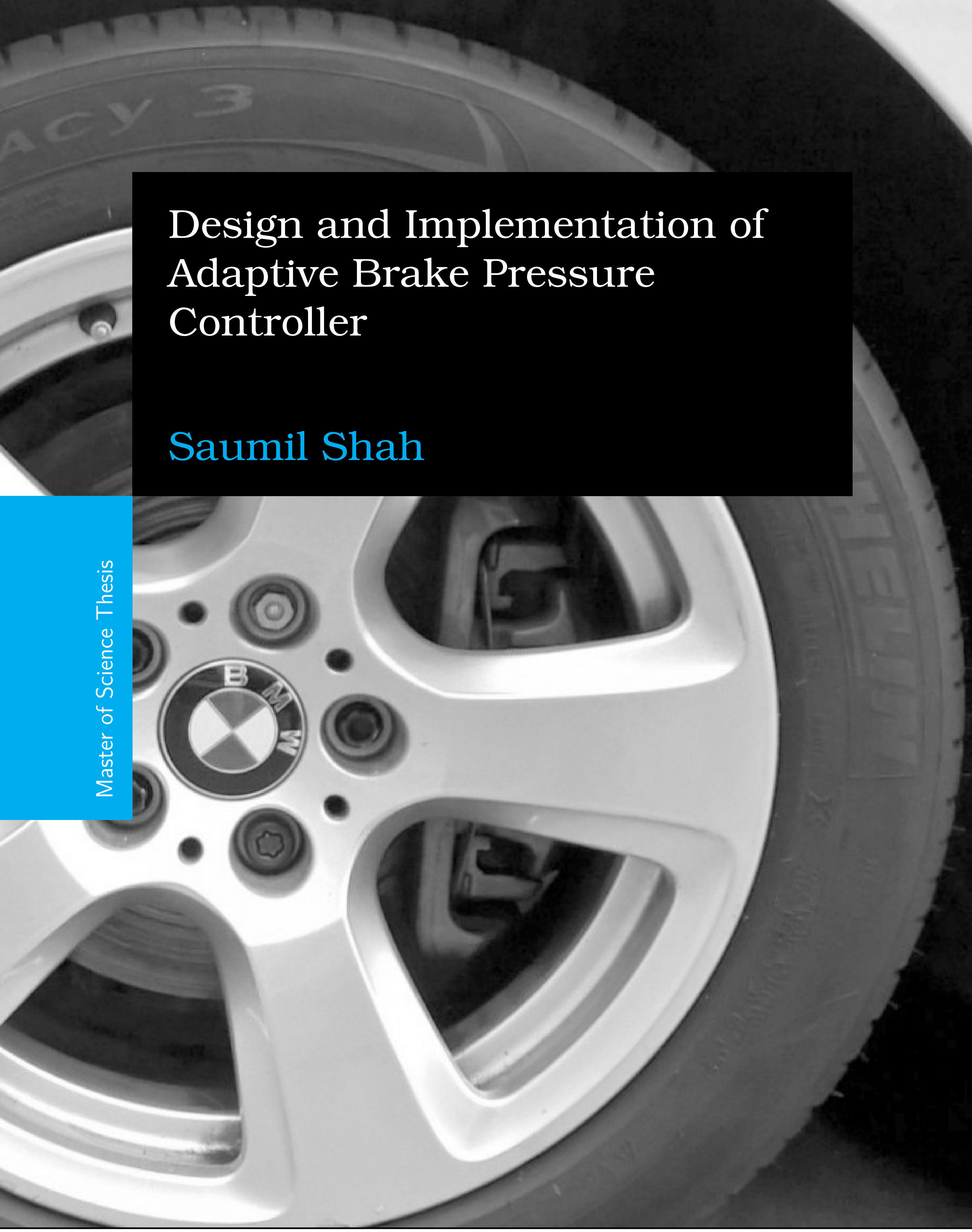

Design and Implementation of Adaptive Brake Pressure Controller

Saumil Shah

Master of Science Thesis

TU Delft Delft University of Technology

Delft Center for Systems and Control

Design and Implementation of Adaptive Brake Pressure Controller

Master of Science Thesis

For the degree of Master of Science in Mechanical Engineering - Control Engineering at Delft University of Technology

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January 19, 2016

Faculty of Mechanical, Maritime and Materials Engineering (3mE) · Delft University of Technology

The work in this thesis was supported by Precision and Microsystems Engineering (P.M.E.) Department at Delft University of Technology (TU Delft). Their cooperation is hereby gratefully acknowledged.

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The undersigned hereby certify that they have read and recommend to the Faculty of Mechanical, Maritime and Materials Engineering (3mE) for acceptance a thesis entitled

Design and Implementation of
Adaptive Brake Pressure
Controller

by

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in partial fulfillment of the requirements for the degree of

Master of Science Mechanical Engineering - Control Engineering

Dated: January 19, 2016

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Abstract

Road safety has been the subject of interest for research from the time the first automotive was invented. Safety has been characterized by many factors but the most prominent is maintaining control over the vehicle motion in all situations. Modern safety systems especially Antilock Braking System (ABS) in combination with Electronic Stability Control (ESC) has brought down the uncontrollable occasions in driving and therefore, sheltering the passengers from accidents. This system ensures the control of the vehicle while braking in varying surface conditions by keeping the friction coefficient close to optimal which helps in preventing wheel lock up and minimizing the braking distance. The current methods employ complex heuristic rules and optimization is still required in algorithm development.

The ABS provides reference pressure signals to be achieved in different wheel brake cylinders to a low level controller termed as the brake pressure controller. This low level controller needs to be as precise as possible considering the challenges of hydraulic line characteristics and unavailability of states. Some researchers have investigated this area earlier and there have been performance issues which are yet to be solved. Of these, the core issue was the inability of the controller to adapt to variable conditions. Hence, an adaptive control approach is proposed to this problem.

The project aims to optimize the functioning of the brake pressure controller. This report will introduce the reader to the test vehicle and its braking system to be controlled. It will also identify the objectives of the controller and learn the limitations of the hydraulic circuit. Further, 2 models derived from the literature will be compared from analysis on experimental data. Finally, the formulation of adaptive control algorithm and the implementation strategy along with control of essential secondary components will be addressed.

This implementation of reliable brake pressure controller along with its performance evaluation will serve as a foundation for realization for future novel ABS algorithms.

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Acknowledgements

I would like to express my sincere thanks to Prof. Edward Holweg for giving me the opportunity to work in this research area. I am grateful to my daily supervisor Stijn Kerst for guiding me throughout this project and introducing me to vehicle and subsystems. I have admired the ease of access granted to me for any doubts and continuous support regarding different aspects of this thesis. Also, I would like to extend my gratitude to Asst. Prof. Manuel Mazo for supervising me and providing critique with respect to control methodologies. I am also thankful to Dr. Barys Shyrokau for becoming a part of my thesis examination committee.

This M.Sc. project was a long journey which would not have been possible without the support of my parents Ashwin and Tejal Shah and my dear sister Devanshi Shah. I continue to remain in awe of the power of their selfless love which empowers me to push my limits and better myself.

A very special thanks to Vrishika Singh for helping me with creating an environment of determination and calm decision making especially in the period marked by personal and professional struggles. My gratitude extends towards Prakhar Kiyawat, Harsh Sapra, Nisarg Gandhi, Munjal Savla and Punit Gandhi who have been the backbone of my life in the TU Delft. Our interactions served as an enlightening and refreshing source of energy to endure studies with a smile.

Finally, I would be remiss if I do not acknowledge the inspirational companionship of Praveen Kumar Jain, Anuj Shah and Nilay Saraf in the course of completing the Control Engineering track. Further, the brainstorming sessions we shared were instrumental in expanding my ken and bolstering my confidence.

Delft, University of Technology — Saumil Shah
January 19, 2016

"Strive not to be a success, but rather to be of value."

— *Albert Einstein*

Chapter 1

Introduction

Road safety has been the subject of research interest from the end of 19^{th} century [15]. It is always seen that need to innovate and technology improvement are the factors that lead to development of a field, and automotive sector has been no different. Safety has been one of the most prominent areas pushing the automotive research to what it is today. This can be seen in Figure 1-1 which highlights the evolution of the safety systems.

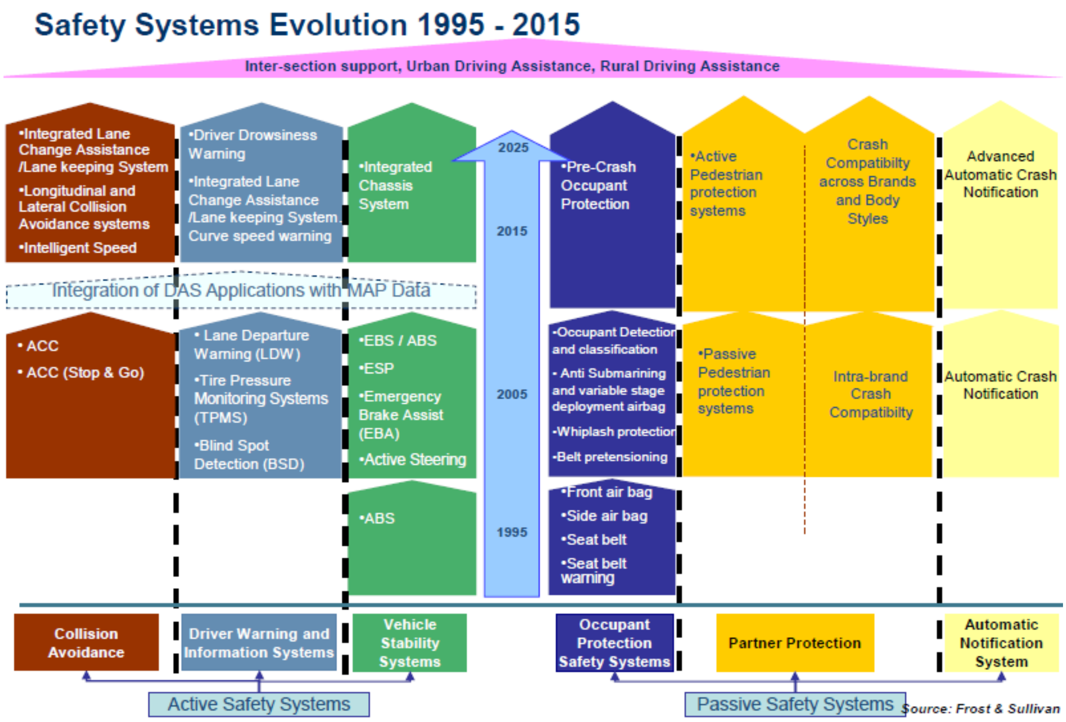


Figure 1-1: Evolution of safety systems in automobile industry [16]

As shown in Figure 1-1, safety systems can be divided into active and passive systems[16]. Passive systems are essentially structural or physical elements in the automotive. They help in minimizing the damage if the crash occurs. Some examples are air-bag, seat belt, and body structure for absorbing impact.

Active Systems are systems which prevent crash situations protecting the passengers of the vehicle. These systems can be supportive, assistive or can also automate some tasks. Examples of support systems can be warnings, navigation whereas the automation can be seen in Autonomous Emergency Braking System. The current stage in automobile development is between full manual control and complete autonomous control. Hence, the current vehicle safety systems are also referred to as Advanced Driver Assistance Systems (ADAS).

ADAS includes smart systems like the Antilock Braking System (ABS), Electronic Stability Control (ESC), Traction Control System (TCS) and Electronic Brake Force Distribution (EBD). These systems help prevent collision, overturning, slipping, under and over steering and other such calamitous events which make the driver lose control of the vehicle. Thus, these systems are essential and have found a way into the guidelines and directives in designing and manufacturing of any vehicle. This is the result of programs such as EuroNCAP and IIHS which are focused on the safety related to the automotive sector [16].

After the introduction of combined ABS and ESC on road vehicles, there has been reduction of fatal accidents by 40% [17, 18] . The graph in Figure 1-2 shows the total number of road accidents and fatalities per total distance travelled, normalised on 1965 data for the EU [1]. In addition, the graph shows when passive safety systems and active safety systems have been introduced, as well as the expected safety potential of ADAS [1].

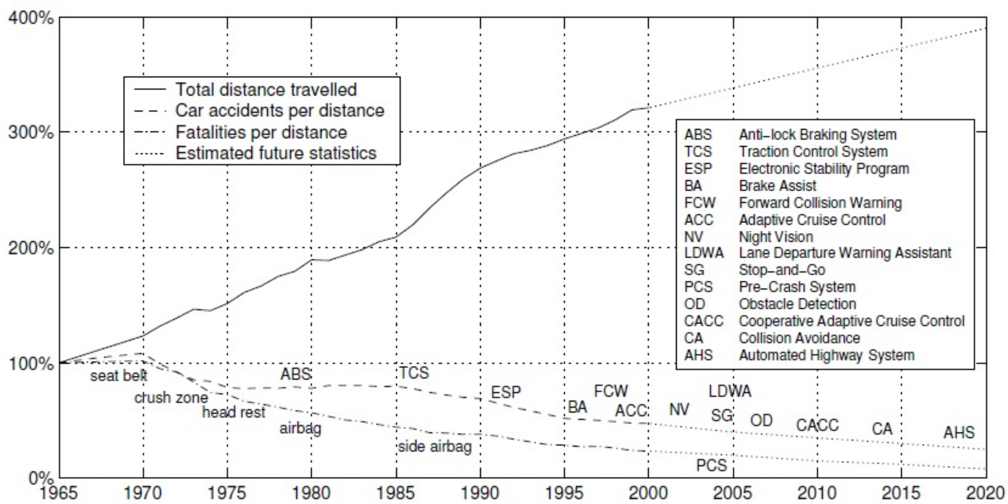


Figure 1-2: Influence of ABS and ESC on road safety statistics [1]

Of these systems, ABS has essentially assisted the driver in maintaining the control of vehicle to prevent accidents and facilitate complete stopping of vehicle. Situations such as slippery road conditions, emergency braking, high speed turning and avoiding collision might cause the driver to lose control (and stability) of the vehicle leading to fatal circumstances. This scheme essentially regulates the hydraulic braking circuit to maintain contact of the road as well as steering capability of the vehicle. These ABS control systems have been developed by many companies over the years but the electronics-based ABS was first started by a collaboration between the premier companies, BOSCH and Mercedes, in 1978 [19]. With the passage of time, BOSCH has become the world leader in the development of ABS and other electronic safety systems. The Figure 1-3 shows the basic overview of ABS control loop as given by BOSCH [2] .

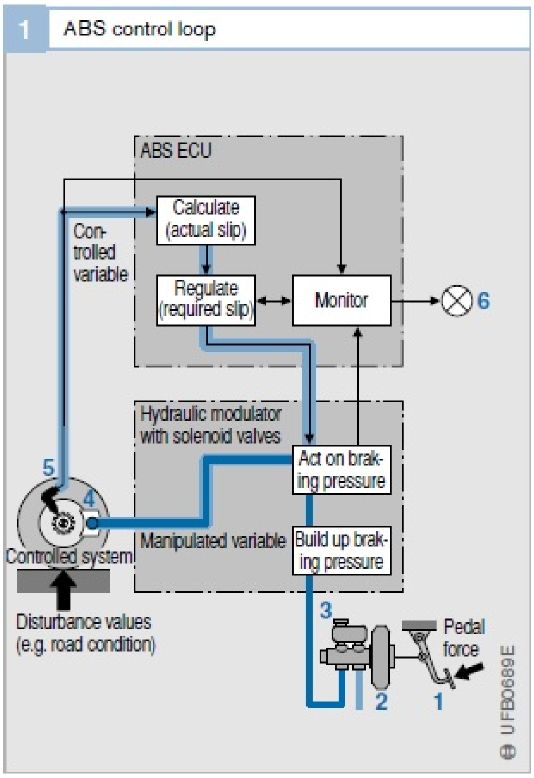


Figure 1-3: ABS control loop [2]

One can understand that the basic function of ABS controller is to regulate the brake pressures and forces depending on the circumstances. The higher level scheme decides the level of braking at each wheel brake cylinders. This level of braking is achieved through a low level controller known as brake pressure controller or Hydraulic modulator as seen in Figure 1-3. The design and implementation of this controller forms the main objective of this thesis.

1-1 ABS and Brake pressure controller

ABS was the first active safety technology to utilize the vehicle's braking system [19]. The main objective of ABS is to detect the potential wheel lock during hard braking and control the braking circuit to provide maximum braking force (based on adhesion coefficient) and directional stability. The sub-objectives of this system are twofold: to reduce stopping distances, to improve stability and steerability during braking. ABS achieves its objectives by cyclically releasing and reapplying brake actuation pressure so that wheel continues to rotate and does not lose traction with the surface. Under conditions of braking where wheel lock may occur, such as emergency braking or braking on low adhesion road surfaces (wet or icy), a road vehicle fitted with ABS will achieve shorter stopping distances than the same vehicle without ABS, because the braking forces at each wheel utilise the maximum tyre/road adhesion coefficient rather than the lower sliding coefficient of friction between the tyre and the road when the wheel is locked and skidding. The most important benefit of ABS is that it improves vehicle safety and stability by allowing steering control under all braking conditions because the wheels are not allowed to lock and skid. There are several algorithms built using the vehicle and tyre-road surface contact dynamics. These algorithms realize ABS objectives by detecting wheel lock, i.e. measuring some parameter(s) associated with the rotation of the wheel being controlled like wheel deceleration or wheel slip, and then comparing this with some preset value to ascertain whether wheel lock is likely to occur. Control actions involving building and releasing of brake pressures at different wheels are then taken to avoid actual wheel lock. More description about the dynamics of Antilock Braking System (ABS) and various algorithms is given in Appendices A-1 and A-2.

As seen earlier, Figure 1-3 provides the hierarchical control scheme of ABS. Measurements from the sensors about vehicle dynamics are taken along with the external input i.e. driver's pressure on the pedal by the high level controller. The required actions result from the algorithm that generate reference pressure signals for each wheel. These reference signals are then achieved through the actuators by low level controller.

As technology advances, new algorithms based on new parameters and theories need to be tested to obtain more optimal control over braking. Literature provides several examples of modern strategies such as fuzzy logic and neural networks for the high-level controller to improve the performance as compared to earlier algorithms but these have mostly been tested in simulations [13]. Hardware implementation and on-road testing of such strategies becomes a challenge because of absence of reliable low-level controller which effectively controls the braking circuit. It has to be noted that ABS-relevant details about the braking circuit and its specifications are not provided by the manufacturer of any vehicle. More importantly, the control strategy used in the modern vehicles has not been availed by ECU manufacturer BOSCH for proprietary and commercial reasons. So, this adds to the challenge of designing a controller for an already manufactured on-road vehicle. Further, significant amount of the available literature is accomplished with different hardware setups. These conditions have shaped the research objectives of this thesis presented in the next section.

1-2 Research Objective

Apart from the difficulty to obtain relevant research work on the brake pressure controller, the most important challenge is to control the hydraulic circuit with changing properties during operation. The brake pressure controller must be able to track the reference with accuracy provided by the higher level controller by attuning to these conditions. Thus, an adaptive approach is desired for this low level controller.

The research objective of this thesis can be broadly stated as the design of adaptive brake pressure controller for the purpose of implementing future novel ABS algorithms. This objective can be divide into the following sub-objectives:

- Studying the hydraulic circuit components and operation to understand the dynamics of the system

- Identifying or deriving models for the control system which incorporate the influential properties of the components affecting the operation
- Setting performance objectives of the brake pressure controller by examining ABS Reference signals
- Selecting appropriate adaptive algorithm by reviewing literature and building a decentralized control structure
- Evaluating the control system performance using suitable performance indicators

The execution of this thesis will benefit future researchers at Delft University of Technology (TU Delft) to test novel ABS strategies on the given setup taking a step further in the direction of vehicle dynamics.

1-3 Thesis Outline

The reader has been introduced to the need of the brake pressure controller in the earlier sections. Further chapters will focus on the process of designing and implementation of the brake pressure controller.

Chapter 2 introduces the reader to the vehicle/setup which was available for experimentation. It explores the Hydraulic Actuated Braking (HAB) circuit with respect to its components, working and limitations. Further, it also points out the influence of several properties affecting the performance of the system. Finally, the secondary control scheme necessary for the brake pressure control problem, involving the accumulator state observer and pump control, is discussed.

The literature review on the methods used for modeling the hydraulic system and controlling it are reviewed in Chapter 3. It also includes recommendations from earlier research done on the test vehicle at Delft University of Technology (TU Delft). The chapter presents an overview of the methods employed and also provides reasons behind the need for the controller to be adaptive. The desired objectives of the controller are also annexed with sub-objectives in terms of reference signals.

Chapter 4 delves into the theoretical background for adaptive filtering. The fundamental scheme of Recursive Least Squares (RLS) is explained to understand its selection for the particular application. Additionally, a partial-update version of RLS is also discussed.

Chapter 5 analyses the simulation results of the control scheme formulated using previously decided models for circuit components: valves and accumulator. These simulations are carried out on experimental data obtained from previous research work at TU Delft [4]. Also, the influence of partial update RLS and forgetting factor is assessed. Subsequently, the simulation results of the estimation models are discussed along with their variants.

With the quality of models assessed in the earlier chapter, the implementation of the brake pressure controller is shown in Chapter 6. The process of implementation as well as the real time control scheme implemented in `Simulink` is explained in detail. The controller analysis experiments and reference signals are decided from the results of previous chapters and then tested on the controller.

The experimental data obtained using the developed brake pressure control system is analysed with respect to its parameters in Chapter 7. Special focus is given on understanding the advantages and more importantly, the drawbacks of the selected models. This chapter uses the experimental data to recommend the estimation model to be used for future implementation.

Chapter 8 finally concludes this thesis by comparing and evaluating the simulation and experimental results. Also, it summarizes the advantages and limitations of the models used for brake pressure control system. Finally, it lays out further recommendation for future work.

As mentioned earlier, Appendices A-1 and A-2 are provided to explain the theory of Antilock Braking System (ABS) to the uninitiated readers.

Chapter 2

System Characteristics

This chapter introduces the vehicle and its subsystem which are going to be employed for research and validation in the first section. Further, it explores the hydraulic HAB layout, the circuit components and their roles in different operation modes.

The next section informs the reader about the properties of the fluid which affect the system during the operation. The understanding of these is important to be able to assess the behaviour of brake pressure signals. Subsequently, the chapter delves into the operation characteristics of the hydraulic circuit where the relation between parameters are observed. The attributes of secondary control scheme consisting of an accumulator and a pump are also studied. Some peculiar features of the hydraulic system are observed towards the end of this chapter which may limit or hinder the performance of any controller.

2-1 Test Vehicle

A partnership between TU Delft and SKF has led to an automotive project in which a BMW 5 series car (seen in Figure 2-1) is modified and equipped with novel instrumentation for research and development in active systems [20]. The research faculty at Precision and Microsystems Engineering department, at TU Delft, uses this vehicle for Vehicle-in-loop (VIL) testing. Since this report focuses on braking, the braking circuit and related components will be discussed.

Every commercial vehicle has an Electronic Control Unit (ECU) which governs the ABS scheme as shown in the Figure 2-2. This ECU is part of the DSC module made by BOSCH [8]. This system has been manufactured for commercial purposes and does not possess the electronic and interfacing capability for research and testing. Hence, the system is modified for researchers to carry out experiments. The original ECU and power amplification stage of the BMW are bypassed and replaced by an AutoBox computer and amplification electronics. This computer is thus able to actuate the components within the hydraulic unit, and thereby function as the ECU and carry out actuation phases. Since the data pertaining to dynamics

Figure 2-1: Test vehicle BMW 5 series E60

of the vehicle is essential, the CAN bus data and wheel speed sensors are tapped and also additional sensors are added. The most important being brake pressure sensors in the hydraulic circuit. More specifications of these modifications will be found in the BMW manual which is currently being formulated.

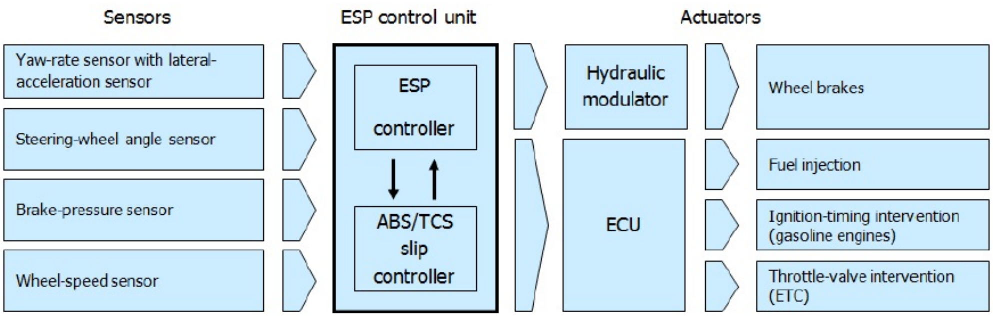


Figure 2-2: ECU block diagram [4]

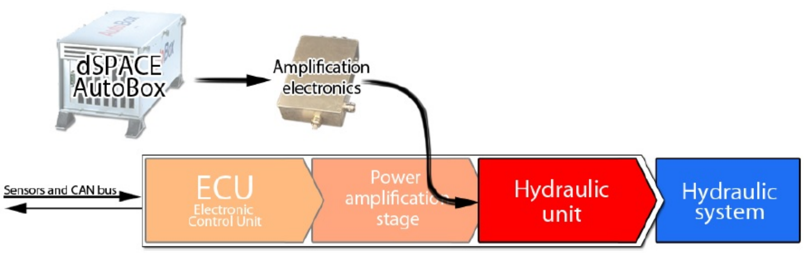


Figure 2-3: Modified DSC unit [20]

In order to avoid conflicts and errors in the BMW CAN bus, an extra (dummy) DSC module, which is not connected to the hydraulic circuit of the car, is placed in the BMW. This dummy module is connected to the original BMW cabling, and hereby the car still thinks that the original DSC of the vehicle is properly functioning. This Autobox contains dSPACE Real

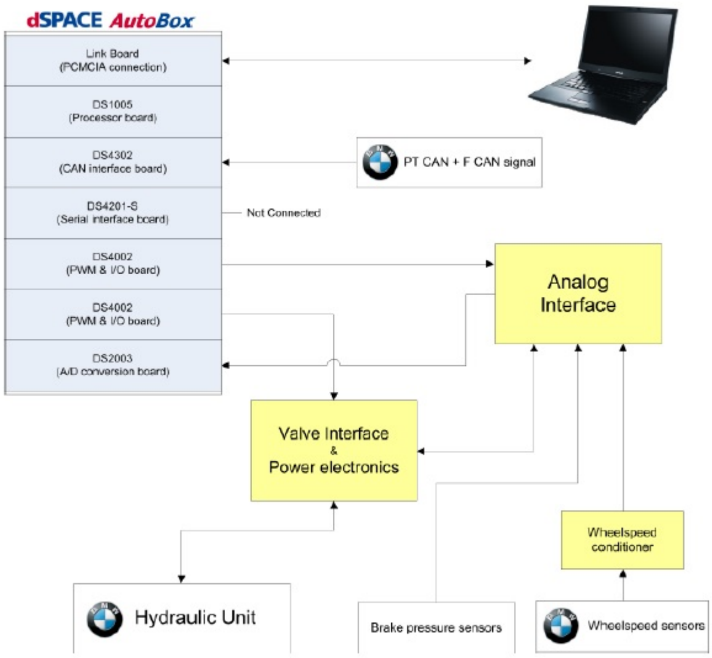


Figure 2-4: Overview of electronics connections within the BMW test vehicle [4]

Time system which is a modular hardware system. This system has the capability to sense and process the data and decide the form of output to be given to the actuators. The dSPACE can be programmed from a connected computer having capability to accept algorithms made in MATLAB and Simulink, and other languages such as C to run on the vehicle (Figure 2-4).

2-2 Hydraulic Circuit

With the interface between the programs and vehicle in place, we delve into the system to be controlled. As it is seen in the Figure 3-1, the brake pressure controller controls the brake circuit. The main characteristic of the Hydraulic Actuated Braking (HAB) type of braking system is that the driver's applied force on the brake lever is directly transmitted to the brakes by a hydraulic circuit. The driver pushes the brake pedal and the force is initially multiplied by the pedal mechanical lever ratio. In our vehicles, a second force multiplication is operated by the vacuum booster and finally a rod pushes the brake fluid inside the master cylinder increasing in this way the brake lines pressure. Safety regulations require each HAB system to have two separate brake circuits, which often results in either a crossed (X) or parallel (II) configuration (Figure 2-5). These configurations can prevent a complete failure of the vehicle braking system, or at least highly reduce the possibility of such an event. If one of the two lines breaks down, the other one allows to stop the vehicle. The main difference between

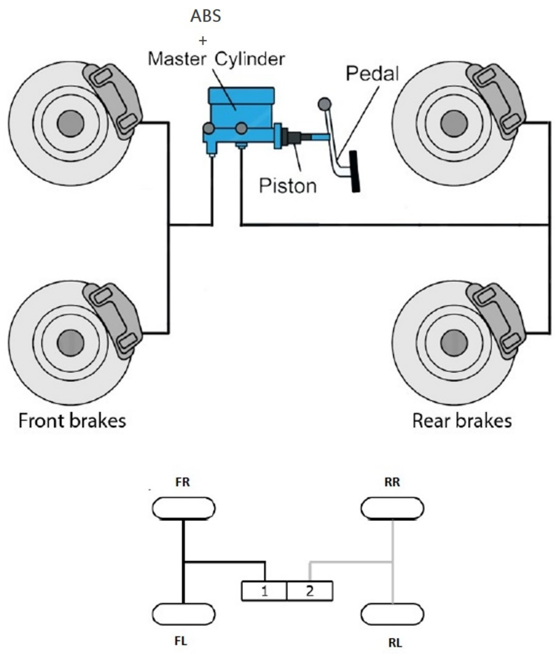


Figure 2-5: Parallel (||) braking configuration [3]

the two is that with the crossed layout (X) the vehicle keeps the lateral stability during the braking action while this could be a problem with the parallel one (II).

In the test vehicle, the parallel configuration is implemented, delivering the fluid separately between the front and rear axles. This configuration corresponds to separate but mirrored hydraulic circuits for front and rear wheels. The Figure 2-6 shows the hydraulic(HAB) circuit diagram for the front subsystem. This layout will be considered as the system for control as the rear subsystem is exactly the same circuit with similar set of components.

The basic components of any HAB system, namely the brake lever, master cylinder, brake cylinders and the pipelines connecting them are seen in the Figure 2-6. The BMW's hydraulic circuit also contains a hydraulic unit for ABS and ESC actuation, which consists of several valves, a pump and an accumulator. During normal operation none of the components of the hydraulic unit are energized or activated, and therefore brake fluid can move freely from master cylinder to brake cylinders. In this way the driver is in direct control of the brake pressure on both wheels. When the ABS system notices that wheel lock is imminent, it uses the hydraulic unit to take over the control of the brake pressure in each line and brake separately by the use of the hydraulic unit [5].

2-2-1 Components

The major components of the hydraulic circuit of the BMW test vehicle are explained as follows (refer [4]):

Brake booster
The driver's foot applies a certain force on the brake pedal. This force is converted to a

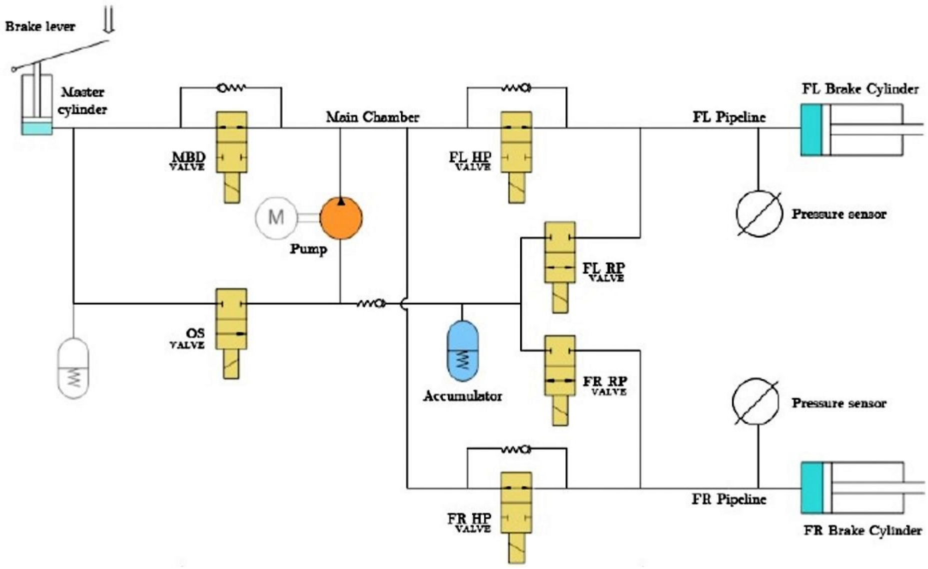


Figure 2-6: Hydraulic Braking Circuit for front wheels [5]

pressure on the brake fluid and immediately amplified by means of the brake booster. A set up is used to act with the master cylinder to provide the brakes with higher hydraulic pressure through a brake booster push-rod. The booster uses vacuum from the engine intake to boost the force applied by the pedal to the master cylinder. Therefore, if the engine is not running, the brake pedal feels very hard to push and ineffective on the braking capability.

Valves

The valves used in this hydraulic circuit are On/Off solenoid valves controlled with the opening duration of the valve. These On/Off 2-way valves and stand out for their low cost, high flow rate gain, small size and simple structure. However, they have actuator dynamics and fluid non-linear behavior, which affects the control accuracy significantly. This makes fine motion control difficult to achieve. So, PWM technique with rapid valve switching timings is used to obtain linear characteristics during short cycle time. Another approach can be the introduction of proportional valves which can solve several issues and provide better control for ABS systems.

There are six valves of the On/Off category for front subsystem as shown in Figure 2-6. The Main Brake Disconnect (MBD) and the Hold Pressure (HP) valves are Normally Open (NO) and the Release Pressure (RP) and the Oil Supply (OS) valves are Normally Closed (NC). The MBD valve is able to disconnect the whole hydraulic circuit when necessary. This valve can also be energized in order to disable the connection between the brake pedal and the pump. In normal operation, driver's pressure applied on the lever is directly transmitted to the cylinder. The HP valves allow the brake fluid to flow towards the brake cylinders when an increase of pressure is required. The RP valves are in charge of releasing brake fluid from the cylinders to the accumulator in order to decrease the pressure on the brake pads. In normal braking operation (when ABS is not active), the MBD and HP valves are open so that the pressure applied on the pedal can directly be transferred to the pads. On the contrary, the OS and RP valves are closed so that pressure is not released from the brake cylinders. This is further explained in the Operation section further.

Brake fluid
The medium of the hydraulic actuators is a Glycolether based fluid namely DOT3 & 4 [4]. It is self-lubricating but compressible. For building a precise controller, the fluid properties such as viscosity and bulk modulus should be considered mostly when the valves are controlled without the measurement of volumetric flow rate i.e. a time-based release approach.

Accumulator
The accumulator is the component of the ABS that stores the brake fluid released by the RP valves during every release phase in the ABS algorithms. This type of accumulator typically uses a spring loaded diaphragm. The pump motor is energized via a relay that is switched on by the ABS control module when it detects that the accumulator is about to reach its limit capacity. By pumping fluid to the Main Chamber, accumulator gets emptied and RP valves can release pressure again.

Pump
It pumps fluid from the accumulator to the pressurized Main Chamber and empties the accumulator. This allows the RP valves to release more fluid from the brake cylinders. This can be also used by the ECU for building pressure without the necessity to apply pressure on the pedal but it does not operate in this mode during ABS operation.

2-2-2 Operation modes

This hydraulic circuit works in three modes of operation as shown in the table

	Action	Hold pressure valve	Release pressure valve	Main brake disconnect valve	Oil supply valve
ABS operation	Hold pressure	Closed (energized)	Closed (de-energized)	Open (de-energized)	Closed (de-energized)
	Build pressure	Open (de-energized)	Closed (de-energized)	Open (de-energized)	Closed (de-energized)
	Dump pressure	Closed (energized)	Open (energized)	Open (de-energized)	Closed (de-energized)
ESC	Build pressure	Open (de-energized)	Closed (de-energized)	Closed (energized)	Open (energized)

Figure 2-7: Operation modes of HAB [5]

1. **Manual operation**
   The fluid is pushed by drivers application of force via pedal. The force on pedal pushes the brake fluid through the pipelines (possible due to MBD and Hold pressure valves being open while the other valves remain closed) towards the front calipers as the brake distribution is equal in the front. The calipers are pushed and brake pads are pushed against the disc to slow the vehicle. As the driver releases the brake pedal, the fluid flows backward cause of pressure difference and the brake pads stop brushing against the disc. The holding of certain amount of brake pressure depends only on the drivers application of force.

2. **ABS operation**
   The MBD valve remains open while the Oil Supply valve is closed. Also the Hold Pressure and Release Valves are normally closed in this operation. This operation mode needs the constant application of drivers pressure on the foot pedal. This pressure is termed as Supply pressure or 'Brake Pressure ABS' by the earlier researchers at TU Delft. This supply pressure is required to be higher than the reference brake pressure to make the desired pressure step. Thus, adequate supply pressure is assumed in the following operation phases.

   Build phase The brake pressure controller controls the Hold pressure valve and opens it for limited time to reach the reference pressure. This is possible due to the pressure difference between main brake line (high) and the wheel brake cylinder(low).

   Hold phase The Hold valves (HP) and Release valves (RP) remain closed during this operation unless stimulated by external signal. This holds the fluid pressure inside the wheel brake cylinders. The pressure is released or increased when one of the connected valves is triggered open.

   Release phase The release phase is executed when the Hold valve (HP) is closed and release valve (RP) is triggered open by the brake pressure controller. The fluid pressure is released due to the pressure difference between the wheel brake cylinder pressure(high) and the accumulator pressure(low). This causes the pressure to drop in the wheel brake cylinder unless the accumulator is full. In this case, the fluid is pumped to the main brake line.

3. **ESC operation**
   In this mode, the Oil Supply valve is opened and MBD valve is closed disconnecting the driver's input in the braking operation. The brake fluid is controlled by the Pump and Oil supply reserve. Apart from these changes, the build pressure, hold pressure and release pressure phases are similar to that of ABS operation explained before.

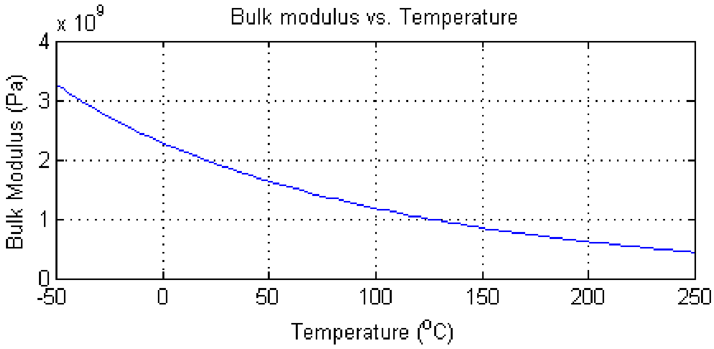
2-3 Influential Fluid Properties

The brake pressure system comprises of several components where the mechanical, hydraulic and electrical properties affect the dynamical behavior of the system. During the operation of control system, the mechanical and electrical properties of the system do not change dynamically unlike the hydraulic properties of the fluid. As mentioned earlier, the brake fluid used by the vehicle setup is a glycol-ether based hygroscopic fluid made from the mixture of DOT 3 and DOT 4 brake fluids (classified under the U.S. Department of Transportation). The brake fluid is an important medium to transfer the force from the driver's pedal to the brake calipers to push the friction material against discs to perform deceleration. It is important for the brake fluid to maintain its ability to transfer forces throughout the operation. However, the following properties of the fluid do not remain constant in the range of operation owing to pressure and temperature changes and can affect its performance.

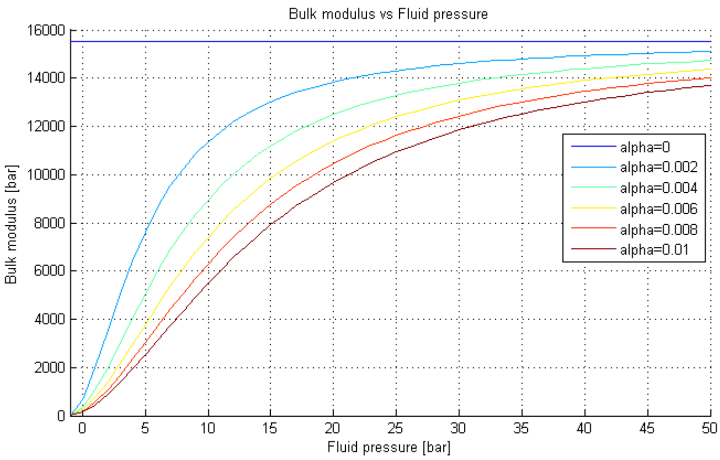
1. **Compressibility**
   The compressibility of fluid is the measure of stiffness of fluid. The stiffer the fluid the lesser amount of pedal stroke i.e. effort to obtain the desired brake caliper pressure. The compressibility of fluid is determined by the parameter known as the bulk modulus (β)

$$\beta = -V.\frac{dP}{dV} \propto \frac{1}{\text{compressibility}} \tag{2-1}$$

where
V Volume of the brake pressure fluid
$\frac{dP}{dV}$ derivative of the pressure of the fluid with respect to the change in volume



(a) Variation of bulk modulus with temperature for DOT 3 & 4 fluid [4]



(b) Bulk modulus v/s fluid pressure at different air content for DOT 3 & 4 fluid where alpha = $\frac{\text{Volume of air}}{\text{Volume of the fluid}}$ [4]

Figure 2-8: Effect of varying temperature and air content on bulk modulus of brake fluid

If the fluid is easier to compress, the derivative of the pressure of the fluid with respect to the change in volume will be smaller. It means that more amount of fluid will be required to make the requested pressure step. This compressibility of fluid is difficult to calculate as it is dependent on temperature, pressure of the fluid, and also the amount of air trapped inside the fluid. The Figure 2-8a shows the effect of temperature variation in the operation range on the bulk modulus. The temperature of the fluid increases due to the proximity of the brake lines to the engine and large amount of heat generated by the pressing of brake pads against the wheel discs. As seen from the plot, this will cause increase in the compressibility of the fluid.

