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MODEL PREDICTIVE CONTROL FOR PASSING ASSISTANCE IN AUTONOMOUS VEHICLES

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Doctor of Philosophy

Supervisor

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The dissertation titled MODEL PREDICTIVE CONTROL FOR PASSING ASSISTANCE IN AUTONOMOUS VEHICLES prepared by MUSTAFA HAMID SALIH AL-JUMAILI and submitted on 26/12/2025 has been **accepted unanimously** for the degree of PhD in Electrical and Computer Engineering.

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I hereby declare that this dissertation meets all format and submission requirements for a PhD dissertation.

I hereby declare that all information/data presented in this graduation project has been obtained in full accordance with academic rules and ethical conduct. I also declare all unoriginal materials and conclusions have been cited in the text and all references mentioned in the Reference List have been cited in the text, and vice versa as required by the abovementioned rules and conduct.

Mustafa Hamid Salih AL-JUMAILI

Signature

DEDICATION

To my beloved father and mother,

for their unconditional love, endless support, and constant prayers.

To my loving wife and wonderful children,

for their patience, love, and unwavering support that kept me going.

To my brothers and sisters,

for their encouragement and belief in me throughout this journey.

To my supervisor Prof. Yasa ÖZOK,

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This work is dedicated with deepest gratitude and heartfelt appreciation.

ABSTRACT

MODEL PREDICTIVE CONTROL FOR PASSING ASSISTANCE IN AUTONOMOUS VEHICLES

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Autonomous or self-driving vehicles are designed to operate without the need for direct driver control over steering, acceleration, and braking. These vehicles are intended to function in self-driving mode without requiring the driver to continuously monitor the road. The aim of this thesis is to present a novel and robust methodology contributing to the improvement of the performance of autonomous vehicles in both simple and complex manoeuvres. In this context, the dual-controller approach is utilized for merging the benefits of a Model Predictive Controller with a Stanley controller into a hybrid system, namely the Model Predictive and Stanley-based Controller (MPS). Each of them is suffering from some shortcomings: MPC can efficiently perform the path prediction but may lag in responding properly under dynamic conditions, while Stanley controller-though widely used for lateral control-exhibits high lateral errors on tight curves and complex road structure. These are combined carefully in the MPS method so that their respective disadvantages counterbalance each other: the predictive capabilities of MPC are combined with the robustness of the Stanley controller to yield superior path-following and vehicle control capabilities.

Extensive analysis of the MPS system will thereafter be implemented to evaluate its performance under a variety of road conditions, namely straight sections, tight corners, and road environments filled with obstacles. The controller that has been developed demonstrates a level of flexibility and attainable adaptability that is appropriate for a wide range of scenarios while retaining lane stability and trajectory accuracy throughout a variety of speeds and road categories. Accordingly, the several measures of performance for tracking accuracy, minimization of errors, and computational efficiency indicate that the MPS system surpasses the single controller approach system, especially in situations where other systems may face difficulties. The paper also performs a comparison analysis with traditional control systems, pointing out that the MPS controller gives better performance in minimizing errors and providing smoother and more reliable vehicle movement under simple and complex conditions.

Conclusively, the research positions the MPS controller as a significant advancement in the field of autonomous vehicle control by proposing an innovative combination of advantages of the model predictive and Stanley controllers. The results obtained so far have shown that MPS can help achieve safer and more precise autonomous driving, thus making it a potential candidate for real-world applications where reliability and adaptability are considered of prime importance.

Keywords: Autonomous Vehicle Driving, Model Predictive Control, MPC, Stanley Control, MPS, Path Tracking.

TABLE OF CONTENTS

LIST OF TABLES

Pages

LIST OF FIGURES

Pages

ABBREVIATIONS

2D	:	Two Dimensions
3D	:	Three Dimensions
ACC	:	Adaptive Cruise Control
AI	:	Artificial Intelligence
AV	:	Autonomous Vehicle
DOF	:	Degree of Freedom
EV	:	Electrical Vehicle
ICR	:	Instantaneous Center of the Rotation
IEEE	:	Institute of Electrical and Electronics Engineers
Kd	:	Derivative Constant
Ki	:	Integral Constant
Kp	:	Proportional Constant
LiDAR	:	Light Detection and Ranging
MIMO	:	Multi Input Multi Output
MPC	:	Model Predictive Controller
MPS	:	Model Predictive and Stanley-based Controller
MPV	:	Multi-Purpose Vehicle
PID	:	Proportional, Integral, Derivative Controller
R	:	Radius of the circle
SQP	:	Sequential Quadratic Programming
SUV	:	Sports Utility Vehicle

LIST OF SYMBOLS

φ : Steering Rate

δ : Wheel Steering Angle

θ : Heading Angle

v : Velocity

$\psi(t)$: The Angle Across the Path Heading to the Vehicle’s Heading

U : Control Inputs

X : States of [x, y, θ, δ]

Ld : Look-ahead Distance

α : The Heading Error Angle

r(t) : The Reference Setpoint

e(t) : The Difference Between an Actual Output and the Desired Setpoint

u(t) : The Process Input Control Value

y(t) : The Output of the Process

k : The Curvature

x_k : The state of the Vehicle at the Time Step (k)

$x_{ref,k}$: The Reference State at Time Step (k)

f(·) : The Dynamic Model of the Vehicle

h(·) : The Inequality Constraint

g(·) : The Equality Constraint

elat : The Lateral Error

$k_{stanley}$: The Gain of STANLEY Controller

π : The Ratio of the Circumference of a Circle to its Diameter (pi =3.14, or 22/7)

1. INTRODUCTION

1.1 REVIEW

Autonomous vehicles are proposed to operate with no supervise input of the driver for steering, acceleration, or braking, and they do not require the driver to constantly monitor the roadway while in self-driving mode. The Institute of Electrical and Electronics Engineers (IEEE) estimates that by 2040, 75% of vehicles worldwide will be autonomous [1]. Autonomous vehicles (AV) hold immense potential for enhancing traffic flow and significantly improving safety, driving the widespread adoption of driverless technology, especially in both developed nations and rapidly growing markets [2], [3]. The advantages related to self-drives are reducing human errors, maximizing fuel efficiency, and reducing traffic congestion through accuracy, safe driving behaviours. Recent developments in computation processing power, sensor precision, and Artificial intelligence have particularly enabled the development of self-driven vehicles and robotics research work that brings the vision of complete autonomous transportation a step nearer.

One important element of the operation of autonomous vehicles is path tracking, defined here as the vehicle's keeping a pre-established path by controlling lateral and longitudinal movements. This element encompasses not only holding the chosen path but also the transient response to changeable road conditions like lane change, negotiating turns, and acceleration or deceleration according to traffic conditions [4]. Similar to the system architecture shown (Figure 1.1), the autonomous vehicle depends upon a very developed network of sensors, processors, and controllers that operate jointly to understand road conditions, obstacles, and environmental conditions in real time.

The design of the optimum route-tracking controller plays a crucial role in achieving reliable and accurate path tracking. A typical controller guarantees the vehicle's trajectory by conforming to the prophesied road configuration while concurrently compensating for several disturbances and uncertainties such as road surface modifications, environmental factors, and sensor miscalculations [5]. This predictive mechanism facilitates tackling sudden obstacles by predetermining road features and environmental parameters so that a smooth, safe, and adaptable vehicle control is enabled.

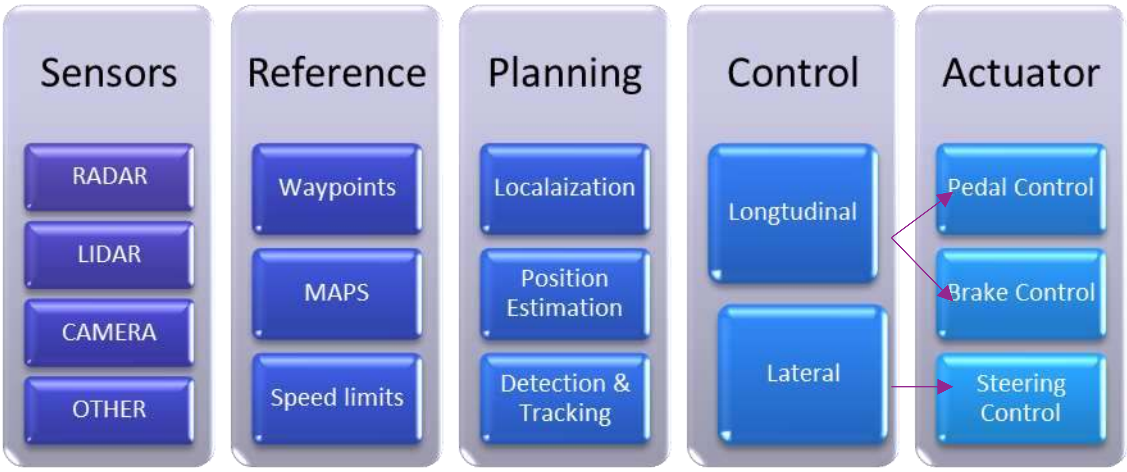

Figure 1.1: Architecture of an Autonomous Vehicle System.

