Implementation and Testing of a Nonlinear Fuzzy Rule Based Algorithm for Antilock Braking of a Scaled Vehicle

by

Anish George Mathews, B.E.

Thesis

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

Master of Science in Engineering

The University of Texas at Austin

December 2002

Implementation and Testing of a Nonlinear Fuzzy Rule Based Algorithm for Antilock Braking of a Scaled Vehicle

Approved by
Supervising Committee:

Raul G. Longoria, Supervisor

Benito R. Fernandez

Dedication

I would like to dedicate this thesis to my parents for their love and support all these years. I also dedicate this thesis to my sister and to my bother-in-law and the rest of my family from India to Chicago.

Acknowledgements

I would like to express my sincere gratitude and thanks to Dr. Raul Longoria for giving me the opportunity to work with him. Dr. Longoria always exhibited confidence in my efforts and I greatly appreciate his guidance and support through my years at the University of Texas at Austin as a Masters Candidate. I would like to thank Dr. Benito Fernandez for helping me understand the underlying soft computing concepts and his thorough examination of my thesis. I would like to thank my family for the love and patience they have showed during my graduate years.

I appreciate the efforts of Amrou Al-Sharif in putting together the scaled vehicle test platform, which provides an opportunity for conducting scaled experiments. I would like thank others who were associated with building the test platform. Chinmaya Patel helped me with the experimentation efforts and also with data from the steady state experiments for estimating tire friction. I would also like to appreciate his efforts in putting together a robust box for the signal conditioning required for the experiments.

I would to thank my research mates at ETC 1.104 for their support and for sharing their views during the research work. I would also like to thank National Instruments for providing the equipment required for the experiments. Ravi Marawar and John Limroth were the two key persons from National Instruments, who helped in the financial and technical aspects of building the test platform. I would thank the Dr. Longoria and the department of mechanical engineering for providing the financial support through my graduate years. Part of this study was also supported by funding from National Instruments and from the National Science Foundation Industry/University Cooperative Research program to the Center for Virtual Proving Ground at the University of Texas at Austin, through grant # EEC-9706083.

Implementation and Testing of a Nonlinear Fuzzy Rule Based Algorithm for Antilock Braking of a Scaled Vehicle

Anish George Mathews, MSE
The University of Texas at Austin
2002

Supervisor: Raul G. Longoria

Conventional Anti-lock Braking Systems that are developed are optimized to maintain directional stability of the vehicle while braking under standard test conditions. The performance of such systems degrades on adverse road conditions (loose gravel/ice/snowy conditions). This thesis presents the idea of an Anti-lock Brake System controller, which adapts to changes in road conditions. It uses fuzzy –rule based algorithms to adapt to changes in surface condition. Simulation studies on vehicle models with the modified ABS controller design were carried out on different surface conditions and were proved to be more effective than standard ABS designs. Experiments on a fully instrumented 1/5th scale car were also performed on test ramp under different surface conditions to validate the simulation results. A real time controller with associated data acquisition devices was used as the control unit.

Table of Contents

List of Tables x

List of Figures xi

Chapter 1: Introduction 1

- Need for Antilock Braking System 2
- Dynamics of Braking 3
- Modules of ABS 5
- Research in ABS 8
- Soft Computing - Introduction 10
- Thesis Overview 11
- Thesis Contribution/ Focus 12

Chapter 2: Soft Computing in ABS 14

- Introduction 14
- Adaptability Issues – Fuzzy Logic Approach 14
- Implementation and Scability Issues 20
- Summary 27

Chapter 3: Fuzzy Model and Simulation 28

- Introduction 28
- Fuzzy Modeling 28
    - Fuzzy Sets and Membership Functions 29
    - Fuzzy "if-then" rules 31
    - Fuzzy Reasoning 31
- Fuzzy Inference System 33
- One Degree of Freedom (Longitudinal) Model 38
    - Bang-Bang Controller 41
    - Fuzzy Logic Controller 44
    - Comparison of the controllers 47
- $1/5^{th}$ Scale Vehicle Model 48

Bang-Bang Controller Design 50
Nonlinear Fuzzy Logic Controller - 1/5th scale vehicle model 54
Comparison and discussion of results 58
Chapter 4: Experimentation 60
Hardware 60
Software..63
Experiment Procedure 66
Results..69
Bang-Bang Controller 70
Fuzzy Logic ABS Controller 72
Conclusion 76
Chapter 5: Conclusion and Recommendations 79
Conclusion 79
Future Work 79
Appendix A. Fuzzy Logic Controller – Longitudinal Model 82
Appendix B. Fuzzy Logic Controller – 1/5th Scale Vehicle Model 87
References 98
Vita 102

List of Tables

Table 1. 1 Comparison Table of Vehicle Safety Systems.....................................2

List of Figures

Figure 1.1 Directional Control under Heavy Braking 3
Figure 1.2 Braking/ Cornering Force Coefficients Vs Slip 4
Figure 1.3 Tire-Surface friction characteristics 5
Figure 1.4 Modules of Antilock Brake System 6
Figure 1.5 Block Representation of an Anti-lock Brake System 7
Figure 1.6 Sampling of ABS Research 8
Figure 1.7 Soft Computing Research in ABS 13
Figure 2.1 Components essential to tackle adaptability in an ABS system 15
Figure 2.2 Simplified Fuzzy Logic ABS System...17
Figure 2.3 Fuzzy Logic System – interaction with the Physical Realm................19
Figure 2.4 Test Platform – Test Track, Test Vehicle and Real-Time Controller .22
Figure 2.5 Block Representation – Interaction between the Simulation and Physical Environment 23
Figure 2.6 Detailed Block Representation – Interaction between Simulation and Physical Environment 24
Figure 2.7 Design Approaches for Fuzzy Logic Controller 26
Figure 3.1 Different Membership Functions from MathWorks 30
Figure 3.2 Example for fuzzy reasoning approaches 32
Figure 3.3 Block Representation – steps in construction of fuzzy inference system 35
Figure 3.4 Bond Graph – Longitudinal Model (Dynamics of Braking)..................39
Figure 3.5 Representative graphs showing the friction- slip characteristics 40
Figure 3.6 Block Representation showing the dynamics of an anti-lock brake system 41
Figure 3.7 ABS Braking Model with bang-bang controller from MathWorks........42
Figure 3.8 Representative Mu-Slip curve for dry concrete 43
Figure 3.9 Simulation Results for bang-bang controller.......................................44
Figure 3.10 ABS Braking Model with fuzzy logic controller 45
Figure 3.11 Simulation Results for fuzzy logic controller 47
Figure 3.12 Complete Simulink Representation of 1/5th Vehicle Model...............48
Figure 3.13 Bond graph representation - ABS braking system model for 1/5th scale vehicle 50
Figure 3.14 Simulink Model of Logic Used by Bang-Bang Controller..................51
Figure 3.15 Representative mu-slip characteristic curves 52
Figure 3.16 Simulation Results –Bang-Bang controller 54
Figure 3.17 Simulink representation of nonlinear fuzzy controller 56
Figure 3.18 Simulation Results – Nonlinear Fuzzy Logic Controller....................58
Figure 4.1 Block Representation of the Hardware Components in Experimental Setup 62

Figure 4.2 Block Representation of Software Modules......................................63
Figure 4.3 Conversion of a fuzzy logic Simulink block into a VI 65
Figure 4.4 Run Time User Interface – Software Module 66
Figure 4.5 Block Representation of the setup for determining friction and cornering coefficient..68
Figure 4.6 Mu-Slip Curve from steady state experiments by Longoria, et. al 69
Figure 4.7 Comparison of Encoder data for Bang-Bang and Fuzzy Controller ...71
Figure 4.8 Acceleration data –Bang-Bang ABS Controller 71
Figure 4.9 Acceleration Data –Fuzzy Logic ABS Controller 73
Figure 4.10 Comparison of Stopping Distances 73
Figure 4.11 Comparison of differential encoder data for two runs with fuzzy ABS under similar conditions..74
Figure 4.12 Comparison of right wheel encoder data for two runs with fuzzy ABS under similar conditions..74
Figure 4.13 Comparison of right slip data for two runs with fuzzy ABS under similar conditions 75
Figure 4.14 Comparison of right brake servo voltages for two runs with fuzzy ABS under similar conditions..75
Figure A.1 Fuzzy Inference System - FIS..82
Figure A.2 Input Membership Functions – Current Slip.......................................83
Figure A.3 Output Membership Functions –Torque Change 84
Figure A.4 Rule Viewer...85
Figure A.5 Surface Viewer..86
Figure B.1 Gain Fuzzy Logic Controller – FIS 87
Figure B.2 Input Membership Functions – Current Slip.......................................88
Figure B.3 Output Membership Functions – Gain Constant 89
Figure B.4 Rule Viewer...90
Figure B.5 Surface Viewer..91
Figure B.6 Proportional Derivative Fuzzy Logic Controller – FIS 92
Figure B.7 Input Membership function – Slip Difference 93
Figure B.8 Input Membership Function – Current Slip...94
Figure B.9 Output Membership Function – PD Constant 95
Figure B.10 Rule Viewer...96
Figure B.11 Surface Viewer...97

Chapter 1: Introduction

Engineers in the automotive industry put a lot of effort in devising systems which ensure safety in road vehicles. A typical passenger car has a lot of features which ensure safety like ABS, traction control system, airbags, energy absorbing steering columns, crumple zones, head restraints and many other safety inventions [1]. “ABS” the acronym for Antilock Braking System is designed to help the driver maintain steering ability and avoid skidding while braking. ABS and Traction Control System deal with the vehicle stability and handling. In recent years, engineers are developing what is called as the “Intelligent Stability and Handling System”. Intelligent stability and handling systems provide the driver with greater control of the vehicle when loss of control is imminent. A comparison chart showing the major features of these systems is shown in Table1.1.

	4 Wheel ABS	**Traction Control**	**Intelligent Stability and Handling Systems**
Prevents wheel lock-up under many road conditions	X		X
Allows driver to maintain control when brakes are fully applied	X		X
Sensors detect impending wheel lock-up	X		X
Pumps the brakes like a driver would, only much faster and more effectively	X		X

Engages when the driver stomps on the brake pedal	X		X
Prevents unwanted wheel spin in low traction situations		X	X
Adjusts vehicle acceleration when driving in low-traction situations, such as rain or snow		X	X
Helps drivers accelerate safely		X	X
Detects a vehicle's position in relation to steering input with use of sensors			X
Monitors and compares a vehicle's movement with the direction a driver is steering			X
Automatically brakes specific wheels, allowing a driver to maintain steering control during a skid			X

Table 1.1 Comparison Table of Vehicle Safety Systems [2]

Need for Antilock Braking System

Antilock braking capabilities in vehicles form the backbone for the research carried out as part of this thesis. During emergency braking, the driver wants to stop and steer the car at the same time. Antilock brake systems help the driver to maintain vehicle stability under emergency braking conditions.

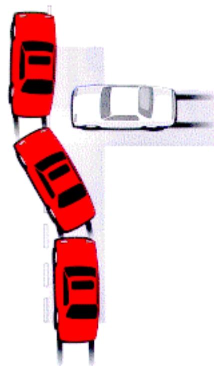


Figure1.1 Directional Control under Heavy Braking [3]

Dynamics of Braking

When a brake torque (braking effort) is applied to a rotating wheel it may cause the tire to deform and slide. This causes the radial component of spin velocity of the tire to differ from its linear velocity. The ratio of the differential velocity to the linear velocity is termed as slip ratio. It is usually expressed as a percentage. It is used to characterize braking performance.

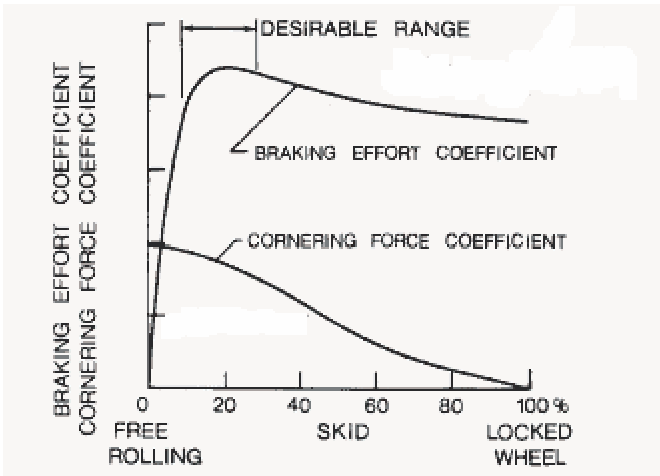
$$\text{Slip Ratio} = (1 - \omega R/V) * 100\%;$$

ω – spin velocity of the wheel

R – radius of the wheel

V – linear velocity of the wheel.

When slip ratio is 100%, then the condition is termed as “wheel lockup”. The following figure shows how the steering ability of the vehicle is greatly reduced when the wheel tends to lock up.



Steering Ability is related to the cornering force coefficient. Braking ability depends upon the braking effort coefficient.

Figure 1.2 Braking/ Cornering Force Coefficients Vs Slip [4]

The braking and steering ability of the vehicle is also limited by the amount of traction the tire can generate. The traction that the tire can generate depends upon the normal force on the tire and the friction (braking effort coefficient) between the tire and the road surface. The friction depends on a lot of factors like the slip ratio, the type of tire, tire tread, tire pressure, road conditions, etc. A set of curves (shown below) illustrates the relationship between friction, slip ratio and different road surfaces for a given tire.

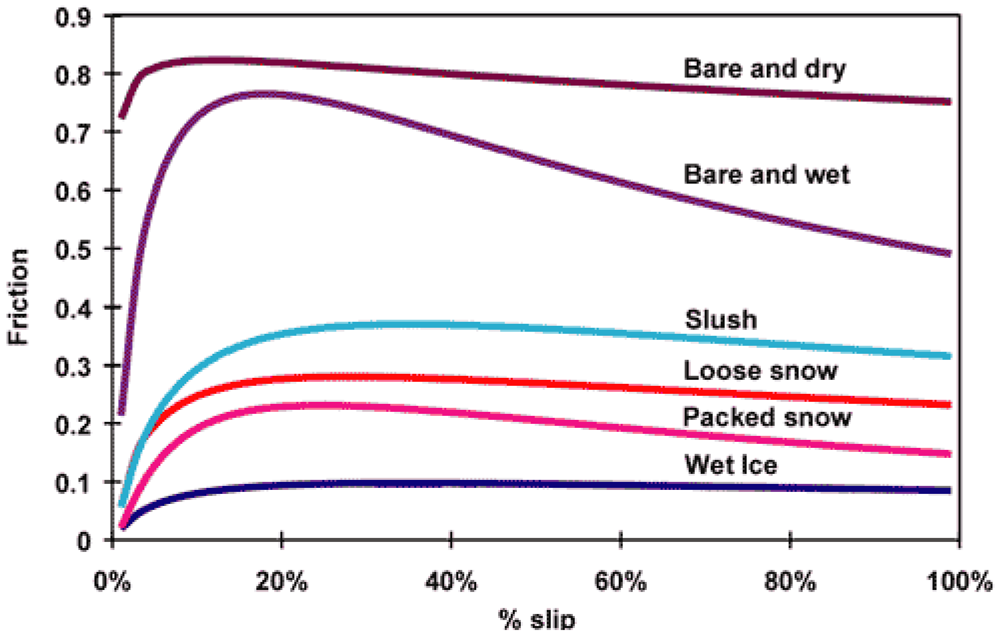


Figure 1.3 Tire-Surface friction characteristics [5]

Antilock braking system operates in such a way so that it does not allow the wheels to get locked and maintains the slip ratio so that friction between tire and the road is kept at an optimal maximum by controlling the brake torque applied to the wheels.

Modules of ABS

A typical Antilock Brake System consists of wheel sensors, electronic control unit, brake actuator control unit and the brake actuator. Some of the advanced system also consists of an accelerometer to determine the deceleration of the vehicle. The following figure shows the basic components of an antilock braking system.

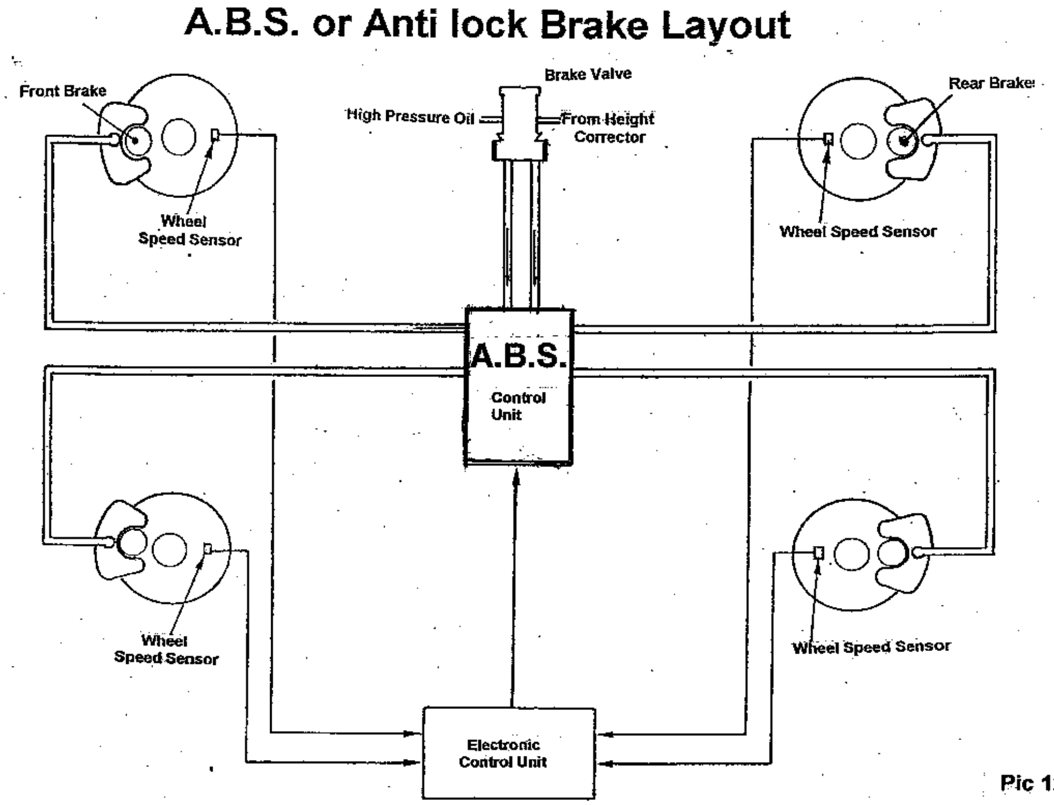


Figure 1.4 Modules of Antilock Brake System [6]

The wheel sensor feeds the wheel spin velocity to the electronic control unit, which based on some underlying control approach would give an output signal to the brake actuator control unit. The brake actuator control unit then controls the brake actuator based on the output from the electronic control unit. The control logic is based on the objective to keep the wheels from getting locked up and to maintain the traction between the tire and road surface at an optimal maximum. The task of keeping the wheels operating at maximum traction is complicated given that the friction-slip curve changes with vehicle, tire and road changes. The above figure (figure 1.3) shows the friction-slip curves due to changes in road conditions alone. The block diagram (figure 1.5) shows the block representation of an antilock brake system. It shows the basic functionality of the various components in ABS systems and also shows the data/information flow.

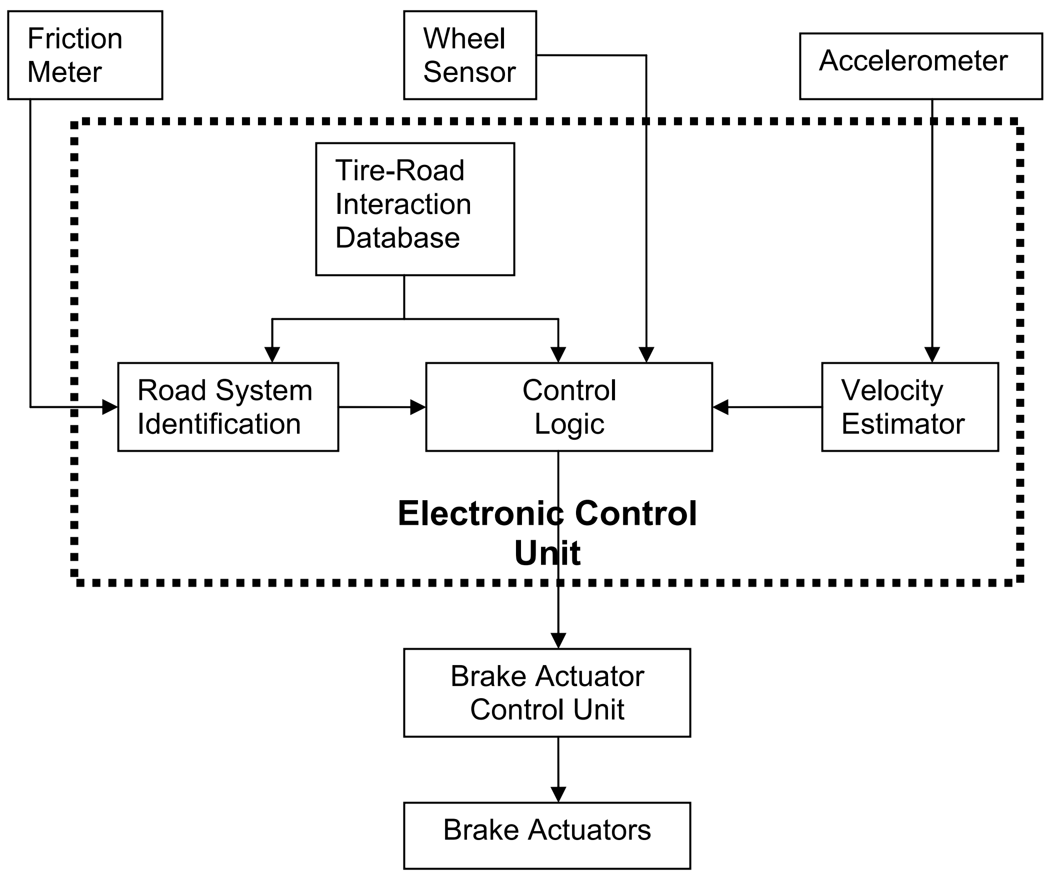


Figure 1.5 Block Representation of an Anti-lock Brake System

Research in ABS

The research that is been carried out in anti-lock brake systems cover a board range of issues and challenges. The following layout shows a sampling of the anti-lock brake research.

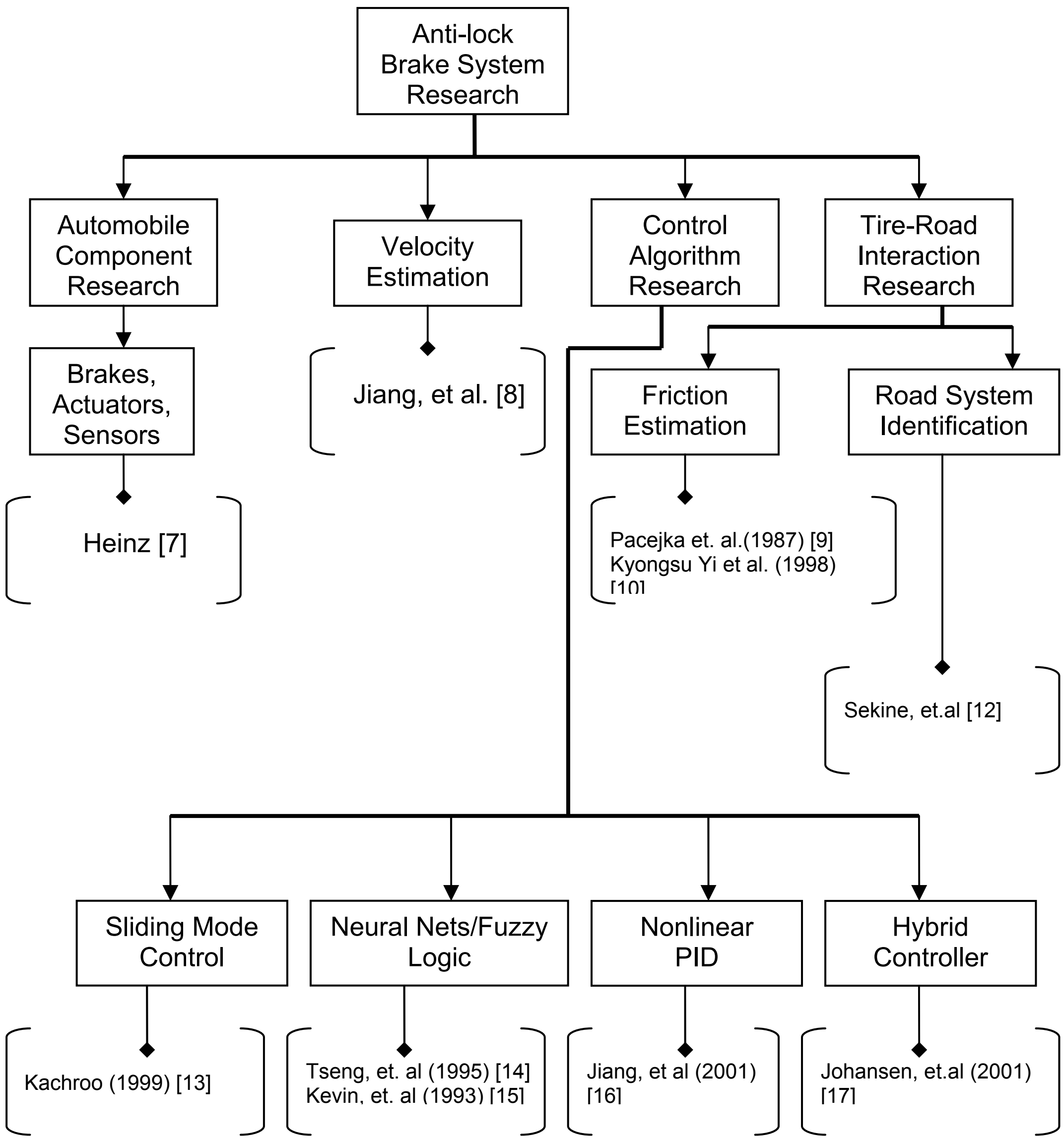


Figure 1.6 Sampling of ABS Research

ABS control is a highly nonlinear control problem due to the complicated relationship between friction and slip (figure 1.3). Another impediment in this control problem is that the linear velocity of the wheel is not directly measurable and it has to be estimated. Friction between the road and tire is also not readily measurable or might need complicated sensors. Researchers have employed various control approaches to tackle this problem. A sampling of the research done is shown in the above figure (figure 1.6). One of technology that has been applied in the various aspects of ABS control is soft computing. The following paragraph gives a brief idea of soft computing and how it is employed in ABS control.

Soft Computing - Introduction

Physical systems described by multiple variables and multiple parameter models having nonlinear behavior, frequently occur in the fields of physics, engineering, technical applications and other sciences. The conventional approaches for understanding and predicting the behavior of such systems based on analytical techniques can prove to be very difficult, even at the initial stages of establishing an appropriate mathematical model. The computational environment used in such an analytical approach is perhaps too inflexible in order to cope with the intricacy and the complexity of the real world physical systems. It turns out that in dealing with such systems, one has to face a high degree of uncertainty and tolerate imprecision. Trying to increase precision can be very costly.

Prof. Lotfi A. Zadeh created in 1965 a separate field of computational environment when he came up with his “fuzzy set” concept [18] to deal with uncertainty and imprecision which is common to real world physical systems. This ushered in a new field of computing - “soft computing”. Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, partial truth, and approximation. In effect, the role model for soft computing is the human mind. The guiding principle of soft computing is: Exploit the tolerance for imprecision, uncertainty, partial truth, and approximation to achieve tractability, robustness and low solution cost [19].

At this juncture, the principal constituents of Soft Computing are Fuzzy Logic, Neural Computing, Evolutionary Computation and Probabilistic Reasoning, with the latter subsuming belief networks, chaos theory and parts of learning theory. The principal contribution of fuzzy logic relates to its provision of a foundation for approximate reasoning, while neural network theory provides an effective methodology for learning from examples, evolutionary computation uses natural evolution principles and probabilistic reasoning systems furnish computationally effective techniques for representing and propagating probabilities and beliefs in complex inference networks.

The soft computing tools are complimentary in nature. In many cases a problem is solved most effectively by using the soft computing tools in combination rather than exclusively. Soft computing techniques have found wide acceptance in intelligent control systems and mechatronics [20, 21]. Some of the applications include industrial process control, machine vision, consumer appliances, automotive, etc. Soft computing represents a significant paradigm shift in the objective of computing - a shift which reflects the fact that the human mind, unlike present day computers, possesses a remarkable ability to store and process information which is pervasively imprecise and uncertain. (For more information, look at references [20, 21]).

Soft computing tools like fuzzy logic and neural networks have been used to tackle the ABS control problem. The layout (figure 1.7) shows a sampling of the research done in this area.

Thesis Overview

Now that a brief introduction of some of the main concepts in the research work has been made, we will take a look at the upcoming chapters in this thesis.

Chapter 1, which is the introductory chapter briefly described the dynamics of antilock braking, modules in the antilock brake system, provides a brief look at the research into antilock brake system and soft computing, and summarizes where soft computing is employed in ABS systems.

Chapter 2 focuses on the soft computing tools used in the controller of an antilock brake system, and sets up the objective for this thesis. It discusses the merits and shortcomings of using such tools in controllers for antilock brake systems. It also compares other conventional controllers to soft computing controllers and attempts to draw an advantage for the soft computing controllers. It also looks at the scalability issues when implementing a soft computing controller on a scaled vehicle.

Chapter 3 briefly goes over the development of a model for the antilock brake system for the test vehicle. It also explains how the fuzzy controller is developed using built-in Simulink tools. Results from the simulation for the model are also detailed.

Chapter 4 explains the experimental setup for testing the controller. It also explains the architecture employed to achieve real time control. Some of the results from the experimentation are outlined.

Chapter 5 concludes the thesis by discussing the results and drawing meaningful conclusions from the research conducted. It presents some suggestions for future work and discusses the merits and shortcoming of this work.