The Figure 2-8b shows the effect of entrapped air in the brake fluid on the bulk modulus of the brake fluid. It is seen that the fluid is more compressible with increasing volume of air. It also helps in understanding the amount of effort required for making a pressure step depending on the pressure range of the operations. If the pressure range is between 0 and 10 bars and a pressure step is made in that range, more amount of fluid will be required as seen by the low value of bulk modulus. The opposite will happen if the pressure range is between $35-50$ bars.

2. **Density**
The density ($\rho = \frac{\text{mass of the fluid}}{\text{volume of the fluid}}$) of the brake fluid is dependent on temperature and its effect is seen in the Figure 2-9 where a linear relationship is used to describe the relationship between the density and temperature [4]. It is seen that for a constant pressure, the temperature increase can decrease the density of the fluid.

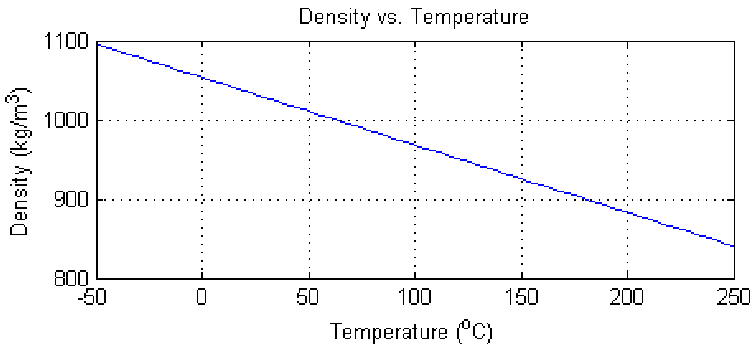


Figure 2-9: Variation of density with temperature in the operation range [4]

3. **Viscosity**
It is defined as the resistance against the flow or shear deformation. The parameter kinematic viscosity is used to see the effect of temperature variation on the fluid viscosity. The kinematic viscosity (ν) is determined by the following equation

$$\nu = \frac{\mu}{\rho} \tag{2-2}$$

where
The dynamics viscosity(μ) can be defined by the Newtonian shear stress equation given below

$$\mu = \frac{\tau}{\frac{\Delta u}{\Delta y}} \tag{2-3}$$

μ : Absolute viscosity (Pa.s)
τ : shear stress (Pa)
Δu : relative velocity between two layers (mm/s)
Δy : distance between two layers (mm)
ρ : Density of the fluid (kg/mm^3)

Decrease in kinematic viscosity increases the pipe flow rate as the contact of the molecules with their neighbors decreases [21]. A constant kinematic viscosity is desired for a reliable brake system operation but its value does not remain constant for the operation temperature range. The kinematic viscosity is plotted with respect to the temperature for brake fluid of given test setup in the Figure 2-10. It is seen that kinematic viscosity decreases with temperature. Thus, though the variation is small it may affect the performance of the system. For a reliable brake system operation, brake fluid must keep a constant viscosity under a wide service temperature range.

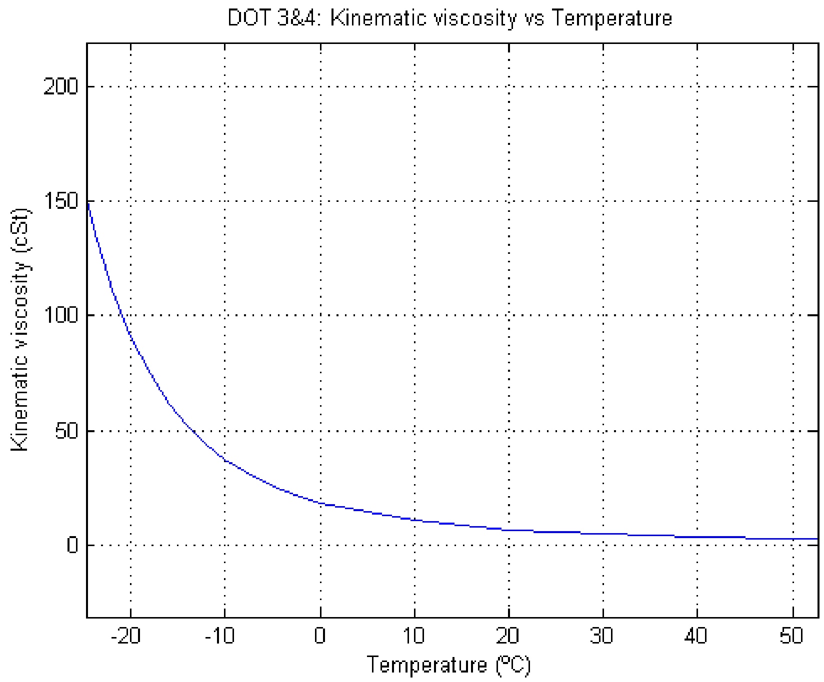


Figure 2-10: Variation of kinematic viscosity with temperature within the operation range [4]

It was seen that the effect of variation of fluid properties is not insignificant. During operation of the brake pressure control system, variation of these properties will require modification in the control input to achieve optimal performance. Hence, it is important for the design of control system to incorporate the effects of fluid behavior in the model of the hydraulic system.

There are also other properties of fluid such as the boiling point which affect the nature of the fluid. Such properties along with other mechanical and electrical properties are discussed by Torres and Kerst [4, 5].

2-4 Operation attributes of hydraulic circuits

In his thesis, Torres [4] carried out different experiments which enabled him to understand the characteristics of the circuit during each operation mode. This required him to study each component of the hydraulic circuit individually and observe its behavior and possible parameters affecting it using background knowledge of dynamics of component and configuration. The most influential components of the circuit were the Valves. They were studied during build and release phases to obtain characteristics such as the minimum valve opening time and noise in the system measurements. Also, these were used to find the relation between different parameters. For instance, the effect of the amount of the pressure applied by driver, the amount of pressure at the wheel-brake cylinder, valve opening time and also voltage applied to the valves was seen during pressure build-up.

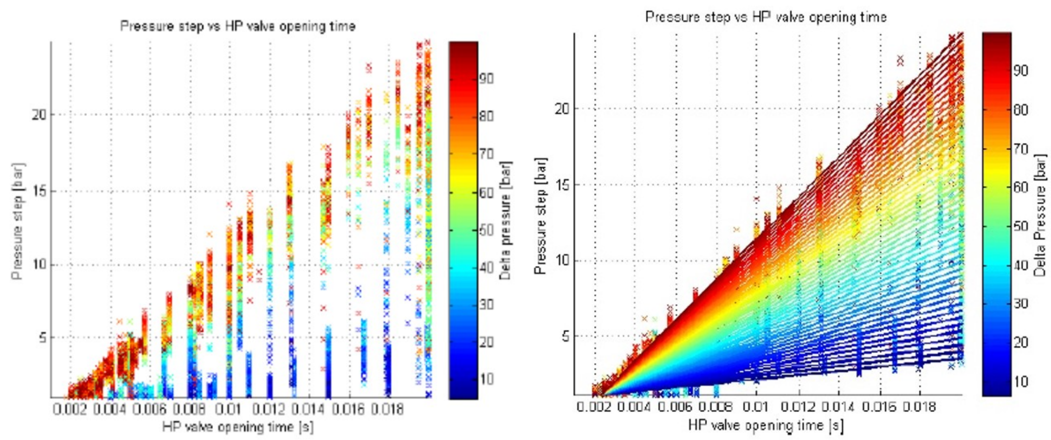


Figure 2-11: Identification experiment for build phase [4]

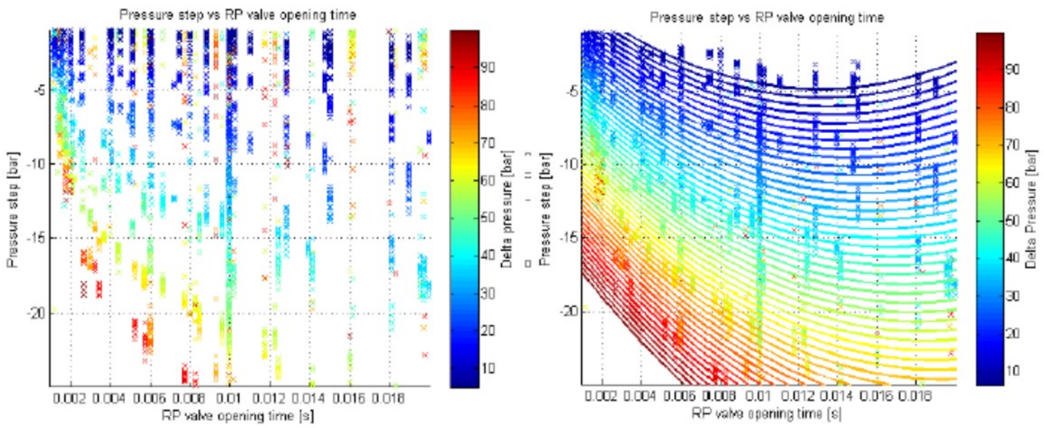


Figure 2-12: Identification experiment for release phase [4]

Examples of these identification experiments can be seen in the Figures 2-11 and 2-12. The left plot in Figure 2-11 shows the variation of pressure step with varying valve opening time with different ΔP (difference in fluid pressures between the supply pressure and the brake cylinder pressure). A strong correlation is observed between the variables and consequently the results from this identification experiment are filtered and used for fitting. The other plot in Figure 2-11 shows linear fit of the data. Similarly, the Figure 2-12 tries to discover the relationship between the pressure step, release valve opening time and delta pressure(delta pressure in release phase corresponds to pressure difference between brake cylinder and accumulator) with a quadratic plot fitted for this dataset.

On the basis of results of these fits, the following linear and quadratic mappings were obtained which are discussed in the Section 3-2. These mappings basically help in estimating a pressure step with the available data. This pressure step is the difference between the value of pressure at brake cylinder before the opening of valves and the value after the settling of brake pressure signal. Thus, the models predicting the system are static in nature as they depict the steady state behavior. Hence, more experiments were carried out for different variables using different fittings to obtain other mappings or static models for approximating the build and release pressure steps. These experimental models will be further analyzed in terms of goodness of fit as a part of thesis.

2-5 Characteristics of Accumulator and Pump

Prediction of accumulator state and pumping of excess fluid from it is very important for effectiveness of the release phase. As there is no sensor fitted in the accumulator that gives the input flow rate or its capacity level, a novel method will be used to determine the accumulator state used by Torres [4].

The influential parameters in predicting the limit are the RP valve opening time, the initial pressure of the brake cylinder from which the fluid is being released and the pressure drop (ΔP) performed by the release phase. The average of maximum accumulator emptying time, from several datasets, from experimentation is found out to be 325.6 ms. From this emptying time, the pump opening time can be estimated for each capacity of the accumulator. By observing the emptying phase (Figure 2-13), it is seen that the pressure is released from the accumulator in a linear manner approximately.

The rate of change of pressure is proportional to the fluid flow [5]. This is modeled in Equation (2-4)

$$\dot{P} = E_{\text{acc}}.Q \tag{2-4}$$

where Q is the volumetric flow and E_{acc} is the constant determined by modeling. [5]. This can be extended to the static pressure which is also proportional to the volume of the fluid. Therefore, a linear relation between the pump opening time and the capacity of the accumulator is obtained as follows:

$$t_{\text{emptying}} = 0.3256 * s \tag{2-5}$$

where t_{emptying} is in seconds and s is the state of the accumulator varying between 0 (empty) and 1(full).

Identification experiments carried out with release phases executed in different pressure ranges made up the dataset useful for analysis. From this dataset, a method to estimate the state or capacity of the accumulator is going to be introduced. The total pressure drop that is released before filling the accumulator to its capacity limit as a function of the pressure range definer is plotted in Figure 2-14. A pressure range definer is a number obtained by dividing the whole operation pressure range into different zones and then get an average pressure range for each

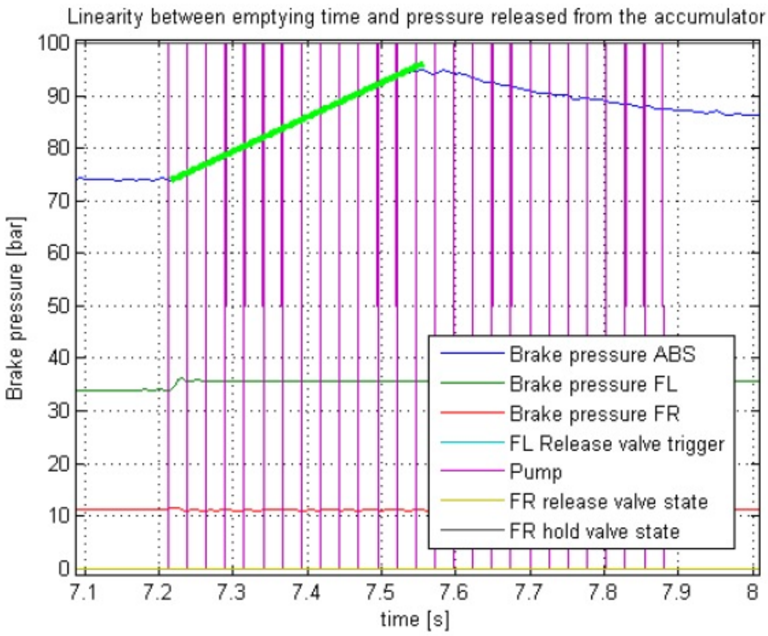


Figure 2-13: Linearity between the accumulator emptying time and the pressure released from the accumulator [4]

interval. For instance, for the pressure range [45, 60] bars, the pressure range definer is the average which is 52,5 bars.

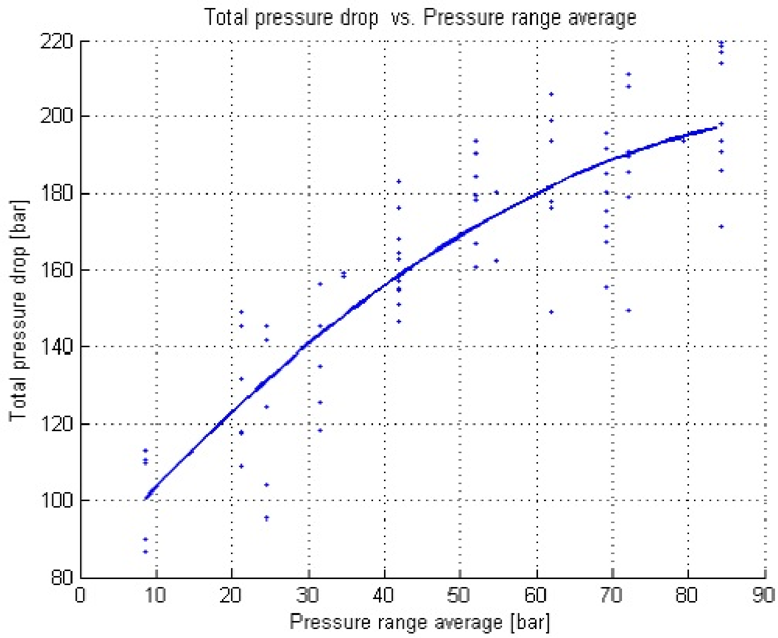


Figure 2-14: Total pressure drop needed to fill the accumulator vs. Pressure range definer when releasing pressure from the brakes to the accumulator [4]

From this plot, an approximation of its relationship can be obtained by using an curve fitting model.

By using this model, the total pressure drop can be estimated for each releasing step made among the entire range. By comparing the actual pressure released at the time with this total pressure drop at a certain pressure range i , an estimation of the accumulator level increment can be calculated in each step as shown in following equation.

$$\Delta s_n = \frac{\text{Pressure actual drop}\rfloor_{\text{range i}}}{\text{Total pressure drop}\rfloor_{\text{range i}}} \tag{2-6}$$

Then, the actual state of the accumulator can be updated by adding the state increment caused by each release step:

$$s_n = s_{n-1} + \Delta s_n \tag{2-7}$$

This formulation is validated in simulation with 5-6% error and thus is selected for implementation.

Apart from selection of model for accumulator state estimator, a pump control strategy needs to be decided. During the ABS operation large release steps can take place at any moment. This is uncertain as the ABS cycle depends on road and vehicle conditions. So, for effective dumping of pressure the accumulator is required to be close to empty at all times.

It is important that the brake circuit is not being released at the time of the pump trigger. This is because, the pump will directly pump the fluid which is being released from the brake cylinder and not the fluid in accumulator. Consequently, the accumulator will not be emptied. Moreover, it will alter the release pressure behavior causing more pressure decrease than required. Thus, the pump will be triggered in hold phase as all the valves are closed and thus the process will be effective.

2-6 Limiting Characteristics of the test setup

Every researcher faces the challenge of retuning the perfectly simulated algorithm for the actual system because of several limitations of the system caused due to manufacturing defects, real system limitations and so on. This section tries to explore the possible issues one may face during the experimentation and implementation of algorithms.

(a) **Noise and Delay** Like every real system, sensor and measurement noise is an issue which will require filtering of the signal. Also the friction, inertia of fluid flow and mechanical parts along with wave propagation can cause delay in executing reference inputs [5]. This will be encountered later while implementation of controller.

Also there are some errors unaccountable for in certain cases. For example in release phases with shorter opening times than 1 ms when neither difference between the supply and brake pressure (ΔP) changes nor the voltage varies for a given opening time, the pressure step still varies from 0 to -3 bars. It can be considered that the pressure steps of more than -1 bar could be caused due to the measurement of badly performed release phases [4]. Since such cases are difficult to quantify, they add to the unpredictability of the system.

(b) **Limited Pressure Step** As discussed earlier, large pressure steps in short time might cause an additional moment on the vehicle making it unstable. Also, during model analysis, it has been found that the outliers also appear more in large pressure steps [4]. Due to these reasons, the maximum pressure step is limited to 15 bars for build phase and -15 for release phase. Steps larger than these will be taken in combination of these steps.

The minimum pressure step is set to 1 bar for build and -1 bar for release so as to avoid the possible disturbances and noises in the system. The enforcement of the minimum pressure step also determines the sensitivity of the controller. This will be discussed in Section 6-4-3.

(c) **Valves Voltage** The voltage supplied to the valves might vary on road cause of loss in potential due to battery depletion. The identification experiments have been performed using measures to mimic this behavior and also valves voltage is used as influencing parameter [4].

(d) **Supply pressure** The application of driver's pressure acts an inherent limitation to the system performance as it is human controlled. This influences the build pressure step immensely and so utmost care should be taken to maintain the supply pressure higher than required pressure at wheel brake cylinder at all times by applying adequate pressure over the pedal.

(e) **Limited opening time** The minimum valve opening times are set by their own structural and physical limitations and also their operating mode. While building, HP valves have minimum opening time of 1.75 ms for both wheels. While releasing, the Front left RP Valve has 0.9 ms and the Front right RP valve has 1.1 ms. Below these times, the valves are not operative at all. Although the maximum opening time does not have any physical limitation, it is preferable to be set in a value which is coherent with the pressure steps needed.

(f) **Uncontrolled Pressure Increase and decrease** Torres faced some strange issues while performing his experiments on the test vehicle [4]. When the accumulator was full, the pressure on the brake cylinder not being simulated increased even with both valves (HP and RP) closed. It is assumed to be caused due to an insufficient amount of voltage at the solenoid valves ensuring an imperfect sealing.

He also observed that when pressure was built in one of the brake cylinders, the other brake line experiences a slight decrease in pressure, even with both valves (HP and RP) closed. It is postulated that when pressure is being built in a brake line, the ABS pressure slightly decreases to provide the amount of fluid needed for that increase. Now, if the other brake line pressure is close to the ABS pressure then fluid might flow back to the ABS line, thus slightly decreasing its pressure. It is pointed out from the HAB circuit represented in Figure 2-6 that even if a HP valve is closed, as it was during these experiments, the fluid can still flow back due to the one-way valve in parallel with the HP valve.

Chapter 3

Brake Pressure Control Approaches

Different brake pressure control approaches can be reviewed only when the objectives of the control are stated. The first section of this chapter makes the reader observe an example of reference pressure signal that the controller has to track. Assessment of the nature of reference signal lays out the objectives for the controller for this thesis.

ABS systems and brake pressure controller have been around for quite a long time. The related literature will be presented and discussed in the second section of this chapter. The different modelling and control techniques will be divided into groups based on their derivation and studied along with their limitations. The Bosch based ABS 8.0 will also be discussed. Furthermore, this section will also include the results of research done at TU Delft.

Additionally, new steady state estimation models for build and release phases are derived from the first principle modelling of the given system. The final section of this chapter will evaluate the brake pressure models and control strategies and provide a selection for further research.

3-1 Controller Objectives

The brake pressure controller can be schematically represented in the following Figure 3-1. In the control scheme, the reference brake pressure signal is the output of the higher level controller. This signal is the the result of the control logic formulated by the high level controller. An example of such a logic explained in the handbook provided by leading ABS manufacturer BOSCH is shown in the Figure 3-2.

Phase 1 Initial application. Output pressure is set equal to input pressure. This phase continues until the wheel angular acceleration (negative as it is decelerating) drops below the wheel minimum spin acceleration ($-a$).

Phase 2 Maintain pressure. Output pressure is set equal to previous pressure. This phase continues until the tire longitudinal slip exceeds the slip(λ_1) associated with the Slip Threshold. At this time, the current tire slip is stored and used as the slip threshold criterion in later phases. This slip is a setpoint to warn that the tire is beginning to lock.

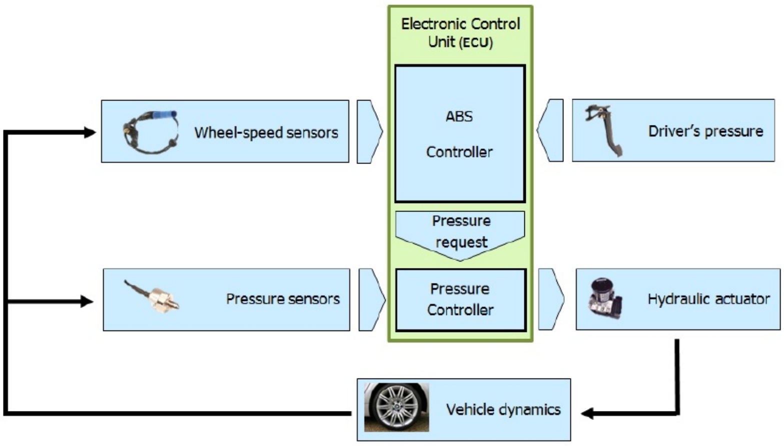


Figure 3-1: Brake pressure controller in the scheme of ABS [4]

Phase 3 Reduce pressure. Output pressure is decreased according to the release rate until the wheel spin acceleration becomes positive.

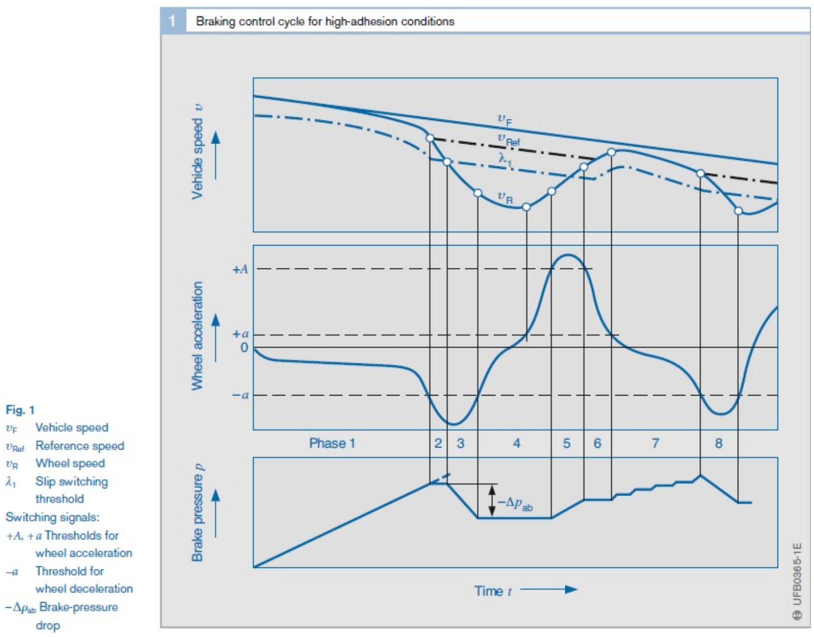


Figure 3-2: Braking cycle control algorithm by BOSCH for ABS [8]

Phase 4 Maintain pressure. Output pressure is set equal to the previous pressure until the wheel spin acceleration (positive) exceeds $(+A)$. This threshold is set to convey if the wheel spin velocity is not increasing excessively as it enters the stable range of slip curve.

Phase 5-6-7 Increase pressure. After the acceleration signal has dropped below the $+a$ threshold, the brake pressure is increased slowly until the wheel acceleration falls below $(-a)$ threshold again to start the second control cycle.

Phase 8: Reduce pressure. At this point an individual cycle is complete, the process returns to Phase 3 and a new control cycle begins.

Each of the above phases begins with a comparison between the current tire longitudinal slip and the value stored during Phase 2. If the current slip exceeds this value, the normal logic is bypassed and resumed at Phase 3. This effectively allows the algorithm to gain knowledge of the wheel slip associated with wheel lock-up on the current surface. This is an adaptive learning algorithm and so as the tire travels onto surfaces with differing friction characteristics, the ABS model is able to maximize its performance accordingly [3].

Sample brake pressure signal during ABS operation Due to the continuing research on ABS in TU Delft, the following figures are examples of desired brake pressure signals given by ABS built by BOSCH. These actual signals are helpful in formulating the expected properties of the controller.

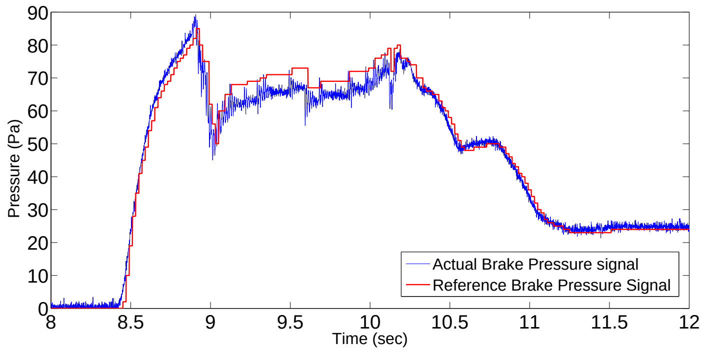


Figure 3-3: Estimated reference and actual brake pressure signal

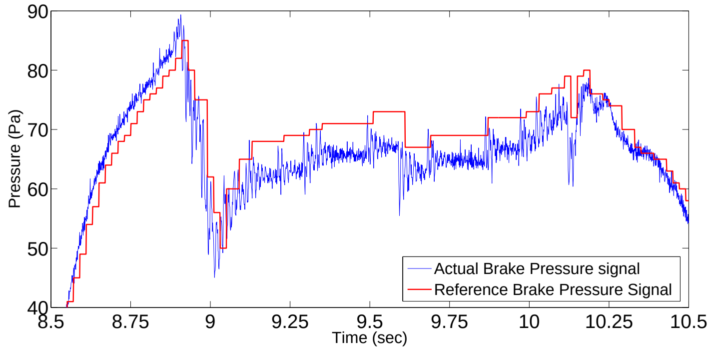


Figure 3-4: Close view of the brake pressure signls during ABS operation

Figure 3-3 shows the requested pressure signal to the low level controller and the actual output of the low level controller. It is seen that the complete operation takes place within 2 seconds on time scale. If we take a closer look at this part as seen in Figure 3-4, we get some interesting information. It is observed that the building pressure steps and releasing pressure steps are not large. Also, the first release step from 85 bars to 50 bars is done in 0.2 seconds whereas the build step from 50 bars to 70 bars takes more than 0.4 seconds. Thus the release phases are executed quickly while opposite holds for build phases. This is done to avoid sudden braking causing jerk motions.

It is also seen that the actual signal follows the changes in required pressure step and which emphasizes the selection of sampling period by taking delay of the actuators and fluid inertia into account.

The error between the estimated and actual pressure is significant in several areas. This might be caused due to erroneous filtering algorithm.

Design Objectives of Brake Pressure Controller
The following objectives are required from the low level controller

1. The desired reference should be tracked within short timespan and minimal lag.
2. The setpoints should be matched with high accuracy and no chattering close to said reference.
3. The settling time of the system should be also taken into account before calculating the error.
4. The sampling period should take into account the delays in the system including smallest valve opening time.
5. Also the reference signal used for validation of the controller should mimic the one used in practice. It should be a dynamics signal with different magnitudes of build and release steps.
6. Also large build and release steps should be executed stepwise by the controller or else resulting jerks might damage the system.

3-2 Brake Pressure Control Literature

The brake pressure controller is a low level controller of the ABS system and most of the literature deals with high level control algorithm only. This is because the brake pressure controller is reliant on the configuration of hydraulic circuit which it has to control. Fundamental differences such as the type of brake fluid (i.e. hydraulic or pneumatic) and the type of valves (proportional or on/off) influence the control methodology for the pressure modulator. The test vehicle used for this thesis has a Hydraulic Actuated Braking (HAB) circuit with on/off solenoid valves [1].

3-2-1 Models derived from First Principles

The most fundamental method of modeling any system is using first principles. Literature provides several examples of researchers using the actual dynamics to model the hydraulic brake system as seen in [22, 12, 23, 24, 25]. This procedure of modeling involves deriving models for operation of individual components of the hydraulic system and then combining them to obtain a complete model. An example of such a decentralized model is seen in Figure 3-5 and Figure 3-6.

[1] The circuit and its components were explained in previous chapter

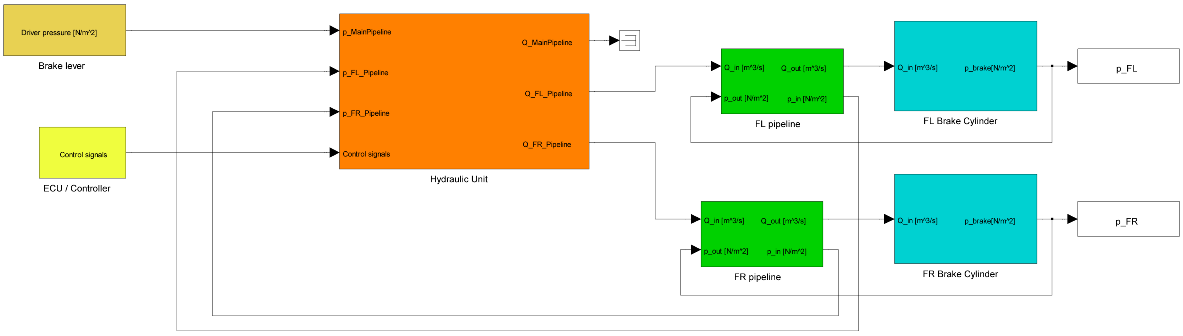


Figure 3-5: Simulink model using individual models for pipelines and brake cylinder [5]

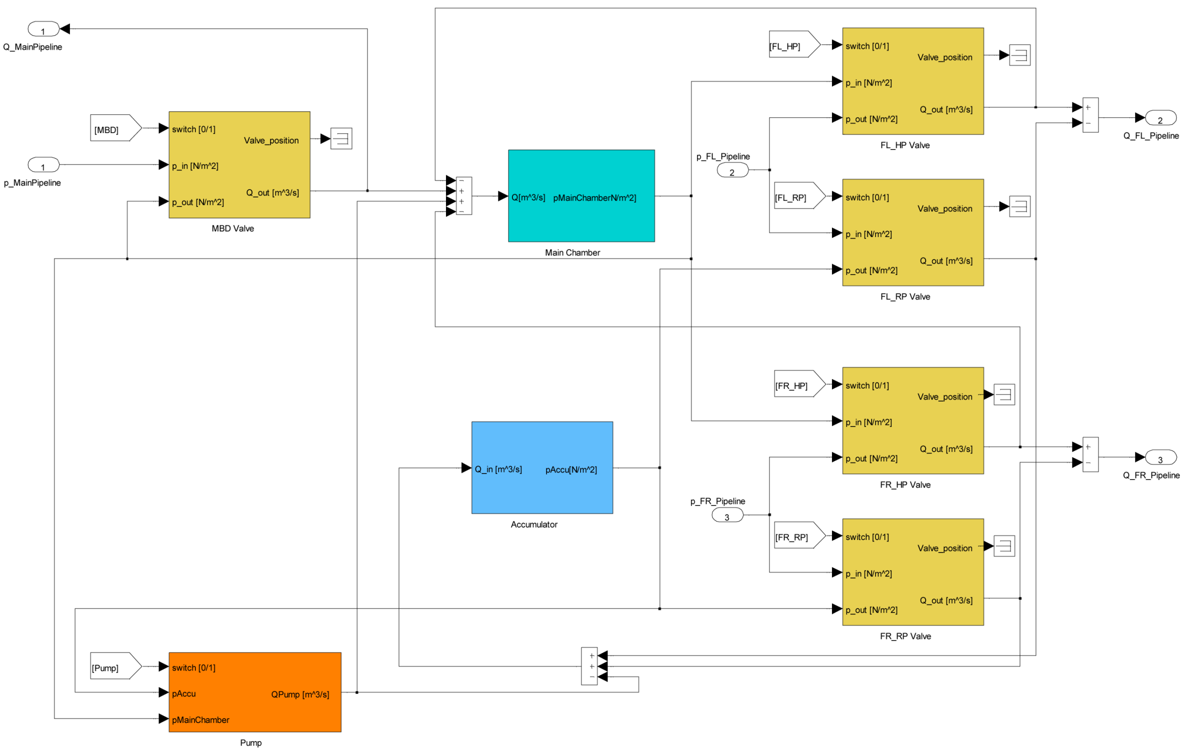


Figure 3-6: Simulink model using individual models for valves, accumulator and pump [5]

Another example of such modeling technique are observed in [?]. Kerst (2012) modelled the important parameters using hydraulic resistances, inductance and capacitance to construct the system. An example of such representation for building brake pressure inside the brake cylinder is seen in the following equations (Refer [5]).

$$C_h(p) = c_1.p^4 + c_2.p^3 + c_3.p^2 + c_4.p + c_5 \tag{3-1}$$

$$Q = y.Q_{\text{nom}}.\sqrt{p_1 - p} \tag{3-2}$$

$$\dot{p} = C_h(p).Q \tag{3-3}$$

where

p	:	pressure in the brake cylinder
p_1	:	current pressure in the supply cylinder
Q	:	Volumetric flow rate through the valve
Q_{nom}	:	Constant
y	:	Percentage of opening of the solenoid valve for build phase
$\dot{p}$	:	Rate of increase of brake pressure
C_h	:	Hydraulic capacitance associated with the brake cylinder
$\begin{bmatrix} c1 & c2 & c3 & c4 & c5 \end{bmatrix}$	:	Coefficients of the fitted polynomial

Some researchers have not modelled the individual components but rather used the model for rate of change of brake pressure [27, 28]. The equations (3-4) and (3-5) model the rate of increase and decrease in brake pressure for a given brake cylinder. The equations (3-6) and (3-7) correspond to a discretized system using the aforementioned equations.

$$\dot{P} = D.\frac{\beta_V}{V}.C_d1.A_1.\sqrt{\frac{2}{\rho}(P_1 - P)} \tag{3-4}$$

$$\dot{P} = D.\frac{\beta_V}{V}.C_d2.A_2.\sqrt{\frac{2}{\rho}(P - P_2)} \tag{3-5}$$

$$P(k+1) = R_1.\int_0^T .\sqrt{P_1 - P(k)}.D.dt \tag{3-6}$$

$$P(k+1) = R_2.\int_0^T .\sqrt{P(k) - P_2}.D.dt \tag{3-7}$$

where

P	:	pressure in the brake cylinder
P_1	:	current pressure in the supply cylinder
P_2	:	current pressure in the accumulator
V	:	initial volume of brake fluid in the brake cylinder
C_{d1} C_{d2}	:	discharge coefficient
A_1	:	opening area of the solenoid valve for build phase
A_2	:	opening area of the solenoid valve for release phase
β_V	:	effective bulk modulus of brake oil
T	:	sampling period
ρ	:	density of brake oil
D	:	duty ratio

It is important to note that the models are used for continuous control strategies. All the aforementioned researchers used basic feedback control techniques and switching schemes (For example Figure 3-7) to control the system.

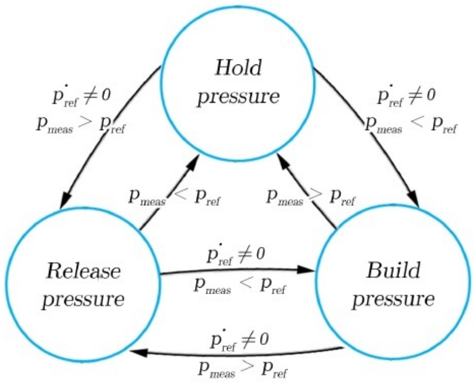


Figure 3-7: Reference based control scheme [5]

The Figure 3-7 shows the switching control scheme based on the reference brake pressure and the current brake cylinder pressure used by a previous researcher at TU Delft [5]. This scheme is essentially a feedback control system relying on the difference between the reference and the obtained pressure to generate a control input for making the necessary pressure step. For example, a build phase is executed when there is a change in the reference pressure where this reference pressure is higher than the recently measured brake pressure at the concerned wheel. If there is no change in the reference pressure, the hold phase is executed.

This method coupled with modeling strategy used in (3-1) worked well in simulations but was not able to perform similarly in real time implementation. It was successful in coping with the propagation of pressure wave and controlling the chattering of the output. However, there were large pressure mismatches. Also feedback control inherently introduces time lag in addition to the fluid inertia already present. This also resulted in being erroneous in making small pressure steps.

The presence of proportional valve is highly suitable for the feedback system but the given hydraulic circuit consists of on/off valves making this approach invalid.

3-2-2 Models using Estimation or Identification

Models can be derived from identification and estimation techniques as well as using empirical data. Since the test vehicle was first fitted with a BOSCH ABS 8.0 system, it is important to know the basis behind its working. The BOSCH built ABS system is a corporate secret and the concept of low level controllers is not dealt in most of the published research work which are based on ABS systems. Although the real algorithm for estimating the brake pressure is unknown, some possibilities can be drawn from the available literature.

Flow Rate Estimation Since the hydraulic system can be standardized to certain extent while changing certain parameters according to requirements, a model based on flow rate cannot be ruled out. This hydraulic model of the system can be estimated from the valve specifications and the pressure sensors. It can then be used to create the inverse hydraulic model and estimate the valve opening time for requested pressure step [29].

The model can be also estimated using the fitting as mentioned in the BOSCH Automotive Handbook [8]. The relation described in the book is as follows:

$$U_{\text{valve}} = \frac{p_{\text{WhlPre}} - p_{\text{Whl}}}{(x_1 + x_2 * p_{\text{Whl}})\sqrt{|p_{\text{circ}} - p_{\text{Whl}}|}} \tag{3-8}$$

where

U_{valve}	: Valve triggering mode
$U_{\text{valve}} > 0$	: Build up pressure
$U_{\text{valve}} = 0$	: Hold pressure
$U_{\text{valve}} < 0$	: Reduce pressure
p_{WhlPre}	: Nominal pressure in wheel-brake cylinder
p_{Whl}	: Pressure in wheel-brake cylinder
p_{circ}	: Brake circuit pressure induced by the driver
$x_1\ x_2$	: Parameters of inverse hydraulic model

This equation shows model fitting where the parameters are selected on the basis of the experiment performed for research by BOSCH.

Deceleration based approach It is also possible that the brake pressure is not exactly a state variable as the actual parameter wanted is the braking torque. It is the braking torque and wheel deceleration parameters which are required for the estimation of the slip. Although the value of the brake pressure is required to calculate the braking torque value, it does not limit itself on controlling the brake pressure value. Now, during the build phase the valves are opened till a required pressure is reached and then it is released when the lower braking torque is required. These steps are carried out by compensating for the delays and losses due to inertia and friction.

This is essentially a simple feedback system with errors in pressure differences reflected in the braking torque/force estimation and wheel deceleration [30].

Identification Another possible method to model the system is to identify the relation between the brake pressure signal and the supply pressure signal as done in the equations (3-9) and (3-10) using Pseudo Random Binary signals (PRBS) [31].

$$y_{\text{inc}} = \frac{b_1.s + b_0}{s^2 + a_1.s + a_0}.u_{inc} + e \tag{3-9}$$

$$y_{\text{dec}} = \frac{c_0}{d_0.s + 1} + e \tag{3-10}$$

where

y_{inc} y_{dec} : pressure in the brake cylinder
u_{inc} u_{dec} : current pressure in the supply cylinder
e : zero mean white noise
$\begin{bmatrix} a_0 & a_1 & b_0 & b_1 & c_0 & d_0 \end{bmatrix}$: identified parametes

Although, the model and data had a great fit in the research done using identification [31], there is no proof of application of this model on real setup.