MPC is a sophisticated, non-traditional control method that is presently gaining wide usage in autonomous vehicles for path following and vehicle motion control [6]. The working principle is to estimate the future location of a vehicle by some horizon and using a mathematical description of its dynamics to compute some optimum direction. By way of iterative optimization, MPC adjusts control inputs such as steering angle, acceleration, and braking to reduce the number of violations of the pre-specified path. With a long-term vision of forecasting future obstacles, road turns, and traffic conditions, the vehicle is planned by the MPC to continue its course with optimum efficiency [7].

Among the several plus point of the MPC, one overwhelming advantage lies in striking a balance between driver comfort, time efficiency, and tracking accuracy multi-objectives [8]. This is because, by incorporating vehicle stability and passenger comfort factors in the calculation of smooth, easy-to-drive trajectories that are free of abrupt manoeuvers and harsh accelerations, the MPC has the potential for achieving a balance between vying multi-objectives. Further, the MPC also provides for maximum time efficiency by virtue of intelligent corrections designed to maintain the vehicle on course in the shortest time safely allowable.

MPC also has state parameter constraints, i.e., speed, position, and heading, and control inputs such as torque and braking force so that the vehicle remains within its safe and feasible regions [9]. For instance, it will be able to furnish limits for the speed and steering so that the vehicle does not enter into a manoeuvre that will destabilize it or threaten the passengers with loss of their lives. The result is that the vehicle's performance for navigating a variety of driving conditions such as sharp turns, stop-and-go conditions, and sudden change of lanes is improved while retaining high accuracy for track keeping that is desired [10]. Robustness of such a control technique therefore makes MPC a contender for the top selection for its applications on autonomous vehicles where accurate tracking and adaptive decision-making are paramount for the assurance of safeguarding the occupants and the reliability in navigating the complicated road networks.

Path tracking is a key element within autonomous vehicle frameworks, allowing for the possibility of properly following a pre-established path with high precision using both longitudinal and lateral motion. This is realized by careful control of longitudinal velocity and lateral steering such that the vehicle is aligned along a pre-established trajectory [11]. The problem lies in the fact that very few path-tracking controllers are able to command high levels of path-tracking accuracy and maintain stable vehicle behaviour concurrently by virtue of having a wide spectrum of dynamics variables that may affect vehicle motion [12], such as road curvature the trajectory is dependent upon; the vehicle's inherent nonlinearity giving rise to highly complicated and possibly unpredictable motion; uncertainties due to variable road conditions or inaccurate sensor measurements; and time-delays in the control system giving a sluggish response that makes precise tracking impossible [13].

The challenges that are brought forth are defined in such a manner that any optimal path-tracking controller will need to have the capabilities of anticipating and thereby preparing for upcoming roadway conditions and/or disturbances [14]. An intelligent controller will respond deftly to sudden curvature changes, gradients, and surface irregularities while ensuring stability and limiting path drift. This forecasting ability will enable the controller to consider upcoming road-setting variations like steep turns or lane changes and apply pre-emptive alterations to ensure smooth and accurate travel along the preset course of travel [15].

Moreover, a controller that is proficient will ideally offset the continuous disturbances and uncertainties that are intrinsic in real driving scenarios like sudden front vehicle braking, wind gusts, or by minor discrepancies in the positioning by the GPS. With the help of future roadway data and real-time compensations, a high-quality path-tracking controller reduces the disturbances so that the vehicle remains stable while sticking to its predestined path [16].

The adoption of advanced control schemes, particularly Model Predictive Control, is central because it allows for the consideration of several potential actions and the choice of the most favourable course of action given expected outcomes. A higher quality path-tracking controller thereby improves the dependability and safety of autonomous vehicles so that they may navigate the complex road networks with a level of accuracy and flexibility equal to or greater than human operators [17].

The model predictive control has been shown also to be one of the most promising autonomous vehicle path tracking technologies given the predictability that it provides; hence it has also been found to be particularly appropriate for highly complex and time-varying driving conditions [18] [19]. By utilizing an internal model of the vehicle to project ahead its future states over a fixed time horizon, the vehicle can make an informed, proactive adjustment in speed, steering, and braking to maintain a specified path. Accurate and responsive, the key features of such predictive approaches, permit the functionality of MPC to deal with abrupt changes in the driving environment that comprises obstacles, road curvature, and other vehicles. The author in [20] developed an MPC controller on a 4 Degree of Freedom (4DOF) vehicle model. Emphasis has been put on preventing rollover accidents- a very important safety feature for all vehicles with a high center of gravity, especially Sports Utility Vehicles (SUVs).

Thanks to the consideration of lateral and longitudinal forces, the MPC approach presented can compute path changes dynamically in a stabilizing fashion, with a minimal risk of rollover due to vehicle rollover on curve or terrain irregularities. Such underpinning is more useful for autonomous systems on challenging terrains or at high speed, where rollover risks are considerably enhanced. One of the important strengths of MPC is that it can track routes with better quality, since it forecasts the future dynamics of vehicles, like path deviations and possible instabilities that will or may appear [21].

This capability for forecasting enables the MPC controller to continuously reassess all the possible future states and to choose those which represent the best corrective or preventive control actions from any deviation with respect to the path [22]. The reason this is so important is it enables the control approach to manage complex, real-world driving conditions where a fixed set of control strategies may fail due to unforeseen variables in hard braking or sharp lane changes. One of the main issues with MPC is related to computational complexity required for real-time operation. Since MPC optimizes repeatedly at each step of control under evolving conditions, it needs to solve a new optimization problem rather frequently [23]. Most of the computational effort is devoted to this process since the controller should compute optimal control actions in fractions of a second for real-time responsiveness. The computational requirements increase even more when higher-order vehicle models, like high-degree-of-freedom or nonlinear dynamics, are employed or longer time horizons and higher resolution are utilized for greater accuracy [24]. Such computational issues become danger in real-time applications; it may take longer to compute the optimal action from the MPC controller than return a response from the vehicle itself, jeopardizing stability and safety. Although the benefits of MPC for path tracking are numerous, its implementation in real autonomous systems demands easing these computational limits by possible acceleration hardware, algorithmic-update simplifications, or adaptive control schemes that lower the processing burden yet do not jeopardize performance [25].

In the real world, the pure MPC technique may be far from being optimal concerning both efficiency of processing and high precision in prediction. According to that, this dissertation proposes a new control architecture for path-following by using a hybrid control model of MPC and Stanley based on vehicle kinematics. An addition of the Stanley control model to the MPC and sharing tasks between the two controllers are being proposed in order to get a reliable, high-performance control model for driverless cars.

1.2 MOTIVATION

This study is motivated by the development of a high-performance, reliable path-following control system for autonomous vehicles, using the combination of two well-established control methods into a novel hybrid control architecture. Current methods usually rely on only one controller; for this reason, they often have certain limitations because of the performance trade-offs involved such as between tracking accuracy and stability and responsiveness. This work seeks to integrate the Stanley controller with MPC, hence reaping the advantages of each controller and reducing their specific drawbacks. Particularly, the efficiency of the Stanley controller in lateral control will be joined with the predictiveness of the MPC approach that will bring a very accurate and stable path-following performance.

The motivation for this research is the potential to combine, in a way not explored so far, these two renowned control strategies. It employs a newly designed hybrid controller which, splitting the control duties among the MPC and the Stanley controller, optimizes the system in varied driving conditions and enables an enhancement in the precision and robustness in the control. In addition to designing the new controller, the thesis also creates a comprehensive mathematical model which facilitates an in-depth exploration in its operations and serves a platform for varied theoretical and actual applications.

Besides this, the thesis goes on with the practical realization of the proposed controller in view of the comparison with other path-following systems. The results obtained confirm that this hybrid controller is able to give the best performance in terms of accuracy and reliability; hence, this can be considered a very efficient solution for autonomous vehicle path following. Therefore, the present research addresses a very important space in the autonomous vehicle control field by developing and validating a controller with improved characteristics relative to the ones proposed so far, hence contributing to the development of safe and efficient technologies for autonomous driving.

1.3 PROBLEM STATEMENT

One of the challenges in the field of autonomous driving is to create systems for path-following control capable of being reliable and at the same time highly precise. Classic path-following controllers, such as MPC and Stanley, suffer from different limitations if adopted as a stand-alone solution. MPC is a controller able to predict with great effectiveness the planning of a path; however, it often has high computational burdens and poor responsiveness in real-time applications. The Stanley controller is thus effective in terms of lateral control but will badly perform on trajectory keeping in case the trajectories are complex or curved. Current control methods hence suffer from a key trade-off between tracking accuracy, stability, and computational efficiency, which restricts their scalability to the diverse dynamic scenarios encountered in real-world autonomous driving.

This thesis fills those gaps, though, by designing a hybrid controller that takes the best of MPC and the Stanley controller in different ways. The hybrid system tries to divide control responsibilities between the two controllers to deliver improved path-following performance with increased stability and computational efficiency. Therefore, the challenge lies in designing and verifying such a high-performance path-tracking control system with MPC combined with the Stanley controller in a way to surpass their individual limitation so that autonomous vehicles are able to move through various driving conditions precisely and safely. This research fills this area of existing control methods by suggesting, modelling, and validating a hybrid system that meets the demands of critical parameters in terms of accuracy, stability, and responsiveness for autonomous vehicle navigation.