Thesis Contribution/ Focus

The research work done as part of this thesis focuses primarily on the controller aspect of ABS control. Given the complicated nature of ABS control, most conventional controllers are optimized to operate under standard test conditions. The performance degrades on adverse road conditions [15]. An adaptive fuzzy logic based controller is developed to adapt to changes in road conditions. It is implemented on a 1/5th scale model vehicle which has been instrumented for ABS control. The platform used for implementation is a real time engine. The implementation on a scaled model vehicle provides a platform for investigating scalability issues in using soft computing tools in antilock brake systems. The thesis also provides an overview of soft computing technology and how it finds application in ABS control.

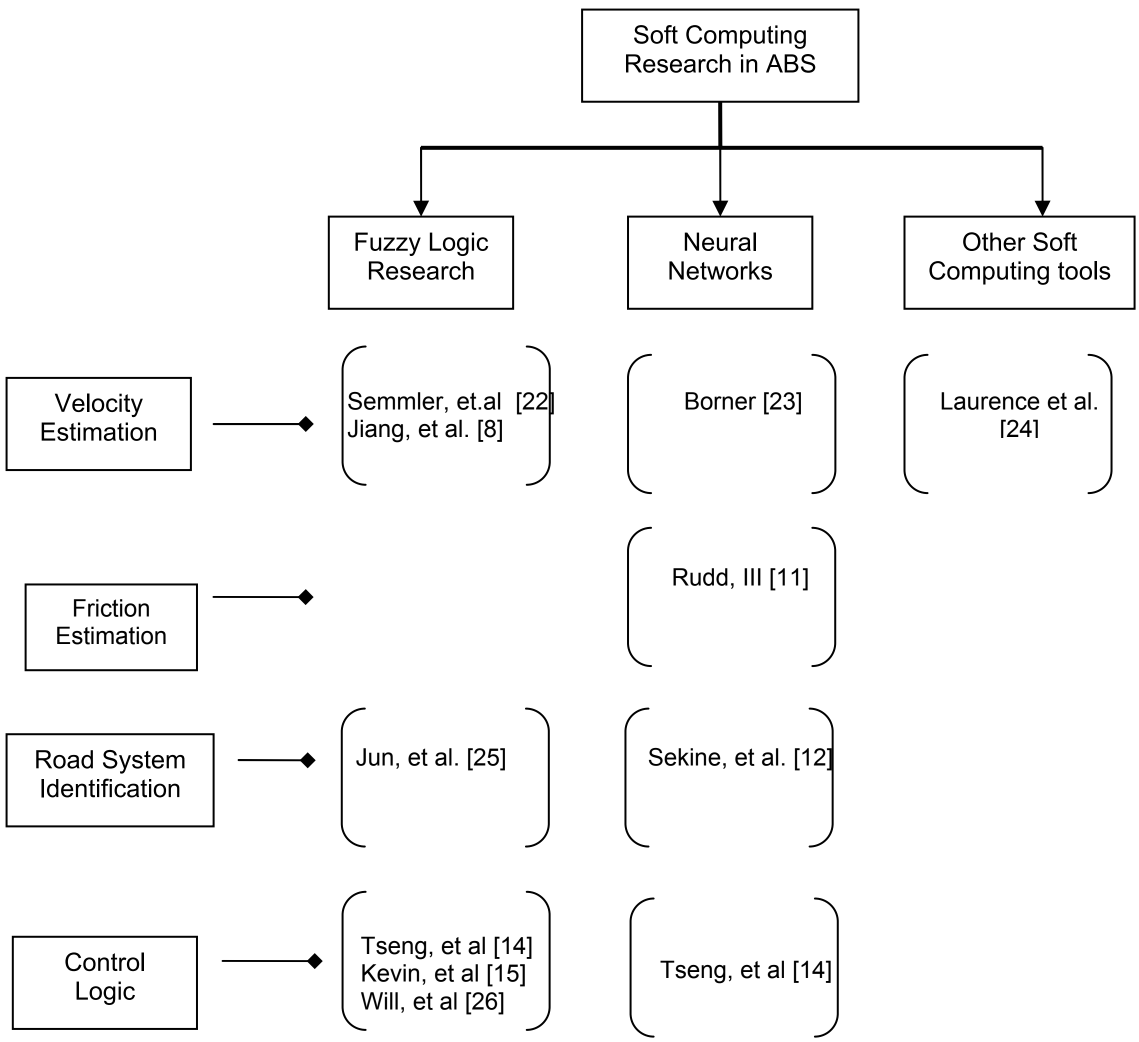


Figure 1.7 Soft Computing Research in ABS

Chapter 2: Soft Computing in ABS

Introduction

As mentioned in the introductory chapter, the antilock brake system controllers have to cope with the complex nature of control dealing with imprecision and uncertainty. ABS controllers are optimized for performance on standard test conditions and due to the nonlinear characteristics of the system's behavior; its performance degrades on adverse road conditions. Hence it has to adapt to the changes in road conditions. This chapter explores the soft computing tools especially fuzzy logic and its utility in solving this adaptability issue.

The motivation for the research stems from the fact that the adaptability issues have been tackled in theory (simulation) using soft computing tools, but there is little or no open literature that deals with the actual implementation. The research is also motivated with the development of scaled test platform which helps investigate the scalability issues while implementing a fuzzy logic adaptive ABS controller.

Adaptability Issues – Fuzzy Logic Approach

Now as mentioned in the introductory chapter, soft computing tools like fuzzy logic, neural networks and genetic algorithms have been employed to tackle complexity in a broad range of real world physical systems. The physical system of focus in the research is the antilock brake system where soft computing tools have found use (as in figure 1.7). The components in a typical antilock brake system are shown in figure 2.1. It shows the components or the information required by the

ABS controller to adapt to changes in surface conditions. As shown, it requires information on the friction characteristics of the road surface. Now there are theoretical and experimental methods available to measure friction between a tire and a particular road surface. To be able provide precise information on the frictional characteristics, the method or algorithm requires complicated and costly sensors. Alternatively friction could be estimated based on the wheel speed data [10]. The other possible methods are to look at the tire models and estimate friction based on the tire dynamics [9].

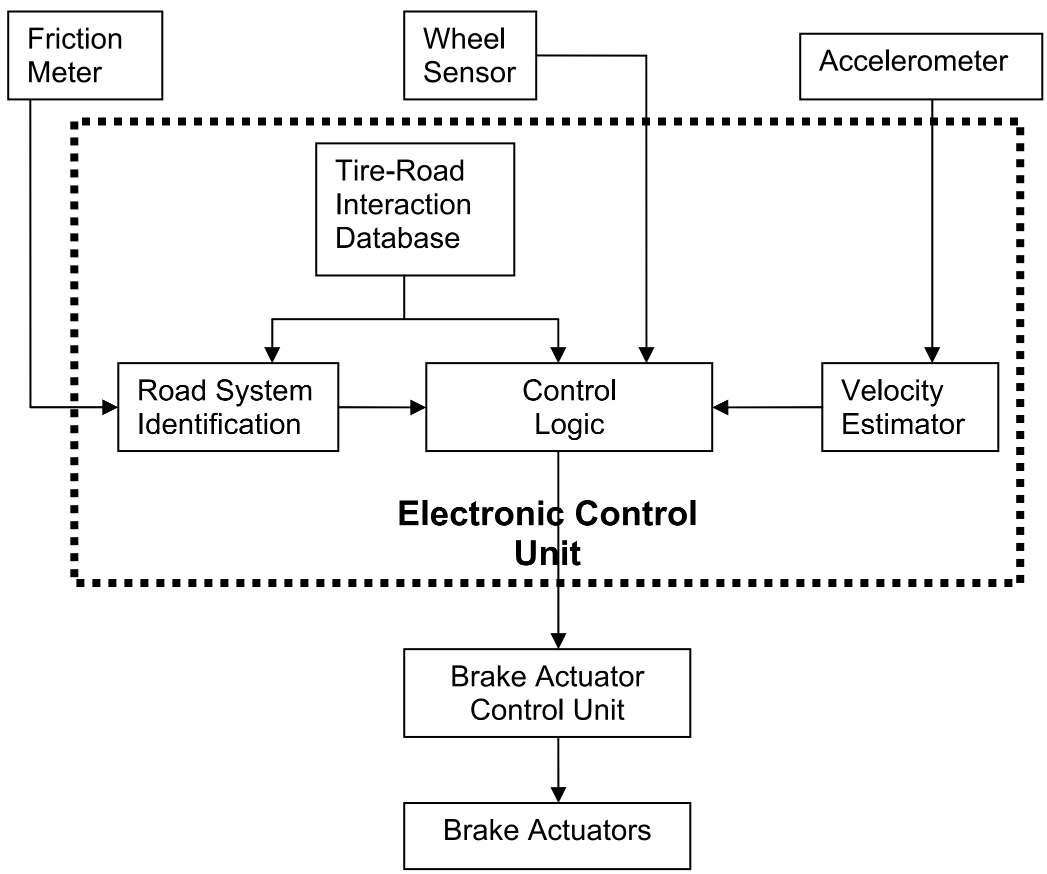


Figure 2.1 Components essential to tackle adaptability in an ABS system

The other variable that is crucial for the antilock brake controller is the vehicle speed. Now, typically there is no direct measurement of the linear vehicle speed possible. It has to be estimated from wheel speed data [8] or an accelerometer is used to measure the deceleration and then the deceleration time history is numerically integrated over time to get velocity [27]. With this data/information, the control unit with a road surface identification system applies the appropriate brake torque to adapt to road surface variations. Now this process as evident requires some complicated and costly sensors to get the precise information that could be used by the control unit to apply the appropriate brake torque. To be precise and certain, it is expensive.

Fuzzy logic on the other hand inadvertently deals with the imprecision and uncertainty to bring about optimal control. Before the advent of antilock brake system in cars, humans did encounter situations during emergency braking where they had to achieve controllability. The manual approach there was to pump the brakes during an emergency situation rather than flooring the brake pedal. The frequency and the magnitude of the pumping action were determined by the human driver based on the sensory feedback the human body received during the emergency braking.

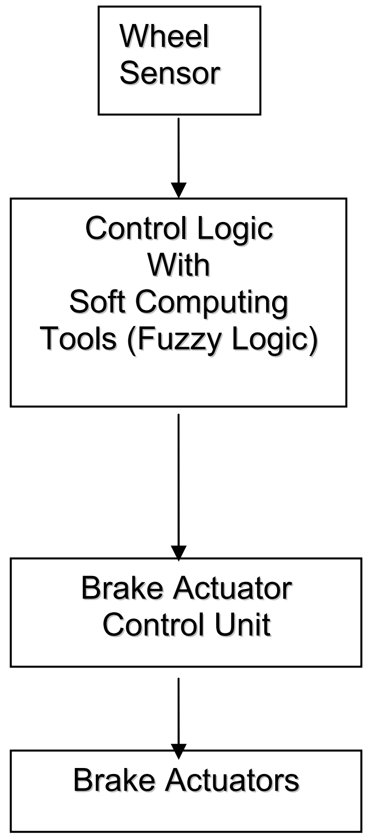


Figure 2.2 Simplified Fuzzy Logic ABS System

Now in the fuzzy logic approach, we take this human knowledge or rather the art by which a human controls the brake during an emergency situation and convert them into "if –then" rules in a computational environment. The complete knowledge of the control process can be deciphered into "if-then" rules which form the back bone for a fuzzy logic based controller. Now the information required by this fuzzy logic based controller is just the wheel speed data. As shown in figure 2.2, the complexity involving the sensors in an antilock brake system is greatly reduced by embedding the knowledge into fuzzy "if-then" rules. This is one of the prime motivations for using soft computing tools especially fuzzy logic in a control situation like ABS.

Before we divulge into the rest of the chapter, we will take a look at the fuzzy logic process itself. The fuzzy logic approach has three main components to it.

1. Receiving of one, or a large number, of measurement or other assessment of conditions existing in some system we wish to analyze or control in fuzzy form– **Fuzzification**
2. Processing all these inputs according to human based, fuzzy "If-Then" rules, which can be expressed in plain language words, in combination with traditional non-fuzzy processing – **Fuzzy "if-then" rules**
3. Averaging and weighting the resulting outputs from all the individual rules into one single output decision or signal which decides what to do or tells a controlled system what to do. The output signal eventually arrived at is a precise appearing, defuzzified, "crisp" value – **Defuzzification** [28]

The following figure describes the components in a fuzzy logic system and also shows the interaction with the physical realm.

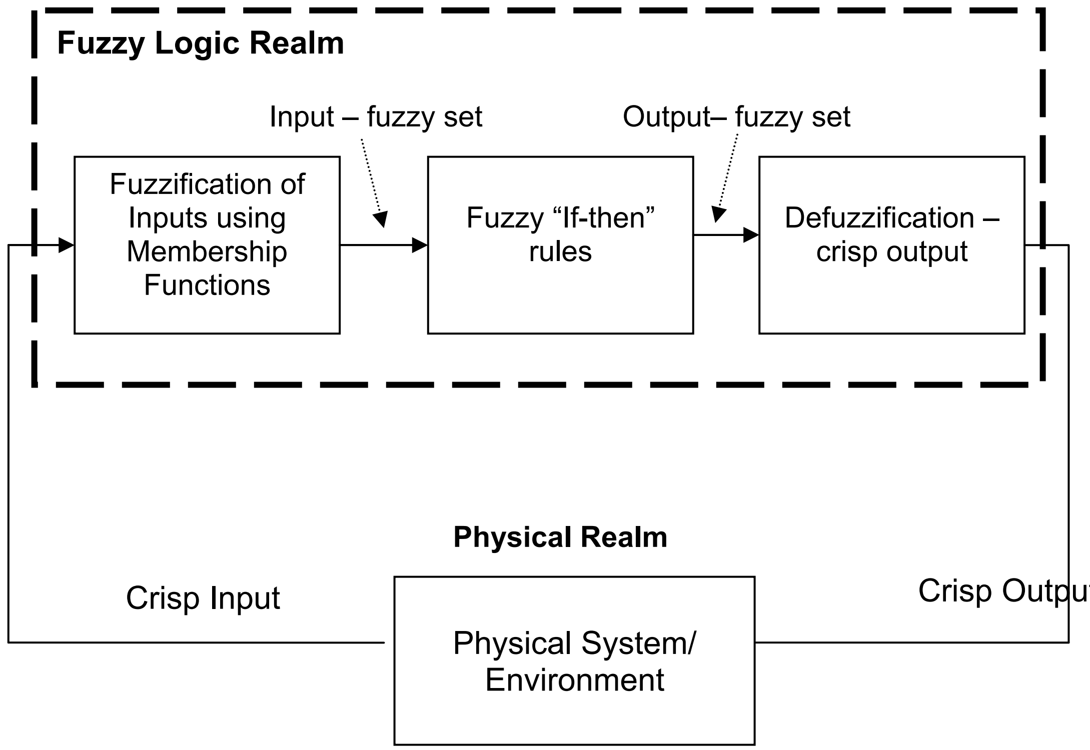


Figure 2.3 Fuzzy Logic System – interaction with the Physical Realm

In our case, the crisp input would be the wheel speed and the crisp output would be the brake torque. The components "fuzzification, fuzzy 'if-then' rules and defuzzification" together form the fuzzy logic controller for the antilock brake systems. Thus we see how fuzzy logic finds its use in the antilock brake systems. The adaptability issue is tackled by employing two fuzzy "if-then" rule sets, which will be discussed in the next chapter. The fuzzy logic controller along with a model of the vehicle is simulated under different road conditions to verify that the fuzzy logic controller indeed can be used to adapt to variations in surface conditions. The results of such a simulation are outlined in the next chapter.

Implementation and Scalability Issues

The other motivating factor in the research was to look at the implementation of the adaptive fuzzy logic controller on a vehicle. The adaptive fuzzy logic controller mentioned here is an ABS fuzzy logic controller based on fuzzy “if-then” rules which adapts to variations in surface conditions. Though there have been theoretical studies conducted in addressing the problem of adaptability of an ABS controller using fuzzy logic [14, 15, 26], no implementation of the proposed theoretical studies have appeared in open literature. It could be very well assumed that vehicle manufacturers and ABS component manufacturers (e.g. Bosch) might have internally used fuzzy logic to practically implement an adaptive fuzzy logic ABS controller without publishing the details. Implementation of a simple (non adaptive) fuzzy logic ABS controller has been attempted as in [29].

Now the question arises “why haven’t the adaptive fuzzy logic controllers based on the theoretical studies [14, 15 and 26] not been implemented?” There might be quite a number of reasons for this. One might be the non- availability of a test vehicle and test bed. The other reason might be the difficulty in converting complicated adaptive fuzzy logic controller models into code to be used in a microcontroller for control. The research work as part of the thesis attempts to implement an adaptive fuzzy logic controller on a scaled vehicle. The attempt is motivated based on two facts. One is the availability of a scaled test platform with a fully instrumented test vehicle and real time controller [30]. The other fact is the environment for developing the adaptive fuzzy controller and the ease in converting it into code for use in a real-time controller.

The test platform is as shown in figure 2.4. The main components are the test track, instrumented test vehicle and the real-time controller. The test track is made up of wooden platforms fitted together to provide a ramp and a flat bed for testing purposes. The test vehicle is a 1/5th scale radio control vehicle made by FG Modellsport. The instrumentation on the radio control vehicle included rotary encoders for the front right and left wheel and also for the rear axle. The front encoders give the wheel speed necessary for the controller. The encoder on the rear axle gives a speed value which is assumed to give the vehicle speed, since brakes are not applied on rear wheels. The brakes for the vehicle on the front wheels are cable actuated brake systems. The cables are actuated individually by servo motors which receive brake signals from the controller. The real-time controller is a National Instruments RT® engine with necessary data acquisition and control boards. More details on the test platform are given by Al-Sharif [30] and also found in the "experimentation" chapter.

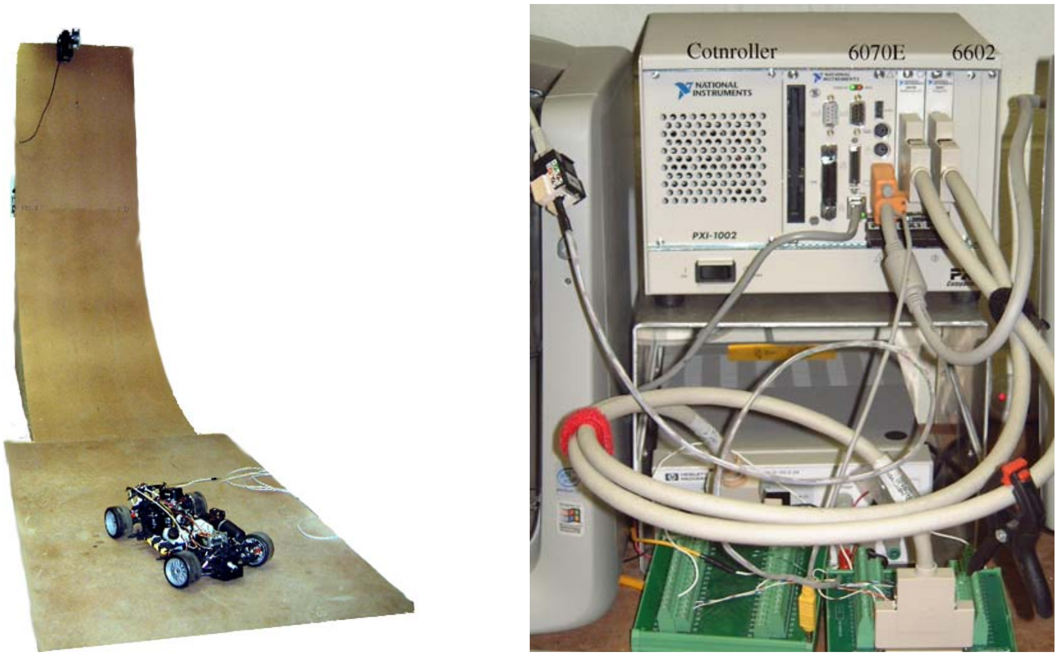


Figure 2.4 Test Platform – Test Track, Test Vehicle and Real-Time Controller [30]

The programming environment used for developing the fuzzy logic controller model is the MATLAB ® environment. The fuzzy logic toolbox and Simulink are used to develop an adaptive fuzzy ABS model and to simulate it under different road conditions. Once the fuzzy logic controller is developed and test under the simulated environment, it is then exported to a form where it could be implemented in real physical environment. The platform used for the physical environment is the graphical programming environment – LabVIEW Real Time. The Simulink Interface Toolkit is used from National Instruments to convert the Simulink model into a virtual instrument (VI), which is a subprogram in LabVIEW. Once the model is converted into a VI, it is used with other data acquisition and control VIs to run ABS tests. The following figure (figure 2.5) shows the interaction between the simulation environment and the physical environment.

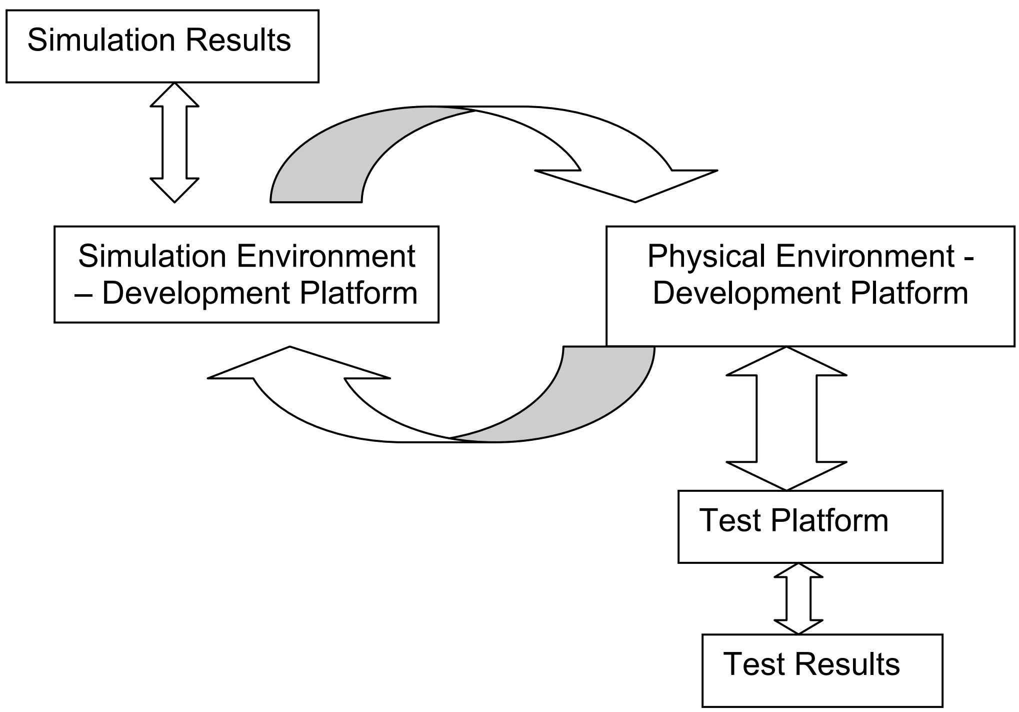


Figure 2.5 Block Representation – Interaction between the Simulation and Physical Environment

A more detailed block representation of the development platforms are shown below (Figure 2.6)

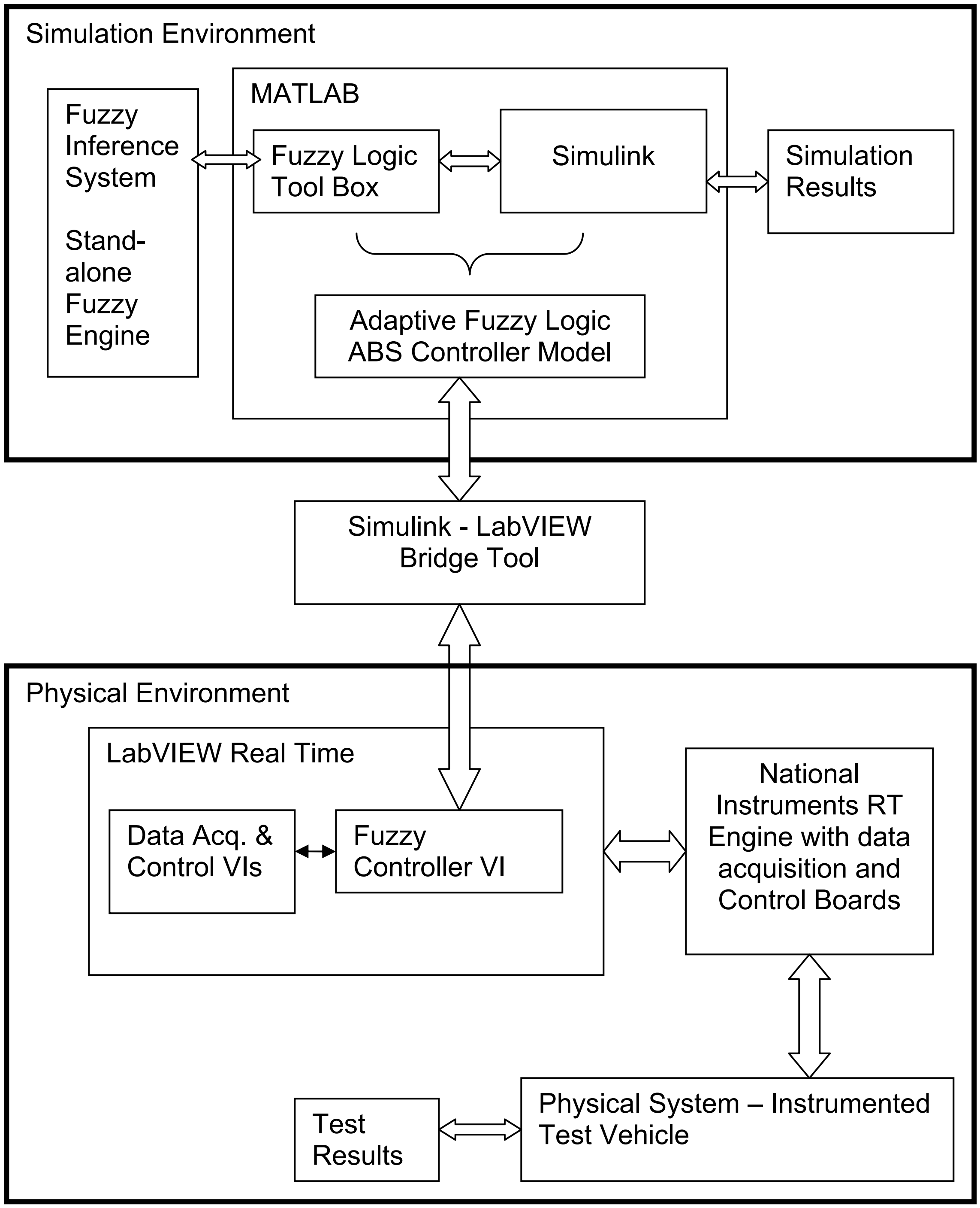


Figure 2.6 Detailed Block Representation – Interaction between Simulation and Physical Environment

Thus we see that an adaptive fuzzy logic ABS controller model developed in a virtual environment can be ported with minor modifications into a physical environment where it is tested and evaluated. This implementation strategy provides the basis for the virtual prototyping of an adaptive fuzzy logic controller.

The scaled test environment provides an ideal platform in the design of the fuzzy logic algorithms. During the design process, fuzzy logic algorithms are tuned to get the optimal rules and parameters. The implementation provides a platform to tune the rules and parameters in the physical environment on a scaled vehicle. Once these rules and parameters are tuned, they can be ported back into the simulation environment where the fuzzy logic controller can be tested on full scale vehicle models. This underscores the importance of using a scaled vehicle platform in design and testing of fuzzy logic controllers.

On the other hand, the fuzzy logic controllers can be tuned in the simulation environment with a scaled model or a full scale model and then ported back to the implementation platform where they are tested on the scaled vehicle. The consistency of the results would indicate that this method of using a scaled test platform in the design process of the fuzzy logic controller is robust. The following figure shows the two approaches in the design of the fuzzy logic controller and how the scaled test platform helps in the design process.

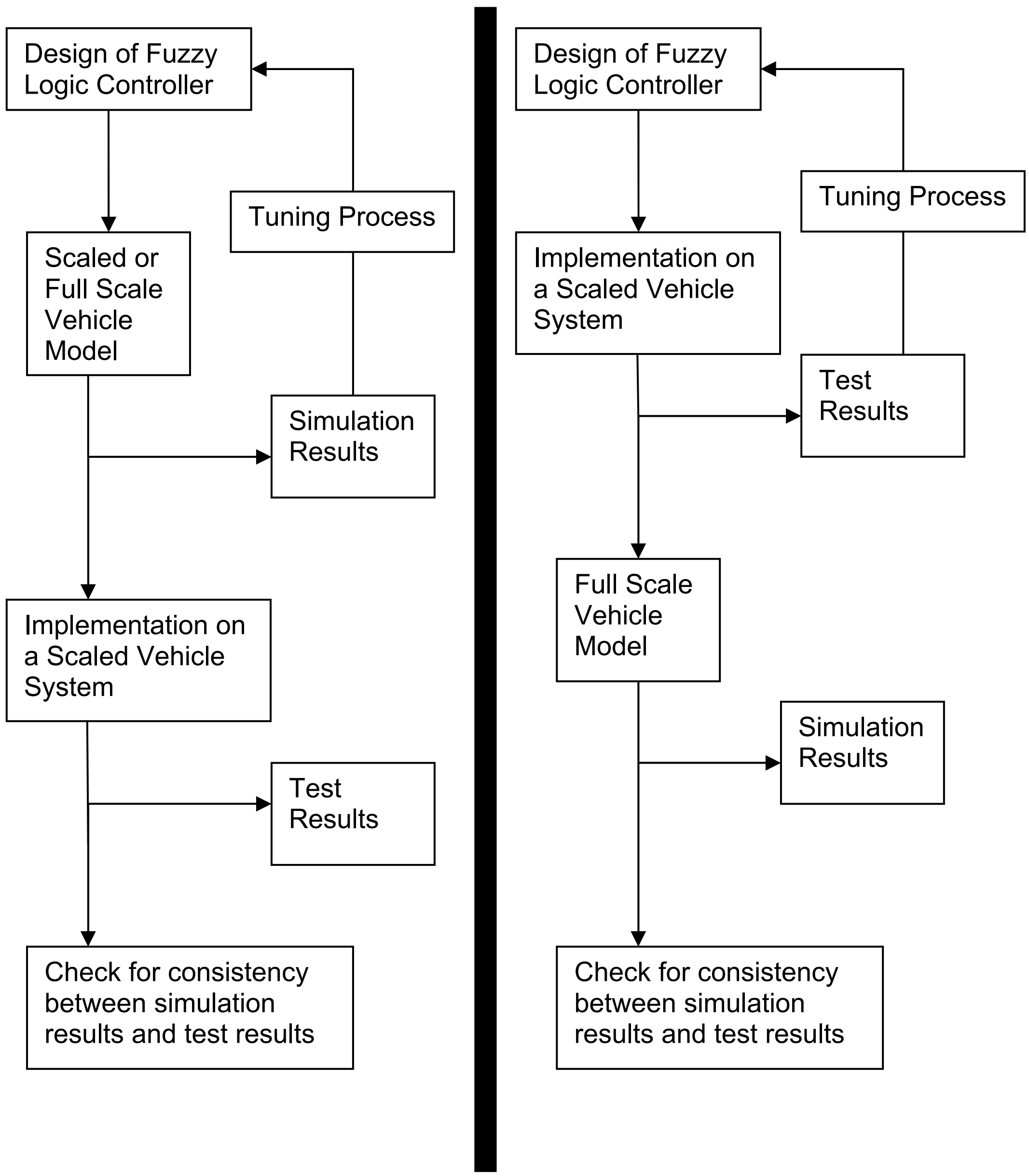


Figure 2.7 Design Approaches for Fuzzy Logic Controller

In this research work, the first approach is taken up ideally because in the simulation environment it is more convenient to change the vehicle models from full scale to $1/5^{th}$ scale model and also convenient to change the road surface profile these vehicles encounter. The design of the fuzzy logic controller is done with the $1/5^{th}$ scale model in the simulation environment. The model and simulation results are discussed in the next chapter. Once the fuzzy logic controller is tuned, it is implemented on the $1/5^{th}$ scale vehicle and experiments are conducted. The details of the experiments and corresponding results are discussed in the "experimentation" chapter. The correlation between the experiment results and the simulation results are also discussed.

