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FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY AND INFORMATION AND COMMUNICATION TECHNOLOGY (DEPARTMENT OF ELECTRICAL AND ELECTRONICS TECHNOLOGY)

Collision Avoidance Car Braking Neuro Fuzzy Controller

MSc Thesis for the Partial Fulfillment of

Master of Science in Electrical Automation and Control Technology Management

By,

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Collision Avoidance Car Braking Neuro Fuzzy Controller

A Thesis submitted to

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FACULTY OF ELECTRICAL AND ELECTRONICS TECHNOLOGY AND INFORMATION AND COMMUNICATION TECHNOLOGY
(DEPARTMENT OF ELECTRICAL AND ELECTRONICS TECHNOLOGY)

In partial fulfillment for the Degree
MASTER OF SCIENCE *in* ELECTRICAL AUTOMATION AND CONTROL TECHNOLOGY MANAGEMENT

By,

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Supervisor,

Dr. Lebsework Negash

DECLARATION

I declare that the work described in this thesis, "Collision Avoidance Car Braking system using Neuro Fuzzy Controller," is my original work that has not been submitted for a master's thesis at this university or anyplace else. All data sources have been adequately mentioned throughout the thesis. Thesis: "Collision Avoidance Car Braking System Using Neuro Fuzzy Controller"

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This thesis proposal was submitted in hopes of receiving my TVTI advisor's approval.

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Thesis on

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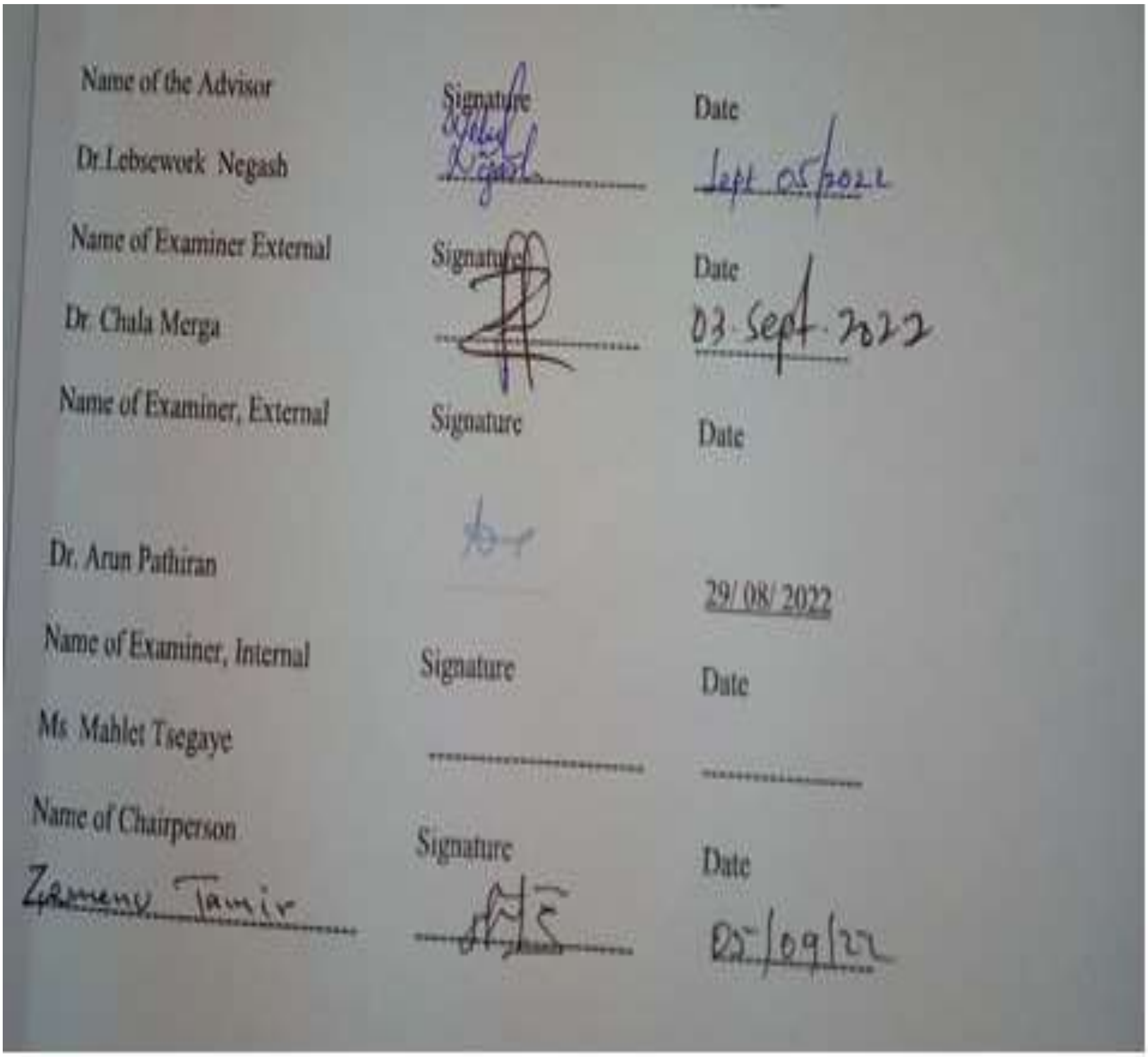
APPROVED BY THESIS ADVISORY COMMITTEE



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ABSTRACT

This thesis deals with a Neuro-Fuzzy Controller (NFC) for collision avoidance a car braking system. Collision avoidance is a major problem of the world today, with an increasing number of individuals causing the deaths and properly damage due to poor car braking control mechanisms.A mathematical and Matlab/Simulink model of the braking system's components has been constructed using a quarter-car model. On the basis of input factors such as slip, road condition, coefficient of friction, and wheel acceleration, two Neuro-Fuzzy Controllers (NFC) have been used to control various parameters, such as optimal slip and brake pedal power. Analysis has been done on the nature of the slip curve over the entire braking period with and without NFCs.Analysis has been done on the type of curve including wheel velocity and vehicle velocity as well as the time required to arrive at the stopping distance with and without NFCs. In comparison to a straightforward PID controller, the neuro-fuzzy control mechanism offers greater real-time control over parameters because it is similar to the human brain in terms of decision-making. Over a straightforward PID controller, fuzzy logic controllers offer superior steerability, slide control, and braking distance.

Key words:- *Neuro-Fuzzy Controller, Quarter car Model, collision avoidance, Neuro Fuzzy toolbox Model*

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ABBREVIATIONS

ABS	Antilock Braking System
CPU	Control Processing Unit
ESP	Electronic Stability Program
EV	Electric Vehicle
FIS	Fuzzy Interference System
FLC	Fuzzy Logic Controller
FOSMC	Functional Order Sliding Mode Controller
GPS	Global Positioning Unit
IOE	Institute Of Engineering
ISMS	Intelligent Sliding Mode Scheme
MATLAB	Matrix Laboratory
MF	Membership Function
PID	Proportionalintegralderivative
RBFNN	Radial Basis Function Neural Networks
Simulink	Simulation And Link
SM	Sliding Mode
SMC	Sliding Mode Controller

CHAPTER ONE

INTRODUCTION

Car collision avoidance systems are intended to reduce the number of accidents and fatalities on roads and highways. Safety systems, such as the seat belt when worn properly and the air bag, are intended to save lives. The reason for researching collision avoidance is so that if a driver is not paying attention for a fraction of a second, a passive system can be implemented to keep the driver, passengers, and others safe.When a driver attempts to decelerate or stop a moving vehicle while braking, cornering, or both on slippery surfaces with asymmetric coefficients of friction, the vehicle's safety is jeopardized. The majority of accidents happen when an obstacle appears in front of the vehicle, and the driver must react immediately after recognizing the danger.This action is determined by a number of factors, including the vehicle's distance from the obstacle, the state of the other lanes (whether they are occupied or not), the road surface conditions, and so on. A vehicle without braking is only safe if there is sufficient clearance before the obstacle, the road is straight, and the friction coefficient on both vehicle sides is the same. If any of these conditions is not met, a single or multiple vehicle crash may occur. Single vehicle crashes are not uncommon even with only longitudinal motion control capability.

Human errors in traffic are gradually being eliminated as technology advances. Many accidents could be avoided in braking situations, for example, if the driver can predict the correct braking pressure for the given stopping distance. This thesis propose the use of a neuro-fuzzy control system, which could be incorporated into a car system, even collaborating with for canceling the driver's reaction time, given the distance of one obstacle and its speed relative to the vehicle.

The proposed system consists of fuzzy controllers linked in cascade, with the first analyzing possible accident situations based on the vehicle's separation distance from an obstacle in a straight line and its relative speed, and the second taking into account road conditions via static friction. The force in percentage that must be applied to the brake pedal for the vehicle to stop safely is the output of these controllers.

1.1 Background

A vehicle collides with another vehicle, a pedestrian, an animal, or a physical obstruction on the road to cause a traffic accident. This may result in accidents, losses of property, and fatalities.Congestion occurs when there are more vehicles on the road than the road can handle.Because of the increased traffic congestion, the trip takes longer than it should. Congestions in traffic can be caused by an accident, taking the wrong route, passing a VIP, or parking illegally. It can happen due to poor road design or misunderstanding of traffic rules. The growth of traffic in this area is non-linear in comparison to the development of infrastructure such as roads, intersections, and bridges, all of which contribute to traffic congestion.Safety is an essential component of human life. Distracted driving, where the driver misses an occurrence because they are preoccupied or not paying attention, careless driving, or faulty braking systems contribute to traffic collisions. The development of automatic braking systems has resulted in significant safety in driving, reducing the total stopping distance and thus reducing the number of accidents and their consequences.This can be accomplished through the use of systems such as Automatic car braking systems(ABS),which can be both useful and beneficial . For efficient and effective speed control and braking, we employ a Neuro-fuzzy controller.

1.2 Statement of the Problem

These cars are Equiped with ABS we respect to neurofuzzy controller to improve speed control over the existing ABS.

Automotive safety applications are increasingly common in today's motorcycles, automobiles, and trucks. Almost all passenger vehicles now have vehicle stabilization systems with electronic stability control. Due to its complexity, there is little room for further ABS development or investigation. Wheel slide prevention is difficult. Due to the unpredictability of the model, nonlinear brake dynamics, and tire-road contact. Nonlinearity characterizes tire force saturation. Changing vehicle parameters, un-modeled dynamics and the coefficient of tire-road friction are all major sources of uncertainty in vehicle dynamics. Because of these uncertainties, the control performance suffers significantly. Based on what has been discussed, these difficulties can be solved by formulating a nonlinear robust ABS control rule. The uncertainties and high nonlinearities in the mathematical model make designing an ABS difficult. Because of these difficulties, ABS is becoming an appealing area of research in the nonlinear systems control framework. Extensive field testing and simulations are used to tune the controllers through trial and error. Neuro-Fuzzy Control is a knowledge-based control technology that thrives in intricate, nonlinear, and undefinable systems. Neuro-fuzzy logic can therefore be applied to ABS.

1.3 Objective

1.3.1 General Objective

This designs and simulates a neuro-fuzzy controller for vehicle accident avoidance.

1.3.2 Specific Objective

This deals seeks to develop a system that will address the following:

- To develop mathematical model for the vehicle.
- To develop MATLAB/Simulink model of the mathematical model.
- To apply Neuro-fuzzy logic controllers and analyze the system's performance with PID controller.
- To Measure and analyze system performance based on brake force, car position, speed, braking duration, and distance traveled.

1.4 Methodology

The primary method of modeling and controlling a car braking system is simulation. Matlab/Simulink R2018a is used to carry out the simulation investigation. The hydraulic actuator, controller mechanisms, and vehicle braking dynamic system were first modelled before simulation. The simulation for wheel slip control of the vehicle braking system, which takes into account slip trajectory during straight-line braking, comes next.

The car braking based system was then examined for an intelligent control technique utilizing online learning and gradient descent. Offline training for this intelligent control requires an Adaptive Neuro-Fuzzy Inference System (ANFIS) tool. Method produces initial parameter and fuzzy rule.For every performance, the outcomes were examined. The controllers were then compared in the final step. Figure 1.1 shows flowchart diagram serves to highlight the thesis execution technique.

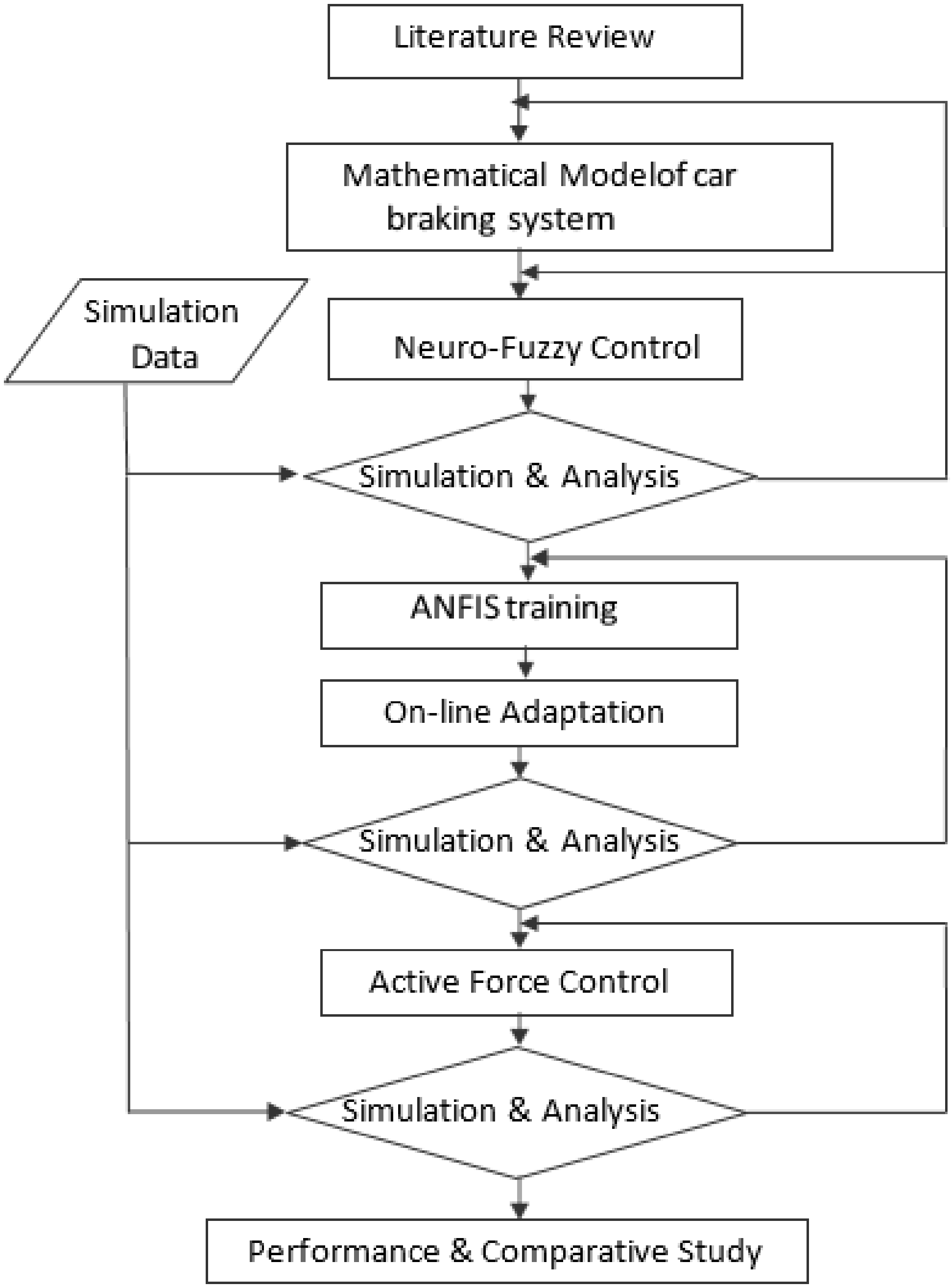


Figure 1.1 Flowchart for implementing the Thesis

1.5 Scope and Limitation of the thesis

This research describes how to design vehicle braking control system using neuro fuzzy systems. The intelligent controller provides obstacles avoidance, unstructured environment adaptation, and vehicle speed scheduling based on neuro-fuzzy system. The system's purpose is to provide speed control, distance and braking in an unstructured and dangerous environment.

1.6 Significance of the thesis

The goal of the Automatic Braking and Speed Control System is to create an automated control system that will keep a safe driving distance from obstacles while driving. This thesis aims to create a control system based on Neuro-fuzzy for vehicle speed control in order to reduce road accidents and effectively ensure safe and stress-free driving. Also this research will look into the issue of road accidents caused by drivers failing to apply their brakes on time. This research will be used in the automobile industry to design a system that limits the speed of a vehicle when it approaches an obstacle. This thesis will teach students how automating cars can eliminate human error.

1.7 Organization of the thesis

Thesis structure is below. In the first chapter, we discuss the setting and drive for the thesis and appraise the current level of car braking system research.Chapter 2 introduces the literature reviews. Chapter 3 covers the model of Car baraking control system.Chapter 4 introduces NFIS and car braking controlle design strategy. Chapter 5 gives information on thesimulation results. Simulating the control strategy validates it. Chapter 6 concludes this thesis and outlines future research.

CHAPTER TWO

LITERATURE REVIEW

This chapter details the literature review's findings.Before beginning the methodology process of the research problem, an extensive review of the current literature is required to become acquainted with an antilock braking system and a Neuro-fuzzy system. Because neuro-fuzzy is new, it's rarely used to increase ABS efficiency. Application approaches are continually being developed and will shortly reach saturation. In the next section, I'll examine earlier attempts to improve vehicle braking systems and how neuro-fuzzy logic and sets play a role. Neuro-fuzzy sets can increase braking system performance, as well.

A car's anti-lock braking system (ABS) stops the wheels from locking up when the brakes are applied. ABS maintains the vehicle's steering abilities under extreme braking circumstances and shortens the stopping distance [17].

Every ABS that's produced will have subsystems. Slip controllers are common in anti-lock braking systems. This subsystem keeps wheel slip within a desirable range or at a specified set-point to prevent wheel lockup during braking. All ABS systems do not estimate or explicitly control wheel slip. They practice speed and acceleration. Focus on the logic that structures each of these subsystems' four wheel slip controls. As safety measures, these wheel slip controllers are only triggered when needed. When the wheel is no longer at risk of locking, these controllers are turned off and the brake is set to manual [18].

Simultaneously, the slip controller must be activated to prevent wheel lockup. The ABS's switching logic is crucial to its proper operation. Normal ABS control [19] combines wheel acceleration with slip control. The measured angular velocities of the wheel are used for wheel acceleration control, which indirectly controls slip by regulating the wheel's acceleration or retardation. An ABS actuator is a hydraulic solenoid valve with three brake pressure settings: decrease, hold, and raise. The controller is activated when wheel retardation falls below a predetermined value for a predetermined time. During the entire ABS active duration, the switching between reduce, hold, and increase actuator modes is controlled either by mentioning a switching surface that uses a weighted sum of acceleration and slip or by using several acceleration and slip thresholds. The slip will be centered around the crucial slip by selecting the proper thresholds. The consequence is a shorter stopping distance because the friction between the road surface and tires is almost at its maximum. This algorithm's undesired side effect is brake vibration. Slip control preserves tire force. Tire maximums improve wheel acceleration control [20].

The reason for this is that in the case of a pronounced maximum, a greater wheel retardation or acceleration can be obtained. ABS controllers are versatile due to their ability to accept unpredictability in friction and tire force.Traditional ABS has some limitations in terms of performance and control. One notable disadvantage of these systems is their inability to control wheel slip and track a specified desired slip within an allowable span. ABS is a rule-based control system with vast tables for different braking situations. The controls are optimized by trial-and-error, field testing, and simulations. Due to its complexity, there is little room for further ABS development or investigation. Active safety systems have undergone extensive study and development to help drivers in hazardous driving scenarios. The Anti-lock Braking System (ABS) manages car braking systems. Excessive brake force can lock the wheels. This reduces braking forces to sliding levels and lateral forces to almost nothing. This increases the stopping distance needed to turn and reduces the vehicle's steering ability [21].

The author [22] defines a fuzzy set as a class with variable membership function gives each fuzzy set object a 0-1 membership group value. Fuzzy sets are given the concepts of union, complement relation, intersection, convexity, inclusion, and so on. Many properties of these concepts are established in the context of these setsIn the real world, items don't have well defined membership criteria. Unlike plants, minerals, and fluids, animals include cows, buffaloes, horses, and other animals.However, some members of the animal class, such as bacteria, starfish, and so on, have an unclassifiable status. In the "class" of all integers greater than one, a number like 5 creates a similar ambiguity.Some categories, such as "the class of short men," "the class of intelligent women," or "the class of integers greater than one," do not constitute sets or classes in the general mathematical sense. Despite this, ill-defined "classes" are important in human mind, especially for identifying patterns, abstracting knowledge, and articulating it.The concept of a fuzzy set provides an appropriate point of departure for the development of a conceptual framework. This framework is similar to the one used for ordinary sets, but it has more uses in information processing and pattern detection. When imprecision is caused by a lack of properly described class membership rules rather than random variables, this architecture offers a simple solution. To understand fuzzy sets, one must first understand set theory. Mathematically, a classical set is simple. Set is a bounded group. These things, which may be part of the set or distinct, fill the room.

According to[23], a very simple clarification for fuzzy sets is indicated. The fundamental idea is to allow for the scaling of membership scores. The scaling allows for ambiguous membershipWhen a set's membership score is 1, all available members are included. A score of 0.8 or 0.9 indicates a strong set member. If the score is below 0.5 but above 0.2 or 0.3, the items are peripheral. 0 means the set has no members. Fuzzy sets are a hybrid quantitative-qualitative study because of this. The classification of fuzzy set memberships allows this theory to be flawlessly implemented in a range of disciplines, including multi-criteria decision making. Many words are used arbitrarily in our daily lives that are normally ambiguous in terms of their usual meanings. Slow, fast, young, old, cold, hot, short, tall, and other words are used to express or describe an event or a system. Humans refer to people as young or old depending on their age. Humans press the brake pedal less or more depending on the road conditions. These examples demonstrate the nature of the human brain acting and making decisions in situations that are unclear and hazy. Fuzzy logic refers to this type of decision-making logic that is similar to that of the human brain. Fuzzy logic is widely used in many fields nowadays, including human-machine interactions, signal aliasing, image processing, machine operational behavior, commercial products, motion control, flow control, temperature control, tracking systems, automation, robotics, and many others. Control systems were one of the first areas where fuzzy logic was used. In practice, fuzzy logic is nothing more than the computation of words. There is the possibility of word computation. Encoding human expertise in common language allows for the development of computerized systems. A fuzzy rule base or fuzzy inference system can do reasoning similar to, but less sophisticated than, the human brain.The core elements of fuzzy logic are fuzzy sets that are distinguished by some short of fuzzy numbers known as membership functions. The concept of fuzziness is derived from uncertainty. If data is difficult to categorize and is not crisp, it is represented by involvement degrees in related grades. Assume that if we mix two colors, say black and white, and try to draw a spectrum on paper, we will get a lot of shades of either black or white. Because those transition shades are neither fully white nor fully black, there is a fuzziness between white and black [24].

There must be a link between the fuzzy world and the uncertain data. Fuzzy membership functions are being considered for the role of bridge. Fuzzy membership functions represent the crisp universe's partitioned subsections of muddy data. Fuzzy sets represent and make use of fuzzy membership functions. Different pictorial and geometric shapes are used to represent fuzzy sets. Because of their simplicity, membership functions rely on well-known mathematical functions [25].

Certain mathematical formulas define membership functions, which represent fuzzy sets of various shapes. Membership functions include triangular, Gaussian, trapezoid, Cauchy, sinusoid, bell, and sigmoid. The membership functions' parameters include the universe's location range and data fuzziness. This simplifies fuzzy-set operations. Detachable parameters allow for flexible membership functions. Linear membership functions, such as triangle and trapezoid, are used more often. Because they're linear. Membership functions of learning algorithms like artificial neural networks are adjusted and determined.

2.1 Literature Survey

The research gap identified after reviewing various types of literature published in various years is summarized in the table below.

- The fuzzy is a widely used in developing automatic braking or speed control system.
- Emphasis on driver safety must be given while developing automatic braking system.