Pressure Estimation Several researchers have employed estimation techniques to only model the rate of change of brake pressure for using in a PWM based controller. Examples of these include the following equations wherein model of rate of change of brake pressure depends on the position of the valve.

$$\dot{p_i} = -\frac{1}{\kappa_{i1}}.p_i \qquad \text{when the valve is in closed position}$$
$$\dot{p_i} = \frac{1}{\kappa_{i2}}.(p_{\text{sup}} - p_i) \qquad \text{when the valve is in open position}$$

where $\dot{p_i}$ is the rate of change of brake pressure, p_{sup} is the supply pressure and κ_{i1} and κ_{i2} are modelling constants [32]. There are other ways to estimate the rate of increase of pressure based on variation of duty ratio as seen in the Figure 3-8. The corresponding equation is seen below [6]

$$P_{\text{est}} = \sum T_0.u^{(t-1)} \tag{3-11}$$

where
P_{est} : estimated pressure
T_0 : control period
u^{t-1} : increasing/decreasing rate in the last period

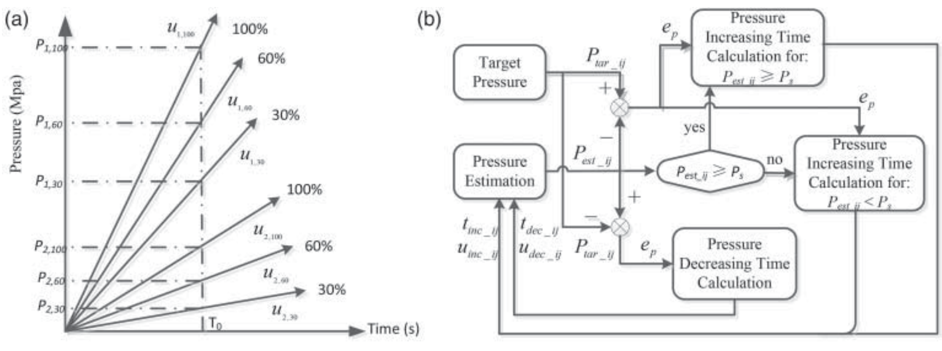


Figure 3-8: (a) The pressure rate fitment and (b) determination of pressure increasing rate and time [6]

There is a recent trend in using the equations derived from the physical dynamics but with parameters fitted on the basis of the test setup as seen in [33, 34]. Their models usually are of the form seen in equations (3-12).

$$\frac{dP_{\text{brake}}}{dt} = \frac{1}{C_e.R_e}.(P_{\text{supply}} - P_{\text{brake}})^{\phi_{\text{inc}}} \tag{3-12}$$

$$\frac{dP_{\text{brake}}}{dt} = -\frac{1}{C_e.R_{e2}}.(P_{\text{brake}} - P_{\text{acc}})^{\phi_{\text{dec}}} \tag{3-13}$$

where

P_{brake}	: current brake pressure at wheel brake cylinder
P_{acc}	: brake pressure at accumulator
t	: time
P_{supply}	: pressure at the main chamber by application of driver's pressure on pedal and brake booster
C_e, R_e, R_{e2}	: equivalent liquid capacity and resistance values in respective processes
ϕ_{inc}, ϕ_{dec}	: throttling index for increase and decrease process

It is important to note that the models covered until now are continuous models and do not estimate the delayed response of the system. This was the reason Kerst (2012) and Torres (2014) (both researchers at TU Delft) started to investigate the feasibility of steady state as mentioned in the Section 2-4. Torres carried out different experiments which enabled him to understand the characteristics of the circuit during each operation mode [4]. These estimation models can be divided into two section depending on whether the parameter of Valves Voltage is considered or not. It is important to note that the models predicting the system are static in nature as they depict the steady state behavior.

Models without Valves Voltage

Linear Model: Linear with regards to the opening time and delta pressure in addition with the cross term between the opening time and delta pressure.

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_3.t_{open}.\Delta P \tag{3-14}$$

Quadratic Model :Quadratic with regard to the opening time only and linear with the respective cross term between the opening time and delta pressure.

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_3.t_{open}^2 + b_4.t_{open}.\Delta P \tag{3-15}$$

Build Linear Model: Linear model with respect to brake and ABS pressure and their respective cross terms with opening times.

$$P_{step} = b_0 + b_1.t_{open} + b_2.P_{brake} + b_3.P_{\text{supply}} + b_4.t_{open}.P_{brake} + b_5.t_{open}.P_{\text{supply}} \tag{3-16}$$

Models with Valves Voltage They are basically the same models as mentioned earlier with the addition of voltage supplied to the valve of the respective phase.

Linear Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_3.t_{open}.\Delta P + b_4.V_{valves} \tag{3-17}$$

Quadratic Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_1.t_{open}^2 + b_4.t_{open}.\Delta P + b_5.V_{valves} \tag{3-18}$$

Build Linear Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.P_{brake} + b_3.P_{\text{supply}} + b_4.t_{open}.P_{brake} + b_5.t_{open}.P_{\text{supply}} + b_6.V_{valves} \quad (3\text{-}19)$$

The parameters of the model are

ΔP	: pressure difference
$\Delta P = P_{\text{supply}} - P_{\text{brake}}$	: for build phase
$\Delta P = P_{\text{brake}} - P_{\text{acc}}$	: for release phase
t_{open}	: Valve opening time
P_{step}	: Predicted pressure step
P_{brake}	: Current brake pressure at wheel brake cylinder
P_{supply}	: Pressure at the Main Chamber by application of driver's pressure on pedal and brake booster
P_{acc}	: Pressure at the accumulator

These experimental models helped to build a feed forward controller which had no delay and was able to generate a control input (valve opening time) by using the inverse mapping [36]. This method relies heavily on the accuracy of the experimental model which did not contain important parameters of the system. Also it was not able to adjust to changing dynamics of the system on the test track. It was also due to exclusion of the current brake pressure from the model of the system.

Another approach that was simulated by Torres[4] was that of Recursive Least Squares (RLS). He was inspired from the feedforward modeling approach and carried out identification experiments to obtain different models of the system with relatively higher accuracy when compared to the simple feedforward approach. He also decided to make it adaptive to the changes happening in the hydraulic circuit by updating the mapping of the system through knowledge of pressure step errors. In his thesis report, he prepares an algorithm which gives results seen in Figure 3-9 for building pressure phase and estimation errors seen in Figure 3-10 from simulation using experimental data from the vehicle .

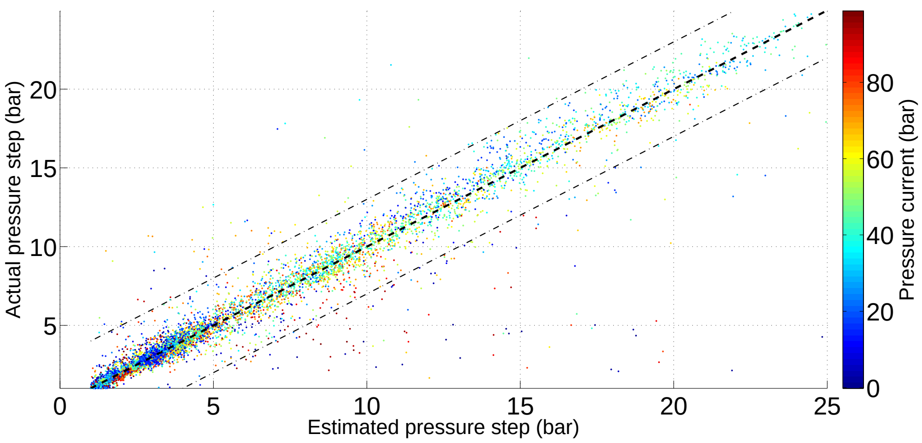


Figure 3-9: Actual v/s estimated pressure using RLS for build phase on FL corner [4]

The graph in Figure 3-9 shows the accuracy of the estimated pressure steps versus reference pressure step dependent on the current brake pressure in the cylinder during the building

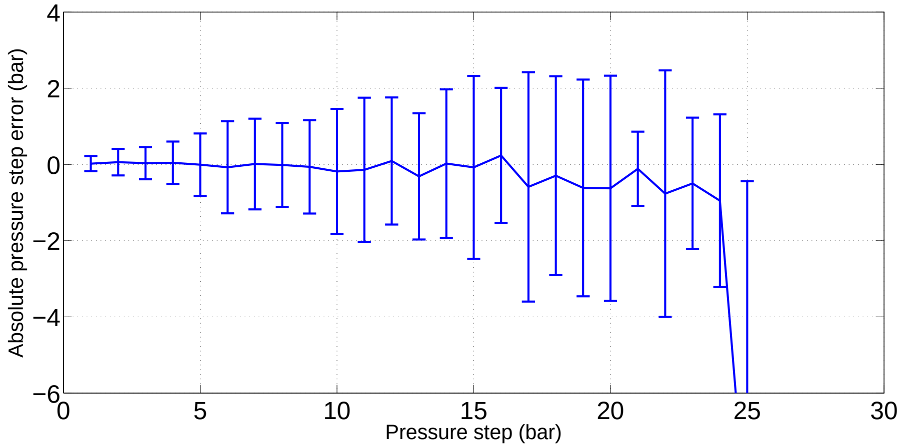


Figure 3-10: Absolute errorusing RLS for build phase on FL corner [4]

Table 3-1: Table showing the relative error and Standard deviation for front wheels [4]

Model	Build Linear	
Statistics Indicator	Relative Error (%)	Standard Deviation (%)
FL Build	9.86	15.51
FL Release	10.10	16.42
FR Build	9.39	14.81
FR Release	7.53	12.75
Overall	9.22	14.87

pressure phase. The error seen during this phase is shown in Figure 3-10. A similar trend was also observed with the release phase but with dependency on pressure difference between wheel brake cylinder pressure and accumulator pressure.

The estimated pressures are obtained using mapping with coefficients which are updated recursively. As mentioned earlier, the pressure step estimated is compared with pressure difference in the wheel brake cylinder before the opening of valves and after settling of brake fluid. The simulated results show the capability of algorithm to adapt to changes by adjusting its mapping. It is also seen from the error graph in Figure 3-10 that the errors increase with pressure step sizes. Hence, smaller steps must be preferred to achieve precision.

The Table 3-1 shows the relative errors i.e. error between the pressure step differences with respect to the estimated pressure step along with standard deviation with respect to the mean of relative error.

$$e_{\text{relative}}(\%) = 100.\frac{|P_{\text{actual}} - P_{\text{estimated}}|}{P_{\text{estimated}}} \tag{3-20}$$

From the Figure 3-10 and Table 3-1table, it is seen that overall relative errors are 10% to 12% which are not too significant. However, the variance is 12-16 % in addition to the mean error of 12% which can be a concern.

The brake pressure system used for experimentation does exempt some algorithms due to the limitations of its components. Let us assume that the model of the hydraulic system can be approximated and proportional valves are present in the system. It would then be possible to incorporate feedback linearization and PID control with variable gains, updated using advanced logic [12, 23]. However, the given system does not have proportional valves making it difficult to obtain precise control. It was also seen that this can be tackled using the Pulse Width Modulation (PWM) control strategies. [24, 25]. However, this was also proven difficult as it required knowledge of states and delays which are difficult to determine. Under these conditions, it is difficult to use a continuous control strategy such as PWM to achieve precise control. Also modern methods involving Artificial Neural Networks and fuzzy logic are used for improving the adaptability of the system[37, 7]. One such example is shown in Figure 3-11. These methods are very complex to be employed for pure brake pressure control.

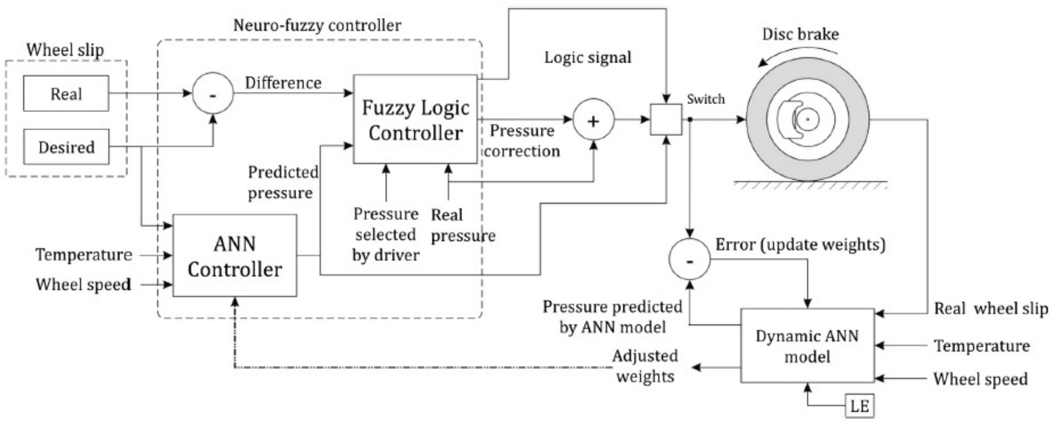


Figure 3-11: Neuro-fuzzy control scheme of longitudinal wheel slip. [7]

3-3 Derivation of new estimation model

The literature review consists of several models derived from the first principles modelling of the system. It was seen that the (3-21) was the most common estimation model used in literature for the build valve. This equation estimates the rate of change of brake pressure as function of system characteristics and fluid properties and the difference between the supply pressure and brake pressure.

$$\frac{dP_{brake}}{dt} = \frac{\beta.C_d.A_d}{V_{s_0}}.\sqrt{\frac{2.(P_{supply} - P_{brake})}{\rho}} \tag{3-21}$$

where

P_{brake}	: Current brake pressure at wheel brake cylinder
t	: time
A_d	: Cross sectional area of the flow passage
ρ	: density of fluid
P_{supply}	: Pressure at the Main Chamber by application of driver's pressure on pedal and brake booster
V_{s_0}	: Initial volume of brake fluid
β	: bulk modulus coefficient $\propto \frac{1}{\text{compressibility}}$
C_d	: Discharge coefficient $= \frac{\text{actual discharge}}{\text{theoretical discharge}} \propto \frac{1}{\sqrt{\text{flow resistance}}}$

Equation (3-21) is a continuous model. The literature showed an attempt to use continuous models based on the first principle and the drawbacks that were encountered in the process. A steady state estimation model is sought in this thesis which will avoid the drawbacks and complex structure of the continuous models. The Section 2-3 also stated the importance of incorporating the influential properties affecting the system behaviour. Thus, the new estimation model will be derived from the (3-21) using discretization as follows:

$$\frac{dP_{brake}}{dt} = \frac{\beta.C_d.A_d}{V_{s_0}}.\sqrt{\frac{2.(P_{supply} - P_{brake})}{\rho}} \tag{3-22}$$

Substituting $R_{build} = \frac{\beta.C_d.A_d}{V_{s_0}}\sqrt{\frac{2}{\rho}}$

$$\frac{dP_{brake}}{dt} = R_{build}.\sqrt{P_{supply} - P_{brake}} \tag{3-23}$$

Replacing the index with ϕ_{build}

$$\frac{dP_{brake}}{dt} = R_{build}.(P_{supply} - P_{brake})^{\phi_{build}} \tag{3-24}$$

Discretizing

$$\frac{\Delta P_{brake}}{\Delta t} = R_{build}.(P_{supply}(k) - P_{brake}(k))^{\phi_{build}} \tag{3-25}$$

$$\Delta P_{brake} = \Delta t.R_{build}.(P_{supply}(k) - P_{brake}(k))^{\phi_{build}} \tag{3-26}$$

Since Δt is the process time of the pressure step, it can be represented as time for which the operation was performed and so it replaced with opening time of the build valve t_{open}. Also, ΔP is difference in pressure achieved at steady state and pressure before the start of the operation. This is the build pressure step made and so ΔP is replaced by P_{step}.

$$P_{step} = t_{open}.R_{build}.(P_{supply}(k) - P_{brake}(k))^{\phi_{build}} \tag{3-27}$$

The equation (3-27) represents the steady state estimation model for build phase. Apart from discretization, the most essential difference seen between equations (3-21) and (3-27) is the relation between the parameters. The square root exponent is replaced with a parameter ϕ_{build}. The value of this parameter depends on the system used and will be defined in the Chapter 5.

Similarly, the estimation for release phase can be derived to be as follows:

$$P_{step} = -t_{open}.R_{release}.(P_{brake}(k) - P_{acc}(k))^{\phi_{release}} \tag{3-28}$$

The negative sign is symbolic of the decrease in the final pressure after the release phase. The release valve opening time is represented as t_{open}. Also, the release pressure step is dependent on the difference between the initial values of brake pressure and accumulator pressure. It was seen in the Section 2-5 system characteristics that the accumulator state is estimated empirically and a definitive value of accumulator pressure is difficult to determine. Therefore, the accumulator pressure is kept constant for all release phases. The value of this constant should be ideally 0 bars but for estimation it is set at 2 bars bearing in mind the pressure increase seen until the pump is switched on. The final release estimation model is seen as:

$$P_{step} = -t_{open}.R_{release}.(P_{brake}(k) - P_{acc})^{\phi_{release}} \tag{3-29}$$

3-4 Conclusion

In this chapter several modelling and control techniques used for control of the brake pressure system were discussed. Also, the limitations of these techniques were noted. The BOSCH based ABS system was also postulated and the controller objectives were derived from literature.

It is vital to decide the nature of the control system to proceed towards the latter stages of this thesis.

Motivation for adaptive control It was stated earlier that the continuous control strategies required accurate knowledge of states and amount of delay in the response. This was also seen by Kerst (2012) wherein model mismatches were the major cause of differences between the estimated and the real pressure signal [5].

It was seen in the Section 2-3 that the influential properties of the system changed with the pressure step. This might be a cause of the model mismatches.

An adaptive control approach would not only identify the correct parameters but it would also adapt with changing environment conditions. An additional advantage of an adaptive algorithm is that the updating parameters will also try to compensate for any error in modeling.

It is important to note that this is a low level controller which is expected to have a rapid response. Further, a complex algorithm like Artificial Neural Networks might create difficulties for practical implementation due to memory power constraints. Therefore, it can be concluded that the adaptive algorithm chosen for this study is Recursive Least Squares (RLS) which has shown promise from the results seen on the experimental data [4]. Although the results are not completely devoid of error, they can be subdued using small pressure steps. Other methods either require significantly higher knowledge about the system or they are proved to be ineffective in updating themselves with changing conditions.

Selection of Brake Pressure Model Since continuous models were not able to cope with model mismatches and delays as observed from the literature, steady state models for estimation of brake pressure are chosen. The empirical models derived by Torres (2014) have shown encouraging results and will be used for remainder of this study.

Nonetheless, it was seen that the empirical results do not account of the actual dynamics of the system and may be susceptible to large errors if the relationship between different parameters is not correctly established. Also, there is significant literature which is dedicated to the use of pressure estimation models derived from the actual dynamics. This led to derivation of an additional steady state model which will be tested along with the empirical models to provide more insight into the modelling aspect of this system.

Chapter 4

Adaptive Control Methodology

In the earlier chapters, the system to be controlled and the models to be employed were discussed in detail. Review of literature on brake pressure modulator also revealed use of model based feedback controller and fuzzy logic approaches [38]. It was also seen that an adaptive control method was the best approach to tackle changing system characteristics saving computational complexity as the model to be considered is not dynamic.

Adaptive control methods can be divided into self-tuning regulators, model-reference adaptive control, gain scheduling and dual control. However, only algorithms for self tuning regulators will be discussed. The first section will delve into the theory of least squares problem and adaptive algorithms. Further, the RLS algorithm will be presented and the parameters characterizing it will be studied. A popular variant of this algorithm known as Partial update RLS will be summarized before proceeding towards the motivation of selecting this algorithm over other adaptive methods.

4-1 Adaptive Filters

If a system is termed adaptive, it possesses the ability to change its behavior or characteristic to conform to new and unknown circumstances. In the sense of control theory and engineering, an adaptive controller is an intelligent controller that can modify its behavior in response to the variations in the dynamics of the process and the character of the disturbances. An adaptive control system consists of two closed loops. One loop is a normal feedback control with the plant and the controller, and the other loop is the parameter adjustment loop, which are shown in the Figure 4-1 [9].

These controllers are termed as Self Tuning Regulators (STR). They comprise of several blocks such as the Estimator block which is an on-line estimation of the process parameters using least-squares or projection algorithms. The Controller Design block in Figure 4-1 represents an on-line solution to a design problem for a system with known parameters or with estimated parameters. The Controller block calculates the control action with the controller parameters computed by its proceeding block. The system can be viewed as an automation of processing

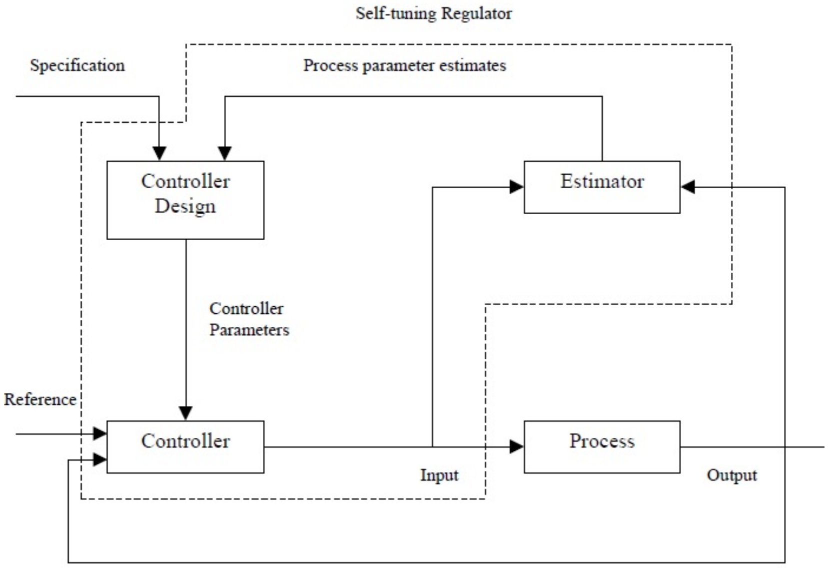


Figure 4-1: Block diagram of an adaptive system [9]

modeling/estimation and design, in which the process model and the control design are updated at each sampling interval. It is possible to simplify the STR by directly estimating the controller parameters and not the process parameters. Thus, it is a flexible scheme which can be implemented by different underlying design choices and estimation methods subject to the performance requirements and the practical conditions. The brake pressure control system is intended to modeled on STR.

In order to explain the working of STR, theoretical background on adaptive control is required. This theory of adaptive filtering can be complicated and the user is advised to refer to books for detail. This literature introduces some portion of the theory but focuses on the algorithms and their effectiveness.

Least Squares Problem Linear least squares is one of the most popular methods to represent a set of overdetermined equations in science and engineering [39]. The problem can be stated as

$$\min_{x} \epsilon^T \epsilon \qquad \text{subject to } \vec{y} = F\vec{x} + \epsilon \tag{4-1}$$

where
$\vec{y} \in \mathbb{R}^m$ is an observation vector or output
$F \in \mathbb{R}^{m \times n}$ is a data matrix
$\vec{x} \in \mathbb{R}^n$ is a parameter vector with
ϵ as residual error.

The above in practical terms means to find a parameter vector that minimize the residual error obtained. This error might be due to several reasons ranging from imperfect modeling to unwanted noise in the system. This noise is modeled as additive noise.

The cost function, which is a 2 norm of the error in Equation 4-1, can be chosen differently. This depends on the type of problem formulation and problem objectives. The main objective of the least squares is to obtain the optimal vector x^*. The cost function can be convex or non-convex. An example of quadratic (convex) function is shown in Figure 4-2.

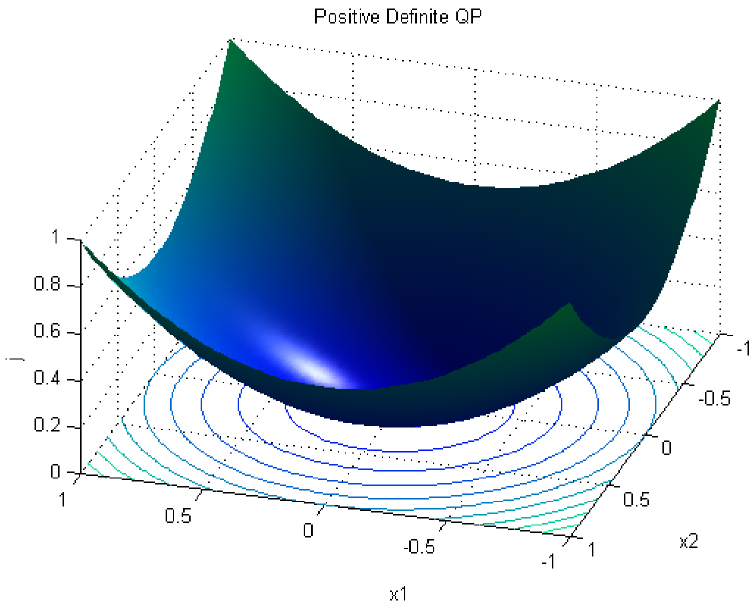


Figure 4-2: A typical quadratic cost function $J(w)$ when w is two dimensional and real valued vector [41]

As one can observe, convex functions as the one in the figure have one optimal value (it can be termed as global minimum). Non convex functions on the other hand have several possible values that minimize the function but not globally optimal. These values are called as local minima. Now to find the optimal vector that will solve the least squares problem, several search methods have been used. Of these, steepest descent algorithm has been used as basis for design of several algorithms with non convex functions.

Let us assume a vector $\vec{w}$ which needs to updated to find the optimal vector that minimizes a cost function $J(\vec{w})$. These algorithms represent different procedures to start from an initial guess $\vec{w}_0$ and progress recursively to converge to optimal $\vec{w}^*$. This can be written as

$$\text{new guess} = \text{old guess} + \text{correction term} \tag{4-2}$$

$$\vec{w}_k = \vec{w}_{k-1} + \mu\vec{p} \tag{4-3}$$

where $\vec{w}_{k-1}$ represents the guess for $\vec{w}$ at $k-1$ iteration and $\vec{w}_k$ is the updated guess at iteration k. The vector $\vec{p}$ represents an update direction vector with scalar μ which induces the effect of step size. The criterion of selection of $\vec{p}$ and μ is to enforce $J(\vec{w}_k) < J(\vec{w}_{k-1})$ so that subsequent iterations may lead to the optimal vector.

This procedure assumes the deterministic nature of the signals which might not be the case practically. However, the procedure for stochastic signals is just an extension of the explained procedure and uses properties of stochastic signals such as estimate and covariance are utilized.

The Least Mean Squares (LMS) and Recursive Least Squares (RLS) approaches based on stochastic steepest gradient descent method will be explained in this chapter. These filters belong to the class of FIR filters. A finite impulse response (FIR) filter is a filter whose impulse response settles to zero in finite time.

4-2 Recursive Least Squares (RLS) Algorithm

The Recursive Least Squares method is commonly used in system identification. RLS algorithms are a class of adaptive filter which used to mimic a desired filter by recursively updating the weight vector $\vec{w}$ at iteration k to the weight vector solution at iteration k-1 of a regularized least square problem. Usually, the RLS is used with exponential weighting in order to incorporate forgetting mechanism into the operation of filter. This forgetting factor λ can give less weight to past data and more to present data. [40]

The algorithm using channel identification as example can be written as follows [4]

- Weighted linear least squares cost function

$$J(k) = \sum_{l=0}^{k} \lambda^{k-l}.|e_N(l,k)|^2 \tag{4-4}$$

  given the desired sequence $d(l)$ where $l = [0, 1, ..k]$ and $w_N(k)$ is the filter coefficient vector at time k and $U_N(k)$ is the input signal vector where N is the order of the filter

- Initialization
  Since there is no input signal before $l = 0$
  $U_N(-1) = 0$

  Also the coefficient vector estimate can be initially estimated as
  $w_N(-1) = 0$
  with covariance matrix being

$$P_N(-1) = \left(\frac{1}{\delta}\right).I_N \tag{4-5}$$

  where δ is a tuning parameter depending on prior knowledge of U_N.

- Form input vector

$$U_N(k-1) = [u(k-N) \;\; u(k-N+1) \;\; u(k-N+2) \;\; ... \;\; u(k-2) \;\; u(k-1)]^T \tag{4-6}$$

  Adding new observation u(k)

$$U_N(k) = [u(k-N+1) \;\; u(k-N+2) \;\; ... \;\; u(k-2) \;\; u(k-1) \;\; u(k)]^T \tag{4-7}$$

- Compute the filter output

$$\hat{d}(k) = U_N^T(k).w_N(k-1) \tag{4-8}$$

- Compute the error

$$e_N(k) = d(k) - \hat{d}(k) \tag{4-9}$$

- Compute the Kalman gain vector

$$K_N(k) = \frac{P_N(k-1).U_N^*(k)}{\lambda + U_N^T(k).P_N(k-1).U_N^*(k)} \tag{4-10}$$

- Update the covariance matrix also known as precision matrix

$$P_N(k) = \frac{1}{\lambda}.[P_N(k-1) - K_N(k).U_N^T(k).P_N(k-1)] \tag{4-11}$$

- Update the adaptive filter coefficient vector

$$w_N(k) = w_N(k-1) + K_N(k).e_N(k) \tag{4-12}$$

The most important difference in RLS algorithm compares to other adaptive algorithms such as Least Mean Squares (LMS) is the updating of covariance matrix $P_N(k)$ of the estimation error along with update of the coefficient vector. Thus, a direct influence of using expectation values and covariance matrix can be observed in the algorithm performance.

Tuning Parameters This algorithm also has two tuning parameters namely δ and λ. $P_N(k)$ is an important parameter as it to remain symmetric positive definite matrix for convergence of coefficients. The value of covariance matrix is also determined by the confidence in obtained values. A large value of δ means high confidence in signal values obtained ($U_N(k)$) and vice versa. So for initial estimate, the $P_N(-1)$ value is 0 if there is perfect prior knowledge of U_N. [41]

The performance of RLS algorithm is also influenced by the forgetting factor λ, which is mainly used to increase the weight of new data and to enhance the adaptability of non-stationary signals so the adaptive filter has a rapid-response capability to the characteristics of changes in the process of input where $0 < \lambda \leq 1$. In other words, it gives exponentially less weight to older error samples. The smaller λ is, the smaller contribution of previous samples. This makes the filter more sensitive to recent samples, thus approaching the true value more rapidly. However, this implies larger fluctuations in the filter coefficients and more sensitivity to noise. A bigger forgetting factor implies bigger contribution of old samples. The case is referred to as the growing window RLS algorithm. In practice, is usually chosen between 0,98 and 1 in order to have good convergence and small variances of the estimates [42].

As compared to LMS algorithms, RLS provides several advantages on account of influence of estimates of signals and tuning parameters.However, it results in increase of computational cost. Now, as the calculations are not only more but involve matrix manipulations, the RLS requires careful implementation. It is also sensitive to numerical errors, which may accumulate and make the algorithm unstable. Thus, RLS requires calculations of higher precision compared to LMS.

4-3 Partial Update RLS

The partial-update method is a straightforward approach to controlling the computational complexity because it only updates part of the coefficient vector instead of updating the entire filter vector. Instead of updating all of the $N \times 1$ coefficients, the partial-update method only updates $M \times 1$ coefficients, where $M < N$. The update of the adaptive filter coefficient as seen in 4-12 is modified to the following equation [43]

$$\begin{aligned} w_i(k) &= w_i(k-1) + K_i(k).e_i(k) && \text{if } i \in \mathcal{I}_M(k-1) \\ &= w_i(k-1) && \text{otherwise} \end{aligned}$$

where w_i corresponds to the i^{th} element of w and $\mathcal{I}_M(k-1)$ is a subset of $1, 2, ..., N$ with M elements at time $k-1$.

The tracking performance and convergence are discussed in detail in [44] and [45]. However, the most important point is the influence of selection of coefficients to be updated which can cause the ill conditioning of correlation matrix $P_N(K)$ which will result in increase in errors and provide aberrations with the convergence profile as compared to the Full RLS update performance [46]. Thus, the selection of coefficients to analyse partial update of coefficients rests on proper selection of coefficients.

4-4 Comparison with other adaptive algorithms

It is imperative to compare the performance of the chosen algorithm with other adaptive methods for estimating coefficients recursively and optimally. These methods when compared for learning characteristics give plots as shown in Figure 4-3.

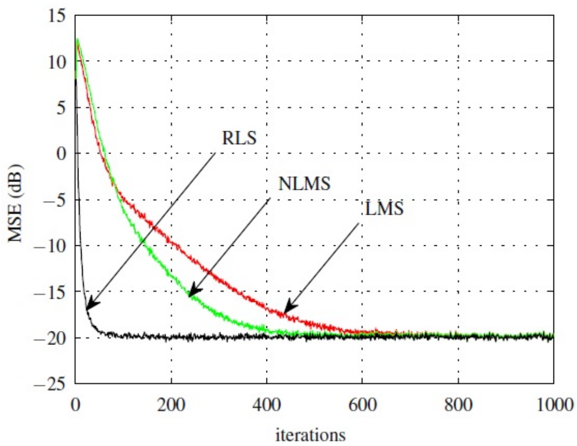


Figure 4-3: MSE along the iterations for LMS ($\mu = 0,01$), NLMS ($\bar{\mu} = 0,05$) and RLS ($\lambda = 0,99$, $\delta = 1$) and ensemble-average of 1000 independent runs [10]

The Figure 4-3 shows the ensemble average learning curve obtained using experiments performed as given by Nascimento and Silva [10]. It is seen that RLS converges very quickly as compared to Least Mean Squares (LMS) and NLMS algorithms. It is also observed that the final error after attaining steady state is the very close and so LMS and RLS can be expected to perform after steady state.

Also the simulations done on experimental data on our test vehicle[4], provide us with the results seen in Figure 4-4. The value of step size for NLMS is $\mu_o pt = 0.9$ and $\lambda = 0.95$ and the parameters ae optimized to achieve no divergence.

Model	Without Valves Voltage				With Valves Voltage			
Adaptive Filter	NLMS		RLS		NLMS		RLS	
Statistics Indicator (%)	Rel. Error	Std. Dev.	Rel. Error	Std. Dev.	Rel. Error	Std. Dev.	Rel. Error	Std. Dev.
FL build	12,76	17,64	12,41	18,08	12,58	17,98	12,49	18,59
FL release	13,52	20,06	9,93	15,93	11,59	18,21	10,00	16,16
FR build	11,93	18,25	10,33	15,44	11,85	17,47	10,50	15,65
FR release	14,01	21,49	7,75	12,98	9,11	15,15	7,68	12,97
Overall	**13,06**	**19,36**	**10,11**	**15,61**	**11,28**	**17,20**	**10,17**	**15,84**

Figure 4-4: Comparison table between NLMS and RLS adaptive algorithms [4]

It is seen that on both models, the RLS algorithm performs better that NLMS counterpart. It is also seen that NLMS performs poorly for estimation in release phase.

Thus, the literature supports Recursive Least squares as chosen adaptive algorithm for developing controller performing brake pressure control. Partial-Update RLS also promises improvement in performance if the input signals lack richness and will also be tested along with the complete RLS algorithm.

Chapter 5

Simulation study of adaptive algorithm using existing dataset

A dataset comprising of measurements taken from the hydraulic circuit is made available due to the identification experiments performed by Torres (2014) [4]. This dataset is crucial for off-line study of RLS performance which will help decide the selection of several variables of the control system before proceeding towards the implementation of the controller on the system.

The first section introduces the procedure used for simulating different models using RLS algorithm. The next section presents the performance indicators which will be used for analysing the simulation results and also implementation results. Further, this chapter analyses the adaptive algorithm on data set by changing its parameters such as model type and forgetting factor. It also studies the effect of using a partial model so as to make the controller computationally less intensive. Further, the parameters of New Estimation model and its performance are evaluated and compared to other models. Thus, this chapter will conclude with the possible models which represent the system dynamics for implementation of brake pressure controller.

5-1 Simulation procedure and Data

The schematic representation of the control scheme can be seen in Figure 5-1. The block diagram in the Figure 6-2 shows typical structure of Self-Tuning Regulator (STR) customized for the given control problem for a specific wheel side (either FL or FR). This block diagram will be discussed in detail in the Section 6-2. It is seen that the valve control block provides the control input (valve opening time t_{open}) to the actual HAB circuit. The Valve Control block utilizes the inverse discretized model for estimation of pressure step. The selected models from literature research need to be tested to evaluate estimation quality. The steps in `MATLAB` algorithm used for simulation of the RLS adaptive estimation and analysis of the estimates can be summarized as shown in Figure 5-2.

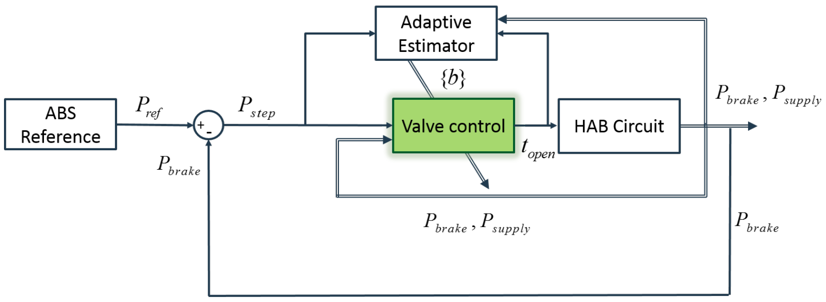


Figure 5-1: Block Diagram of brake pressure control system for single corner

Data acquisition
As stated earlier, the data used for simulation is from the identification experiments performed by Roger Torres [4]. This dataset includes several build and release pressure step with varying amplitudes. The data is calibrated and made available for simulation. The input data can be analyzed at this stage if necessary.

Sorting and Filtering
The dataset has several experiments with no order. A copy of dataset is created and then the values are arranged using experiment identifiers to obtain congruent data. Now the modified data is filtered to remove outliers consisting of values outside the mapping range. This mapping range is time based and pressure step range based. The time based range is the range in which the pressure step was performed whereas the pressure step range is the maximum and minimum limits of build and release step range respectively. Now data obtained during triggering of pump are also neglected. This data is finally divided into two groups namely build data and release data.

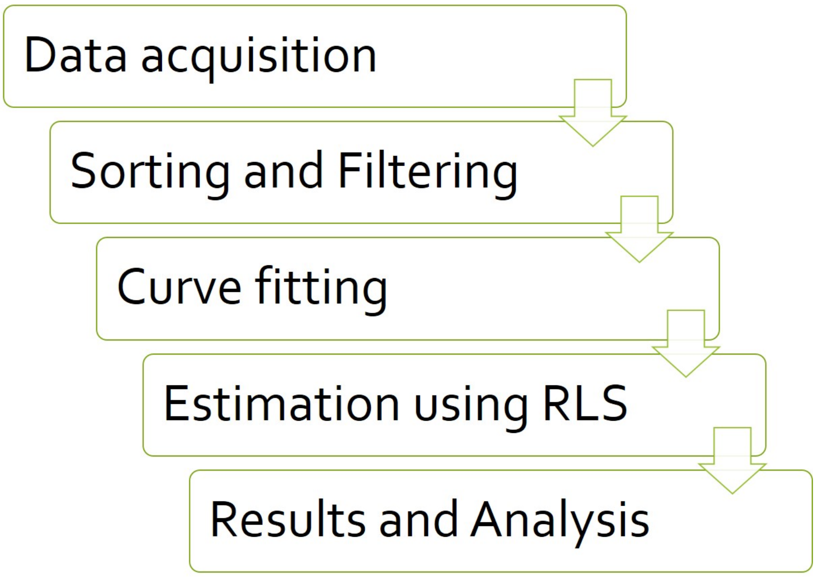


Figure 5-2: Simulation flowchart for analysis of adaptive filtering

Curve Fitting
After selecting a model which is going to be used for filtering, the initial coefficients are

obtained from curve fitting. This is done by parameter estimation of the coefficient vector of the model which best fits the build and release data respectively. Thus, we obtain different initial coefficient vectors for build and release phases. The values of the diagonal covariance matrices are decided on the logic explained in RLS technique. Large values correspond to large uncertainty on the measurement values. This matrix is tuned to be close to the steady value obtained after simulation.

Estimation using RLS
The original dataset without sorting is used for simulation of adaptive filter step by step as seen in RLS algorithm. Also, the data values are treated as observed data and obtained time stepwise. This estimates the pressure step and updates the coefficients and covariance matrix using error in estimation.

5-2 Performance Indicators

The estimated pressure steps and coefficient vector as well as covariance matrix values are stored for each time step. Estimated pressure step is then compared to the actual pressure step from data available and errors are plotted and analyzed. The trends of variation of coefficient and covariances can also be observed. These simulations are analyzed with relative error and standard deviation. They are defined as follows:

$$e_{relative}(\%) = 100.\frac{|P_{actual} - P_{estimated}|}{P_{estimated}} \tag{5-1}$$

$$\mu_{\text{relative}}(\%) = \frac{\sum\limits_{i=1}^{N} e_{relative}(i)}{N} \tag{5-2}$$

$$S.D.(\%) = 100.\frac{\sqrt{\frac{1}{N}\sum\limits_{i=1}^{N}\left(e_{relative}(i) - \mu_{\text{relative}}\right)^2}}{N.e_{relative}} \tag{5-3}$$

where P_{actual} is the actual brake pressure step i.e. steady value of pressure in bars obtained after pressure step is made. $P_{estimated}$ is the estimated brake pressure step or filter output. N is the number of samples and μ_{relative} and $S.D.$ represent the mean and the standard deviation of relative estimation errors.
In literature, several other parameters are also available of which the popular one to quantify performance of filters is Excess Mean Square Error(EMSE) and tap error vector [47, 48]. It is seen that the EMSE is calculated as addition of mean square error and the variance of noise while tap-error vector is difference between a priori defined coefficients and estimated coefficients. Thus they both require additional knowledge of the system unavailable to us. Hence the relative error and standard deviation with respect to mean relative error are used for comparison.

5-3 Influence of Forgetting Factor(λ)

The performance of Recursive Least Squares (RLS) algorithm is influenced by the forgetting factor (λ), which is mainly used to increase the weight of new data and to enhance the adaptability of non-stationary signals so the adaptive filter has a rapid-response capability to the characteristics of changes in the process of input. The value of forgetting factor varies as $0 \leq \lambda \leq 1$. When the value of λ is small, the algorithm has quick convergence but will become unstable; when λ is bigger, the algorithm has slower convergence speed and is stable [49].

It is a popular practice to choose λ in the range $0.95 - 0.99$ which approximately corresponds to remembering the 20-100 most recent measurements. Higher forgetting ($\lambda \approx 0$) will have a negative effect on the performance when no changes occur, since the estimates are based on few data. This means that a trade-off has to be made between the responsiveness when changes occur and the performance when the parameters are constant. It is also a trade-off between alertness and noise sensitivity, and will depend on how much the system changes compared to the noise level in the measurements. If these properties remain constant, a good trade-off in the selection of λ can be made a priori, either on formal grounds or by some initial tuning of the forgetting factor [50].

Since the noise levels obtained in measurements are fairly constant, the forgetting factor value is selected by varying it in simulations and study its effect of performance of adaptive algorithm. It is expected that ABS algorithm will make sudden pressure steps so selection of low value of λ will be illogical. The Table 5-1 comprises of variation of forgetting factor value in the range of $0.85 - 1$ using the build linear model. λ values lower than this give far more erroneous results and hence are not considered for examination.

Table 5-1: Performance analysis of different forgetting factor λ with highlighted results showing the optimum values

Forgetting Factor	Overall Estimation Errors			
	Absolute(%)		Normalised about $\lambda = 0.95$	
	Relative Error (%)	Standard Deviation (%)	Relative Error	Standard Deviation
0.85	9.69	16.18	1.05	1.09
0.86	9.73	16.17	1.05	1.09
0.87	9.50	15.84	1.03	1.07
0.88	9.37	15.60	1.02	1.05
0.89	9.20	15.28	1.00	1.03
0.9	9.12	15.06	0.99	1.01
0.91	9.09	15.01	0.98	1.01
0.92	9.10	14.96	0.99	1.01
0.93	9.19	15.08	1.00	1.01
0.94	9.08	14.66	0.98	0.99
0.95	9.22	14.87	1.00	1.00
0.96	9.30	14.65	1.01	0.99
0.97	9.63	14.86	1.04	1.00
0.98	10.17	15.12	1.10	1.02
0.99	11.40	16.13	1.24	1.08
1	16.11	21.24	1.75	1.43

The middle section shows the overall results while the right section in Figure ?? shows the same values normalized around the value of 0.95. It is observed that the maximum value of forgetting factor has the highest mean error. This can be correlated with our knowledge about necessity of forgetting factor being less than 1 for rapid response systems. Since the system has its best performance at $\lambda = 0.94$, it will be chosen for initial implementation.