Summary

Thus this chapter briefly explained the motivation for the research work undertaken as part of this thesis. It drew the reason for using fuzzy logic for the adaptive ABS control and also explained the implementation strategy using a scaled test platform.

Chapter 3: Fuzzy Model and Simulation

Introduction

The "Fuzzy Model and Simulation" chapter briefly explains the steps involved in the construction of the fuzzy logic ABS controller. The process is usually referred to as fuzzy modeling. Once the fuzzy logic ABS controller is constructed, it is then verified with a vehicle model. In the research work, the fuzzy logic ABS controller was first simulated using a longitudinal model, later it was simulated with vehicle model of 1/5th scale vehicle. The process of verification with the vehicle model involves tuning the fuzzy logic controller to find the optimal parameters and rules. The simulation results from the simulation runs with the two vehicle models are also discussed. Different road surfaces were used to verify the adaptability nature of the fuzzy logic ABS controller. The vehicle (brake system in particular) simulation is also done with some standard controllers to compare the results with the fuzzy logic ABS controller.

Fuzzy Modeling

The fuzzy logic process was explained in brief in the previous chapter. Here we will try to go a little further to help us understand the construction of a fuzzy logic ABS controller. In the literature different names like fuzzy rule based system, fuzzy inference system, fuzzy expert system, fuzzy model, fuzzy associative memory, fuzzy logic controller or simply fuzzy systems are given to systems where concepts of fuzzy logic are applied.

As described in the previous chapter, there are three main components (fuzzifier, “if-then rules” and defuzzifier) in a fuzzy logic system. These three components together are sometime referred to as the fuzzy inference system (FIS). It is a computing framework based on the concepts of fuzzy sets theory, fuzzy “if-then” rules and fuzzy reasoning. The fuzzy inference system attempts to implement a nonlinear mapping of the inputs and outputs. This mapping is accomplished by a number of fuzzy “if-then” rules, each of which describes the local behavior of the mapping.

Fuzzy Sets and Membership Functions [21]

If X is a collection of objects denoted generically by x, then a fuzzy set A in X is defined as a set of ordered pairs:

$$A = \{(x, \mu_A(x)) \mid x \text{ in } X\}$$

$\mu_A(x)$ is called the membership function (MF) of x in A. The membership function maps each element of X to a value in the continuous range (0,1).

The definition of the fuzzy set is an extension of the classical set in which the characteristics function is permitted to have continuous values between 0 and 1. If the value of the membership function $\mu_A(x)$ is restricted to either 0 or 1, then A would be reduced to a classical set and $\mu_A(x)$ would be the characteristic function of A. As in classical set, the fuzzy set also has operations (like Union, Intersection, Complement) and the operators are referred to as fuzzy operators.

There are various classes of the membership functions (parameterized functions), which play an important role in fuzzy systems. Some of them are triangular MF, trapezoidal MF, gaussian MF, bell MF, sigmoidal MF, etc. Membership functions can be either one-dimensional or two-dimensional depending upon the application. The membership functions are shown in figure 3.1.

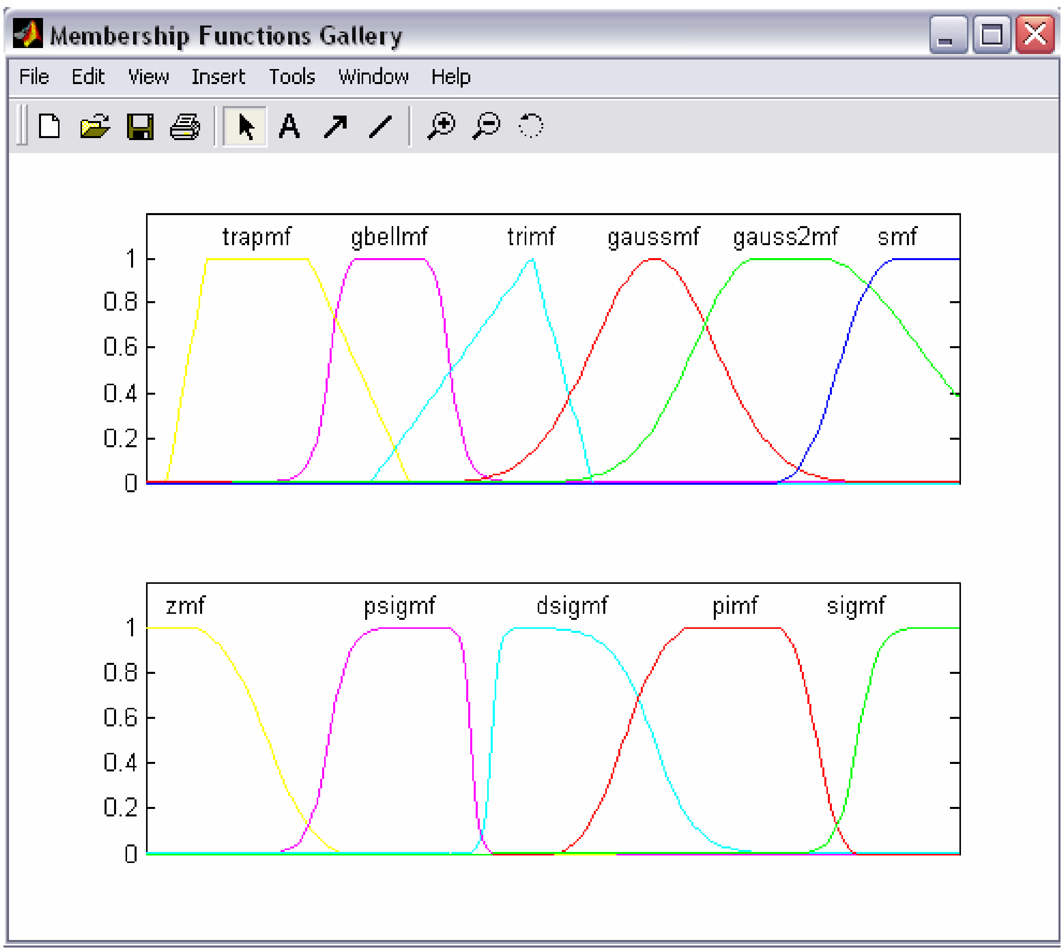


Figure 3.1 Different Membership Functions from MathWorks

Fuzzy "if-then" rules

A fuzzy "if-then" rule (or fuzzy rule, fuzzy implication, fuzzy conditional statement) assumes the form

If x is A then y is B;

where A and B are linguistic values defined by fuzzy sets on the universes of discourse X and Y, respectively. The "x is A" is referred to as antecedent or premise, while "y is B" is referred to as the consequence or conclusion.

Ex: if pressure is high then volume is small

Fuzzy Reasoning

Fuzzy reasoning also called as approximate reasoning is an inference procedure used to derive conclusions from a set of fuzzy "if-then" rules and one or more conditions. There two approaches in fuzzy reasoning are the "max-min composition" and the "max-product composition". Let us take a look at some example fuzzy "if-then" rules to understand the two approaches.

Ex: If 'service' is poor AND 'food' is rancid THEN 'tip' = cheap.
If 'service' is poor OR 'food' is moderate THEN 'tip' = moderate

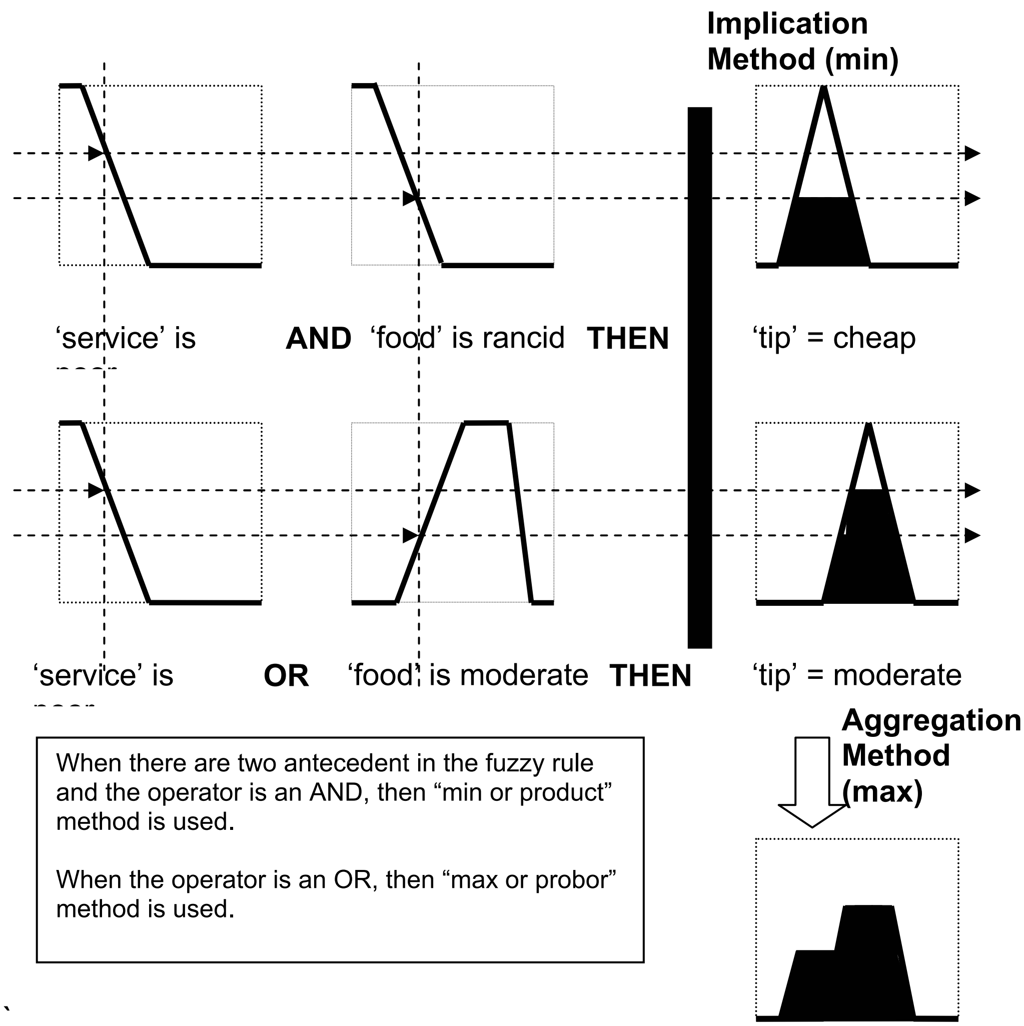


Figure 3.2 Example for fuzzy reasoning approaches

When the implication method is 'min' and the aggregation method is 'max', the fuzzy reasoning approach is called 'max-min approach'. On the other hand if the implication method is 'prod', then the approach is called 'max-prod approach'. When the "min" (minimum) function is used for the implication method, it truncates the output fuzzy set and when the "prod" (product) function is used, it scales the output fuzzy set. The following reference [21] gives more information on these fundamental concepts (fuzzy sets, membership functions, fuzzy rules, fuzzy reasoning, etc).

Fuzzy Inference System

The fuzzy inference system utilizes the above mentioned fuzzy logic concepts while implementing a nonlinear mapping of the inputs and outputs. The construction of the fuzzy inference system is referred to as fuzzy modeling. Conceptually, fuzzy modeling can be pursued in two stages [21]. The two stages being

- identification of surface structure; loosely trying to structure the knowledge available on the target system (process to control), taking advantage of the domain knowledge
- identification of a deep structure; refining the surface structure with help of numerical data or tuning process to get to the optimal parameters

The first stage includes the following tasks:

1. Selecting relevant input and output variables
2. Choose a specific type of fuzzy inference system model
3. Determine the number of linguistic terms associated with each input and output variables.
4. Design a collection of fuzzy "if-then" rules.

There are three most common types of fuzzy inference systems. The main difference between the three approaches is the way in which a crisp values is defuzzified from the given set of fuzzy rules and weights for each rule. The three types are

1. Mamdani fuzzy inference model
2. Sugeno fuzzy inference model
3. Tsukamoto fuzzy inference model

More details on these three fuzzy inference models and its characteristics are given in reference [21]. For the construction of the fuzzy logic ABS controller we will use the mamdani fuzzy inference model.

The identification of the deep structure, which is the second stage in the fuzzy modeling process outlined in [21] has the following tasks.

1. Choose an appropriate family of parameterized membership functions
2. Determine the parameters of the membership functions used in the rule base
3. Refine the parameters of the membership function using optimization techniques.

The second stage in the fuzzy modeling process explains the process of selection of the membership functions and its parameters. The parameters are refined by tuning the fuzzy model. The tuning is done with the help of simulations with the vehicle models. Though the two stages outline what is involved in the fuzzy modeling process, each development environments have their unique steps in constructing the fuzzy model. The following paragraphs explain the steps in constructing the fuzzy inference system in the MATLAB environment.

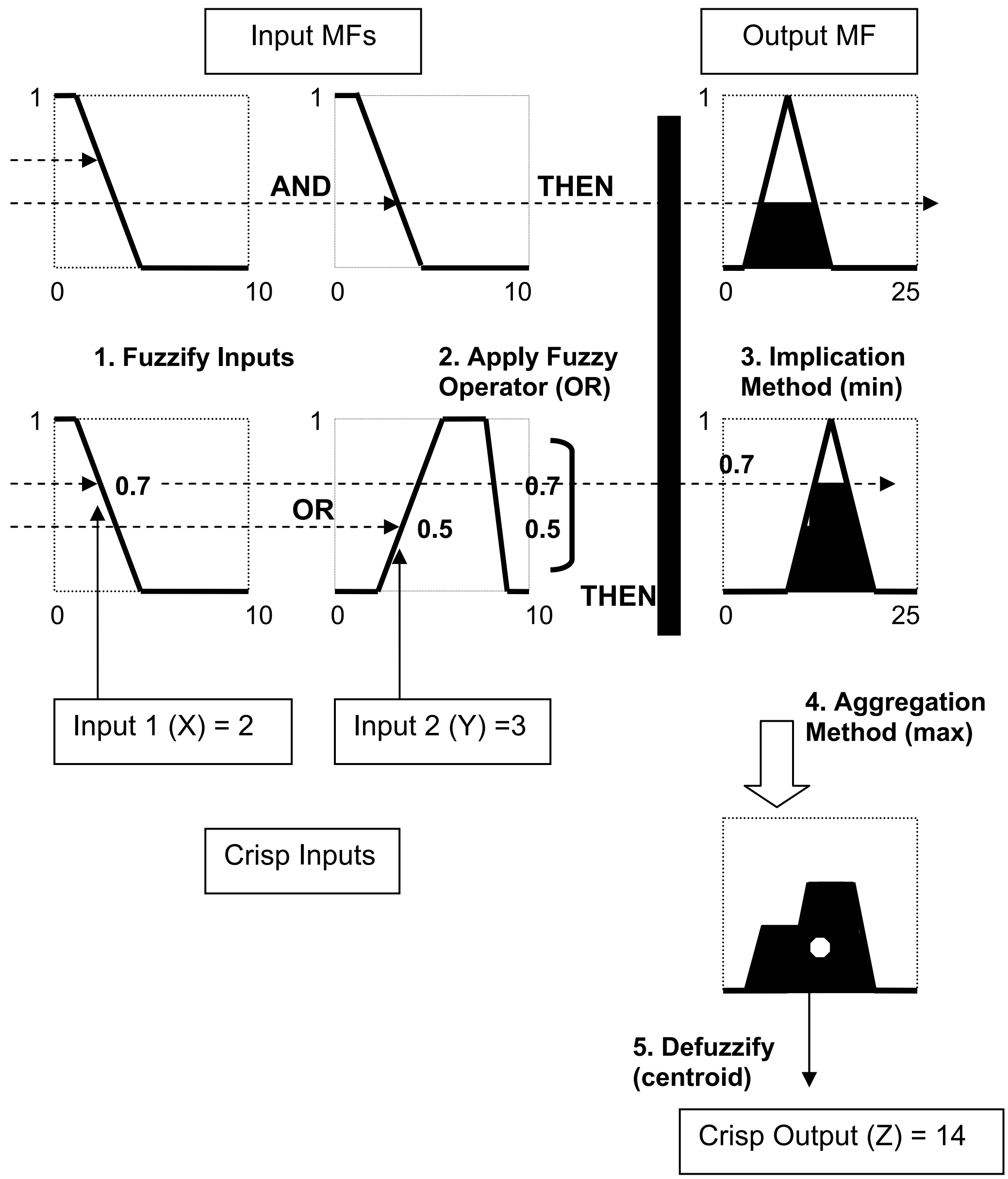


Figure 3.3 Block Representation – steps in construction of fuzzy inference system [31]

The above figure shows the steps involved in the construction of the fuzzy inference system in the MATLAB environment. The five steps involved are

1. Fuzzify Inputs:

   The first step involved in the processes is to convert the crisp inputs into fuzzy inputs by determining the degree to which they belong to each of the appropriate fuzzy sets via membership functions. The output of this process is the fuzzy degree of membership in the qualifying linguistic set (value between 0 and 1).

2. Apply Fuzzy Operator:

   Once the inputs are fuzzified, we know the degree to which each part of the antecedent of a fuzzy rule has been satisfied. If a given fuzzy rule has more than one antecedent, then the fuzzy operator (generally AND, OR) is applied to the membership values of the fuzzified input variables. At the end of this process we get a cumulative number which indicates the fuzzy degree of membership for that particular rule.

3. Apply Implication Method:

   Before applying the implication method of each of the fuzzy rule, the output from the previous step is scaled based on the weight of that particular rule. Typically the weights of the rules are 1, but at times to indicate the importance of one rule of the other, each rule might be given a different weight. A consequent in a fuzzy rule is a fuzzy set represented by a membership function. The consequent is reshaped using a function (usually a single number) associated with the antecedent in the implication process. The input for the implication process is the single number given by the antecedent, and the output is a fuzzy set. The two methods “min” and “prod” are supported for the implication process. The “min” (minimum) truncates the output fuzzy set, and the “prod” (product) scales the output fuzzy set.

4. Aggregate all outputs:

   Now we have output fuzzy sets (truncated or scaled) for each of the fuzzy rule in the fuzzy inference system. To make a decision we need to combines these fuzzy sets. This is process is referred to as aggregation. The input to the aggregation process is the individual output fuzzy sets, the output being a one fuzzy output set for each output variable. Since the aggregation process is cumulative, any of the following methods [max (maximum), sum and probor (probabilistic OR)] could be used.

5. Defuzzify:

   The input to this process is aggregate fuzzy set and the output is a single number for each output variable. The centroid, bisector, middle of maximum, largest of maximum and smallest of maximum could be used as defuzzification method.

The above figure gives an overall picture in the construction of fuzzy inference system. For more information the appropriate MATLAB functions and GUIs involved in the construction of the fuzzy inference system (FIS), please refer to the MATLAB Fuzzy Logic Toolkit Help Guide [31].

One Degree of Freedom (Longitudinal) Model

Now that we have sufficiently looked at the fuzzy logic concepts and steps involved in the construction of a fuzzy inference system in the MATLAB environment, let us focus on the vehicle models used to tune and verify the FIS. The first model taken up in the research work was the 'longitudinal model'. The reason being the longitudinal model in essences captures the dynamics of braking and is a good model to test the controller. Also as part of their example programs, MathWorks had included a simulation of a "bang-bang" ABS controller that works with the longitudinal model.

The bond graph methodology was used to model the physical system involved. The bond graph tool, an energy-based technique for modeling physical systems, was invented by Henry Paynter [32]. The modeling process is intuitive and the state equations can be deduced by looking at the bond graph [33]. The bond graph representation of the longitudinal model showing the dynamics of the brake system is shown in figure 3.4.

The longitudinal model is presented here to explain the dynamics of the tire during braking. The 'controller', which supplies the braking torque 'Tb', is modeled as a 'modulated resistor', which is being controlled, by the slip velocity and the type of tire-surface interaction so as to achieve the prime function of an anti-lock brake system. The ‘tire-surface interaction’ is also modeled as a ‘modulated resistor’, modulated based on surface friction (as function of slip velocity) shown in figure 3.5.

Bond Graph Representation of the Dynamics of Brake Systems

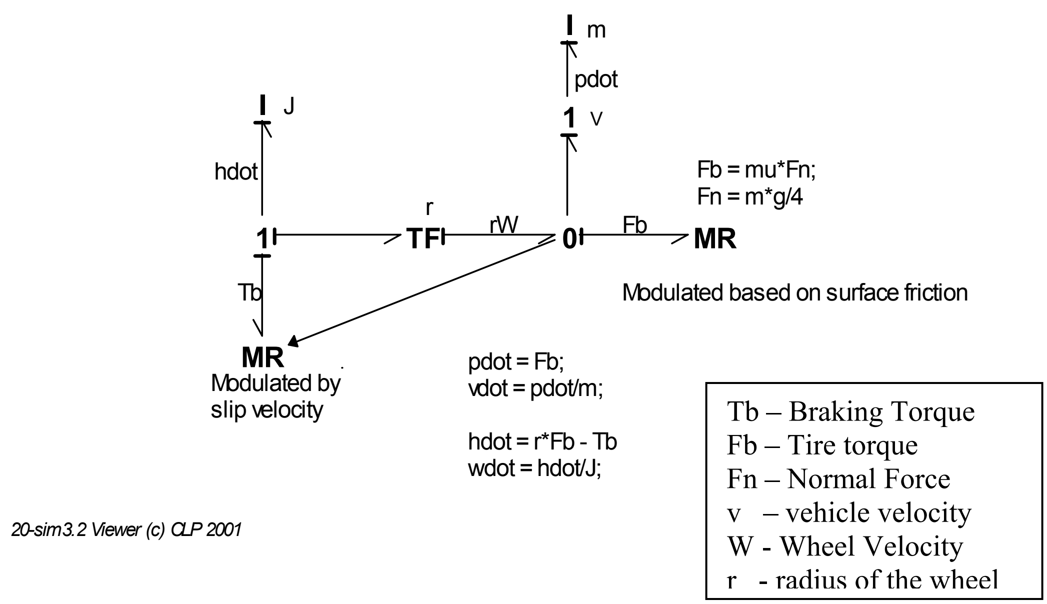


Figure 3.4 Bond Graph – Longitudinal Model (Dynamics of Braking)

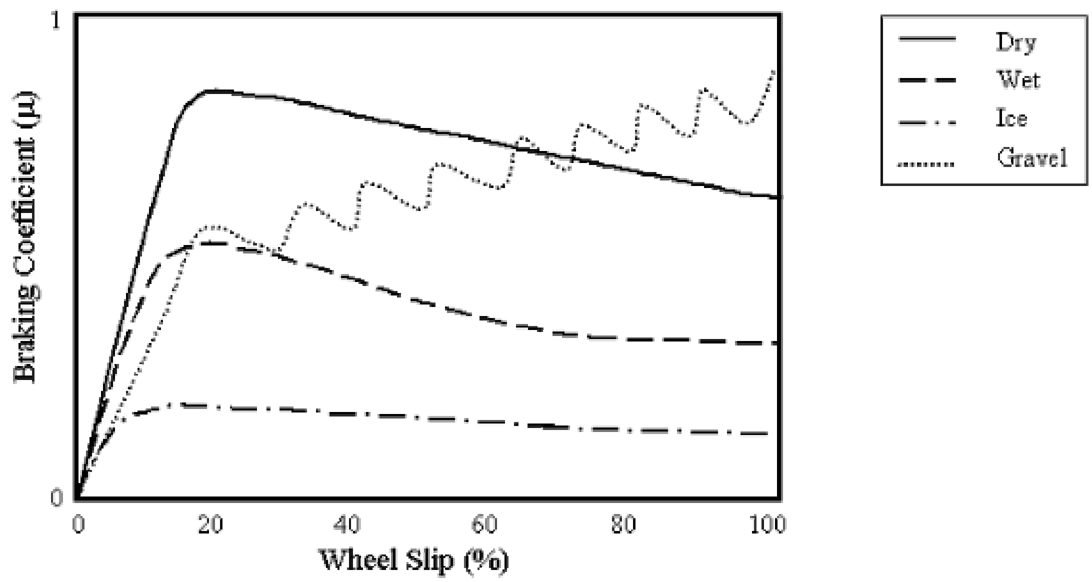


Figure 3.5 Representative graphs showing the friction- slip characteristics [34]

The following figure (figure 3.6) shows the block representation of the anti-lock brake system. The figure shows the interaction between the vehicle dynamics, wheel dynamics, tire-road surface dynamics and the controller. The controller would take in a slip value and the output of the controller is the braking torque which is applied to the wheel to bring the vehicle to a halt.

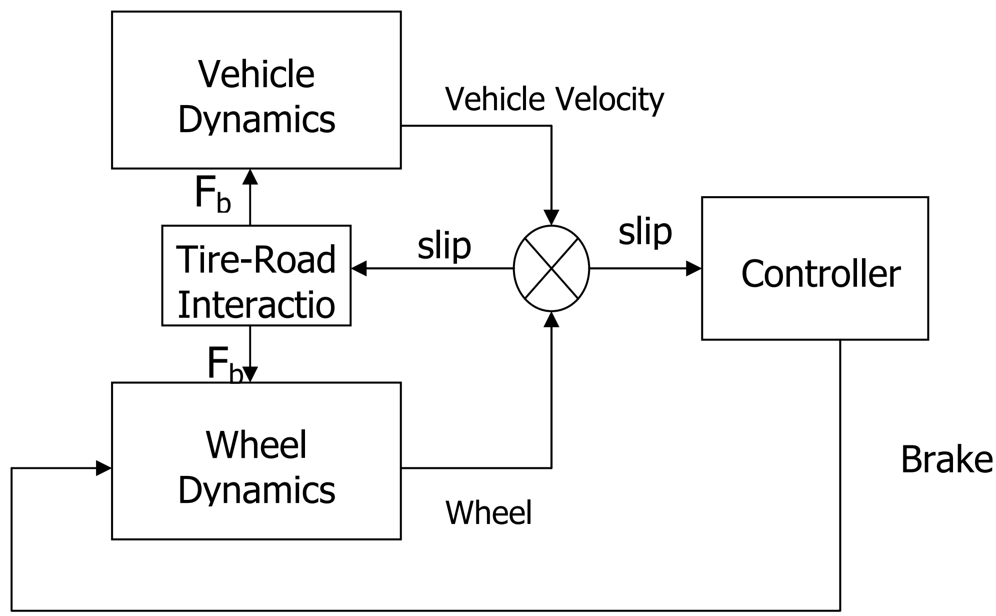


Figure 3.6 Block Representation showing the dynamics of an anti-lock brake system

Bang- Bang Controller

Before constructing the fuzzy logic controller to work with the longitudinal model, simulation runs were carried out with a bang-bang controller. The bang-bang controller is devised around the fact that the tire friction is high around the 20% slip value. The bang- bang controller is basically an “on/off” type controller, where the brake torque is applied when the slip value is off the target and vice versa. The simulation is performed in Simulink, a simulation toolbox in MATLAB. The following figure (figure 3.7) shows the Simulink block diagram for a bang-bang controller with the longitudinal model (developed by the MathWorks as a demo).