Table 2.1 Research gap identifications

S.N	Researchers	Findings	Research Gap
1	Clairetal.,(1997)	Without fuzzy ABS, braking pressure develops quickly, and the wheels lock up. Because of this, the car's behavior deteriorates, it's harder to steer, and it takes longer to stop.	For optimal slip, different types of road conditions are not defined.
2.	Harifietal.,(2 007)	An ABS was designed to achieve maximum retardation while preventing wheel locking. A sliding mode (SM) controller was designed to control wheel slip, Enhancing the inherent switching surface reduced chattering.	The time it takes for the vehicle to reach the stopping distance is not specified.
3	Sharkawy,(2 010)	The use of proportional integral derivative (PID) controllers in ABS reduces the stopping distance of the vehicle while keeping the slip ratio of the tires within set-points.	There is no comparison with FLCs.
4	Vazquez etal.,(2010)	Sliding mode (SM) was used for an ABS and it was discovered that this type of controller is robust against unmatched and matched perturbations. Additionally, the ability to reduce sliding friction grows.	The time required to reach the stopping distance is not specified
5	Beraetal.,(20 11)	ABS actuation rate must be very fast in extreme driving conditions. When mechanically designing the brake system Actuator, consideration is given to peak brake force, actuation rate, and so on, in order to achieve the desired actuator response time, maximum force, and so on, while taking proper care to extend the fatigue life of brake system components and lower brake pad wear.	There is no mention of different road conditions and their respective optimal slips.

6	Alyetal.,(2011)	Different control techniques for ABS systems were developed for different road conditions, Intelligent control solutions such as fuzzy logic controllers were designed to ensure ABS system reliability.	The optimal slip is determined without the use of a controller.
7	Sanchez-Torresetal.,(2011)	The creation of a sliding mode (SM) regulator improved ABS performance and closed loop system efficiency.	The results are not compared to a model that employs FLCs.
8	Tangetal.,(2013)	Combining Functional Order Sliding Mode Controller (FOSMC) with Sliding Mode Controller (SMC) and fractional order dynamics shows that FOSMC can deal with ABS system uncertainties and track wheel slip more quickly than integer order SMC with proportional-derivative or proportional sliding surfaces.	NouseofFLCs.
9	Dousti et al.,(2014)	Multiple model switching observers were used to estimate the ideal reference slip value. Actuator, consideration is given to peak brake force, actuation rate, and so on, in order to achieve the desired actuator response time, maximum force, and so on, while taking proper care to extend the fatigue life of brake system components and lower brake pad wear.	Respective optimal slip not mentioned
10.	Aksjonov et.al,(2016)	Automatic driving safety systems, such as ABS and ESP, assist vehicle drivers in better controlling the vehicle and avoiding road accidents.	No controller is used to achieve optimal wheel slip.

11.	Xiaoetal.,(2016)	ABS, which is based on fuzzy control, can effectively prevent wheel locking, braking more effectively, and slip rate is also more close to the optimal slip ratio of near 0.2.	Time forvehicle toreachstoppingdistance is notmentioned.
12.	Gowda &Ramachandra (2017)	The control of vehicle speed and wheel speed at the same time improves braking performance with the bang-bang controller.	Only threetypes of roadconditions areconsidered.
13.	Ezeetal.,(2018)	PID controllers are used for linear slip control with four different types of road conditions.	Slip control isnot done
14.	Mirzaeinejad ,(2018)	RBFNNs outperform sliding controllers in anti-lock braking systems (ABS).	Slip control Performance isnot done

CHAPTER THREE
MODELING CAR BRAKING SYSTEM

3.1 Introduction

The problem of traffic congestion is global. This issue is mostly the result of human driving, which includes reaction times, delays, and mistakes in judgment that can impede traffic flow and cause accidents. Driver inattentiveness and distraction are major contributing factors in many of these collisions. The most crucial system in an automobile is the braking system. Failure of the brakes might have disastrous effects. The driver often uses the brake pedal to manually operate a car's braking mechanism. As a result, an autonomous car braking system will be adopted to prevent such an accident. Brakes turn a vehicle's kinetic energy into thermal energy.

3.2 Vehicle Dynamics

A full vehicle model that details all important vehicle features is rarely used in control system design. To reduce controller design complexity, a model that incorporates the vehicle's fundamental characteristics must be used. In order to design this thesis, a system modeling is required to provide a method for the control system. As a result, a descriptive model of the system is created as a hypothesis of how the system might work.A vehicle model with system identification collision Control to track a set of velocity and maintains a safe distance is right image (Figure 3.1).

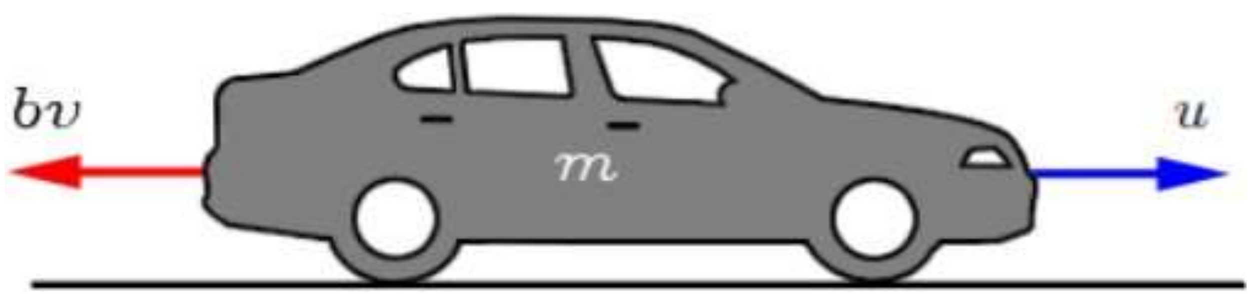


Figure 3.1 Real time car block model

If the inertia of the wheels is ignored and air drag (which is proportional to the car's speed at low speeds) is assumed to be the opposing force, the problem is reduced to a simple first order system. The car will be modelled for controllers using Newton's second law of motion.

$$\epsilon F = ma$$
$$u - bv = ma \tag{3.1}$$

Thus the motion of the car can be written as,

$$m\dot{v} + bv = u \tag{3.2}$$

where u is the input force provided by the engine to move the car at a certain velocity. Though it is intuitive to think of an input as something related to the gas pedal, unfortunately, representing such a system accurately becomes extremely complicated. So, for the time being, we will simply assume that our engine can produce a certain amount of force without investigating how that force translates to real-world situations.A quarter car model with the essential characteristics of the entire vehicle was chosen.

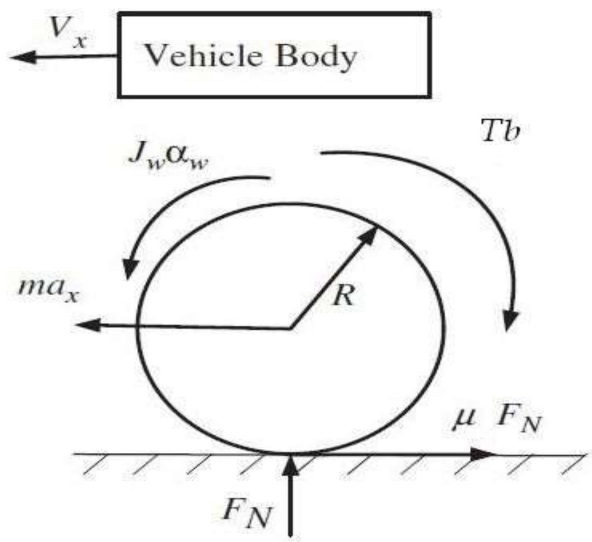


Figure 3.2 Vehicle dynamics [9]

Figure 3.2 depicts the quarter car model's free body diagram. The force balance equation is written in the longitudinal direction as

$$ma_x = -\mu F_N \Rightarrow m\frac{dv_x}{dt} = -\mu F_N \tag{3.3}$$

Torque at wheel centre will be given

$$J_\omega \alpha_\omega = \mu R F_N - T_b \Rightarrow J_\omega \dot{\omega} = \mu R F_N - T_b \tag{3.4}$$

A slip ratio will be given as follows:

$$\lambda = \frac{v_x - \omega R}{v_x} \tag{3.5}$$

By differentiating equation 3.5 both sides with respect to time, so that

$$\dot{\lambda} = \frac{\dot{v}_x(1-\lambda) - R\dot{\omega}}{v_x} \quad (3.6)$$

Where

V_x = Linear velocity of vehicle

a_x = Linear acceleration of vehicle

ω = Rotational speed of wheel

$^{\alpha}\omega$ = angular acceleration of wheel

Tb = braking torque

λ = slip ratio

μ = friction coefficient

R = radius of tyre

M = mass of the model

When using brakes, input torque and vehicle speed determine slip ratio. This creates state variables:

$$X_1 = S_x, \quad X_2 = V_x, \quad X_3 = \lambda \quad (3.7)$$

Two pair of input and two outputs Data training :-

Input1

- velocity
- wheel slip

output1 - slip ratio

Input2 _

- Wheel Acceleration
- Slip error

Out put 2- Optomal slip

1. Define the Parameters: - are usually used for defining some characteristics of modelled objects.

➢ It uses generally numeric parameters are used.

i. Parameters of vehicle:-

ii. Radius

iii. Mass

iv. Cofficients of surface (Jω)

v. Gravitational acceleration – 9.8m/s2

vi. Braking torque

vii. Initial linear velocity

viii. Initial rotational speed

1. **Define the Variable:-** are generally used to store the result of model simulation or model some characteristics of objects, changing overtime.

Input variables

i. Velocity

ii. Slip error

iii. Wheel slip

iv. Wheel Acceleration

Output variables

i. Slip ratio

ii. Brake force

where S_x is the stopping distance.

The state space of equation 3.6 will be given by:

$$\dot{X}_1 = X_x,$$
$$\dot{X}_2 = \frac{-\mu F_N}{m},$$
$$\dot{X}_3 = \frac{-\mu F_N}{x_2}\left(\frac{1 - X_3}{m} + \frac{R^2}{J_w}\right) + \frac{R}{J_w x_2} T_b \tag{3.8}$$

3.3 Tyre Modelling

According to the information presented in figure 3.3, a tyre is composed of a single wheel that is responsible for transporting one-fourth of the total mass of the vehicle and that travels with a constant velocity along its length at all times. Before the brakes are applied, the wheel rotates at an angle with a velocity of before being propelled in the direction of the longitudinal movement by the mass m. The production of tractive force is the result of friction between the tire and the road surface. The torque that is produced by the tyre as a result of its reaction to this force is what causes the wheel to roll. The wheel will start to slow down if the driver applies the brake torque, eventually coming to a complete halt.

The vehivle dynamics is designed on the following assumptions:

- Only the vehicle's longitudinal dynamics are taken into account.
- The vehicle is believed to be braking on a flat road, thus the vertical and horizontal movements are disregarded.

Figure 3.3 is a free-body diagram of an automobile. One-fourth of the vehicle's mass is carried by one wheel. The car has a beginning velocity V_o , but $t = t_o$, when the brakes are applied, its longitudinal velocity approaches zero at $t = t_f$. The circumstance implies it. $v(t_f) = 0$

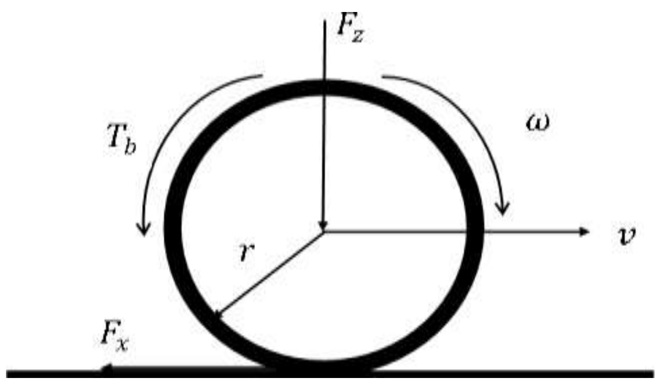


Figure 3.3 Single wheel system of the car [10]

The following equation describes the car, tire, and road intersection after applying the brakes.

$$\dot{v}_x = -\frac{1}{m}(\mu_x(\lambda_x)F_x + Cv_{x^2}) \tag{3.10}$$

V_x is the vehicle's longitudinal speed, C is the smooth friction coefficient, and μ_x is the tire-to-road friction. f_2 is the wheel's conventional drive, while λ_x is tire slip. Since the car is slowing while moving straight, only forces will affect its rate of deceleration F_z and F_x.

The wheel rotational dynamics will be :

$$\dot{\omega} = \frac{1}{J}(r\mu(\lambda)F_z - B\omega - T_b(sign(\omega))) \tag{3.11}$$

The ω wheel's angular speed, J is the wheel's rotational inertia, r is the tire radius, B is the viscous contact coefficient of the wheel bearings, and tb is the successful braking torque. The following equation represents brake actuator power:

$$\dot{T}_b = \frac{1}{T}(-T_b + k_b P_b) \tag{3.12}$$

The k_b braking pick upbrake pedal pressure is converted to torque by, which is influenced by the brake radius, brake pad friction coefficient, brake temperature, and the number of pads.Gain converts brake pedal pressure to torque.

Friction between tires and road affects both braking and traction. Wheel slip can deform and slide tyre or road tread [11].

The longitudinal slip is given by:

$$\lambda_x = \frac{v_x - r\omega}{v_x} \tag{3.13}$$

And the lateral slip will be

$$\lambda_x = \frac{\omega r \sin\alpha}{v} = (1-\lambda_x)\sin\alpha \tag{3.14}$$

Friction coefficient described as

$$\mu_x = \frac{F_x}{F_z}(\lambda, \mu, \alpha, v_x). \tag{3.15}$$

Demonstrates how slip, the surface's ideal friction coefficient, the steering angle, and the velocity all affect the friction coefficient.

The wheel slip dynamics is:

$$\frac{d\lambda}{dt} = \frac{\partial\lambda}{\partial v}\frac{dv}{dt} + \frac{\partial\lambda}{\partial\omega}\frac{d\omega}{dt} + \frac{\partial\lambda}{\partial r}\frac{dr}{dt} \tag{3.16}$$

$$\dot{\lambda} = \frac{\omega r}{v^2}\dot{v} - \frac{r}{v}\dot{\omega} \tag{3.17}$$

By combining equations 3.11 and 3.12 gives:

$$\dot{\lambda} = -\frac{1}{v}\left(\frac{\omega r}{mv} + \frac{r^2}{J}\right)F_x + \omega r\left(\frac{B}{Jv} - \frac{C}{m}\right) + \frac{T_b r}{Jv} \tag{3.18}$$

By rearranging equation 3.18 and $F_x = \mu F_z(\lambda)$ the slip dynamics will be.

$$\dot{\lambda} = \omega r\left(\frac{B}{Jv} - \frac{C}{m} - \frac{\mu F_z}{mv^2}\right) + \frac{r^2 \mu F_z}{Jv} + \frac{T_b r}{Jv} \tag{3.19}$$

Then can be rewritten

$$\dot{\lambda} = (1-\lambda)\left[\frac{Bmv - CJv^2 - J\mu F_z}{mJv^2}\right] + \frac{r^2 \mu F_z}{Jv} + \frac{T_b r}{Jv} \tag{3.20}$$

Now we conculude $v \rightarrow 0$ the slip dynamics $\dot{\lambda} \rightarrow \infty$ which occurs when the wheel lock-up. The analytical tyre model is developed using key factors such as anistropic stiffness properties, dynamic friction coefficient, translational, bending, and twisting compliance of the carcass, and arbitrary pressure distribution.

3.3.1 Problem Formulation

The slip ratio λ and road adhesion coefficient $\mu(\lambda)$ have a strong nonlinear relationship that is affected by both the tire model and the road conditions. The frictional coefficient and wheel slip ratio describe how braking can preserve a vehicle's steerability and stability while allowing for shorter stopping distances than a locked wheel stop. The friction coefficient can alter based on the road surface (dry or wet), the angle at which the tires are sliding, the tire brand (summer or winter), the vehicle speed, and the tire-to-road slip ratio. [12]'s friction model is used. It calculates the friction coefficient based on slip ratio and linear speed. This tire's specs are:

$$\mu(\lambda) = c_1(1 - e^{-c_2\lambda}) - c_3\lambda \tag{3.21}$$

$$\lambda_k = \frac{1}{c_2}\log\frac{c_1c_2}{c_3}$$

$$\mu(\lambda_k) = c_1 - \frac{c_3}{c_2}\left(1 - \log\frac{c_1c_2}{c_3}\right) \tag{3.22}$$

where, $\mu(\lambda)$ = friction coefficient, λ = slip and C_1, C_2, C_3 are constants which depend upon road condition [16]. That is:

C_1 represents the maximum value of the friction curve;

C_2 represents the friction curve shapes;

C_3 represents the friction curve variance between the maximum value and the value at = 1; and C_4 represents the wetness characteristic value. It is in the 0.02–0.04s/m range.

Burckhardt's tire friction model was used to simulate a brake system in this paper.

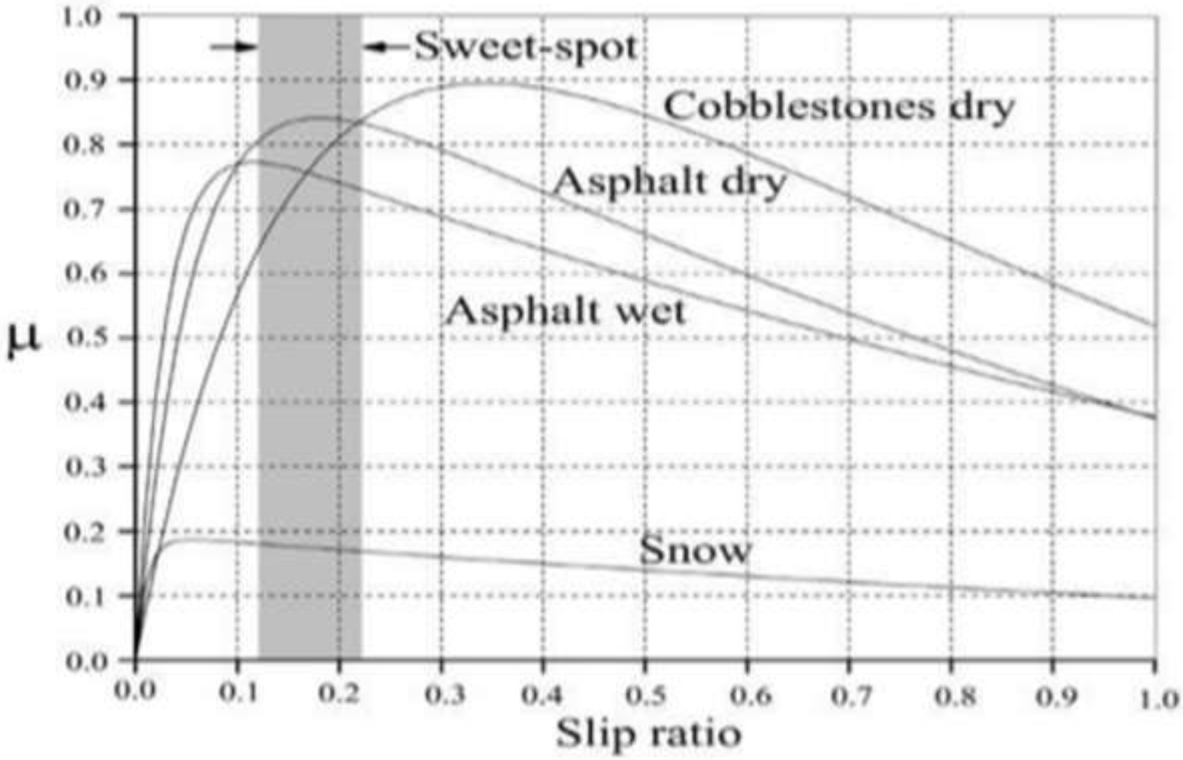
Table 3.1 Coefficients of Burckhardt equation [5]

Road surface condition	C1	C2	C3
Dry Asphalt	1.2801	23.990	0.52
Dry Concrete	1.1973	25.186	0.5373
WetAsphalt	0.86	33.82	0.35
Cobblestone	1.37	6.46	0.67
Snow	0.1946	94.129	0.0646
Ice	0.05	306.39	0

There is an optimal tire-to-road friction coefficient for a given wheel slip ratio. This varies by road type. Figure 3.4 demonstrates that the frictional coefficient is highest when the wheel is locked and the wheel slip ratio is one (1). When the wheel slip ratio λ is approximately 0.2, it's excellent for most road surfaces. The brake controller adjusts the wheel slip ratio to 0.2 to increase the frictional coefficient μ for any road surface.

3.3.2 State space form of of brake equation

the slip dynamics' state space will be specified as follows



$$\begin{aligned}
\dot{\omega} &= \frac{1}{J}(r\mu(\lambda)F_z - B\omega - T_b(sign(\omega)) \\
\dot{v} &= -\frac{1}{m}(\mu(\lambda)F_z + Cv^2) \\
\dot{T}_b &= \frac{1}{r}(-T_b + k_b P_b) \\
\lambda &= \frac{v - r\omega}{v}
\end{aligned} \tag{3.23}$$

Where the states are selected as:

$x_1 = \omega$, $x_2 = v$ and $x_3 = T_b$ the control input is $u = P_b$ which is braking pressure and the output is given $y = \lambda$ is slip. Therefore the state space is clarified in vector form as

:

$$\begin{aligned}
\dot{x} &= f(x, u) \\
y &= h(x)
\end{aligned} \tag{3.30}$$

CHAPTER FOUR
CONTROLLER DESIGN

4.1 Introduction

Fuzzy logic control simulates a human who can run a plant without a mathematical model. Fuzzy logic control does this. The control specialist establishes linguistic rules for control. Fuzzy set theory is used to translate these control rules into a calculus that can mimic the actions of a control expert.The knowledge of the control master is necessary for the formulation of good language guidelines, then the interpretation of these procedures into the The framework of fuzzy set concept is not codified and involves subjective judgments. The choice of membership features can significantly affect FLC quality. Therefore, techniques for fine-tuning fuzzy logic controllers are needed. The tuning issue may be resolved with the aid of neural networks. A neural network trained in frequently referred to as a "black box ," despite the fact that it can learn from provided data. A trained neural network cannot be used to extract structural information, nor can it be enhanced with more input to speed up learning. A fuzzy logic controller, on the other hand, is made to operate with organized knowledge in the system of rules, and almost every part of the fuzzy system stays very clear and simple to understand. There isn't a formal framework for choosing the differentdesign criteria, thus trial then error is usually how these parameters are optimized. Fuzzy logic tuning issues and design challenges can be resolved by combining neural networks and fuzzy logic.The consequential network will be clearer and simpler to identify as semantics or fuzzy logic control rules. This strategy avoids the problems of both strategies while combining their well-known advantages.

4.2 Fuzzy Logic Control plot

When making decisions, humans frequently use ambiguous or inaccurate ideas that can remain conveyed linguistically. One approach to modeling this decision-making process that Zadeh [21] presented makes use of the notion of approximative rational, which enables some language eras to be scientifically protected. He pioneered fuzzy set theory for control problems. He supported approximating (fuzzy) situations whose facts, objectives, and restrictions are too complex or ambiguous for a detailed scientific analysis. All problems are affected. Mamdani and Assilian [21] initially introduced fuzzy control.

4.2.1 Language variables and Membership functions

Linguistic variables indicate process steps and govern characteristics like time, distance, and speed. Fuzzy sets are an extension of normal or crisp sets. Fuzzy sets can illuminate the variable. Classical and fresh sets are smaller than fuzzy. The classical set can only represent a tiny quantity of information or data, such as "0" or "1," or a few discrete bits. A membership function describes any fuzzy set by determining how much of it includes crisp values. This is a percentage. If the referential set is infinite, these values are a continuous membership function. Membership functions might be triangular,trapezoidal,bell-shaped,and monotonous (Figure (3.1).

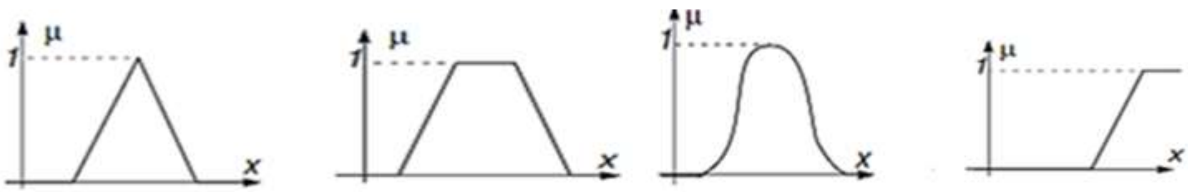


Figure 4.1 Different membership function forms include,triangular,trapezoidal,bell-shaped Figure, monotous and square [21].

The address domain (dynamic range) of each language variable must be characterized before performing any fuzzy function. In a world where people speak, each fuzzy set corresponds to a language level.

4.2.2 Notation of Language regulation

The main idea of a fuzzy logic system, as mentioned in the previous section, is to use language if-then rules to convey human knowledge. All rule is divided into two parts:

- The preceding part , denoted by if............
- The following section, define by then...........