However, very often both the measurement noise level and the rate of variation in the system may change. The system may be subjected to abrupt changes, or may change its dynamics considerably over a short period and then remain constant for a long while. In such cases also the choice of forgetting factor must be adapted to the changing environment.

There are several ways in which forgetting factor might be updated. The most popular one is by Fortescue, Kershenbaum and Ydstie (1981) [51] and algorithm of Wellstead and Sanoff (1981) [52] which use suitably weighted sum of a posteriori errors resulting from the most recent value of parameter estimates or from past estimates and select a forgetting factor by a recursive relation. Thus λ is updated at each time step based on the errors in estimation.

Another issue with classic method of forgetting is of estimator windup. When the signals are poorly excited, old information is continuously forgotten while there is very little new dynamic information coming in. This might lead to the exponential growth of the covariance matrix and as a result the estimator becomes extremely susceptible to numerical and computational errors. This is known as estimator windup.

One popular refinement to the RLS with forgetting scheme is the concept of directional forgetting for reducing the possibility of the estimator windup when the incoming information is non-uniformly distributed over all parameters. The idea is that if a recursive forgetting method is being used, the information related to non-excited directions will gradually be lost. This results in unlimited growth of some of the elements of the covariance matrix and can lead to large estimation errors. Implementation of the concept of directional forgetting is again ad hoc and is reflected in updating the covariance matrix. For example, if the incoming information is not uniformly distributed in the parameter space the proposed schemes perform a selective amplification of the covariance matrix. The estimator wind-up can also occur if we are estimating multiple parameters that each vary with a different rate. A solution to this problem is known as vector-type forgetting or selective forgetting. The idea is again implemented in the update of covariance matrix. Instead of dividing all elements by a single λ, P is scaled by a diagonal matrix of forgetting factors [53].

This issue can be tackled once the controller is tested on the vehicle. It should be noted that this will lead to increase in computational complexity of the control system and might result in delay in response to input.

5-4 Models for valve control and their variants

The estimation models selected from the literature include empirical model and the derived New Estimation model. The empirical models are restated from Section 3-2-2:

Models without Valves Voltage

Linear Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_3.t_{open}.\Delta P \tag{5-4}$$

Quadratic Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_1.t_{open}^2 + b_4.t_{open}.\Delta P \tag{5-5}$$

Build Linear Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.P_{brake} + b_3.P_{\text{supply}} + b_4.t_{open}.P_{brake} + b_5.t_{open}.P_{\text{supply}} \tag{5-6}$$

Models with Valves Voltage

They are basically the same models as mentioned earlier with the addition of voltage supplied to the valve of the respective phase.

Linear Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_3.t_{open}.\Delta P + b_4.V_{valves} \tag{5-7}$$

Quadratic Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.\Delta P + b_1.t_{open}^2 + b_4.t_{open}.\Delta P + b_5.V_{valves} \tag{5-8}$$

Build Linear Model

$$P_{step} = b_0 + b_1.t_{open} + b_2.P_{brake} + b_3.P_{\text{supply}} + b_4.t_{open}.P_{brake} + b_5.t_{open}.P_{\text{supply}} + b_6.V_{valves} \tag{5-9}$$

The parameters of the model are

ΔP	: pressure difference
$\Delta P = P_{\text{supply}} - P_{\text{brake}}$	: for build phase
$\Delta P = P_{\text{brake}} - P_{\text{acc}}$	: for release phase
t_{open}	: Valve opening time
P_{step}	: Predicted pressure step
P_{brake}	: Current brake pressure at wheel brake cylinder
P_{supply}	: Pressure at the Main Chamber by application of driver's pressure on pedal and brake booster
P_{acc}	: Pressure at the accumulator

The coefficients of the different models $\{b\} = \begin{bmatrix} b_0 & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 \end{bmatrix}$ will be updated recursively. It is important to notice that the maximum number of adaptive coefficients vary for different models. The Linear Model without valves voltage has 4 coefficients whereas the Build Linear Model with valves voltage has 6 coefficients. The number of adaptive coefficients can be changed for different models. Updating of several coefficients may lead to issues in practical implementation due to computational load and estimator windup issue. Estimator windup is result of the errors arising due to algorithm not being adaptive to different rates of changing parameters. Also this being a low level control algorithm, it is required to be efficient not only in terms of performance but also utilizing computational power. Higher complexity might also be a source of delay which can be fatal as the ABS algorithm is only activated in situations which driver does not have any control over the vehicle.

It is thus imminent to check the performance of partially varying models. This may help in removing certain parameters whose influence cannot be neglected but can be compensated through other parameters. This can be achieved in two ways. The first method is to remove coefficients from the group and check their performance. This is a partial model. For example, a partial build linear model with only two varying parameters can be seen as

$$P_{step} = b_0 + b_1.t_{open} + b_2.P_{brake} \tag{5-10}$$

The partial build linear model is affine in valve opening time (t_{open}) and current brake pressure (P_{brake}) parameters only. This results in less coefficients to update via complex calculations saving effort. However, this also makes the algorithm lose degrees of freedom in adjusting the coefficients or gains of the parameters. Now the update will be more drastic and errors are expected to rise.

It is also possible to not remove the selected parameters but keep their coefficients constant. This can be explained by a partially static build linear model as follows

$$P_{step} = b_0 + b_1.t_{open} + b_2.P_{brake} + c_3.P_{\text{supply}} + c_4.t_{open}.P_{brake} + c_5.t_{open}.P_{\text{supply}} \tag{5-11}$$

In the above equation, the coefficients of the parameters of valve opening time and current brake pressure along with the constant offset are varied but the rest are kept constant i.e c_3, c_4, and c_5 are constants. This helps in maintaining the influence of all parameters but reduces the degrees of freedom of the updating algorithm. In this case, the optimization takes place with some coefficients only. It is important that the value of the constants be properly chosen as they cannot be changed and it is possible that the coefficients will not be able to compensate for these incorrect values and make the mapping unstable. An option would be to fit a curve for large dataset and get the initial parameter vector set.

New estimation model Apart from the empirical models, the New Estimation models derived in Section 3-3 are also used for simulation study. The build and release models are restated below

$$P_{step} = t_{open}.R_{build}.(P_{supply}(k) - P_{brake}(k))^{\phi_{build}} \tag{5-12}$$

$$P_{step} = -t_{open}.R_{release}.(P_{brake}(k) - P_{acc})^{\phi_{release}} \tag{5-13}$$

The New Estimation models has four parameters namely R_{build}, ϕ_{build}, $R_{release}$, and $\phi_{release}$. ϕ_{build} and $\phi_{release}$ are indices which define the relationship between the data signals and estimated variable. They are determined by observing which index perform better in estimation using dataset. The details are presented in the Appendix B. The values of ϕ_{build} and $\phi_{release}$ are set to 0.5 and 1 respectively.

The R_{build} and $R_{release}$ are the coefficients which will be updated recursively for the adaptive algorithm. These models are simulated for estimating the pressure step and are analyzed with respect to the performance indicators obtained for both wheels FL and FR and also both phases Build and Release.

5-5 Results of simulation using existing experimental dataset

This section will highlight the results of the simulation using the models and their variants explained in the previous section. Simulation results from different empirical models are summarized in a table as shown in Table 5-2 and Table 5-3.

Table 5-2: Errors obtained using Models without valves voltage

Model	Without Valves Voltage					
	Quadratic		Build Linear		Linear	
Statistics indicator	Rel. error	Std. Dev.	Rel. error	Std. Dev.	Rel. error	Std. Dev.
FL Build	12.45	18.09	9.87	15.51	13.00	18.83
FL Release	9.93	15.93	10.10	16.43	11.04	17.07
FR Build	10.33	15.42	9.40	14.81	11.28	16.92
FR Release	7.75	12.98	7.53	12.75	9.51	15.40
Overall	10.12	15.61	**9.22**	**14.87**	11.21	17.05

Table 5-3: Errors obtained using Models with valves voltage

Model	With Valves Voltage					
	Quadratic		Build Linear		Linear	
Statistics indicator	Rel. error	Std. Dev.	Rel. error	Std. Dev.	Rel. error	Std. Dev.
FL Build	12.33	18.07	9.87	15.40	12.88	18.89
FL Release	10.29	16.90	10.12	16.52	11.10	17.30
FR Build	10.52	15.74	9.53	14.86	11.39	16.97
FR Release	7.68	12.97	7.55	12.69	9.56	15.59
Overall	10.20	15.92	**9.27**	**14.87**	11.23	17.19

The overall values of relative error and standard deviation between tables show that addition of valves voltage does not result in significant improvement of the pressure estimation. However, since the dataset is taken in laboratory with relatively constant battery considerations, no firm conclusion can be drawn from this overview. It is easily seen that by increasing model order i.e. making it quadratic shows a small decrease in estimation errors. The build linear model performs better than linear model especially in the build phases of both wheels. This can be attributed to the inclusion of current brake pressure (P_{brake}) as an independent parameter. In build phase, the linear model was dependent on delta pressure ($\Delta P = P_{\text{supply}} - P_{brake}$) and hence the influence of current brake pressure was undermined. This was not the case for release pressure as delta pressure in that case was $\Delta P = P_{brake} - P_{acc}$ which is the difference between brake and accumulator pressure. But since the accumulator pressure is ideally very low for releasing fluid, delta pressure now becomes $\Delta P \approx P_{brake}$. Hence, no significant improvement is seen in the estimation.

Amongst the empirical models, the Build Linear model without Valves Voltage has the least estimation error. Using different sets of coefficients, the performance of partially varying Build linear model without valves voltage was observed. Every combination of parameters was simulated in sets varying from {1-6}. It was observed that it became more difficult for algorithms to optimize as the number of varying coefficients became smaller leading to bigger estimation errors. The following table compares different combinations for set of 2 coefficients with both partial model and partial static model cases.

Table 5-4: Data for Build Linear Model without Valves Voltage by keeping 2 different coefficients varying

Varying Coefficients	Partial Static Model		Partial Model	
	Rel. error (%)	Std. Dev.(%)	Rel. error (%)	Std. Dev. (%)
b_0 & b_1	13.29	18.38	23.52	29.62
b_0 & b_2	10.40	15.66	16.536	23.14
b_0 & b_3	12.63	17.36	24.50	30.85
b_0 & b_4	10.91	16.08	17.26	23.68
b_0 & b_5	12.66	17.40	21.81	27.66
b_1 & b_2	10.95	16.03	14.49	20.13
b_1 & b_3	12.80	17.65	22.41	28.37
b_1 & b_4	10.90	16.10	17.99	23.64
b_1 & b_5	12.93	17.64	23.36	29.28
b_2 & b_3	10.54	15.72	15.10	22.07
b_2 & b_4	14.88	20.20	19.91	26.28
b_2 & b_5	10.83	15.80	11.99	16.98
b_3 & b_4	11.08	16.25	15.61	22.15
b_3 & b_5	13.34	18.55	22.27	28.41
b_4 & b_5	10.84	16.00	15.49	20.84
Average	11.93	16.99	18.82	24.87
Normalised	1.29	1.14	2.04	1.67

The average values are normalised on average relative error and standard deviation in full model case shown for Build Linear model without Valves Voltage in Table 5-2. As expected, there is a large error induced in partial model as compared to partial static model because of loss of influencing parameters making the mapping incorrect. The partial static model does not give a very large error and can be tested on vehicle for further evaluation if the initial mapping is better approximated.

This analysis was also carried out for all sets of partial static model. In the case of Build Linear model without voltage, the set varies from 0 to 6 as shown in Table 5-5. It was seen that the error reduced with more adaptive coefficients. However, there were certain combinations such as b_0 & b_2 and b_2 & b_3 in Table 5-4 which show small difference in estimation when compared to full model.

It can be concluded that a partial static model with specific combinations, which produce relatively low estimation errors, can be employed before the full model and check model effectiveness in real time and compare with the full model.

Furthermore, the New Estimation model is tested on the identification dataset with parameters defined in Appendix B. Keeping the forgetting factor value same, the average mean

Table 5-5: Comparing different coefficient sets for Build Linear Model without valves voltage

No. of varying coefficients	Overall Estimation Errors			
	Absolute(%)		Normalised about result for 6 number of coefficients	
	Relative Error (%)	Standard Deviation (%)	Relative Error	Standard Deviation
0	16.18	20.79	1.75	1.40
1	13.19	17.90	1.43	1.20
2	11.93	16.99	1.29	1.14
3	10.58	15.89	1.14	1.07
4	9.83	15.31	1.06	1.03
5	9.40	14.96	1.06	1.02
6	9.22	14.87	1.00	1.00

relative errors and standard deviations of the build and release phases for both the wheel sides FR and FR and the overall results are compared with that of the Build Linear model with two varying coefficients in the Table 5-6.

Table 5-6: Performance comparison of New Estimation model and build linear model

Model	Phase	Mean relative error (%)	Mean standard deviation (%)
New Estimation model	Build steps	13.39	18.60
	Release steps	19.24	24.14
	Overall	16.31	21.37
Build linear model with 2 varying coefficients	Overall	11.93	17.00

The overall results conveys small deterioration in performance of the New Estimation model over the Build Linear model. Further, the build phase estimation errors are close to that of the Build Linear model but the release phase shows poor performance than the earlier model. This may be attributed to the lack of rich information from the system regarding the release phase as the only varying parameter available is that of the brake pressure P_{brake}.

5-6 Conclusion

In this chapter, procedure of the simulation with several estimation models was carried out on the dataset collected from earlier experimentation. The simulation procedure was discussed and the performance indicators were defined. These indicators helped in analyzing the performance of the models and their variations. Also, the forgetting factor value was selected based on the identification data.

The empirical models obtained from Torres (2014) [4] were compared with each other and the Build Linear model without Valves Voltage was selected on the basis of least estimation error criteria. Different variations of the Build Linear model with different number of adaptive coefficients and different combinations of those coefficients were tested to analyse the variation in performance. It was seen that the the performance did not deteriorate significantly even by keeping two varying coefficients. The number of varying coefficients was reduced for simplification of the adaptive algorithm as well as to remove any redundancy and correlation in updating of the coefficients.

The parameters of New Estimation model governing the relationship between the variables were found by observing the trend of estimation errors with increasing values of the parameters. This New Estimation model was then simulated using the identification set and the performance was compared to the Build Linear model with two varying coefficients. The Build Linear model was found superior but not too significantly.

The simulation carried out using the identification dataset covers the vast pressure range of operation significantly. However, the evolution of coefficients in the actual experiments and its performance needs to be observed to make a thorough assessment. Hence, the Build Linear model with two varying coefficients and the New Estimation model will be analysed based on th experimental data to select the better model for the adaptive controller.

Chapter 6

Real Time Implementation of Adaptive Controller

The earlier chapters have explained Recursive Least Squares theory and its performance in estimation during simulations on the identification dataset. This chapter will focus on the implementation of the controller using the acquired knowledge of adaptive filtering scheme and hardware characteristics.

The chapter starts with Section 6-1 which will provide a brief revision about communication with the vehicle and the nature of the data obtained from the AutoBox. Subsequently, the chapter delves into control system and different challenges faced during its practical implementation. Important features pertaining to the system, such as pump control strategy and identifying real-time sources of error, are also discussed. The next section shows the types of reference signals used for evaluating the performance of the controller.

6-1 Communication and Interfacing with the vehicle

The implementation of the controller on hardware requires communication of the laptop containing the `Simulink` program and the HAB circuit which is made possible through `dSPACE` control system inside the AutoBox as explained in the section Section 2-1. The `dSPACE` control System acquires all data, processes it and determines the output to the actuators. The programming of the `dSPACE` system is done by the use of the laptop customized for this interaction by installing the associated `dSPACE ControlDesk` software.

This `dSPACE` system is a modular hardware system and so addition and/or change of hardware boards inside is possible. This feature enables it to be flexible. The main boards inside the AutoBox include DS1005 PPC board which is the processor board, and PCMCIA link board providing connection to laptop. Amongst the 5 boards used for communication with different parts of the vehicle, the relevant boards for this thesis are

- DS4002 PWM & I/O board - valve and pump control communication

- DS2003 AD conversion board - brake pressure measurement

More information on specification of the AutoBox and it's relevant components can be found in *dSPACE Manual for BMW* which is currently being written.

The data available from these boards are in the form voltage signals and need to be calibrated to obtain the true value as the original signals are in another scale, offset from the ground voltage or a combination of both. These calibration parameters are identified through testing done in [4]. Since, an optimal set was found in those identification experiments, it is being used in the initialization file for the program. It is recommended that the calibration procedure to be carried out for each batch of tests as the disturbances affecting the measurement slightly vary each time. The data is made available for control with a sampling frequency of 2000 Hz which was also identified in [4].

The control system can be implemented in `Simulink` by using requisite `dSPACE ControlDesk` blocks for communication which specify the aforementioned board names. Moreover, a script in `C` language is required to encode the commands from control system for the DS4002 board.

After, the control system is compiled using the required boards and `C` encoding script, the `dSPACE ControlDesk` is used to interface and run tests using compiled control system. An example of interface available when carrying out the experiments is shown in Figure 6-1.

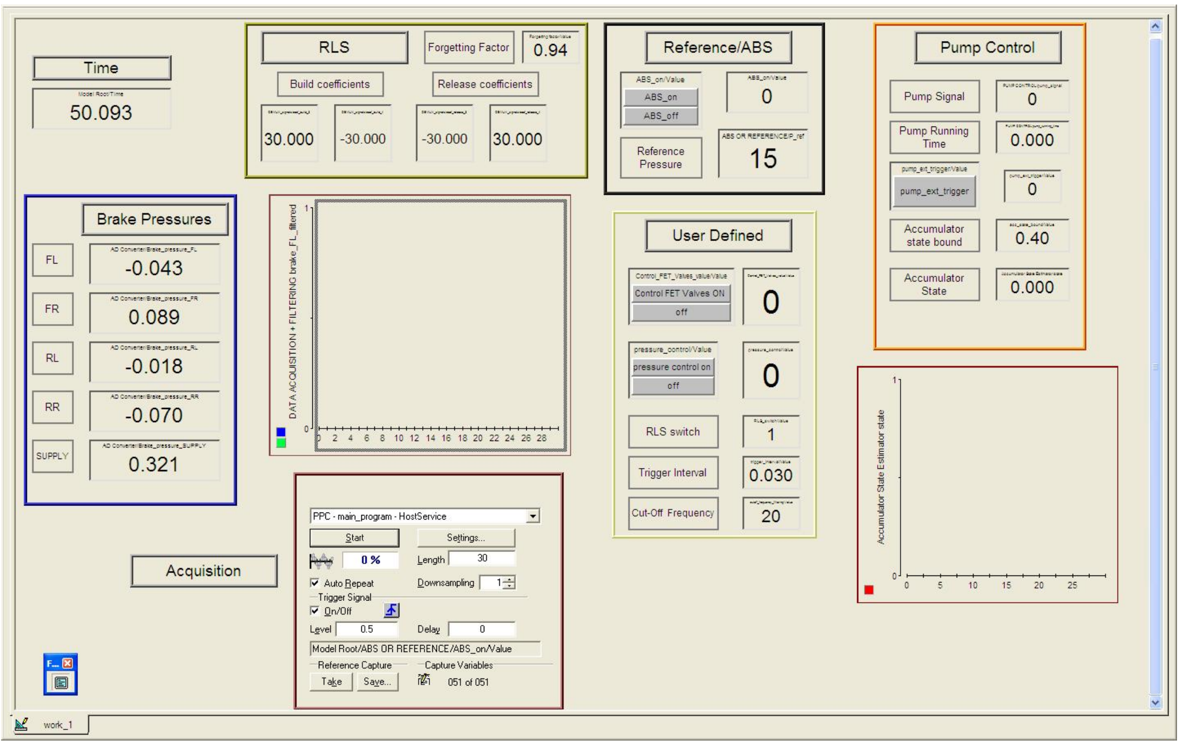


Figure 6-1: Example of Interface in `dSPACE ControlDesk`

The user has the option to set the duration till which he might want to acquire information. One also has to specify the variables to be acquired and the signals to be displayed and plotted. User should be aware that the signals provided to the control system will be the same as in the `Simulink` control loop and so adequate safeguarding should be done to prevent damage to the system.

6-2 Control Loop Structure

The simulations of the adaptive algorithm, provided in previous chapter, were carried out using data from a variety of experiments with different pressure ranges. This data contained the steady state values of the pressure steps performed at the same time instant. This is not possible in the real time environment because of the time of control execution and settling of the signal. Also, the calculation of accumulator state and the effect of pump control was not dealt with in simulations. These challenges make the design of the control loop structure the most important part of the implementation process. A simple and decentralized control structure helps tremendously in analysis as well as troubleshooting of the control system. For the given brake pressure control problem, the control loop structure can be schematically shown by Figure 6-2 and Figure 6-3.

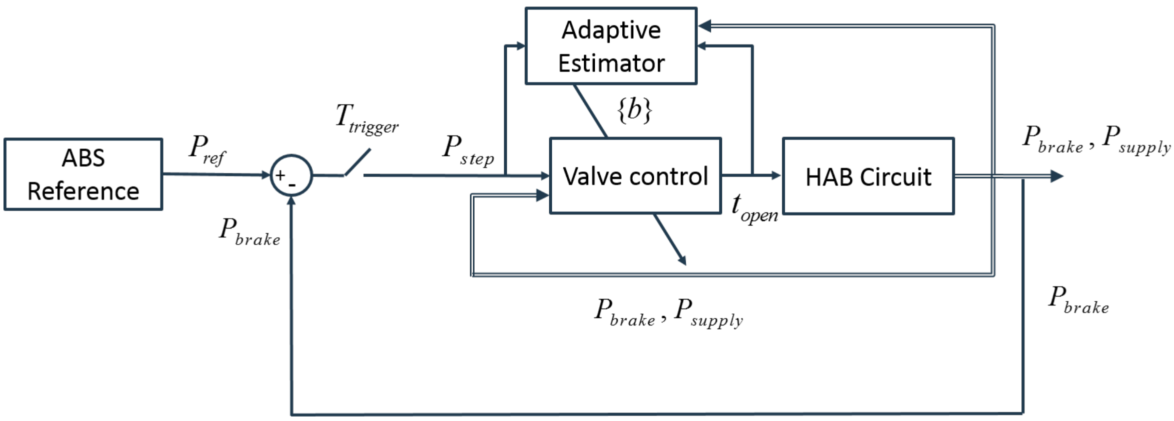


Figure 6-2: Block Diagram of brake pressure control system

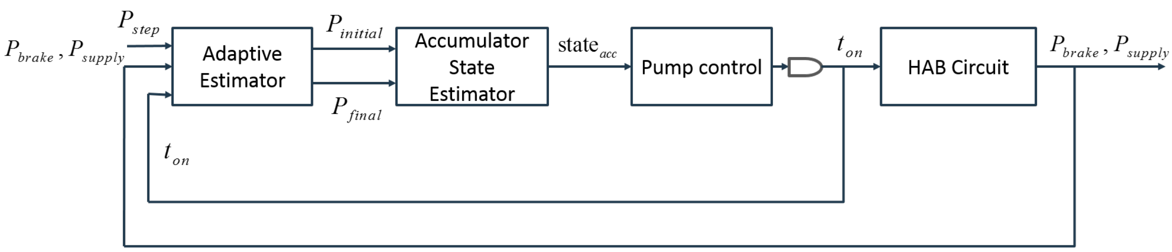


Figure 6-3: Block diagram of the control system implemented in `Simulink`

The block diagram in the Figure 6-2 shows typical structure of Self-Tuning regulator customized for the given control problem for a specific wheel side (either FL or FR). The HAB circuit represents the hydraulic circuit which provides current values of brake and supply pressures(P_{brake},P_{supply}) , and state of pump. The ABS Reference block provides the reference (P_{ref}) which needs to be tracked. The Valve Control block receives the pressure step (P_{step}) to be taken by the difference between the reference and the current brake pressure. It executes the new pressure step request by calculating the valve opening time (t_{open}) for each valve using the estimation models selected in Section 5-4. This executed pressure step is then processed to update the Build and Release Mapping using RLS algorithm by Adaptive Estimator. The control system is being triggered at fixed time intervals ($T_{trigger}$) between successive pressure steps.

The Figure 6-3 is the schematic representation of the secondary control problem i.e. timely emptying of the accumulator. The Adaptive Estimator provides the released pressure data in the form of initial brake pressure at the time of release (P_{initial}) and the final brake pressure at steady state after release (P_{final}) to the Pump Control block. The Pump Control block uses this data to calculate the accumulator state and then runs the pump (t_{on}:running time of the pump) when the accumulator state has crossed the specified bound. These blocks and their function will be explained in the upcoming sections in detail.

It should be noted that this control scheme only controls single corner braking. This is because each wheel will have its own distinct tyre-contact dynamics during slipping, and therefore, making it important to provide different brake pressures at different wheels to control the vehicle. Since FL and FR corners of the vehicle share the hydraulic circuit, as shown in Figure 2-6, it becomes mandatory to keep the other wheel side's valves closed to have avoid loss of supply pressure.

The control structure shown in Figure 6-2 depicts schematic representation of the controller. However, there are few changes to be made before implementing on setup. The previous scheme encounters certain algebraic loop challenges. For example, the Adaptive Estimator cannot process the given data and update the mapping simultaneously while executing the same pressure step. This is solved by adding a unit delay block before updating the Valve Control mapping. Similarly, the output of Pump Control block is delayed as it uses the processed data for calculating the accumulator state (which is already seen in the Figure 6-3). The control structure after adding delay blocks and updating the actual data flow is shown in Figure 6-4.

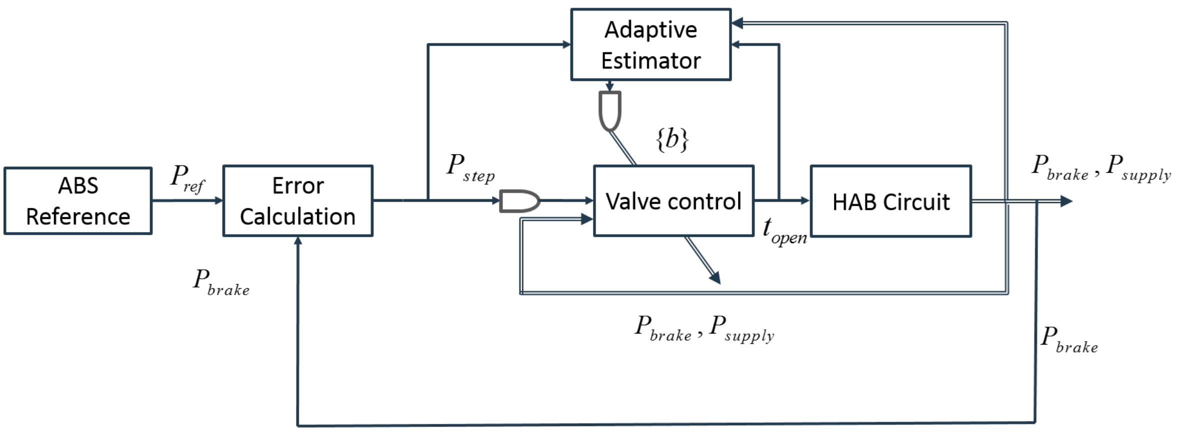


Figure 6-4: Block diagram of the control system implemented in `Simulink`

A major difference from the earlier block diagram is the addition of the Error Calculation block which replaces the summing block. Apart from of calculating the next pressure step, the error calculation also provides the trigger intervals between successive pressure step requests ($T_{trigger}$) and provides bounds to the minimum and maximum pressure step request to be processed.

The control system is thus formulated but still poses some challenges due to physical limitations and real-time considerations. These challenges have been segregated for better understanding and will be explained in the next section. The subsections will also explain the steps taken to solve these challenges.

6-3 Physical Constraints

A poor design of control loop will not only result in bad performance but can also make the system unstable. Instead of assisting the driver in an uncontrollable scenario, an unstable controller will lead to fatal situation. The first step in designing a controller for physical setups is to realize and include the physical constraints into the control loop. This ensures the desired working range for the actuators (i.e. the valves and pump motor) and prevents the damage to the system.

The physical limit challenges faced during the operation of the controller can be divided into following categories

- Minimum valve opening time
- Maximum pressure step
- Trigger interval and Maximum valve opening time

Minimum valve opening time

It was found through identification experiments [4], that each valve had a minimum time limit for which it can be opened. This is the time taken by the valves for opening and closing. The values for all the valves of FL and FR are mentioned in Section 2-6. Therefore, a common minimum valve opening time of 1.75ms for hold valves and 1.1ms for release valves has been set.

Now, this set minimum valve opening time is a limitation to the accuracy of pressure control. Let us consider an example; imagine a pressure step request to be executed involving smaller opening time than the prescribed limits. In a non-fatal scenario, accuracy is preferred over execution of pressure steps and this pressure step will not be taken. However, in the case of ABS systems, it is crucial that the reference is tracked and therefore even a small pressure step should be executed. The facilitation of these are done by opening the valves for the minimum opening time possible. This will cause inaccuracy in the pressure step executed and might spawn corrective actions. Nevertheless, this is limitation of the hardware which has to be considered.

Maximum pressure step

During simulations and identification experiments, it was found that the RLS algorithm gives larger estimation errors for large pressure steps. Also considering the fluid inertia and the hydraulics system response, a larger time delay will be observed to obtain a reliable reading of the actual pressure reached after a large pressure step. This can be made more accurate by dividing large pressure steps into small steps which are executed sequentially. Hence, there is a user imposed limit on maximum pressure step that can be executed at a given instant.

This step is limited to 10 bars for the given controller. It should be noted that large pressure steps[1] are executed but only in different steps for accuracy.

Trigger interval and Maximum valve opening time

The sampling period for acquisition of the hydraulic data is 0.5 milliseconds (corresponding to frequency of 2000 Hz). This period is smaller than the actuation of valves. Thus, a sampling period has to be decided which takes into account the actuation and settling time while also being quick enough to respond to dynamic ABS reference signal. This sampling period is referred to as trigger interval in this report. It corresponds to the minimum time interval between successive pressure step requests.

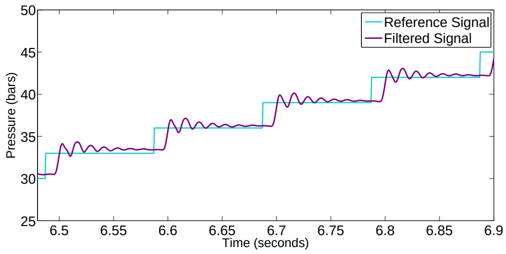


Figure 6-5: Observing Settling time for small pressure steps

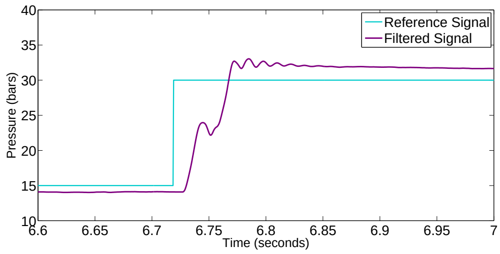


Figure 6-6: Observing Settling time for large pressure steps

As seen in Section 3-1, the brake pressure signal tracks at maximum frequency of 50 Hz i.e. a time period of 20 milliseconds. The limit provided to the maximum pressure step executed at a given instant also limits the maximum opening time of the valve and helps in determining the trigger interval to be set. Now, it is possible to determine the valve opening time for pressure step of 10 bars in different pressure ranges. This value was found experimentally to be approximately equal to 20 milliseconds. So, the trigger interval was decided to be 30 milliseconds allowing additional time for the transients to die.

The settling time for different pressure steps are different as seen in Figures 6-5 and 6-6. It is seen that for small pressure step of 3 bars, the settling period is approximately more than 50 milliseconds. In the Figure 6-6, a large pressure step of 15 bars is seen to be executed in steps. The second pressure step which corresponds to approximately 7 bars takes 100 milliseconds to completely settle. Although, the decided trigger interval value is not enough for the transients takes to settle completely, the required duration of $50 - 100$ milliseconds is significant in a critical situation where faster tracking is the most necessary criteria. So, the trigger interval value is kept 30 milliseconds to obtain quicker response. In addition, the reader is made to note that in the absence of a pressure request, no trigger interval is provided to allow responsive tracking of the reference.

This trigger interval is user-definable and so can be modified if necessary. Also, since the trigger interval is set, the maximum valve opening time limit was also established at 25 milliseconds. This bound is required to avoid loss of control in situations when adequate supply pressure is not available for build pressure request. It is possible that the valve is allowed to be open for a longer time in an attempt to build pressure. However, this situation will also be tackled in the online sources of error section later.

[1] Provided adequate supply pressure is available

6-4 Functional analysis of different blocks

As disclosed earlier, this controller will form a building block for future implementation of novel ABS algorithms. Decentralization of the duties of each block will help for future users to understand the working of the controller and also identify areas for their analysis. An accurate control scheme representation is shown in Figure 6-4. This section will focus on each block of the control loop and its functions. This will help the reader understand the real time implementation challenges and solutions of the adaptive controller.

The blocks of the control system are divided as follows:

1. ABS or Reference block
2. HAB Circuit Data block
3. Error block
4. Adaptive Estimator block
5. Valve Control block
6. Pump Control block

An addition to the above blocks is the User Defined Parameters block which enables users to tune the system to their requirements. There are several constants, such as the forgetting factor for the RLS, which can be tuned within their permissible ranges. Additionally, the user is made aware of the possible tuning parameters.The User Defined Parameters block is a simple block with several tunable constants of other blocks inside it. This will not be discussed in detail. The reader is advised to bear in mind the Figure 6-4 and Figure 6-3 before proceeding further to understand the primary significance of each block.

6-4-1 ABS or Reference Block

The reference block ot ABS block corresponds to the higher level controller shown in Figure 3-1. The main purpose of the higher level controller is to provide a reference pressure request calculated using the vehicle dynamics and tyre-contact mechanics. The higher level controller monitors the vehicle continuously and in case of hard braking and imminent wheel-lockup, it switches on the low level control system and take control of the hydraulic circuit. Thus, trigger signal and reference pressure are the two outputs of the ABS.

6-4-2 HAB Circuit Data

The HAB Circuit Data block represents the DS2003 board. In the Figure ??, the HAB Circuit block is a combination of data acquisition block and valve and pump communication. As mentioned earlier in Section 6-1, HAB Circuit Data block is used for providing brake pressure measurement to the control system from the sensors after filtering.

Signal Filtering

The sensors of brake pressure signals are susceptible to noise and so it is required to filter the signals in order to obtain a better estimate. The sampling frequency of the signal is 2000 Hz, which is very large. This large frequency invites sensor noise to influence the system. Hence, filtering is very crucial to the performance of controller.

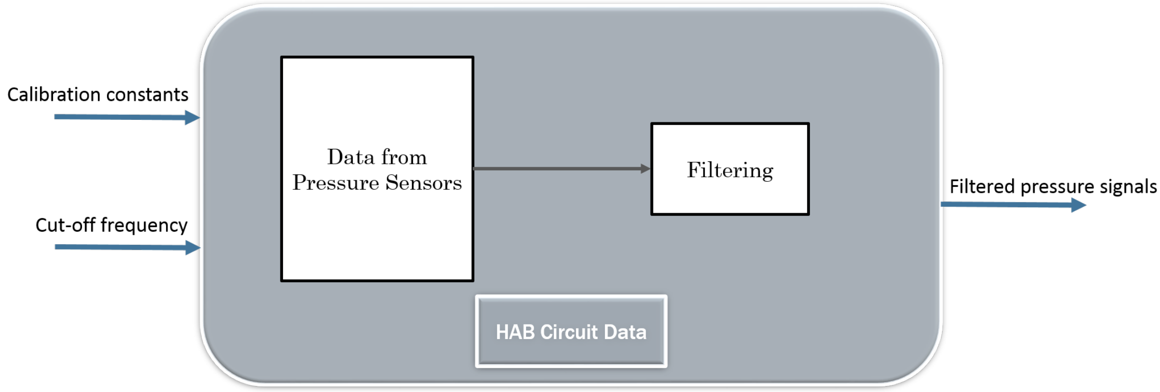


Figure 6-7: Functional block representation of HAB in `Simulink`

A real-time second order discrete low pass filter is introduced for each signal which will be used for processing. This filter is found in the HAB Data Acquisition block as seen in it's functional diagram in Figure 6-7. The signals to be filtered include brake pressure signals of both FL and FR and the supply pressure signal. Additional input from the user determines the cut-off frequency for the filtering. It is possible to use the filtered signal to obtain the first and second derivative of the signal to observe the change of brake pressure signal to be controlled. This is useful to obtain settling time of the system after pressure step.

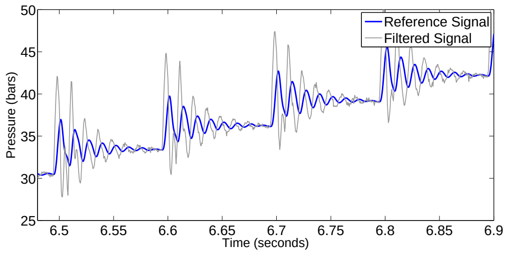


Figure 6-8: Actual and filtered brake pressure signals for cut-off frequency of 70 Hz

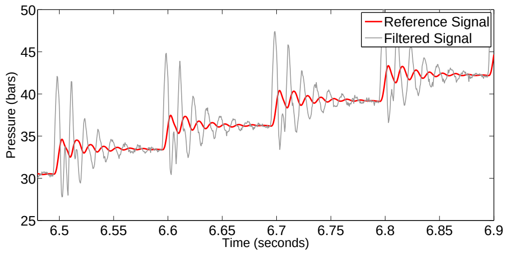


Figure 6-9: Actual and filtered brake pressure signals for cut-off frequency of 40 Hz

Selecting a cut-off frequency is important so that relevant data is not filtered out in the process. It is already known that the trigger interval of the control system is 30 milliseconds which corresponds to 33.33 Hz. This is also the operating frequency of the system i.e. the maximum frequency at which the controller will give output. Thus, by Nyquist- Shannon sampling theorem, the sampling frequency ($N_{sampling}$) should be greater than twice that of frequency of data to be measured (N_{data}) to avoid aliasing [54].

$$N_{sampling} > 2.N_{data} \tag{6-1}$$

Thus, the cut-off frequency for filtering can be safely set to 70 Hz. A snapshot of real time filtering is seen during some build pressure steps in Figure 6-8. The behavior of brake fluid while making a pressure step is also observed. Due to its liquid state, the brake fluid flows forth and back inside the valve while making a pressure step. This is known as liquid sloshing. It is observed in Figure 6-8 where the filtered and unfiltered brake pressure signals have transients with frequency values close to each other. Thus, the frequency of liquid sloshing is very close to cut-off frequency and is not filtered.

Now, it is pertinent to select a cut-off frequency lower than 70 Hz as the influence of liquid sloshing during transience is detrimental to measurement for control purposes. Hence, a lower cut-off frequency of 40 Hz is selected, to approximate the average pressure at the wheel corner,which is still greater than the operating frequency of control system. The filtered signal can be seen in Figure 6-9. It is seen that the influence of sloshing is reduced.

6-4-3 Error block

The Error block triggers the system intermittently, using the specified trigger interval, to provide the new pressure step request (obtained using Eq. (6-2)) by comparing the reference data and current brake pressure at the appropriate wheel-side.

$$P_{\text{step}} = P_{\text{ref}} - P_{\text{brake}} \tag{6-2}$$

where
P_{step} : Pressure step request
P_{ref} : Reference pressure to be tracked
P_{brake} : Current Brake Pressure at appropriate wheel side

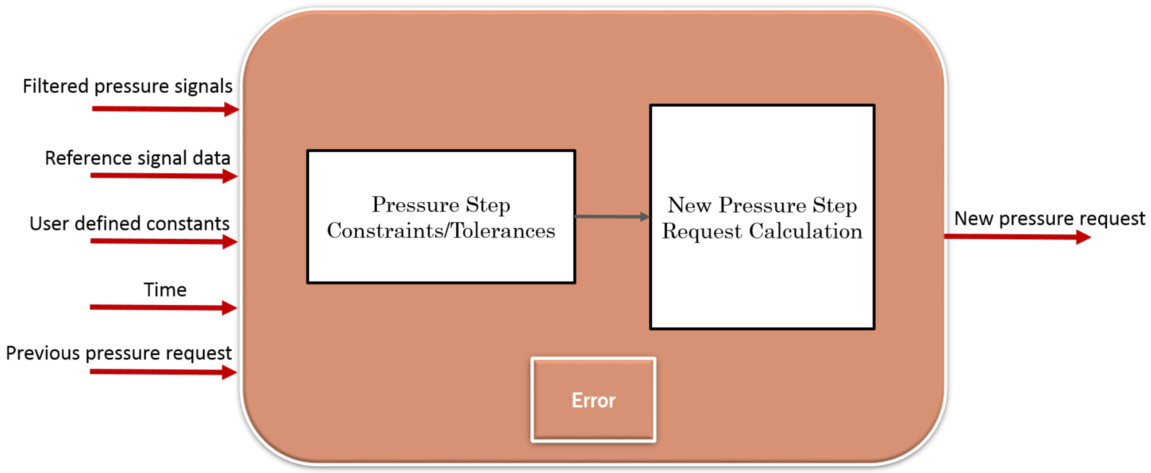


Figure 6-10: Functional block representation of Error and Trigger Block in `Simulink`

Thus, it is the first block that gets triggered if the ABS or reference signal is provided . The functional block representation of this block is seen in Figure 6-10. As expected, the primary output of this block is pressure request signal. Also, it provides the information on whether the executed pressure step is a part of a large pressure step. This information is useful for detection of corrective pressure steps.

The pressure request calculated is bounded by the maximum and minimum pressure step constraints. These constraints are also used for error tolerance provision.