1.4 THESIS OBJECTIVES

The objectives of this dissertation are defined as follows:

a. Design an Innovative Hybrid Controller: Develop a path-following control system that can leverage the vehicle kinematics with aspects from the Stanley controller and Model Predictive Control (MPC) in order to enhance efficiency in the manoeuvring of self-driving cars.

b. Develop a Robust and High-Performance Control Structure: Implement a control structure in which the responsibility is shared between the Stanley controller and the MPC, utilizing their own strengths so that the resulting vehicle path tracking can be reliable and efficient.

c. Design a Novel Combination of Controller Types: Design and verify a hybrid approach that combines two widely used control methodologies Stanley and MPC presenting its first implementation in a combined autonomous ground control system.

d. Construct a Mathematical Model of the Recommended Controller: Derive and analyze the mathematical model sustaining the hybrid control structure in a bid to enhance theoretical understanding and inform implementation.

e. Confirm the Controller with Comparative Research: Put the designed controller into play and conduct a comparative analysis with alternative path-tracking systems, proving its superior tracking precision, steadiness, and overall performance.

1.5 PROPOSED WORK

This research explores the design, modelling, and verification of a new hybrid path-following controller for autonomous vehicles that blends Model Predictive Control with the Stanley controller. The hybrid solution developed in this paper strives to combine the predictive advantages of the MPC with the dynamic lateral control provided by the Stanley controller in the best possible way while surmounting some inherent limitations in their implementations. The resulting system should allow for improved tracking precision and steadiness while also providing better computational efficiency, thereby making it more amenable to real-time autonomous vehicle applications.

Our design starts with the control structure that integrates in a systematic fashion long-range trajectory planning with MPC and moment-by-moment lateral control with the Stanley controller. This should partition control functions such that the system can potentially manage sharp corners and roadside hazards and still perform smooth and precise path tracking. The overall mathematical model of the hybrid controller will be constructed in analyzing the coordination between these two control methods in order to get some understanding of how each works at adding value in the area of stability, precision, and responsiveness in the system.

The designed controller will first be simulated in a virtual environment, in which a variety of testing evaluations will be carried out, including simple and more advanced scenarios: along a straight track, through corners, and in the presence of moving hazards. From these evaluations, a number of the performance criteria will be extracted, such as tracking accuracy, stability, responsiveness, and computational demand.

This will then be compared with the hybrid controller and its benefits and the traditional path-following systems, independent MPC or simply the Stanley controller. This will emphasize the superiority of the proposed hybrid controller in terms of adaptability, tracking performance, and computational load with varying driving conditions. Lastly, the tuning of the controller parameters will also be explored in order to add further efficiency in the performance of the controller, and thus show the applicability and performance of the hybrid system in actual autonomous vehicle navigation.

This work tends to provide answers to some of the key shortcomings of existing methods and thus aims at contributing towards a robust and high-performance solution for path following. At the same time, embedding the MPC and Stanley controller in one framework will significantly enhance safe and precise driving for an autonomous vehicle; thus, this hybrid controller is promising for the next generation of autonomous vehicle systems.

1.6 THESIS OUTLINES

The structure of the dissertation is presented as follows:

Chapter One: The introduction of the thesis, which comprises a number of subtitles like review of the general concepts, motivation of the study, thesis objectives, problem statement, the proposed work, thesis outlines, and a summary of the chapter.

Chapter Two: This chapter gives a background of literature and related studies, levels of automation, from no automation to full automation, presenting a state of the art, types of autonomous control models such as PID Control Model, Pure Pursuit Control Model, Pure, Stanley Controller, and Model Predictive Controller.

Chapter Three: The methodology of the study and detail of the simulations are presented. There are two parts like the Simulink part and the programming part, which are both performed using MATLAB.

Chapter Four: This chapter presents and discusses the results of the study and give the suitable explanations of all results.

Chapter Five: It gives a conclusion of the thesis and explains the main contribution of the proposed work. In addition, a future work prospective in the field of autonomous control models is presented.

1.7 SUMMARY

Chapter 1 summarizes the challenges and developments of autonomous vehicle control: reliable path-following systems are important for safe and efficient driving. For an autonomous vehicle, precise tracking is necessary in keeping it stable on the road and following the route drawn on maps, which again requires stringent control of both lateral and longitudinal motions. While classic controllers, including Model Predictive Control and the Stanley controller, are in wide use, each of these controllers has its drawbacks when deployed singularly. While MPC does the best job of predictive path planning, it can be computationally intensive with reduced responsiveness in real-time applications, and the Stanley controller does a fine job of maintaining lateral control but may not keep up the accuracy for complex scenarios or high-speed applications. This chapter presents for the first time a hybrid control method for combining MPC with the Stanley controller in a way that leverages complementary strengths of each. The proposed hybrid controller attempts to reduce the inherent trade-offs in each stand-alone controller by sharing control responsibilities between the two, with the objective of enhancing tracking accuracy and stability while improving computational efficiency. The introduction also enumerates the objectives of the study in developing, modelling, and validating this hybrid controller to show its benefits from existing path-following systems.

The chapter also gives the motivation of the research, motivating a high-performance controller which shall be able to handle a wide range of driving conditions. The hybrid architecture not only introduces a novel approach to path-following control but also provides a complete mathematical model with a plan for implementation, setting the basis for the rest of the thesis. The work finally aims to contribute toward a robust and feasible solution for autonomous vehicle guidance by developing and testing a controller with the potential to enhance accuracy, stability, and responsiveness in real-world applications.

2. LITERATURE AND RELATED STUDIES

2.1 BACKGROUND

Driverless car technology is becoming popular in most of the developing and developed nations due to the huge potential the industry has to provide in the areas of traffic flow, road safety, and removal of human error [26]. The driverless cars leverage complex systems that couple the power of artificial intelligence with machine learning and sophisticated sensor technologies to move on the roads with minimal or no human intervention. This growth mirrors rebuilding trust in the capability of the systems to transform urban mobility and logistics [27].

The recent advances in computer processing power and sensor technologies have pushed the research and development of autonomous driving and robotics significantly forward. These points are helpful to enable more reliable and efficient autonomous systems possible even for complicated driving scenarios. Path tracking is one of these key technologies in this regard, whereby a system is being developed for controlling longitudinal and lateral movement of a vehicle for following a predefined path with acceptable accuracy [28].

For the autonomous vehicle to, for instance, be in a good state, this path-tracking controller must overcome challenges of unexpected obstacles, traffic flow dynamics, and even road surface wetness. The ideal controllers deliver robust rejection of disturbances combined with uncertainty and preview knowledge of upcoming road curvature information. They then optimize stability, precision, and flexibility for the vehicle to be able to perform its role in secure and smooth journeys [29].

Essentially, path tracking is a very important task in the autonomous vehicle system that controls the longitudinal and lateral motion of the vehicle to allow it to follow the scheduled route accurately [30]. It is a primary operation for ensuring safe and effective operation, especially in dynamic and complex driving environments. However, precise path tracking while ensuring vehicle stability poses a serious engineering challenge [31].

There are several reasons for this. Road curvature will create variations in the required changes of velocity and steering, hence requiring a controller that would cater to curving trajectories and tight turns [32]. Further, nonlinearity in dynamics involved in automotive-such as changing tire forces, variations in speed, and variable load distributions-presents challenge in designing a reliable tracking system [33]. It is also added to by uncertainties such as those due to inaccurate sensors, by externalities such as wind or road slopes, and by unpredictable behaviour of other cars in the neighbourhood. Finally, there are inherent time delays in the vehicle itself from perceiving the signal to responding via actuators that add to the challenge of attaining precise and stable path following [34].

A desired path tracking controller has to completely solve these difficulties. The controller should be able to anticipate and integrate, in advance, road data like upcoming curves or slope transitions to make optimum control decisions [35]. It must also strongly reject disturbances and uncertainties, including any external conditions that are unfavourable for the vehicle to continue its trajectory. With the integration of advanced algorithms and predictive modelling, modern controllers attempt to strike an appropriate balance among precision, responsiveness, and stability-related mutually competitive requirements for the improved safety and reliability of autonomous vehicle applications in practical scenarios [36].

2.2 LEVELS OF AUTOMATION

Different levels of automation in a vehicle have summarized by Khan et al. [37] that clearly explain the road map for progressive autonomous driving technologies and their features: Levels of automation in vehicles ranging from Level 0-which means no automation-to Level 5- full autonomy, where driving responsibilities progressively shift from the human driver to the vehicle itself.

2.2.1 Level 0: No Automation

This level describes when the vehicle has no features of automation. The driver has full control of both lateral (steering) and longitudinal guidance of the vehicle. Systems at this level may provide warnings, such as collision alerts, but cannot take vehicle control.

2.2.2 Level 1: Driver Assistance

This level introduces basic assistance systems where the driver remains entirely in charge of the vehicle but is assisted by features either to lateral or longitudinal control but not simultaneously to both. An Adaptive Cruise Control (ACC) is the example of level 1 automation, where there is an adjustment of the car's speed to maintain a cautious following distance, yet it does not handle steering [38].

2.2.3 Level 2: Partial Automation

Vehicles at this level assist both lateral and longitudinal guidance under specific conditions, thereby mitigating workload for a car driver. However, the driver is obliged to constantly monitor the system and be prepared to assume control of the vehicle at any moment. Examples include systems combining ACC with lane-keeping assistance.

2.2.4 Level 3: Conditional Automation

In this stage, the vehicle can manage most driving tasks autonomously in certain scenarios, such as on highways. The driver may occasionally use some non-driving activities, like using a phone, but must be able to intervene if the system encounters a situation where it cannot operate properly. This thus demands the driver's alertness for him/her to regain control whenever prompted.