The state of the system that should activate the rule is described in the section before, and the action that the worker who controls the method must perform is described in the section after. If-then rules can take many different forms. The general one is that certain outcomes can be inferred if a certain set of conditions are satisfied. Zadeh was the first to put up the following fuzzy rule notation: R1 states that if x = A, then y = B. The linguistic values A and B are defined on the conversational domain linguistic variables x and y using the appropriate fuzzy set membership functions. Takagi and Sugeno proposed a variant in which the output component employed the input variables in a non-fuzzy equation R2, and the only fuzzy sets stayed in the foundation part of the principle:If x = A, then y must likewise equal A, where A is the linguistic label, according to Zadeh's rule. The fuzzy inference system that emerges when f(x) is a first order polynomial is known as a first-order Sugeno fuzzy model. A zero-order Sugeno fuzzy model, or a subset of the Mamdani inference system, exists when f is constant. A single fuzzy node in this paradigm describes each subsequent rule separately (before defuzzified consequent).

4.2.3 Techniques of Fuzzy Reasoning

Probability theory dominated the field of uncertainty quantification Among scientific theories from the late 19th to the late 20th centuries. However, Max Black's studies on vagueness in 1937 and Zadeh's [21] introduction of fuzzy sets both posed challenges to the progressive progression of the depiction of uncertainty using probability theory. Uncertainty can appear in a multitude of forms, including vagueness, ambiguity, ignorance, and natural variability. It can also fuzzy be (not sharp, unclear, inaccurate, or estimated), vague (not specific, amorphous), ambiguous (alsoseveral options, contradictory), and complexity (conflicting, random, chaotic, or unpredictable).A fuzzy logic system consists of decision guidelines that each set is subjected to, a process for creating an output, and sets that are used to classify input data (fuzzification) (defuzzification). The fuzzy controller's brain is the inference unit. It decides the degree to which each measured value belongs to a specific labeled gather by applying fuzzy control activities from the knowledge base to the current prepare state. Figure 3.2 illustrates the structure of a fuzzy controller.

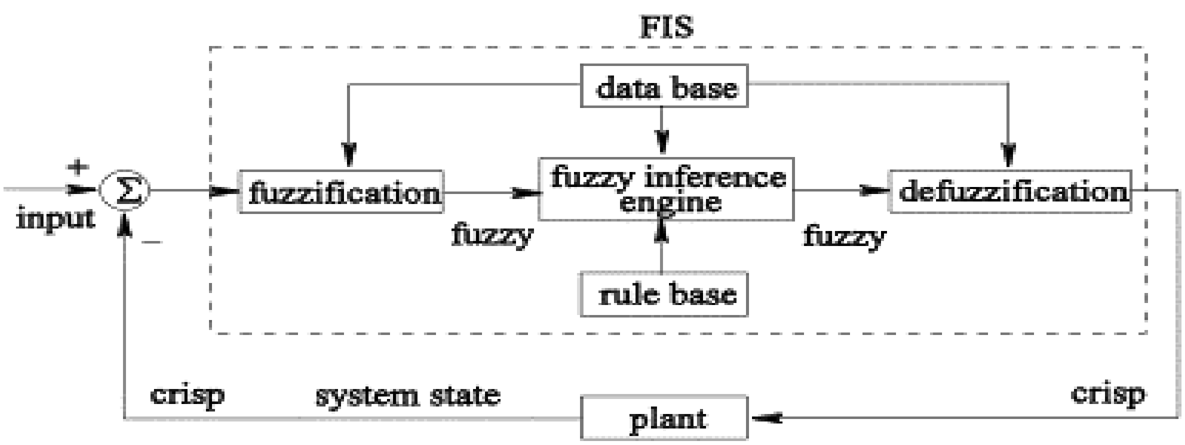


Figure 4.2 General Construction of fuzzy inference system

On the actual continuous interval [0 1], where 0 and 1 stand for both full membership and no membership' Zadeh expanded the idea of binary membership to encompass several "degrees of membership”. The X-universe television shows that can accept "variations of membership " are referred to as "fuzzy sets" by Zadeh. A function called a fuzzy set converts a set's elements to real values between 0 and 1. $\mu A(x) \in [0\ 1]$ represents the symbol, functional mapping, and represents the degree of membership of an element x in the fuzzy set A. As a result, μA(x) is a value on the unit interval indicating the degree to which an element x belongs to a fuzzy set A [21]. Fuzzy logic is not the same as predicate logic. Claims about the world are referred to be crisp values in predicate logic and can be true or untrue. Inputs are given values in fuzzy logic based on how much of a fuzzy set they are a part of. Membership functions, which give a numerical value to the degree of a set instance's similarity to it, are used to define fuzzy sets. The actions produced by fuzzy control systems are based on fuzzy logic and fuzzy rules.The fuzzy logic controller's basic units are as follows:

1. Perplexity
2. Fuzzy Rule Foundation
3. The Fuzzy Inference Engine
4. Clarification

4.2.3.1 Fuzzification

"Fuzzification" turns a crisp number blurry. The fuzzier stage transforms crisp input values using membership functions. This can be done by noting that many numbers considered to be fresh and deterministic are actually questionable. This can be done by recognizing fresh and predictable numbers. If the variable's imprecision, ambiguity, or vagueness causes uncertainty, utilize a membership function. Because a fuzzy set's membership function represents all fuzziness, a fuzzy attribute or action's description can express its fuzziness. There's no limit to how one can define fuzzyness or graphically depict fuzzyness' membership functions.

4.2.3.2 Fuzzy Rule Foundation

The IF-THEN run the show within the fuzzy run the show base specifies thesystem's behavior in a premise-consequent form, laying the groundwork for approximate (imprecise) reasoning.

4.2.3.3 Engine for Fuzzy Inference

Using a fuzzy run the show base, the fuzzy deduction motor maps input fuzzy sets to yield fuzzy sets.

4.2.3.4 Defuzzification

Fuzzy output sets are transformed into clear output values using the defuzzifier. Even if the majority of the information we are exposed to on a daily basis is ambiguous, most actions or judgments taken by either humans or machines are clear-cut or binary. As a result, in a number of engineering applications.Sometimes it's necessary to "defuzzify" the results of a fuzzy systems investigation. In other words, it might eventually need to transform from fuzzy outcomes to crisp results. Fuzzification, on the other hand, is the process of turning aaccurate amount into a fuzzy quantity. A fuzzy quantity can be made exact via a technique known as defuzzification. The Max Participation Work, Centroid Strategy, Weighted Average Strategy, Mean Max Rule, Center of Sums, and To Start (or End) of Maxima are a few of the techniques used in the defuzzification process [21]. A fuzzy control system's structure is shown in Figure 4.2. A car's braking system uses a fuzzy control system in which the crisp sensor values are to begin with interpreted into linguistic classes within the fuzzifier, followed by the firing of the appropriate rules in the fuzzy inference engine, which produces a fuzzy output value that is then translated into the fresh turning point or speed within the defuzzifier.The actuator receives the outcome as a command.

4.3 Fuzzy control design principles

Assumptions are made when building a fuzzy control system. Six major assumptions are made while choosing a fuzzy rule-based control scheme.

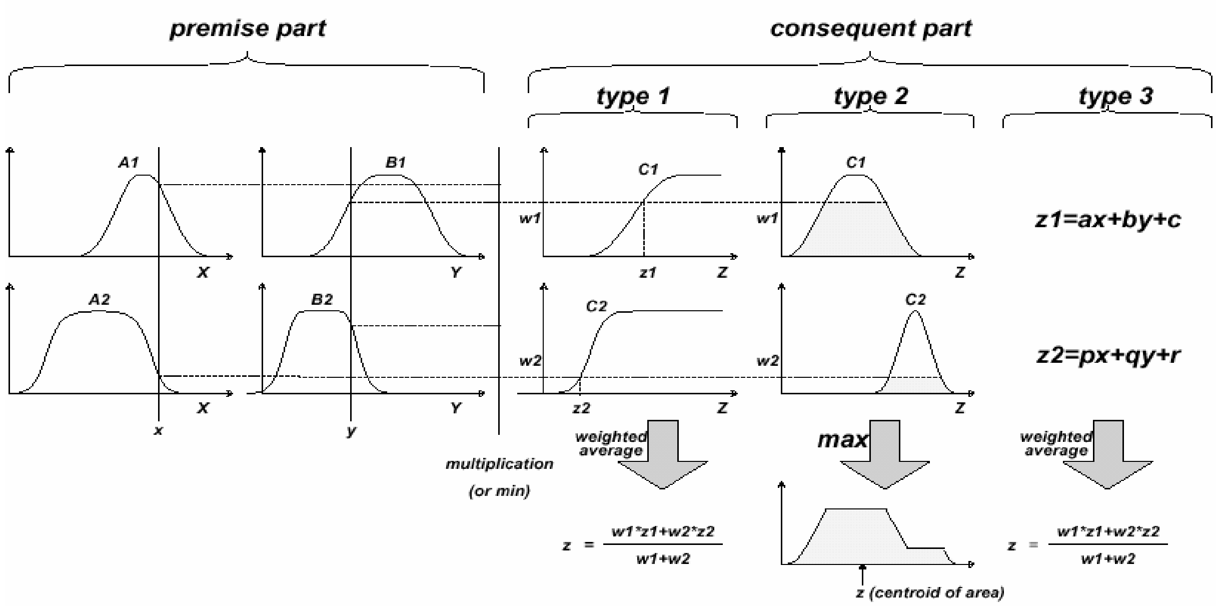
1. The state, input, and output variables can typically be watched, measured, or computed, making the plant observable and controllable.
2. There is a body of knowledge that can be derived from data from input-output measurements, engineering common sense, intuition, or linguistic principles.
3. There is a remedy.
4. A "good enough" answer, not necessarily the greatest one, is what the control engineer looks for.
5. The controller will be built with a precision range that is acceptable.

6. Stability and optimality concerns, which are still unresolved in fuzzy controller design, are not explicitly addressed.

The following are the steps in planning a basic fuzzy control framework:Determine the plant's parameters (inputs, states, and outputs).

a. Each variable's range or discourse universe should be divided into a numeral of fuzzier subsets, each with a unique languagecode.
b. Give each fuzzy subset a membership function, or define one.
c. To establish the rule-base, assign fuzzy linkages between the fuzzy subsets of the inputs or states and the fuzzy subsets of the outputs..
d. Choose suitable scaling factors to normalize the input and output variables to the [0, 1] or [1, 1] intervals.
e. Fuzzify the controller's inputs.
f. Infer the output contributed by each rule using fuzzy approximate reasoning.
g. Add the fuzzy outputs suggested by each rule.
h. Use defuzzification to produce a clean output

Most fuzzy inference systems can be classified into three types based on the types of fuzzy reasoning and fuzzy if-then rules used, as shown in Figure 4.3



plot type-1 plot type-3

Figure 4.3 Commonly used fuzzy reasoning mechanisms (adopted from [27])

Their differences lie in the outcomes of their fuzzy rules, and thus their aggregation and deffuzification procedures differ accordingly.

Type 1: Tsukamoto Fuzzy Inference System

The overall output in type 1 systems is calculated as a weighted average of each rule's crisp output, which is spoken to by the terminating quality and yield participation capacities of the run the show.

The product or least of the output of input membership functions can be used to determine the rules firing strength. The yield participation functions utilized must be non-decreasing monotonically [22].

Type 2: MamdaniFuzzy inferernce system

Standard fuzzy sets are utilized in both the fore runners and consequents of the rules in type 2 frameworks, known as the Mamdani show, and a deffuzification strategy is utilized to get a crisp value from the yield. By applying the "max" work to the fuzzy yields of each rule, the overall fuzzy output is calculated. Several approaches, such as center of zone, bisector of range, mean of maxima, most extreme model, and so on, could be used for final crisp output [23, 24].

Type 3: Sugeno Fuzzy Inference System

Type 3 systems use Sugeno's fuzzy if-then rules [25]. Each rule produces a linear combination of input variables and a constant. Final output is weighted average of rule outputs.

4.4 Artifical Neural Networks

Artificial neural frameworks are used to mimic the functioning of biological brain neuron networks.Neuroscientists accept that these models are greatly simplistic. Though, we employ them in the hopes that they will provide some light on the fundamentals of organic computation.

Associative networks, connectionist models, neuromorphic systems, parallel distributed processing models, and many other terms are used to refer to ANN models in the literature. Their structure is based on what we now know about the organic nervous frame. In reality, they are similar systems made up of numerous computing components associated by links with varying weights.

4.5 Mode of Artficial Neuron

McCulloch and Pitts introduced simpler neurons in 1943, which boosted neural networks. This began the modern age. These neurons served as biological models and conceptual building blocks for computing circuits. Real neuron complexity is reduced when modeling artificial neurons. Inputs (analogous to synapses) are compounded by weights (representing signal strength) to determine neuronal behavior. Another character calculates the artificial neuron's output (presently and after that depend on a certain edge). ANNS coordinated information-gathering by synthetic neurons.

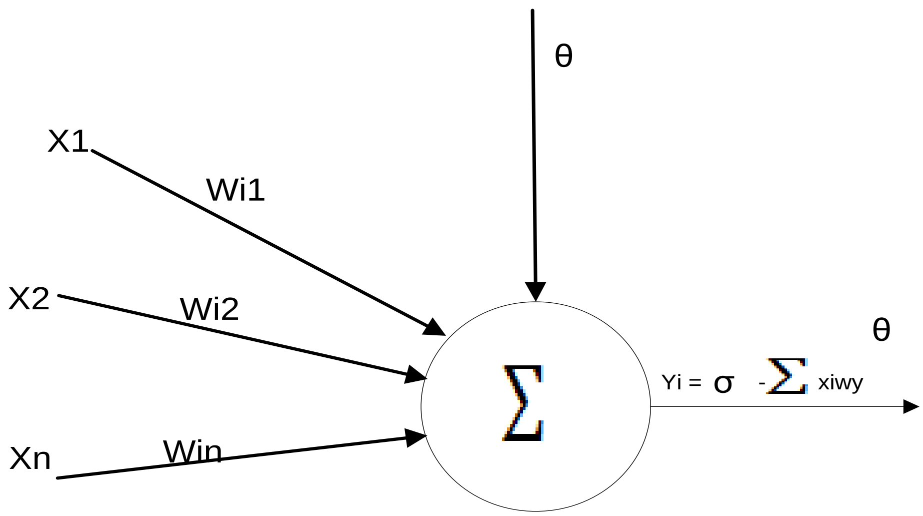


Figure 4.4 Artificial Neurons [22]

In Figure 4.4, xj represents the input stimuli ,which can be either 1 or 0, speaking to the firing or non-firing state of neuron j. The synaptic weight wij, which represents the strength of the synapse that connects neuron j to neuron i can be positive (excitatory) or negative (inhibitory). This neuron adds n weighted inputs and then applies *an* initiationfunction to the result. The node θ is distinguished by an inner threshold as well as the type of actuation work (nonlinearity) Nonlinearities of various types are depicted in figure 4.5.

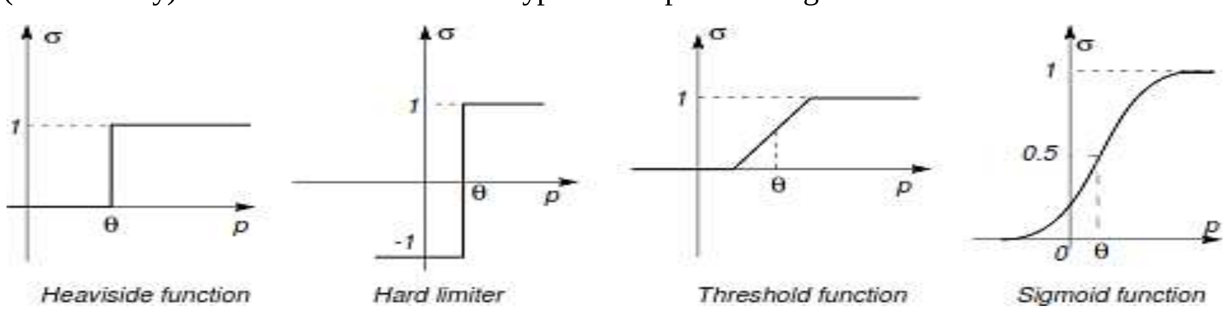


Figure 4.5 Non linnearities in the typical of artificial [21]

Given that it is thought to be the most similar to the input/output work of a real organic neuron, the most common ork might be a sigmoid work [21]. Why is there so much talk about neural networks when it is evident that this model does not mimic an actual neuron? The ability to learn new information and apply it to novel situations is the most important component. Once trained on a collection of data, a neural network can extrapolate and produce conclusions for scenarios not included in the training set. The architecture, center characteristics, and training or learning processes of neural systems define them.

4.6 Network Topology

In the last section, we looked into ANN processing units. This section discusses unit connections and data transmission. This network's most crucial distinction:

4.6.1 Feed-forward neural networks

Networks with feed-forwarding transfer data from input to output. Multiple layers of data processing are possible, however feedback is not provided. These are connections between layers and between output and input. Well-known FNNs include Perceptron and Adaline.

4.6.2 Recurrent neural networks

Systems with links for input. The network's dynamical qualities, as opposed to feed-forward systems, are pivotal; in a few occasions, the activation values of the units go through a unwinding stage, causing the network to develop to a steady state where these actuations no longer alterIn other applications, the dynamical behavior is the network's output since the change in the activation values of the output neurons is substantial enough. All three authors have provided RNN examples: Anderson, Kohonen, and Hopfield.

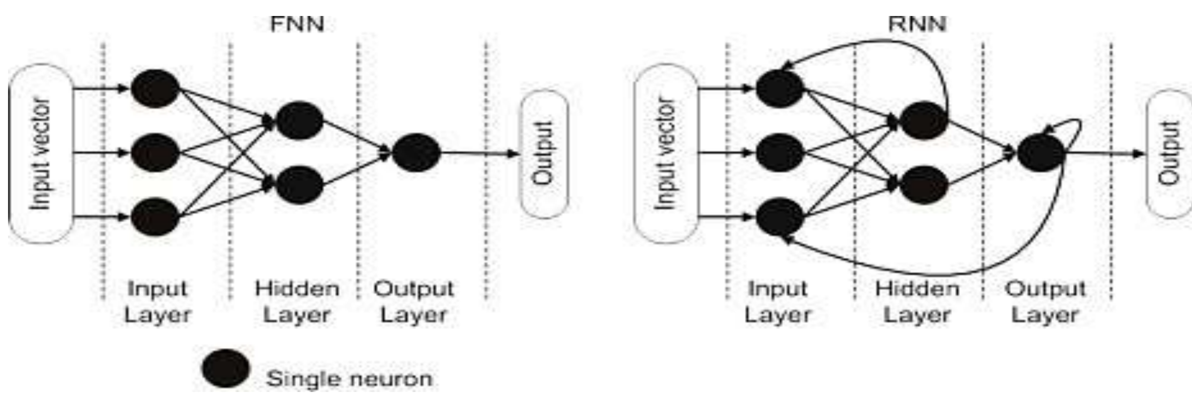


Figure 4.6 Artificial neural network structure with feed-forward and recurrent loops

4.7 Training of Artificial Neural Networks

To develop the intended outputs, artificial neural networks need a certain set of inputs. ANNs can be evaluated in several ways. ANNs can learn in two ways:

4.7.1 Unsupervised learning

When the learning objective is not precisely stated in expressions of particular right examples, unsupervised learning is utilized. The correlation of the input data is the only source of information. These correlations must be categorized by the network, which must then provide output signals that fit the input category.

4.7.2 Supervised learning

Based on a comparison between the network's outputs and the desired outputs, the weights are modified. By employing well-known input/output patterns, we "train" the network how to do the necessary calculation. The weights of the connections between units change as a result of either of the learning paradigms mentioned above depending on some modification rule. The Hebbian learning rule, which Hebb introduced in his seminal book "Organization of Behaviour," is the basis for nearly all learning rules for models of this kind. The key notion is that the connectivity between two active units, j and k, needs to be enhanced.

The properties of the fundamental preparing units in an fake neural arrange:

$$\Delta\omega_{jk} = \gamma y_{jk} \tag{4.1}$$

Where γpropotionalconsistent t speaking to the learning rate. Another common run the show is to adjust the weights based on the difference between the actual and desired activation of unit k rather than the actual activation.

$$\Delta\omega_{jk} = \gamma y = (dk - yk \tag{4.2}$$

Where dk denotes the wanted actuation given by a instructor. This is also known as the Widrow-Hoff run the show or the delta run the show. The yield of a single layer organize with an yield unit with a straight activation work is essentially given by

$$y = \sum_{j} \omega j x j + \theta \tag{4.3}$$

This simple arrangement shows the relationship between an output unit's respect and an input unit's value. The linear relationship is the primary focus here, and the network is employed for function approximation. The network represents a hyperplane in high-dimensional input spaces with multiple output units. Consider the scenario where we wish to train the network to fit a hyper-plane to a set of input samples.. Here's how: x^p and desired (or target) output values d^p as well as possible. The yield of the network varies from the target value d^p by $(d^p - y^p)$ for each given input sample, where y^p is the actual output for this pattern. To adjust the weights, the delta-rule now employs a cost or error-function based on these differences. The error function is the summed squared error, as indicated by the name least mean square. In other words, the total error E is defined as

$$E = \sum_P E = \frac{1}{2}\sum_P (d^p - y^p)\,2 \qquad (4.4)$$

where p denotes the range of input patterns and E^p denotes the error on pattern p Using a technique known as gradient descent, the LMS process determines the values of all the weights that minimize the mistake work. According to the current design for weight, the impression is to convert the weight in proportion to the subordinate of the mistake's negative value:

$$\Delta_{p\omega j = -\gamma \frac{\partial E^P}{\partial \omega j}} \qquad (4.5)$$

where γ could be a constant of proportionality. The fractional derivative

$$\frac{\partial E^P}{\partial wj} = \frac{\partial E^p}{\partial y^p}\frac{\partial y^p}{\partial \omega j} \qquad (4.6)$$

$$\frac{\partial E^p}{\partial y^p} = -(d^p - y^p) \qquad (4.7)$$

Since of the direct units (condition (4.3)

$$\frac{\partial y^p}{\partial wj} = xj \qquad (4.8)$$

Such that

$$\Delta_{p\omega j} = \gamma \delta p x_j$$

where is the distinction between the target yield and the real yield for design p.

Minsky and Parpet found that a single-layer perceptron can't communicate with an exclusive-or work. The delta rule adjusts weight for target and actual yields of either polarity and for continuous and parallel input and yield units. The network can be extended with a multi-layer perceptron to overcome the XOR problem, but the input weights to the hidden units cannot be changed. Rumelhart, Hinton, and Williams proposed this in 1986. Faults in output layer units are back-propagated to find errors in hidden layer units. The method is sometimes called the back-propagation learning rule. Back-propagation is a multi-layer network and nonlinear activation function generalization of the delta rule.

4.7.3 Algorithm of Back-Propagation

Because we are now using nonlinear activation functions in our units. The delta rule for linear displayed within the past area for direct capacities must be generalized o the set of non-linear actuation capacities.