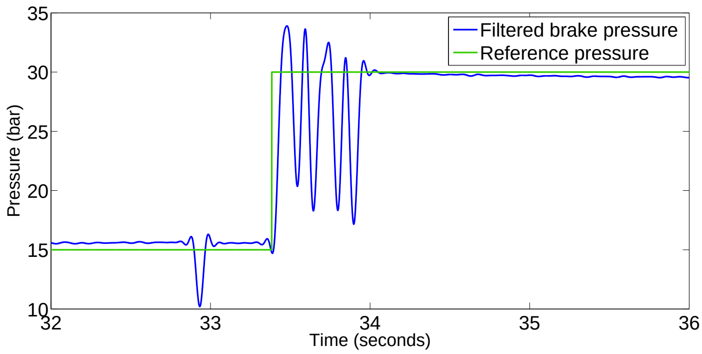


Figure 6-11: Error calculation without tolerance region resulting in chattering

Tolerance calculation

An important feature of this Error block is the tolerance calculation. It is already established that the brake pressure signal values are unreliable during the transient phases due to delays and sloshing effect. It is important to let the system settle to obtain an accurate estimation of steady state pressure reached. A quick and responsive controller does not allow the system to settle and evaluates the tracking error for an unsettled and oscillatory brake pressure. This evaluation leads to erroneous pressure requests which cause the controller to execute subsequent build and release steps. Thus, it behaves like a bang-bang controller. These subsequent execution of build and release phases are termed as chattering. Since, the liquid sloshing effect is not completely filtered, an error tolerance had to be provided to avoid chattering. Thus, a confidence region was created around the desired pressure step such that no subsequent pressure requests were triggered if the current pressure lay within this confidence region.

The Figure 6-11 and Figure 6-12 shows plots with and without the bounds or tolerances. The response of the system is significantly improved and prevented from becoming unstable. The values of the tolerance depends on the pressure step to be made. These values were obtained from the RLS simulations and correspond to the maximum prediction error obtained while making a pressure step in simulations of the RLS algorithm (seen in Figure 3-10 under Section 3-2-2). The figure shows a pressure step of 15 bars and hence, there is a large tolerance region of ± 5 bars because of large overshoot possible. An important point to note is that the tolerance changes with reference pressure to achieve the requisite tracking performance.

The tolerance region also helps in early settling of the fluid and measuring the final steady state value of the executed pressure step. These tolerance values are provided by modifying the minimum and maximum pressure step constraints. Although, the values of these constraints depend on pressure step, the constraints are initialized every time the reference changes to avoid loss of tracking.

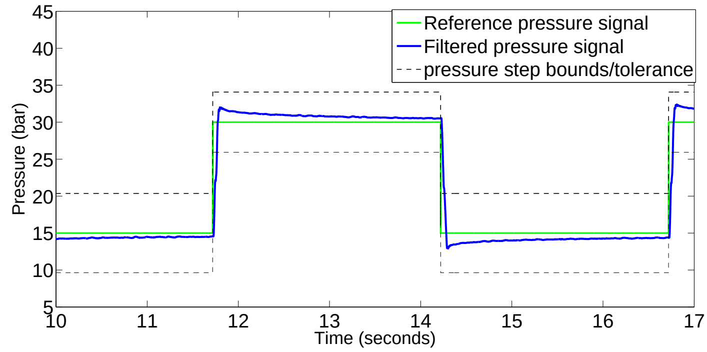


Figure 6-12: Error calculation with tolerance regions resulting in smooth performance

6-4-4 Adaptive Estimator block

The most intricate implementation is of adaptive estimator block as seen in Figure 6-4. The Adaptive Estimator block observes the executed pressure step and processes its characteristics to update the build and release mapping for the Valve Control block for execution of next pressure step. The models used in Section 5-4 are used for estimation of build and release steps. As stated earlier, the coefficients of the model are the parameters which will be updated to optimize the model. In the case of Build Linear model, the coefficients are $\{b\} = \begin{bmatrix} b_0 & b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix}$ different for build and release phases whereas for the new estimation model the coefficients are R_{build} and R_{release}. These coefficients are updated according to nature of the executed pressure step.

The major tasks of the Adaptive Estimator block are namely, selecting appropriate data of the executed pressure step, updating the mapping and estimating the next pressure step. As these tasks are complicated, the adaptive estimator block was divided into three sub-blocks. The `Simulink` model of the block is shown in Figure 6-13.

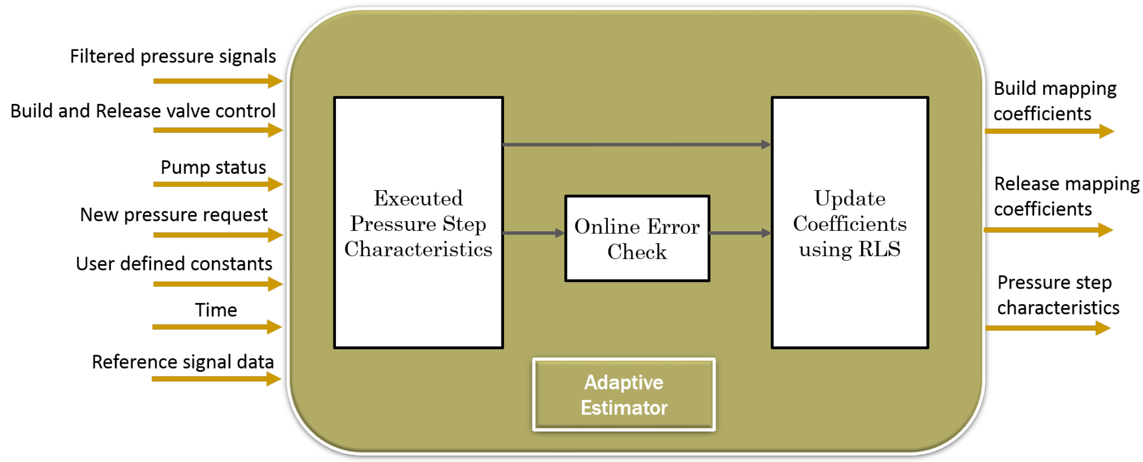


Figure 6-13: Functional block representation of Adaptive Estimator block in `Simulink`

The Adaptive Estimator block as shown is divided into Executed Pressure Step Characteristics block, Online Error Check block and Update Coefficients using RLS block. The sole objective of the Executed Pressure Step Characteristics block is acquiring and sending data which defined the executed pressure step. This includes filtered values of the current and final brake pressure signals, and supply pressure value.

$$\text{Pressure step Characteristics} = \begin{bmatrix} P_{\text{intial}} & P_{\text{supply}} & P_{\text{final}} & P_{\text{request}} & t_{\text{build}} & t_{\text{release}} \end{bmatrix}$$

It also includes the opening times of the valves obtained from Build and Release Valve control data. All the signal values except the final brake pressure value are easily available at a given instant. The final brake pressure value corresponds to brake pressure value after the pressure step is executed and ideally when the brake pressure reaches steady state. The final brake pressure value is thus, obtained after a certain time lapse either due to steady state achievement or due to next pressure step request. This final pressure calculated is then sent along with the earlier data to the next block. Also, this data is also sent to Pump Control block as seen in Figure 6-4.

The Online Error Check block inspects any causes of error in pressure step apart from incorrect prediction. If these causes are present in the executed pressure step, then it informs the Update Coefficients using RLS block and the model coefficients are not updated. These are discussed in detail in Section 6-4-4.

The Update Coefficients using RLS block receives the data required for updating the coefficient set. According to the nature of pressure step request (build or release), it first estimates the pressure step and calculates the error with actual pressure step achieved as seen in Eq. (6-3). This error is the estimation error which is reduced by updating corresponding coefficients using the Recursive Least Squares (RLS) method. This updated coefficient set is then available for the next pressure step request.

$$\text{error}_{\text{estimate}} = P_{\text{actual}} - P_{\text{estimated}} \tag{6-3}$$

where
P_{actual} : Actual pressure step made
$P_{\text{estimated}}$: Estimate pressure step as seen in Equation (7-4)

Online Sources of Error

The adaptive algorithm updates the model coefficients with estimation error of the previous coefficient set. This requires use of proper data which define the pressure step executed. The hydraulic system along with controller is prone to several errors which may or may not be caused by concurring operations. It is important that the controller still remains operational and does not diverge towards incorrect model coefficients caused due these errors. Thus, it is important that the control system has the knowledge of these disturbance causing errors and can tackle them in real time. These errors are inspected by the Online Error Check function in Adaptive Filter Block as seen in Figure 6-13.

The causes of disturbance errors can be divided as follows:

(a) **Inadequate supply pressure**
It has been made clear in the Section 2-6 that an adequate amount of supply pressure is required to build pressures. It is not possible to obtain a brake pressure equal to or higher than the supply pressure at any given time. This supply pressure is managed by the amount of force applied by the driver and is not subject to control in case of ABS operation. If supply pressure is not sufficiently provided by the driver, it will result in failure of the control system to build the desired pressure step. An example of this situation is seen in Figure 6-14.

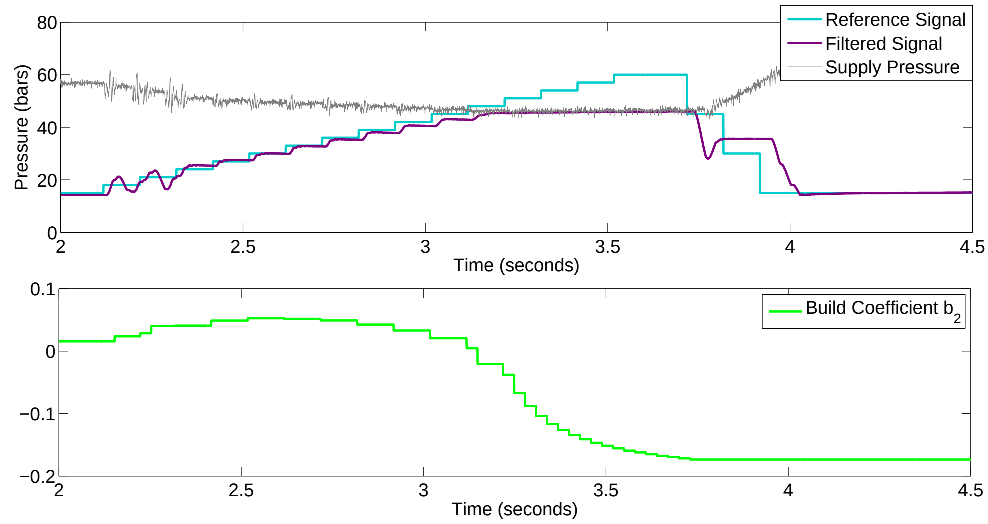


Figure 6-14: Inadequate supply pressure error

The first sub-figure shows the control system trying to track a staircase reference signal with inadequate supply pressure. The error caused due to inability of the system to make a pressure step forces the model to adapt leading it away from the optimal set of values. This is seen in second sub-figure in Figure 6-14. Hence, an update of the coefficient set is avoided by introducing an inadequate supply pressure flag.

The equations Eq. (6-4) and Eq. (6-5) form the conditions for this flag. In the event of this flag, the update of the coefficients will be stopped and previously updated coefficient set will be protected.

$$P_{\text{supply}} \leq P_{\text{ref}} \tag{6-4}$$

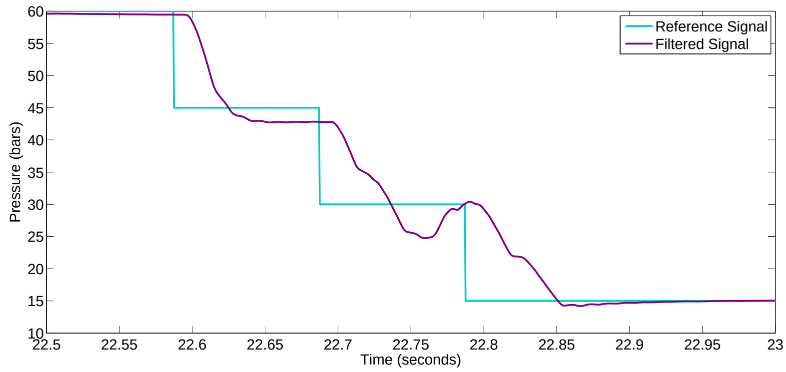
$$P_{\text{supply}} \leq P_{\text{brake}} \tag{6-5}$$

where
P_{supply} : Supply pressure provided by driver's foot
P_{ref} : Reference or ABS pressure signal
P_{brake} : brake pressure at the given wheel corner

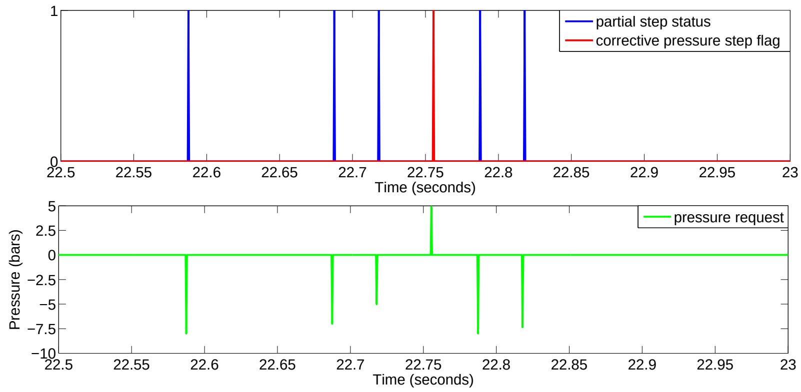
(b) **Inaccurate update of corrective pressure steps**
Another problem which affects the adaptive algorithm are the values of data captured when the fluid has not settled. Due to quick responsive nature of controller, it is possible that an error is calculated outside the tolerance during the transient state

leading to corrective pressure step. This corrective pressure step uses incorrect initial brake pressure value and is highly inclined to miscalculation for updating the coefficient set.

The Figure 6-15 shows an instance of corrective pressure step. The first plot of the figure shows tracking of a release staircase reference signal. Since the release pressure steps are large, they are executed in parts. The Error block provides the information on whether the executed step is a partial step or not. This partial step status is observed in second plot. The final plot reveals the pressure requests taken in the process. It is seen that while performing the second release step, the control system dumps more pressure than required and therefore, executes a build pressure step to reduce the tracking error. This corrective pressure step data is processed using transient values of brake pressure values. This causes the build coefficient set to step away from the previous coefficient set similar to that seen in Figure 6-14.



(a) Reference and brake pressure signal for successive release steps



(b) Partial step status and corrective pressure step flag

Figure 6-15: Example of detection of corrective pressure steps

This update is avoided by checking for consecutive non-partial[2] pressure requests (P_{request}) executed for the same reference (P_{ref})as seen in second plot of Figure 6-15. The corrective step is avoided by using the conditions seen in Algorithm 1.

[2]Not executed in parts

Algorithm 1 Checking for corrective pressure steps

```
if P_ref = P_ref_prev AND P_request then
    if partial_step_status = 0 OR sign(P_request_prev) ≠ sign(P_request) then
                                                        ▷ sign: sign function
        error_flag = 1
    end if
end if
```

(c) **Pumping period**
During the pumping period, all the valves are required to be closed so that the accumulator is emptied and brake fluid is not drawn from other sections of the circuit. Thus, all the operations are stopped by the controller to empty the accumulator. So there will be no update of coefficients for the pressure request executed just before the pumping started for the same reasons as explained in the corrective pressure steps. Since there will be no pressure request executed during that period, there will be no update of coefficients as well. The condition used for avoiding any pressure step during pumping period is given in the Algorithm 2.

Algorithm 2 Condition for Guaranteeing no pressure step during pumping period

```
if t_pump = 1 then                  ▷ t_pump : trigger for switching on the pump
    P_request = 0
end if
```

6-4-5 Valve Control block

The Valve control block uses the pressure request generated by the Error block along with the current brake and supply pressures and the coefficient set from the Adaptive estimator block to calculate the valve opening time of the Hold valve and Release valve depending on the nature of pressure step request. The opening times of the valves are calculated from the inverse of estimation models (from Section 5-4) as seen in the following equations

$$t_{\text{open}} = \frac{P_{\text{request}} - b_0 - b_2.P_{\text{brake}} - b_3.P_{\text{supply}}}{b_1 + b_4.P_{\text{brake}} + b_5.P_{\text{supply}}} \tag{6-6}$$

$$t_{\text{open}} = \frac{P_{\text{request}}}{R_{\text{build}}.(P_{\text{supply}} - P_{\text{brake}})^{\phi_{\text{build}}}} \tag{6-7}$$

In the above equation, everything corresponds to the same variables except P_{request} which is the pressure step request to be executed. The Valve control communicates with each valve using three parameters: valve state, valve trigger, and valve pulse length. The valve state corresponds to the normally open or close state of the valve. The valve trigger is used to change the state of the valve and the duration for which it changes is determined by the valve pulse length or the valve opening time calculated above. For example, during a build pressure step, the Hold Valve in the Figure 2-6 will be normally closed with valve state 1. It will be triggered open with the calculated opening time for making a build pressure step. Similarly, the opening time can be calculated for the Release Valve.

6-4-6 Pump Control block

As seen in Section 2-5, pump control is very important for releasing of brake pressures. The system must be prepared to dump large pressure if required at all times. This requires regular pumping of fluid back to the main pipeline. Also discussed is the methodology for calculation of the accumulator state to achieve pump control without the presence of any sensor inside the accumulator. This method utilizes the data acquired by the 'Executed Pressure Step Characteristics' block (present in the Adaptive Filter scheme Figure 6-13) during release phases to update the accumulator state.

The functional block representation of Pump Control block is shown in Figure 6-16. The sub-block 'Accumulator state Estimator' calculates the accumulator state after each release pressure step executed. The Pump Control Executor block executes the signal for switching on the motor running the pump for the amount of time determined by the accumulator state. It can also switch the pump on if asked by the emergency pump trigger or the external trigger signals. The external trigger can be provided by the user or reference to prepare the accumulator for large release of pressure or during malfunctioning of the controller whereas, the emergency pump trigger is used as an corrective action for accumulator state error.

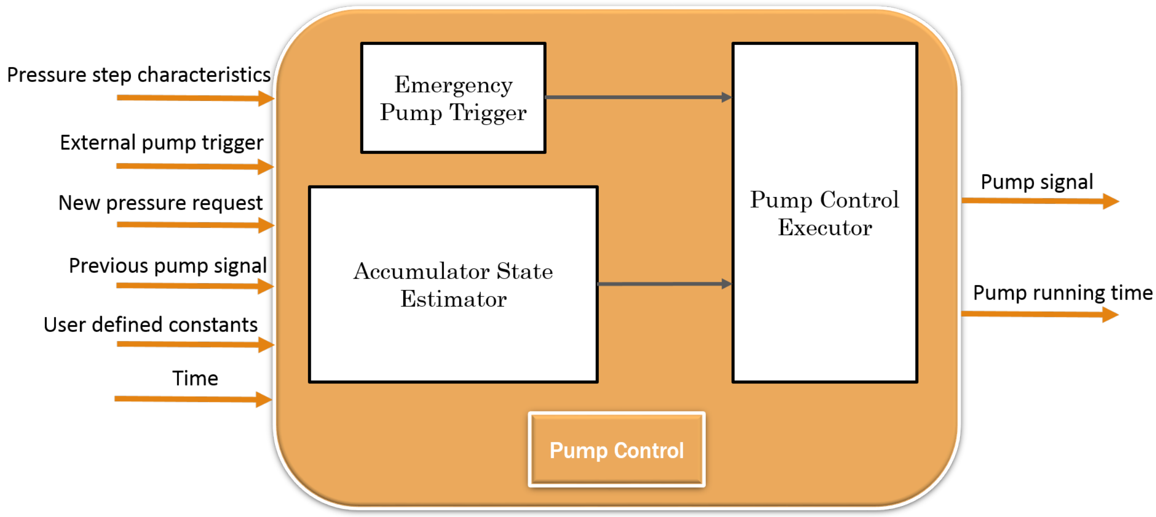


Figure 6-16: Functional block representation of Pump Control Block in `Simulink`

The 'Accumulator State Estimator' block uses an empirical method for calculation of state and so it is susceptible to errors especially while corrective release steps are taken. Due to possibility of calculating erroneous state values and more importantly, to allow high release of pressure at any given point during the operation, the pump is turned on when it crosses accumulator state bound set to 40 % . This necessitates frequent pumping of fluid to sustain our requirement. Also, as the accumulator state reaches value closer to the bound, the controller schedules the pumping when the system is at steady state to prepare the pump for future release phases. The pump is triggered when the brake pressure has achieved steady state. This is done by calculating the first and second order difference of brake pressure signal (P_{brake}) and compared to constants (c_1 and c_2) observed at steady state[3]. This can be represented as seen in the Algorithm 3.

Algorithm 3 Scheduling pump trigger when accumulator state is near the bound

if $\text{acc}_{\text{state}} < 0.4$ **AND** $\text{acc}_{\text{state}} \geq 0.3$ **then**
  if $\Delta P \leq c_1$ **AND** $\Delta^2 P \leq c_2$ **then**
    $t_{\text{pump}} = 1$ ▷ t_{pump}: trigger for switching on the pump
    pump_flag $= 3$ ▷ Flag designated for this operation
  end if
end if

It is important to take keep two vital precautions in consideration while operating the pump. The pump motor should not be switched on or kept running when the accumulator is empty. This will cause the motor coils to overheat and damage it. This was achieved by a maximum bound to be placed on motor running time which was calculated from identification experiments in [4]. Secondly, all the valves must be closed while the pumping is in process. This will ensure the pumping of fluid is from the accumulator only and also help in stability of the system so that no sudden rise and fall of pressures are experienced. In addition, the pump is made independent of execution of any phase.

Emergency pump trigger

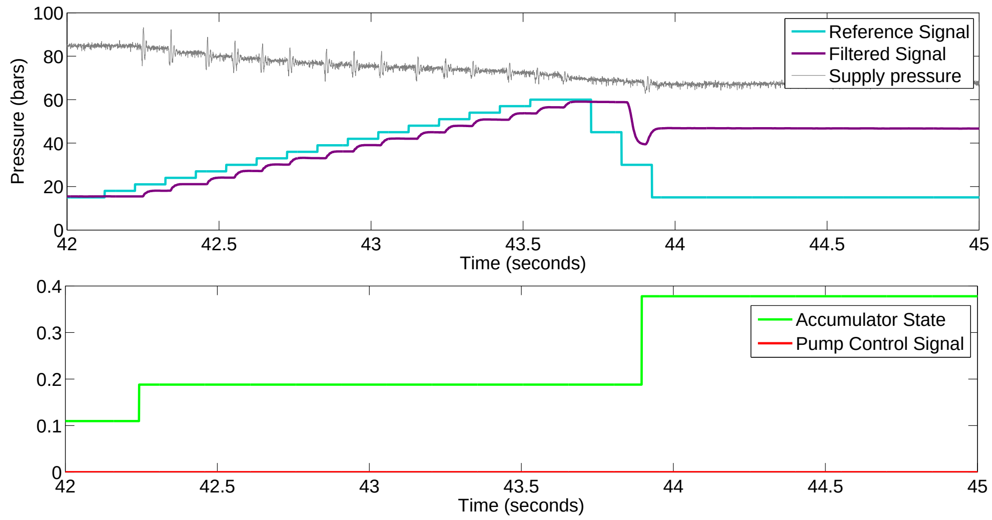


Figure 6-17: Inability to release pressure

The accumulator state estimate is also prone to errors due to corrective pressure steps and running of pump. The update of model coefficients may be stopped from becoming sub-optimal but the accumulator state calculation cannot be stopped even if there is a possibility of faulty measurement of the brake pressure due to transience or liquid sloshing. This makes

[3]It should be noted that the first and second order differences of brake pressure (ΔP_{brake} and $\Delta^2 P_{\text{brake}}$) settle for time intervals greater than 100 milliseconds between successive pressure requests

the accumulator state to become uncertain which can prove fatal. The Figure 6-17 gives one such instance when pressure is not being released.

The first plot in the figure shows the brake pressure and reference pressure signals during real-time experimentation. However, during the release phase, the brake pressure does not track the reference signal. The accumulator state is on the verge of crossing the accumulator state bound as seen in the second plot. During this operation, the release valve is continuously being triggered. It is clear that the accumulator is full and requires pumping. However, the control system is unable to detect this because of faulty accumulator state estimation. In the operation of actual ABS system, such an event will prove fatal as the vehicle will crash due to its inability to regulate pressures. Hence, an emergency trigger is added to facilitate release of pressure in such conditions. It is triggered when the control system detects two successive but non-partial release pressure requests separated by trigger interval as seen in Algorithm 4 (similar to detection of corrective pressure steps). Thus, a possibly fatal situation is averted.

Algorithm 4 Emergency pump trigger because of inability to release pressure

if partial_step_status $= 0$ **AND** $P_{\text{request}} < 0$ **then**
  if $sign(P_{\text{request\_prev}}) = sign(P_{\text{request}})$ **then** ▷ *sign*: sign function
    $t_{\text{pump}} = 1$
  end if
end if

6-5 Sample Reference Signals

In the actual scenario, the desired reference signal will be calculated by the higher level controller as shown in Figure 3-1. This controller will use vehicle dynamics and tyre-road contact mechanics to calculate the desired braking required at each wheel. This reference signal is thus uncertain and different with different conditions. However, it is important to analyze the control system so that it can track this uncertain reference signal with accuracy and characteristics mentioned in Section 3-1.

The following signals are hence selected for the analysis of different aspects of the implemented adaptive control system.

1. Block signal
2. Staircase signal
3. ABS reference mimicking signal

The block signal is the basic signal to test the tracking of the controller and response of the hydraulic system. It provides clear understanding of the delays affecting the system. It is not very dynamic which is very important to capture the settling time and gives a clear picture of the execution of phases. Also, the high build and release pressure step of 15 bars helps in analyzing the performance in large pressure steps. An example of block reference signal is shown in Figure 6-18. Further, a block signal of small magnitude will also be used to check the convergence of the RLS algorithm.

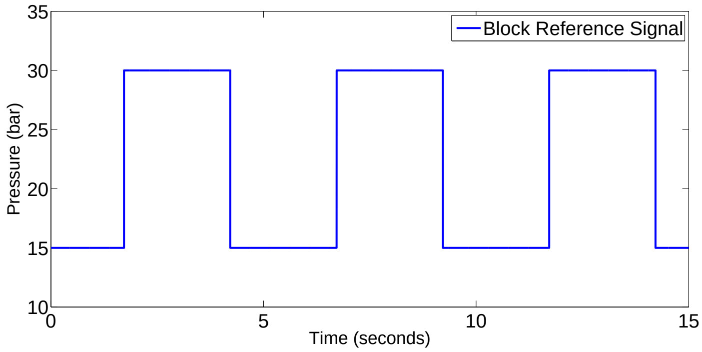


Figure 6-18: Block reference signal

The staircase signal is a signal which is an intermediary signal between the simple block signal and the ABS reference mimicking signal. It was observed in Section 3-1 that the build steps were executed in small steps to avoid jerk and instability. The build staircase signal has small building pressure steps and quick large release pressure steps. This repeating signal helps in understanding the performance for small pressure steps and more importantly in the evolution of the coefficients. An example of this signal is seen in figure. Similarly, a release staircase signal is used as well.

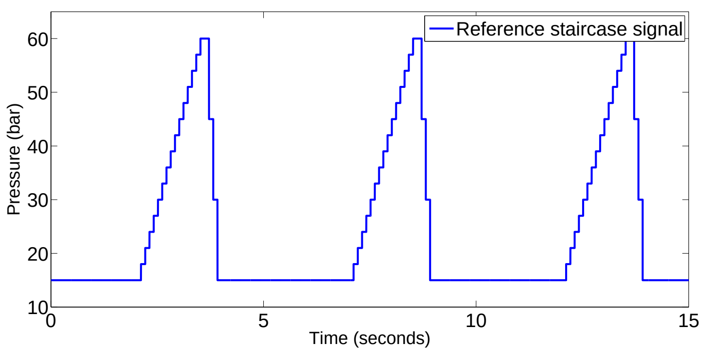


Figure 6-19: Staircase Reference Signal

The ABS reference mimicking signal is the signal which was built to approximate the nature of the actual signal. Using the reference signals in Section 3-1, the following reference signal was modeled.

The highlights of this reference signal is easily seen in Figure 6-20. The brake pressure values are kept between $10-60$ bars so that adequate supply pressure can be provided without much effort. The signal starts from higher value as it would in the real scenario. It includes the dynamic nature of the reference signal with small build steps and quick releases combined with an eccentric cyclical nature. This is the ultimate test of the controller in fast paced environment. Care should be taken to not harm the setup in the process.

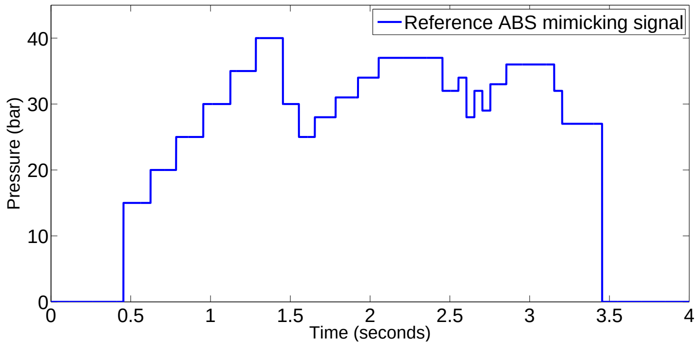


Figure 6-20: ABS reference mimicking signal

6-6 Conclusion

In this chapter, the process of implementation of the brake pressure control system was explained in detail. The block diagrams in Figure 6-4 and Figure 6-3 gave a schematic overview of the system. The physical limitations of minimum valve opening time and maximum pressure step helped in defining the constraints for the control output. The parameter of trigger interval was also established based on the settling time of the brake pressure signal observed for small and large pressure steps. This set the maximum valve opening time for build and release pressure steps. More importantly, it set the maximum rate at which successive pressure steps could be executed.

The block diagrams Figure 6-4 and Figure 6-3 also divided tasks to different blocks. These blocks were studied in terms of their functions and steps taken to achieve them. Additional function apart from the brake pressure control were also added for better transparency in the working of the control system and also tackle errors in real time. These include online errors resulting from corrective pressure steps, inadequate supply pressure and control actions during pumping period.

The pump control strategy used may encounter problems if large release step is required to be executed and the accumulator state is less than the bound. This may also arise due to incorrect estimation. The above scenarios resulted in an additional function to empty accumulator in emergency situations to facilitate smooth tracking of reference signals. Finally, different reference signals were selected to evaluate the performance of the control system using different models. It was seen that though the implementation was discussed, the performance was not discussed in detail. This will be the main subject of the next chapter involving analysis of the experimental data.

Chapter 7

Experimental Data Analysis

Implementation of the control scheme and its attributes have been studied in detail. The performance of this controller with different reference signals needs to be evaluated. This chapter will primarily focus on analysis of the experimental results and the adaptive nature of the controller.

The simulation (refer Section 5-1) helped to test the various structures of estimation models. However, it was not possible to evaluate the evolution of coefficients and covariance signals. This shortcoming has been solved in the following sections and thus, the RLS algorithm is carefully studied for various scenarios.

The first section compares the performance of the control system for different signals using both the models. The evolution of coefficients and covariance signals are examined. Next, different structures of the adaptive mapping are tested and compared with the simulation results. The most important structure being the Full update Recursive Least Squares (RLS) algorithm. The evolution of all the coefficients are observed and analysed. Subsequently, the limitations of these models observed in their performance is discussed and improvements are suggested.

Further, the parametric sensitivities are also studied with a sub-optimal initial coefficient set prompting the algorithm to converge to an optimal set. This helps in understanding the influence of the parameters and how they affect the convergence rate. This chapter ends with the conclusions from the analysis of various scenarios and final selection of the model used for future testing of the brake pressure system.

7-1 Performance Analysis with different reference signals

The models Build Linear and New Estimation model will be compared with their performance and the coefficient evolution for different reference signals with the forgetting factor kept constant at value of 0.94. The performance indicators used are restated from the Section 5-2as follows

$$e_{relative}(\%) = 100.\frac{|P_{actual} - P_{estimated}|}{P_{estimated}} \tag{7-1}$$

$$\mu_{\text{relative}}(\%) = \frac{\sum_{i=1}^{N} e_{relative}(i)}{N} \tag{7-2}$$

$$S.D.(\%) = 100.\frac{\sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(e_{relative}(i) - \mu_{\text{relative}}\right)^2}}{N.e_{relative}} \tag{7-3}$$

where P_{actual} is the actual brake pressure step i.e. steady value of pressure in bars obtained after pressure step is made. $P_{estimated}$ is the estimated brake pressure step or filter output. N is the number of samples and μ_{relative} and $S.D.$ represent the mean and the standard deviation of relative estimation errors.

7-1-1 Staircase reference signal

The performance of the adaptive control system when the reference staircase signal is tracked in successive instances is seen in the Figure 7-1. The reference staircase signal is representative of ABS signal in building small pressure steps and large release steps.

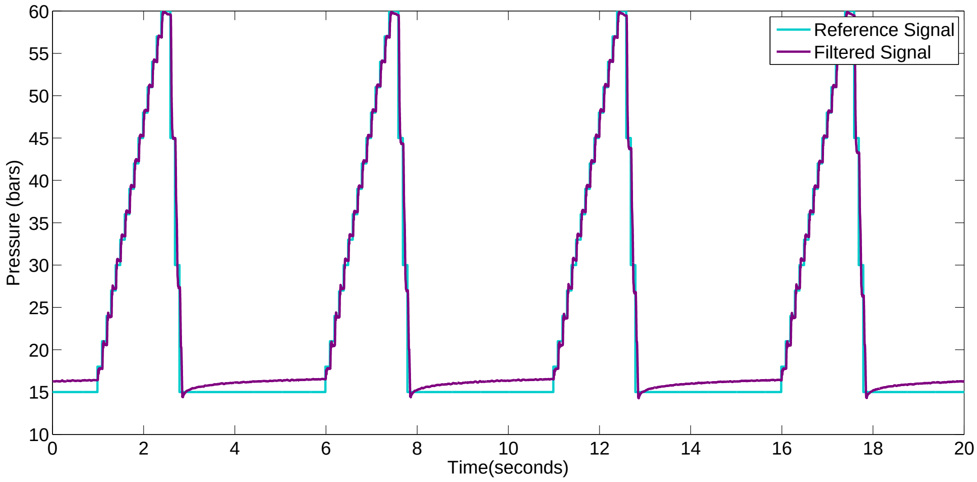


Figure 7-1: Nominal performance of the controller for staircase signal

The performance of the controller (seen in Figure 7-1) is devoid of any online errors and chattering issues with the optimal set of coefficients obtained used as the starting point. Hence, a superior tracking is seen with minimal error. These results were obtained using the Build Linear Model with two varying parameters as seen in Section 5-4.

$$P_{step} = c_0 + c_1.t_{\text{open}} + b_2.P_{\text{brake}} + b_3.P_{\text{supply}} + c_4.t_{\text{open}}.P_{\text{brake}} + c_5.t_{\text{open}}.P_{\text{supply}} \quad (7\text{-}4)$$

As seen in the Equation (7-4), the two varying coefficients (b_2 and b_3) correspond to the brake and supply pressure signals. The mean relative error over build phases over each instance of the staircase reference is seen in the Figure 7-2. It is seen that the mean and standard deviation of the relative error do not vary much.

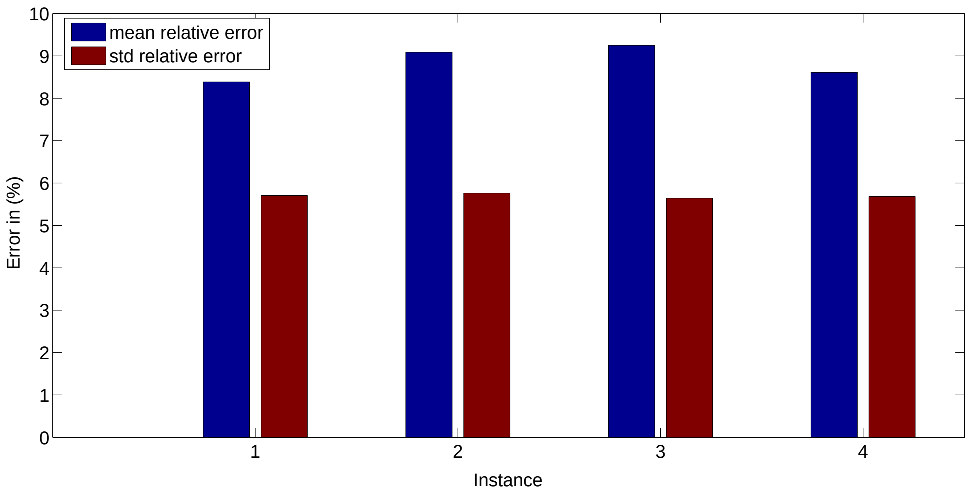


Figure 7-2: Staircase references performance: Build phase mean relative error evolution with each instance

Using the experimental data, the New Estimation model (as seen in Section 5-4) was also tested to evaluate and compare the performance with the Build Linear model. The mean relative estimation errors and their standard deviations are seen in the Table 7-1. The New Estimation model performs 1.6% better in the mean estimation errors of the build phase as compared to Build Linear model. The standard deviation increases by 1%. An increase in the release estimation error is also observed but the release phase is not analysed for staircase reference as there are very few instances of release pressure steps.

Table 7-1: Performance comparison of models for staircase reference

	Build linear model		New Estimation model	
Phase	Mean relative error (%)	Std. deviation, (%)	Mean relative error (%)	Std. deviation, (%)
Build steps ($P_{step} = 3$ bars)	**8.68**	5.82	**7.08**	6.91
Release steps ($P_{step} = 15$ bars)	10.02	13.38	15.66	15.93

The evolution of build coefficients are shown in Figure 7-3 for the adaptive algorithm with Build Linear model. The coefficients are varying within a given range. It can be implied that the optimal coefficient set for the given mapping lies within that range. As expected large deviations are seen for larger estimation errors and the as the error goes on decreasing so does the rate of change of coefficients. However, the estimation error is not the only parameter

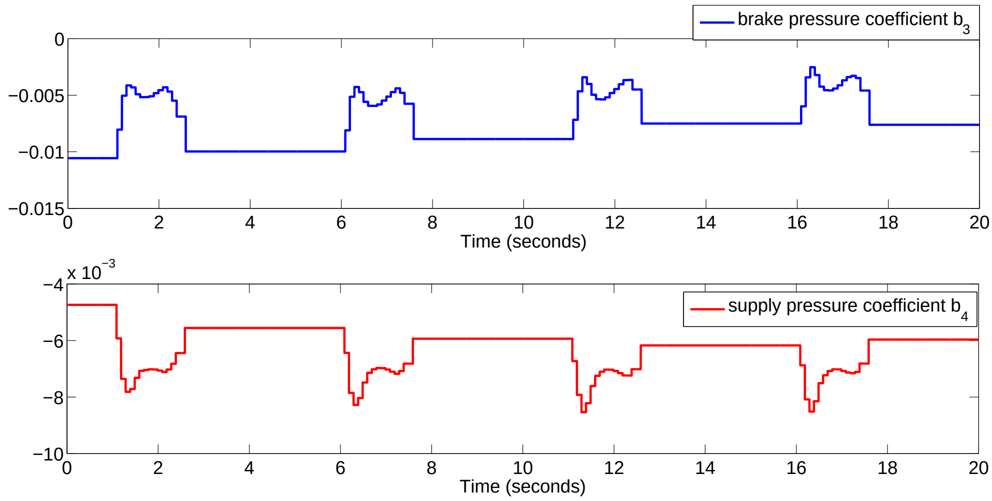


Figure 7-3: Build Linear model: Coefficient evolution

affecting the rate of change of coefficients. The parameter estimate covariance signals also influence the rate of change of the coefficients. It is thus, important to observe their evolution. This can be seen in Figure 7-4.

It is seen that the covariance signals also vary within a given range. The most important inference which can be drawn from this nature of the covariance signals is that the current coefficient set lies within a small range of the optimal set. This is also seen from the absolute values of the covariance signals which are in the order of 10^{-4}.

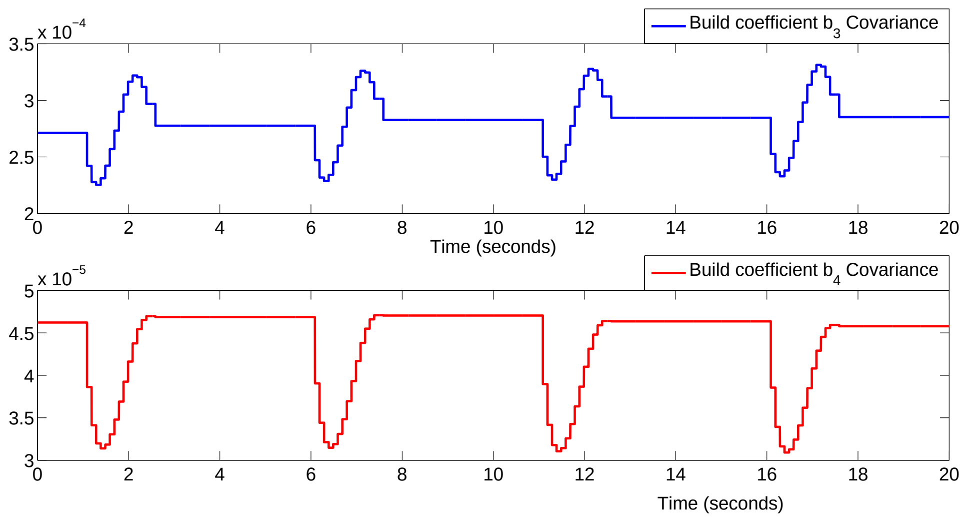


Figure 7-4: Build Linear model: Covariance evolution

Further, the evolution of coefficient and its covariance in the Figure 7-5 for the build coefficient of the New Estimation model is observed. The covariance values are higher than those seen in Figure 7-4 but it is due to the combined covariance of input signals which consist of brake pressure, supply pressure and the valve opening time. The R_{build} coefficient shows a non-linear behaviour compensating for the change in physical properties of the system. Additionally, one instance of the coefficient evolution of both models is compared in the Figure 7-6. It can be easily seen that the variation in coefficient for the same forgetting factor value and the same reference conditions is very different. The R_{build} coefficient varies by 3.73% as opposed to the earlier Build Linear model where the coefficient varies greater than 50%.