2.2.5 Level 4: High Automation

This level of automation means that the vehicle will be able to execute all driving tasks for specific operational conditions without human intervention, such as on a predefined route or in a geofenced urban area [39]. Unlike Level 3, no driver availability is required at any moment. These systems, however, are not fully autonomous across all environments but may be limited to particular scenarios, including good weather conditions or in delimited areas.

2.2.6 Level 5: Full Automation

This is the highest level of automation. Under this highest level of automation, the vehicle can drive itself independent of any human input under all conditions. The need for a driver is not required, and all passengers are riders. Level 5 is targeted to handle complex traffic conditions, very adverse weather, and all terrains without human intervention [40].

2.3 STATE OF THE ART

Sotelo's study [41] outlines the lateral control approach with applications in autonomous vehicle according to the Ackerman system. For the steering control performance, speed is one of the considerations, hence versatile at both low and high speeds. Sinder [42] presented a development of strategies for control and steering wheel algorithms for path tracking. This paper routes tracking using geometric, kinematic, and dynamic models. A paper presented by Zhou et al. [43] employed an adaptive inverse control model in cancelling the effects of backlash created within the steering system. Park et al. [44] proposed a geometry-based pure pursuit method for a steering control system. In the research mentioned above, the performance of the model was improved by incorporating a PID controller as well as a compensator.

Wang et al. [45] develop a system for further enhance of the performing of Model Free Control (MFC), they have developed its integration of the extreme seeking control method, which may also provide a new approach to tuning the MFC control gain. Takahama et al. [46] explain the usage of MPC with adaptive cruise control during traffic congestion. Hu et al. [47] reported research on the integrated movement control of autonomous ground vehicles, considering improved actuator failures, tracking performance, and input saturation.

They considered the restrictions to get a better result in a shorter period by utilizing MPC's characteristics. Vivek et al. [48] compare Stanley, a linear quadratic regulator, against route tracking systems that use MPC controllers. The route tracking was completed successfully using the three controllers. Cibooglu et al. [49] present a hybrid control system for following the trajectory of the autonomous vehicle. Two prominent geometric route tracking approaches, Stanley and Pure-Pursuit, are combined with a simple and practical methodology.

The goal of this thesis is to establish a balance between the complication of MPC control model and the Stanley's control model simplicity. MPS mixes the two models such that the greatest features of each are exploited. One of the most difficult issues in the industry is developing a system that is both fast and precise. What is required is a creative technique that reduces the cost of established models, as the MPC, while improving the accuracy of others, such as the Stanley. The limits of current models are MPC model evaluates the system's complexity in terms of processing power requirements. Stanley controller is prone to path-following errors, which cause the vehicle to deviate from the track. Table 2.1 compares research papers focusing on autonomous vehicle control using Model Predictive Control. The comparison emphasizes their contributions, strengths, and limitations.

Table 2.1: Literature Comparison of Using MPC Autonomous Control Models.

Reference	Focus Area	Strengths	Limitations
[50] Lin C. et al. (2022)	Path tracking in dynamic environments	Effective in dynamic obstacle avoidance; real-time capability	Limited to 2D environments; scalability issues
[51] Falcone P. et al. (2007)	High-speed vehicle control	Robustness at high speeds; low computational overhead	Assumes perfect sensor inputs
[52] Yang S. et al. (2024)	Adaptive MPC for varying road conditions	Adaptive to changing road conditions; maintains stability	High computational cost for adaptation
[53] Emam M. et al. (2024)	Urban traffic navigation	Integrated traffic light scheduling and path planning	Lacks experimental validation
[54] Pinho J. et al. (2023)	Learning-based MPC	Online learning improves performance over time	Requires extensive training data
[55] Zuo Z. et al. (2021)	Cooperative vehicle control	Enhances multi-vehicle coordination	Communication delays can degrade performance
[56] Muluneh H.et al. (2024)	Lane-changing manoeuvers	Smooth lane changes; ensures safety constraints	Limited to highway scenarios

Table 2.1: Literature Comparison of Using MPC Autonomous Control Models (Table Continued).

Reference	Focus Area	Strengths	Limitations
[57] Jhang J. et al. (2020)	Autonomous parking	High accuracy in tight spaces	Computational complexity in real-time scenarios
[58] Chen Y. et al. (2020)	Energy-efficient autonomous driving	Reduces energy consumption	Focused only on electric vehicles
[59] Alrifaee B. et al. (2016)	Predictive collision avoidance	High success rate in avoiding collisions	Requires accurate prediction of dynamic obstacles
[60] Chen Set al. (2024)	Robust control under uncertainty	Handles model uncertainties effectively	Conservative behavior in some situations
[61] Muraleed A. et al. (2023)	Pedestrian interaction modeling	Accounts for pedestrian dynamics	Limited validation in complex environments
[62] Shi S. et al. (2017)	Distributed MPC for platooning	Efficient in multi-vehicle platooning scenarios	Communication overhead increases with fleet size
[63] Yu S. et al. (2021)	Nonlinear MPC for off-road vehicles	Maintains stability in off-road terrain	High computational demand for nonlinear dynamics
[64] Zheng S. et al. (2017)	Vehicle stability enhancement	Enhances stability in extreme maneuvers	Requires accurate tire model parameters
[65] Peitz S. et al. (2017)	Multi-objective MPC	Balances fuel efficiency and travel time	Requires complex weighting factor tuning
[66] Costa G. et al. (2023)	Autonomous racing applications	Achieves high performance in racing scenarios	Limited to structured environments
[67] Zhang L. et al. (2020)	Integrated lateral and longitudinal control	Smooth integration of control tasks	Limited scalability to heterogeneous vehicles

Table 2.1: Literature Comparison of Using MPC Autonomous Control Models (Table Continued).

Reference	Focus Area	Strengths	Limitations
[68] Prasath G. et al. (2009)	Robust control under sensor noise	Maintains performance under noisy sensor inputs	Performance degrades with extreme noise
[69] Cheng Z. et al. (2024)	Hierarchical MPC for urban driving	Combines high-level planning with low-level control	High complexity in hierarchical structure
[70] Bae S. et al. (2023)	Real-time control in dense traffic	Low computation time; maintains safety constraints	Focused on specific traffic scenarios
[71] Alsuwian T. et al. (2022)	Emergency braking scenarios	Effectiveness in emergency situations	Limited to longitudinal control
[72] Zhang H. et al. (2022)	Vehicle platooning in mixed traffic	Effective in mixed autonomous and human-driven traffic	Requires reliable vehicle-to-vehicle communication
[73] Mueller K. et al. (2020)	MPC with vision-based feedback	Utilizes vision for accurate control	Susceptible to poor lighting conditions
[74] Sudianto Aet al. (2023)	Sensor fusion in MPC	Combines LiDAR and camera inputs effectively	High computational demands
[75] Ortega J. et al. (2024)	High-speed overtaking manoeuvers	Ensures safety during high-speed overtaking	Focused only on highway driving
[76] Zhao Z. et al. (2021)	Energy-efficient MPC for hybrids	Optimizes fuel consumption and emissions	Limited to hybrid vehicles
[77] Zheng L. et al. (2023)	Traffic-aware MPC	Incorporates real-time traffic flow data	Relies on reliable traffic data inputs

Table 2.1: Literature Comparison of Using MPC Autonomous Control Models (Table Continued).

Reference	Focus Area	Strengths	Limitations
[78] Li X. et al. (2021)	Shared control between human and MPC	Improves safety in shared control scenarios	Requires seamless human-MPC interaction
[79] Mohseni F. et al. (2021)	Distributed MPC for cooperative driving	Efficient in complex traffic networks	Communication delays impact performance

2.4 SELF-DRIVING APPLICATIONS

Autonomous driving technology is applied across various industries, transforming how we transport, deliver, and move. Some of the primary applications of autonomous driving are: Personal Autonomous Vehicles (Self-Driving Cars): Urban Mobility: Autonomous consumer-use cars can navigate through intricate urban routes, giving a more comfortable and safer means of mobility. Ride-Sharing Services: Companies like Uber and Lyft are developing autonomous vehicles to offer ride-hailing services without the need for human drivers [80]. EVs: Autonomous driving is combined with electric vehicles in most cases to make them self-driven but at the same time 'eco-friendly' to enhance sustainability. Autonomous Public Transportation Self-Driving Buses: The autonomous buses can run on fixed routes within cities [81]. They offer a better and more efficient option for public transportation. Shuttle Services: These vehicles operate independently to offer short distance travel to people moving within the campus, airport, business park, and other controlled environments.

Trains and Trams: Some metropolitan cities are adapting driverless trains and trams in metro systems to introduce more punctuality and safety. Freight and Logistics Autonomous Trucks: Self-driving trucks will be designed to handle long-haul freight transportation in order to reduce costs and improve delivery time. Last-Mile Delivery: Autonomous delivery vehicles and robots can be utilized in the last leg of the delivery process from the local distribution centers to the customers' doorsteps [82].

Warehouse Automation: Autonomous vehicles, including forklifts and robots, efficiently move goods in warehouses, increasing productivity and consequently reducing labour costs in the process. Agriculture: Autonomous Tractors: A self-driving tractor will be able to carry out tasks such as plowing and seeding to even harvesting with great precision. It reduces human labour input and increases crop yields. Crop Monitoring Drones: Self-flying crop monitoring drones with onboard sensors will be capable of crop health monitoring, irrigation optimization, and other modes of pest control [83].