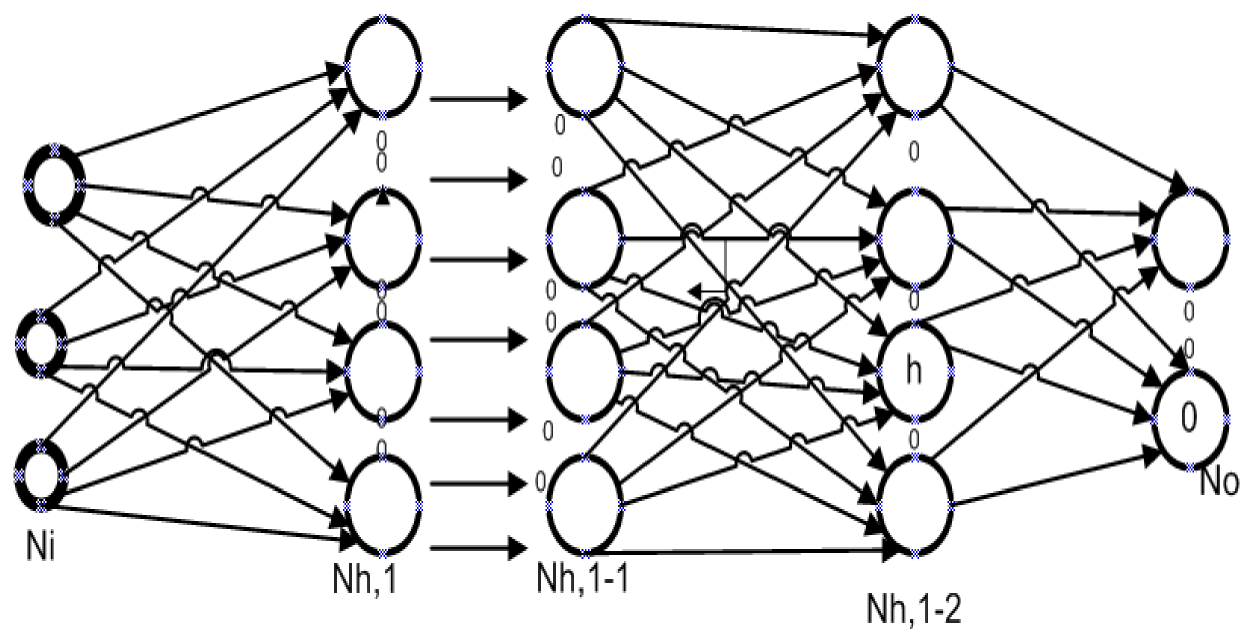


Figure 4.7 A multi layer network with 1 layer of elements[22]

The total input, which is determined by: is a differentiable purpose of the activation.

$$yk^p = F(SK^p) \tag{4.9}$$

Where

$$Sk^p = \sum_j \omega jkyj^p + \theta k \qquad (4.10)$$

The generalization of the delta run the show described in the preceding section must be accurate, thus we set.

$$\Delta_{p\omega jk = -\gamma \frac{\partial E^P}{\partial \omega jk}} \qquad (4.11)$$

The error measure E^p is characterized as the complete quadratic error for design p at the yield units, which is given by:

$$E^P = \frac{1}{2}\sum_{0=1}^{NO}(do^P - yo^{p)2} \qquad (4.12)$$

Where d_o^p is the specified yield for unit o when design p is clamped. We added set $E = \sum_p E^p \ P$ as a summed squared error. We will moreover type in

$$\frac{\partial E^P}{\partial \omega jk} = \frac{\partial E^P}{\partial sk^p}\frac{\partial sk^p}{\partial \omega_{jk}} \qquad (4.13)$$

From equation (4.10) we see that, the moment figure is computed as:

$$\frac{\partial sk^p}{\partial \omega_{jk}} = yj^P \qquad (4.14)$$

Where

$$\delta p_k = -\frac{\partial E^\rho}{\partial sp_k} \qquad (4.15)$$

If we change the weights according to, we'll get an upgrade run the show that comparable to the delta run the show described within the past segment, coming about in a slope plunge on the mistake surface.

$$\Delta p\omega_{jk = \gamma\delta\rho_{kyj^\rho}} \qquad (4.16)$$

The trick is determining what δ_p^k should be for each unit k within the network. The intriguing result is that there's a basic recursive computation of these's that can be realized by engendering error signals in reverse through the network. To compute δ_p^k, This partial derivative must be written as the product of two components using the chain rule. The first part reflects conversion error as a function of the unit's output, while the second reflects output change as a function of input. We've since This partial derivative must be written as the product of two components using the chain rule. The first part reflects conversion error as a function of the unit's output, while the second reflects output change as a function of input. We've have:-

$$\delta\rho_k = \frac{\partial E\omega^\rho}{\partial yk^\rho}\frac{\partial Ey^\rho}{\partial sk^\rho} \tag{4.17}$$

Using equation (4.9), we can get that

$$\frac{\partial yk^\rho}{\partial sk^p} = Fsk^\rho \tag{4.18}$$

This, when evaluated at the unit's net input, is essentially the subordinate of the squashing work F. We take into account two scenarios when calculating the first compute of condition (3.17). Assume that unit k is an output unit k=o of the organization in the initial example. In this instance, it adopts that definition from the EP.

$$\frac{\partial E^\rho}{\partial y0^\rho} = -(do^\rho - yo^{\rho)} \tag{4.19}$$

which is the same outcome as the ordinary delta run the appear gave us. When conditions (4.18) and (4.19) are substituted into condition (4.17), we obtain

$$\delta o^\rho = (do^\rho - yo^\rho)F'(so^\rho) \tag{4.20}$$

for any output unit Second o, if k is not an output unit but a hidden unit k = h, we do not know how much the unit contributes to the network's output error. On the other hand, the error measure can be expressed as a function of the net inputs from the output layer to the hidden layer: $E^p = E^p\left(s_1^p, s_2^p, ..., s_j^p, ...\right)$ and we use chain rule to write:

Substituting the over condition into equation (4.17) Yields

$$\delta h^\rho = F_{sh}^\rho \sum_{0=1}^{No} \delta o\omega ho^\rho \tag{4.22}$$

Equations (4.20) and (4.22), for example, provide a recursive procedure for computing the's for all units in the network, which are then used to compute the weight changes according to equation (4.20). (5.16). This procedure is the generalized delta rule for a nonlinear feed-forward network [22].

While error surface of a complex networkhas many slopes and valleys, the slope descent causes the network to become caught in a neighborhood least when there's a significantly more profound least adjacent. This problem can be avoided with the help of probabilistic approaches, although they are often slow. The number of hidden units could be increased as an alternative solution. Although this will work because the error space has more dimensions, there is a lower risk of getting caught and it seems like there is a cap on the amount of concealed units. When there are too many hidden units, the system is stuck in local minima.The previous discussions indicated that artificial neural network systems have a variety of benefits, some of which are as follows:

- Artificial neural networks are robust computer systems that can mimic the functions of biological brains by connecting a large number of basic processing modules. Artificial neural networks are effective, reliable, fault tolerant, and noise tolerant because to their tremendous parallelism.
- They can take information from training data and apply it to fresh circumstances.
- They can be applied to real-world tasks including pattern recognition, function approximation, and prediction in addition to brain modeling.
- They do, however, have some drawbacks.
- Both information representation and knowledge extraction in artificial neural networks are challenging.
- They are prone to fitting too tightly.

4.8 Neuro-Fuzzy Control method

Problem-solving is being done using neuro-fuzzy computing. We will generate a FIS if the data is linguistically encoded; else, we will use an ANNS (preparing). We must determine the fuzzy sets, fuzzy operators, and information base prior to developing a FIS. The user is required to supply both the architecture and the learning strategy when creating an ANN for an application. Building an integrated system that incorporates the various ideas makes sense because the flaws in these systems seem to be additive. While ANN values a linguistic rule base, FIS values learnability.

4.8.1 Type of neuro fuzzy

As overall, neuro-fuzzy systems refer to any combination of techniques based on neural networks or fuzzy logic. The various combinations of these techniques can be classified as follows.

4.8.2 Neuro-Fuzzy System in Collaboration

Neural networks are used in the early stages of a cooperative system. Once the neural networks have defined the sub-lock for the fuzzy system using the training data, the fuzzy framework is activated (fuzzy sets and fuzzy rules).The non-changeable structure of agreeable neuro-fuzzy systems is a downside [23].

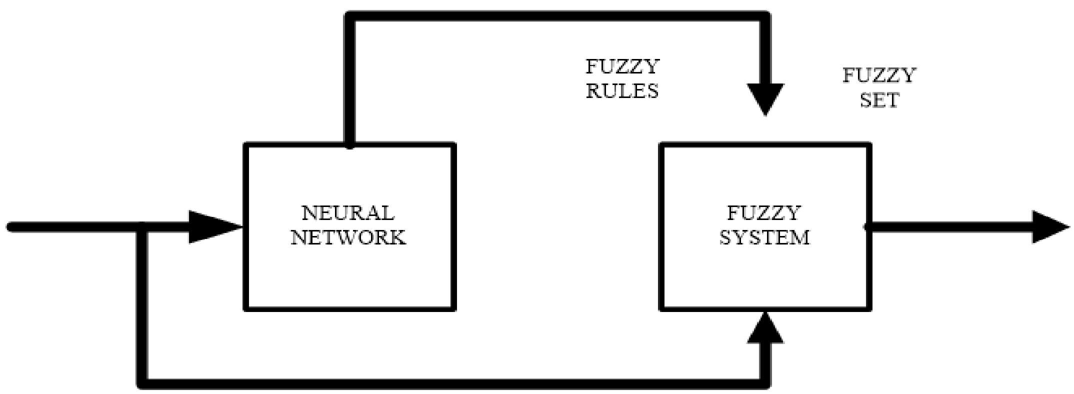


Figure 4.8 Cooperatve Neuro fuzzy_system[23]

4.8.2.1 Concurrent Neuro-Fuzzy System

Because the neural network communicates with the fuzzy system, a concurrent system is not a neuro-fuzzy system. This implies that the neural network processes the outputs of the concurrent system after pre-processing the inputs of the fuzzy system. The inability to interpret neuro-fuzzy system results in their entirety is a limitation [23].

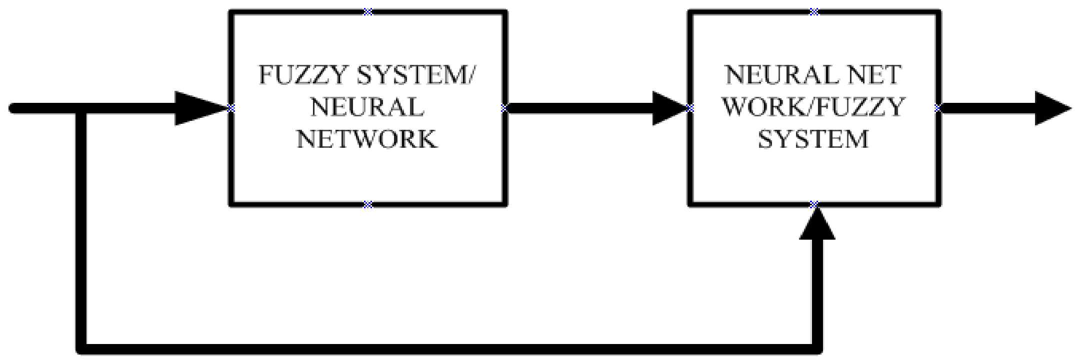


Figure 4.9 Simultaneous Neuro-Fuzzy system [23]

4.8.2.2 A hybrid neuro-fuzzy system

According to Nauck [24], a fuzzy system uses a gradient-based or neural network-influenced learning algorithm to generate its parameters (fuzzy sets and fuzzy rules) through input/output pattern processing. Neuro-fuzzy systems can be viewed as fuzzy rules.In the same way that fuzzy rules are created entirely from input/output data, this framework can be completely made from input/output information. The resulting system from combining fuzzy frameworks and neural systems has the benefits of pattern learning and simple translation of its functionality. Because hybrid neuro-fuzzy systems are a relatively new research topic, each researcher needs defined their own specific models. In essence, these models are comparative, but they differ significantly.

4.9 Adaptive Neuro-Fuzzy Controller model

Guide a vehicle through an obstacle-filled map to a given target. The only information available at any time is the distance between the nearest obstacles and the angle to the goal, and we can only control the vehicle's velocity in each possible direction. We train a neuro-fuzzy system forcar braking system of the vehicle by using the successful paths for each fuzzy system. These models outperform fuzzy systems on seen maps, but generalize well to unseen maps while reducing oscillations near the target. Neuro-fuzzy Inference System (NFIS) architecture is as shown in figure 4.10, where nodes of the same layer have similar functions. The output of i^{th}node in layer l is denoted as Ol, i.

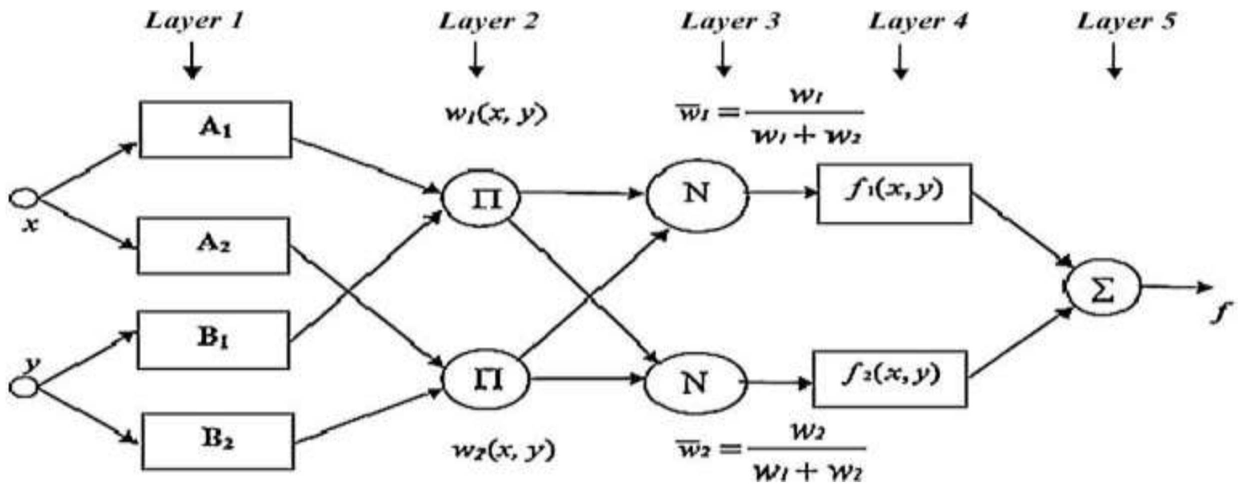


Figure 4.10 Equivalent NFIS architecture [23]

Layer 1: Every node *i*in this layer is an adaptive node with a node function

$$\boldsymbol{O1, i = \mu Ai(x), fori - 1\ , 2\ or} \qquad (4.23)$$

$$\boldsymbol{O1, i = \mu Bi - 2\ (y), fori = 3,, 4,}$$

Where x (or y) is center I's input and Ai (or Bi-2) is the center's phonetic title (either "minor" or "major") Any parameterized participation work may be deemed A's (or B's) enrollment work. This study assumes the generalized Gaussian membership function.

After

$$\mu_A(x) = exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \qquad (4.24)$$

Where {ci, ai} is the parameter set. These are called preface parameters.

Layer 2: Each hub in this layer could be a settled hub labeled Π, whose yield is the item of all the approaching signals

$$.O_{2i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y), i = 1,2 \qquad (4.25)$$

Layer 3: Here, the ith center calculates the extent of the ith rule's ending quality to the aggregate of all rule's ending quality.

$$O_{3,i} = \overline{W_\iota} = \frac{w_i}{w_I + w_2}, i = 1,2 \qquad (4.26)$$

Layer 4: Every node *i*in this layer is an adaptive node with a node function

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p^x{}_i + q_i + r_i) \qquad (4.27)$$

Layer 5: This layer has only one fixed, lettered node. It adds all incoming signals to compute the output.

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{4.28}$$

4.10 Hybird Learning Algorithm

The Crossover Learning Calculation may be a combination of least square and back-propagation strategy. Inside the least square technique, the yield of a show y is given by the parameterized expression.

$$Y = \theta 1 * f1(u) + \theta 2 * f2(u) + \cdots \ldots \ldots \ldots \ldots \ldots \ldots .. + \theta n * fnu) \tag{4.29}$$

Where$u1, u2, \ldots un$isthemodel'sinputvector,$f1, \ldots \ldots, fn$areknownfunctionsof$u$,andθ1, θ2, θn are unknown parameters to be optimized. To identify these unknown parameters θi, usually a trainingdatasetofdatapairs $\{(ui, yi), i = 1, \ , m\}$istaken;substitutingeachdatapairinequation 3.42 a set of linear equations is obtained, which can be written as in matrix form.

$$A*\theta=y \tag{4.30}$$

Where A is an m×n network, θ is an n×1 unknown parameter vector and y is an m×1 yield vector. Since by and large m>n, rather than correct arrangement of the condition 4.31 an error vector e is communicated to account for the modeling error, as

$$A * \theta + e = y \tag{4.31}$$

And examined for θ =θˆ which reduces sum of squared error.

$$E(\theta) = \sum_{i=1}^{m} (y_i - a_i{}^T \theta)^2 = e^T e \tag{4.32}$$

E (θ) is called the objective function. The squared error in equation 3.32 is minimized when θ =θˆ, called Least Squares Estimator (LSE) that fulfills the ordinary equation.

$$A^T A \theta = A^T y \tag{4.33}$$

If A^TA is nonsingular, θ is unique and is given by

$$\theta = (A^T A)^{-1} A^T y \tag{4.34}$$

In Backpropagation learning, the most crucial step is iteratively acquiring a point vector whose components are the error degree derivative in relation to a parameter. It's crucial. In a feed-forward adaptive network with L layers and N(l) hubs, hub I's yield work can be expressed as xl,i and fl,i at this time.

$$Xl, i = fl, i(xl - 1,1, \dots\dots\dots . xl - 1, N(l - 1), \alpha, \beta, \gamma, \dots\dots) \qquad (4.35)$$

Where α,β,γetc are the parameters of this hub. Accepting that the given preparing information set has P passages, an error degree can be characterized for the pth (1≤p≤P) passage of the preparing information set as the whole of squared errors:

$$E_P = \sum_{k=1}^{N(L)} (d_k = \pi r^2\, k_l\,, l)^2 \qquad (4.36)$$

Where d_k is the k^th^ component of the p^th^ wanted yield vector and $_{k\ l,k}$ is the $_k$th component of the real yield vector made by showing the pth input vector to the organize. The assignment here is to play down an common error degree, which is characterized as

$$E = \sum_{p=1}^{P} E_p \qquad (4.37)$$

To utilize steepest descent to reduce error, first get the point vector. The point vector is computed by iteratively passing a shape of derivative data from yield to input. This begins with the computation. "Back-propagation" describes this technique.

$$\in_{l,i} = \frac{\boldsymbol{\partial E_p}}{\boldsymbol{\partial X_{l,i}}} \qquad (4.38)$$

For i^{th} output node (at layer L)

$$\in_p = \frac{\partial E_p}{\partial X_{l,i}} \qquad (4.39)$$

Therefore $\in_{l,i} = -2\left(d_i - X_{i,i}\right)$

For the inner center at the ith position of layer l, the error signal can be decided iteratively by the chain rule:

$$\in_{l,i} = \frac{\partial E_p}{\partial X_{l,i}} = \sum_{m=1}^{N(l+1)} \left(\frac{\partial E_p}{\partial X_{l+1,m}} * \frac{\partial f_{l+1,m}}{\partial X_{l,i}} \right) = \sum_{m=1}^{N(l+1)} \frac{\in_{l+1,m}\, \partial f_{l+1,m}}{\partial X_{l,i}} \qquad (4.40)$$

The incline vector is defined as the derivative of the error measure with respect to each parameter. If α is a parameter of the i^{th} node at layer *l*, we have

$$\frac{\partial E_p}{\partial \alpha} = \frac{\partial E_p}{\partial X_{l,i}} * \frac{\partial f_{l,i}}{\partial \alpha} = \epsilon_{l,i} * \frac{\partial f_{l,i}}{\partial \alpha} \quad (4.41)$$

The derivative of the total error measure E with respect to αis

$$\frac{\partial E}{\partial \alpha} = \sum_{p=1}^{p} \frac{\partial E_p}{\partial \alpha} \quad (4.42)$$

Accordingly, for simplest steepest parentage without line minimization, the update formula for general parameter α is

$$\Delta\alpha = -\eta * \frac{\partial E}{\partial \alpha} \quad (4.43)$$

Where, η is the learning rate

So, for parameter α it may be written that

$$\alpha_{new} = \alpha_{old} + \Delta\alpha = \alpha_{old} - \eta * \frac{\partial E}{\partial \alpha} \quad (4.44)$$

In this learning method, upgrading occurs when the whole set of defining information coordinates is displayed. Parameter updates are dependent on over circumstances. "Age" refers to preparing information before integrating it. Each age gets updated. Currently, 'S' is assumed to be the whole set of parameters, and 'S1' and 'S2' are the input and output parameter sets. 'S' symbolizes all parameters.

Data generation:- to design the NFIS controller, some data is needed, i.e., a set of two dimensional input vectors and the associated set of one-dimensional output vectors are required.

Rule extraction and membership functions:- The second phase, after data collection, is to guess the primary guidelines. The recommendations are then derived using subtractive clustering. Theserulesarenotsoclosetotheidentifiedsystem. Optimizing these regulations is necessary. After removing clustering from the fuzzy inference system, hybrid learning was used to change the above parameter. This approach learns the premise membership function parameters via back propagation and optimizes the consequent equation parameters using linear least-squares estimation. Training will continue till error measure is consistent.

4.11 Neuro-Fuzzy Controller for Car Braking System

Nuero-fuzzy logic, which is applicable for non-linear continuous time, is not suitable for discrete time. An ideal value is chosen for the coefficient of friction. The behavior of logging the driving and applying it to the control system is functional for development. The wheel speed sensor sends a signal that calculates tire velocity and tire angular acceleration. The Mamdani model is used to select the parameters of a membership function.The maximum braking force is determined by the tire friction coefficient. Thre two neuro-fuzzy system are designed in this model. One controller determines the optimal slip based on various road conditions and their coefficient of friction based on slip. The other controller is used to determine the required braking force based on the slip error and wheel acceleration. The fuzzy algorithm is adaptable and works effectively in this case to distribute braking torque. This scenario's neuro-fuzzy controller is based on a fuzzy algorithm. Neural networks are used to develop fuzzy algorithms, which is a major gain. A fuzzy controller uses fuzzy logic to emulate human thought processes. Fuzzy rules are a large collection of "If then" statements that consume memory and increase calculation time. The neuro-fuzzy controller, a combination of fuzzy algorithms and neural networks, develops rules by using the network's self-study capacity, intersperses the rules throughout the network, and provides outputs using high-speed concurrent calculation rather than rule search and reasoning.The proposed problem is static friction, which occurs when a moving vehicle encounters an obstacle or any other situation that requires the vehicle to come to a complete stop and the road condition is known (dry or wet asphalt). In order to avoid a frontal collision and provide a smooth stop, the designed neuro-fuzzy controller must apply the correct pressure on the brake system. Unlike Boolean logic, neuro-fuzzy logic allows intermediate logic values, which means that a value can take any value between 0 and 1, or false and true.A neuro-fuzzy controller has the property of approximating values by using inference, which means that they are real solutions but do not correspond to a logical truth. Fuzzy logic is composed of inputs and outputs that allow for degrees of pertinence; thus, the final solution is obtained by aggregating the results of a mathematical operation, such as the calculation of the center of mass.The input sets in this case are determined by vehicle speed (0 to 110km/h), distance (up to 320m), and road condition (ice or dry asphalt). The pressure to be applied to the brake system will be the output set. As previously stated, by determining the proper brake pressure, it is possible to provide, in addition to a smooth stop, the avoidance of potential collisions.Furthermore, given the changes in the input variables, the brakes must be applied only as needed for stopping and must not suffer large excursions (unless absolutely necessary), stopping the vehicle with minor adjustments. Other considerations, however, must be made for this to be valid, such as the use of ABS brakes to avoid skidding, limiting the system to static friction, and ensuring that the percentage of system output pressure is proportional to the vehicle's deceleration. The system is connected in cascade to verify the application of the brake independent of the road situation (static friction). The first controller's output is obtained through the analysis of the inputs "speed" and "distance" on an ideal surface (like dry concrete, for example). The pressure to be applied under ideal conditions is the output. The second controller is in charge of associating the first controller's output as an input of the second, i.e., cascade controllers, in addition to the "friction" input, which takes track conditions into account, to finally obtain an output closer to reality.

For example, if the vehicle is approaching an obstacle at a high speed, the system must apply a significant amount of braking to avoid a collision. Similarly, if the vehicle is too far away from an obstacle or any stopping condition, gentle braking will result in enough deceleration for a safe stop. The variables in an automated system could be obtained via sensors such as a tachometer for vehicle speed, or even a laser rangefinder or doppler radars for the first two variables, and the third input could be obtained via the vehicle's own ABS system.Which has wheel locking sensors, with greater sensitivity to road characteristics, certain that the lower the friction coefficient, the greater the possibility of the wheels remaining blocked during braking. The braking system actuator may also be linked to the ABS system.

Some objectives and assumptions can be derived from the situation as described below:

1. The brakes must only be applied to the extent required to stop (soft stop);
2. The vehicle must come to a complete stop before any collision;
3. The vehicle is in a straight line with the obstacle on a flat and level surface;
4. The brake system is ABS, ensuring that the wheels do not lock and limiting the system to consider only static friction;
5. The application of brake pressure is proportional to the vehicle's deceleration;
6. Controller input variables are available; and
7. The vehicle's top speed is 120 km/h.

As a result, the neuro-fuzzy controller sets and rules can be identified. The controller's development begins with physics equations that can relate the variables "speed" and "distance" to form the input set "distance" in an ideal situation, and then relate the variable "static friction."