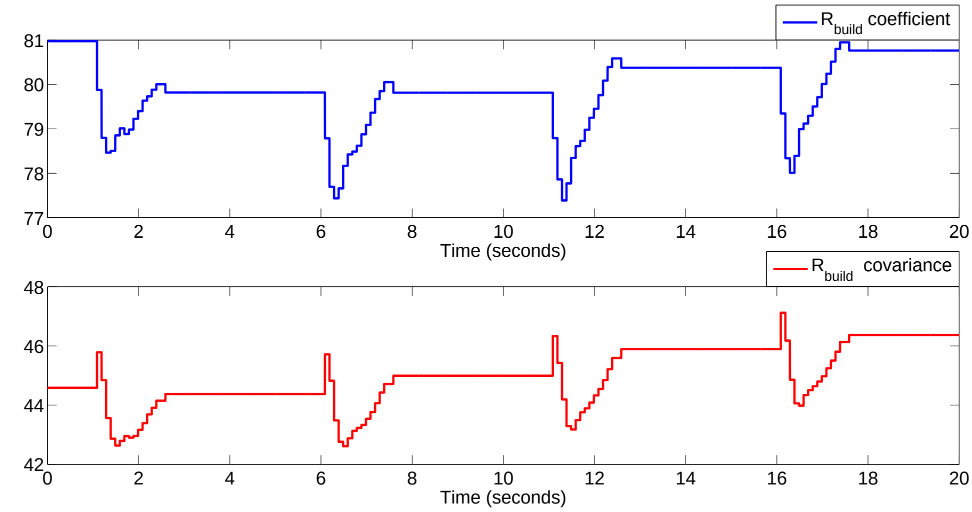


Figure 7-5: R_{build} coefficient and covariance evolution for staircase reference data

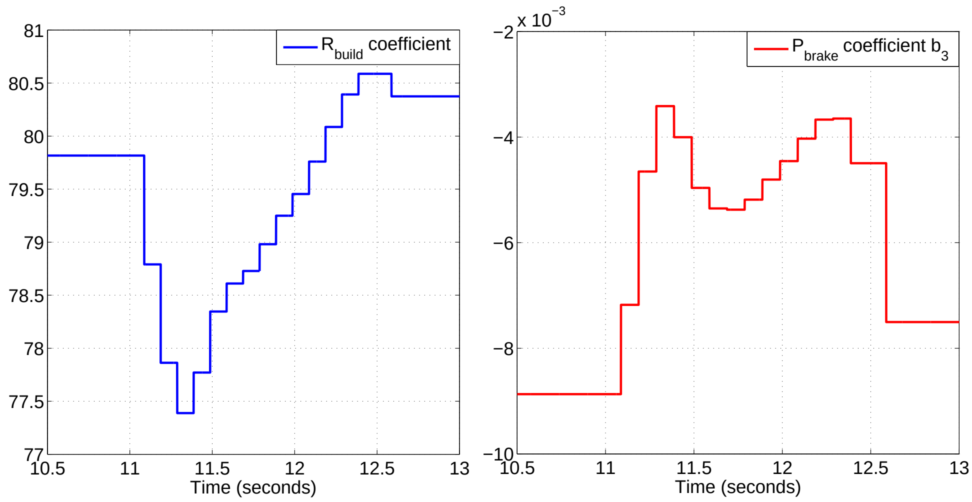


Figure 7-6: Comparison between coefficients R_{build} of New Estimation model and b_3 of Build Linear model for staircase reference

7-1-2 ABS mimicking reference

The brake pressure controller performance is also analyzed for more dynamic reference signal. The reference signal (as seen in Figure 7-7) is inspired from the brake pressure signal seen in the actual ABS performance Section 3-1. The brake pressure controller tracking capability is also observed in the plot. The build staircase-like steps are tracked comfortably. However, the same cannot be said about the quick release steps. Higher estimation errors of magnitude greater than 4 bars are observed in those cases and often corrective steps are taken. It is important to note that these quick steps are made at a high frequency of 20 Hz (or 50 milliseconds) giving too less time for the system to settle. This may also lead to incorrect measurements from pressure sensors inviting corrective pressure steps whilst the fluid is in transience. Although, some deterioration in performance is seen, no instability and chattering phenomena are observed. It is important to note that this experimentation also has varying supply pressure which was almost constant for earlier reference signals. This helps in simulating the real scenario where the drivers pressure on the pedal might not be constant.

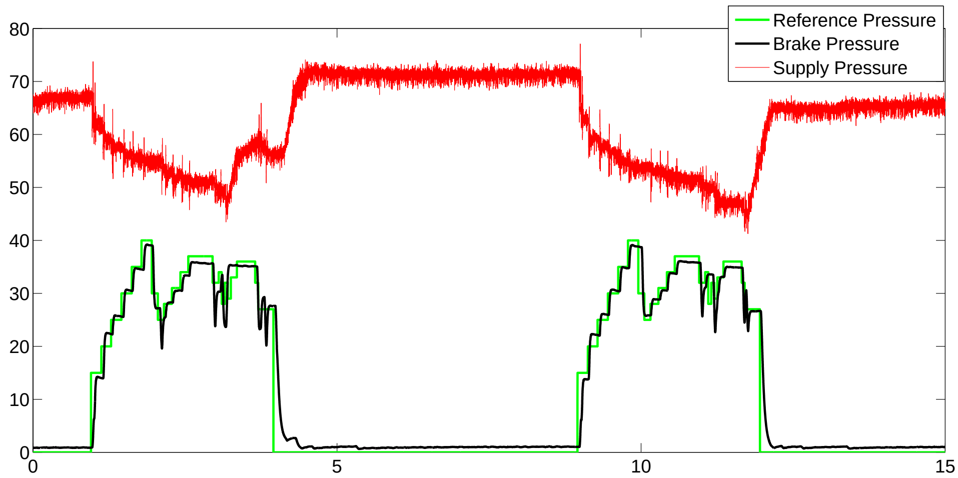


Figure 7-7: Supply pressure and brake pressure signals for ABS mimicking reference

The performance of the adaptive controller using the to models is seen in the Table 7-2. The build phase estimation errors are significantly lesser than the release phase estimation errors. An enhancement of performance is seen in case of build steps for the New Estimation model with mean relative error being 6% less than that of Build Linear model. However, a decline in release pressure step estimation is also seen as the new model has an increment of 7.5% in estimating release pressure steps over the Build Linear model. This maybe due to lack of rich information as the there is no proper estimate of the accumulator pressure.

Table 7-2: Performance comparison between estimation models for dynamic reference (results highlighted for comparison)

	Build linear model		New Estimation model	
Phase	Mean relative error (%)	Std. deviation, (%)	Mean relative error (%)	Std. deviation, (%)
Build steps	**27.15**	22.39	**21.27**	23.19
Release steps	65.02	78.38	72.52	71.30

The evolution of the adaptive coefficients for the Build Linear model used for build and release phases are observed in the Figure 7-8. A closer observation of the Figures 7-8a and 7-8b reveals that the coefficient signals seem to be correlated as the evolution of signals looks mirrored on the horizontal axis. On calculation, the correlation coefficient between the two

Table 7-3: Performance comparison with static coefficients

	Build Linear model	Build Linear model with Static coefficient set $\{b\}$	New Estimation model	New Estimation model with Static coefficient R_{build} $\{b\}$
Mean relative error (%)	**8.68**	**11.2**	**7.08**	**7.55**
Std. deviation, (%)	5.82	4.87	6.91	7.61

signals comes out to be -0.9162 which confirms high correlation. Thus, a coefficient can be replaced as a function of another making one coefficient redundant. The correlation coefficient for release phase coefficients as observed in Figure 7-8c and Figure 7-8d is also calculated to be -0.85 showing high dependence.

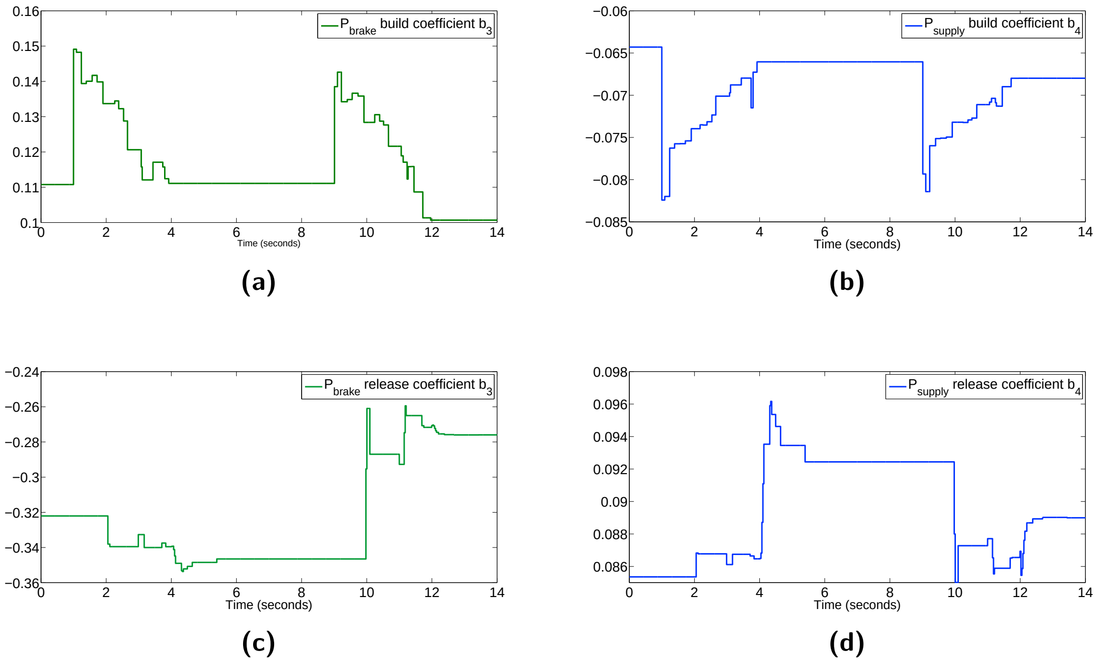


Figure 7-8: Coefficient Evolution of Build Linear model on ABS mimicking reference signals

The coefficient evolution of R_{build} and $R_{release}$ is observed in Figure 7-9. It is seen that the R_{build} varies by 10% whereas $R_{release}$ varies by 7.58%. The variation in coefficients increase due to a dynamic signal response but it is still very less than the coefficient variation of the earlier model which is with a staircase reference.

7-2 Effect of static coefficients

The experimental data obtained for the reference of staircase signals as seen in Figure 7-1 is used for simulating the Recursive Least Squares (RLS) algorithm without a single adaptive coefficient. Thus, no coefficient is updated to minimize the estimation errors. The results from this analysis is summarized in the Table 7-3.

The staircase reference data is used for this analysis. The Table 7-3 show the performance of average value of the coefficient and compares it to the adaptive coefficient performance

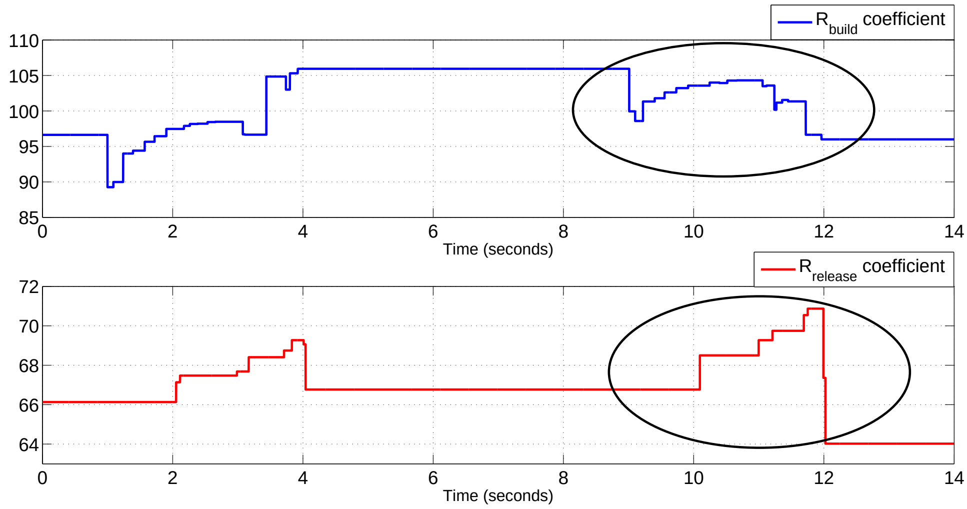


Figure 7-9: Coefficient evolution of build and release coefficients of New Estimation model for ABS mimicking reference with areas encircled for observing variation in coefficients

Table 7-4: Performance comparison with different static coefficients for New Estimation model

Performance Indicators	New Estimation model		
	Adaptive coefficient	Static coefficient ($R_{build} = 80$)	Static coefficient ($R_{build} = 90$)
Mean relative error (%)	7.08	7.55	**14.05**
Std. deviation, (%)	6.91	7.61	**10.46**

of the New Estimation model. As expected, the mean estimation errors increase due to no updating of the model coefficients. It is seen that the performance does not decline much for New Estimation model with static coefficient (R_{build}) suggesting the proximity to the optimal coefficient value. In the case of Build Linear model with static coefficient, the mean relative build error increases by 2.5% whereas the relative release error increases by 4% as compared to the adaptive case. Also present in the table are the estimation errors of using static coefficients using Build Linear model which are greater by 4%.

The performance of the controller using static coefficient can however be harmful if a wrong coefficient is chosen for the model as seen in the Table 7-4. A new value of R_{build} is chosen to analyse the effect of a sub-optimal coefficient. The results show a high deterioration (almost twice the original mean relative estimation error) of performance even for 12% deviation from the optimal coefficient. Thus, the importance of adaptive coefficient is necessary to combat changes in the brake pressure system. A similar decline will also be observed if a static coefficient is used for a dynamic pressure reference.

The evolution of relative error of build steps averaged over each instance can be seen in the Figure 7-10. Unlike the performance seen in Figure 7-2, the mean relative error goes on increasing with each instance indicating lack of updating of model coefficients.

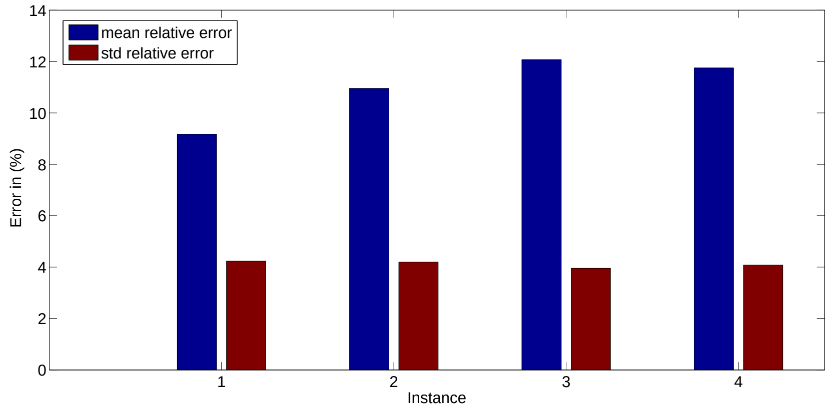


Figure 7-10: Static Mapping : Build phase mean relative error evolution with each instance.

7-3 Effect of using Full Update RLS

Until now, the Build Linear model has utilized only two adaptive coefficients. It is important to study the effect of the increasing the number of adaptive coefficients on the estimation properties of the algorithm. It was seen in the Section 5-5 that the mean relative error differed from the partial-update model by 2%. This is also validated on the obtained data. The additional information of the evolution of coefficients and covariance signals will also help to analyze the performance better.

The Full Update adaptive algorithm is then simulated by updating complete coefficient set ($\{b\} = \begin{bmatrix} b_0 & b_1 & b_2 & b_3 & b_4 & b_5 & b_6 \end{bmatrix}$) proportional to the estimation errors achieved. The results are summarized in the table.

Table 7-5: Performance comparison of partial and Full update Build Linear model (highlighed in blue for build phase)

Performance Indicators	Build Linear model			
	Build steps ($P_{step} = 3$bars)		Release steps ($P_{step} = 15$bars)	
	2 varying coefficients	6 varying coefficients	2 varying coefficients	6 varying coefficients
Mean relative error (%)	8.68	**3.80**	13.38	10.02
Std. deviation, (%)	5.82	**3.79**	11.09	8.57

The effect of Full Update RLS is significant and mean build estimation error drops to 0.11 bars. Also the release estimation error drops with a difference of 1.5% seen in relative comparison. The evolution of mean relative error can be seen from Figure 7-11. The mean error is seen to remain consistent but the deviation about it keeps increasing but it still remains less than that of performance seen in Figure 7-2. Thus, a significant improvement in performance is seen in the estimation capabilities of the algorithm owing to increase in the degrees of freedom. It is important to see if the coefficients and covariance signals also confirm the improvement in performance.

The Figure 7-12 show the evolution of two coefficients of the Build Linear model and the evolution of their covariance signals can ne seen in Figure 7-13. The evolution of other

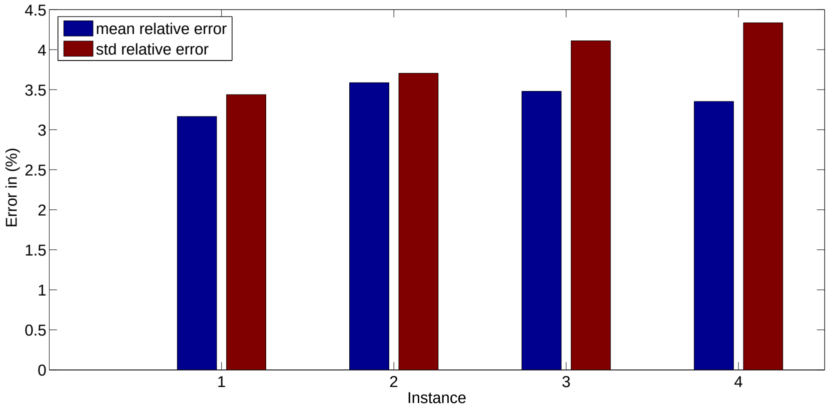


Figure 7-11: Full-Update RLS algorithm : Build phase mean relative error evolution with each instance

coefficients are similar and can be seen in Appendix C-1. The first observation which can be made is that the values of coefficients have changed. This is expected as the earlier coefficient set was optimal for only two varying coefficients whereas the algorithm now tries to optimize the coefficient set for six varying coefficients. However, it is also seen that the coefficients vary within a large range. The covariance signals show the uncertainty in the estimation process.

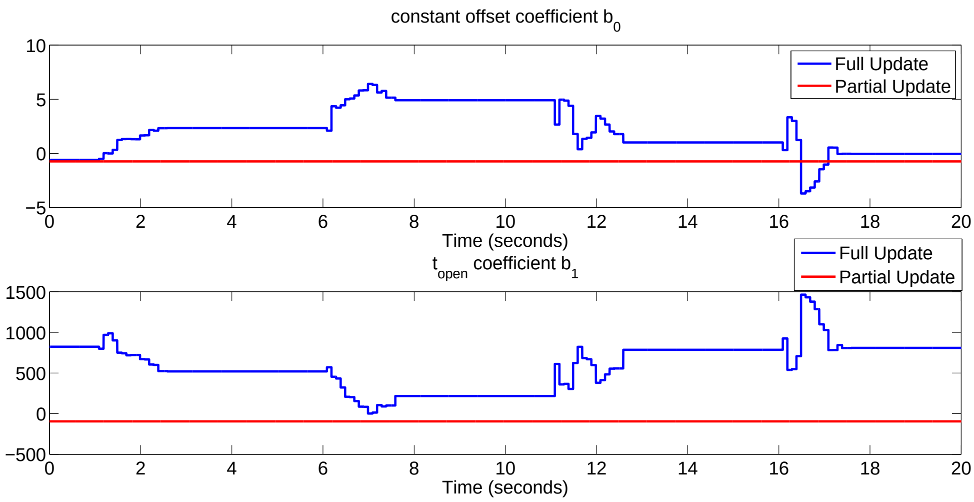


Figure 7-12: Evolution of coefficients b_0 and b_1 for Full Update RLS

The covariance signals for the coefficients except b_0, b_1 have a magnitude greater than order of 10^4 implying large uncertainty in the coefficient values. Thus, a large estimation error may disrupt the coefficient set and make the estimation unstable. This is due to estimator windup as signal is not rich to optimize complete coefficient set. In this case, the regression vectors (the variables corresponding to the coefficients) fail to excite the parameter space making the value of covariance increase to a large value. Since, the adjustment of the parameter estimates is proportional to covariance values, the algorithm becomes extremely noise sensitive. Even small excitations in the directions which correspond to large covariance values result in large

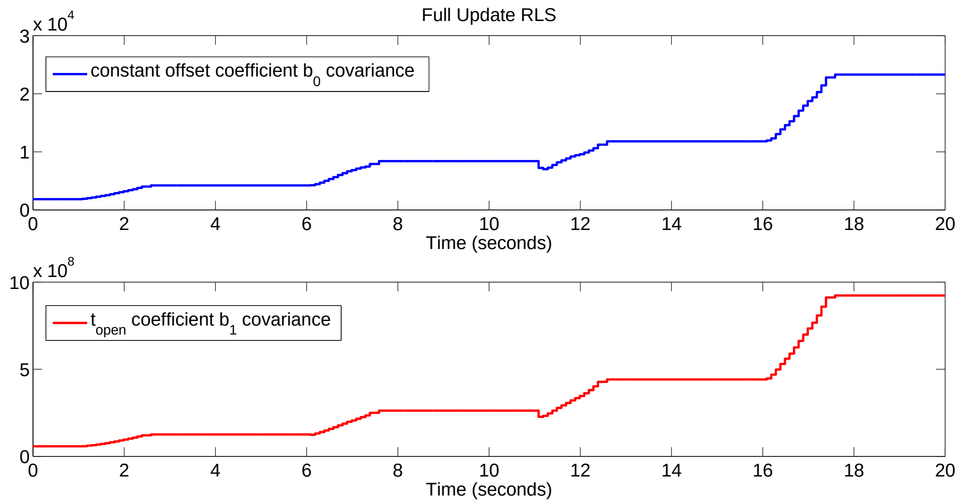


Figure 7-13: Evolution of covariance signals of b_0 and b_1 for Full Update RLS

changes of estimates. This is dangerous for the controller performance if implemented on the actual setup.

7-4 Discussion on model limitations

7-4-1 Build Linear model

Although the Build Linear model used for implementation of an adaptive brake pressure controller shows good performance in tracking reference signals, there are some issues which need to be addressed. These can be listed as follows:

(a) Variation of Coefficients

(b) Correlation

(c) Representation of the dynamics

Variation of Coefficients The evolution of coefficient was seen in Figure 7-3 and Figure 7-6 for staircase reference signal. It is seen that the coefficient of brake pressure signal varies as much as 58.82% whereas the supply pressure coefficient varies 41.67% throughout the staircase build steps. This highlights two majors issues with model being used for adaptive control. Firstly, the coefficients have not converged since there is still a large variation observed. Secondly, the large variation may lead to instability. It has to be noted that the reference signal used is staircase signal with equal build steps of 3 bars. Even for small estimation errors the coefficients seem to vary more than 50%. This is very high for a controller and steer away from the optimal coefficients even with small errors. These coefficients will lead to inaccurate estimation of pressures and add to the uncontrollability of the vehicle in actual scenario.

Correlation The previous section with ABS mimicking reference made one observe the high correlation between the coefficients of the Build Linear model. A similar observation can be made for the build coefficients for the staircase reference signal as seen in the Figure 7-3. Thus, the input signal information is not rich enough for two adaptive variables. So, a new analysis is carried out on the experimental data of the staircase reference signal with one adaptive variable (the coefficient of P_{brake}). The partial model used for this analysis is seen in (7-5). The only adaptive coefficient is b_3.

$$P_{step} = b_1 + b_2.t_{open} + b_3.P_{brake} + b_4.P_{supply} \tag{7-5}$$

where P_{step} is estimated pressure step and t_{open}, P_{brake} and P_{supply} represent the valve opening time, brake pressure and supply pressure respectively.

The performance results can be seen in the Table **??**. It is seen that the performance deteriorates by 5% in case of mean relative error and standard deviation. Even though it eliminates the correlation issue, it does improve the performance of the controller.

Table 7-6: Build phase performance comparison with Build linear and partial models

	Build Linear model	Partial model
Mean relative error (%)	8.68	**12.28**
Std. deviation, (%)	5.82	**10.27**

Representation of the dynamics Another issue with the Build Linear model and other empirically obtained models is the lack of representation of the physical dynamics of the system. The RLS controller tries to adapt to the changing physical dynamics but it is vary difficult to observe them. The relationship between several parameters is not linear as observed in the literature review Section 2-3. The controller tries to compensate this nonlinear relationship along with changing properties of the system. This may be the cause of large variation of coefficients observed earlier in this section.

7-4-2 New Estimation model

Although the New Estimation model provides better performance for estimation of build pressure steps and smaller variation in coefficient evolution, it does not estimate the release pressure steps accurately as seen in the analysis carried out in the earlier sections. The drawback of the release model as visible in Equation (3-29) is the lack of rich information representing the accumulator pressure variation. As explained earlier, the absence of sensors and measurements of accumulator state that the estimation of accumulator pressure cannot be used reliably. Also, the Build Linear model which also does not use accumulator pressure provides better performance than the New Estimation model for the release phase. So, it is important to investigate the effect of other parameters such as supply pressure on the model for estimation of release pressures.

A rudimentary analysis was carried out by adding supply pressure to see the effect on the performance for tracking the ABS mimicking reference signal. The model for the release pressure is modified to the following equation

$$P_{step} = -t_{open}.R_{release}.(P_{brake}(k) - P_{acc})^{\phi_{release}} + c_1.P_{supply}(k) \tag{7-6}$$

The coefficient c_1 is first kept adaptive and then using a high covariance values it is allowed to converge to obtain best fit. This value is then used as the constant coefficient value c_1. Note that the only varying coefficient updated will be $R_{release}$ for adaptive controller.

Another analysis is also carried out using the same procedure as above albeit by adding a constant instead of supply pressure parameter as seen in the following equation.

$$P_{step} = -t_{open}.R_{release}.(P_{brake}(k) - P_{acc})^{\phi_{release}} + c_2 \tag{7-7}$$

The performance results of both the signals are compared in the following table with the earlier models.

Table 7-7: Release phase performance comparison with different estimation models (results highlighted for comparison)

	Build Linear model	New Estimation model	New Estimation model with supply pressure	New Estimation model with constant
Mean relative error (%)	65.02	**72.52**	46.75	**39.33**
Std. deviation, (%)	78.38	71.30	57.50	**58.18**

It is seen that the addition of both the new models show more accuracy in the release pressure step estimation than the New Estimation model without any extra parameters and also better the Build Linear model. The model with the constant performs better than the supply pressure suggesting the relationship to be different than that derived in Equation (3-29). The coefficient evolution of the model seen in Equation (7-7) is also observed in the Figure 7-14.

It is observed that the variation of $R_{release}$ coefficient has increased to 40% about the average coefficient value. This is a large variation though possible for a dynamic reference signal. Thus, one can observe that though the performance has improved tremendously, the variation of coefficient has also increased. It is highly recommended to carry out additional testing on the release phase by exploring different relationships using the given parameters.

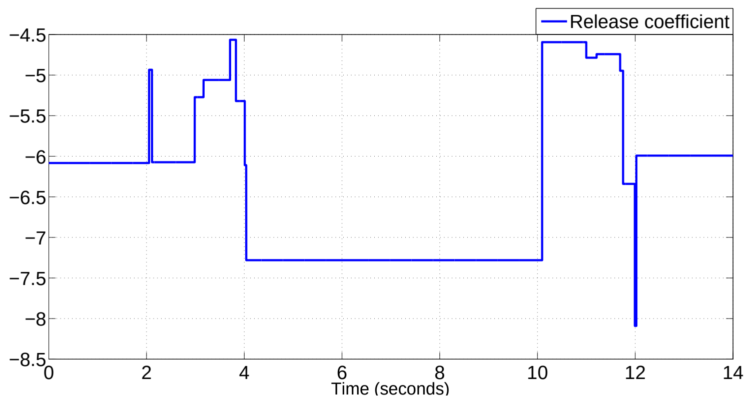


Figure 7-14: Evolution of R_{release} for model shown in Equation (7-7)

7-5 Importance of adaptive nature of controller

This section focuses on the validation of the use of adaptive controller for brake pressure control. Two examples of changing conditions are observed where the property of adaptivity helps in optimizing the performance.

7-5-1 Effect of sub-optimal coefficient set

The importance of an adaptive controller is realized in the face of changing conditions. During an ABS operation, several parameters responsible for making a desired pressure step may change. An example of such a situation is provided in Figure **??** and Figure **??**. The plots show 6 instances of the build staircase signal tested on the adaptive control system. Due to lack of supply pressure, the reference is unable to track the reference in the first instance. In this scenario, the coefficients are incorrectly updated leading to erroneous model. [1]. The performance of this erroneous model is seen in the second instance which shows a far deteriorated performance of the algorithm with a lot of chattering. The adaptive control system realizes this and adapts to the given system and by the 4th instance, it significantly reduces the chattering and gives a smooth performance. This is also confirmed by looking at the mean relative error (estimation error in percentage relative to the pressure step request) in build steps shown in the Figure 7-17. The erroneous coefficient set leads to a staggering 100 % error in estimation. This is significantly reduced to within 10 % after the RLS appropriates updates the coefficient set. This example clearly shows the significance of an adaptive algorithm in a error prone scenario.

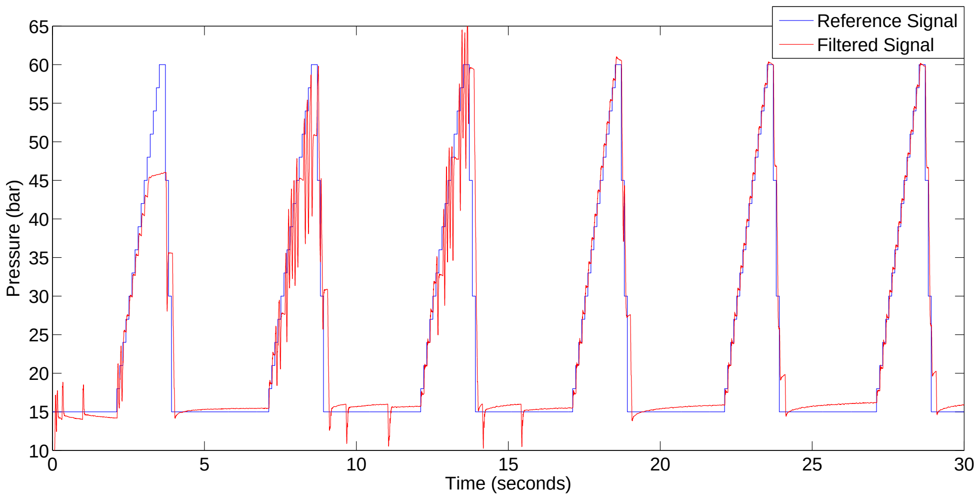


Figure 7-15: Reference and brake pressure signals in error prone scenario

[1]The update of coefficients due to inadequate supply pressure is not stopped here for the sake of analyzing its performance

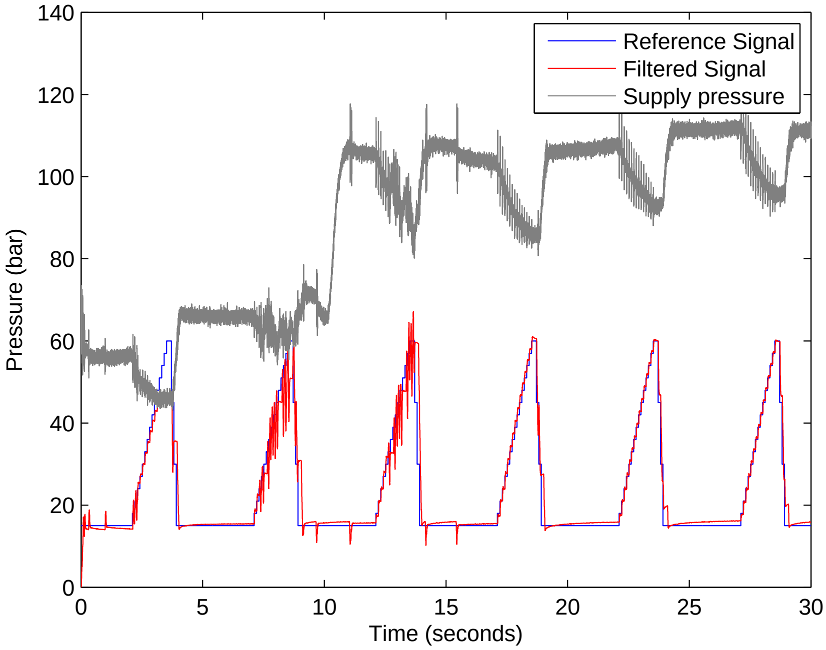


Figure 7-16: Performance of adaptive controller in error prone scenario : Reference, Brake and supply pressure signals

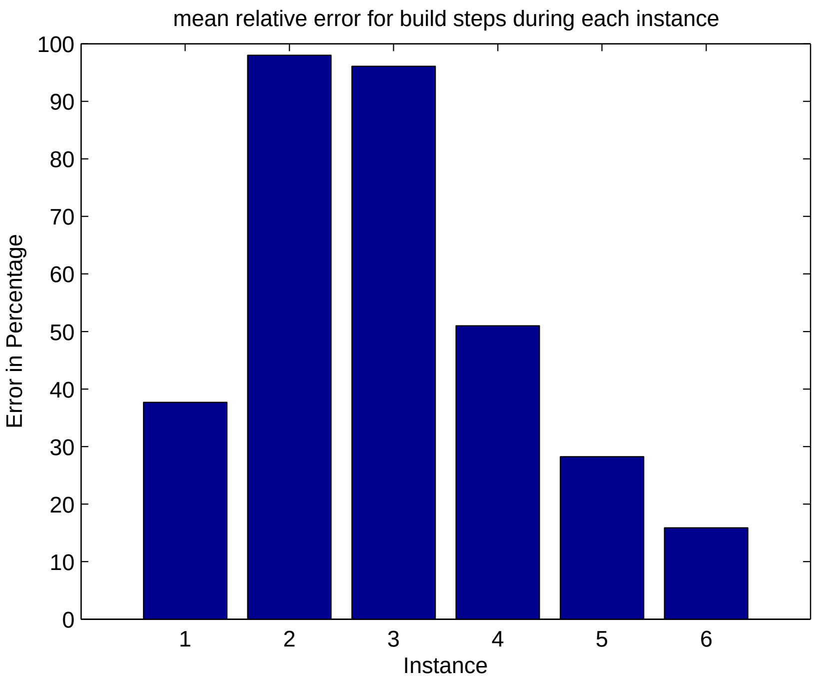


Figure 7-17: Performance of adaptive controller in error prone scenario :Mean relative error evolution (in %)

7-5-2 Different timestamps for same experiment

The importance of adaptivity for the controller is realized in this analysis by observing the coefficient evolution for same experiments carried out on the vehicle at different time instances. Keeping all the variables such as supply pressure, reference pressure, forgetting factor etc. same, two staircase reference signal datasets are generated using the controller at different timestamps. These datasets are used for simulating the New Estimation model and the coefficient evolution are compared. The coefficient evolution of the first experiment data is seen in Figure 7-18 and that of the second experiment is seen in Figure 7-19. It is seen that the trend of the evolution of coefficient is similar except that the average values of variation of coefficients are different. The mean coefficient value changes by 3.33% of the coefficient value from the first experiment.

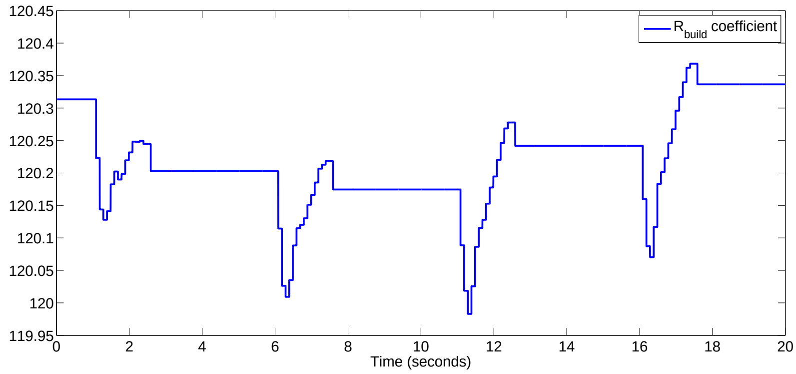


Figure 7-18: Experiment 1: Coefficient Evolution on staircase reference signals carried out earlier

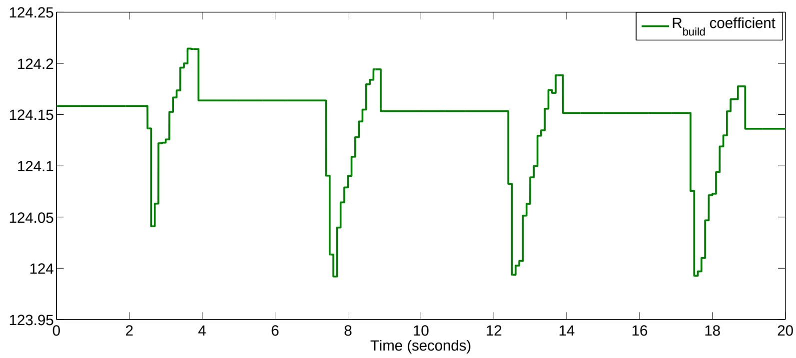


Figure 7-19: Experiment 2: Coefficient Evolution on staircase reference signals carried out later

It was seen in the Section 2-3 that the fluid resistance changes with time and so does other properties which depend on the temperature of the fluid. This changes the value of the coefficient in the Equation (3-27) and hence provides an explanation for the this changing coefficient value. Thus, the controller adapts to a new value for optimal performance. Also, the New Estimation model helps to observe effect of changing parameters as it is derived from the physical dynamics.

7-6 Parametric Sensitivity

This section will explore the parametric sensitivity of the adaptive control algorithm not only in terms of estimation error but also in terms of convergence rate of the coefficients and covariance evolution. The analysis is carried out by starting with a coefficient set which is sub-optimal and the convergence to the optimal set is observed. The effect of changing the forgetting factor and the initial input signal covariance values are observed in the performance of the algorithm.

7-6-1 Sub-optimal coefficient set

There are two ways in which the effect of sub-optimal coefficient set can be observed. The first case is by only choosing the coefficients b_2 and b_3 to have a different set of initial values. In this case, the static coefficients remain the same and the updating coefficients are expected to converge in the range of values of the optimal set as used in the nominal performance. The next case involves modifying the initial values of coefficients which remain static and observe the changes in the nature of update of the varying coefficients.

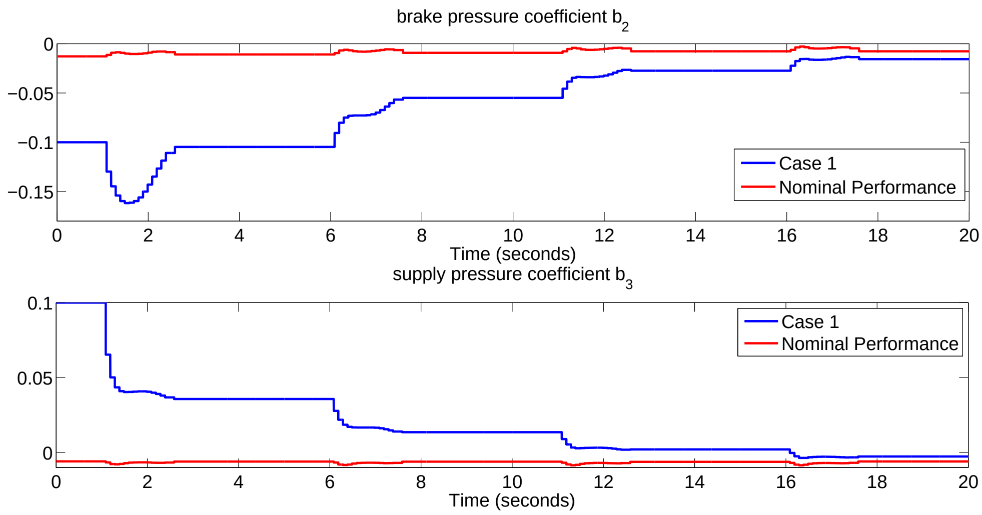


Figure 7-20: Case 1 : coefficient evolution

The analysis is carried out using the same experimental data used for analyzing the nominal performance. However, only the build phase is analyzed as there are very few release steps taken to analyze the effect of varying coefficient on the algorithm. The build mapping coefficient starts with an initial map comprising of the coefficient set as shown below:

$$\begin{bmatrix} b_0 & b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix}_{optimal} = \begin{bmatrix} -0.73 & -95.4582 & -0.0128 & -0.0059 & -1.8477 & 11.2807 \end{bmatrix} \quad (7\text{-}8)$$

Case 1 :Varying b_2 and b_3

The initial coefficient set modified for the analysis is shown as follows

$$\begin{bmatrix} b_0 & b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix}_{modified} = \begin{bmatrix} -0.7383 & -95.4582 & -0.1 & 0.1 & -1.8477 & 11.2807 \end{bmatrix} \quad (7\text{-}9)$$

It is important to note that the coefficient set is not modified drastically to observe convergence to the optimal coefficient set. The coefficient and covariance plots are presented as shown in the Figure 7-20 and Figure 7-21. The nominal performance corresponds to the performance of the controller when the coefficients are already in the optimal range and have stopped converging albeit small variation in a given range. It is seen that the covariance plots

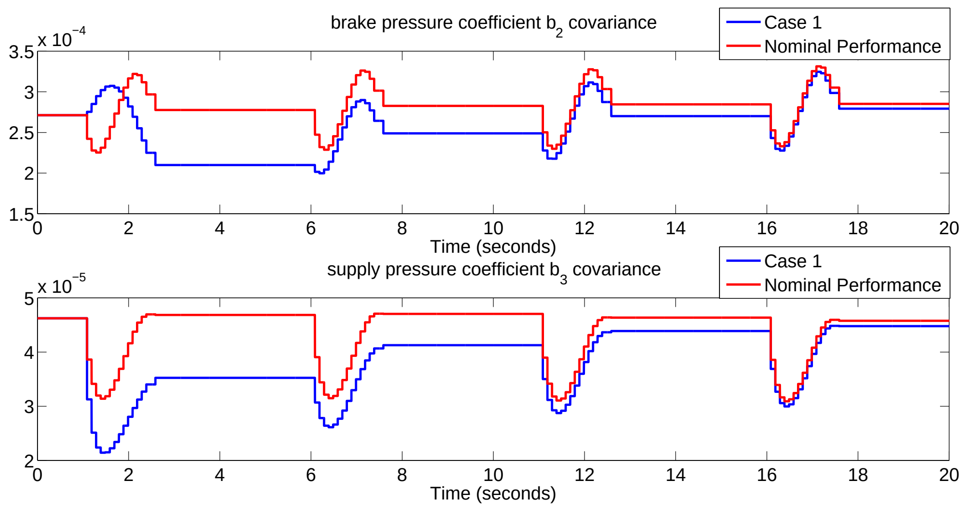


Figure 7-21: Case 1 : covariance evolution

and coefficient plots eventually converge to the optimal coefficient set. It can be deduced that initially the estimation error is large and significantly updates the coefficients to converge to the optimal range and in turn reduce the estimation errors. It can be also observed that the convergence of algorithm is slow and it is important to perform an intervention to increase the convergence rate.