Automation of Harvesting: The harvesting of crops can be done by self-autonomous machines with minimal human intervention, thus making it more efficient and reducing labour costs [84]. Mining and Construction: Autonomous Haul Trucks: They are applied in the mining industry where the trucks haul the ore without drivers. This would enable round-the-clock operation and improvement in safety [85]. Construction Equipment: Robotic bulldozers, excavators, and other devices can be used to accomplish operations like digging, grading, and material hauling, thereby improving productivity at the construction sites [86].

Monitoring: The autonomous vehicles patrol for potential safety threats on construction sites, avoid accidents, and enhance compliance with the requirements. Emergency Response and Safety Autonomous Ambulances: Autonomous ambulances can transport patients faster and safer, with paramedics still inside the vehicle to attend to them [87]. Search and Rescue: Autonomous vehicles, drones included, could be mobilized in disaster zones for search-and-rescue operations, locating individuals in areas that are hard to reach or dangerous for people. Firefighting Robots: Autonomous firefighting vehicles can navigate hazardous environments to help extinguish fires and evacuate victims [88]. Military and Defense: Unmanned ground vehicles are useful in reconnaissance, explosive ordnance disposal, and logistics, which reduces risks to human soldiers [89]. Autonomous Convoys: Capability of military convoys in using autonomous driving technology to improve coordination and reduce the need for human drivers in dangerous areas. Surveillance drones are autonomous drones put into service for monitoring and intelligence gathering in war zones [90]. Healthcare and Assisted Living Autonomous Wheelchairs: This will promote easy indoor and outdoor navigation by the elderly or disabled persons with minimal effort [91].

Robotic Assistants: Autonomous robots could help with caregiving, dispensing medicines, or helping with daily tasks both in hospitals and at homes [92]. Transportation for the Disabled and Elderly: These unmanned vehicles can possibly create a means of transportation for the disabled and elderly-a means which will give them independence and a better quality of life [93]. Entertainment/Leisure Theme Park Rides: Self-driving cars working in theme parks offer guided tours or rides which can greatly enhance visitor experiences. Tourist Shuttles: Autonomous shuttles can lead tourists around a beautiful area while giving information about it and keeping them safe without involving a driver [94].

Recreational Drones: Autonomous drones are utilized for several purposes, such as recreational photography, sports tracking, and many more [95]. Smart Cities Traffic Management: Autonomous vehicles can be deployed within a smart city for the smooth flow of vehicles, congestion, and disturbance in city streets. Public Safety: Autonomous patrol vehicles will monitor city areas and feed real-time information into the law enforcement system [96]. Infrastructure Maintenance: Autonomous vehicles can carry out the inspection of infrastructure, such as roads and bridges, maintaining and extending resource efficiency, thus reducing maintenance costs [97].

Marine and Space Autonomous Ships: Self-navigated ships are in development to carry cargo. Other than reducing the need for a large crew, self-navigated ships would mean improved safety at sea [98]. Autonomous Drones: Drones for environmental monitoring, delivering packages, or surveillance could independently cover large areas efficiently [99]. Urban Air Mobility: It is a consideration for the future where autonomous air taxis would reduce time and congestion while traveling [100]. Retail and Shopping Autonomous Delivery Robots: There are small robots that can deliver packages or groceries to customers' homes, adding more convenience to online shopping. Autonomous Store Assistants: Robots can assist customers inside a store, perform inventory management, and even other tasks like cleaning [101].

2.5 TYPES OF AUTONOMOUS CONTROLLERS

2.5.1 PID Control Model

A PID control model is a feedback mechanism in a control loop that measures the difference between an actual output produced and a predetermined setpoint by a process, then uses that difference to provide corrective action to the process [102]. The use of PID controllers is very extensive in many industrial and robotic process controls.

They play a vital role in Self-Driving cars in controlling driving parameters like steering, throttle, etc. The complex algorithms in the self-driving car basically calculate a trajectory and a velocity for the self-driving car to drive. Autonomy is realized only if the car adheres to the trajectory with the given speed. This is exactly where the PID controller comes in to make sure that the self-driving car adheres to the computed parameters. Any deviation from the computed parameters means unforeseen or catastrophic results.

The PID term is the summation of three terms: Proportional, Integral, and Derivative. The diagram below shows how the three components are involved in the final response [103]. Where: the reference setpoint is r(t), the difference between an actual output and the desired setpoint is e(t), the process input control value is u(t), and the output of the process is y(t) as explained in (Figure 2.1).

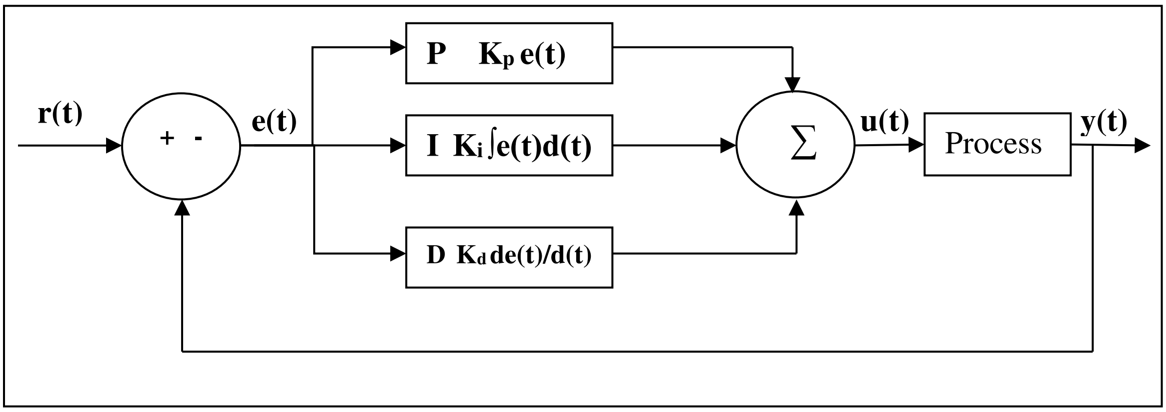

Figure 2.1: PID Control Model Process.

Proportional (P): This involves taking a fraction of the existing error value. The fraction is determined by a constant and is denoted by letters Kp. It aids in calculating the response that is required to rectify the process. As it needs an error to create a proportional response, without an error, the proportional part of the response does not exist.

Integral(I): This takes all previous error rates and accumulates them over time. While the integral term will continue to expand as long as the error does not reach zero. As the error rate is eliminated, the integral term will no longer expand. If an error persists after applying the proportional control, the integral term attempts to eradicate it by adding the accumulation error values. The proportionate effect will get weaker as the mistake decreases. The integral constant is denoted as Ki.

Derivative (D): This term helps to predict the future trend of error by looking at how it's changing now. It's used in making the system smoother. If the change happens fast, then the control or smoothing effect is stronger. The derivative constant is called Kd. The error term e(t) is received by the Controller. This error term is multiplied by the right constants and added together to get the process input. The new error is obtained by subtracting the Process output from the setpoint reference. This new error is sent back to the Controller for a corrective response.

Mathematical terms of the PID controller [104]:

$$u(t) = Kp \cdot e(t) + Ki \int e(t)dt + Kd \frac{de(t)}{dt} \tag{2.1}$$

u(t) represents the control signal. The error (the difference between desired and current speed) is denoted by e(t), while the proportional, the integral, and the derivative gains are represented by Kp, Ki, and Kd, respectively. A PID controller's efficiency is highly related to the right tuning of its gains (Kp, Ki, and Kd). Modifying each gain changes the system's reaction in certain ways, as shown in Table 2.2.

Table 2.2: PID Tuning Gaines Effect.

Increasing	Effect
Kp	Strengthens reaction to errors, decreases rise time, and may increase overshoot
Ki	Eliminates steady state errors, and may increase oscillations
Kd	Decreases overshoot, reduces oscillations, and potentially decreases settling time

2.5.2 Pure Pursuit Control Model

The Pure Pursuit model represents one of the most popular geometric path-tracking controllers for autonomous vehicles [105]. By definition, a geometric path tracking controller relies only on vehicle kinematics and reference path geometry to decide about control actions. This removes complicated dynamic modelling, and such an approach is simple but effective for a variety of conditions during path-following tasks.

Pure Pursuit finds a look ahead point, a specific point a fixed distance ahead of the vehicle on the referencing path. The distance in front is often called a look-ahead distance and is one of the main parameters that affects the performance of the controller. A smaller look-ahead distance increases the tracking accuracy of sharp turns but may result in instability or overcorrection; a larger look-ahead distance allows for smoother motion but may create a deviation from the path, especially in tight curves.

The objective of the vehicle, controlled by the Pure Pursuit, is to move in the direction towards the look-ahead point using an appropriate steering angle. This steering angle is computed geometrically according to the present position and coordination of the vehicle, and also the position of the look-ahead point. More precisely, the algorithm computes the curvature of the circular arc that goes through the present position of the vehicle and reaches the look-ahead point. From this curvature, the required steering angle is derived, considering the geometry of the vehicle-for example, the wheelbase, as shown in (Figure 2.2).