The equations below were used:

$$d = \frac{V_o + V_f}{2}.t \qquad (4.45)$$

$$V_f = V_o + a.\Delta t$$

Thus, the following equations can be combined to find the maximum deceleration for the total stop of the vehicle (deceleration is proportional to brake pressure):

$$a = \frac{-V_o^2}{2.d} \qquad (4.46)$$

The maximum possible deceleration can be calculated using this equation, but first the minimum distance to full stop must be determined. The following well-known equations can be applied:

$$momentum = \frac{m.V^2}{2} \qquad (4.47)$$

$$work = -\mu.m.g.d$$

In theory, the required work energy equals the change in linear momentum, so:

$$work = \Delta Momentum \qquad (4.48)$$

$$-\mu.m.g.d = \frac{m.V_f^2}{2} - \frac{m.V_o^2}{2}$$

The minimum stopping distance is then equal to:

$$d_{stop} = \frac{V_o^2}{2.\mu.g} \qquad (4.49)$$

To elaborate, first use the previous equation to calculate the minimum stopping distance and then use the acceleration equation to calculate the maximum deceleration the vehicle can accept for a total stop.Finally, based on the rules of the neuro-fuzzy controller design and considerations, the system can be simulated with the input sets so that the controller is efficient.

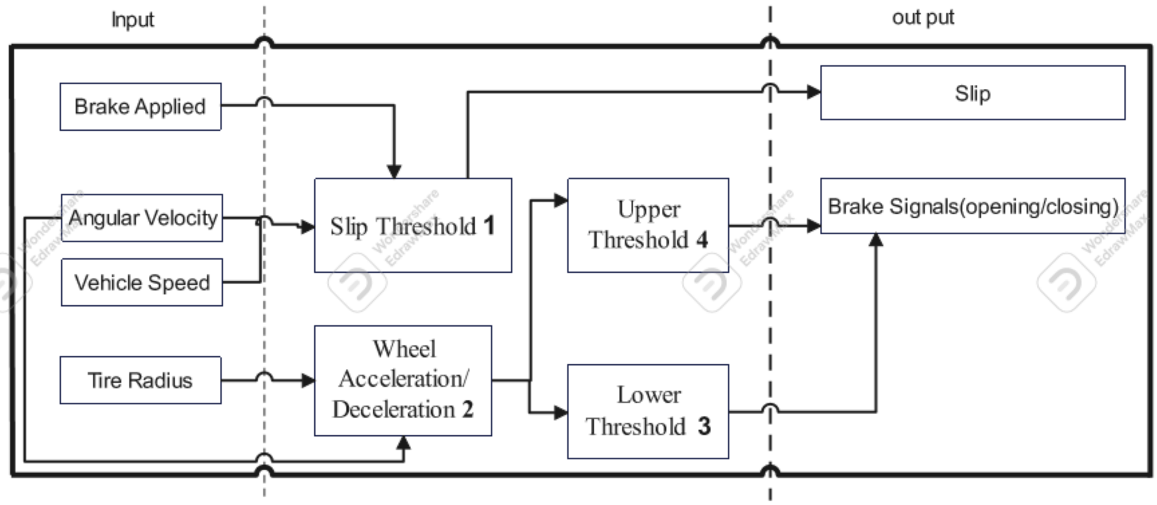


Figure 4.11 Signal Processing Block Diagram

A feedback control system in which a sensor monitors the output (slip ratio) and sends data to the controller, which adjusts the control (brake pressure modulator) as needed to maintain the desired system output.

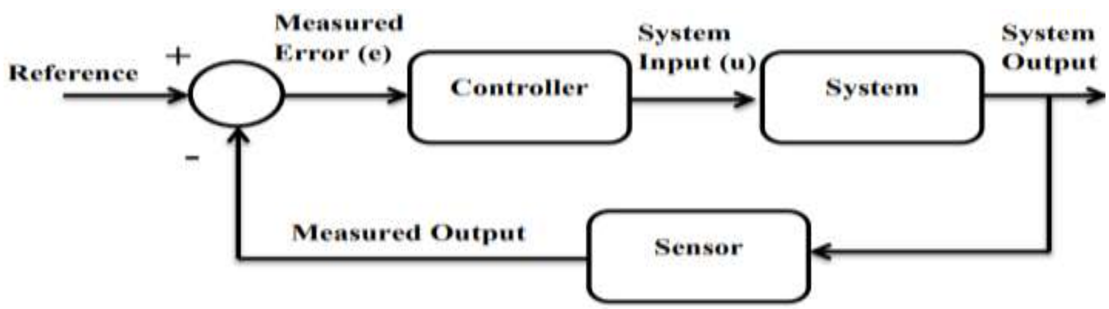


Figure 4.12 The Block Diagram of Feedback Control Syst

CHAPTER FIVE
RESULTS AND DISCUSSION

5.1 Introduction

This part reports simulation findings for the problem mentioned in the previous sections. Simulation has been utilized as a tool for visualization, planning, and strategic decision-making in R&D since the early 1900s. Simulating a neuro-fuzzy controller helps control a vehicle's braking environment. Simulating the vehicle's braking mechanism yielded results. The controller was developed using MATLAB/Simulink R2018a.

5.2 Neuro-Fuzzy Based Car Braking System

Car braking system was controlled by two neuro-fuzzy controllers (NFC). The frist neuro-fuzzy controller takes as input vehicle speed and wheel slip to determine optimal slip based on the current road condition. The second neuro-fuzzy Controller uses slip error and wheel acceleration as input to determine the required brake force to minimize excessive slip and avoid wheel locking. The brake actuator subsystem is configured based on its mathematical model, which provides angular acceleration of the wheels at the output node.

Similarly, vehicle speed and stopping distance are calculated using blocks that allow the previous sections' mathematical equations to be applied. The vehicle speed and wheel speed are then used to calculate the vehicle's relative slip, which is then fed as feedback to the summation block, which generates an error signal by comparing the existing slip to the optimal slip. The brake force is then calculated based on whether the error slip signal is positive or negative. The feedback slip signal is also fed into the mu-slip conversion block, which converts the slip into the coefficient of friction using Burchardt's mathematical model.The wheel speed sensor sends a signal that calculates tire velocity and tire angular acceleration.

The Mamdani model is used to select the parameters of a membership function. When braking, the tire speed becomes less than the vehicle speed. The maximum braking force is determined by the tire friction coefficient.One controller determines the optimal slip based on various road conditions and their coefficient of friction based on slip. The other controller is used to calculate the required braking force based on the slip error and wheel acceleration. Appendix A contains the entire training data set. Toolbox capabilities ANFIS builds a Sugeno-type FIS from input/output data. The membership function parameters are changed via back propagation or least squares. Fuzzy systems can learn from the data they model with this modification. Neuro-Fuzzy Designer has four components to enable different workflows. This app helps with the following:

1. Loading, Plotting, and Clearing the Data
2. Generating or Loading the Initial FIS Structure
3. Training the FIS
4. Validating the Trained FIS

The Neuro-Fuzzy Designer Structure is given in Figure 5.1 below.

5.2.1 Data Loading, Plotting, and Clearing

To prepare a FIS, it must to begin with load a Training information set with the specified input/output information of the framework to be demonstrated. Any information set to be stacked must be an cluster, with the information organized as column vectors and the yield information within the last column.

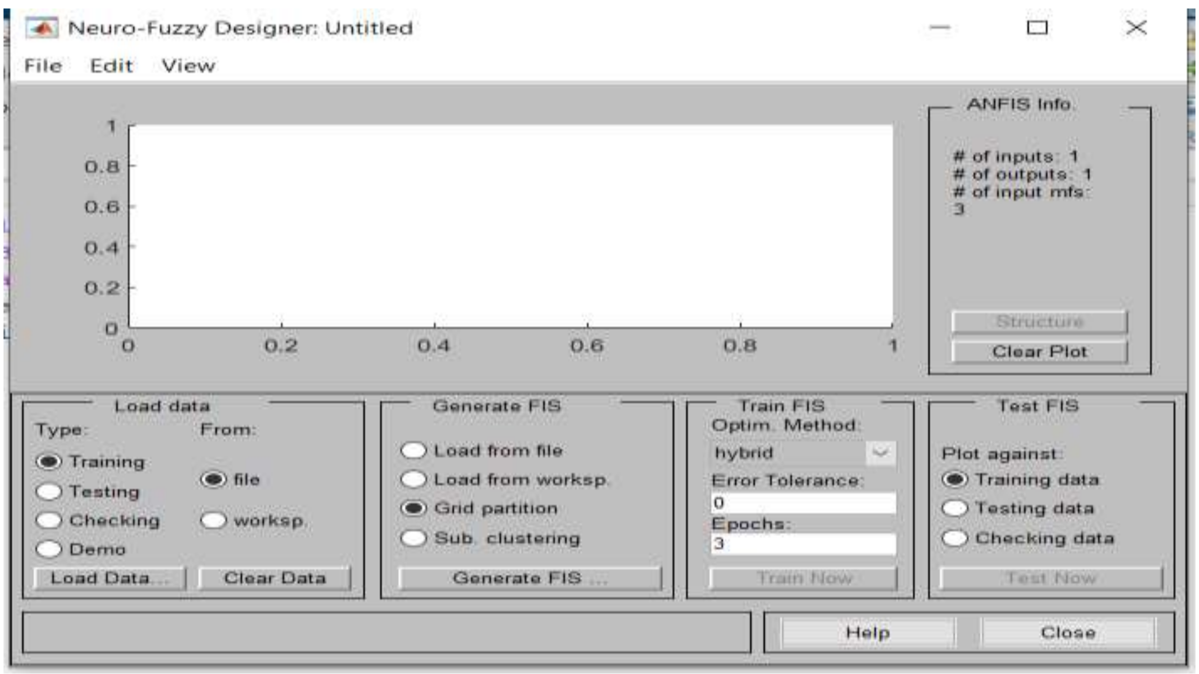


Figure 5.1 The Neuro-Fuzzy Designer Structure

To load a data set using the Load Data portion of the designer:

1. Specify the data Type.
2. Select the data from a file or the MATLAB workshop.
3. Click Load Data.

The data is displayed in the plot after it has been loaded. The training, testing, and checking data are each annotated in blue with circles, diamonds, and pluses.

To clear a specific data set from the designer:

1. In the Load Data area, select the data Type.
2. Click Clear Data.

This action also removes the corresponding data from the plot.

5.2.2 Creating or Loading the First FIS Structure

Before FIS training, a model framework must be created. Perform one of the following to specify model structure:

- Load a Sugeno-type FIS structure saved previously from a file or the MATLAB workspace.
- Create the initial FIS model by using one of the partitioning techniques listed below:
- ✓ Grid segmentation: - Creates a single-output Sugeno-type FIS from data using grid partitioning.
- ✓ Sub.clustering: - Creates an initial model for ANFIS training by performing subtractive clustering on the data first.

Click Structure to see a graphical representation of the initial FIS structure.

5.2.3 Training the FIS

After loading the training data and generating the initial FIS structure, start training the FIS. The following steps show how to train the FIS.

1. Select hybrid or backpropaga as the optimization method in Optim, Method. The optimization methods simulate the training data by training the membership function parameters.

   Note: The hybrid optimization method combines least-squares and back propagation gradient descent.
2. To set the training stopping criteria, enter the number of training Epochs and the training Error Tolerance. The training process is terminated when the maximum number of epochs is reached or the training error goal is met.
3. To train the FIS, click Train Now. This action modifies the parameters of the membership function and displays the error plots.

5.2.4 Testing the Trained FIS

After the FIS has been trained, validate it with data that is different from the data used to train the FIS.

To validate the trained FIS, do the following:

1. Select the validation data set and press the Load Data button.
2. Select Test Now.

In the plot, this action plots the test data against the FIS output (shown in red).

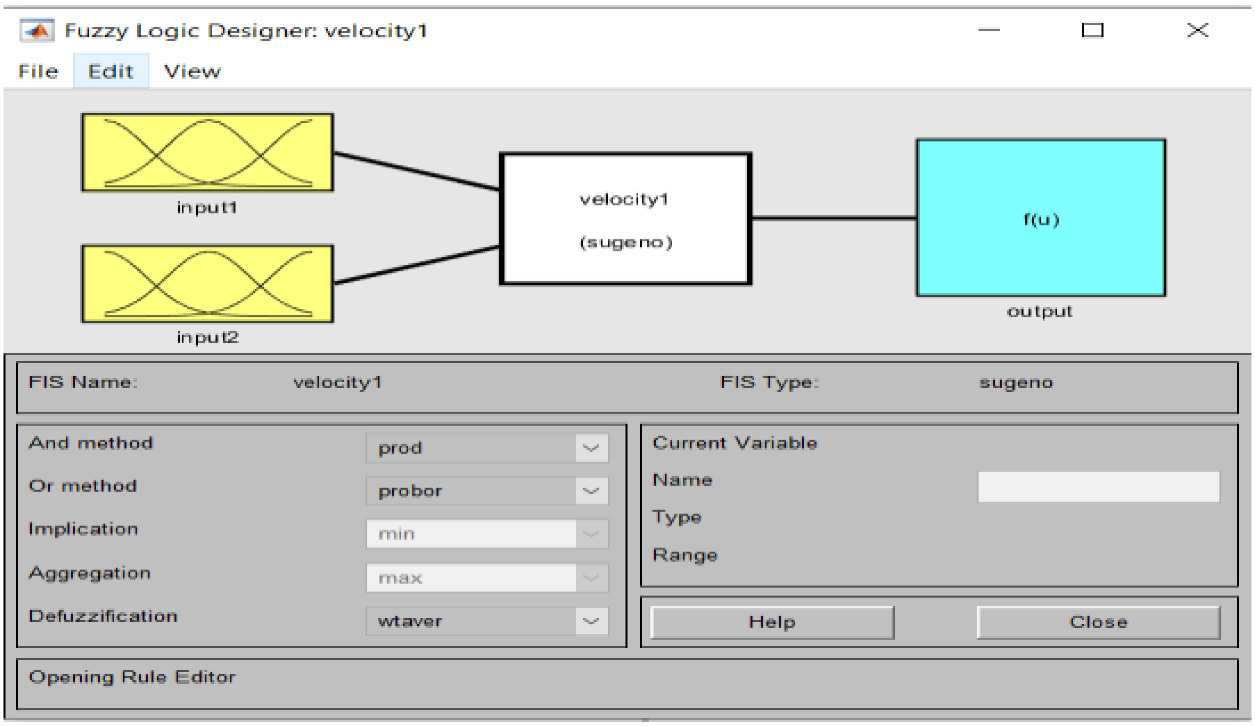


Figure 5.2 Optimal slip Structure.

Figure 5.2 shows the optimal slip controller data1 has two linguistic variables as inputs: the “Velocity” and the “wheel slip”. And it has one linguistic variable as outputs: Optimal slip. The model structure view, their membership functions, fuzzy if-then rule base, fuzzy rule view and surface view are shown in figures below as follows:

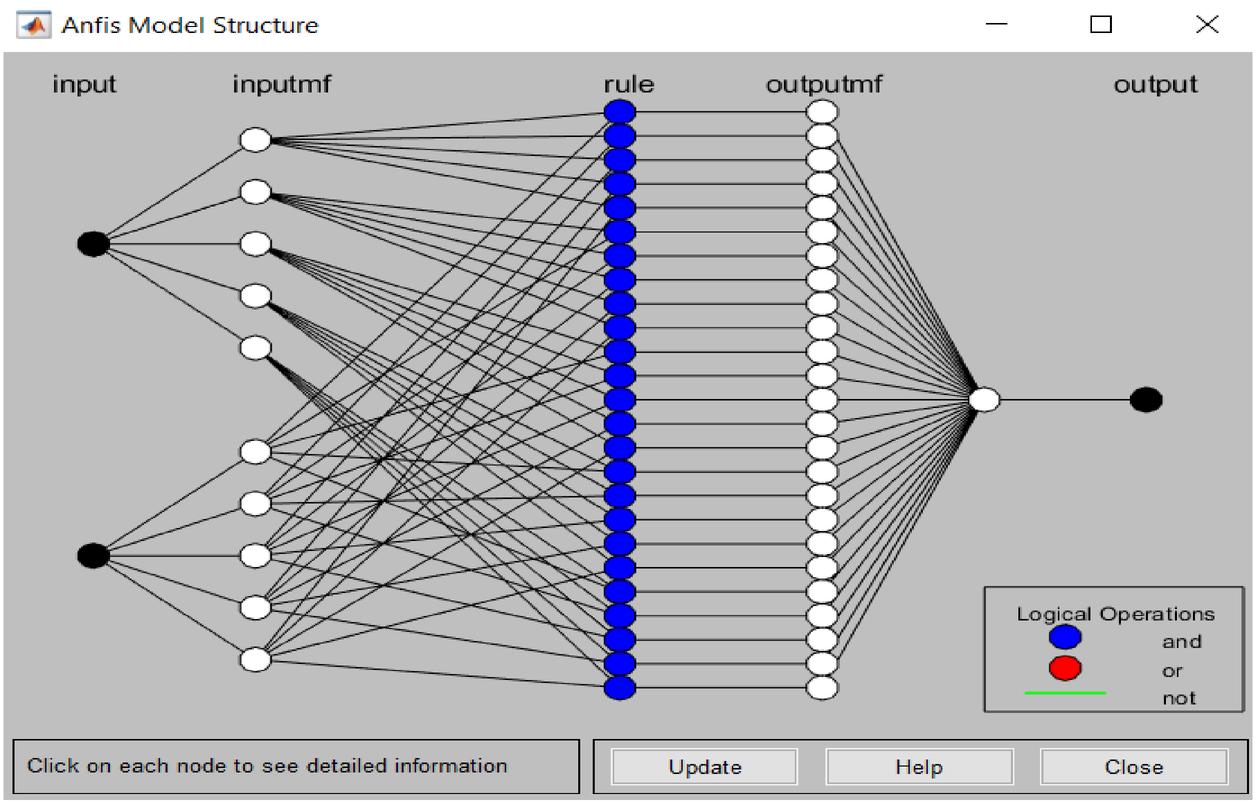


Figure 5.3 Optimal slip Controller Model Structure View.

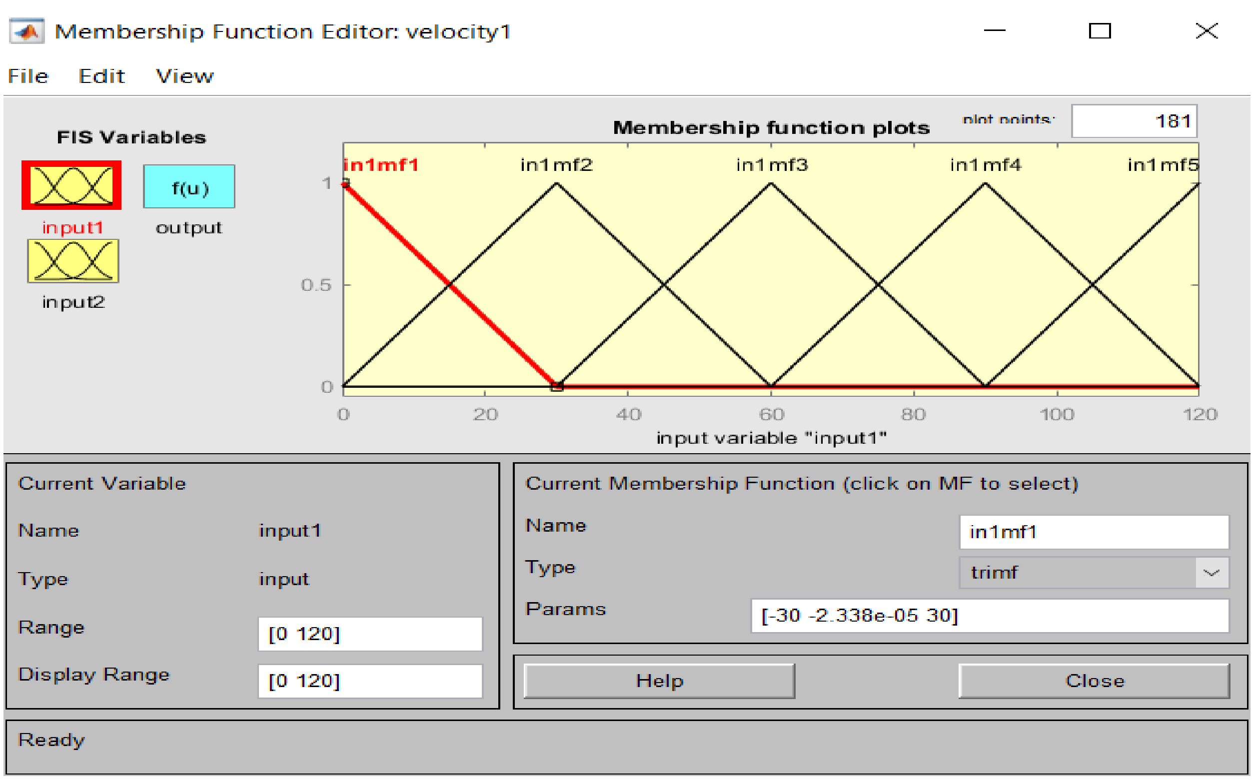


Figure 5.4a Membership function for input linguistic variable “Velocity”.

In the universe of discourse [0, 120], Figure 5.4a depicts the input linguistic variable "velocity" with its linguistic terms: mf1, mf2, mf3,mf4 and mf5.

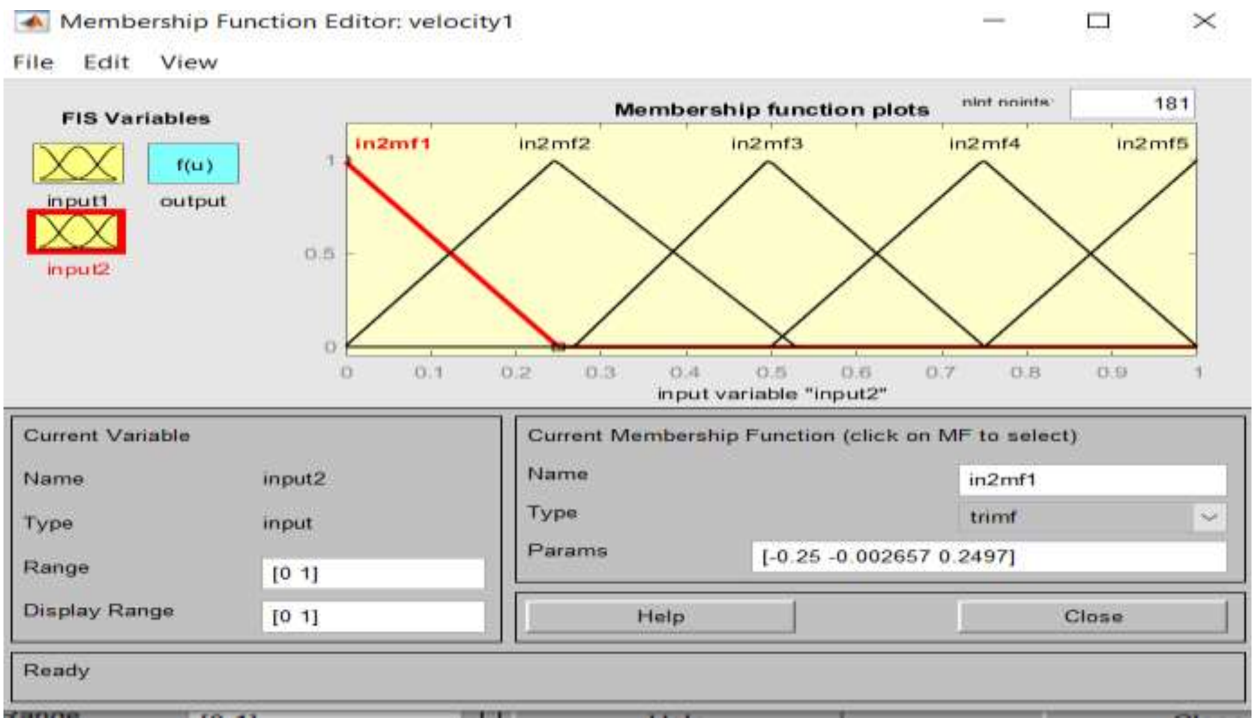


Figure 5.4b Membership function for input linguistic variable “wheel Slip”

Figure 5.4b depicts the input linguistic variable "Slip" in the interval [0 1] with its linguistic terms: mf1, mf2, mf3,mf4 and mf5.