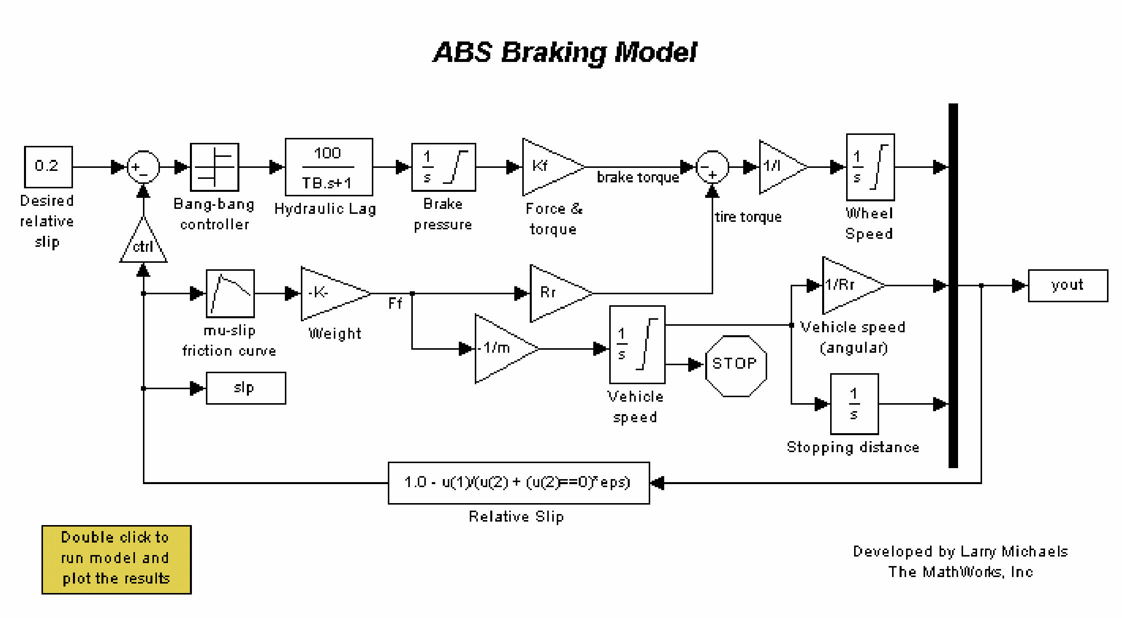


Figure 3.7 ABS Braking Model with bang-bang controller from MathWorks.

The simulation results for simulation run with dry concrete as the road surface profile (figure 3.8) are shown in figure 3.9.

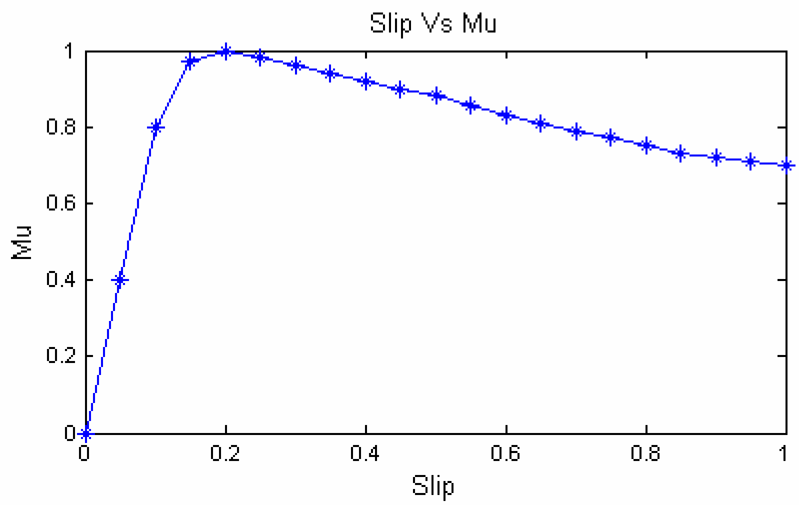
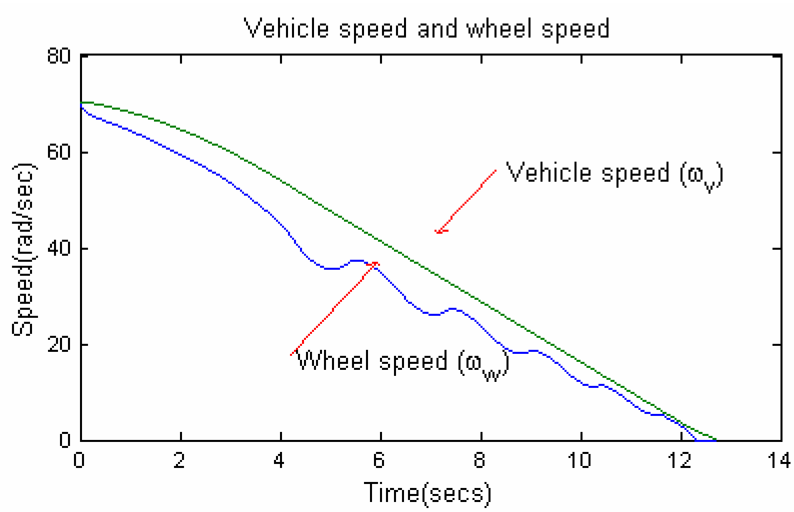
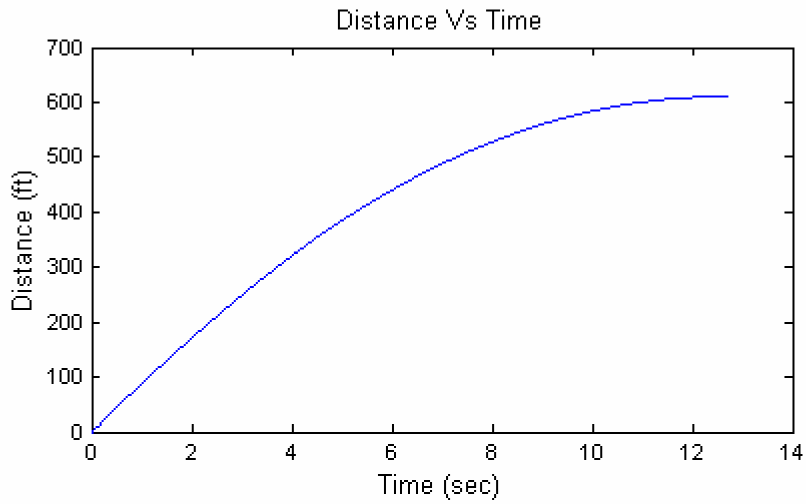


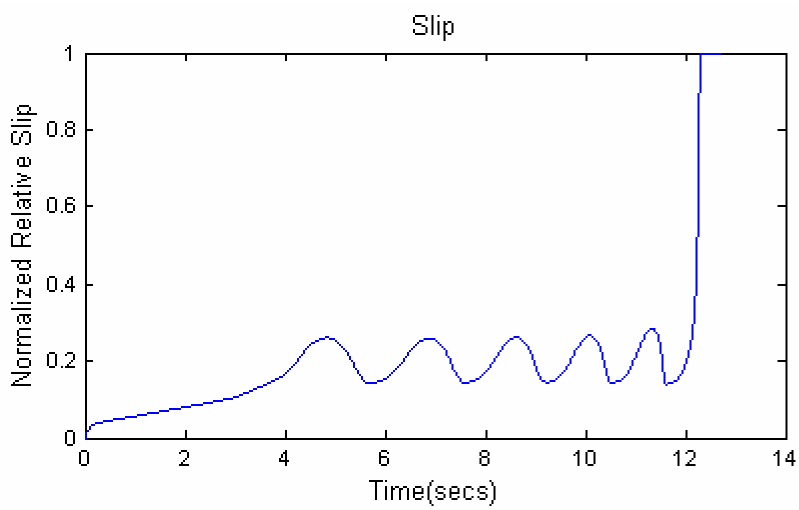
Figure 3.8 Representative Mu-Slip curve for dry concrete



(a)



(b)



(c)

Figure 3.9 Simulation Results for bang-bang controller

Fuzzy Logic Controller

One of the major objectives in the research work was to construct an adaptive fuzzy logic controller which could be implemented on a 1/5th scale model vehicle. The logical step towards that objective was to construct a fuzzy logic controller to work with a longitudinal model and run some simulations. The crisp input would be the slip value and the output from the fuzzy logic controller would be the brake torque. The following figure (figure 3.10) shows a Simulink block diagram for the ABS braking model with the fuzzy logic controller. The membership functions of the input and output variables, the fuzzy "if-then" rules, and the methods employed and the fuzzy surface associated with the fuzzy logic controller is shown in Appendix A [Fuzzy Logic Controller – Longitudinal Vehicle Model].

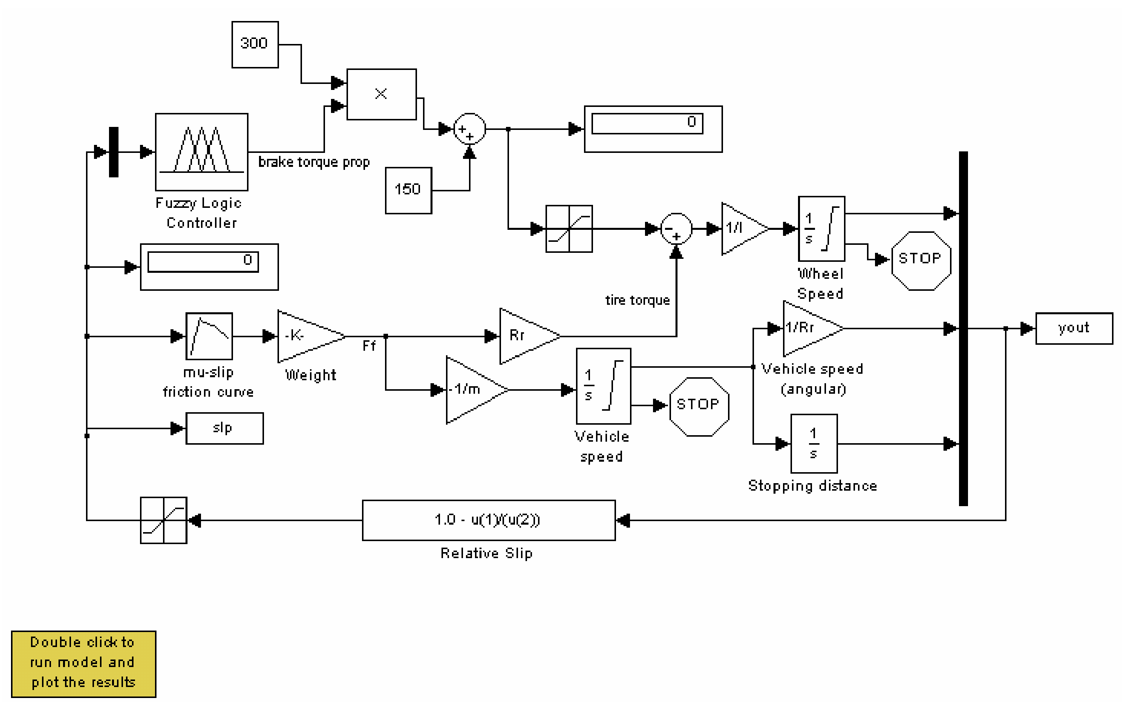
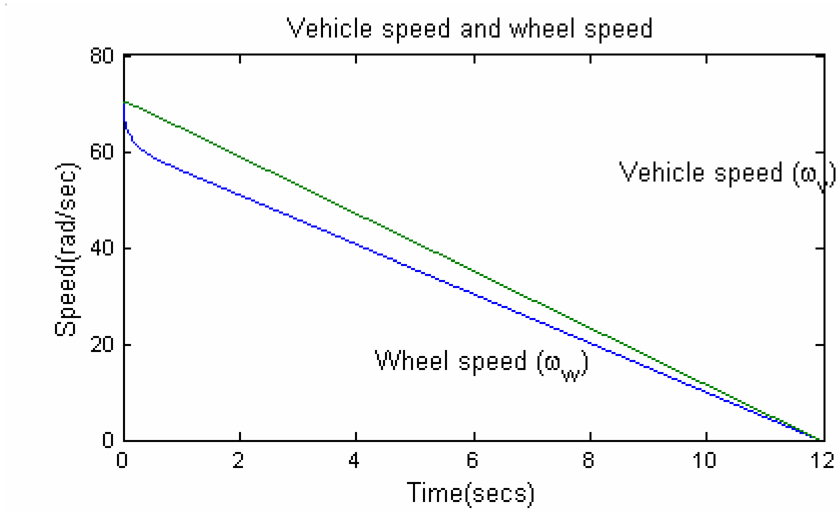
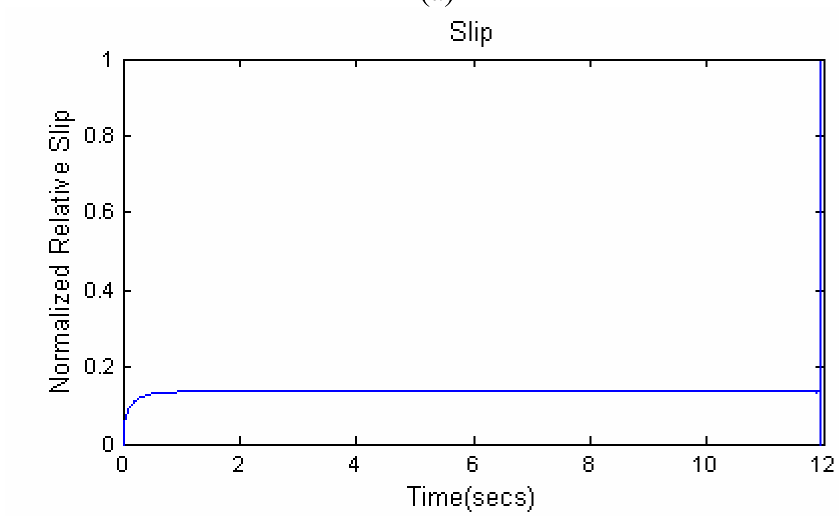
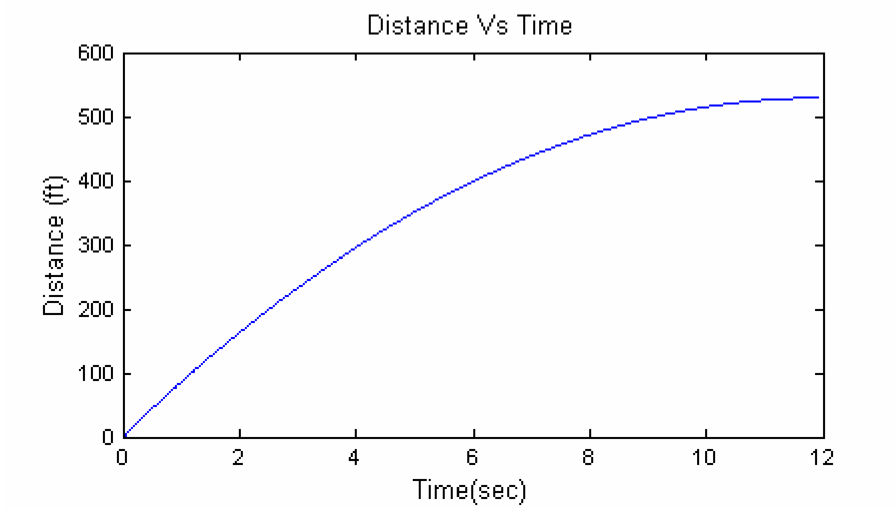


Figure 3.10 ABS Braking Model with fuzzy logic controller

The simulation results for simulation run with dry concrete as the road surface profile (figure 3.8) are shown in figure 3.11.


Vehicle speed and wheel speed
Speed(rad/sec)
Time(secs)
Vehicle speed (ω_v)
Wheel speed (ω_w)
0
20
40
60
80
0
2
4
6
8
10
12
(a)


Slip
Normalized Relative Slip
Time(secs)
0
0.2
0.4
0.6
0.8
1
0
2
4
6
8
10
12
(b)



(c)
Figure 3.11 Simulation Results for fuzzy logic controller

Comparison of the Controllers

There are two significant points to note from the simulation results. One is that the stopping distance is lower with a fuzzy logic controller than the bang-bang controller. The other being the wheel velocity is better controlled with the fuzzy logic controller. The variation in slip during the control process is minimal in the case of the fuzzy controller. This shows the fuzzy logic controller is ideally suited for the ABS systems, where better stopping distance and better controllability are its main aspects.

One of the other desirable features is that the fuzzy logic controller constructed adapt to different surface conditions. Now when the simulation was run with different road surfaces (like wet and ice), the fuzzy logic controller would not adapt directly, one had to manually tweak the parameters to make it work. The next step was to construct a nonlinear fuzzy logic controller with gain-scheduling which would work with different road surfaces. Now instead of making it work with the longitudinal model, it was decided to make it work with the 1/5th scale model vehicle (available for implementation), so once the fuzzy logic controller is constructed it could be ported to the real physical system.

1/5th Scale Vehicle Model

The base of the physical system for the 1/5th scale vehicle model and the longitudinal model is the same. Both the models deal with vehicle dynamics, wheel dynamics, tire-road surface dynamics and the controller dynamics. The physical components in each of these subsystems vary from one vehicle model to another. Modeling of the 1/5th scale vehicle with the vehicle dynamics, wheel dynamics, tire-road surface dynamics, the controller and the brake system dynamics was developed by Al-Sharif [30]. The model was verified to work with a bang-bang controller in that earlier research work. Hence the model was adapted here with a slight modification for testing the adaptive fuzzy logic controller. The Simulink block diagram for the complete model is as follows (figure 3.12).

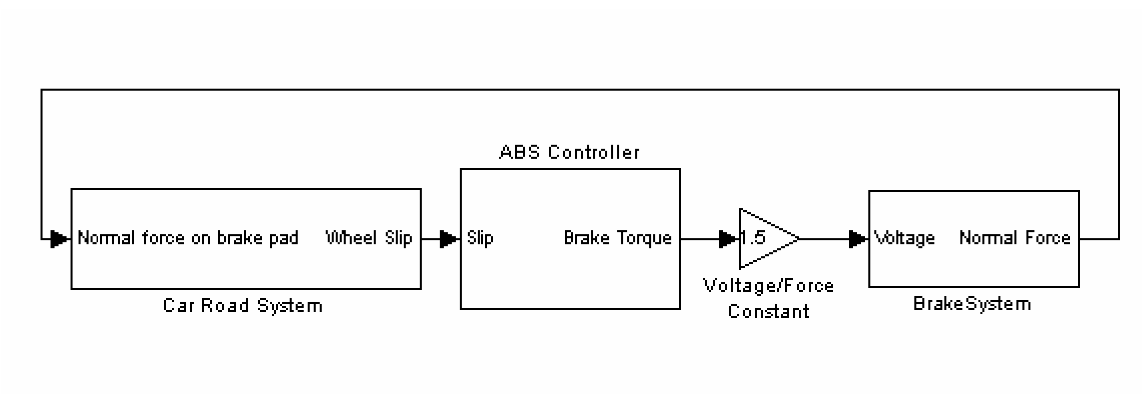


Figure 3.12 Complete Simulink Representation of 1/5th Vehicle Model

The modeling approach of the entire system was to divide it into three subsystems, the vehicle-road system, brake system and the controller. The vehicle-road system model, which deals with the vehicle dynamics, wheel dynamics and tire-road surface dynamics, is similar to the longitudinal model discussed earlier. The brake system models the caliper brake system found on the 1/5th scale vehicle. The controller model is basically a set of logic statements (bang-bang controller) or fuzzy “if-then” rules (fuzzy logic controller) that gives the required brake torque for an input slip value. As the focus is on the construction of the fuzzy logic controller, the individual subsystem bond graphs are not detailed here. More information on the individual subsystem bond graphs and the Simulink representations are described by Al-Sharif [30]. The complete bond graph of the ABS system is shown below (figure 3.13). The dotted line (information signals) which connects the vehicle-road system and the brake system represents the ABS controller.

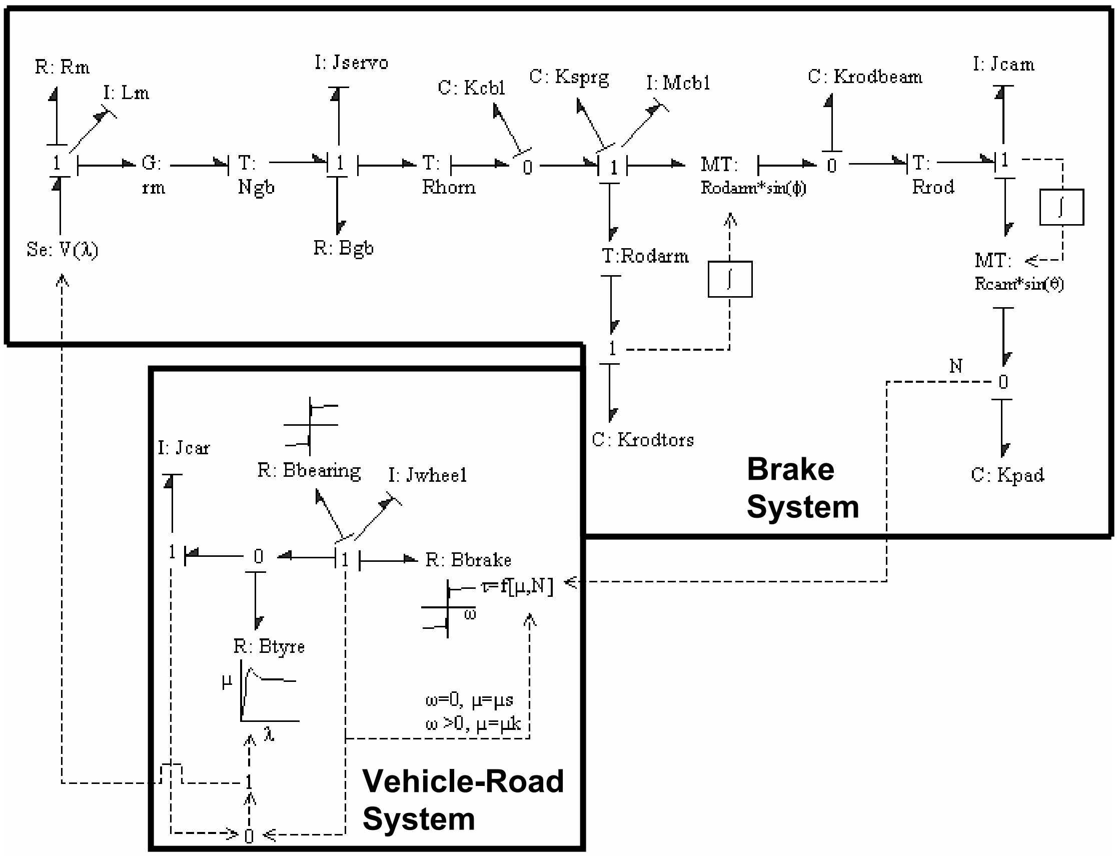


Figure 3.13 Bond graph representation - ABS braking system model for 1/5th scale vehicle

Bang-Bang Controller Design

The bang-bang controller for the 1/5th scale vehicle model follows the logic statements

If the wheel slip falls below a certain predetermined value, λ_{low}, the control system sends a signal to the brake system to apply the maximum brake force.

If the wheel slip goes above a predetermined value, λ_{high}, a signal to implement the minimum brake force is sent.

If the wheel slip is in the sweet spot region, the current signal is maintained to hold the current brake force setting.

The sweet spot region is the region between the λ_{low} and the λ_{high} values in the friction-slip characteristics curve. Ideally the bang-bang controller tries to control brake torque so that the slip value stays in the sweet spot region. The following figure (figure 3.14) shows the Simulink representation of the controller.

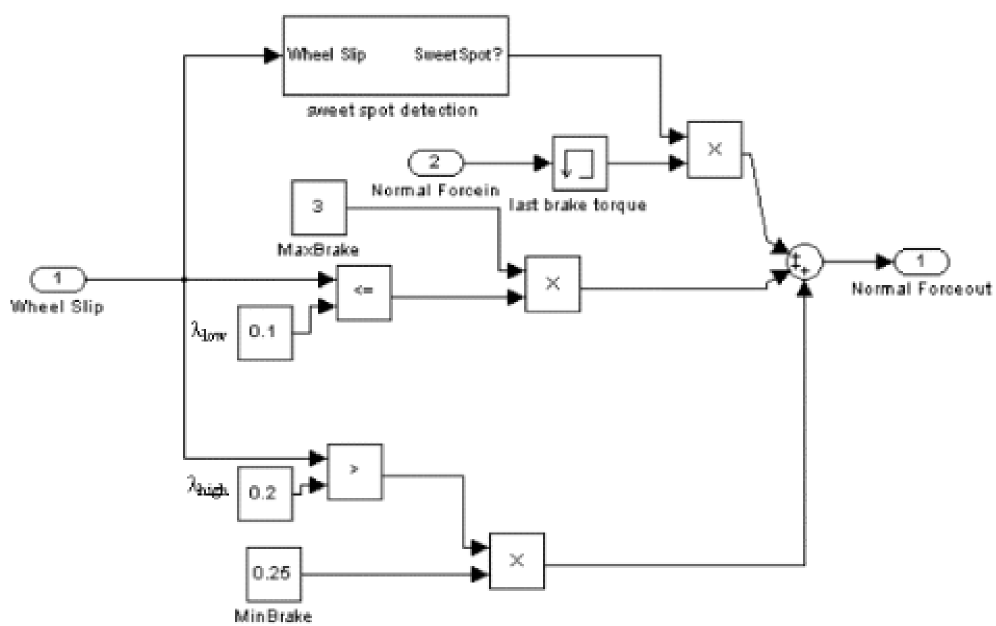


Figure 3.14 Simulink Model of Logic Used by Bang-Bang Controller [30]

Earlier we have looked at the simulation where only one road-surface profile was used in longitudinal model simulation. To verify the adaptability of the controller, we have to vary the road-surface profile during the simulation run. The bang-bang controller was tested with two different road surfaces in a single simulation run. For the first 3 sec of the simulation (t =< 3 sec), a representative mu-slip curve for ice was used and for the rest of the simulation (t > 3sec) the representative curve for dry concrete was used. A variable step stiff type solver (ode15s) was used for integration purposes in the simulation. The following figure (figure 3.15) shows the representative curves of the road-surface characteristics used for the simulation. The simulation results are also shown in figure 3.16.

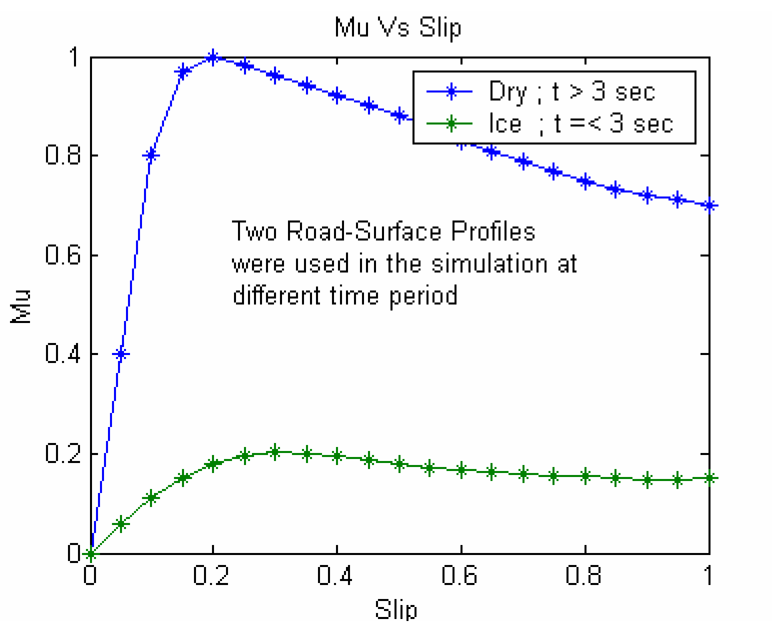
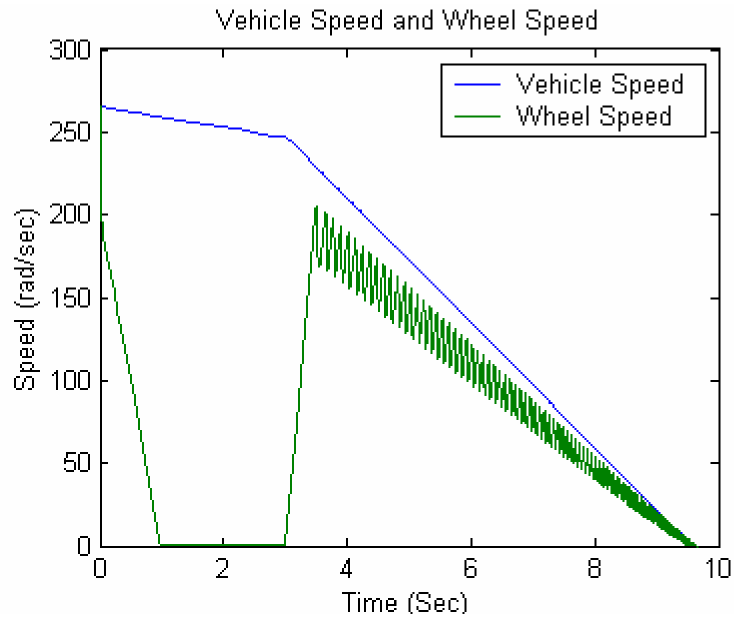
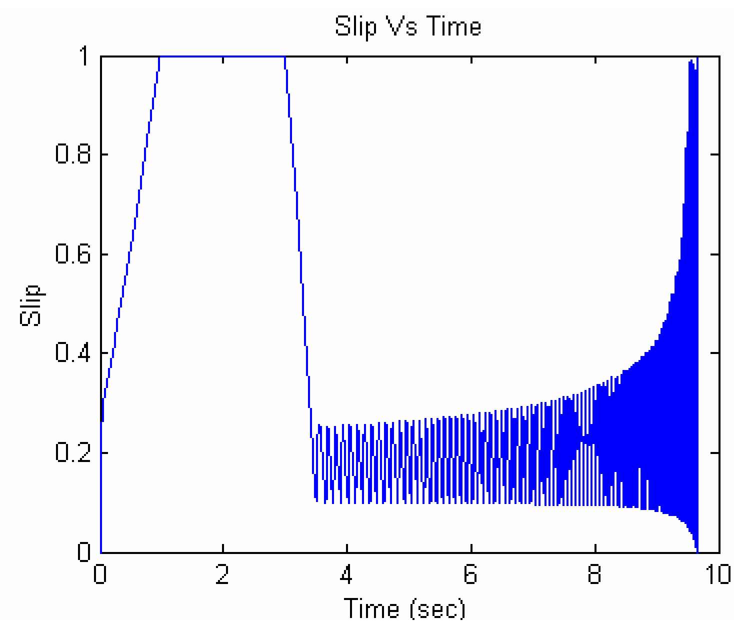


Figure 3.15 Representative mu-slip characteristic curves.