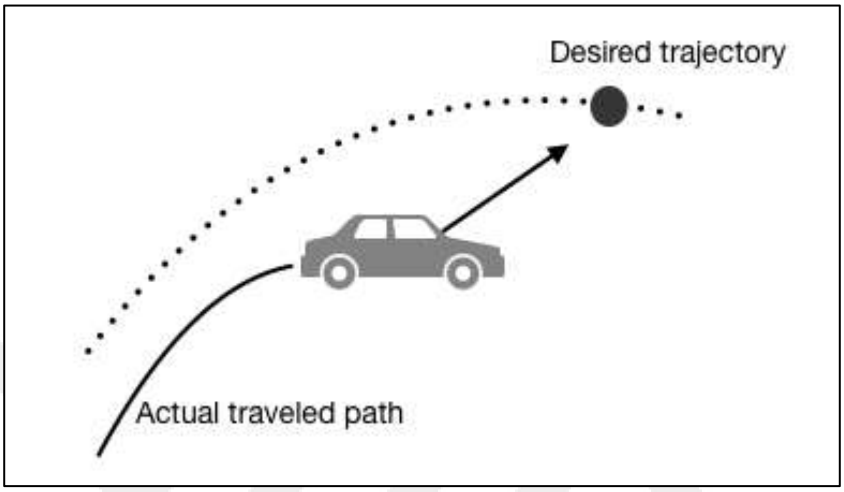

Figure 2.2: The Geometric Path Tracking of Pure Pursuit Model.

If the Pure Pursuit controller is continuously updating the look ahead point and recalculating the steering angle as the vehicle progresses, the vehicle will then follow the desired path. On the other hand, its performance may be affected or depends on several factors such as the choice of the look ahead distance, speed of the vehicle, and complexity of the reference path. Despite these kinds of challenges, Pure Pursuit remains a popular choice for applications requiring efficient and straightforward path-following, particularly in situations where computational simplicity and real-time performance are at a premium.

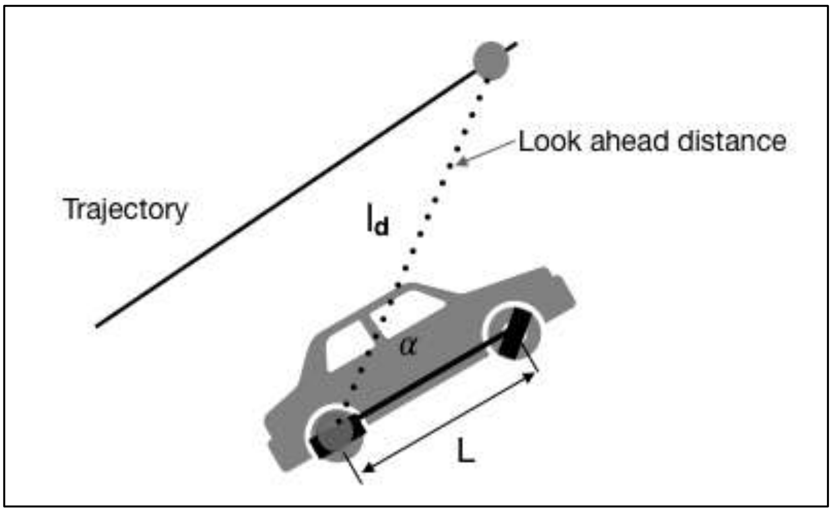

Figure 2.3: The Target Point of Pure Pursuit Model.

For (Figure 2.3) above, the target point can be considered as the red marker. The look-ahead distance, (ld), can be considered as a distance between the target point and the rear axle of the vehicle. The main task of the control model is to steer the vehicle in such a way that it faces in a direction to be aligned with the path for its travel towards the target point.

The geometrical relations that describe this process can be seen in (Figure 2.4) below. Let (α) be the angle between the vehicle's heading direction, that is, its longitudinal axis, and the line from the rear axle to the target point. This angle is normally referred to as the heading error angle.

Because the vehicle is modelled as a rigid body, its motion traces a path that is circular in nature when it is steered. This circular motion has a center called Instantaneous Center of the Rotation, or ICR [106]. This circle has a radius (R) that is dependent on the steering angle and vehicle geometry. The ICR, coupled with the radius (R), defines the curvature of the vehicle's trajectory while it moves toward the target point.

From this geometric relationship, the controller calculates the required steering angle that will result in a minimum value of the heading error to steer the vehicle properly along the desired path. This would mean that transitions toward the target point would be smooth while the vehicle maintains stability and tracks the reference trajectory. This forms the basis of geometric path tracking controllers such as the Pure Pursuit approach used in the implementation of path-following in autonomous vehicles.

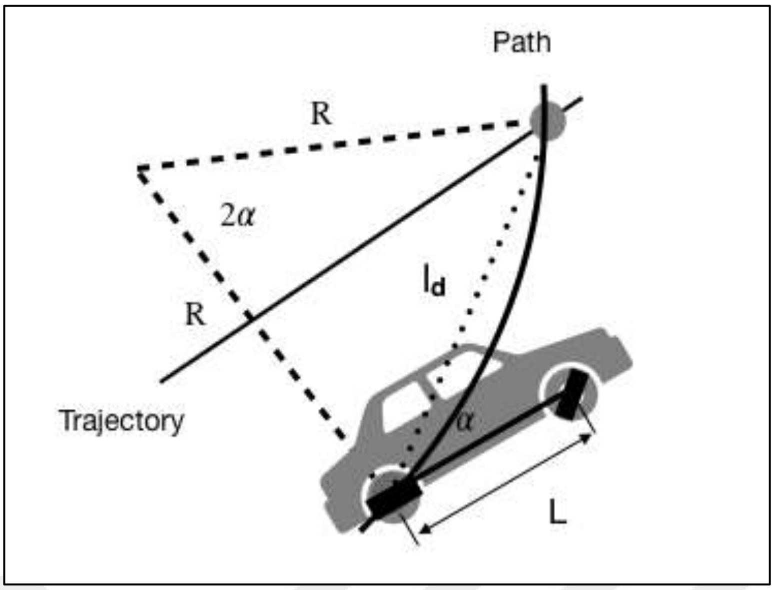

Figure 2.4: Relationship of Pure Pursuit Geometric.

2.5.2.1 Pure pursuit formula

From the sines law [107]:

$$\frac{l_d}{\sin 2\alpha} = \frac{R}{\sin\left(\frac{\pi}{2} - \alpha\right)} \tag{2.2}$$

$$\frac{l_d}{2\sin\alpha\cos\alpha} = \frac{R}{\cos(\alpha)} \tag{2.3}$$

$$\frac{l_d}{\sin\alpha} = 2R \tag{2.4}$$

$$k = \frac{1}{R} = \frac{2\sin\alpha}{l_d} \tag{2.5}$$

(k) is the curvature. By using the bicycle model.

$$R = L \,/\, \tan(\delta) \tag{2.6}$$

So, the steering angle δ will be calculated as:

$$\delta = \tan\left(\frac{2L\sin\alpha}{l_d}\right) \tag{2.7}$$

The Pure Pursuit control model is a simple control model that simplifies vehicle dynamics by considering only the negligible dynamic forces with no-slip conditions at the wheels. However, simplicity comes with several limitations. For instance, it can be tuned to be quite aggressive at low speeds and potentially unsafe when the vehicle is operating at higher speeds. A common improvement to better handle this is the dynamic adaptation of the look ahead distance, (l_d), according to the vehicle’s speed so that the controller can maintain stability and precision across a wide range of speeds.

$$l_d = K_{dd} * V_f \tag{2.8}$$

So, the steering wheel angle has changed as:

$$\delta = \arctan\left(\frac{2L\sin\alpha}{K_{dd} * V_f}\right) \tag{2.9}$$

2.5.2.2 Pure pursuit controller effectiveness

Considering the described concept of cross track error: it is the lateral distance between the target point and the vehicle's heading vector, as illustrated in (Figure 2.5). The smaller the cross track error, the closer the vehicle is to the intended path, reflecting improved path-tracking accuracy.

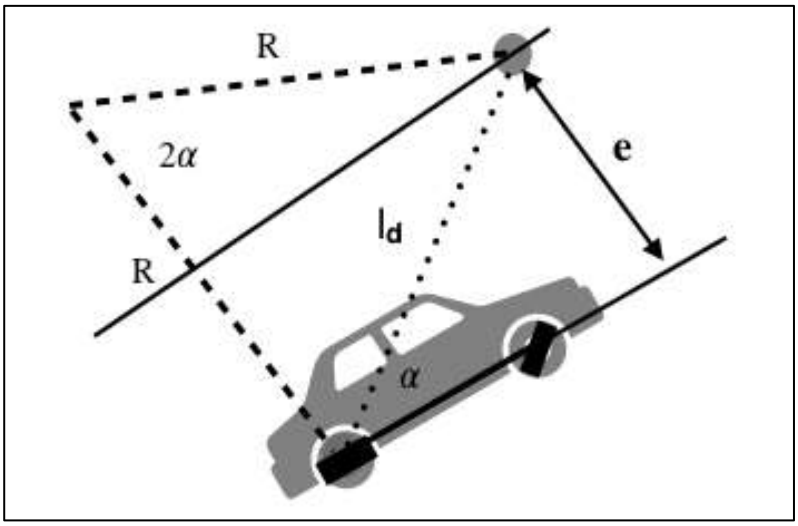

Figure 2.5: The Model Cross-Track Error.