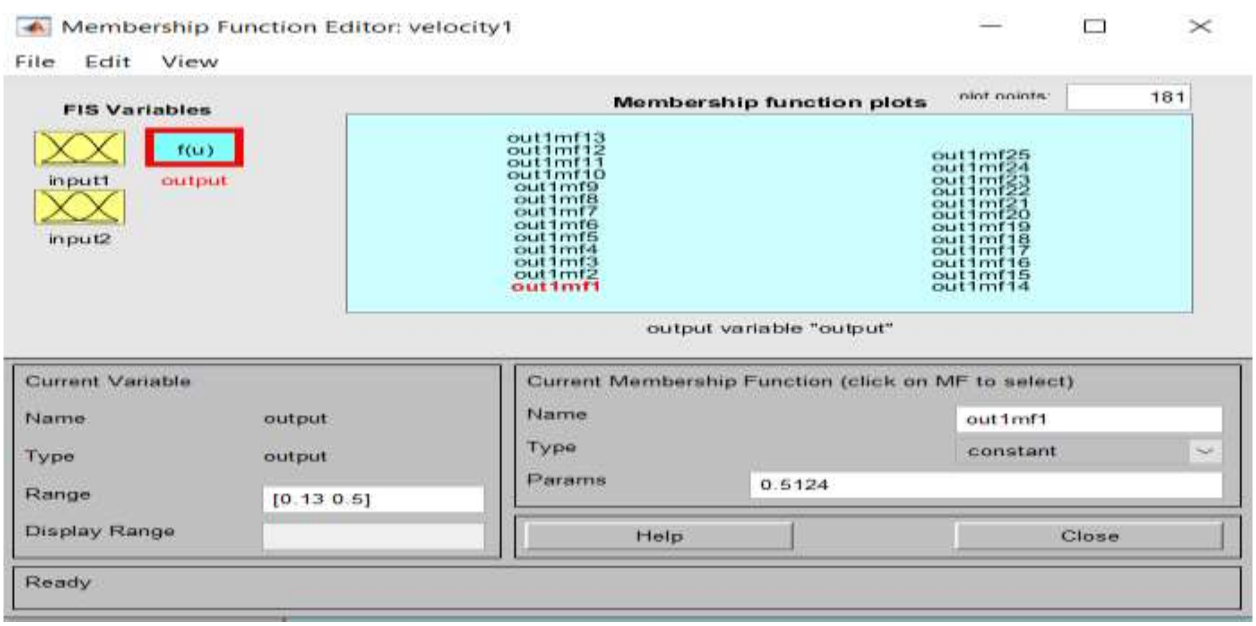


Figure 5.4c Membership function for output linguistic variable “Optimal Slip”

The output linguistic variable linear speed "Optimal slip" has twenty five linguistic terms in the interval [0.13 0.5] as shown in Figure 5.4c.

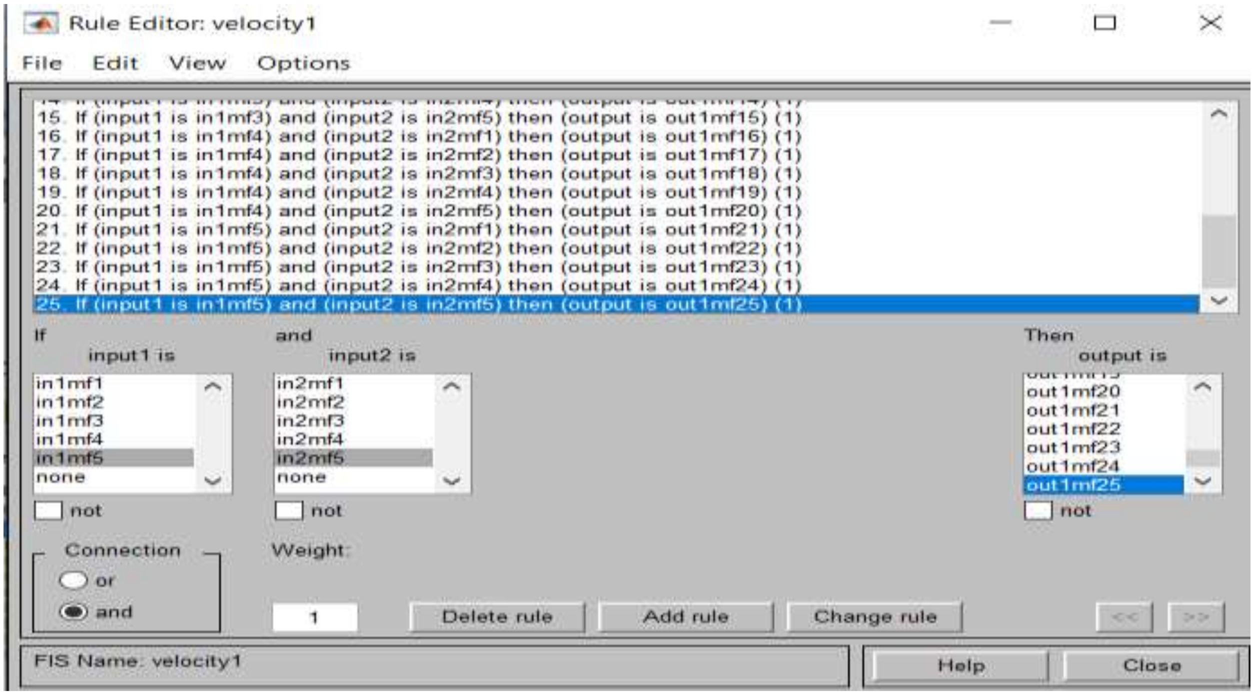


Figure 5.5 Optimal slip controller rule.

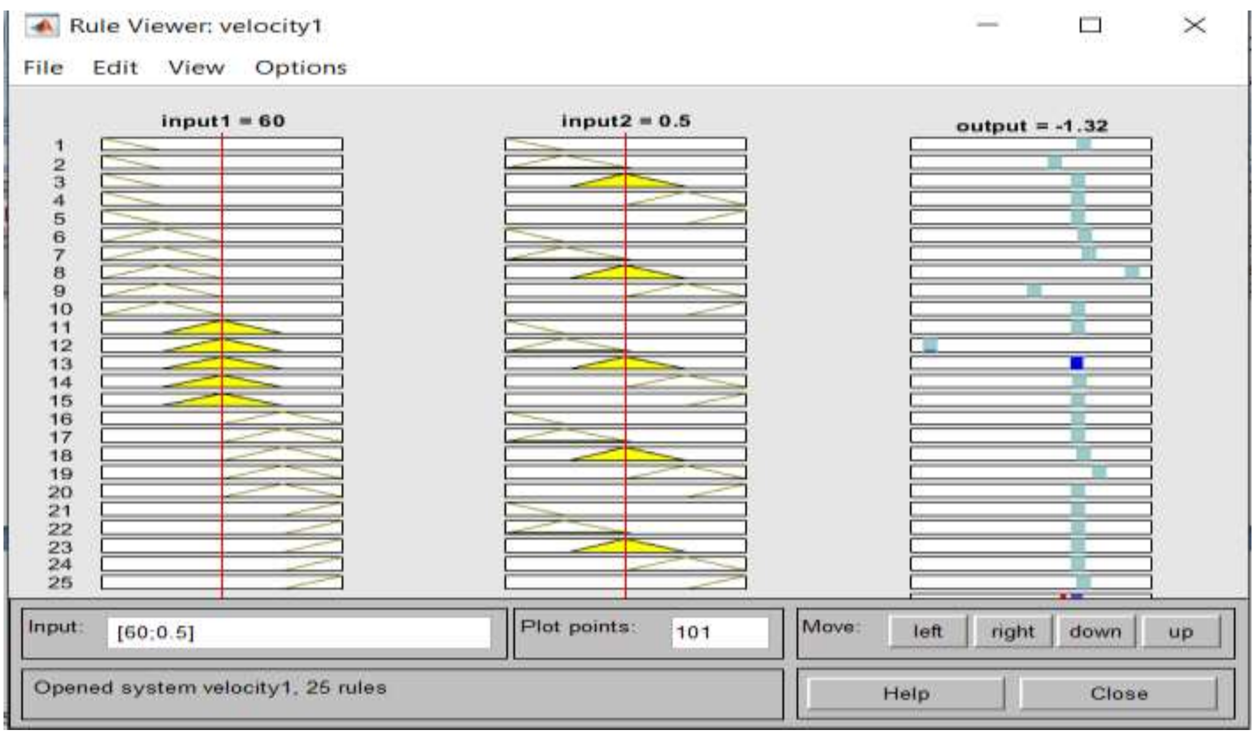


Figure 5.6 Optimal slip controller rule view.

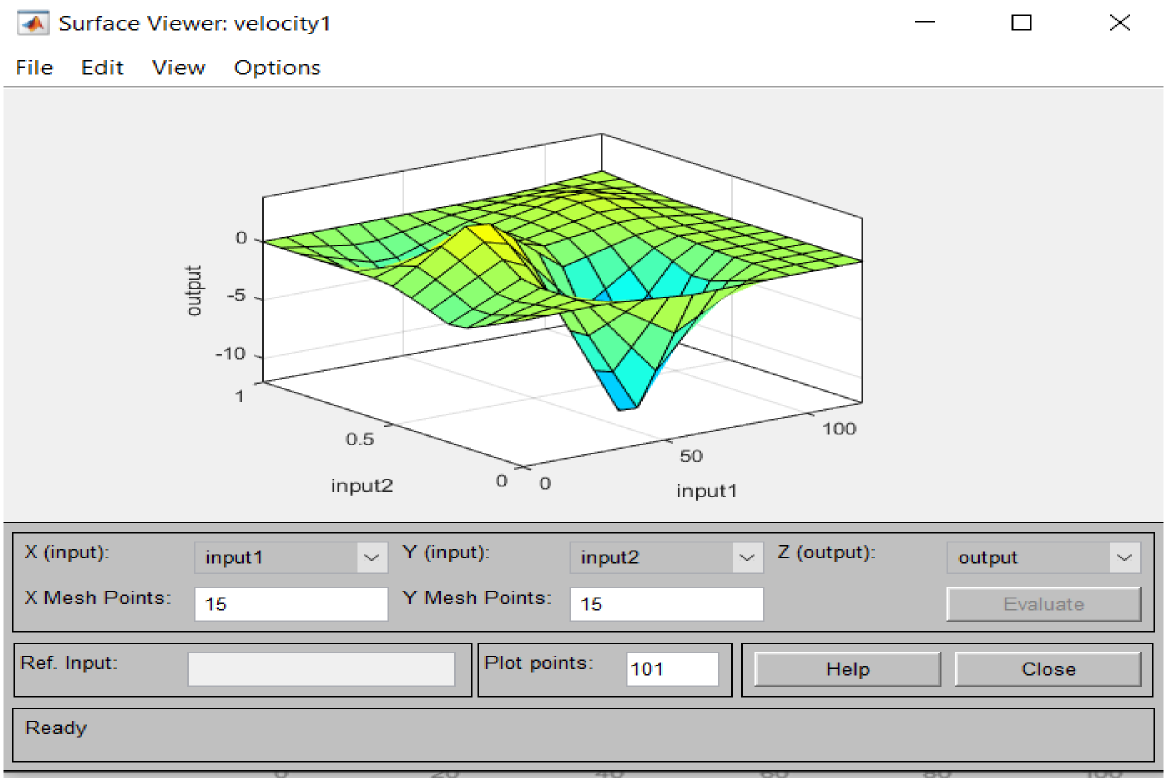


Figure 5.7 Optimal slip controller surface.

Figure 5.7 shows the 3D surface view of neuro-fuzzy optimal slip controller in velocity, wheel slip, and optimal slip.

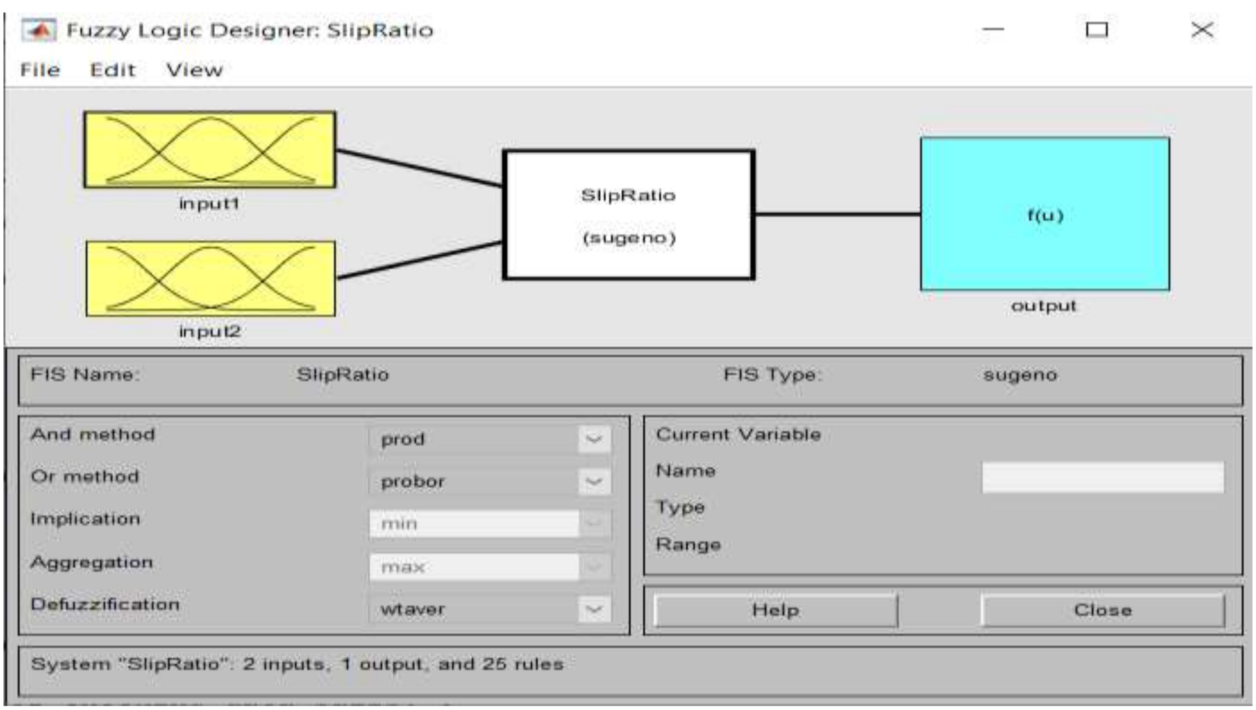


Figure 5.8a Braking force Controller Structure

The braking force controller in Figure 5.14 has two linguistic variables as inputs: "slip erro" and "wheel acce," and one linguistic variable as output: slip ratio. Figures below show the model structure view, their membership functions, fuzzy if-then rule base, fuzzy rule view, and surface view:

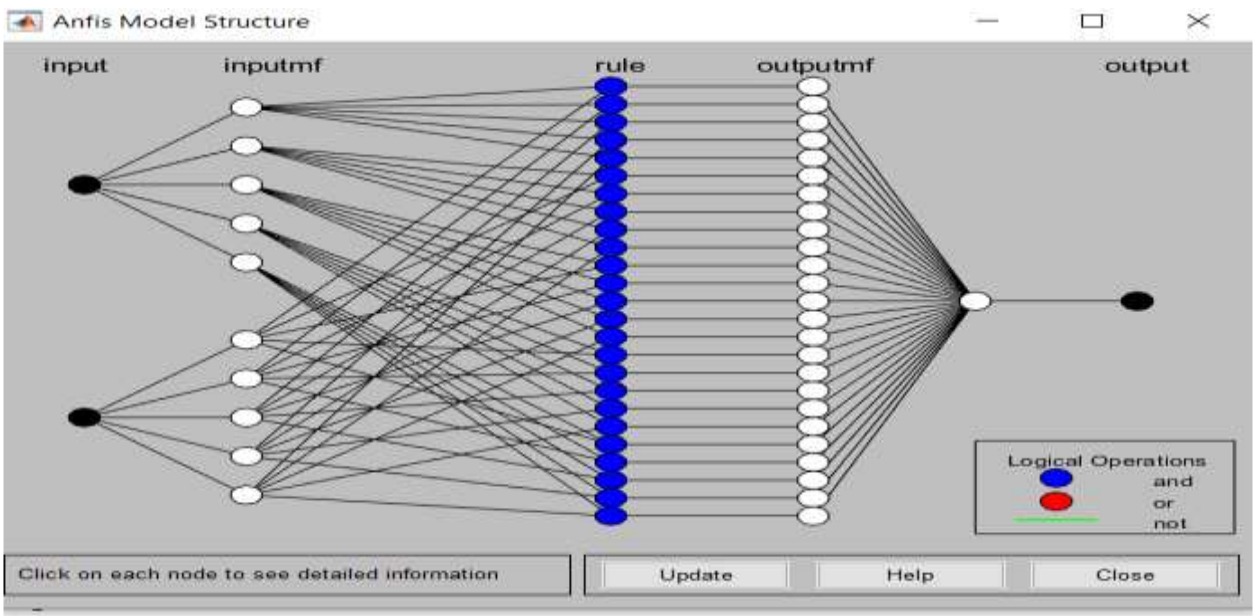


Figure 5.8b Braking force controller Model Structure View.

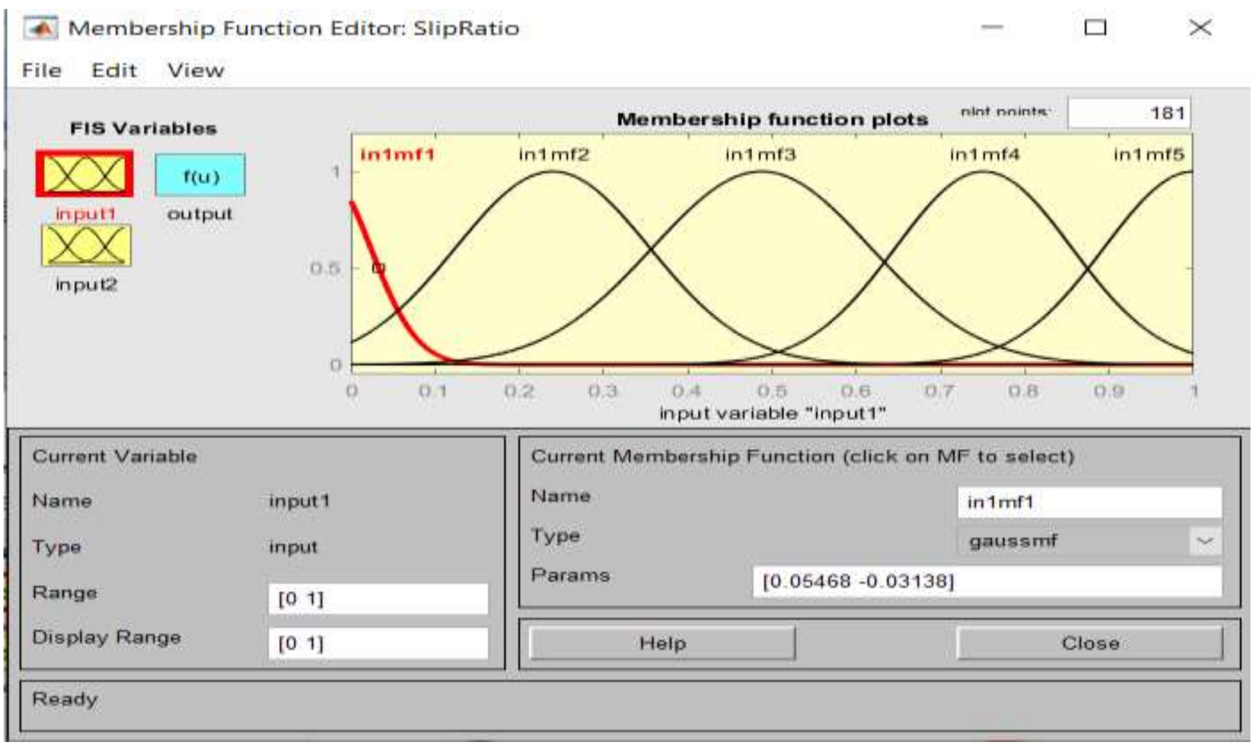


Figure 5.9a Membership function for input linguistic variable “slip_error”

Figure 5.9a shows the input linguistic variable “slip_error” with its five linguistic terms: mf1, mf2, mf3,mf4 and mf5in the interval [0 1].

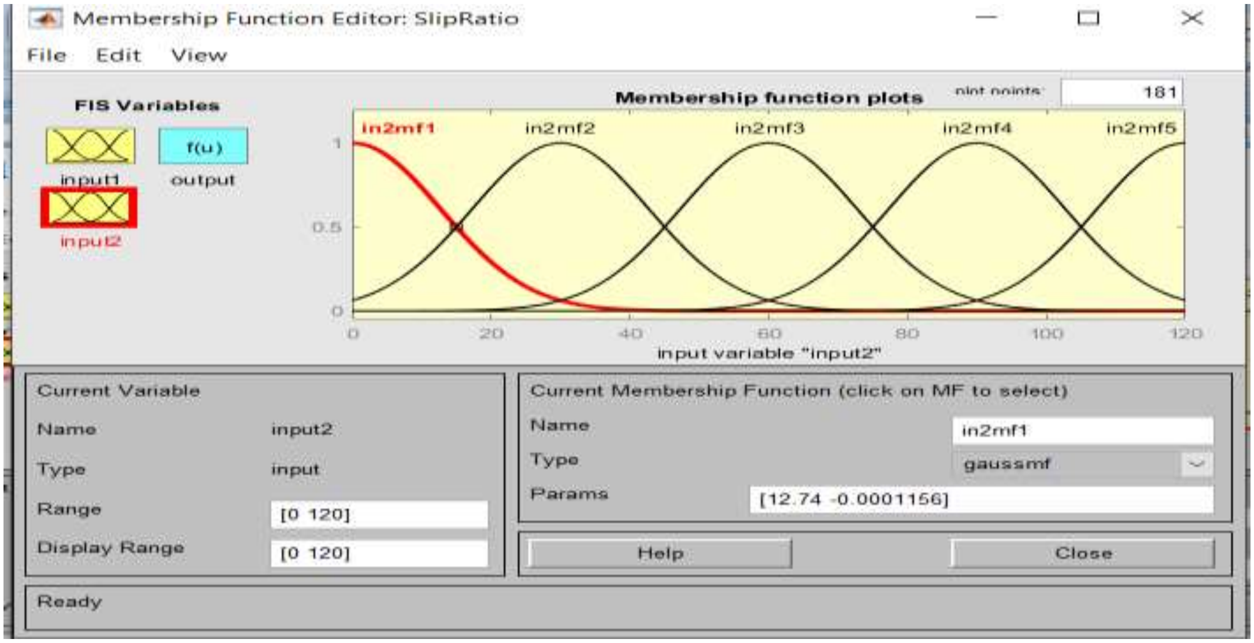


Figure 5.9b Membership function for input linguistic variable “wheel_acce”

Figure 5.9b depicts the input linguistic variable "wheel acce" in the interval [0 120] with its fivelinguistic terms: mf1, mf2, mf3,mf4 and mf5.

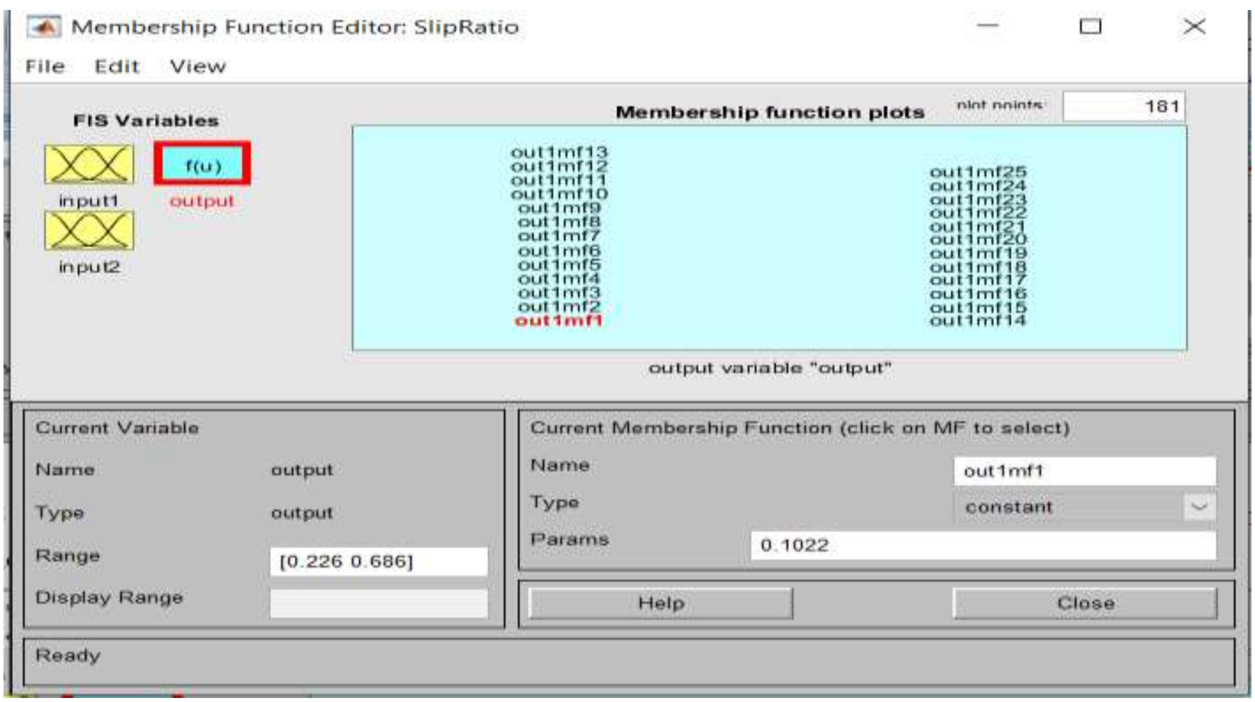


Figure 5.9c Membership function for output linguistic variable “slip_ratio”

Figure 5.9c shows the output linguistic variable wheel slip ratio with its twenty five linguistic terms in the interval [0.226 0.686].

