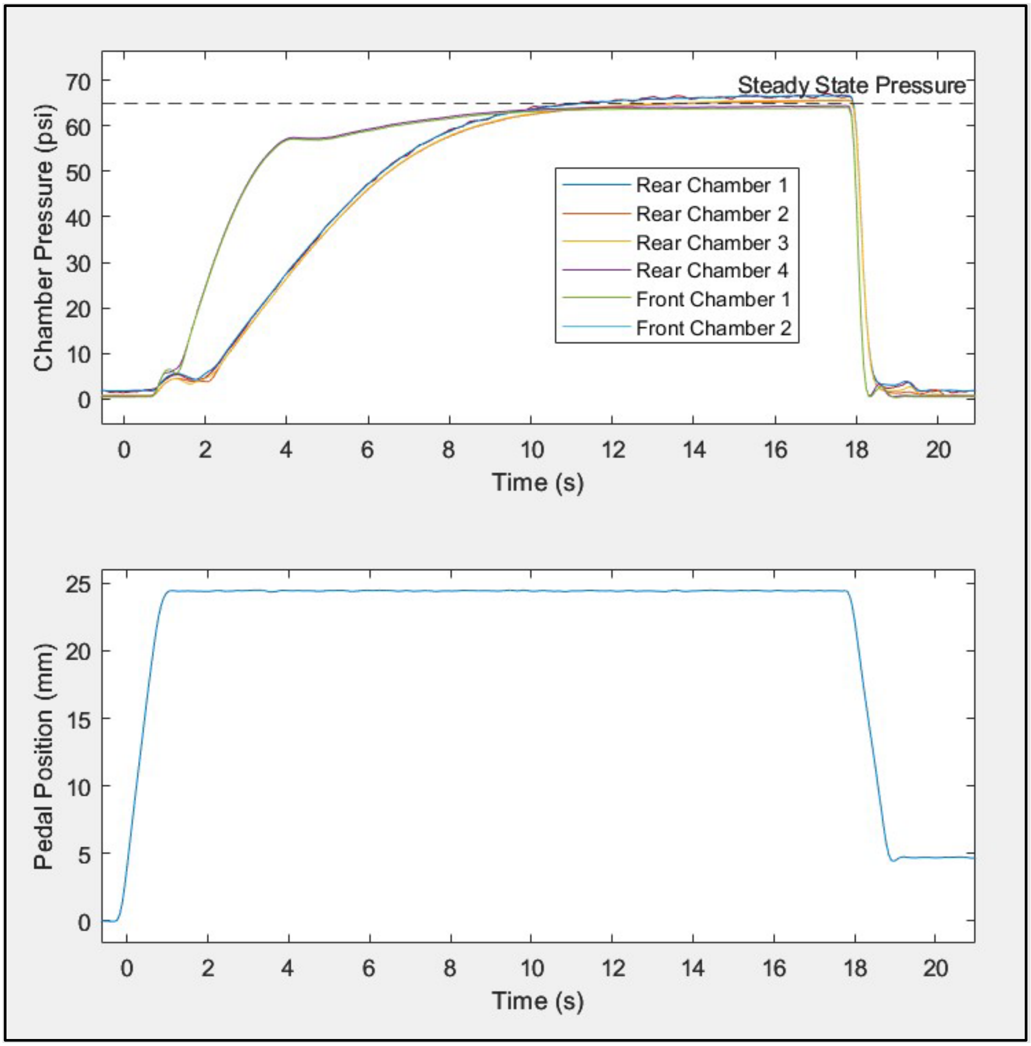

Figure 17. Graph. Chamber pressure and pedal input for 70 psi supply.

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: supply pressure, pressure rise time, and 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 start time of the pedal input is also determined in similar fashion but using a lower limit. The supply pressure is known and can easily be found from the pressure gauge of the supply tank. The parameter we want 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 used the gradient descent machine learning model for a three-input one-output case to predict the leak in the system. The model was made using data from a rear brake chamber. The data was processed using MATLAB (full code available in the Appendix), and the parameters in Table 2 were obtained:

Table 2. Training Data Set

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	1,154	1.5
50.307	8.699	60	1,168	2
42.305	7.1409	60	1,317	2.5
41.73	7.4963	60	1,522	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	1,172	1.5
59.23	8.0985	70	1,824	2
57.007	8.1015	70	2,313	2.5
54.275	8.1005	70	2,276	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	1,417	1.5
75.648	7.9217	80	2,132	2
72.545	7.9216	80	2,391	2.5
70.808	8.0376	80	2,566	3
78.218	7.86	80	172	0.5

Using these input parameters, we trained the gradient descent machine learning model. Gradient descent is an optimization algorithm for finding a local minimum of a differentiable function. Here, the differentiable function used is a cost function that contains the errors in prediction, is constructed, and is minimized to obtain the best fit. Figure 18 shows the cost function for the model to show convergence.