The correlation between the cross track error and the curvature (k), as we know,

$$\sin(\alpha) = \frac{e}{l_d} \tag{2.10}$$

$$k = \frac{2sin\alpha}{l_d} \tag{2.11}$$

So it will be,

$$k = \frac{2}{{l_d}^2} e \tag{2.12}$$

The above equation shows that curvature (k) increases directly with cross track error. The increase in cross track error causes the curvature to rise higher, which in turn forces the vehicle to steer more aggressively towards the desired path. Proportional gain, ($2/\boldsymbol{l_d}^2$), is something that can be tuned experimentally to improve responsiveness of the system.

In other words, Pure Pursuit is essentially a proportional control for the steering angle, taking the cross track error as its input. This approach properly reduces the cross track error by steering the vehicle on track via appropriate adjustments of the steering angle.

2.5.3 Stanley Controller

In Stanley's approach, the reference is with respect to the vehicle's front axle. This formulation can handle both a heading error and the track error together [108]. The track error here is defined as the perpendicular distance of the front axle from the nearest point along the reference path as shown in (Figure 2.6).

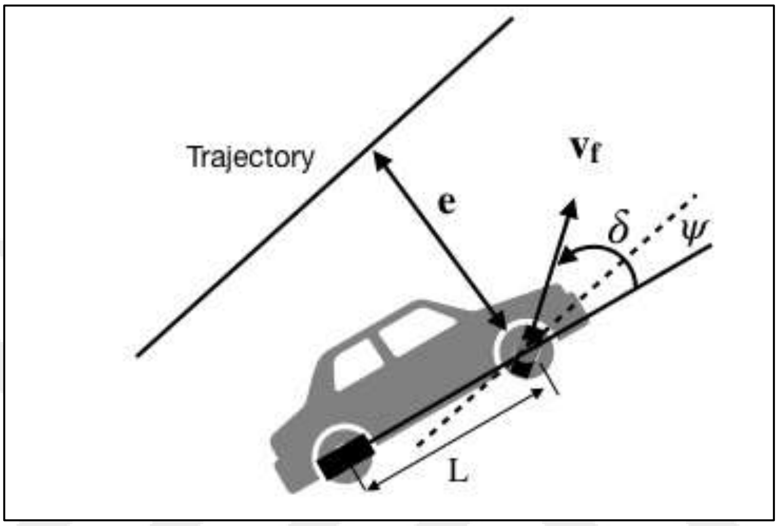

Figure 2.6: The Geometric Relationship of Stanley Model.

Where:

ψ(t) denotes the angle across the path heading to the vehicle's heading.

δ is the steering wheel angle.

Three lateral's laws of the Stanley approach. This law is to remove the heading error.

$$\delta(t) = \psi(t) \tag{2.13}$$

Secondly, this law is to remove cross-track error. It recognizes the nearest point between the path to the vehicle, denoted as e(t), and the steering angle can be modified as:

$$\delta(t) = tan^{-1}(\frac{ke(t)}{v_f(t)}) \tag{2.14}$$

The final step is following the maximum limitations of wheel steering angle.

$\delta(t) \in [\delta min, \delta max]$ So, we will have:

$$\delta(t) = \psi(t) + tan^{-1}(\frac{ke(t)}{v_f(t)}) \quad (2.15)$$

One adjustment for the model is by adding softening constant. This will be capable of verifying a non-zero denominator.

$$\delta(t) = \psi(t) + tan^{-1}(\frac{ke(t)}{k_s + v_f(t)}) \quad (2.16)$$

The Stanley control model takes both the heading error and the cross track error into account to position the vehicle correctly on the path. Let us consider two cases: First, if a heading error is much larger and the cross-track error is smaller as in (Figure 2.7), the angle (ψ) becomes large. This makes the steering angle (δ) larger, the vehicle steers in the opposite direction, and aligns its orientation with the trajectory, hence correcting for the heading error.

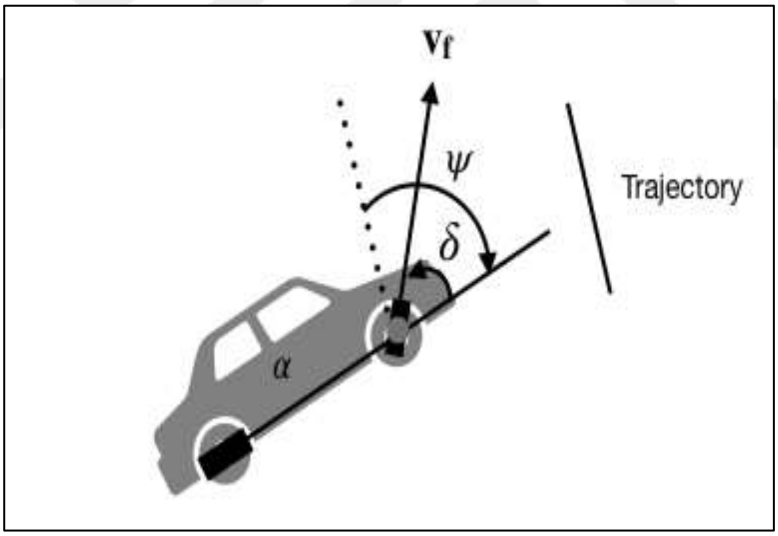

Figure 2.7: The Vehicle Has a Large Heading Error.

This scenario will be shown as in the (Figure 2.8),

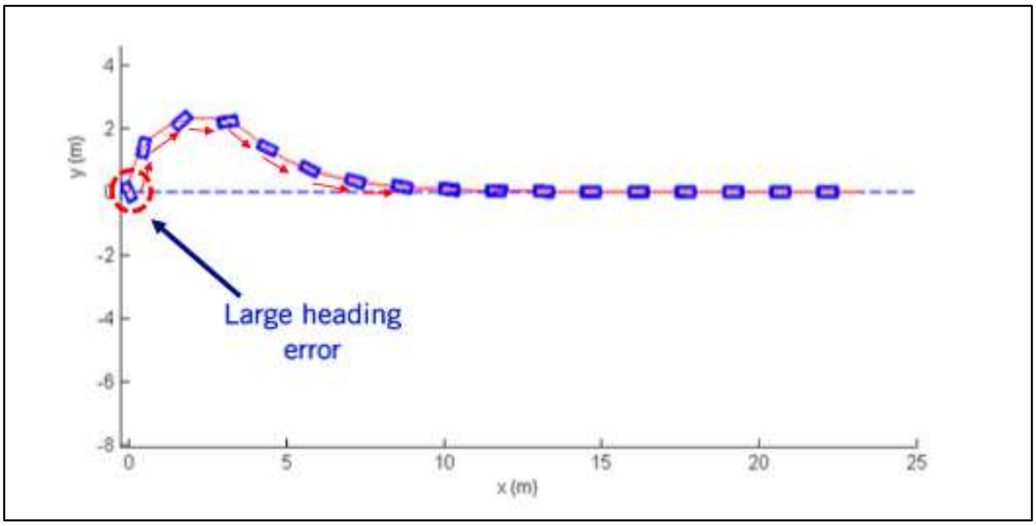

Figure 2.8: Correcting of the Large Heading Error Process.

Next, if the heading error is small with large cross-track error, that could make,

$$tan^{-1}(\frac{ke(t)}{v_f(t)}) \approx \frac{\pi}{2} \tag{2.17}$$

Then, the steering wheel angle can be,

$$\delta(t) \approx \psi(t) + \frac{\pi}{2} \tag{2.18}$$

Considering the heading error $\psi(t) = 0$,

$\delta(t)$ will be $= \pi/2$.

That produces the vehicle moves towards the path as in (Figure 2.9),

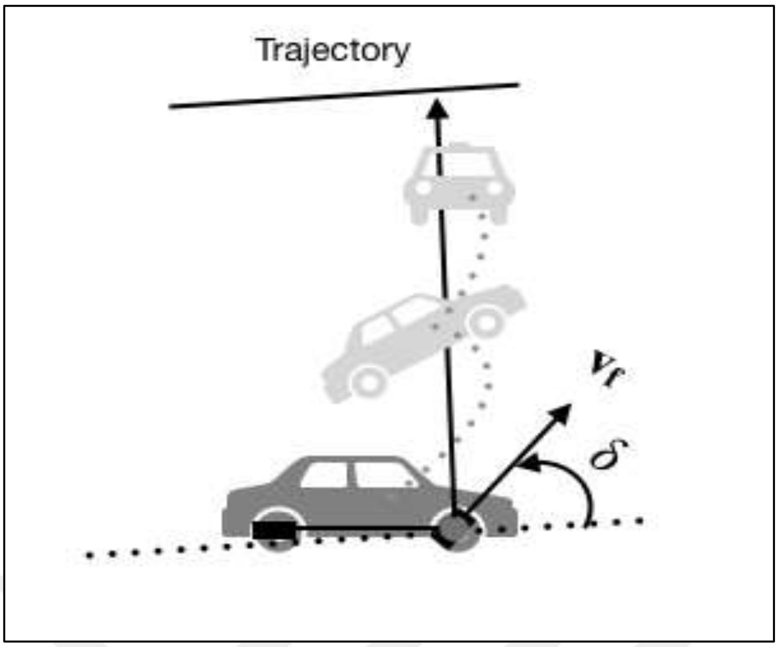

Figure 2.9: Steer Towards the Path with Large Cross-Track Error.