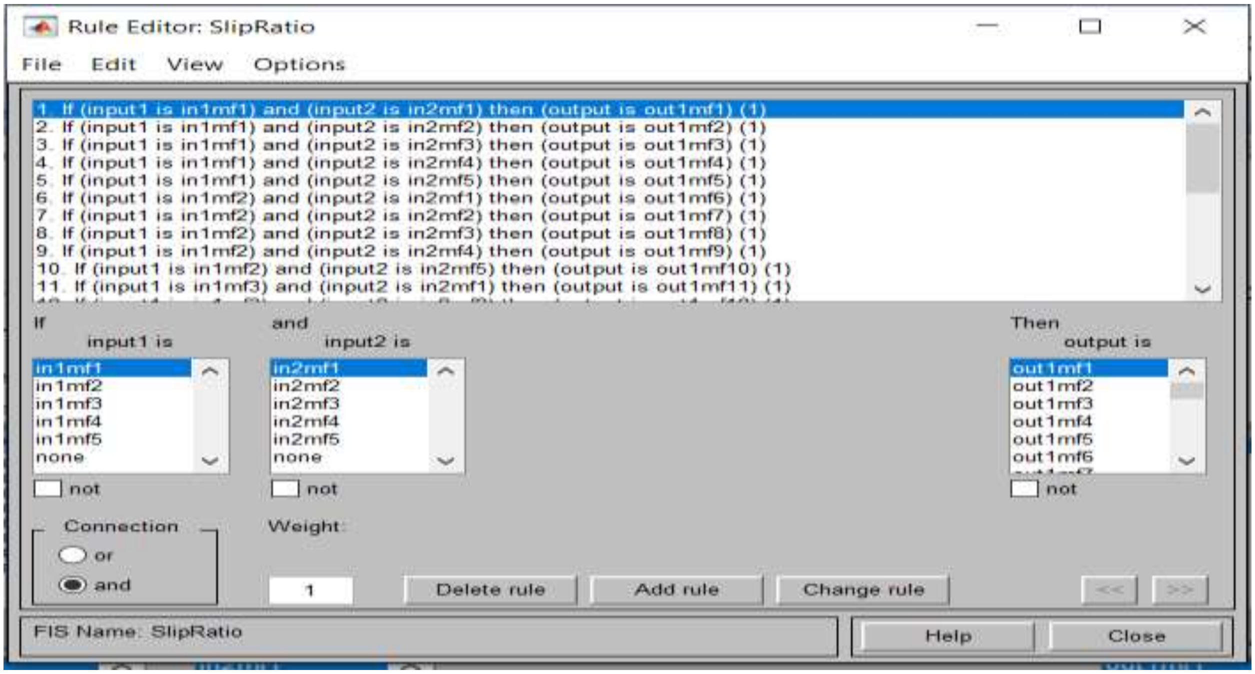


Figure 5.10 Slip ratio controller rule.

Figure 5.10 shows neuro-Fuzzy slip ratio controller has nine if-then rule bases and the fuzzy rule view is shown in Figure 5.11 with their correspondence value.

Figure 5.11 Slip ratio controller rule view

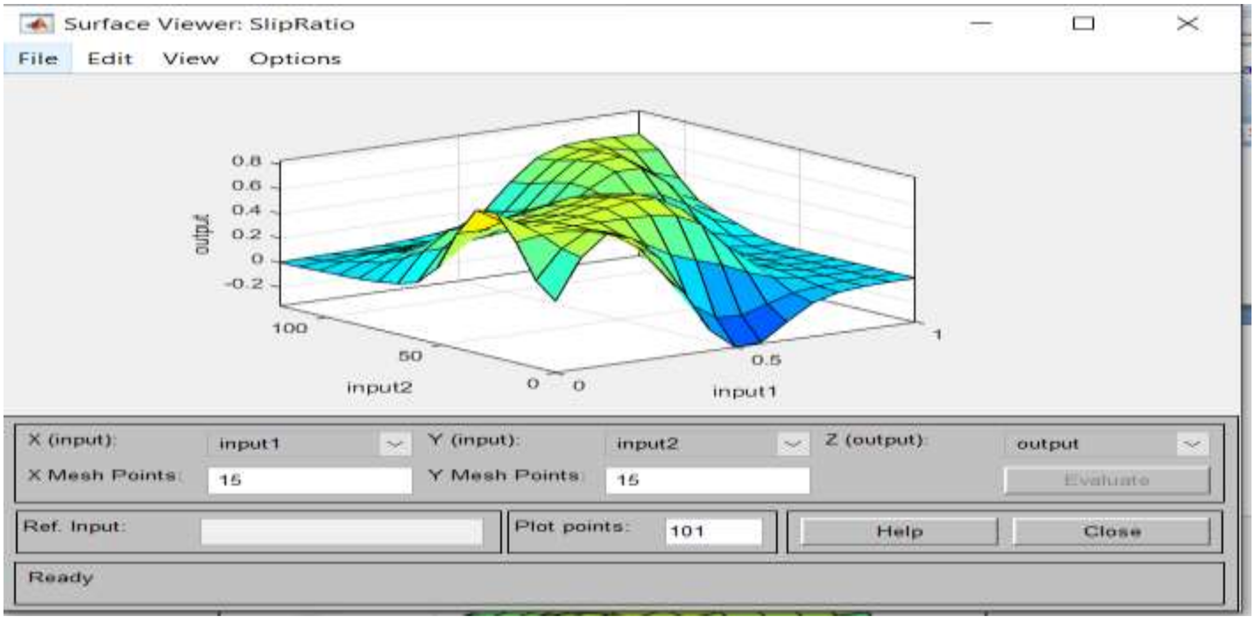


Figure 5.12 Slip ratio surface view.

Figure 5.12 shows the 2D surface view of neuro_fuzzy used to determine required brake force controller with slip error, wheel acceleration and slip ratio.Figure 5.13 shows the MATLAB Simulink block diagram used to simulate the system response for this control structure.

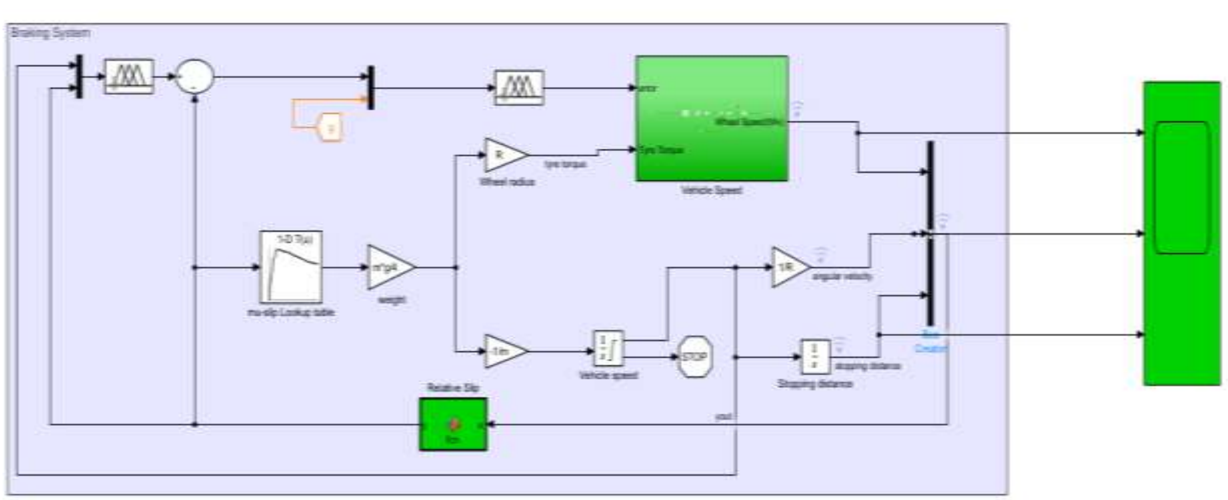


Figure 5.13 Braking System Simulation Model

A braking system is an automobile safety system that prevents a vehicle's wheels from locking as brake pedal pressure is applied - often abruptly in an emergency or with a short stopping distance. This gives the driver steering control, preventing skidding and traction loss. The brake pressure applied by a hydraulic fluid pumped throughout the system as a result of the driver pressing on the brake pedal is momentarily released, the brakes are freed, and the car's wheels and tires can rotate again. This intervention takes place hundreds of times per second. The car's braking system prevents a brake-induced skid by releasing and reapplying the brakes, allowing the driver to continue steering.Slip Threshold is a subsystem that calculates wheel slip using Angular Velocity and Linear Velocity. Wheel acceleration/deceleration is a subsystem that calculates wheel acceleration/deceleration and generates signals for braking system. Lower Threshold is a subsystem that determines the lower speed threshold and compares it to the slip threshold. Upper Threshold is a subsystem that calculates and compares upper and slip thresholds. The braking maneuver is affected by the road conditions, which include frictional coefficient and wheel slip. At a slip value of 0.2, the optimal frictional coefficient for achieving maximum braking pressure when stopping the car is obtained. As a result, this value serves as the reference slip value for obtaining the best braking torque. Therefore,the designed braking controller will be depends on:

- Brake Applied, Angular Velocity, Vehicle SpeedTire Radius as input parameter.
- Slip (0<slip<1) and Brake Signals as output parameter.

This system Simulation model's variables and parameters include initial velocity Vo of $16.6 \sim 27.7 m/s$, vehicle mass m of $250 \sim 450 kg$, effective wheelrolling radius Rw of 0.356m, wheel inertia Jw of 1.04 kgm^2, braking torque Tb of 0.01Nm, hydraulic system amplification factor K of 1, desired slip ratio of 0.2, and gravitational acceleration of $9.81 m/s^2$.

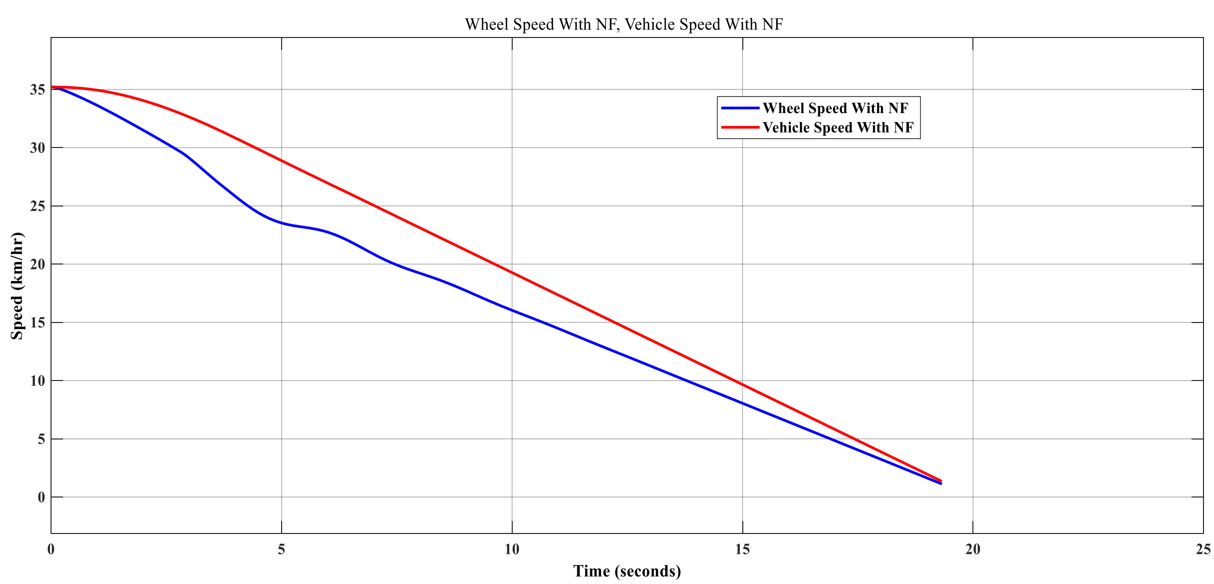


Figure 5.14 The vehicle and when Braking Wheel speed

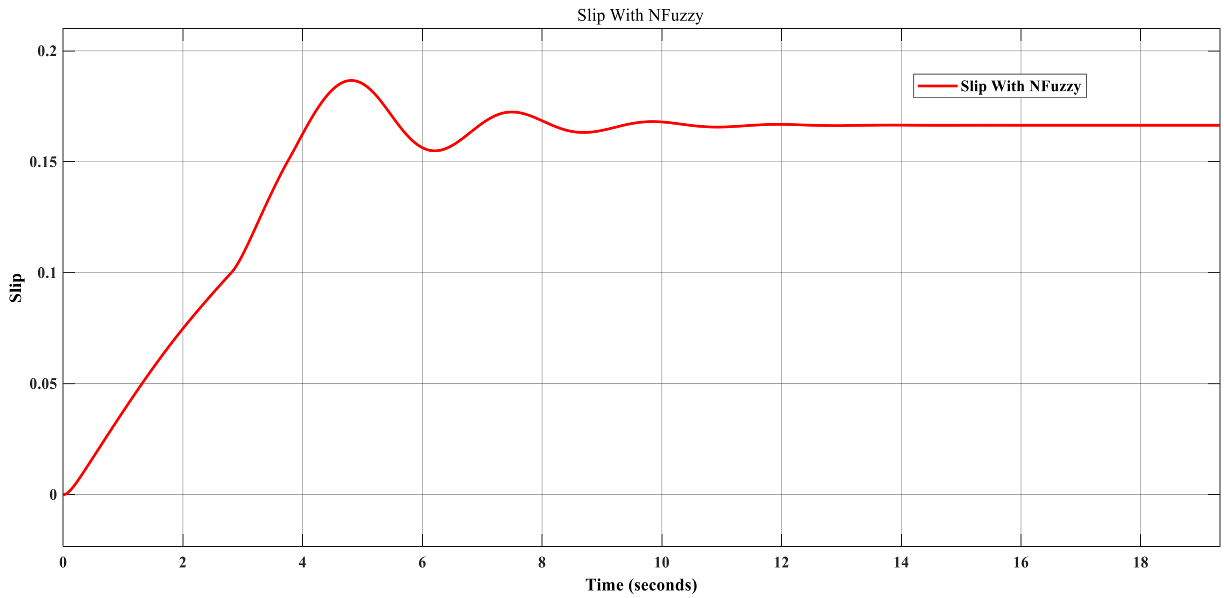


Figure 5.15 Variation in Normalized Relative Slip When the brake is applied

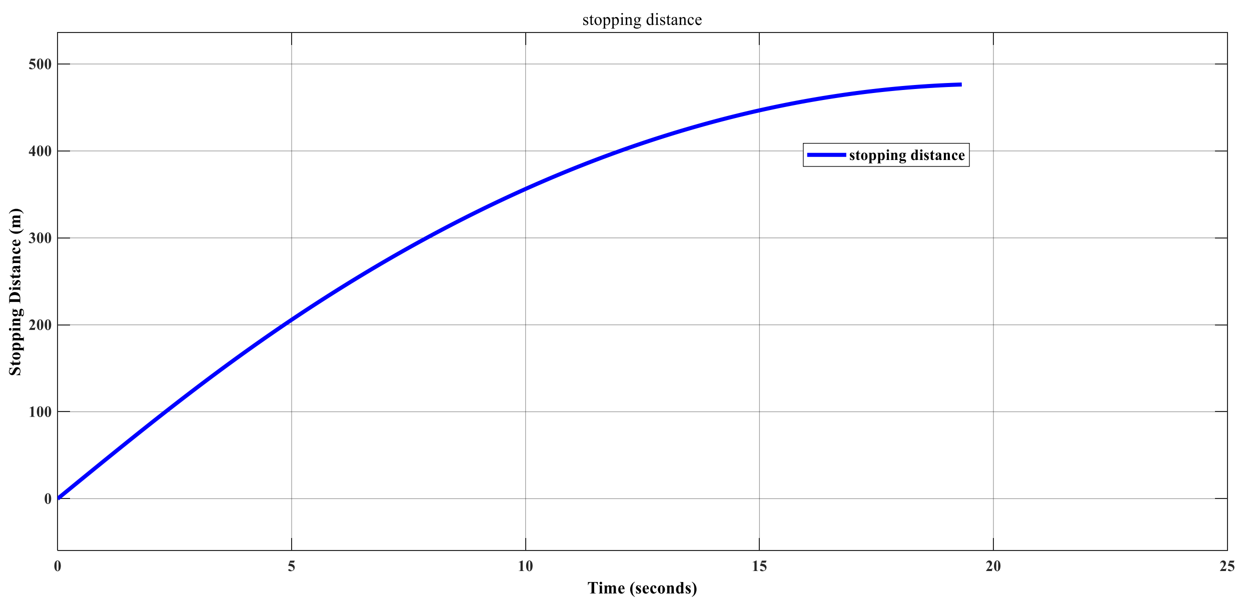


Figure 5.16 Stopping Distance between the Car and Obstacle

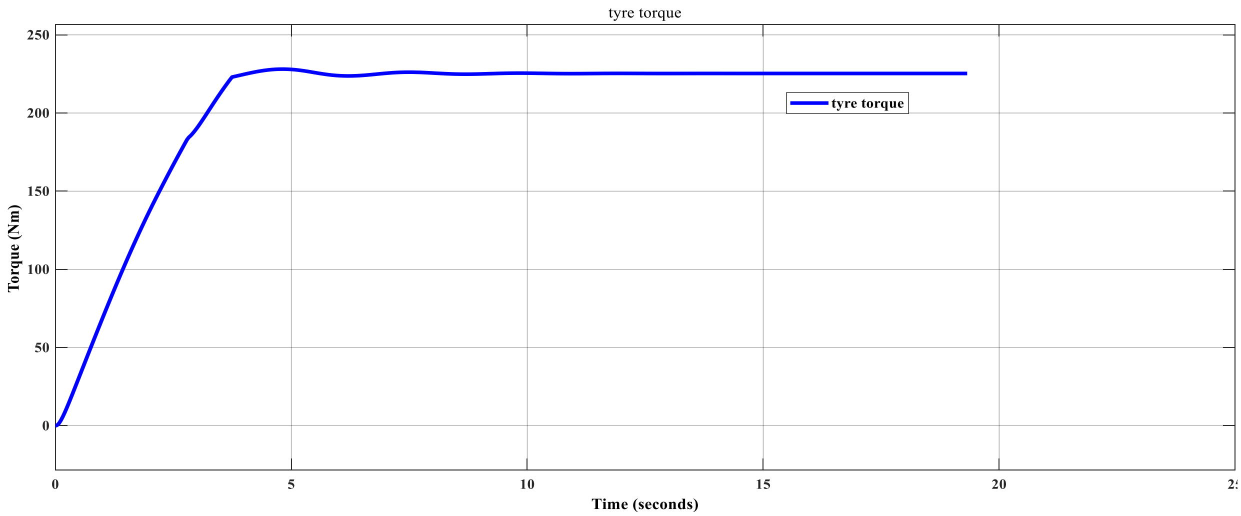


Figure 5.17 Tyre torque

5.3 PID Based Car Braking System

The slip level is maintained by the neuro-fuzzy controller at 0.15 to 0.25, which is within the allowed tolerance level, as opposed to the PID controller. Figure 5.20 displays the normalized relative slip measured by the wheel speed sensor during deceleration. According to the graph, when the car slows down and the slip value is between 0.15 and 0.20, the controller tells the brake circuit to release the brake, causing the slip value to rise to between 0.20 and 0.25. When the car stops, the slip value increases to one, indicating that the angular wheel velocity is zero. This occurs continually but in microseconds to preserve stability and ease of steering of the vehicle while applying brakes (vehicle is at rest).

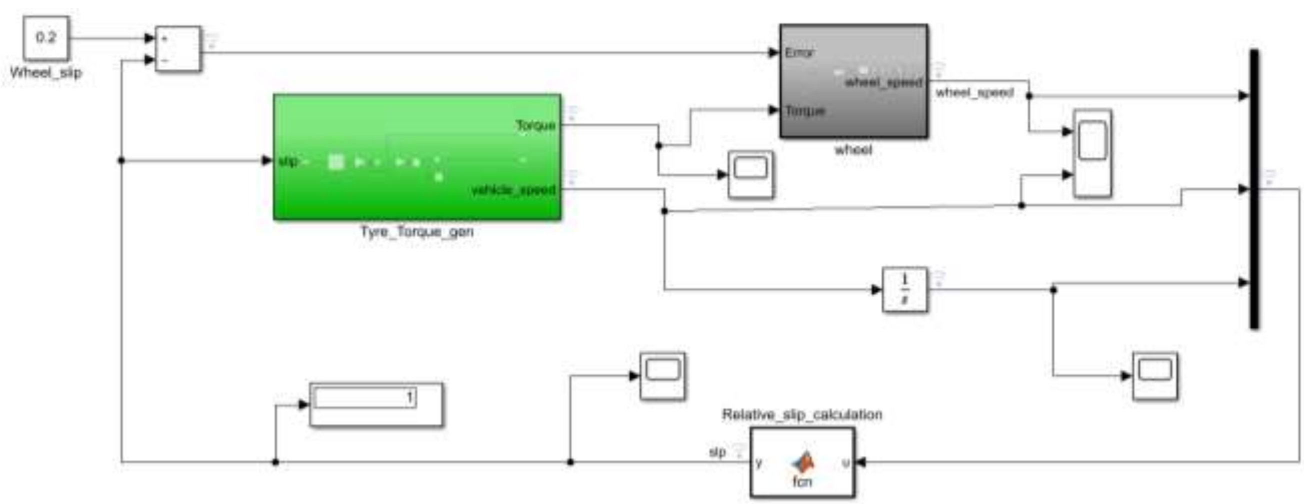


Figure 5.19 Optimal car Braking system

The simulation results from the model with Neuro-fuzzy controllers were compared to the simulation results from a model with a simple PID controller. Figure 5.20 illustrates the optimal slip curve with the same parameters but using a PID controller, which is very non-linear. Indicates that the nature of the curve remains somewhat linear when the brake is applied for 2 seconds, but then changes rapidly until 19 seconds, when it achieves final linearity.Steerability is extremely difficult to achieve during this rapid change of optimal slip. Using this type of curve to achieve optimal slip is not recommended for the safe and effective performance of the braking system.

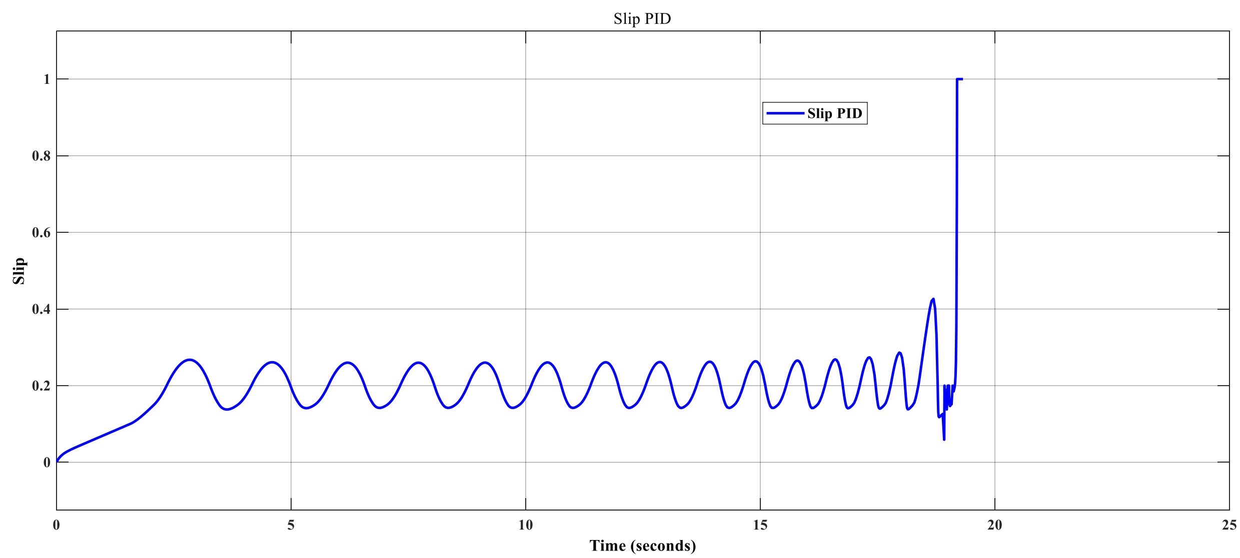


Figure 5.20 Simulation result of Slip with PID controller

Figure 5.21 illustrates the velocity versus time curve simulation result for the model with a PID controller. After 19 seconds, the curves for wheel velocity and vehicle velocity converge to zero.