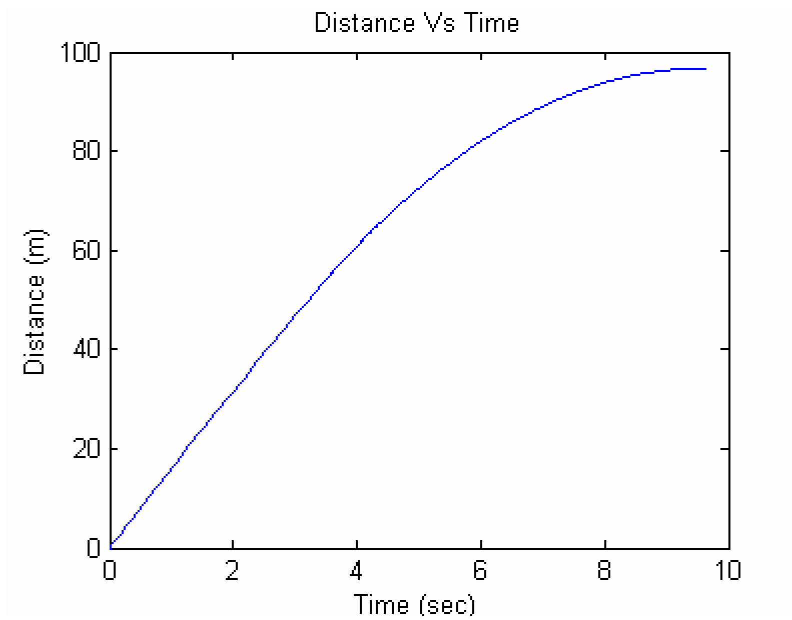
Vehicle Speed and Wheel Speed
Vehicle Speed
Wheel Speed
Speed (rad/sec)
Time (Sec)
300
250
200
150
100
50
0
0
2
4
6
8
10

(a)



Slip Vs Time
Slip
Time (sec)
1
0.8
0.6
0.4
0.2
0
0
2
4
6
8
10

(b)



(c)

Figure 3.16 Simulation Results –Bang-Bang controller

Nonlinear Fuzzy Logic Controller – 1/5th scale vehicle model

The earlier fuzzy logic controller used in the longitudinal model was not able to adapt to the different surfaces and the parameters were tweaked manually to make it work. In the construction of the nonlinear fuzzy logic controller for the 1/5th scale vehicle model, a new approach was used. In the earlier approach, the fuzzy logic controller looked only at the slip values and the output was the gain constant which would be multiplied by a weight term (constant) and a bias (constant) would be added to that output. This approach would shift the brake torque based on the weight and the bias terms. In the new approach, it was decided to look at not just the current slip value but also at the previous slip value. The information on the previous states would in essence convey what is happening when a certain brake torque is applied.

The approach was to look at two different fuzzy logic controllers or rather two different fuzzy inference systems with different “if-then” rules and input/ output variables so that the manual tweaking of the bias and weight terms (of the previous fuzzy controller) can be replaced by a FIS. The two FIS devised are the “gain fuzzy controller” and the “proportional derivative (PD) fuzzy controller”. The gain fuzzy controller is similar to the one used with the longitudinal model. It looks at the current slip values to give an output which will essentially tell the system whether or not to increase or decrease the output brake torque. The proportional derivative fuzzy controller looks at two inputs; one is the current slip value and the other is the difference in the current and previous slip values. The output of the PD fuzzy controller is a constant which proportionate the gain constant based on the fuzzy “if-then” rules. Both these fuzzy controller in tandem provide the nonlinear nature required for the ABS controller to adapt to the different road surfaces. The membership functions of the input and output variables, the fuzzy “if-then” rules, and the methods employed and the fuzzy surface associated with these fuzzy logic controllers are shown in Appendix B [Fuzzy Logic Controller – 1/5th scale vehicle model]. The following figure shows the Simulink representation of the nonlinear fuzzy controller.

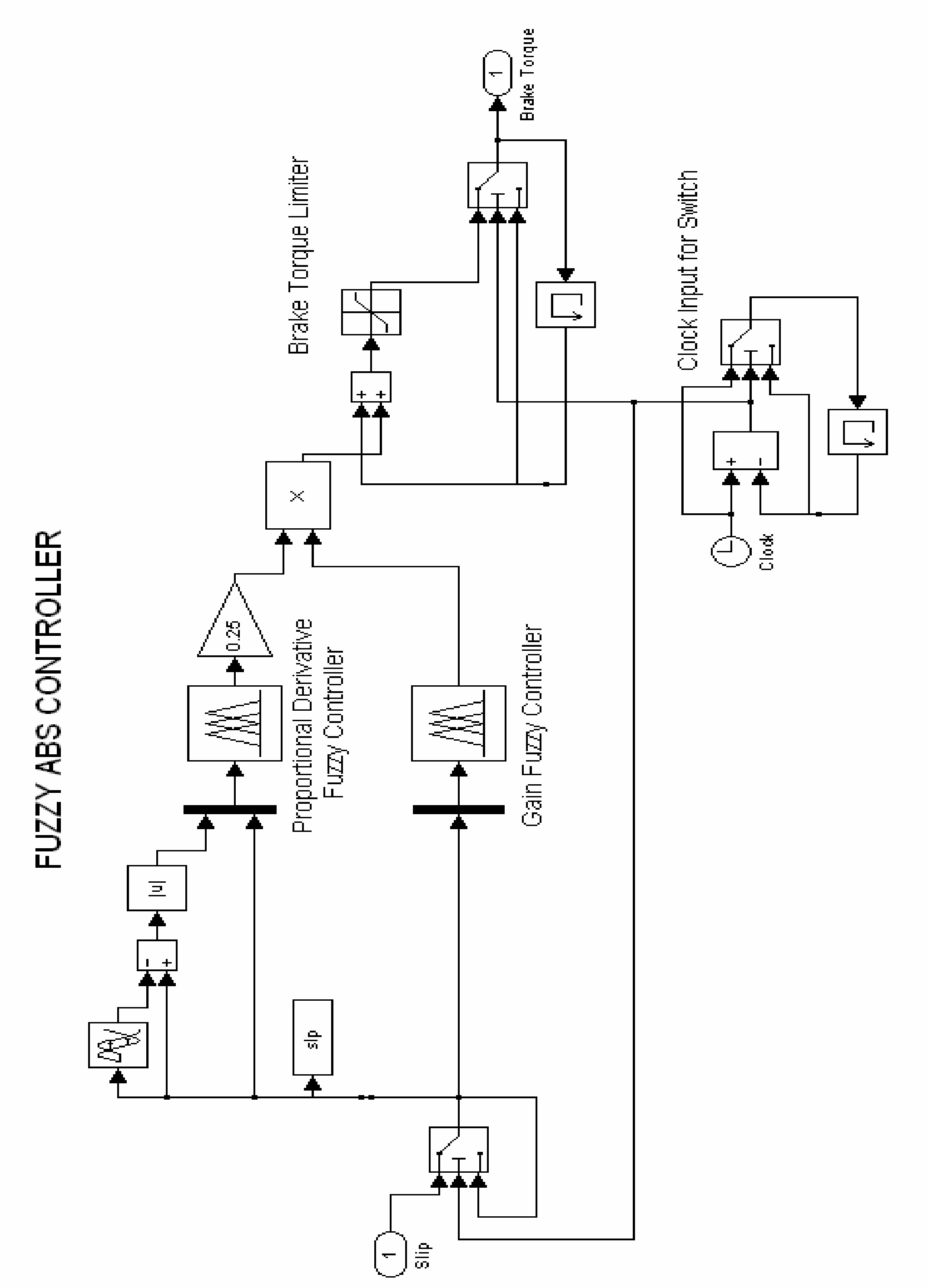
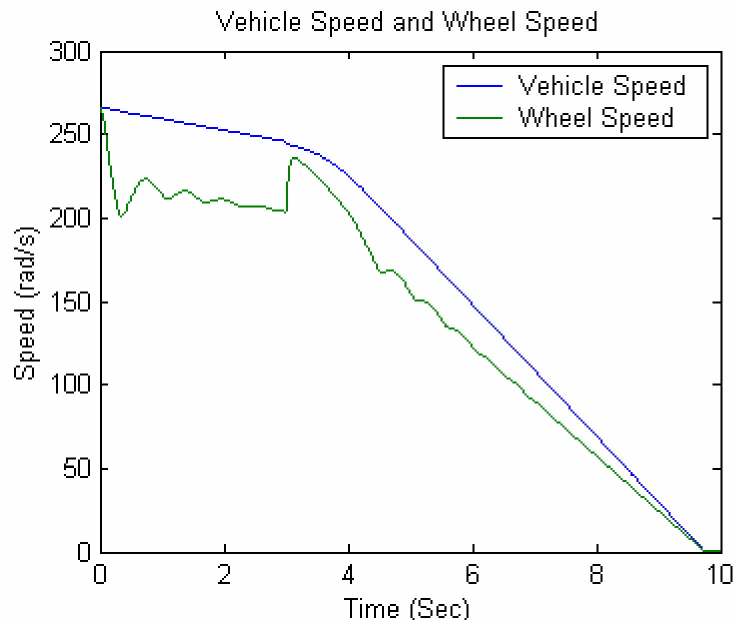
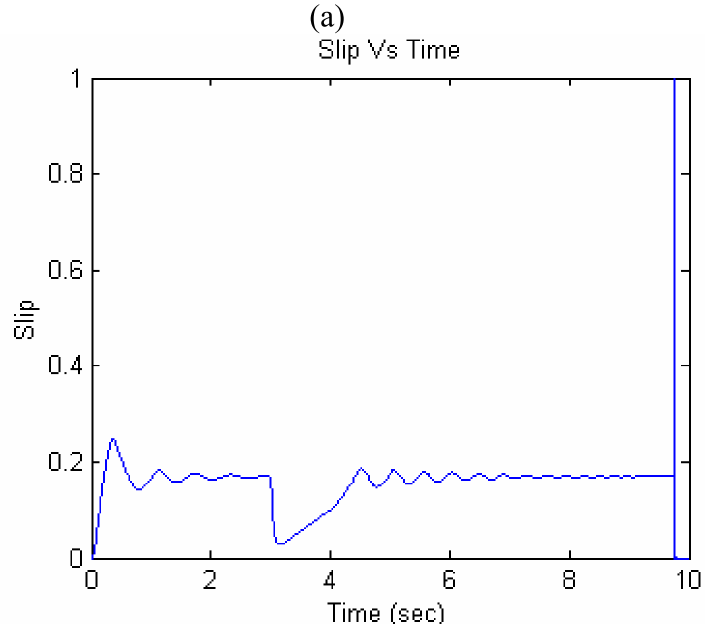


Figure 3.17 Simulink representation of nonlinear fuzzy controller.

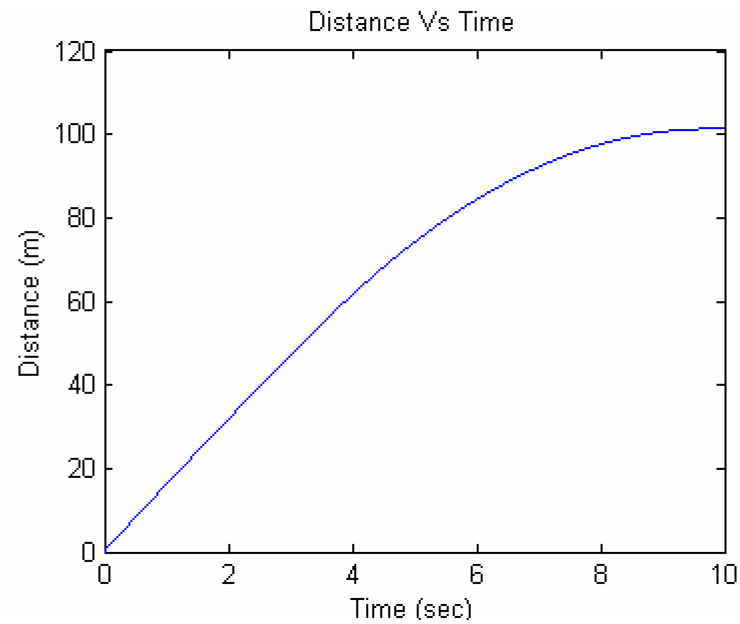
Simulation runs were carried out to validate the adaptive nature of the fuzzy logic controller. The road profile (two different road surfaces) as described in the previous section (figure 3.15) was used in the simulation runs. The results of the simulation are shown in the figure 3.18.



(a)



(b)



(c)

Figure 3.18 Simulation Results – Nonlinear Fuzzy Logic Controller

Comparison and discussion of results

Looking at the results, it can be said that the fuzzy logic controller is able to adapt to changes in road surfaces, while bang-bang controller does not. Various road surface profiles were taken up in different simulation runs and it proves that the constructed fuzzy logic controller is adaptive to changes in the road surface conditions. It is interesting to note that the stopping distance with the bang-bang controller is lower than the fuzzy logic controller. The reason is because during the control process with bang-bang controller, the wheel is locked for a good 2 seconds, which typically slows the vehicle down significantly and hence lower the stopping distance. However, a prime objective of the antilock brake system is to maintain controllability at all times. As explained earlier, when the wheel is locked, the control over the vehicle can be lost. Thus, we see that although the fuzzy logic controller takes a longer time to stop, it certainly satisfies the prime objective of the antilock brake system. The other interesting point is the variation of slip over time in the control process. With the fuzzy logic controller, the variation of slip over time is very minimal.

Overall, the simulation data validates the hypothesis – can a fuzzy logic controller be able to adapt to changes in road-surface conditions? Though the road-surface characteristic curves used in the simulation were representative curves, it can be stated that fuzzy logic controller is adaptive to changes in road-surface conditions in the simulation environment. The next stage would be to implement this nonlinear fuzzy logic controller in a real physical environment and further validate. The following chapter explains experiments and results from implementing on a 1/5th scale vehicle. These results would throw light on the validity of the ABS model (vehicle-road system, brake system and controller model) and also provide insights into the issues encountered while implementing a fuzzy logic controller.

Chapter 4: Experimentation

As described in the previous chapters, the implementation of the fuzzy logic ABS controller is done on a scaled test platform. The test platform consists of a test track, test vehicle and a real-time controller with associated signal conditioning and data acquisition hardware. The test platform is the hardware component of the test setup. The software component is LabVIEW Real Time ® (RT), a graphical programming language as mentioned in the previous chapters. The data acquisition and control software is programmed using National Instruments' (NI) LabVIEW RT and the software is run on the real-time controller to be able to achieve deterministic real-time ABS control. The real-time control issues are discussed in more detail in [30].

Hardware

The test track has a ramp to accelerate the vehicle and a flat bed where the vehicle decelerates due to the application of brake according to the control algorithm. The unique feature with this arrangement is that the flat bed could be replaced with different surfaces.

The test vehicle is a 1/5th scale Porsche GT2 made by FG Modellsport [35]. The test vehicle was instrumented with encoders, accelerometer and brake servos. The encoders provide wheel speed data. The encoders are found on the left and right wheels and another encoder is located on the differential. Since the brakes are not applied on the rear wheels, the differential should approximately give the vehicle speed as required for the control algorithm. The test vehicle also has brake servos for right and left wheels. The brake system, as explained earlier, is a cable brake system actuated by brake servos. An accelerometer is also mounted on the rear end of the vehicle to provide the acceleration data during the run.

The real time controller is a National Instruments' RT Engine (NI PXI – 8156B) running LabVIEW RT. The data acquisition and control hardware comprises of NI 6070E (Multifunction I/O DAQ card) and NI 6602 (Timing I/O card). All of these three modules are plugged into the PXI chassis (NI PXI 1000B). The software module resides in the NI RT Engine. The timing I/O card is used to acquire the speed data from the three encoders. The Multifunction I/O DAQ card is used for controlling the brake servo voltage and also for acquiring the acceleration data from the accelerometer.

In addition to the data acquisition and control hardware, there is some signal conditioning hardware to condition the signals. The raw signals from the encoders are noisy and hence signal conditioning is used to filter the noise. The signal conditioning hardware essentially consists of a buffer for the encoder signal and a transconductance amplifier for the output voltage signals. The encoder signal is passed through a buffer (op-amp inverter) to provide a clean signal to the control algorithm. The output voltage for the brake servos from the multifunction I/O card is passed through a transconductance amplifier (voltage to current converter) to get a proportional current to drive the brake servo. From the bond graph model for the servo, which is essentially a gyrator, it can be seen that if we supply a voltage, then it basically controls the speed of the servo arm motion. If we supply a current, it basically controls the torque of the servo arm. Now to control the brake pad force, it would be ideal to supply the current to the brake servos instead of the voltage, hence a transconductance amplifier to provide a proportional current. The figure 4.1 shows the hardware components in the experimental setup.

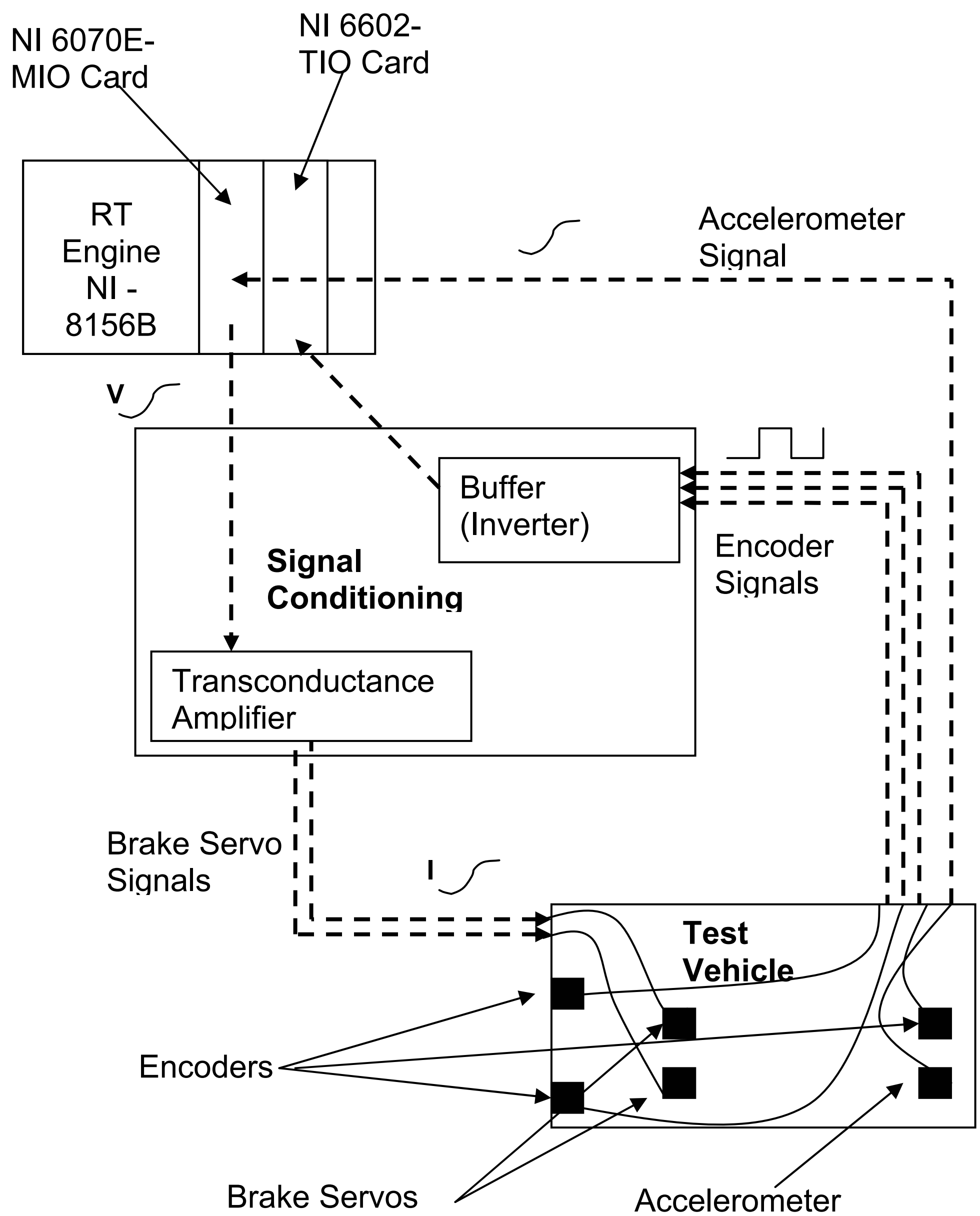


Figure 4.1 Block Representation of the Hardware Components in Experimental Setup

Software

The software is the brain of the ABS control system. The software in the experimental setup is implemented in LabVIEW RT. The typical components found in the software are a data acquisition module, control algorithm module, control application module and data log module. The figure 4.2 shows the various software modules.

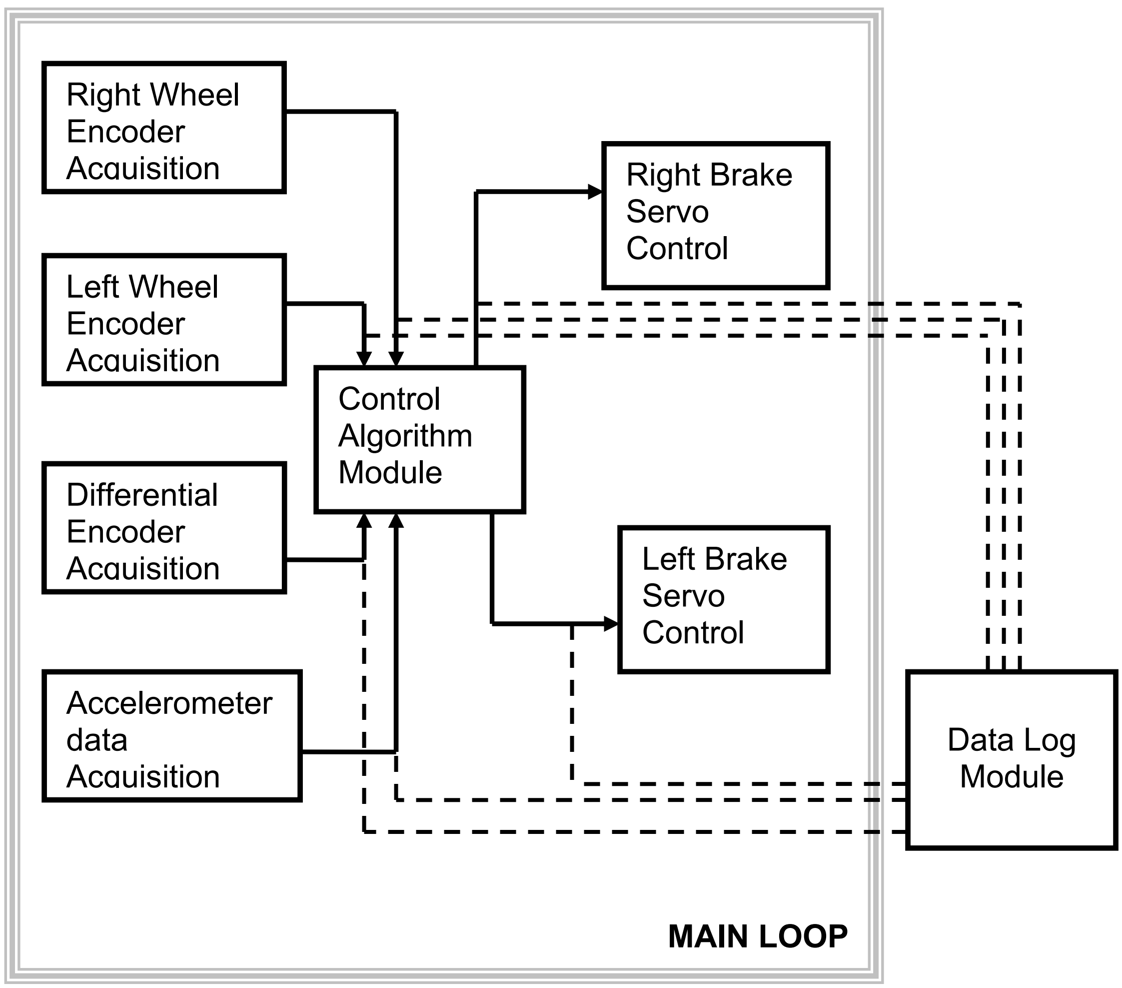


Figure 4.2 Block Representation of Software Modules

The encoder data and acceleration data acquisition modules are together referred as data acquisition module. The data acquisition module has routines for acquiring data from the sensors. The control algorithm module has the fuzzy logic controller, which takes the speed data and gives a voltage output for each of the brake servos. The control application module (left and right brake servo control) has routines which apply the appropriate voltage output to the brake servos. The data log module logs the data during the experiment run.

The control algorithm module is similar to one built in Simulink. Using the Simulink Interface Toolkit (from National Instruments), it is possible to convert a Simulink block diagram into a *.dll (dynamic link library) that can be used by LabVIEW RT. The control algorithm module in LabVIEW RT is a dll call to a function which has the fuzzy logic embedded in it. Figure 4.3 shows the process of converting the simulink block into a labview subroutine (VI – virtual instrument).

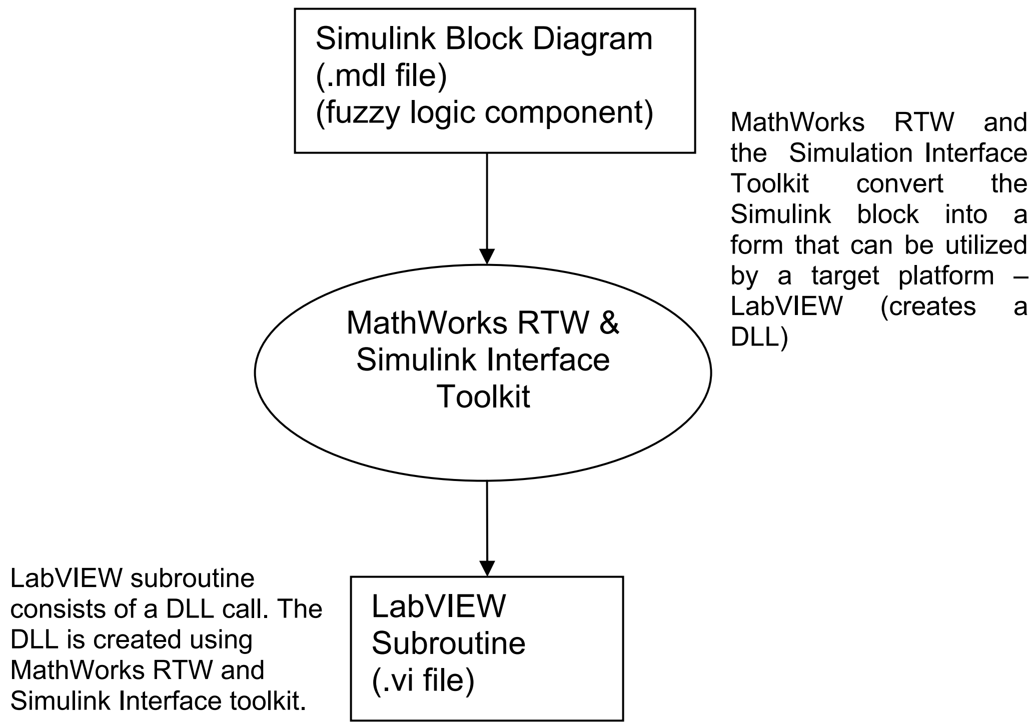


Figure 4.3 Conversion of a fuzzy logic Simulink block into a VI.

MathWorks RTW (Real Time Workshop) is used to convert Simulink blocks into code that can be used on different target platforms. The National Instruments' Simulink Interface toolkit provides the tools to use the RTW to convert Simulink blocks into LabVIEW subroutines. The LabVIEW subroutine created through the conversion process needs to be modified slightly to be used in the control algorithm module. The run time user interface for the software module is shown in figure 4.4.

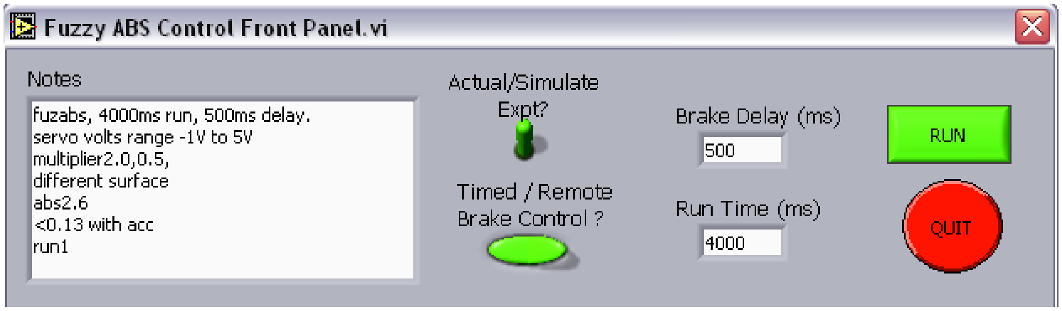


Figure 4.4 Run Time User Interface – Software Module

Experiment Procedure

Experimental runs are performed to look at the performance of the fuzzy logic ABS controller. The fuzzy logic ABS controller which was tuned during the simulation process is used here in the implementation. The main focus is to compare the fuzzy ABS controller with a bang-bang ABS controller and look at the differences in performance. The experiments performed are straight line ABS braking.

The vehicle is pulled back onto the ramp of the test bed by means of a steel cable. Once the vehicle has reached a sufficient height on the ramp, it is allowed to stabilize. The software is downloaded on to the RT Engine target. The user interface queries the user for the run time, brake delay time and whether to it is timed or remote braking and also whether we are simulating the run or doing actual experiments. Once the appropriate inputs are set, the “run” button is clicked. This starts the outer loop of the software which dis-engages the steel cable. Once the steel cable is released, the vehicle accelerates down the ramp and after the brake delay time, the control loop (main loop) is activated. The main loop is shown in figure 4.2. For every iteration of the main loop, data from the encoders and the accelerometer is acquired and send to the control algorithm module. The control algorithm module then sends a control output (based on the logic used) to the brake servo control modules. This continues until the “run time” has elapsed. Once the run is completed, data is saved on to the hard disk for post processing.

The experiments were repeated with different initial heights (release points), different brake delay times for both bang-bang controller and fuzzy logic controller. Two different surfaces were used. One was a smooth plastic surface and the other was a smooth wooden surface. Though the surfaces do not resemble any real world condition encountered by vehicles, it was used here to compare the two controllers (bang-bang and fuzzy logic) under different environments.