Case 2 :Varying coefficient set except b_2 and b_3

It is also important to observe whether the coefficients are able to converge and give an optimal performance if the coefficient which are static have different values than their optimal set. The modified coefficient set used in this case is as follow :

$$\begin{bmatrix} b_0 & b_1 & b_2 & b_3 & b_4 & b_5 \end{bmatrix}_{modified} = \begin{bmatrix} 2 & -50 & -0.0128 & -0.0059 & -6 & 5 \end{bmatrix}$$

Using the above variation, the RLS is tested again and the coefficient and covariance plots are plotted. As expected, the optimal coefficient value changes and it lies in a different range of values as seen in Figure 7-22. The covariance plot in Figure 7-23 shows similar trend in the same range as in case of nominal performance.

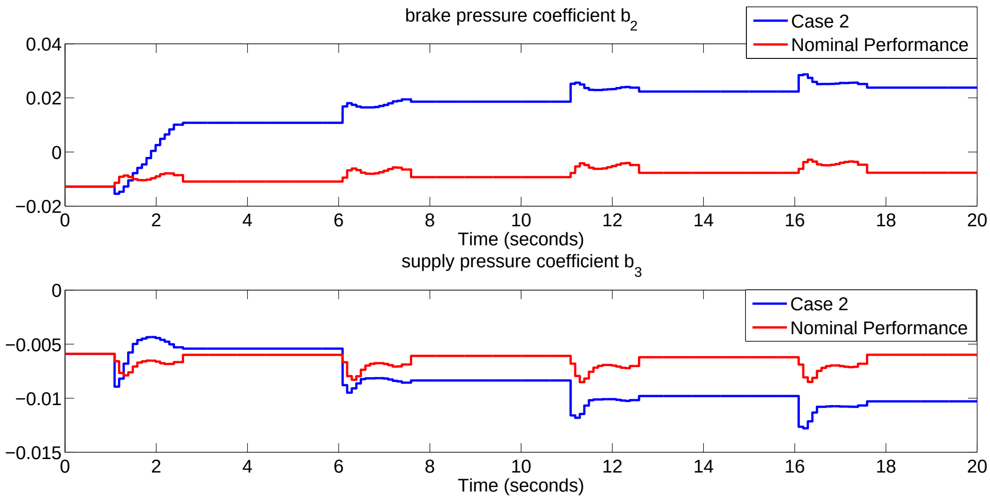


Figure 7-22: Case 2 : coefficient evolution

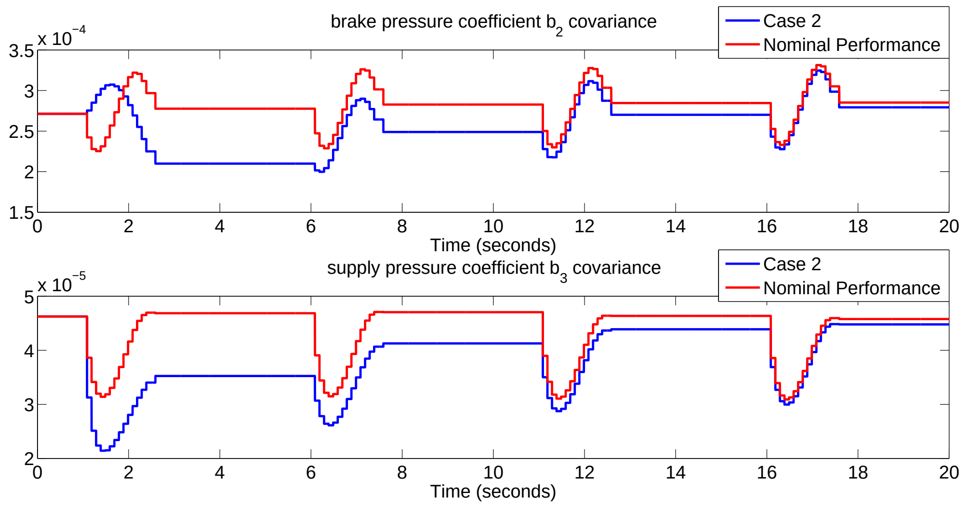


Figure 7-23: Case 2 : covariance evolution

7-6-2 Influence of forgetting factor

Now that we have the performance of controller in the case of incorrect coefficient set , it is imperative to improve the convergence rate of the updating algorithm. The two most important influence on the convergence rate of coefficient are the forgetting factor and covariance values. The effect of each of these parameters are observed in the upcoming sections.

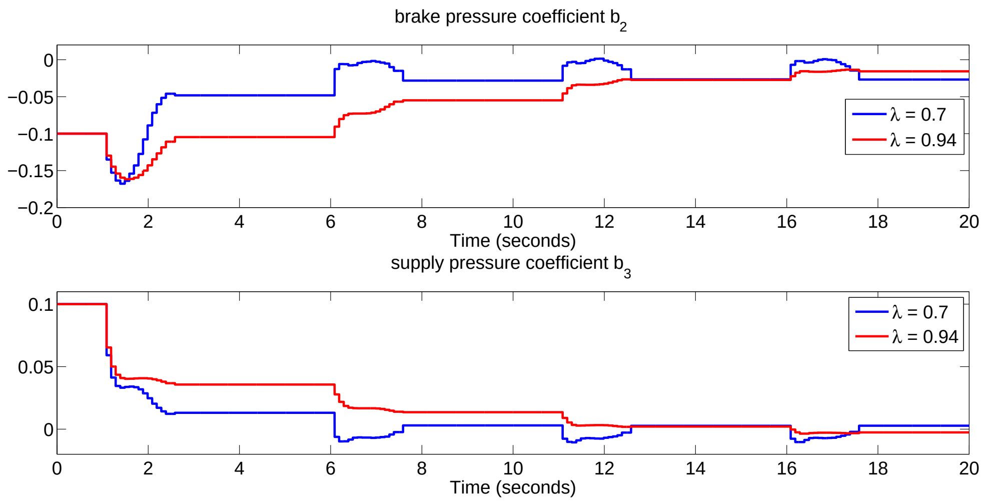


Figure 7-24: Influence of forgetting factor on coefficient evolution

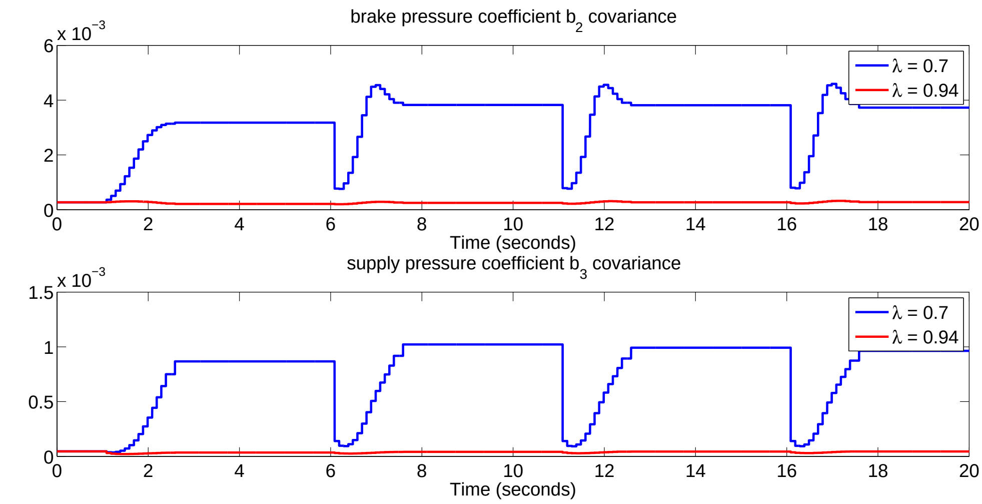


Figure 7-25: Influence of forgetting factor on covariance evolution

The forgetting factor of the current algorithm was fixed at 0.94 from the simulations of the identification dataset in the Section 5-4. This value corresponds to less forgetting and does not let the algorithm adapt easily to new data i.e. it does not place more weight on the New Estimation errors and does not deviate drastically from the old coefficients. This makes the updating algorithm reject noisy estimates. However, incorrect model due to changing physical constants hinders the convergence rate of the algorithm. This can be changed by introducing more forgetting. An example of simulation, which runs on the experimental data obtained from the nominal performance with modified coefficients as seen in Case 1, using forgetting factor $\lambda = 0.7$ is presented in Figure 7-24 and Figure 7-25.

It is seen that with higher forgetting the coefficients quickly converge to the optimal set as compared to Case 1. The covariance signals are also increased as a result in the beginning. Though, the convergence rate is increased the forgetting factor cannot be kept constant at 0.7 which can be observed from the latter part of coefficient evolution after convergence as seen in Figure 7-26 . It is seen that the variation of coefficients is a lot more than the nominal performance case. It is because of increased weight on New Estimation errors. This is not desired and can be avoided using varying forgetting factor approach.

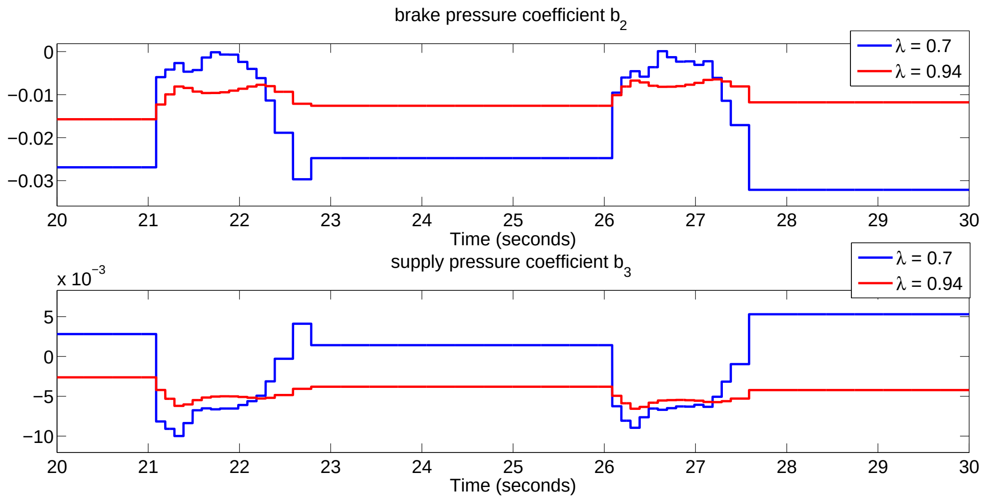


Figure 7-26: Influence of forgetting factor on coefficient evolution after convergence

7-6-3 Influence of Covariance

The input signal covariance values also affect the rate of convergence of the coefficients. A large value of the covariance implies a large uncertainty in the estimation of those coefficients which adds uncertainty in estimating the pressure step. An advantage of this nature of evolution of covariance is that if the estimation errors are low and the input signals are filtered then the covariance reduces to smaller values even if the initial covariance was large to start with. Hence, it was difficult to observe the effect of covariance values in simulation of the identification dataset (in Section 5-4) as it was difficult to observe the variation of coefficients.

The initial covariance values for signals of varying coefficients for the nominal performance are as shown below:

$$P_{\text{cov}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 2.7124 * 10^{-4} & 0 & 0 & 0 \\ 0 & 0 & 0 & 4.6220 * 10^{-5} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{7-10}$$

These are the same values used when the coefficients were modified in Case 1. Now, it is important to observe the effect of increasing the covariance values on the performance of the algorithm. This is done by modifying the initial covariance set as follows

$$P_{\text{cov}} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 10^{-2} & 0 & 0 & 0 \\ 0 & 0 & 0 & 10^{-3} & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{7-11}$$

Notice that the coefficient being updated are b_2 and b_3 only and hence only the corresponding covariances are updated. The Figure 7-27 and Figure 7-28 show the performance of the algorithm after the modification. It is seen that the coefficient converge at a faster rate as compared to Case 1. Thus, the initial covariance values are as significant change in the forgetting factor.

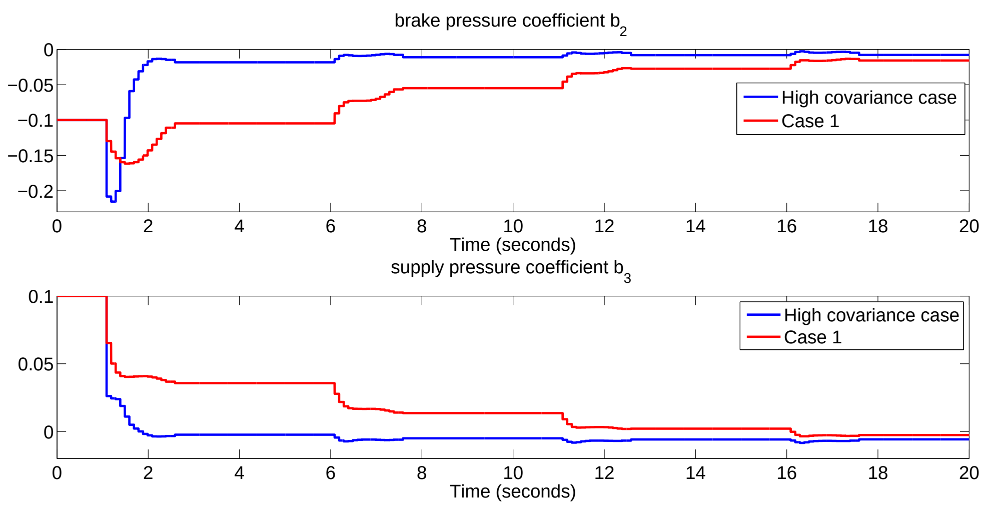


Figure 7-27: Influence of initial covariance values on the evolution of coefficients

However, as the values converge to the optimal set, one can observe an important difference between the influence of forgetting factor and covariance values as seen in Figures 7-29 and 7-30. As the coefficient converge, the covariance also reduces and converges naturally within the range. The coefficients also update with the variation seen in the nominal case and no incorrect scaling of update takes place as seen in the forgetting factor case. Thus, the modification of covariance values act as varying forgetting factor. This property can be used

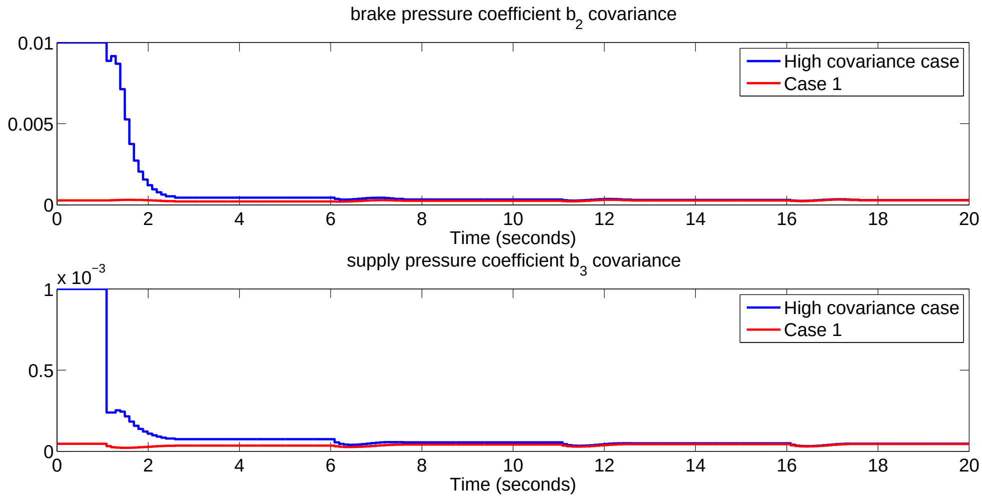


Figure 7-28: Evolution of covariance signal with different large initial value

to enhance the performance of the controller when it is faced with incorrect coefficient set and large estimation errors. When the model will be updated to become accurate and estimation values are small, the covariance values will also be small. In the case of large estimation errors, this covariance values do not increase swiftly and thus it takes a longer time to converge as seen in case 1. In order to facilitate faster convergence, the covariance values can be increased when detected with the presence of a large estimation error. This is a recommended future work to use this knowledge and enhance the performance of the low level controller.

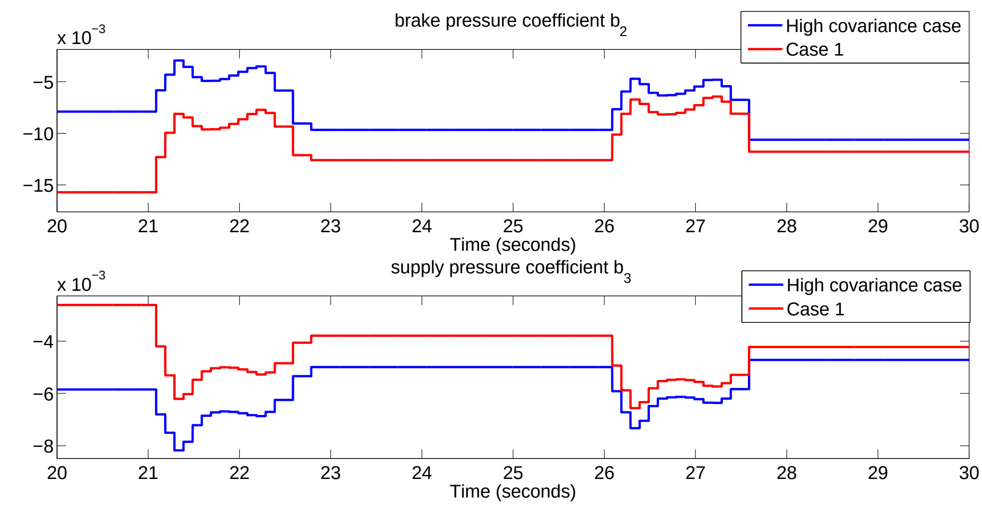


Figure 7-29: Influence of initial covariance values on the evolution of coefficients after convergence

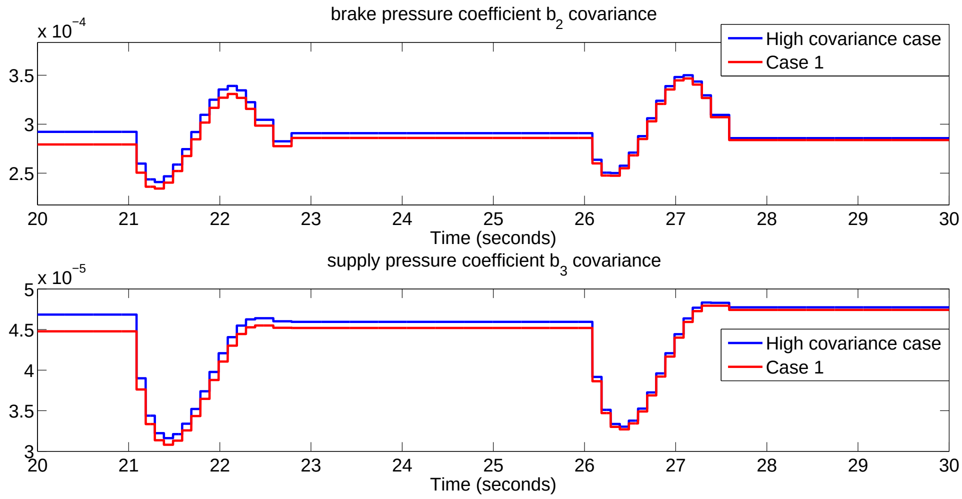


Figure 7-30: Evolution of covariance signal with different large initial value after convergence

7-7 Conclusion

In this chapter, the performance of the adaptive control system was analyzed along with the nature of evolution of the coefficients and covariance signals. The reduced estimation errors and the covariance signals indeed highlight the convergence of the coefficients for estimating the pressure step.

The performance of the Build Linear model and New Estimation model were compared for different cases. The model for estimating build pressure steps provided better performance with both staircase and ABS mimicking reference signals. Also, the coefficient evolution showed far less variation than the earlier model showing the stability of the controller. The Build Linear model was also seen to have large coefficient variation and high correlation amongst the coefficient values. As mentioned earlier, these properties add to the uncontrollability of the vehicle behaviour making the usage of Build Linear model fatal for on road vehicle testing.

The New Estimation model also helps in analysing the system performance better as it is derived from physical dynamics and the influence of changing properties can be observed. However, the release model displayed poor performance and some modifications were suggested but they need to be tested to validate the results.

Thus, it can be concluded that the New Estimation model for build phase and release phase should be chosen over the Build Linear model for future testing on the hydraulic system with aforementioned guidelines.

Further, the influence of different model structures was studied. The Static model gave large errors in estimation as expected and acknowledged the need for an adaptive algorithm. On the other hand, the Full Update RLS algorithm performed better than the nominal case but it gave an insight into the estimator windup problem. This is a known limitation of the use of Full Update RLS for the not so dynamic data. There is a possibility to solve this issue using different values of forgetting factor for different parameters [53].

The influence of sub-optimal coefficient set was observed and though the algorithm eventually converged to the optimal range, it had a slow convergence rate. In order to increase convergence, the effect of forgetting factor and covariance values was seen on the performance of the controller. Both showed improvement in convergence rate but a higher forgetting (low forgetting factor value) was more sensitive to noisy estimates. Hence, increase in covariance values was chosen to be the solution in case of high estimation errors. It is important to note that similar performance can be obtained using time varying forgetting factor also.

Chapter 8

Conclusion and Recommendations

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This chapter summarizes the progress achieved in the implementation of the adaptive brake pressure controller and revisits the analysis of the results obtained. It is followed by highlighting the contributions made by this research work. Finally, recommendations are provided for future research based on the experience gained during this thesis, .

8-1 Summary

After establishing the need for a brake pressure controller, Chapter 2 studied the hydraulic braking circuit to be controlled in detail. Not only did it provide an overview of the working of the hydraulic braking circuit but it also highlighted its limitations and addressed the secondary control system consisting of accumulator and pump. This also gave an insight on the properties of the fluid ,namely viscosity,density,and compressibility amongst others, which affect the system performance.

The review of literature and earlier work done at Delft University of Technology (TU Delft) carried out in Section 3-2 was necessary in order to select the models used for the implementation. The work performed by earlier researchers resulted in the selection of steady state estimation models based on physical dynamics and on empirical relations. The variation of physical constants of the HAB circuit and optimization of estimation parameters provided the motivation of adopting an adaptive approach. In addition, the brake pressure evolution during the operation of ABS control helped in understanding the desired response of the system and also helped in designing the reference signals for controller evaluation.

Further, the selection of Recursive Least Squares (RLS) and its theoretical background imparted the formulation of adaptive algorithm. It was tested in Chapter 5 using the dataset obtained from the earlier experimentation on the test setup. The empirical estimation model Build Linear model without valve voltage was selected after comparing with other empirical models. It was also evaluated for partial update of the coefficient vector. This partial update

Build linear model was seen to have 3% increase in mean estimation error as compared to the full update model. Also, the new estimation model derived in Section 3-2 was tested in a similar manner. The mean estimation errors of partial update Build Linear Model in simulation were 6% less than that of the new estimation model. However, the unavailability of coefficient evolution was a limitation in the performance assessment of different models in simulation.

The implemented control scheme was explained in detail in Chapter 6. The brake pressure control system was tested on the vehicle hydraulic circuit with different reference signals. The control system was able to track the system very accurately with estimation errors within 9% using Build Linear model for staircase and block reference signals. It also showed a smooth performance with no chattering effects even in the case of highly dynamic reference signal. However, the adaptive control system with Build Linear model showed some deterioration in release pressure step performance with a dynamic reference signal.

The adaptive nature of the controller was also tested by using suboptimal coefficient set. Though the coefficients did not converge to a single value, they varied within a specific range with a peculiar pattern. It was clear that the estimated dynamics were nonlinear but it was difficult to understand the reason of trend of coefficients. It was also seen that the convergence rate of the coefficients was dependent on the forgetting factor value and signal covariance values. Increasing the forgetting resulted in increasing the influence of the new data and increased adaptivity but it also increased estimation errors after converging within the optimum range of values. On the other hand, increasing the covariance values also gave a similar convergence rate sans the increased estimation errors.

Although the Build Linear model performed well in testing, the coefficients evolution showed a variation of more that 40% for tracking a staircase signal with equal pressure steps. This is a cause of concern as small error can make the controller deviate from the optimal coefficient values risking the stability of the control system. A high correlation was also observed in using more updating coefficients for adaptive algorithm. This helps in understanding the lack the richness of the incoming information and redundancy in the use of given number of adaptive coefficients. These results are reflected in the experimental data using a more dynamic reference as well.

The new experimental data was also used to test different variations of the model and also compare it to the estimation model derived from the physical dynamics. The Full Update Build Linear model showed the best performance with mere 3.8% mean estimation error. Nonetheless, it was seen that the coefficients and covariance value did not achieve steady state and were continuously increasing. The new estimation model showed improvement of the estimating the build pressure steps of more than 5% in case of a dynamic ABS mimicking reference. Also, the coefficient evolution showed a smaller variation in the coefficients (less than 15%) even for a dynamic reference signal. Thus, the importance of nonlinear relation between the rate of change of brake pressure and brake pressure and supply pressure signals became evident. The release phase performance of New estimation model was poor in comparison to Build Linear model. Subsequently, the performance was improved by adding a constant parameter to the new estimation model resulting in the 32% reduction in estimation errors but with increased variation of the release coefficient.

Another advantage of using the new estimation model was the representation of the influential properties (as discussed in Chapter 2) in the model. Similar experiments carried out on the same controller resulted in the convergence of the coefficients to different values signifying the change in one or more of the influential properties. This also bolsters the advantage of providing adaptive nature to the controller.

8-2 Thesis Contributions

The thesis contributions made can be highlighted as follows:

- A new estimation model was derived from the actual dynamics of the system. The parameters of this model were identified for the given test setup.
- An adaptive control system for estimating brake pressure was built in `Simulink` and successfully implemented on the vehicle. This control scheme also included accumulator state estimation and pump control functions.
- The performance of the control system was tested with different signals. Also, the parametric sensitivity of the algorithm and its effect on the convergence rate was analyzed with respect to influence of forgetting factors and covariance signals.
- The low level controller was also equipped with ability to tackle real time sources of error. Further, addition of user configurable parameters completes this tool which can be used to attune the control system to future novel ABS algorithms.

8-3 Recommended Future work

The control system developed for this thesis can be used for the building and testing higher level ABS and ESC controllers. However, there are certain areas in thesis which can be delved into for further research.

Modelling

- Release pressure step estimation model
  It was seen that the release pressure step estimation model was erroneous for both the models. The New Estimation model was modified to improve the results but it came at the cost of increase in variation of coefficients. A study dedicated to establish the relationship of variables in the release model is recommended. The release pressure step model also suffers because of lack of information of accumulator pressure.
- Accumulator state
  The Accumulator state is estimated from the given parameters but it can be improved. The accuracy of the accumulator state prediction is difficult to test. This was bypassed in the control system by turning on the pump for small accumulator state value. A better prediction may also lead to better estimation of accumulator pressure which may benefit the release pressure step estimation.

Control

- Varying forgetting factor
  Keeping a constant forgetting factor determines the rate of adaptivity and convergence to optimal coefficient set. A time varying forgetting factor value which is a function of estimation error may optimize the algorithm. A similar approach can be also applied to manipulating the covariance values using estimation errors only. This approach has an advantage of not require time based variation.

- Control Methodology
  The existing setup and control system provide an opportunity to test intelligent control strategies such as Fuzzy logic and Neural Networks using the existing estimation models or the vast experimental dataset. This may also reduce the reliance on incorporation of complete dynamics of the system.

Testing

The current control system is tested in the laboratory on a static vehicle. The analysis of this controller will heavily benefit from an on road testing of the system where phenomena such as depletion of battery voltage may play an important role. It should be noted that the hydraulic system aboard the BMW test vehicle is not manufactured for testing purposes. Thus, rigorous testing should be avoided to safeguard the valve coils and the control board from overheating.

Appendix A

ABS Theory

A-1 Dynamics of braking

Braking dynamics are necessary to the reader for clear understanding of the operation of ABS and so the following definitions and equations are explained to make the reader familiar with it.

Braking System - All the vehicle systems and components whose functions are related to reduce the vehicle speed or bring the vehicle to halt or to hold the vehicle stationary if already halted [8].

A typical braking procedure can be illustrated in the following Figure A-1. Consider a car driving with certain velocity. When an obstacle is detected by the driver, he tries to brake the motion of the vehicle. The time transpired between the detection of obstacle and its counter action is termed as reaction time. The distance covered during this reaction time increases linearly with the velocity of the vehicle, whereas the braking distance, increases quadratically [14].

The time periods and intervals are described as [8]:

Before t_0:	Reaction time
t_0 :	Initial application of force on control device
t_1 :	start of deceleration
t_1' :	end of pressure build up time
t_2 :	fully developed deceleration
t_3 :	end of maximum retardation
t_4 :	end of braking operation (vehicle is stationary)
$t_1 - t_0$:	initial driver response time
$t_1' - t_1$:	pressure build-up time
$t_3 - t_2$:	mean maximum retardation range
$t_4 - t_1$:	active braking distance
$t_4 - t_0$:	total braking time

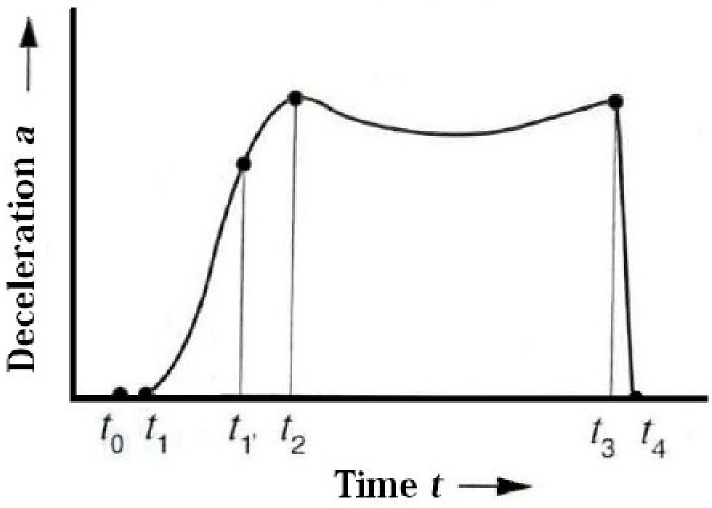


Figure A-1: Time and Deceleration during braking to a stop [8]

The ABS is a closed-loop control system to prevent wheel lock and is activated during emergency braking. ABS focuses on reducing the braking distance covered during time interval t_2 to t_3. These distances can be reduced with the use of ABS by more than 10 % [55]. However, under certain road conditions, the distances may be longer (i.e. on snow). Taking into account the non-linearity and uncertainty of the interaction between the tyre and the road is vital for good performance of the ABS [56].

A-1-1 Wheel Dynamics

Tyre forces are generated at the contact area between the road and the tyre. They depend on several factors such as tyre properties, slip, vertical load and road conditions. These forces have three components: the longitudinal or tractive force , the lateral force and the vertical or normal force. By only considering the longitudinal dynamics, the following free body diagram of the wheel can be represented

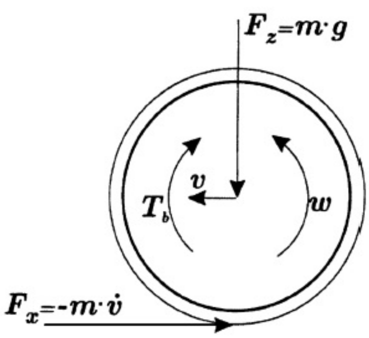


Figure A-2: Single corner free body diagram in braking

Under the assumption of straight line braking,F_y is assumed to be 0 while the longitudinal tyre force is related to the vertical force in a non-linear way. However, for normal loads it is often modelled by the following relation:

$$F_x(\lambda, F_z) = \mu(\lambda)F_z \tag{A-1}$$

where μ is the friction coefficient which is dependent on the longitudinal slip. That is,by a function that depends linearly on vertical force and nonlinearly on wheel slip:

$$\lambda = \frac{v_x - r\omega}{v_x} \tag{A-2}$$

where ω (rad/s) denotes the angular velocity of the wheel and v_x (m/s) the speed of the vehicle and r (m) the wheel's radius. This definition of slip implies that at wheel lock ($r\omega = 0$) the slip is 1. When braking, slip varies from 0 to 1. In addition to the tractive forces, the wheel must also generate a cornering force to direct the vehicle. Cornering force or side force is the lateral force produced by a vehicle tire during cornering . The more cornering force you have available the less you have to slow down for corners.

This lateral force is also dependent on the slip ratio known as side slip angle (α_t) as shown in Figure A-3.

The coefficient of friction has a different relationship with slip ratio depending on the contact characteristics between tyre and road. Figure A-4 shows this dependency of friction coefficient on the slip ratio for several different road surfaces.

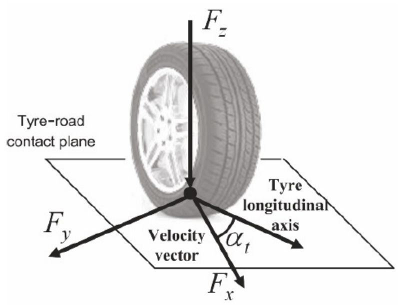


Figure A-3: Tyre road contact forces [11]

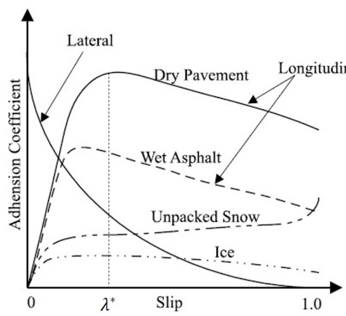


Figure A-4: Longitudinal and Lateral slip v/s Friction coefficient for different surfaces [12]

It can be seen from the Figure A-4 that higher value of α_t results in lower adhesion whereas there is a peak in different longitudinal slip (λ) curves which signifies maximum adhesion. The value of slip for maximum adhesion for dry pavement road type is marked as λ^*. Also, different road surfaces generate different slip values and therefore, different traction forces. As expected, icy road corresponds to the most slippery surface whereas dry asphalt road gives the highest friction with much larger linear gradient as well. An important point to be noted is the dependency of slip ratios upon each other. To achieve a larger longitudinal slip, the lateral slip has to be reduced and vice versa. Since our braking performance will not be based on cornering and will be centered on longitudinal dynamics, the lateral forces will be neglected.

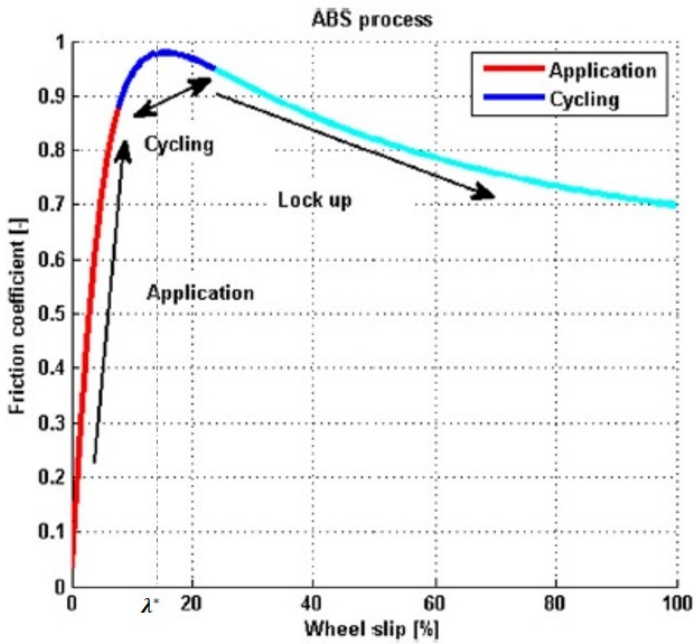


Figure A-5: ABS operation zone in friction-slip curve [13]

The Figure A-5 signifies the operating areas of the ABS. It is already known that $\lambda = 0$ corresponds to a pure rolling wheel and $\lambda = 1$ to a locked wheel. Also the friction coefficient μ is related to the capability of the tire to transform the vertical load and the sum of torques acting on it in a longitudinal force. So the higher the friction coefficient is, the higher will be the corresponding longitudinal force. From Figure A-5 we can see that the friction coefficient reaches the maximum value at the slip value of 15%. When the slip ratio is below 15%, the slip ratio can increase the friction. Once the slip ratio exceeds it, the traction force will decrease as a result of the decrease of adhesive coefficient.

It was also seen that the steering ability will be decreased as the slip is increased from the Figure A-5. This physical phenomenon is the main motivation for ABS brakes, since avoiding high longitudinal slip values will maintain high steerability and lateral stability of the vehicle during braking.

Thus, the curve can be divided into a stable zone with a linear gradient which is termed as 'Application' and an unstable zone 'Lock up' with an almost constant progression. The cycling portion takes place near the optimum slip value (λ^*) which is the area of operation of ABS control loop.

Equations of motion
The wheel dynamics are usually based on a single wheel and a quarter car model where only the longitudinal dynamics are considered. Despite its simplicity it provides a sufficient description of the dynamics and it is therefore useful for understanding and design of control systems. From the free body diagram illustrated in Figure A-2, tyre forces and velocities are used to describe the dynamics by the following equations of motion:

$$J\dot{\omega} = rF_x - T_b \tag{A-3}$$

$$m\dot{v_x} = -F_x \tag{A-4}$$

where J ($kg.m^2$) is the wheels moment of inertia, m (kg) the quarter mass of the car and T_b (N.m) the braking torque applied at the wheel.
Ideally, the torque acting on the wheel is to be taken as $T_e - T_b$ where T_e is the engine torque but since it is assumed that during ABS braking the clutch pedal is kept engaged disconnecting the drive-shaft and hence one can neglect the engine torque [57] .
Besides, the braking torque applied to the wheel is a function of the braking pressure and,ignoring braking inertia and friction, can be described by:

$$T_b = \mu_b A_b r_b P_b \tag{A-5}$$

where (μ_b) is the friction coefficient between brake pad and brake disk, A_b (m^2) is the brake pads surface area, r_b (m) is the brake pads distance from the center and P_b (Pa) is the brake pressure.

A-1-2 Objectives and Challenges

Anti-lock brake systems (ABS) were originally developed to prevent wheels from locking up during hard braking. Locking of the wheels reduces the braking forces generated by the tires and results in the vehicle taking a longer time to come to a stop. Further, locking of the front wheels prevents the driver from being able to steer the vehicle while it is coming to a stop.

Modern ABS systems not only try to prevent wheels from locking but also try to maximize the braking forces generated by the tires by preventing the longitudinal slip ratio from exceeding an optimum value

An anti-lock system consists of a hydraulic modulator, wheel speed sensors, and an electronic control unit. The ABS is a feedback control system that modulates the brake pressure in response to wheel deceleration and wheel angular velocity to prevent the controlled wheel from locking. The system shuts down when the vehicle speed is below a pre-set threshold. The objectives of anti-lock systems are threefold : to reduce stopping distances, to improve stability, and to improve steerability during braking:

1. **Stopping Distance**: The distance to stop is a function of the initial velocity, the mass of the vehicle, and the braking force. By maximizing the braking force the stopping distance will be minimized if all other factors remain constant. However, on all types of surfaces, there exists a peak in friction coefficient. It follows that by keeping all of the wheels of a vehicle near the peak, an anti-lock system can attain maximum frictional force and, therefore, minimum stopping distance.

2. **Stability**: Although decelerating and stopping vehicles constitutes a fundamental purpose of braking systems, maximum friction force may not be desirable in all cases. For example, if the vehicle is on surface such that there is more longitudinal friction on one side of the vehicle than on the other one,(for example one side on dry asphalt and the other on a wet surface because of a water patch on the street), applying maximum braking force on both sides will result in a yaw moment that will tend to pull the vehicle to the high friction side and contribute to vehicle instability, and forces the operator to make excessive steering corrections to counteract the yaw moment. If an anti-lock system can maintain the slip of both rear wheels at the level where the lower of the two friction coefficients peaks , then lateral force is reasonably high, though not maximized. This contributes to stability and is an objective of anti-lock systems.

3. **Steerability**: As seen in the earlier section good peak frictional force control is necessary in order to achieve satisfactory lateral forces and, therefore, satisfactory steerability. Steerability while braking is important not only for minor course corrections but also for the possibility of steering around an obstacle during the braking maneuver.

ABS brake controllers pose unique challenges to the designer. Depending on road conditions, the maximum braking torque may vary over a wide range. The tire slippage measurement signal which is crucial for controller performance, is both highly uncertain and noisy. On rough roads, the tire slip ratio varies widely and rapidly due to tire bouncing, brake pad coefficient of friction changes and the braking system contains transportation delays which limit the control system bandwidth[3]. And so the friction between the road and tire is also not readily measurable or might need complicated sensors.

ABS control is a highly non-linear control problem due to the complicated relationship between friction and slip. Another impediment in this control problem is that the linear velocity of the wheel is not directly measurable and it has to be estimated.

A-2 ABS Algorithms

The algorithm of ABS controller depends on the system configuration and assumptions based on which there are two methodologies involving:
(a) Only Continuous Dynamics and/or
(b) Discrete Actuators
Since, this project requires controller to work on a hydraulic circuit with discrete actuators (HAB), only the discrete actuators based algorithms are analyzed. Other algorithms are suited for Brake-by-wire or Electro-Hydraulic brake system(EHB)[11].