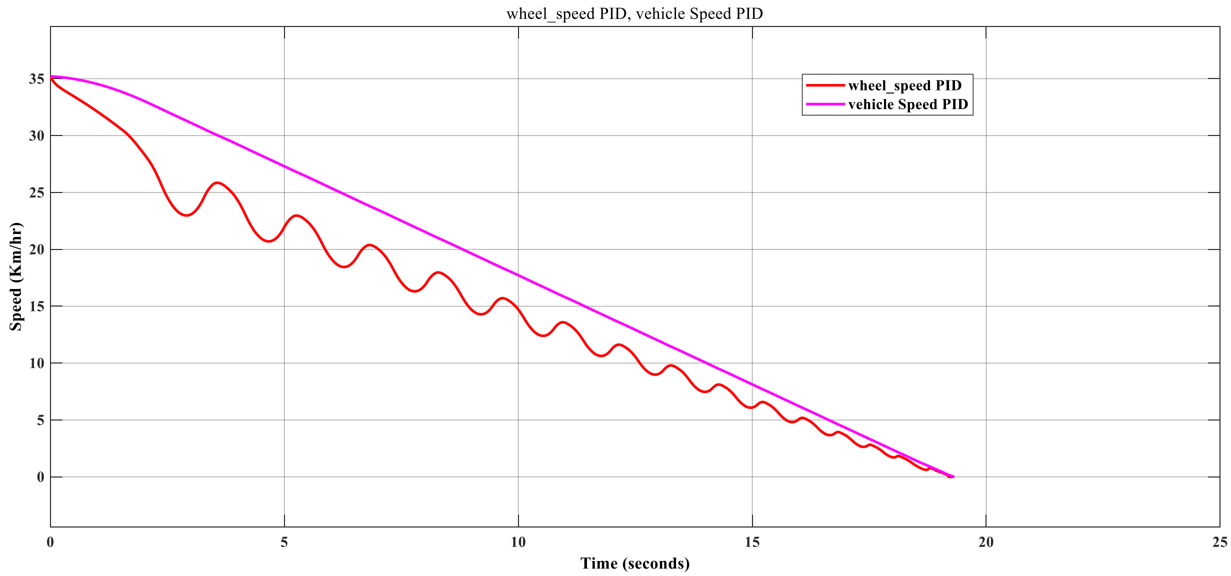


Figure 5.21 Simulation result of wheel and vehicle Speed for PID controller

The car decelerates and stops in the smallest amount of time 19 seconds despite the fact that the wheel speeds are not uniform when the brake is applied abruptly, as seen in figure 5.21. This is made possible by the neuro-fuzzy controller's smooth control. Before the vehicle stops or steers to prevent skidding, the neuro-fuzzy controller synchronizes the speed of the vehicle with the wheel speeds. As seen in figure 5.21, the controller keeps track of the vehicle speed and modifies the wheel speed to match the vehicle speed before the vehicle stops. Figure 5.22 shows the simulation result stopping distance versus time PID feedback control. The stopping time and distance are slightly reduced here. The stopping distance is 353.8 m and the stopping time is 19 seconds.

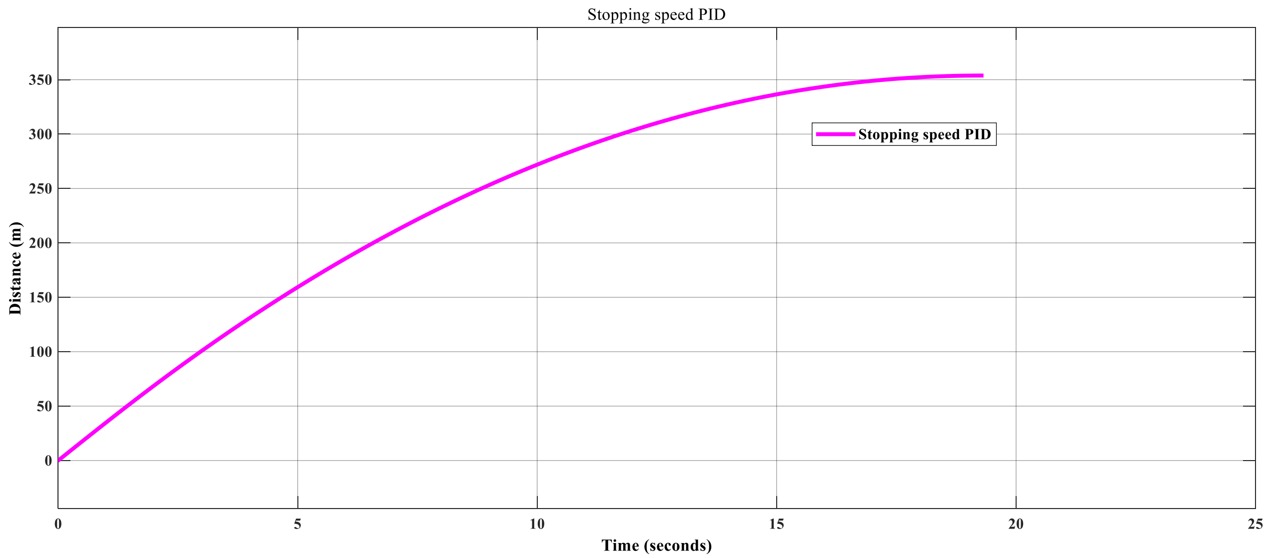


Figure 5.22 Simulation result of stopping distance with PID controller

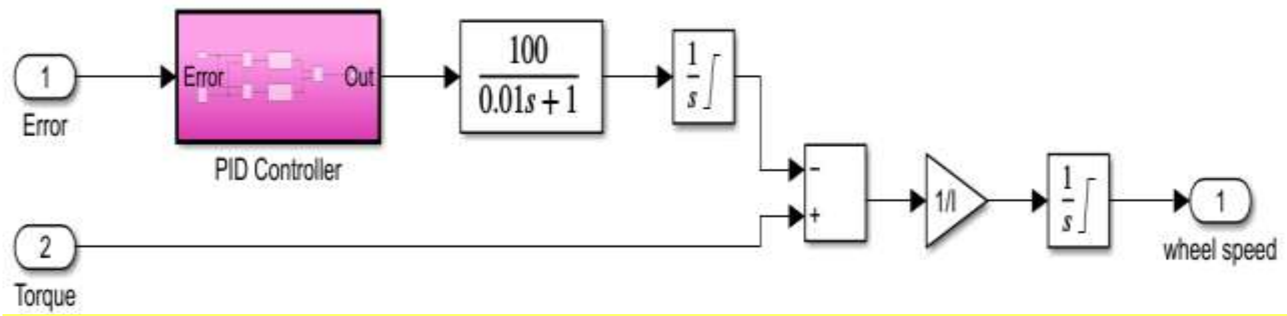


Figure 5.23 PID controller

5.4 Stability and Performance evaluation of the Neuro-fuzzy and PID Controller

Now contrast Figures 5.15 and 5.20's depictions of optimal slip results and the times needed to achieve them with and without fuzzy logic controllers. It is obvious that the fuzzy controller model offers significantly greater control over slip than the other models. Until the vehicle comes to a stop, the curve gradually ascends to the ideal value. Better slip improves the vehicle's control and steerability.

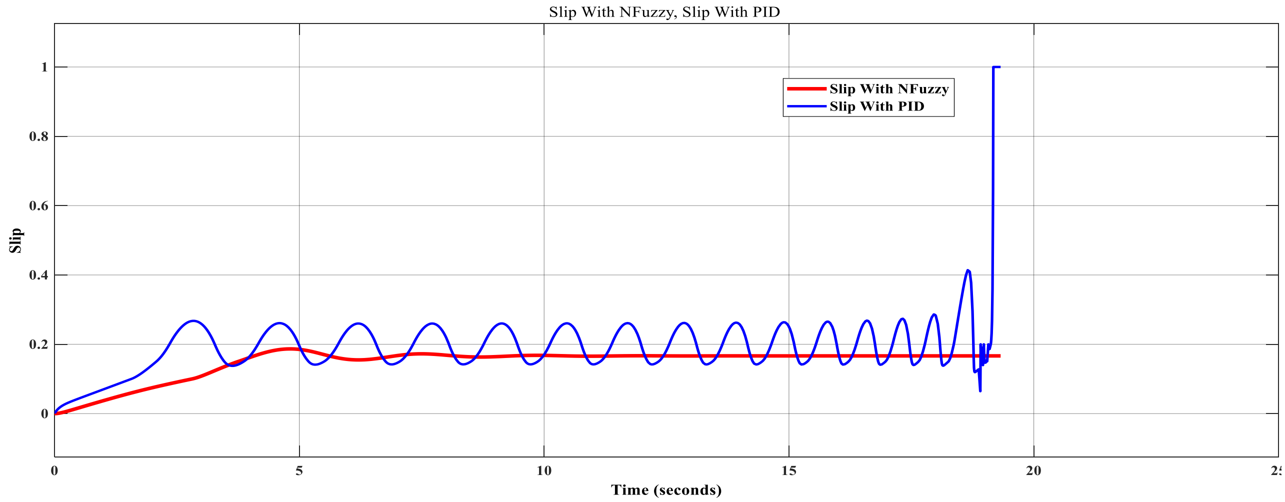


Figure 5.24 Comparison between slip and fuzzy controller

Figures 5.14 and 5.21 are compared, and it is obvious that the model with fuzzy controls takes less time to stop the vehicle approximately 17 seconds while the model without fuzzy controllers takes more time approximately 19 seconds. Therefore, when fuzzy controllers are utilized in a vehicle's braking system, the valuable 2 seconds are accomplished for stopping the vehicle. The existing system used PID controller in the electronic control unit of the vehicle to prevent the locking up of wheels while the modelled system uses Fuzzy Logic to design the controller and hence the system is more reliable and stable than the existing system and will have consumer acceptance. From the table 5.1, it can be summarized that the modelled system has high values of braking deceleration, short stopping time and high braking torque compared to that of the existing PID controller. As a result, compared to the current system, the car might be stopped quickly. In contrast to the previous PID system, the simulation results revealed that the curve settles down smoothly when decelerating and the car will not feel any jerks at high braking situations.

Table 5.1 Comparison of PID controller with Neuro-Fuzzy Controller

Parameters	Neuro-Fuzzy controller	PID controller
Stopping time (s)	17.20	20
Braking Deceleration(m/s^2)	-8.92	-5.64
Braking Torque(Nm^2)	581.93	476.72

5.5. Discussions

A mathematical model of various Antilock braking system components such as vehicle dynamics, tire, wheel slip, and brake actuator has been developed. Tire, wheel slip, brake actuator and two neuro-fuzzy controller MATLAB/Simulink models have also been developed. The first neuro-fuzzy controller has been given input parameters in order to obtain the best slip of the road condition as an output. The second neuro-fuzzy controller was given input parameters in order to get the car braking control as an output. Finally, the concept of how to apply braking force in various road conditions has been clarified. In Matlab/Simulink, a car braking system with neuro-fuzzy controllers was created, and the simulation results were compared to a car braking system with a simple PID controller. The use of a neuro-fuzzy controller improves the vehicle's slip control, steerability, and stopping distance. The vehicle comes to a stop after 17.20 seconds with fluctuations in slip, whereas the vehicle comes to a stop after 17 seconds with stable wheel slip and better steerability. As a result, neuro-fuzzy controllers outperform PID controllers in terms of wheel slip control, steerability, and stopping distance. Now, as shown in Figure 5.15, compare the optimal slip results and the time required to achieve them with and without the neuro-fuzzy controller. The model with neuro-fuzzy controllers clearly provides much better control over slip. The curve rises smoothly to the optimal value and remains there until the vehicle comes to a halt. Better slip gives the vehicle more control and steerability.The velocity curve for the model with the neuro-fuzzy controller is shown in Figure 5.14. The model with neuro-fuzzy controllers achieves better results in stopping the vehicle with better steerability and control.When compare Figures 5.14 and 5.21, it can clearly see that the model without neuro-fuzzy controllers takes nearly 19 seconds to stop the vehicle, whereas the model with neuro-fuzzy controllers takes nearly 17 seconds. When neuro-fuzzy controllers are used in a vehicle's antilock braking system, the valuable 2 seconds are achieved for stopping the vehicle.

CHAPTER SIX
CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

The control objective is to shorten the stopping distance, restrict the slip ratio, and enhance the performance of the controlled system. The simulation results for various scope readings are displayed in Figures 5.13 through 5.17. The car decelerates and comes to a complete stop in the smallest amount of time (17.20 seconds) when the brake is rapidly applied, as illustrated in figure 5.13. This is made possible by the neuro-fuzzy controller's smooth operation.Before stopping or steering, the neuro-fuzzy controller first synchronizes the vehicle's speed with each of its wheels to prevent skidding. As seen in Figure 5.13, the controller keeps track of the speed of the car and modifies the wheel speed so that it matches the car's speed immediately before it comes to a stop. When compared to the bang-bang PID controller, the neuro-fuzzy controller keeps the slip level between 0.15 and 0.25, which is within the allowed tolerance level.The normalized relative slip recorded by the wheel speed sensor while braking is shown in Figure 5.14. The controller signals the hydraulic brake circuit to release the brake when the slip value is between 0.15 and 0.20 during braking, raising the slip value to 0.20–0.25 at that point. The slip value increases to one as the vehicle comes to a halt, indicating that the angular wheel velocity is zero. This happens continually but in microseconds to preserve vehicle stability and steering ease when applying brakes (vehicle is at rest).A graph of the frictional coefficient vs slip value is shown in Figure 5.15. The graph demonstrates that the frictional coefficient reaches its maximum value of 1 at a slip value of 0.2. The system has now produced the most amount of braking torque necessary to completely stop the car. The neuro-fuzzy system maintains the braking system within this slip value to achieve peak performance. The rising time and overshoot are decreased with the neuro-fuzzy controller compared to the PID controller.Figure 5.16 illustrates how the vehicle's stopping distance was shortened to 120 m in 17.20 seconds to prevent a collision. The crucial braking distance, which is always greater than the stopping distance, is calculated by the system when an impediment is identified. The neuro-fuzzy system alerts the hydraulic braking system when the car is approaching the critical braking distance. Assuming a speed of 40 m/s, the critical braking distance is 165.5 m, meaning that when the vehicle stops, the obstruction will be 45.5 m distant. Figure 5.4 displays the first Neoro-Fuzzy design's rules in a smooth surface view. The neuro-response is produced when sensor signals are received. fuzzy's In order to use the maximum amount of braking force to stop the vehicle, the controller will send a strong braking signal to the second fuzzy when the obstruction (OB) signal is high. If it is low, the controller will give the second controller the order to lightly brake the car in order to slow it down.Here, you can view changes made to the system to see if it behaves as planned. When signals from error, error change, and neuro-fuzzy are received first and tasks are carried out using fuzzy rules, Figure 5.12 illustrates the reaction of the second neuro-fuzzy system. The brake force appears to be excessive if the first controller transmits a strong braking signal that tells the second controller to raise the braking pressure.The hydraulic braking system lessens the brake pressure when it receives a weak signal from the neuro-fuzzy or when the car is preparing to steer. The relationship between wheel speed, vehicle speed, and stopping distance when the brake is applied is shown in Figure 5.16. This shows how the second neuro-fuzzy system reacts when tasks are completed using fuzzy rules and signals from error, error change, and neuro-fuzzy are received first.The brake force appears to be excessive if the first controller transmits a strong braking signal that tells the second controller to raise the braking pressure. The hydraulic braking system lessens the brake pressure when it receives a weak signal from the neuro-fuzzy or when the car is preparing to steer. The relationship between wheel speed, vehicle speed, and stopping distance when the brake is applied is depicted in Figure 5.14.This thesis focuses on modeling an automatic braking system with a neuro-fuzzy logic controller based on sensor fusion, which can address the issue of drivers who frequently fail to apply the brakes in an emergency situation and can automatically slow down a vehicle due to the detection of obstacles. The resultant system may achieve measurements with high accuracy, low stopping times, and better short distance measurement thanks to the attachment of ultrasonic sensors in the vehicle. The method is ideal in situations with limited parking, busy traffic, emergencies, and restricted regions.

6.2 Reccomendation

This study has limitations that provide avenues for future research in the same field. The following are some suggestions for broadening the scope of this thesis work: More inputs to the neuro-fuzzy controller can be added to the model to further modify it. The road slope can be used as an input parameter when controlling the braking force applied to the vehicle.Car braking models using neuro-fuzzy logic controllers can be compared to car braking models using other controllers such as PID controllers, Sliding mode (SM) controllers, and FOSMC controllers, and the results with the difference in time for stopping the vehicle can be analyzed.

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APPENDIX A

Tyre Data For Training

Table A1.1: Data training to determine the optimal slip

Input		Output
Velocity	Slip	Optimal Slip
0.00	0.00	0.00
1.20	0.01	0.12
2.40	0.02	0.23
3.60	0.03	0.35
4.80	0.04	0.45
6.00	0.05	0.56
7.20	0.06	0.66
8.40	0.07	0.75
9.60	0.08	0.83
10.80	0.09	0.91
12.00	0.1	0.98
13.20	0.11	1.04
14.40	0.12	1.1
15.60	0.13	1.14
16.80	0.14	1.19
18.00	0.15	1.22
19.20	0.16	1.25
20.40	0.17	1.28
21.60	0.18	1.3
22.80	0.19	1.32
24.00	0.2	1.33
25.20	0.21	1.34
26.40	0.22	1.35
27.60	0.23	1.36

28.80	0.24	1.36
30.00	0.25	1.36
31.20	0.26	1.36
32.40	0.27	1.36
33.60	0.28	1.35
34.80	0.29	1.35
36.00	0.3	1.34
37.20	0.31	1.34
38.40	0.32	1.33
39.60	0.33	1.32
40.80	0.34	1.31
42.00	0.35	1.3
43.20	0.36	1.3
44.40	0.37	1.29
45.60	0.38	1.28
46.80	0.39	1.27
48.00	0.4	1.26
49.20	0.41	1.25
50.40	0.42	1.23
51.60	0.43	1.22
52.80	0.44	1.21
54.00	0.45	1.2
55.20	0.46	1.19
56.40	0.47	1.18
57.60	0.48	1.17
58.80	0.49	1.16
60.00	0.5	1.15
61.20	0.51	1.14
62.40	0.52	1.13
63.60	0.53	1.12

64.80	0.54	1.11
66.00	0.55	1.1
67.20	0.56	1.09
68.40	0.57	1.08
69.60	0.58	1.07
70.80	0.59	1.06
72.00	0.6	1.05
73.20	0.61	1.04
74.40	0.62	1.03
75.60	0.63	1.02
76.80	0.64	1.01
78.00	0.65	1
79.20	0.66	0.99
80.40	0.67	0.98
81.60	0.68	0.97
82.80	0.69	0.96
84.00	0.7	0.95
85.20	0.71	0.94
86.40	0.72	0.93
87.60	0.73	0.93
88.80	0.74	0.92
90.00	0.75	0.91
91.20	0.76	0.9
92.40	0.77	0.89
93.60	0.78	0.88
94.80	0.79	0.87
96.00	0.8	0.87
97.20	0.81	0.86
98.40	0.82	0.85
99.60	0.83	0.84

100.80	0.84	0.83
102.00	0.85	0.83
103.20	0.86	0.82
104.40	0.87	0.81
105.60	0.88	0.8
106.80	0.89	0.79
108.00	0.9	0.79
109.20	0.91	0.78
110.40	0.92	0.77
111.60	0.93	0.77
112.80	0.94	0.76
114.00	0.95	0.75
115.20	0.96	0.74
116.40	0.97	0.74
117.60	0.98	0.73
118.80	0.99	0.72
120.00	1	0.72

Table A1.2: Data training to determine the brake force

Slip Error	Wheel Acce.	Brake Force
0.00	0.00	0.00
0.12	1.20	0.06
0.23	2.40	0.11
0.35	3.60	0.16
0.45	4.80	0.22
0.56	6.00	0.27
0.66	7.20	0.31
0.75	8.40	0.36
0.83	9.60	0.4
0.91	10.80	0.43
0.98	12.00	0.47
1.04	13.20	0.5
1.1	14.40	0.52
1.14	15.60	0.54

1.19	16.80	0.57
1.22	18.00	0.58
1.25	19.20	0.6
1.28	20.40	0.61
1.3	21.60	0.62
1.32	22.80	0.63
1.33	24.00	0.63
1.34	25.20	0.64
1.35	26.40	0.64
1.36	27.60	0.65
1.36	28.80	0.65
1.36	30.00	0.65
1.36	31.20	0.65
1.36	32.40	0.65
1.35	33.60	0.64
1.35	34.80	0.64
1.34	36.00	0.64
1.34	37.20	0.64
1.33	38.40	0.63
1.32	39.60	0.63
1.31	40.80	0.63
1.3	42.00	0.62
1.3	43.20	0.62
1.29	44.40	0.61
1.28	45.60	0.61
1.27	46.80	0.6
1.26	48.00	0.6
1.25	49.20	0.59
1.23	50.40	0.59
1.22	51.60	0.58
1.21	52.80	0.58
1.2	54.00	0.57
1.19	55.20	0.57
1.18	56.40	0.56
1.17	57.60	0.56
1.16	58.80	0.55
1.15	60.00	0.55
1.14	61.20	0.54
1.13	62.40	0.54

1.12	63.60	0.53
1.11	64.80	0.53
1.1	66.00	0.52
1.09	67.20	0.52
1.08	68.40	0.51
1.07	69.60	0.51
1.06	70.80	0.5
1.05	72.00	0.5
1.04	73.20	0.49
1.03	74.40	0.49
1.02	75.60	0.48
1.01	76.80	0.48
1	78.00	0.48
0.99	79.20	0.47
0.98	80.40	0.47
0.97	81.60	0.46
0.96	82.80	0.46
0.95	84.00	0.45
0.94	85.20	0.45
0.93	86.40	0.44
0.93	87.60	0.44
0.92	88.80	0.44
0.91	90.00	0.43
0.9	91.20	0.43
0.89	92.40	0.42
0.88	93.60	0.42
0.87	94.80	0.42
0.87	96.00	0.41
0.86	97.20	0.41
0.85	98.40	0.4
0.84	99.60	0.4
0.83	100.80	0.4
0.83	102.00	0.39
0.82	103.20	0.39
0.81	104.40	0.39
0.8	105.60	0.38
0.79	106.80	0.38
0.79	108.00	0.37
0.78	109.20	0.37

0.77	110.40	0.37
0.77	111.60	0.36
0.76	112.80	0.36
0.75	114.00	0.36
0.74	115.20	0.35
0.74	116.40	0.35
0.73	117.60	0.35
0.72	118.80	0.34
0.72	120.00	0.34

Figure A1.1 Input-1 and output

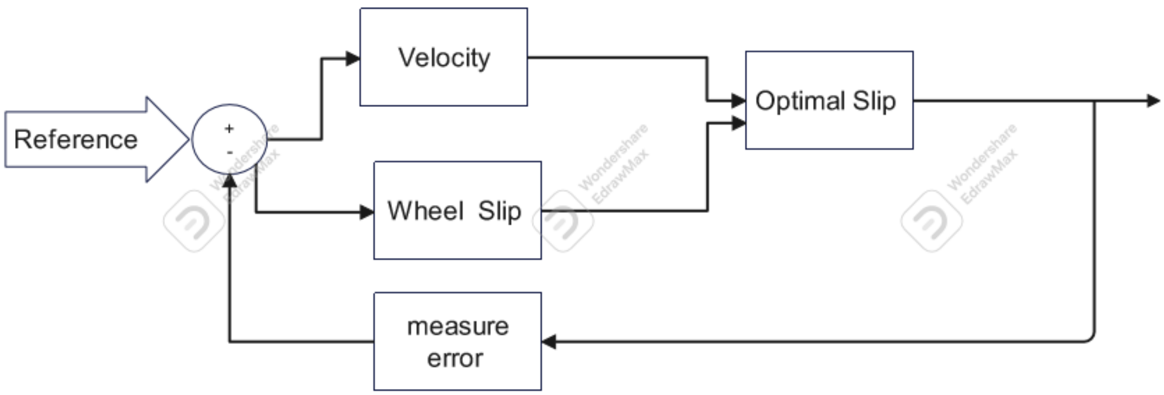

Figure A1.2 Input-2 and out put