A second set of experiments were performed by Longoria, et. al [36] as part of an ongoing research to determine steady state friction and cornering coefficients. In the steady state experiments for determining the friction coefficient, the vehicle is held stationery and one of the wheels is placed on top of an aluminum drum. The aluminum drum is driven by a motor. Optical encoders are used to get the speed data for the drum and the wheel. A known brake torque is applied by means of a prony brake apparatus. At steady state, the brake torque would be balanced by the torque generated due to the friction between the wheel and the drum. Friction coefficient is deduced from the brake torque and the normal load on the tire. To determine the cornering coefficient, the wheel is steered at a known angle and clamped in that position. The drum is driven by the motor and the brake torque is applied with the help of the prony brake. The lateral tire force that is developed is countered by holding the vehicle the steady at the initial steer position using a spring scale. At steady state, the steer angle would be the side slip angle. Cornering coefficient is deduced from the lateral tire force and the normal force on the tire. The block representation of the setup is shown in figure 4.5.

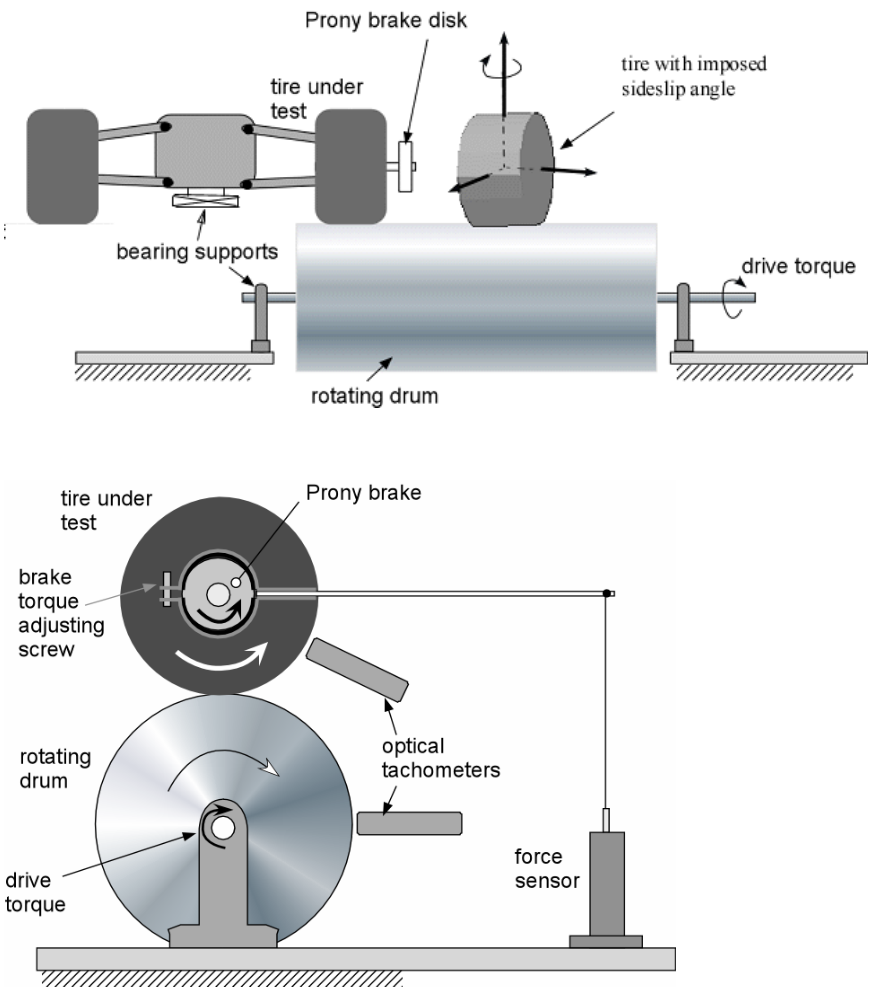


Figure 4.5 Block Representation of the setup for determining friction and cornering coefficient [36].

Results

The data from steady state experiments outlined in the previous section shows the general trend of a mu-slip curve and also shows that the cornering coefficient decreases as slip value increases. From the figure 4.6, it is seen that the vehicle is stable (moderately high friction and high cornering coefficient) when the slip value is maintained between 0.1 and 0.25.

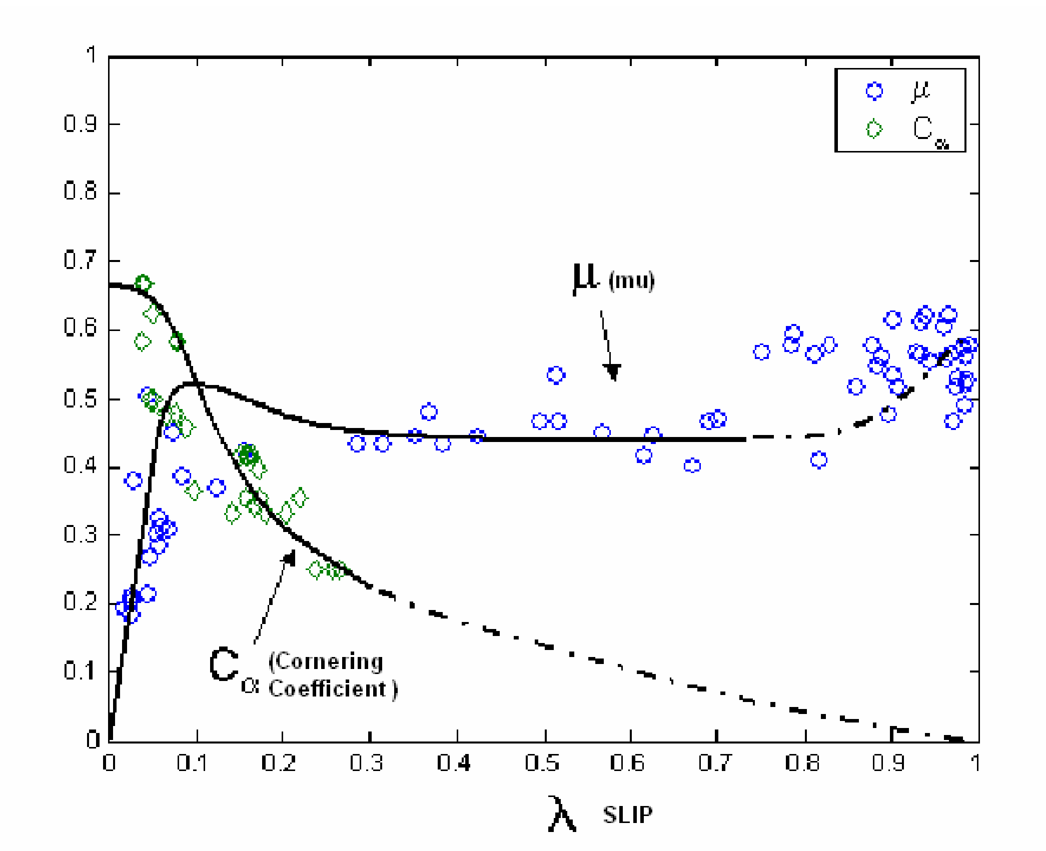


Figure 4.6 Mu-Slip Curve from steady state experiments by Longoria, et. al [36].

The following sections describe the results from experimental runs performed using the bang-bang controller and the fuzzy logic controller where the brake time delay was 500 ms and the run time was 4000 ms. The release point was kept the same for the experiments. The release point and the brake time delay determine the maximum velocity that the vehicle would reach before the control logic kicks-in. As the test bed was not long enough, slow speed runs were carried out. When the release point was higher, the vehicle would not stop within the test bed and would crash into the safety zone.

Bang-Bang Controller

The bang-bang control logic as used in the simulation was used in the experiments. Data from the experiments were logged and plotted. The brake servo voltage applied is either -1V or 5V. A brake control voltage of -1V would release the brake servo and a voltage of 5V would engage the brakes completely. The left brake servo did not respond to -1V or rather did not release. But the right brake servo worked fine. The data from the right wheel can be used to illustrate the difference between the bang-bang and the fuzzy logic controller. The surface used was the smooth wooden surface. The figure 4.7 shows the right wheel encoder and the differential encoder data for both bang-bang and fuzzy controller. During the first 500 ms (iterations), the vehicle comes down the ramp picking up speed, and after that ABS kicks in. The difference between the bang-bang and fuzzy is clearly seen in the right wheel encoder data. It can also be seen that at certain points during the run with the bang-bang controller, the wheel locks up. Figure 4.8 shows the acceleration data (raw data) for the run.

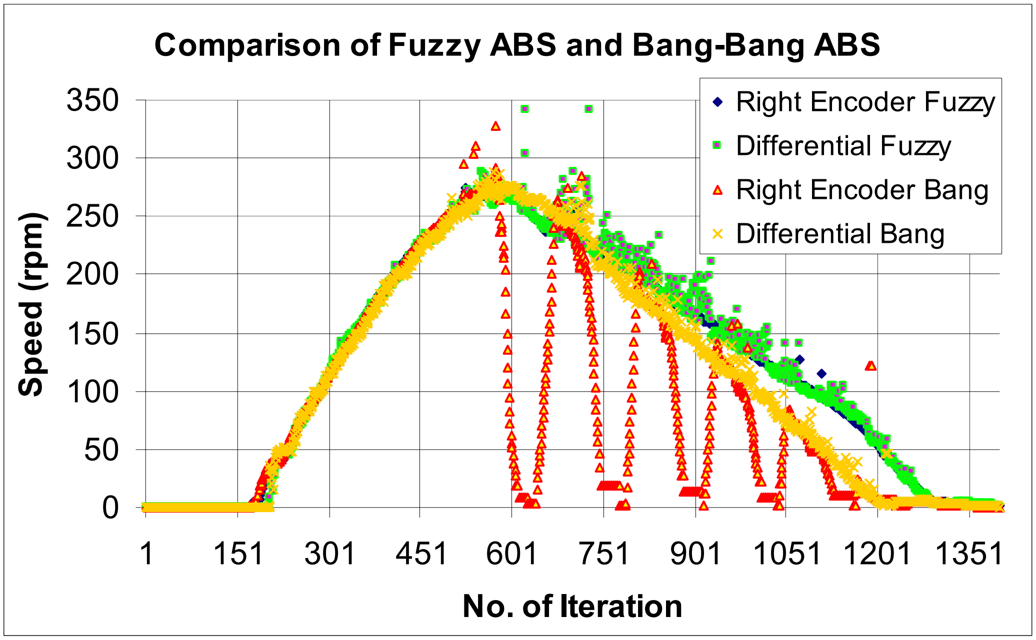


Figure 4.7 Comparison of Encoder data for Bang-Bang and Fuzzy Controller.

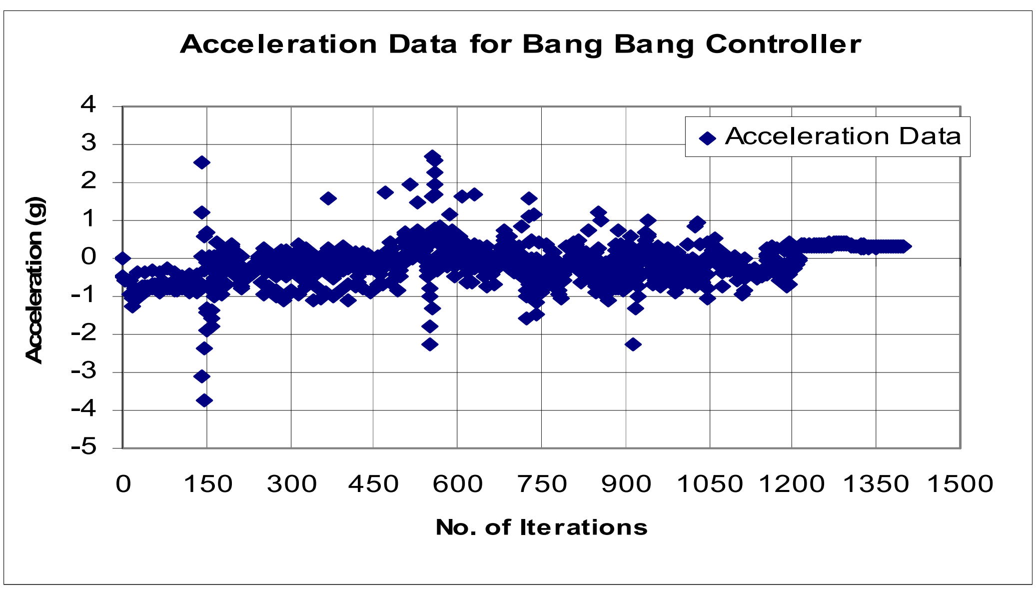


Figure 4.8 Acceleration data –Bang-Bang ABS Controller

Fuzzy Logic ABS Controller

The fuzzy ABS control logic simulation block is converted into LabVIEW subroutines as explained earlier. The fuzzy control logic takes in the slip data and provides a voltage that is applied to the brake servos. While applying the brakes based on the voltage output from the fuzzy controller, it is seen that it gradually increases from 0V to a positive value and when the fuzzy controller detects an impeding wheel lock condition, it sends an output to release the brakes. Now the voltage to release the brakes is -1V. Then again, the voltage is increased based on the fuzzy controller output to apply the brakes and again to release the brakes a -1V is applied. This cycle continues until the vehicle comes to a stop.

The experiment data plots from the runs for fuzzy logic controller with the wooden surface are shown in figure 4.7. The plot shows the right wheel encoder data and the differential encoder data. It can be seen that with the fuzzy logic controller, the wheel does not lock up, thereby maintain controllability during braking. The figure 4.9 shows the acceleration data (raw data) for the run. Figure 4.10 shows the comparative stopping distance plots for the fuzzy and the bang-bang controller.

Similar runs with the fuzzy logic controller were performed using the plastic surface. It was seen it took longer for the vehicle to stop on the plastic surface. The variables (run time, brake delay time and release position) were kept the same for these runs. The only difference from the earlier runs is the surface. Figures 4.11, 4.12, 4.13 and 4.14 show the data from two runs under similar conditions. The loop rate for each iteration was around 1.5 ms.

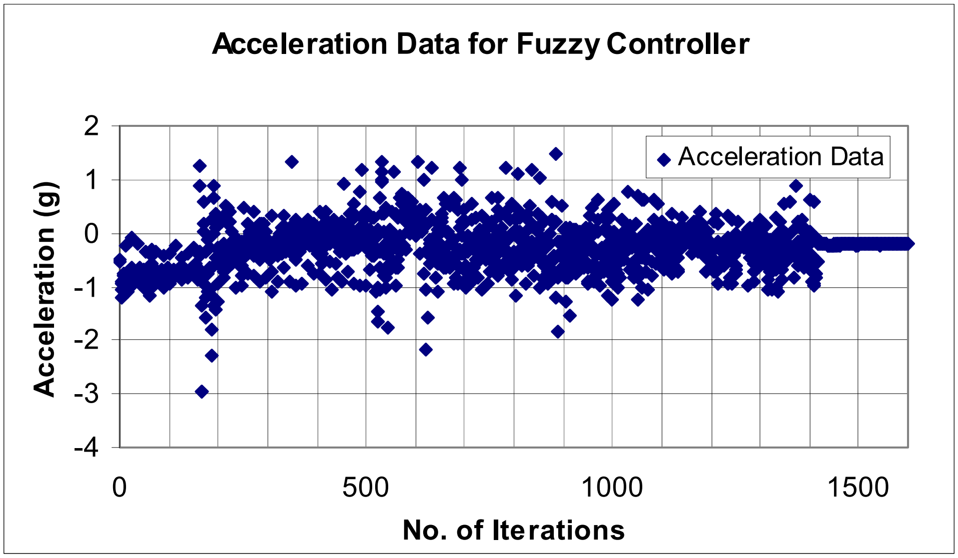


Figure 4.9 Acceleration Data - Fuzzy Logic ABS Controller

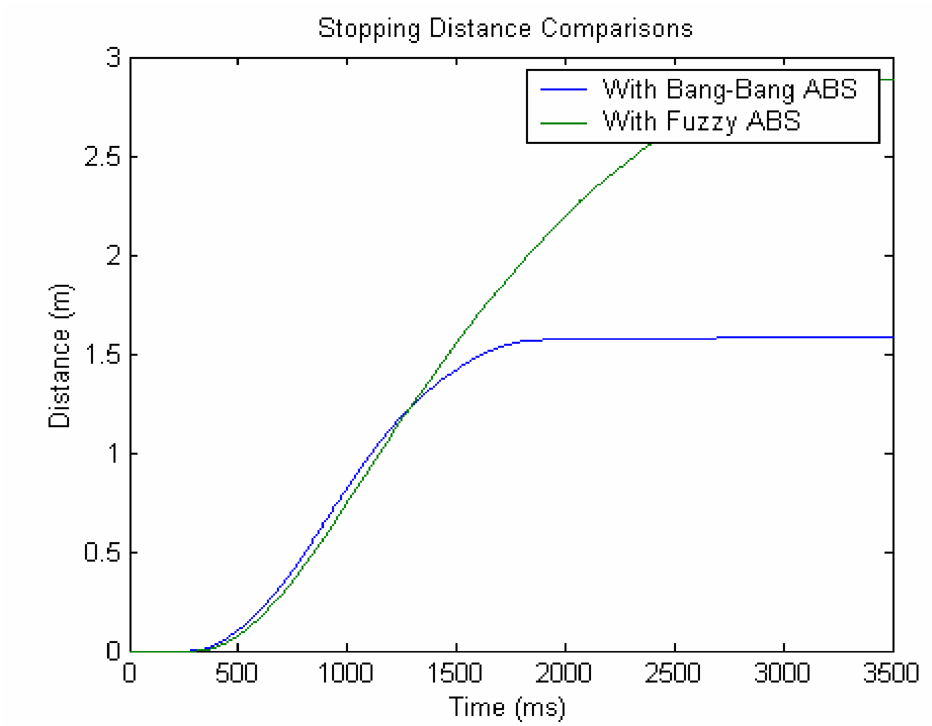


Figure 4.10 Comparison of Stopping Distances

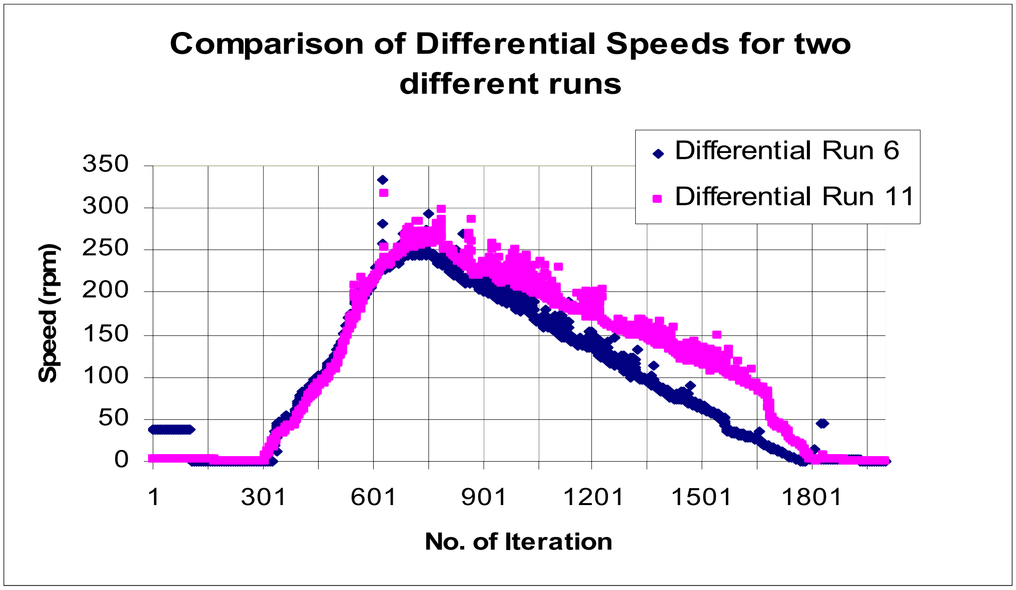


Figure 4.11 Comparison of differential encoder data for two runs with fuzzy ABS under similar conditions

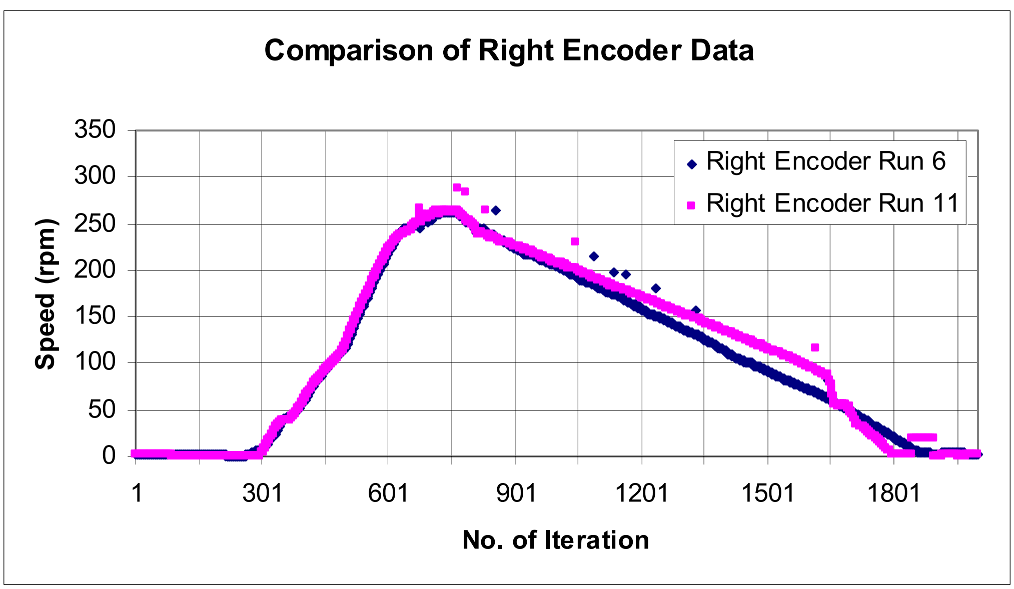


Figure 4.12 Comparison of right wheel encoder data for two runs with fuzzy ABS under similar conditions

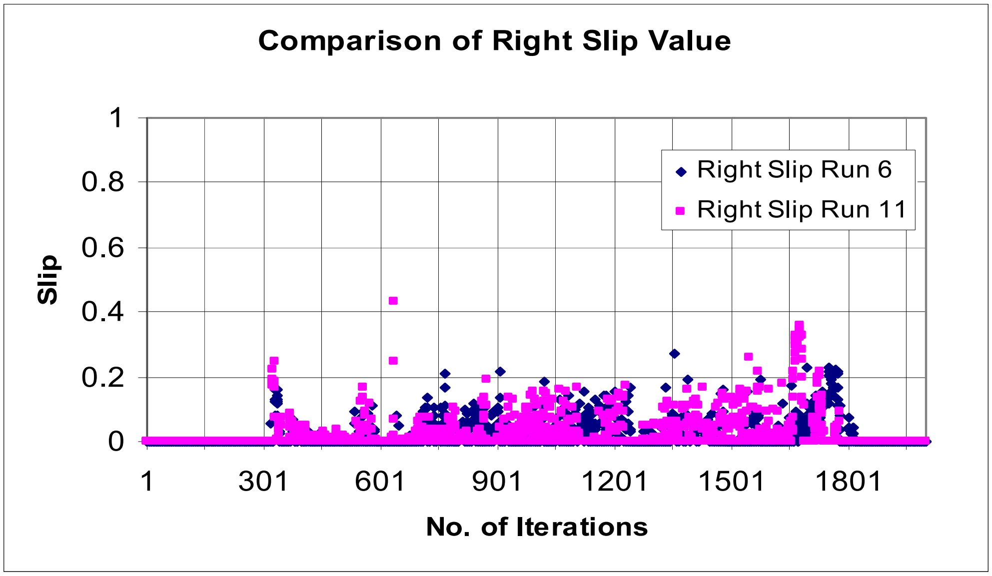


Figure 4.13 Comparison of right slip data for two runs with fuzzy ABS under similar conditions

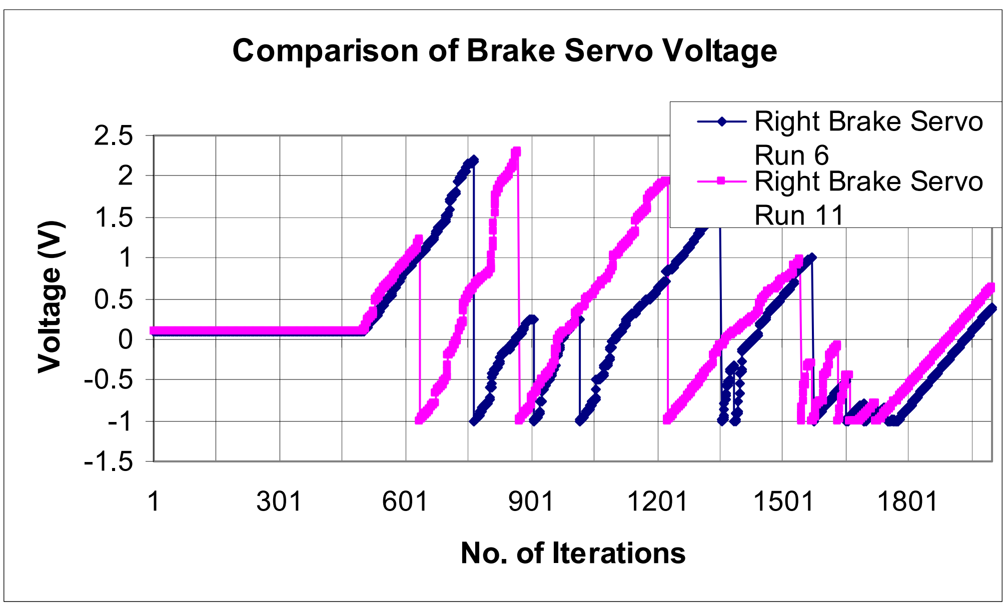


Figure 4.14 Comparison of right brake servo voltages for two runs with fuzzy ABS under similar conditions

Figure 4.13 shows the slip data from the experimental runs with the fuzzy controller. It can be seen that the slip value is maintained under 0.2 during the entire run. As seen from the steady state experiment results (figure 4.6), this ensures that vehicle maintains controllability during the run, which is one of the prime objectives of an antilock brake system.

In figure 4.14, only the right brake servo voltage profiles are shown as the response of the left brake servo to the applied voltage was not as expected. As explained earlier, the left brake servo would not release even when applied a negative voltage. The solution to this issue is to replace the left brake servo, but this was not done in time for these experiments because the data from the right wheel was sufficient to explain the implied results. From the plots for the different runs, it is seen that there is variability when repeating the experiments under similar conditions. These variations are normal and are within acceptable limits. The conclusions drawn from these experiments are reasonably proven.

Conclusion

A main result from the experiments conducted, is demonstrating the ability to model a fuzzy controller in a simulation environment and to implement it on a real time controller (National Instruments' RT Engine) using a systematic set of software and hardware tools. This method provides for a rapid prototyping environment, where the ABS controller can be developed and tested in a simulation environment with various vehicle models (longitudinal model and 1/5th scale vehicle model) and easily ported to a real-time controller for actual experiments on a scaled test platform. The experiments proved that the approach can be successful and can be used in the future to model and test more complex controllers.

The experimental data shows expected trends when compared with the simulation results. The experimental run with the bang-bang controller shows the wheel tending to lock up more often while braking. Generally when the slip value increases, the cornering coefficient decreases (figure 4.6) and thereby the vehicle loses controllability. With the fuzzy logic controller, it can be seen that the slip values tend to fluctuate between 0.10 and 0.20, where the friction and cornering coefficient is high. During the entire run, the fuzzy logic controller ensures that the wheel does not lock up and thereby achieves controllability throughout the run. Even though steer is not introduced in the experiments, it can be assumed that should a steer be introduced, the fuzzy logic controller would still control the slip value so that the cornering coefficient is high. The variation of slip value is also minimal with the fuzzy logic controller.

One other fact from the experimental data is the longer stopping distance with the fuzzy logic controller. As explained by the simulation, the primary reason is that with the bang-bang controller, the wheel locks up a couple of times thereby slowing the vehicle very quickly. Another reason is the loop rate. With the fuzzy logic controller each loop takes an additional 1 to 2ms, hence the frequency of the control output is lower in the case of the fuzzy logic controller. With better optimization, the loop rates can be reduced. The application of the brake control voltage is also another factor in reducing the stopping distance. The limitation with the brake servo is that to release the brake, a negative voltage is required and to reapply the brakes, the voltage has to be increased from -1V. It would be ideal to have a brake system where a decrease in the applied voltage would tend to proportionally release the brake rather having to go all the way to -1V.

So it is seen from the experiments that the results match up with the simulation data. Since the brake servos are controlled individually, it is anticipated that adaptability can be demonstrated on split mu surfaces. In a split mu surface, each wheel encounters different surface conditions. For example a vehicle with right wheels on snowy shoulder and the left wheels on dry or wet road surface. These and other tangible experiments (like experiments with steer) are considered future work.

Chapter 5: Conclusion and Recommendations

Conclusion

It is seen from the simulation and experiment results that fuzzy logic can be used as a controller in an antilock brake system. Also when compared with a bang-bang controller, it performs better on smooth surfaces (low mu surfaces). It has better controllability; the slip values are controlled in the region where the cornering coefficient and the friction coefficient are high. The scaled test platform is quite ideal for slow to medium speed runs. For high speed runs, the flat portion of the test bed may not be sufficiently long to bring the vehicle to a complete halt. Also different surfaces might be used in future tests to evaluate the control algorithms. The rapid prototyping environment as explained earlier is a very flexible approach for modeling and testing and tuning complex control algorithms. Antilock brake system as seen is a nonlinear system and the use of fuzzy logic for better controllability shows that the soft-computing tools may be used in other control problems where uncertainty and non-linearity exists.

Future Work

In the explorations made during this research, there were quite a few areas that were identified where future research may be taken up. The brake system used in the test platform is a cable-actuated one powered by brake servos. As was indicated in the Experimentation chapter, an ideal brake system is one which would respond to the applied voltage in both directions (release and actuation in a similar fashion, not necessarily linear). A hydraulic actuated brake system should be considered as an improvement over the cable-actuated one. On the other hand, a comparative study of the different brake actuations could be taken up as part of future research to determine an optimal brake system for the 1/5th scale vehicle.