The fundamental objective of the different ABS algorithms is to be at the friction peak value(corresponding to λ^*) which gives the maximum braking torque seen in the Figure A-4

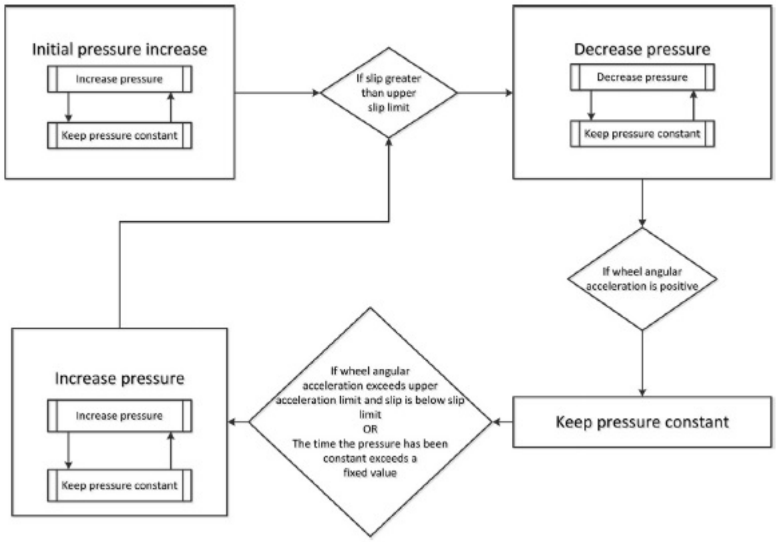


Figure A-6: Flowchart of the ABS algorithm [13]

and regulate using the flowchart A-6 .Thus, the ABS controller is activated by logic dependent on the instability of the vehicle and uncontrollable road conditions. This requires building, releasing and holding of pressures at each wheel following a cyclic path. This loop is followed until the deactivation criteria are met disengaging the ABS and shifting the control back to the driver. Different algorithms care based on different choices of control variable such as wheel slip or wheel deceleration. The algorithm employed by leading manufacturer of ABS systems BOSCH is based on wheel deceleration algorithm and was explained in Chapter 2. The algorithms can be explained as follows:

1. **Wheel Slip Regulation Control**
   Wheel slip control scheme is very powerful technique if it is used in continuous dynamics based systems. This is because wheel slip (λ) is the natural variable for control and is good for setpoint selection and stability. However, in the case of available braking system (HAB), this scheme is modified and uses the estimated slip values to regulates it modifying the braking pressure at each wheel to cycle around the peak value as shown in A-8. The logic is executed phase-wise as shown in Figure A-7 where u is the rate of change of braking torque. These figures show one of several algorithms present for wheel slip regulation control. The horizontal and vertical lines mark the thresholds of a switching logic. The advantages and limitation of this scheme can be stated as follows [58]:

   Advantages

   - Wheel slip provides clear mapping as it is easy to observe the effectiveness.
   - The set-point for different surfaces can be selected easily.
   - It also provides mathematical bounds on thresholds and stability.

   Disadvantages

- It is not easy to estimate vehicle speed and hence the wheel slip. Also the value of slip where maximum brake force is unknown (not easy to estimate in realtime).
- Ideally a very tight box of thresholds would be optimal but it is not robust.
- The rate at which brake pressure is increased and decreased is required to be high for optimal control but is limited by hardware which shows poor performance of algorithm.
- It exhibits poor disturbance rejection properties.

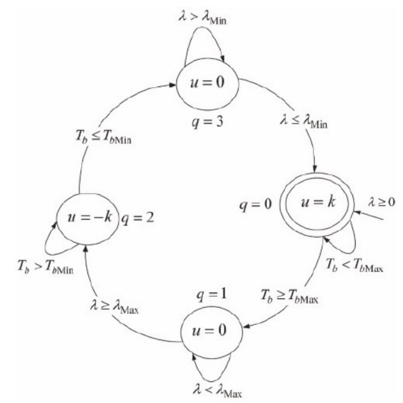


Figure A-7: ABS switching scheme for wheel slip regulation[11]

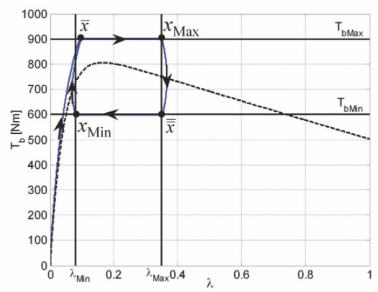


Figure A-8: longitudinal slip v/s Braking torque for wheel slip regulation [11]

2. **Wheel Deceleration based algorithm** The basic idea is to observe the evolution of wheel acceleration during phases while keeping the brake pressure constant and then act to the change caused by increasing or decreasing the pressure. Examples of such algorithm are 5-phase which is shown in Figure A-10 and 11 phase ABS systems. The horizontal lines marked with different ϵ represent the thresholds of the system. These algorithms come closest to the commercial ABS systems [58].

   Advantages

   - It exhibits better disturbance rejection properties than Wheel slip Control.
   - It uses only measurement available without the need of advances estimation techniques..
   - it automatically seeks the optimal slip.

   Disadvantages

   - It is not optimal.
   - It cycles around the peak.
   - it needs two phases at constant torque that are used to estimate the position of the peak.
   - it is expensive in terms of tuning.

3. **Other Hybrid Algorithms** There are several options available in literature owing to the development of technology and techniques. Some of them are

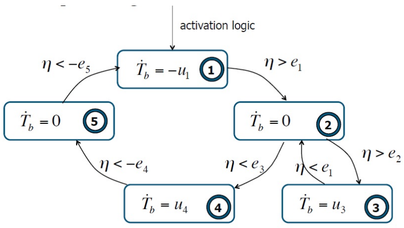


Figure A-9: 5 phase ABS switching scheme for wheel deceleration based control[11]

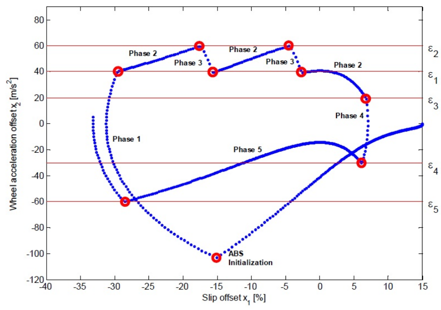


Figure A-10: longitudinal slip v/s wheel deceleration for 5 phase ABS system [14]

(a) **Mixed Slip Deceleration Control** This control logic [58] combines the advantages of the above algorithms to obtain controller possessing the stability characteristics of the Wheel Slip Regulation control and disturbance rejection properties of the Wheel Deceleration based control. The efficacy of this scheme still depends on the quality of estimation of the wheel slip and proximity to equilibrium.

(b) **Brake Force based Control** Recently there has been progress in estimating the brake force experienced at the wheel [5]. This promises smarter and efficient control of the system as it also utilizes one of the direct variables i.e. Brake Force as state. Nonetheless, this scheme also posses the characteristic of switching control logic.

One may also find examples of variable PID gains, Gain Scheduling, Sliding mode Control as well as Neural Networks to substitute or enhance the above mentioned switching control law [13]. However, these techniques are still in their nascent stages and have not found wide platform for implementation.

Appendix B

Defining Parameters of new estimation model

The new estimation models obtained have 4 parameters namely R_{build}, ϕ_{build}, $R_{release}$, and $\phi_{release}$. The parameters R_{build} and $R_{release}$ are difficult to determine as there are no measurements available to monitor them. Also, these properties change with time, temperature and pressure as seen in the Section 2-3. Hence, they will be used as coefficients to update the models using Recursive Least Squares (RLS) algorithm.

As stated earlier, the relation defining parameters ϕ_{build} and $\phi_{release}$ will be defined based on system performance. Using the identification dataset as seen earlier, the mean relative errors and standard deviation of the relative errors are plotted against varying values of the parameters ϕ_{build} and $\phi_{release}$. These plots are seen in Figure B-1 and Figure B-2.

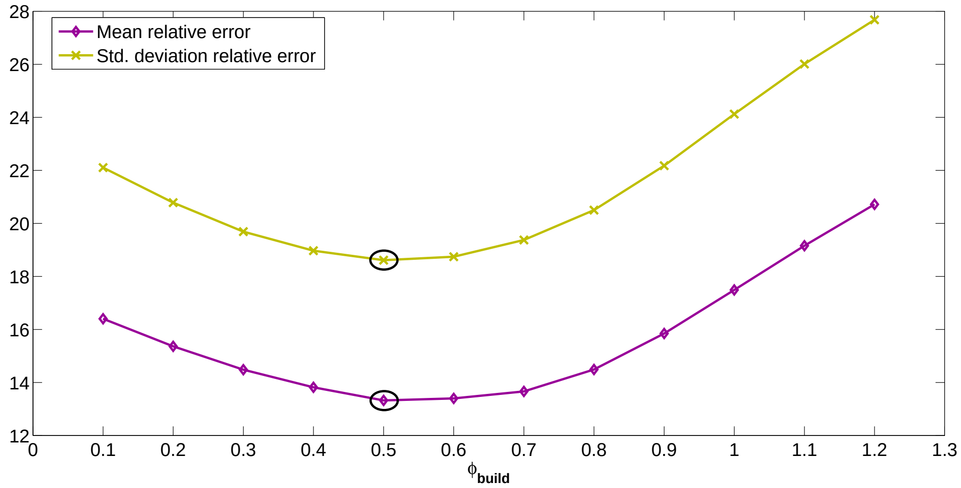


Figure B-1: Average mean and std. deviation relative error for both wheel sides for increasing ϕ_{build}

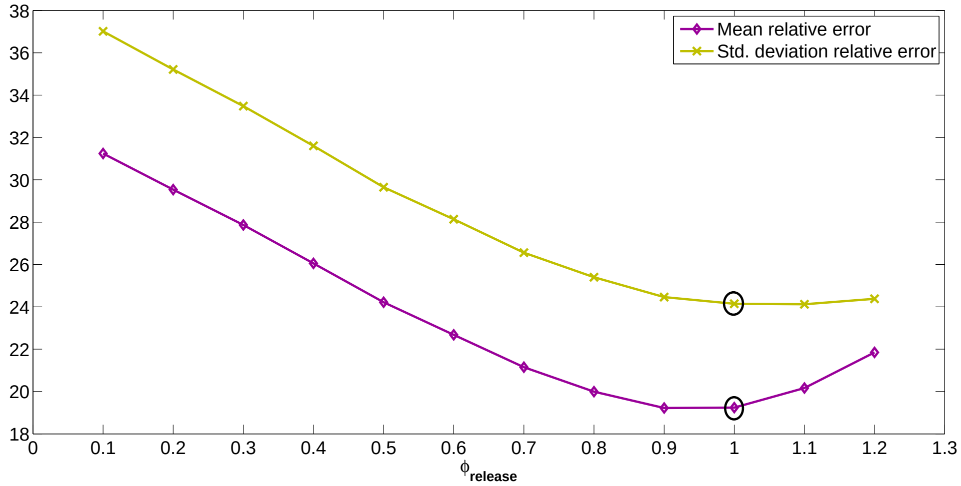


Figure B-2: Average mean and std. deviation relative error for both wheel sides for increasing $\phi_{release}$

Figures B-2 and B-1 show a non-linear trend with increasing value of the parameters. The minimum value of the relative errors and standard deviation (marked in black ellipses) help in defining the value of the parameters for the brake system used in this thesis. Thus, the values of ϕ_{build} and $\phi_{release}$ are set to 0.5 and 1.

Appendix C

Experimental Results

The adaptive control system is implemented and tested in real time. As discussed in functional description of Adaptive Filter block earlier, the Build linear model is used for estimating pressure steps where b_2 and b_3 adapt recursively to changing dynamics. Thus, a partial update RLS is employed with the forgetting factor kept constant at value of 0.94. The figures C-1 and C-2 show the performance of the controller in real time with block and staircase signals as references respectively.

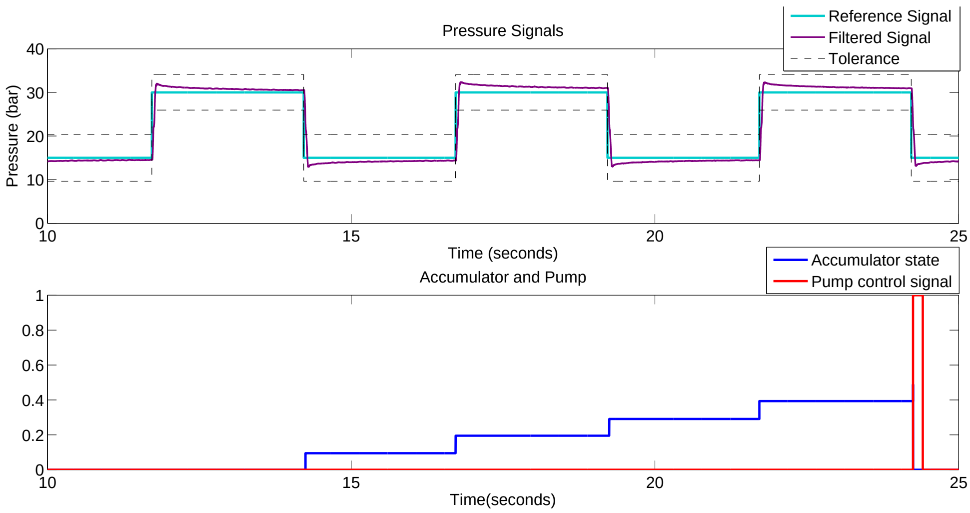


Figure C-1: Block Signal Performance

In both the cases, the reference is precisely tracked with no chattering and no unstable behaviour. The errors lie within tolerance and also settle down to provide accurate pressure steps. Also, the accumulator is emptied when its state is reaches 40% of its total capacity.

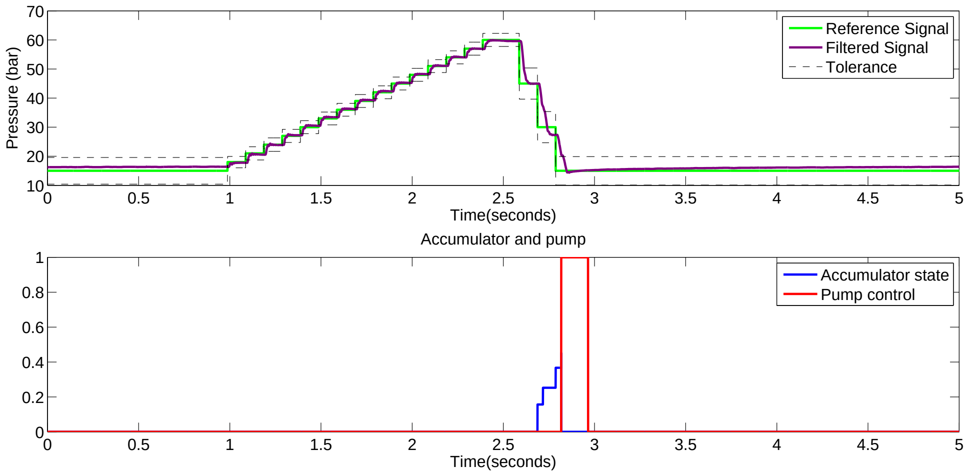


Figure C-2: Staircase Signal Performance

C-1 Full Update RLS

The coefficient and covariance evolution for Build linear model using Full Update Recursive Least Squares (RLS) algorithm is presented in the following figures.

C-2 Small pressure steps

The RLS algorithm can be considered effective if a convergence to optimal set of coefficients is observed. This is a challenging task as the each pressure step made depends on the operating pressure range of brake pressure values. Thus, the same pressure step made at lower brake pressure values will have a different mapping than that at higher brake pressure values. This means that there exists a different mapping for combination of pressure step and operating range. However, the actual coefficient values are unknown and hence a recursive approach will help in updating the mapping for each pressure range.

In order to test the RLS algorithm, a reference block signal of magnitude 2 bars is tracked by the adaptive controller. This can be observed in the Figure C-5. The fixed operation range of this reference, i.e. between 15 and 17 bars, makes the mapping fixed[1]. Thus, the RLS algorithm should converge to an optimal set of coefficients.

The Figure C-6 shows the coefficient evolution for the partial update adaptive algorithm while tracking the reference seen in Figure C-5. It is observed that the build and release coefficients do not vary significantly (within the order of 10^{-4}) making the mapping almost constant. This means that the Recursive Least Squares (RLS) algorithm has converged for the given operating range.

[1] provided all the other mapping variables are kept constant such as the supply pressure

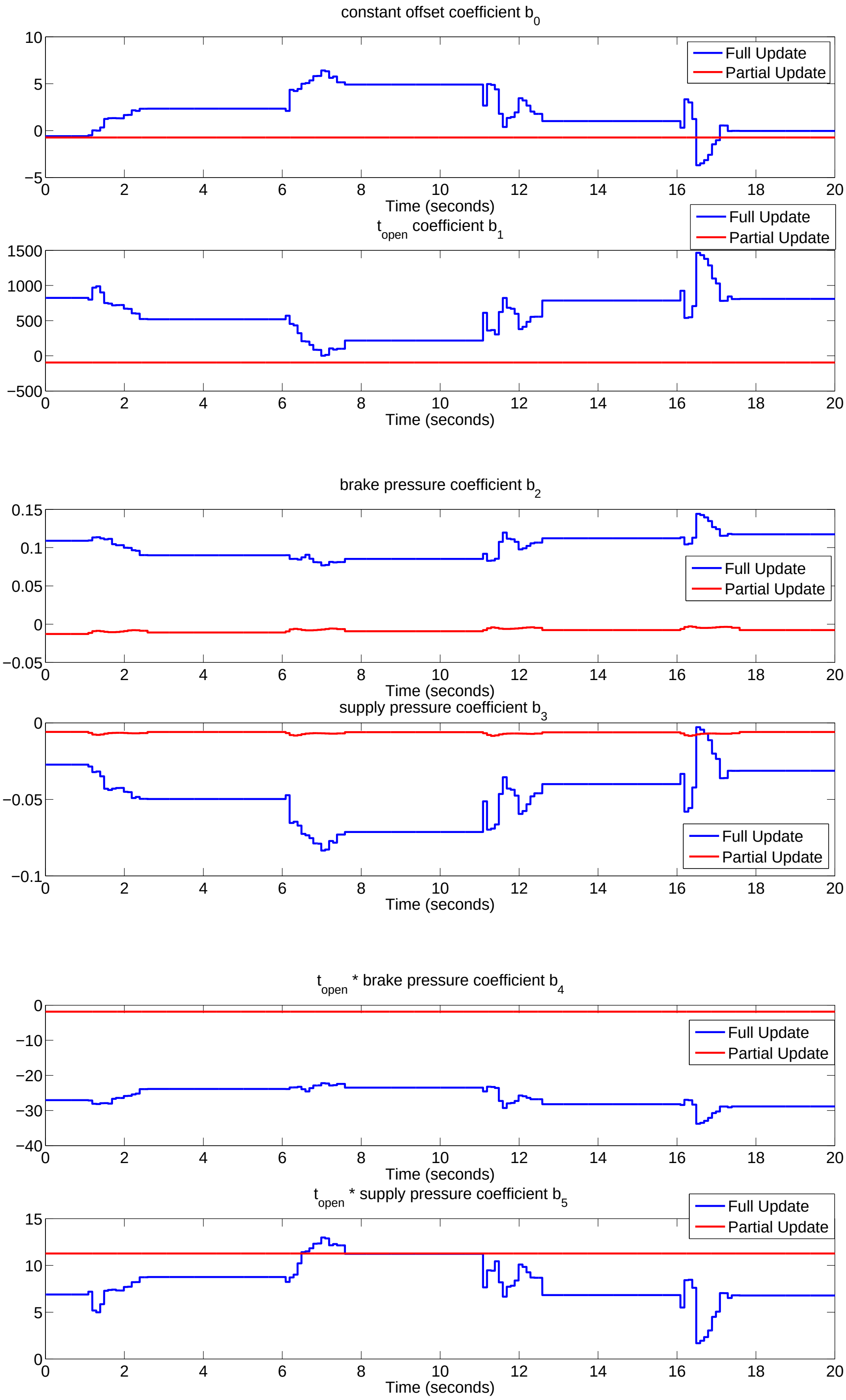


Figure C-3: Coefficient Evolution for Full Update RLS algorithm

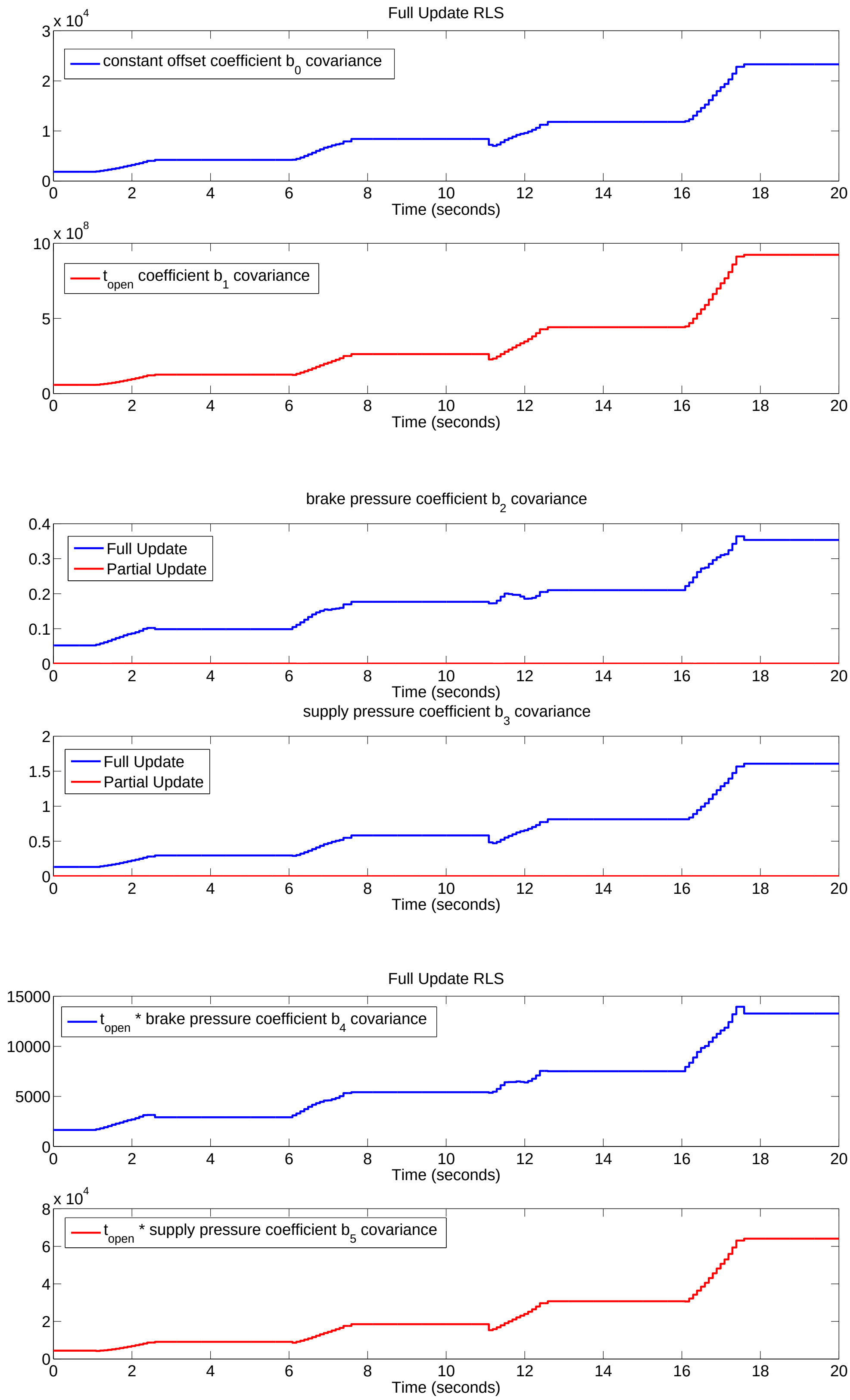


Figure C-4: Covariance Evolution for Full Update RLS algorithm

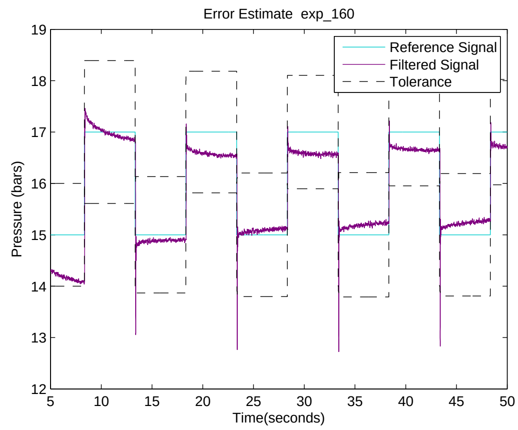


Figure C-5: Brake pressure signal for small reference pressure steps

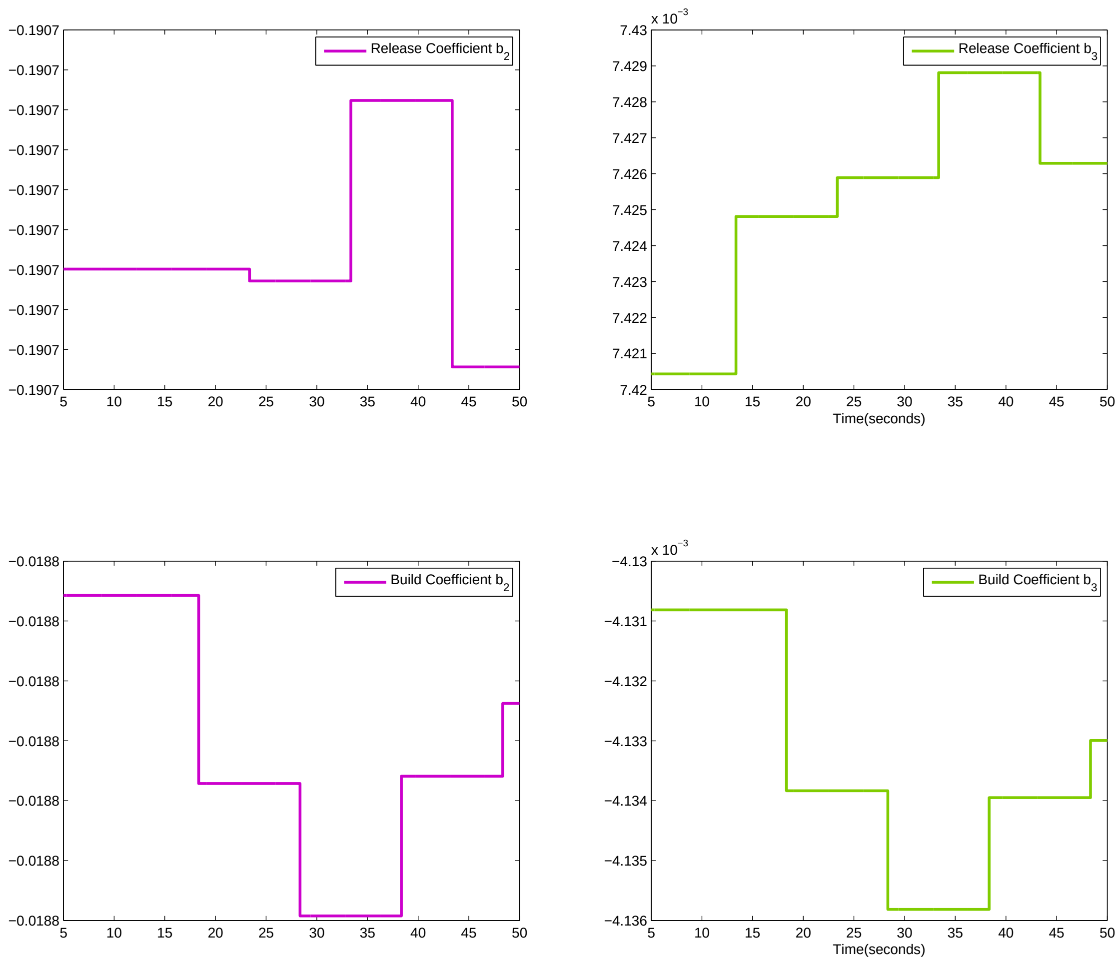
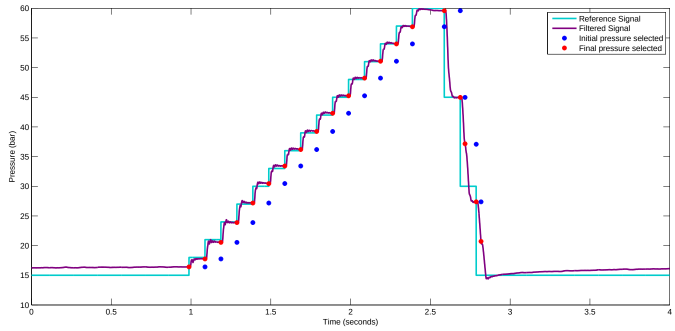
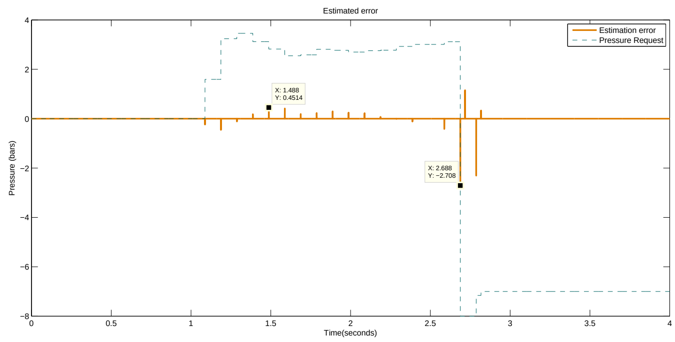


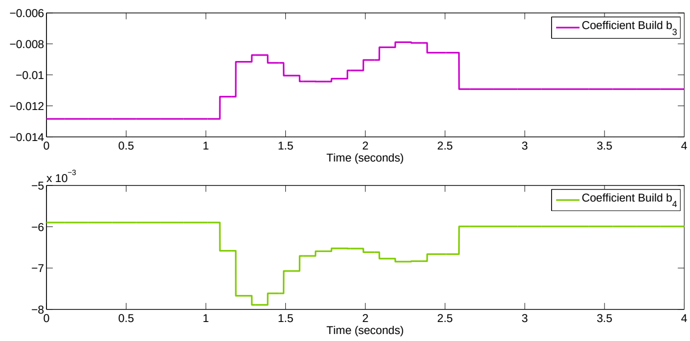
Figure C-6: Update of Build and Release coefficients operating in a small pressure range



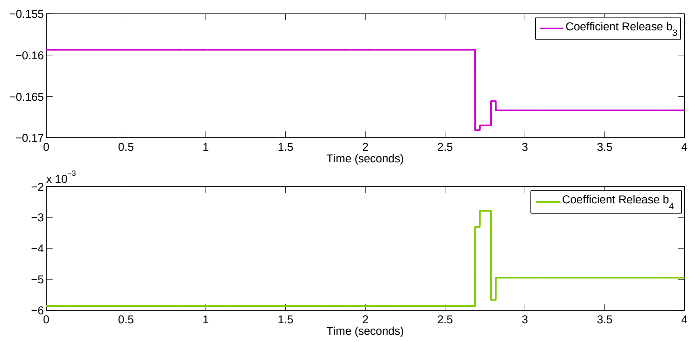
(a) Brake pressure signal and accumulator state



(b) Estimation Error and pressure step request



(c) Build Coefficients evolution



(d) Release Coefficients evolution

Figure C-7: Coefficient Evolution on staircase signals

Bibliography

[1] O. Gietelink, J. Ploeg, B. De Schutter, and M. Verhaegen, "Development of advanced driver assistance systems with vehicle hardware-in-the-loop simulations," *Vehicle System Dynamics*, vol. 44, no. 7, pp. 569–590, 2006.

[2] K. Reif, "Brakes, brake control and driver assistance systems,"

[3] N. Geromel, "Modelling and control of the braking system of the electric polaris ranger all-terrain-vehicle," 2014.

[4] R. Torres Sabaté, *Design of an adaptive brake pressure controller for the antilock braking system.* PhD thesis, TU Delft, Delft University of Technology and Universitat Politècnica de Catalunya, 2013-2014.

[5] S. Kerst, *Design and Implementation of a Novel Force and Brake Pressure based Anti-lock Braking System.* PhD thesis, TU Delft, Delft University of Technology, 2012.

[6] L. Li, G. Jia, J. Chen, H. Zhu, D. Cao, and J. Song, "A novel vehicle dynamics stability control algorithm based on the hierarchical strategy with constrain of nonlinear tyre forces," *Vehicle System Dynamics*, no. ahead-of-print, pp. 1–24, 2015.

[7] V. Ćirović and D. Aleksendrić, "Adaptive neuro-fuzzy wheel slip control," *Expert Systems with Applications*, vol. 40, no. 13, pp. 5197–5209, 2013.

[8] R. B. GmbH, *Automotive Handbook 7th Edition.* Bentley Publishers.

[9] Z. Wu, *Simulation study and instability of adaptive control.* PhD thesis, Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Master of Science in Electrical Engineering in The Department of Electrical and Computer Engineering by Zhongshan Wu BSEE, Northeastern University, China, 1996, 2001.

[10] V. H. Nascimento and M. T. Silva, "Adaptive filters," *THEODORIDIS, S.(Ed.)*, 2014.

[11] S. M. Savaresi and M. Tanelli, *Active braking control systems design for vehicles*. Springer Science & Business Media, 2010.

[12] M.-c. Wu and M.-c. Shih, "Simulated and experimental study of hydraulic anti-lock braking system using sliding-mode pwm control," *Mechatronics*, vol. 13, no. 4, pp. 331–351, 2003.

[13] A. A. Aly, E.-S. Zeidan, A. Hamed, F. Salem, *et al.*, "An antilock-braking systems (abs) control: A technical review," *Intelligent Control and Automation*, vol. 2, no. 03, p. 186, 2011.

[14] J. Tigelaar, *Design and Vehicle Implementation of an Adaptive ABS*. PhD thesis, TU Delft, Delft University of Technology, 2011.

[15] M. P. Hagenzieker, J. J. Commandeur, and F. D. Bijleveld, "The history of road safety research: A quantitative approach," *Transportation research part F: traffic psychology and behaviour*, vol. 25, pp. 150–162, 2014.

[16] R. Happee, "Automotive crash safety : Active and passive systems." lecture notes.

[17] S. A. Ferguson, "The effectiveness of electronic stability control in reducing real-world crashes: a literature review," *Traffic injury prevention*, vol. 8, no. 4, pp. 329–338, 2007.

[18] A. Høye, "The effects of electronic stability control (esc) on crashesâĂŤan update," *Accident Analysis & Prevention*, vol. 43, no. 3, pp. 1148–1159, 2011.

[19] A. J. Day, *Braking of road vehicles*. Butterworth-Heinemann.

[20] S. Kerst, "Bmw manual.".

[21] G. Elert, "The physics hypertextbook."

[22] F. Cheli, A. Concas, E. Giangiulio, and E. Sabbioni, "A simplified abs numerical model: Comparison with hil and full scale experimental tests," *Computers & Structures*, vol. 86, no. 13, pp. 1494–1502, 2008.

[23] W. K. Lennon and K. M. Passino, "Intelligent control for brake systems," *Control Systems Technology, IEEE Transactions on*, vol. 7, no. 2, pp. 188–202, 1999.

[24] M. Taghizadeh, A. Ghaffari, and F. Najafi, "Modeling and identification of a solenoid valve for pwm control applications," *Comptes Rendus Mecanique*, vol. 337, no. 3, pp. 131–140, 2009.

[25] J. Zhang, C. Lv, X. Yue, Y. Li, and Y. Yuan, "Study on a linear relationship between limited pressure difference and coil current of on/off valve and its influential factors," *ISA transactions*, vol. 53, no. 1, pp. 150–161, 2014.

[26] C. Lu and M.-C. Shih, "Design of a hydraulic anti-lock braking modulator and an intelligent brake pressure controller for a light motorcycle," *Vehicle System Dynamics*, vol. 43, no. 3, pp. 217–232, 2005.

[27] B. Zhu, J. Zhao, Y.-d. Li, and X. Hua, "The integrated chassis control based on the hydraulic brake pressure fine regulation," in *Intelligent Vehicles Symposium, 2009 IEEE*, pp. 1359–1364, IEEE, 2009.

[28] J. Zhang, C. Lv, J. Gou, and D. Kong, "Cooperative control of regenerative braking and hydraulic braking of an electrified passenger car," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, p. 0954407012441884, 2012.

[29] S. J. Eckert, M. A. Salman, and N. M. Boustany, "Hierarchical brake controller," July 25 1989. US Patent 4,850,650.

[30] M. H. AL-MOLA, M. Mailah, P. M. Samin, A. H. Muhaimin, and M. Y. Abdullah, "Performance comparison between sliding mode control and active force control for a nonlinear anti-lock brake system," *WSEAS Transactions on Systems and Control*, vol. 9, pp. 101–107, 2014.

[31] B. Moaveni and P. Barkhordari, "Identification and characterization of the hydraulic unit in an anti-lock brake system," *Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, p. 0954407015612656, 2015.

[32] S. Choi and D.-W. Cho, "Design of nonlinear sliding mode controller with pulse width modulation for vehicular slip ratio control," *Vehicle System Dynamics*, vol. 36, no. 1, pp. 57–72, 2001.

[33] N. Ding and X. Zhan, "Model-based recursive least square algorithm for estimation of brake pressure and road friction," in *Proceedings of the FISITA 2012 World Automotive Congress*, pp. 137–145, Springer, 2013.

[34] L. Wei, D. Haitao, and G. Konghui, "Research on esc hydraulic control unit property and pressure estimation," in *Intelligence Computation and Evolutionary Computation*, pp. 625–631, Springer, 2013.

[35] J. Zhang, C. Lv, X. Yue, Y. Li, and Y. Yuan, "Study on a linear relationship between limited pressure difference and coil current of on/off valve and its influential factors," *ISA transactions*, vol. 53, no. 1, pp. 150–161, 2014.

[36] S. Kerst, "Brake pressure control skf/bmw project.".

[37] D. Aleksendrić, Ž. Jakovljević, and V. Ćirović, "Intelligent control of braking process," *Expert Systems with Applications*, vol. 39, no. 14, pp. 11758–11765, 2012.

[38] H. Kim, "Design of the electronic brake pressure modulator using a direct adaptive fuzzy controller in commercial vehicles for the safety of braking in fail.," *JSME International Journal Series C*, vol. 45, no. 1, pp. 246–257, 2002.

[39] M. Verhaegen and V. Verdult, *Filtering and system identification: a least squares approach.* Cambridge university press, 2007.

[40] J. Wang, "A variable forgetting factor rls adaptive filtering algorithm," in *Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications, 2009 3rd IEEE International Symposium on*, pp. 1127–1130, IEEE, 2009.

[41] A. H. Sayed, *Adaptive filters.* John Wiley & Sons, 2011.

[42] P. Andersson and T. Majuri, "Advanced control of electro hydraulic forestry machine," 2012.

[43] B. Xie, *Partial Update Adaptive Filtering.* PhD thesis, Virginia Polytechnic Institute and State University, 2011.

[44] S. C. Douglas, "Adaptive filters employing partial updates," *Circuits and Systems II: Analog and Digital Signal Processing, IEEE Transactions on*, vol. 44, no. 3, pp. 209–216, 1997.

[45] A. W. Khong, P. Naylor, *et al.*, "Selective-tap adaptive filtering with performance analysis for identification of time-varying systems," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 15, no. 5, pp. 1681–1695, 2007.

[46] K. Dogancay, *Partial-update adaptive signal processing: Design Analysis and Implementation.* Academic Press, 2008.

[47] V. H. Nascimento, M. T. Silva, L. A. Azpicueta-Ruiz, and J. Arenas-Garcia, "On the tracking performance of combinations of least mean squares and recursive least squares adaptive filters," in *Acoustics Speech and Signal Processing (ICASSP), 2010 IEEE International Conference on*, pp. 3710–3713, IEEE, 2010.

[48] J. Arenas-García, C. Moriana-Varo, and J. Larsen, "Combination of recursive supervised and semisupervised filters for improved unbiased estimation," in *Wireless Communication Systems (ISWCS), 2010 7th International Symposium on*, pp. 364–368, IEEE, 2010.

[49] J. Wang, "A variable forgetting factor rls adaptive filtering algorithm," in *Microwave, Antenna, Propagation and EMC Technologies for Wireless Communications, 2009 3rd IEEE International Symposium on*, pp. 1127–1130, IEEE, 2009.

[50] P. Andersson, "Adaptive forgetting in recursive identification through multiple modelsâĂă," *International Journal of Control*, vol. 42, no. 5, pp. 1175–1193, 1985.

[51] T. Fortescue, L. Kershenbaum, and B. Ydstie, "Implementation of self-tuning regulators with variable forgetting factors," *Automatica*, vol. 17, no. 6, pp. 831–835, 1981.

[52] P. Wellstead and S. Sanoff, "Extended self-tuning algorithm," *International Journal of Control*, vol. 34, no. 3, pp. 433–455, 1981.

[53] A. Vahidi, A. Stefanopoulou, and H. Peng, "Recursive least squares with forgetting for online estimation of vehicle mass and road grade: theory and experiments," *Vehicle System Dynamics*, vol. 43, no. 1, pp. 31–55, 2005.

[54] R. Marks, *Introduction to Shannon sampling and interpolation theory.* Springer Science & Business Media, 2012.

[55] R. B. GmbH, "Automotive brake systems (1st)."

[56] C. Canudas-de Wit, P. Tsiotras, E. Velenis, M. Basset, and G. Gissinger, "Dynamic friction models for road/tire longitudinal interaction," *Vehicle System Dynamics*, vol. 39, no. 3, pp. 189–226, 2003.

[57] I. Ait-Hammouda and W. Pasillas-Lépine, "Jumps and synchronization in anti-lock brake algorithms," in *AVEC 2008*, pp. N–A, 2008.

[58] M. Corno, "Vehicle dynamics b: Anti-lock brakiing system." lecture notes.

Glossary

List of Acronyms

ADAS	Advanced Driver Assistance Systems
TU Delft	Delft University of Technology
ABS	Antilock Braking System
ESC	Electronic Stability Control
EBD	Electronic Brake Force Distribution
ECU	Electronic Control Unit
EU	European Union
EuroNCAP	The European New Car Assessment Programme
FL	Front Left Wheel Side
FR	Front Right Wheel Side
HAB	Hydraulic Actuated Braking
IIHS	Insurance Institute for Highway Safety
LMS	Least Mean Squares
MBD	Main Brake Disconnect
NLMS	Normalised Least Mean Squares
PID	Proportional-Integral-Derivative Controller
PWM	Pulse Width Modulation
RLS	Recursive Least Squares
STR	Self Tuning Regulator

TCS Traction Control System

DSC Dynamics Stability Control

STR Self-Tuning Regulator