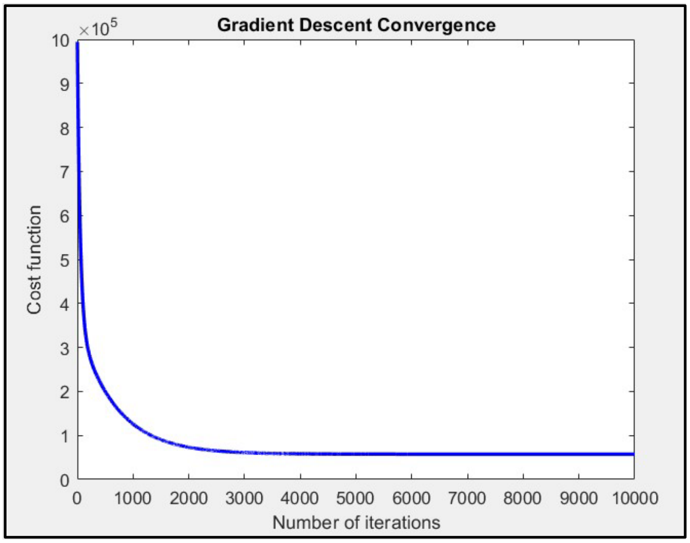

Figure 18. Graph. Gradient descent convergence.

The value to which the cost function converges is 57,475.7, thus indicating a standard deviation in prediction of 339.04 ft/min. Models made with front brake chambers also yielded similar standard deviations. Two random tests were conducted to validate the model. The first test was conducted at 65 psi supply pressure and one and a half turns of the FCV. The predicted leak velocity was 1,300 ft/min, and the actual leak velocity was 1,412 ft/min. The second test was conducted at 70 psi and one and a half turns of the FCV. The predicted and actual values were 624 ft/min and 726 ft/min, respectively. Therefore, the total leak in the system can be determined to a reasonable amount of accuracy.

Figure 19 shows the error distribution over the training data set. Except for a select few points with >20% error, most points fall under 10% error. Thus, the machine learning model predicts the leakages in the system accurately.

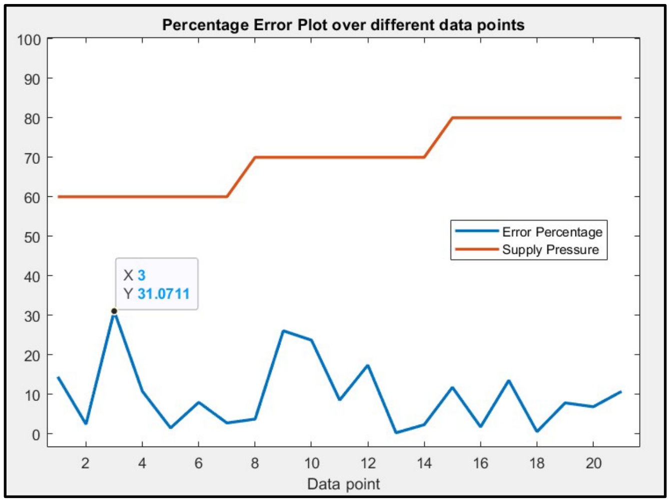

Figure 19. Graph. Error distribution over training data set.

Conclusions and Recommendations

Diagnostics of the brake system are 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 for 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 built based on this model would thus completely eliminate the requirement for separate tests.

The same experiments may be repeated on actual trucks to obtain pressure transient data that 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 in real time. Having a separate diagnostic tool that 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 determine the torque transmitted to the S-cam exactly, as the force acting on the push rod can be calculated from the brake chamber pressure, as discussed. 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 the brake system's performance is evaluated accurately.

We have described a comparatively rigid test procedure 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 nonlinear regression problems as long as the features or inputs are roughly linear and lie within a particular delta. However, a model using nonlinear 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 to find the average. The response time of the velocity sensor is about 0.5 seconds and thus not suitable for transient leak detection. Using an air flow meter can provide better accuracy, which will be required for pedal input dependent models.

Additional Products

https://safed.vtti.vt.edu/projects/development-of-a-diagnostic-system-for-air-brakes-in-autonomous-and-connected-trucks/

https://dataverse.vtti.vt.edu/dataset.xhtml?persistentId=doi:10.15787/VTT1/9SWAHY

Education and Workforce Development Products

Rex Foster, "Modelling the Pressure Transients and Push Rod Extension of a Multi-Chamber Pneumatic Braking System" M.S. Thesis, Texas A&M University, 2021.

Jaikrishnan Soundararajan, "Minimum Time Headway and Stabilizing Control Gains for Vehicle Platoons with Time Delay," M.S. Thesis, Texas A&M University, 2021.

Reyshwanth Ganeshan, "Diagnostics Using Machine Learning for Air Brakes in Commercial Vehicles," M.S. Thesis, Texas A&M University, 2023.

Technology Transfer Products

R. Ganeshan and S. Darbha, "Development of a Diagnostic System for Air Brakes Using Machine Learning Methods," in preparation for submission to IEEE Conference on ITSC, 2024.

Data Products

This data set includes data that describes the pressures in the rear and front chambers of the air brakes in a typical commercial vehicle under hard braking. The data also contains pedal travel (mm) and air leakage velocity (ft/min) from the system. This data was used to build a machine learning model to predict the amount of leakage in the system, given the pressure traces of any chamber under hard braking. All the data reported is time series data, and there are 23 tests performed under various different conditions. https://doi.org/10.15787/VTT1/9SWAHY

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Appendix. MATLAB Code

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
```

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
```