The approach taken to determine the fuzzy rules and parameters to be used in the fuzzy logic controller were by a process of manual tuning. ANFIS or **A**daptive **N**euro **F**uzzy **I**nference **S**ystem is a soft computing approach where neural networks are used to determine the fuzzy logic parameters (membership functions). To start with, the basic membership functions are used and as the neural network trains on the data, the membership functions are tuned to better represent the control process.

One other question that needs to be answered is whether the fuzzy logic controller developed for the scaled vehicle would hold well for a full scale vehicle. To be able to compare the scaled implementation and a full scale implementation, it would be necessary to extract dimensionless variables. The Buckingham's Pi theorem looks into the dimensional analysis of these variables. The Buckingham's pi theorem is one such approach to look at the scaling issues. Work has to be done in this direction to ascertain the scalability issue.

Split mu surface conditions occur when the left and the right wheels encounter different surfaces. This affects the performance of the antilock brake system and the stability of the vehicle. Since the fuzzy logic controller implementation looks at each wheel individually, it should work for split mu conditions. Split mu experiments and other tangible experiments could be conducted to look at the performance of antilock brake systems, with preliminary testing on the scaled vehicle.

Another factor that has some scope of improvement is the “control” loop rate. The controller can be optimized to lower the loop rate, thereby increasing the frequency of control output. The flat test bed used for the implementation is not long enough for high speed runs. The only other solution is to have a longer test track. The experiments conducted were straight brake runs with no steer. It would be interesting to look at the performance of the antilock brake system controllers on runs where the steer is introduced. The cornering coefficient kicks in during a steer. Indeed, it might be said that the controllability of the vehicle during braking and steering is a much more critical issue to examine in ABS experiments.

Appendix A. Fuzzy Logic Controller – Longitudinal Model

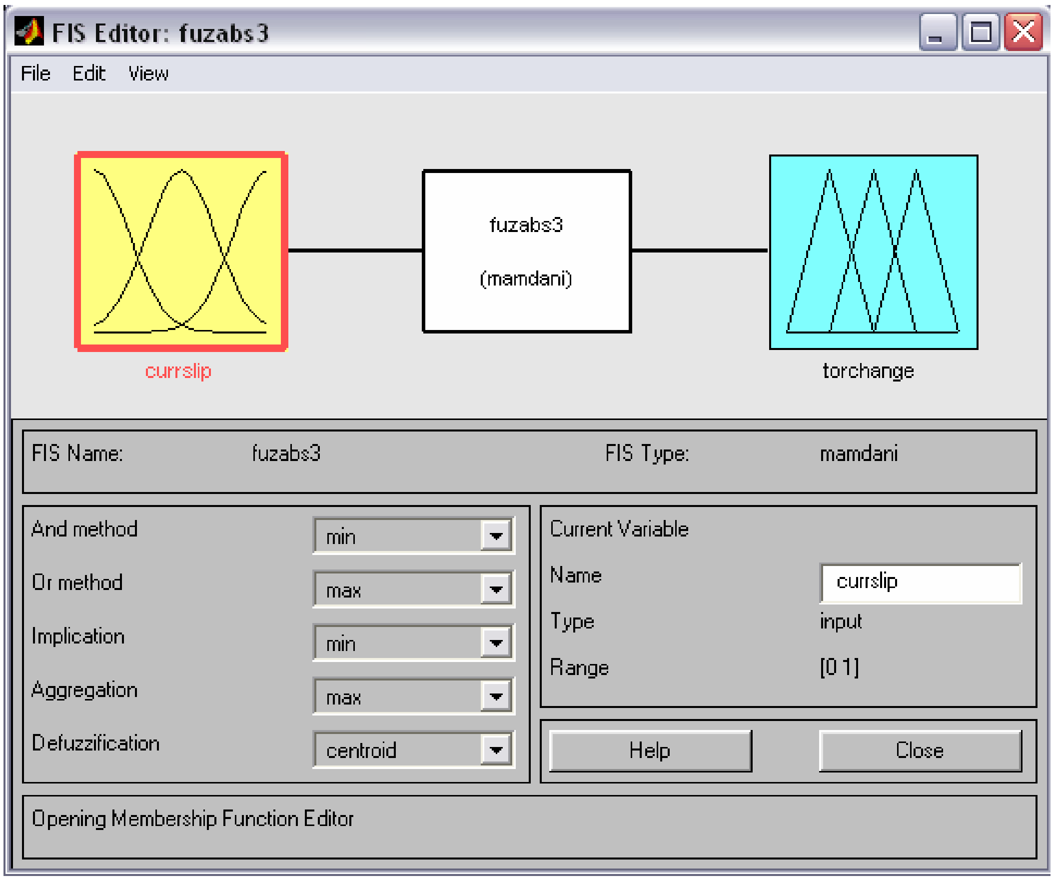


Figure A.1 Fuzzy Inference System - FIS

The figure shows the Fuzzy Inference System (FIS) used in the longitudinal model. The figures in the following pages show the input membership functions, output membership functions, fuzzy if-then rules and the controller surface.

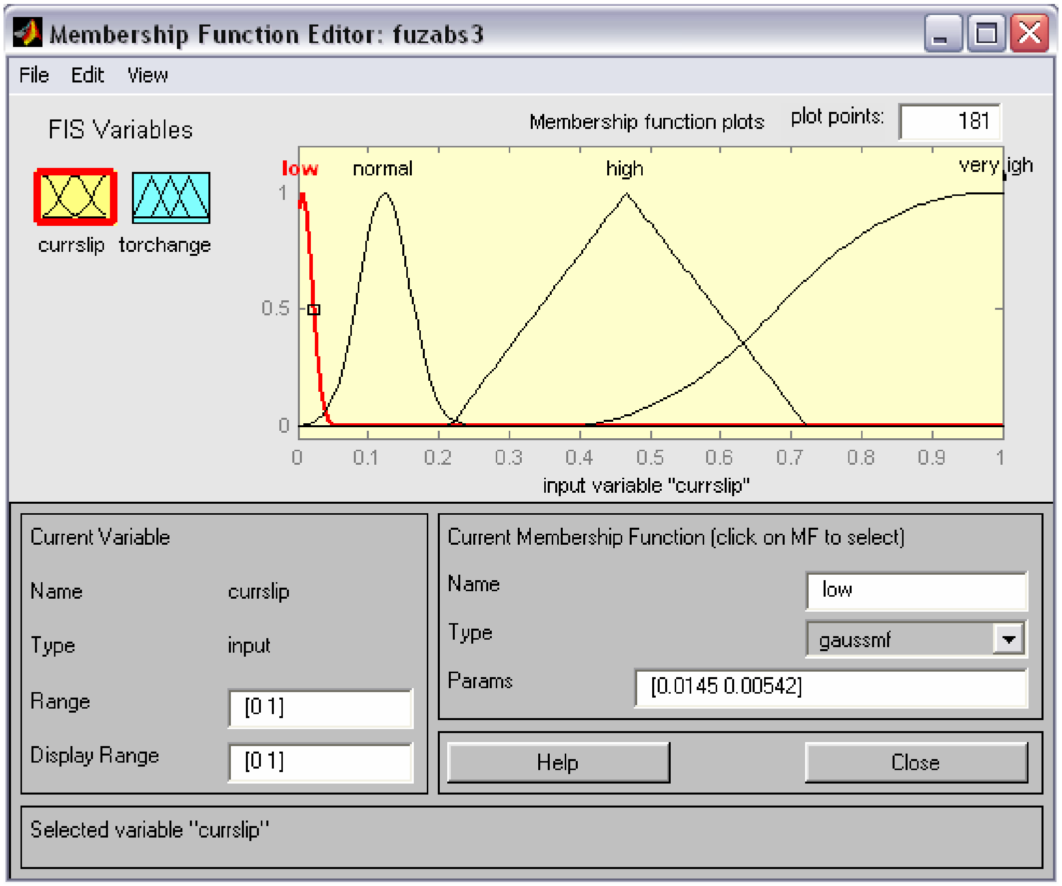


Figure A.2 Input Membership Functions – Current Slip

The figure shows the membership functions for the input variable "currslip". It shows four different membership functions (low, normal, high and very high) spread over a range [0 1].The "low" and "normal" membership functions (mf) are of the type "gaussian mf". The "high" membership is a "triangular mf". The "very high" is a "pimf" type membership function.

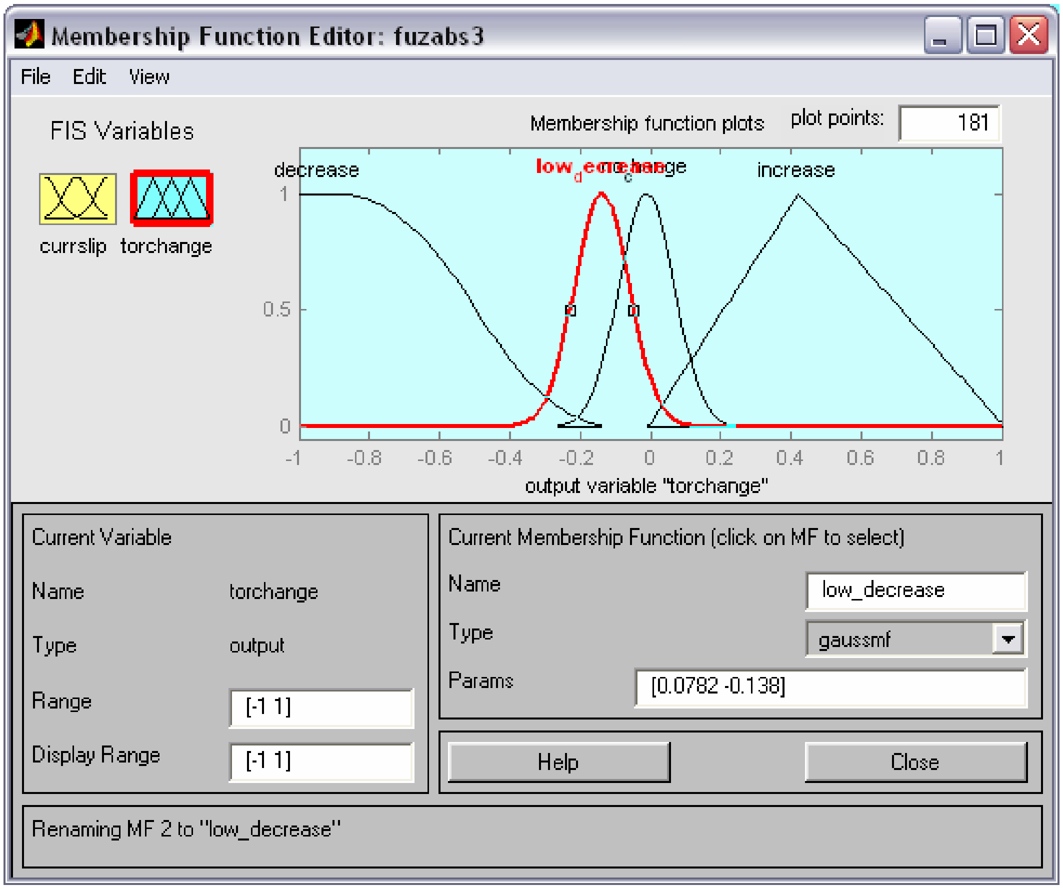


Figure A.3 Output Membership Functions – Torque Change

The figure shows the membership functions for the output variable "torchange". It shows four different membership functions (decrease, low_decrease, no_change and increase) spread over a range [-1 1].The "low_decrease" and "no_change" membership functions are "gaussian mf". The "increase" membership is a "triangular mf". The "decrease" is "zmf" type membership function.

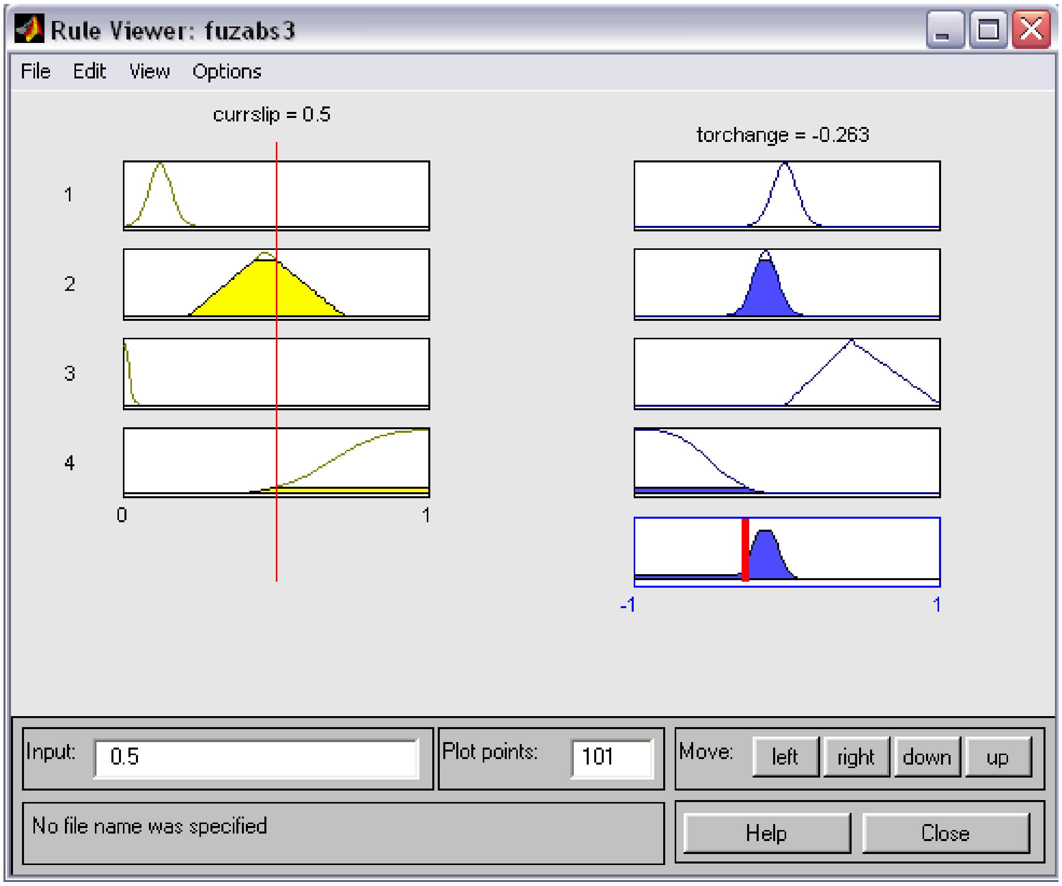


Figure A.4 Rule Viewer

For the “currslip” input shown by the red vertical line on the left, of the four rules shown only two are "activated" by a membership value greater than zero. Each rule is weighted on the right (blue areas) and a compounded average is computed (thick red line in the bottom-right to generate a "crisp" (analog) signal as the controller action.

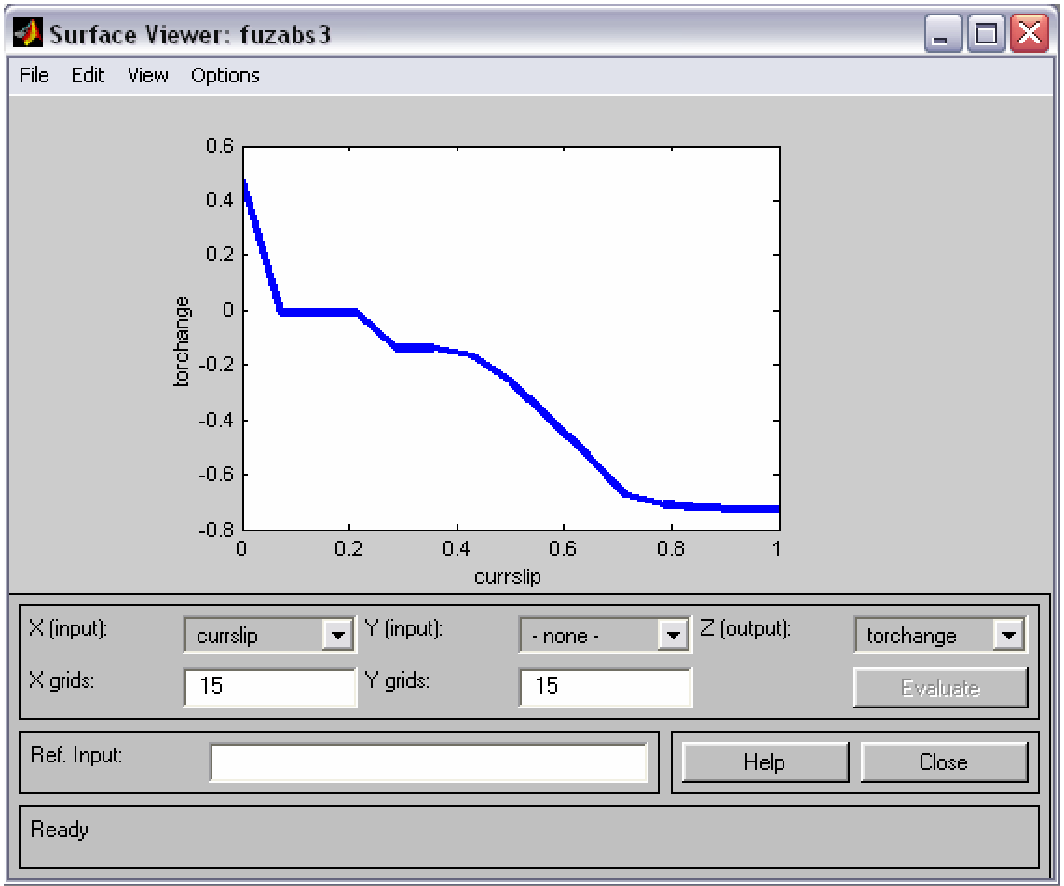


Figure A.5 Surface Viewer

The figure shows the control surface generated as a result of the fuzzy rules. It shows the relationship between the input and the output for the controller.

Appendix B. Fuzzy Logic Controller -1/5th Scale Vehicle Model

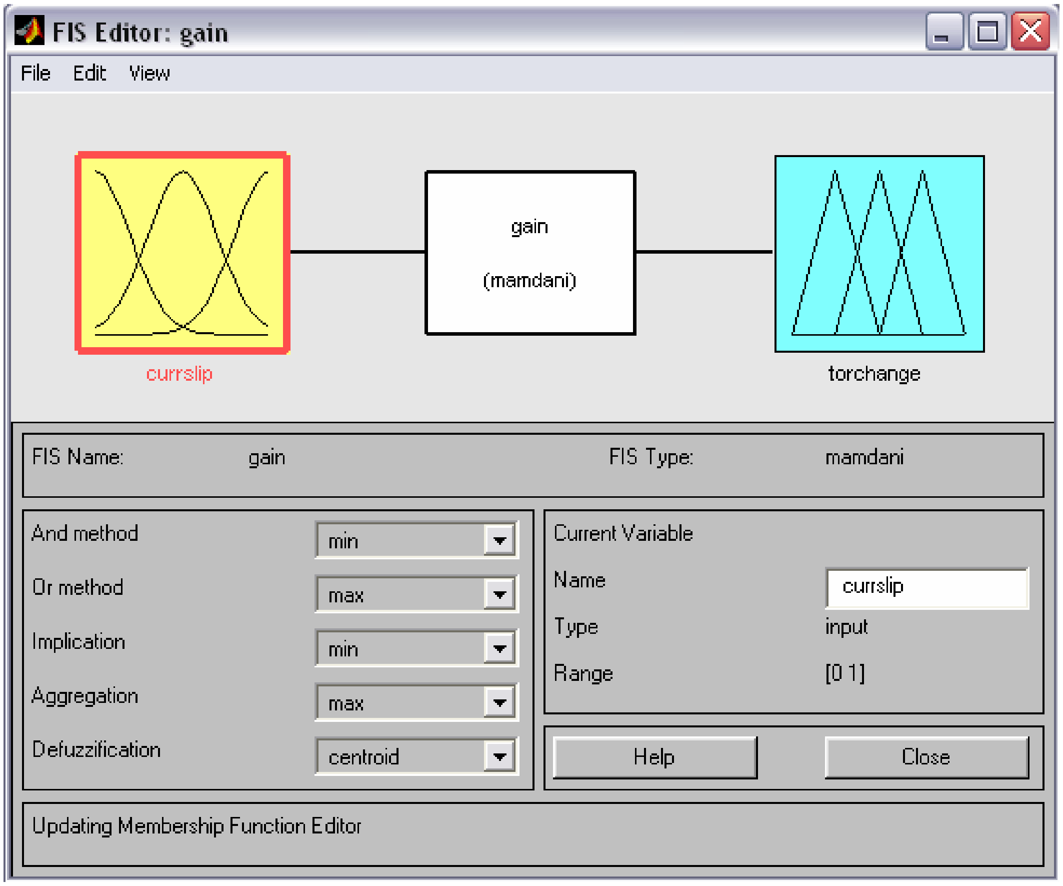


Figure B.1 Gain Fuzzy Logic Controller - FIS

The Gain Fuzzy Logic Controller is similar to FIS used for the longitudinal model with slight modifications.

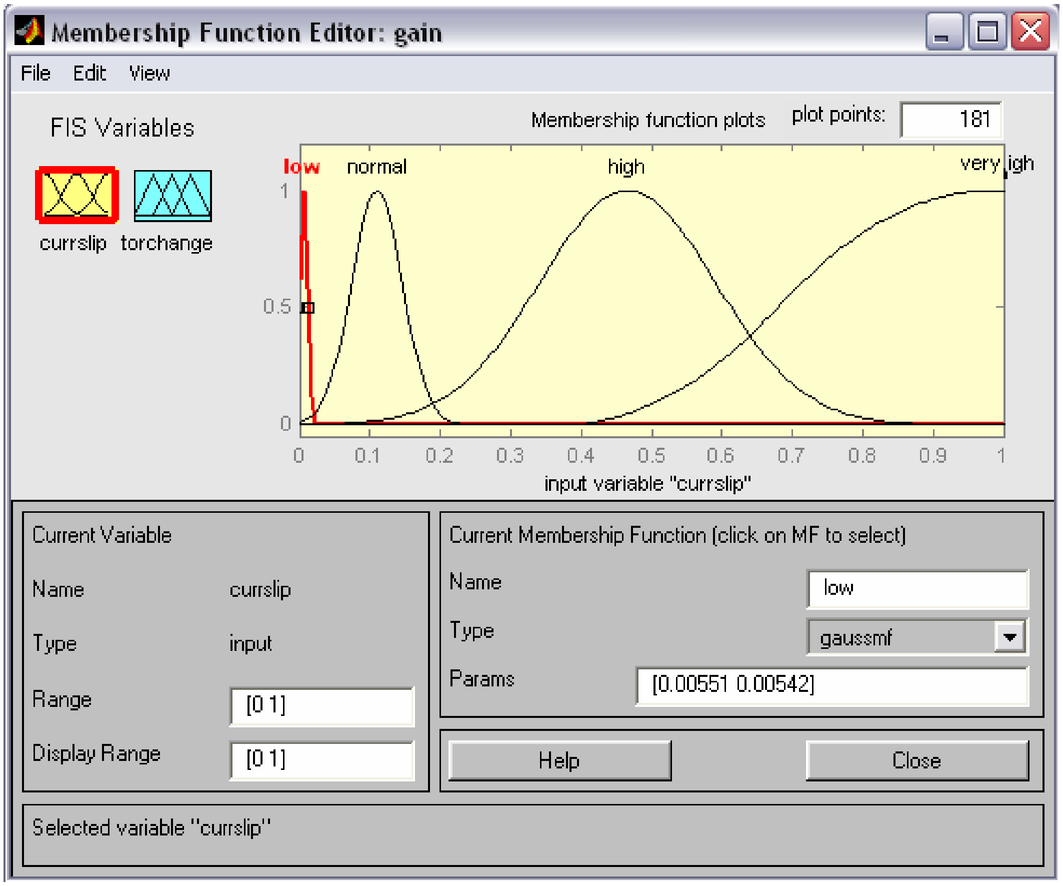


Figure B.2 Input Membership Functions – Current Slip

The figure shows the membership functions for the input variable "currslip". It shows four different membership functions (low, normal, high and very high) spread over a range [0 1].The "low" ,"normal" and "high" membership functions are of the type "gaussian mf". The "very high" is a "pimf" type membership function.

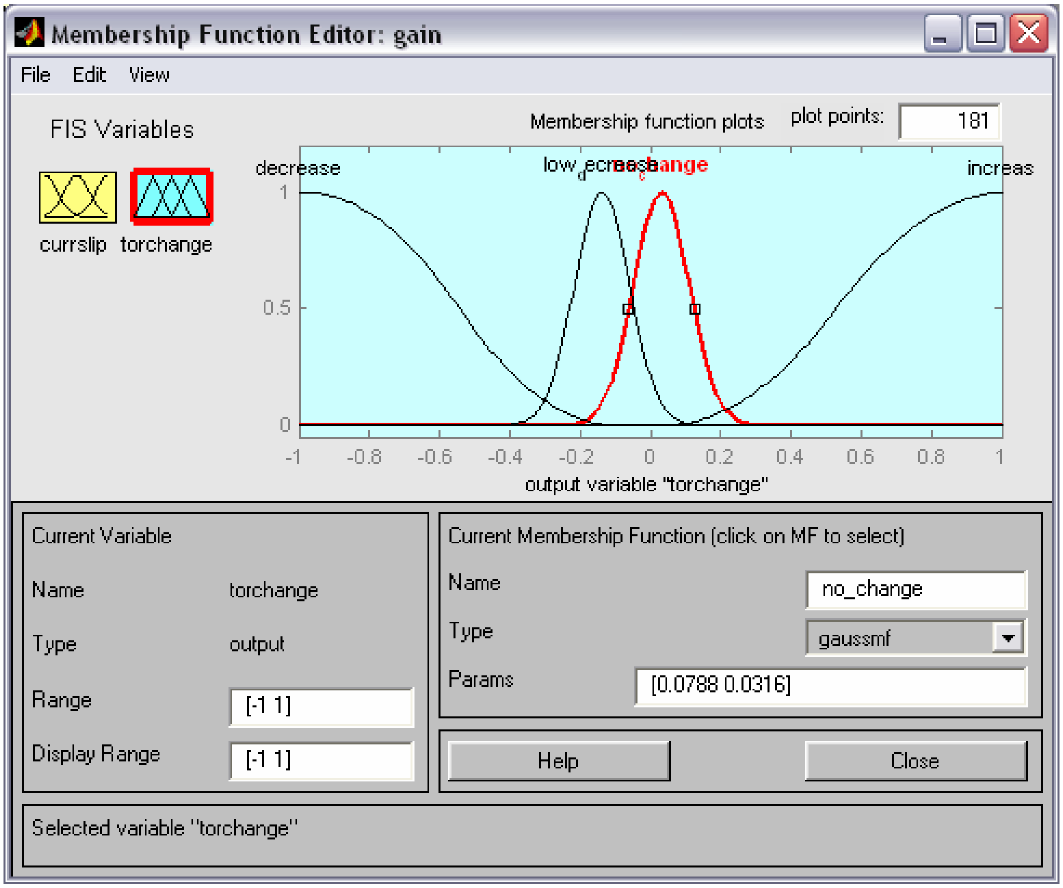


Figure B.3 Output Membership Functions – Gain Constant

The figure shows the membership functions for the output variable "torchange". It shows four different membership functions (decrease, low_decrease, no_change and increase) spread over a range [-1 1]. The "low_decrease" and "no_change" membership functions are "gaussian mf". The "increase" membership is of the type "smf". The "decrease" is a "zmf" type membership function.

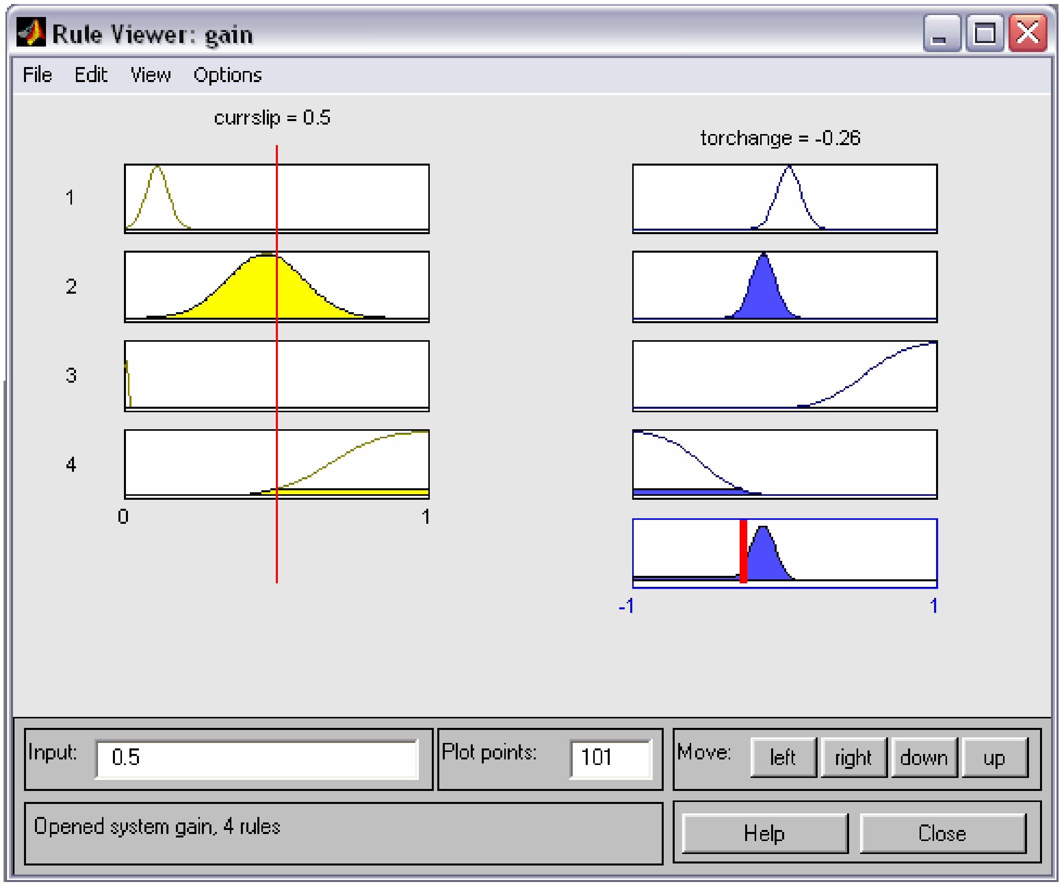


Figure B.4 Rule Viewer

For the “currslip” input shown by the red vertical line on the left, of the four rules shown only two are "activated" by a membership value greater than zero. Each rule is weighted on the right (blue areas) and a compounded average is computed (thick red line in the bottom-right to generate a "crisp" (analog) signal as the controller action.

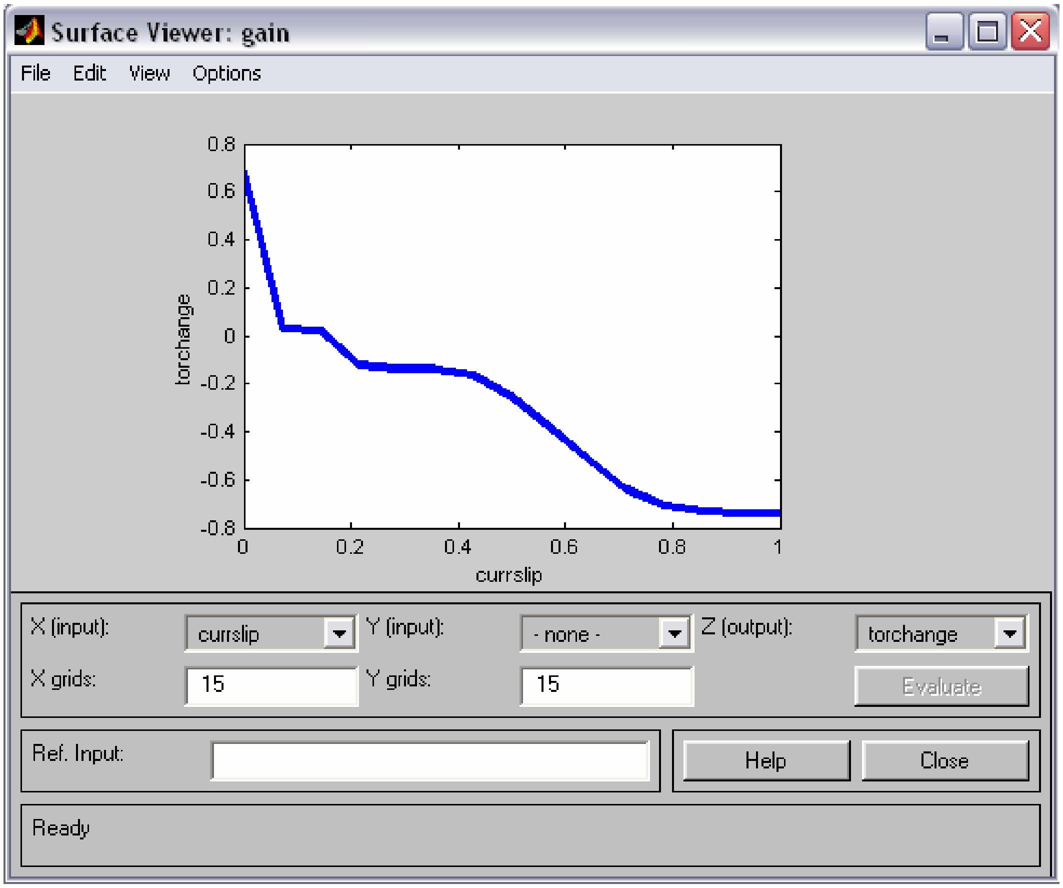


Figure B.5 Surface Viewer

The figure shows the control surface generated as a result of the fuzzy rules. It shows the relationship between the input and the output for the controller.

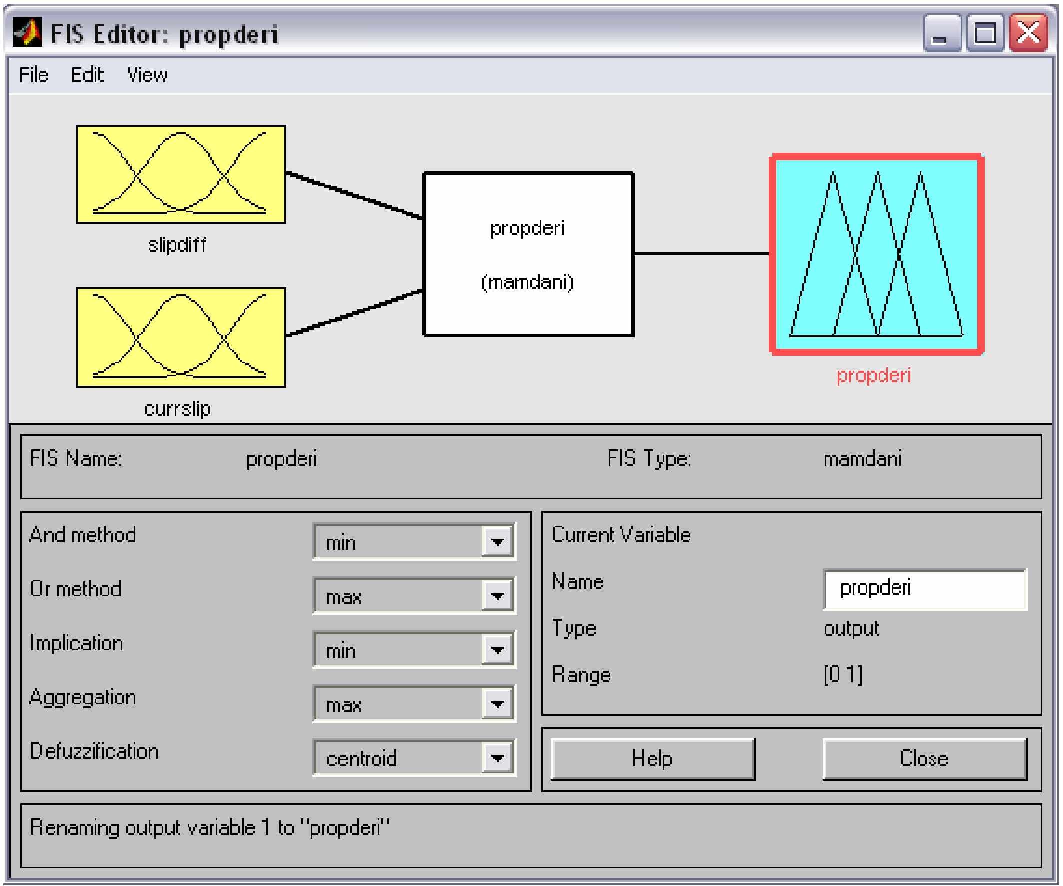


Figure B.6 Proportional Derivative Fuzzy Logic Controller - FIS

The figure shows the Proportional Derivative Fuzzy Inference System (FIS) used in the 1/5th scale vehicle model. The figures in the following pages show the input membership functions, output membership functions, fuzzy if-then rules and the controller surface.

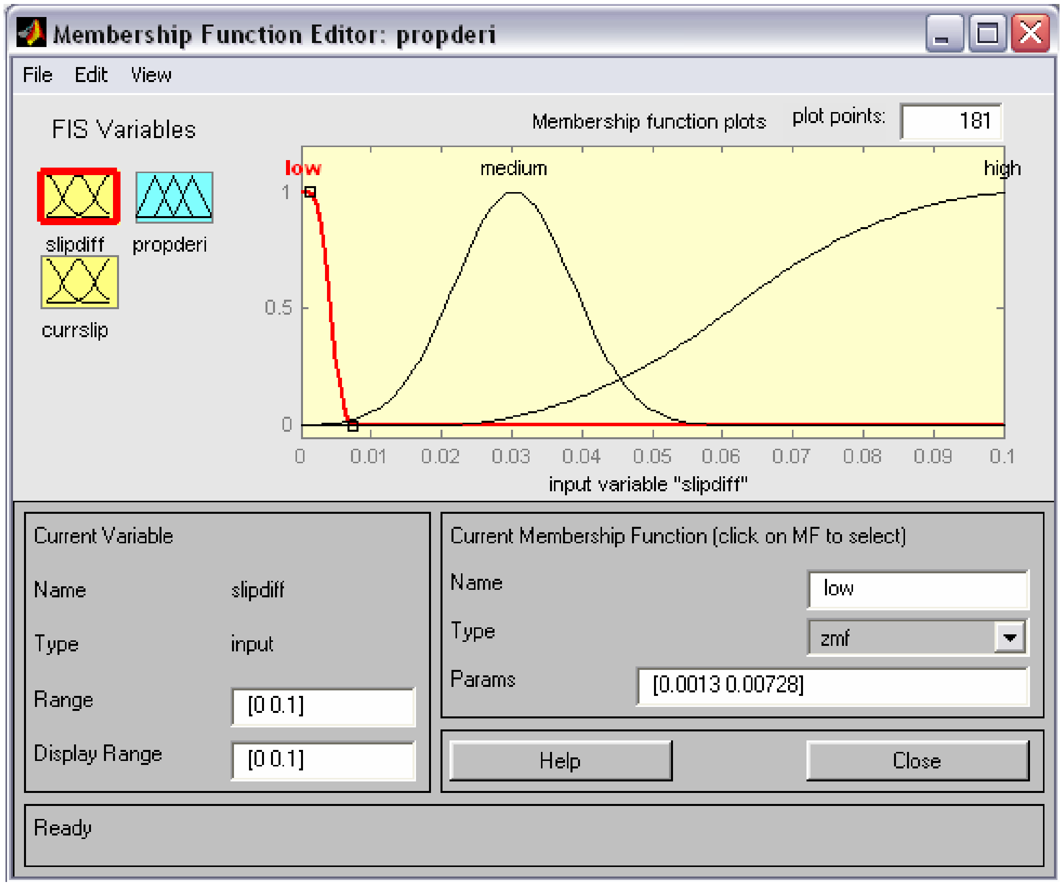


Figure B.7 Input Membership function – Slip Difference

The figure shows the membership functions for the input variable “slipdiff”. It shows three different membership functions (low, medium and high) spread over a range [0 1]. The “low” is “zmf” type membership function. The “medium” is a “gaussian mf” type membership function. The “high” membership is a sigmodial membership function “smf”.

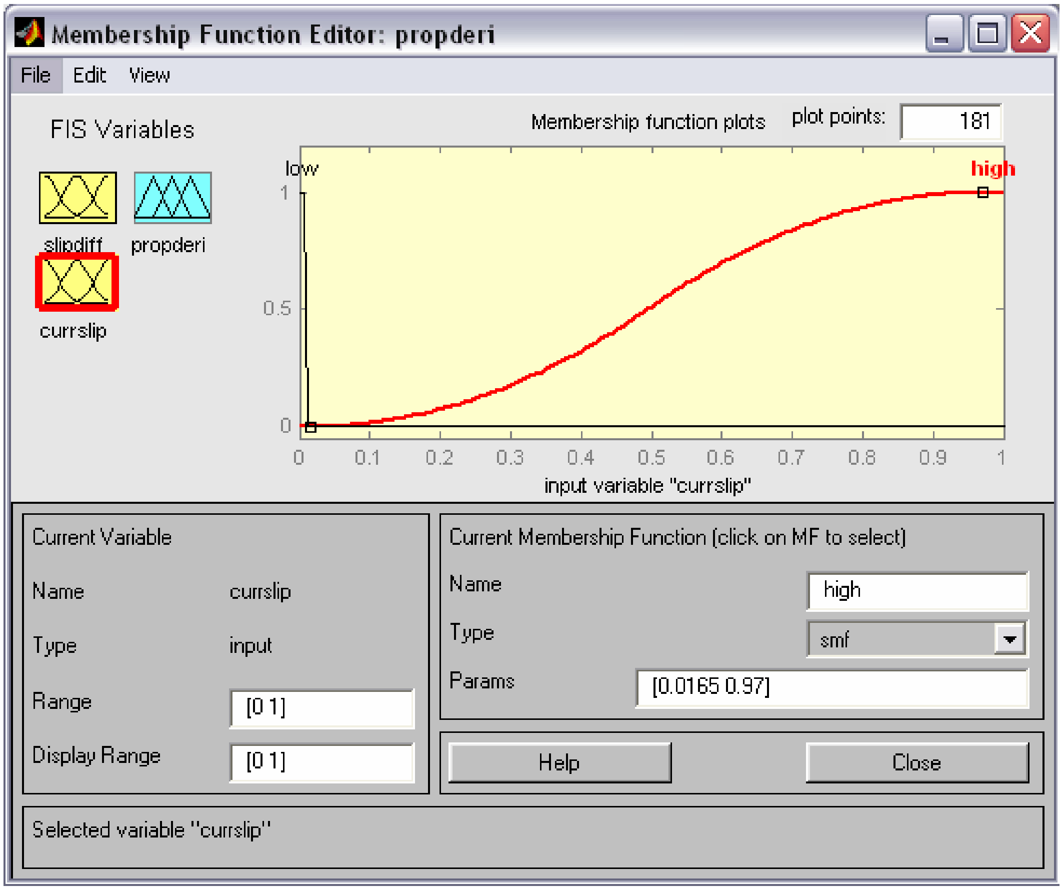


Figure B.8 Input Membership Function – Current Slip

The figure shows the membership functions for the input variable "currslip". It shows two different membership functions (low and high) spread over a range [0 1]. The "low" is "zmf" type membership function. The "high" membership is a sigmodial membership function "smf".

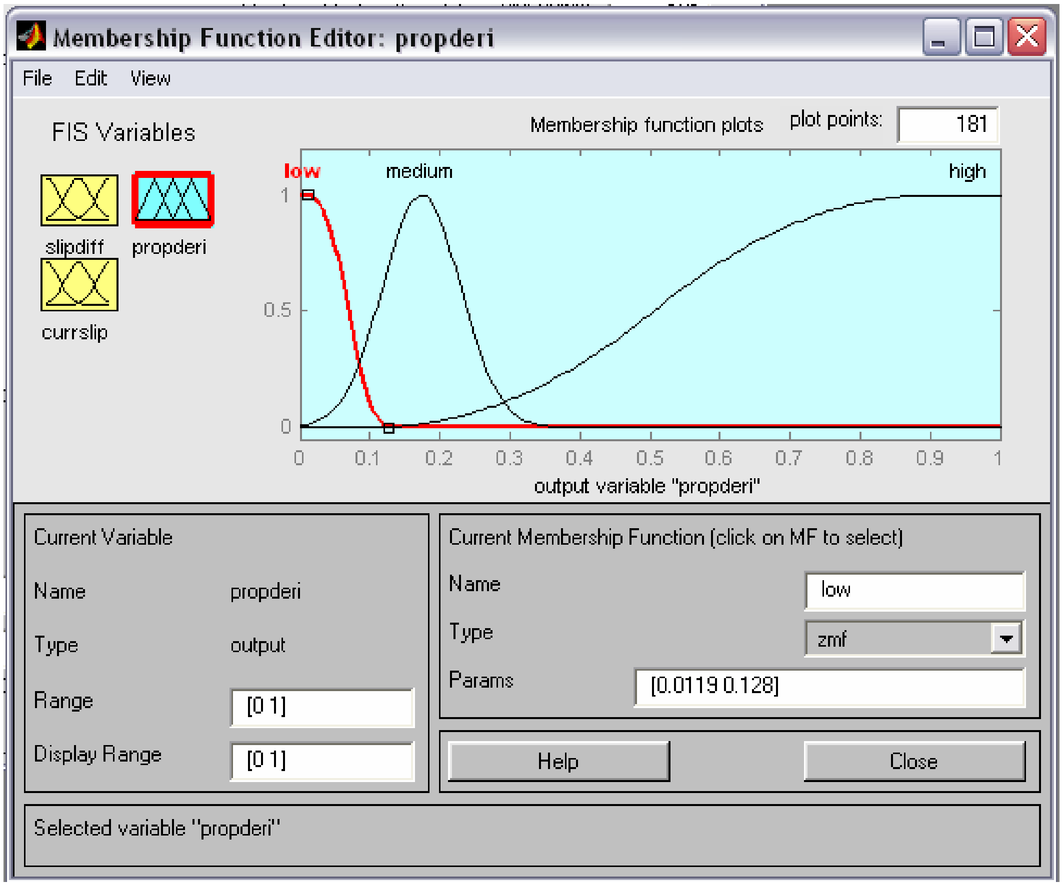


Figure B.9 Output Membership Function – PD Constant

The figure shows the membership functions for the output variable "propderi". It shows three different membership functions (low, medium and high) spread over a range [0 1]. The "low" is "zmf" type membership function. The "medium" is of type "gaussian mf". The "high" membership is a sigmodial membership function "smf".

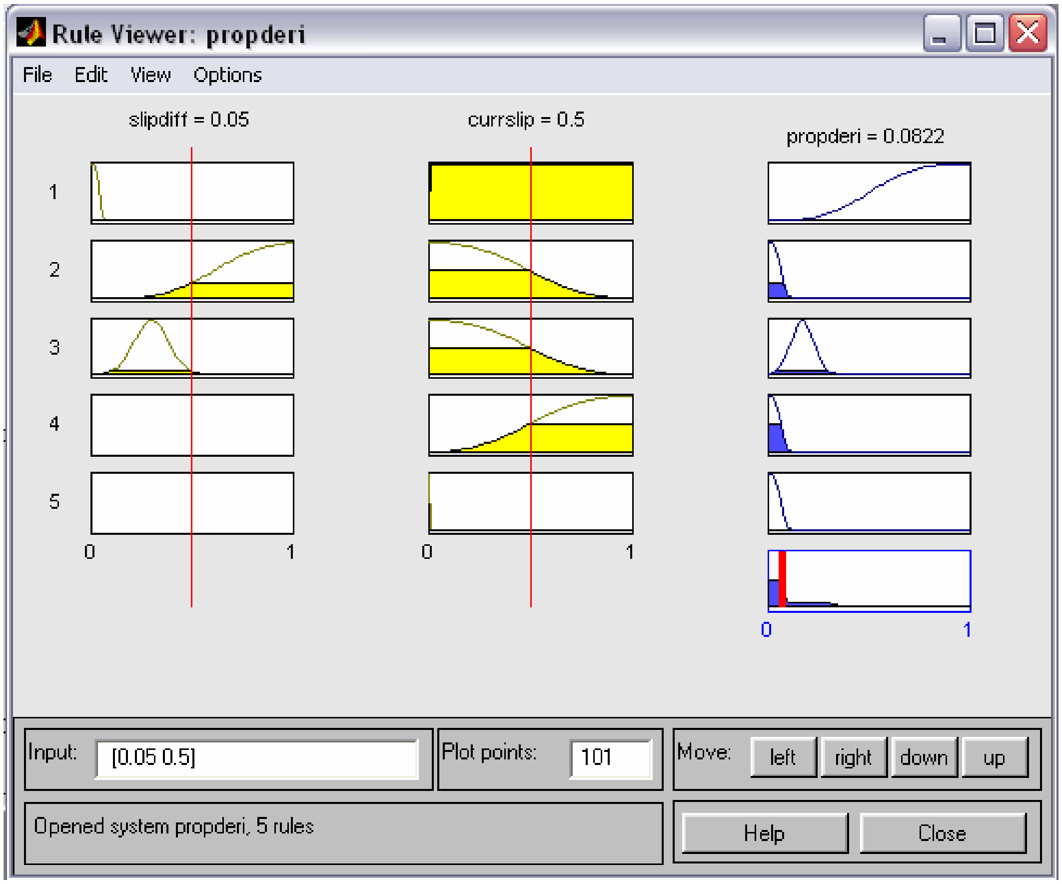


Figure B.10 Rule Viewer

For the “currslip” and “slipdiff” input shown by the red vertical lines on the left, of the five rules shown only three are "activated" by a membership value greater than zero. Each rule is weighted on the right (blue areas) and a compounded average is computed (thick red line in the bottom-right to generate a "crisp" (analog) signal as the controller action.

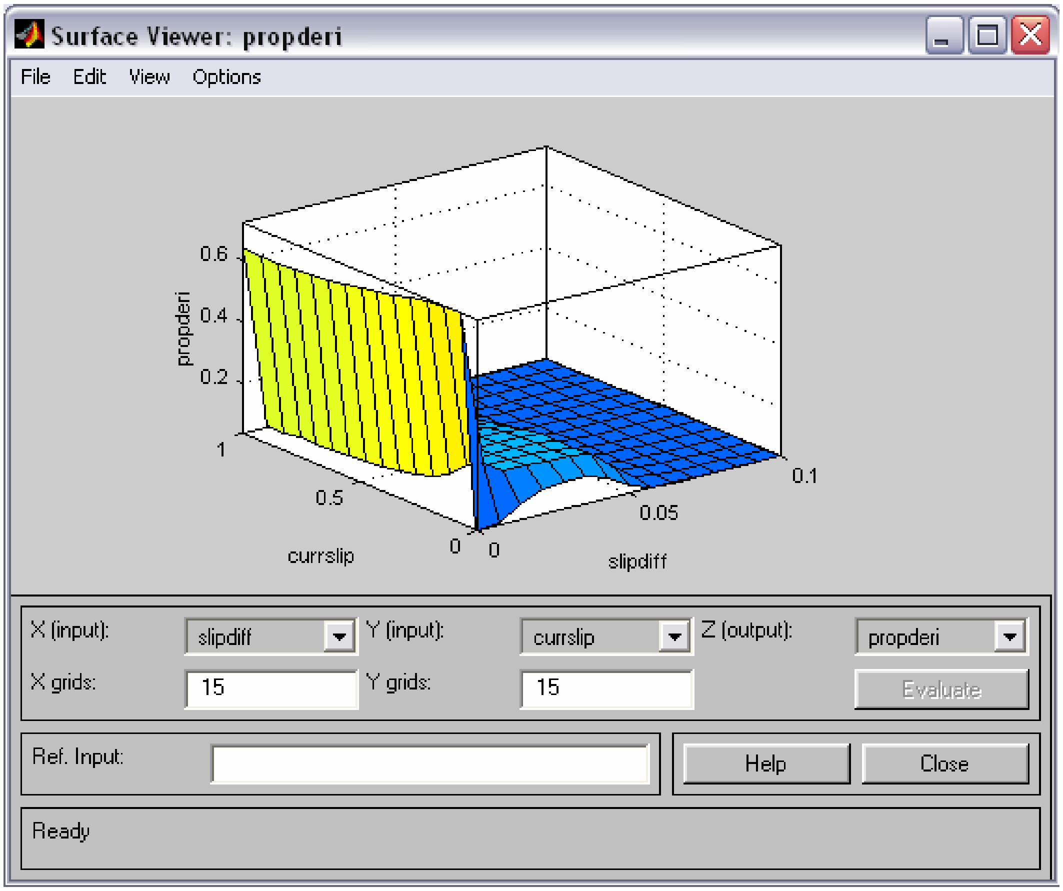


Figure B.11 Surface Viewer

The figure shows the control surface generated as a result of the fuzzy rules. It shows the relationship between the inputs and the output for the controller. The surface is a 3-D one with two inputs and one output.

References

1. Web Reference - http://www.cvma.ca/Issues/Safety.html

2. Web Reference - http://www.abs-education.org/ishs/newtechca.html

3. Web Reference - http://www.tc.gc.ca/roadsafety/tp/tp13082/abs1_e.htm

4. Wong, J. Y., *Theory of Ground Vehicles*. New York, NY: John Wiley & Sons, Inc. 1993

5. Web Reference - www.vti.se/nordic/2-00mapp/ noart1.html

6. Web Reference - http://www.fam.aust.com/keller/cit1/pic12.gif

7. Leffler, H., *The Brake System of the New 7 Series BMW with electronic brakes and wheel slip control*, SAE SP -1075, 1995.

8. Jiang, F., Gao, Z., *An adaptive nonlinear filter approach to vehicle velocity estimation for ABS*, Proceeding of 2000 IEEE International Conference on Control Applications, pp 490-495, Anchorage, 2000.

9. Bakker, E., Nyborg, L., Pacejka, H.B., *Tyre Modelling for Use in Vehicle Dynamics Studies,* SAE Paper No. 870421, Society of Automotive Engineers, Inc. 1987.

10. Yi, K., Hedrick, K., Lee, S., *Estimation of Tire-Road Friction using Observer Based Identifiers*, Vehicle System Dynamics, Vol.31, No.4, pp. 233-261, 1999.

11. Rudd, III., *Antiskid control of multi-wheel vehicles using coupled and decoupled Kalman filtering incorporating pitch weight transfer,* U S Patent # 6,220,676, 2001.

12. Sekine, et al., *Road Surface condition-detecting system and anti-lock brake system employing the same,* U S Patent # 5,586,028, 1996.

13. Unsal, C., Kachroo, P., *Sliding Mode Measurement Feedback Control for Antilock Brake Systems,* IEEE Transactions on Control Systems Technology, Vol. 7, No. 2, 1999.

14. Tseng, C.H., Chi, C.W., *Aircraft Antilock Brake System with Neural Networks and Fuzzy Logic,* Journal of Guidance, Control and Dynamics, Vol. 18, No. 5, 1995.

15. Layne, J.R., Passino, K.M., Yurkovich, S., *Fuzzy Learning Control for Antiskid Braking Systems,* IEEE Transactions on Control Systems Technology, Vol. 1, No. 2, 1993.

16. Jiang, F., Gao, Z., *An application of Nonlinear PID Control to a Class of Truck ABS problems,* Proceedings of the 40th IEEE Conference on Decision and Control, Orlando, Florida, 2001.

17. Johansen, T. A. et al, *Hybrid Control Strategies in ABS,* Proceeding of the American Control Conference, Arlington, VA, 2001.

18. Zadeh, L.A, *Fuzzy Sets,* Information and Control 8(3): 338-353, 1965.

19. Web Reference - http://www.cs.berkeley.edu/projects/Bisc/bisc.memo.html

20. Ross, T.J., *Fuzzy Logic with Engineering Applications,* McGraw Hill Publication, 1995.

21. Jang, J.S.R, Sun, C.T., Mizutani, E., *Neuro-Fuzzy and Soft Computing,* Prentice Hall Publication, Upper Saddle River, NJ, 1997.

22. Semmler, S. et al, *Estimation of Vehicle Velocity using Brake by Wire Actuators,* 15th Triennial World IFAC Congress, 2002.

23. Borner, A., *Neuro-Fuzzy Approach in Measurement: Road Vehicle Velocity Estimation,* IEEE International Workshop on Intelligent Signal Processing, 1999.

24. Laurence, P. et al., *Identification of steady-state vehicle behaviour using a bezier curve optimized with genetic algorithms,* IFAC-IEEE: AVCS'98, pp 253-258, 1998.

25. Jun, et al, *An Investigation into Fuzzy Control for Antilock Braking System based on Road Autonomous Identification,* SAE 2001-01-0599, 2001.

26. Will, A.B., Zak, S.H., *Antilock brake system modeling and fuzzy control,* Int. J. of Vehicle Design, Vol. 24, No. 1, 2000.

27. Kachroo, P., Smith, K., *Experimental setup and testing for verification of similarity between road tire interaction characteristics of scaled models and full scale vehicles,* SPIE Vol. 3207, 1998.

28. Web Reference - http://www.fuzzy-logic.com/Ch1.htm

29. Nelson, D.E, et al., *Implementation of Fuzzy Logic for an Antilock Braking System,* IEEE International Conference on Computational Cybernetics and Simulation, Vol. 4 , pp 3680 -3685, 1997.

30. Al-Sharif, A., *Design and Development of a Scaled Test Laboratory for the study of ABS and other Active Vehicle System,* Thesis, The University of Texas at Austin, August 2002.

31. MATLAB Reference Files - MATLAB Fuzzy Logic Toolkit Help Guide

32. Paynter, H.M., *Analysis and Design of Engineering System,* MIT Press, 1961.

33. Karnopp, D. et al., *System dynamics : modeling and simulation of mechatronic systems*, 3rd ed. New York, 2000.

34. Athan, T. W., Papalambros, P. Y., *Multicriteria Optimization of Anti-Lock Braking System Control Algorithms*, Engineering Optimization, v 27, n 3, Gordon & Breach Science Publ Inc, Newark, NJ, USA, p 199-227, 1996.

35. FGModellsport, “*FGModellsport Catalog 2000”,* RC World and RC Publishers, July 2000.

36. Longoria, R.G., Al-Sharif, A. and Patil, C., *Modeling and Laboratory Testing of Scaled Vehicle System Dynamics and Controls*, International Journal of Vehicle Autonomous Systems, Special Issue on Autonomous Road Vehicles, to appear.

Vita

Anish George Mathews was born in Thiruvella, India on January 31, 1978 to K Mathews Varughese and Rachel Mathews. He was the second child in the family with his sister Anila Mathews being the elder one. He completed his high school education in 1995, at Carmel Garden Matriculation Higher Secondary School in Coimbatore, India. In June 1995, he started attending the undergraduate program in mechanical engineering at P S G College of Technology in Coimbatore, India, one of the top schools for engineering in India. During his years at P S G Tech, he was among the top 2% of his class. He was awarded the Jawaharlal Nehru Summer Research Fellowship during the year 1998 for his research work at the National Aerospace Laboratories, India. In December 1999, he received the degree of Bachelor of Engineering in Mechanical Engineering with distinction from the Bharathiar University through P S G Tech. After his undergraduate education, he took up work as a Project Engineer at Soliton Automation, Coimbatore, India. In August 2000, he joined the Masters program in Mechanical Engineering at the University of Texas at Austin. He was awarded a research assistantship from his thesis supervisor. Later on, he was also awarded teaching assistantships. He conducted Dynamic Systems and Controls Laboratory for groups of 10-14 students as part of this teaching assistantship award. He was also awarded the N K Wright Memorial Presidential Scholarship, one of the University's most prestigious student awards, for the year 2002-2003. In

Sept 2002, he joined Soliton Automation again as a Project Leader and began developing Soliton business's presence in the US market.

Permanent Address:
4/B Jayanthi Nagar,
K. P Colony,
Coimbatore - 641030,
India

This thesis was typed by the author.