While the vehicle's heading changes in response to the steering wheel angle, the heading improvement works to counterbalance the cross-track correction in a way that the steering angle is smoothly returned to zero. As the vehicle reaches the reference path, the cross track error decreases and the steering wheel angle starts to change to align the heading of the vehicle with the trajectory, as shown in (Figure 2.10) below.

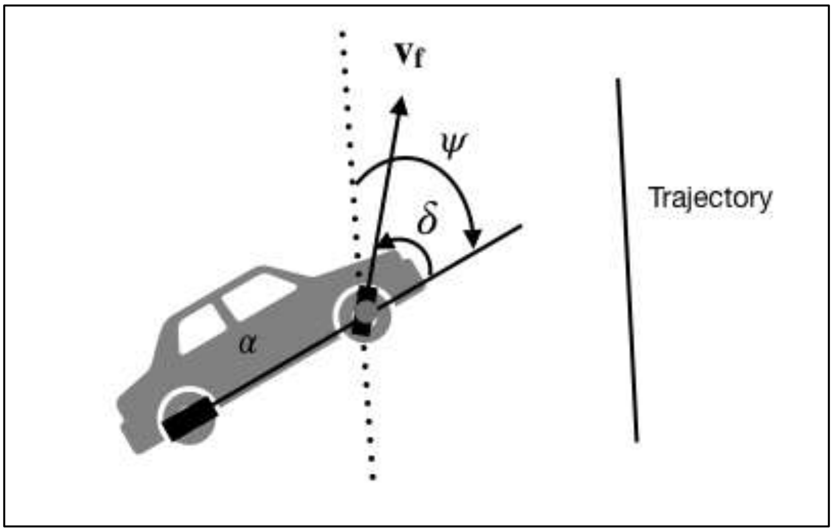

Figure 2.10: Steering Align the Path when the Cross-Track Error Drops Down.

Correcting of the large cross-track error process for this scenario can be shown in (Figure 2.11),

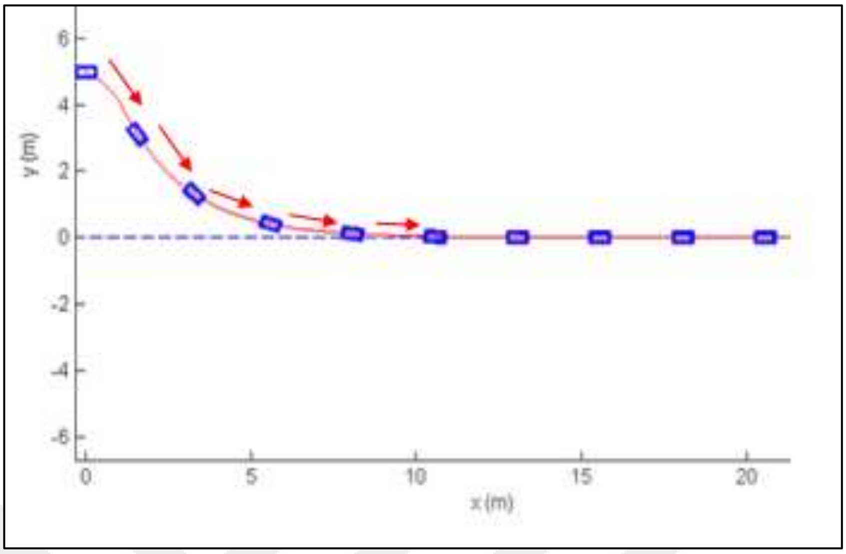

Figure 2.11: Correcting of the Large Cross-Track Error Process.

Stanley is a simple model but effective controller and steady approach for lateral control.

2.5.4 Model Predictive Controller

MPC is a sophisticated optimization-based control technique that seeks to reduce a cost function for a controlled dynamic system over a predictable, receding time horizon [109]. In each step, the MPC control model estimates or predicts the current state of the model and computes the sequence of future control actions that optimize performance over the future time horizon. That optimization is done by a mathematical model of the system while taking into consideration any constraints on control inputs or system states.

Once the optimal sequence is determined, it only applies the first control activity to the system and discards the rest. At the next time step, the whole process is repeated, updating system states and recalculating the optimal control sequence. This iterative approach therefore provides flexibility in adapting to dynamic changes either within the system or in the environment [110], as depicted in (Figure 2.12).

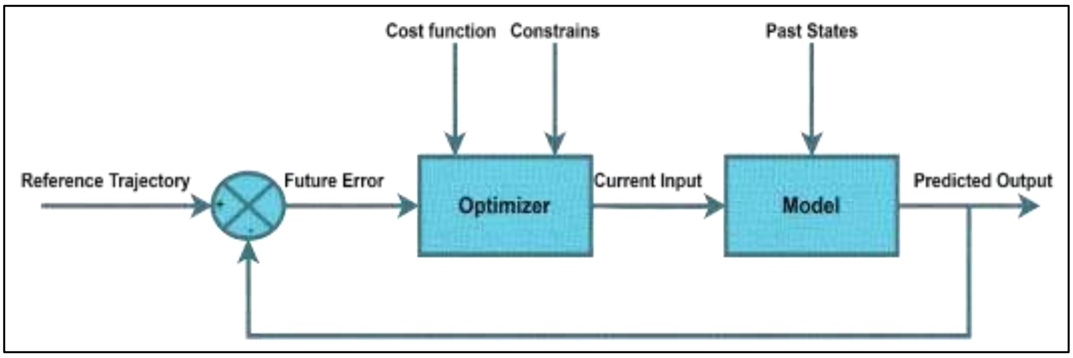

Figure 2.12: Structure of the Model Predictive Control System.

Model Predictive Control (MPC) has many desirable characteristics that make it one of the most sophisticated control techniques: it can handle time delays, handle MIMO systems, and be inherently robust to modelling errors. Specific terminal constraints can also be imposed to guarantee nominal stability.

Some of the prime merits of MPC are that explicit consideration of system constraints optimizes the safety and efficiency of the operation. When possible, MPC also integrates information on future reference signals and disturbances to yield more predictive and adaptive control strategies. (Figure 2.13) shows a graph explanation of the principle of the MPC controller with horizons of N1, N2, Nu [111].

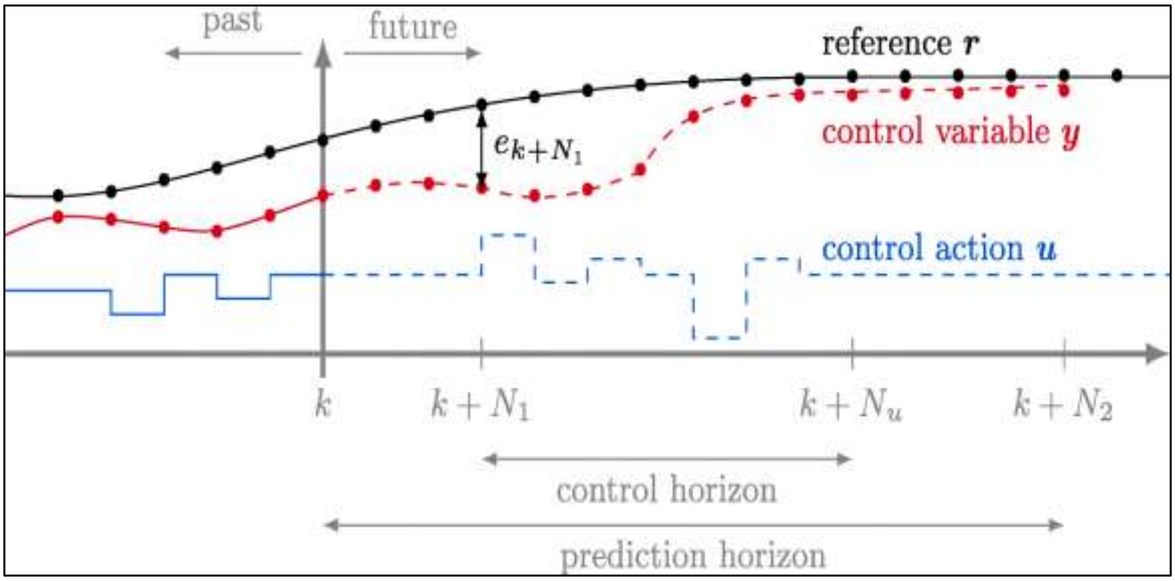

Figure 2.13: Principle of Model Predictive Control with Horizon [111].

In the most basic version of linear MPC, the cost function should be quadratic, and the constraints and system dynamics must be linear. Traditionally, the design of an MPC controller for this system will include several structured phases, which are captured and summarized in (Figure 2.13). This will ensure that the derivation of an optimum and robust control performance is systematic. Different types of MPC are used for autonomous control systems, Table 2.3 presents a comprehensive comparison of these MPC types.

Table 2.3: Comparison of MPC for Autonomous Control Models

Model	Description	Advantages	Disadvantages	References
Linear MPC	Uses linear models to predict future system behaviour.	Computationally efficient, suitable for simple systems.	Limited accuracy for nonlinear systems, struggles with uncertainties.	[112]
Nonlinear MPC	Employs nonlinear models to capture complex system dynamics.	Improved accuracy for nonlinear systems, handles constraints effectively.	Higher computational cost, requires careful model selection and parameter tuning.	[113]
Robust MPC	Incorporates uncertainty and disturbances in the control design.	Enhanced robustness, better performance in uncertain environments.	Increased complexity, potential for conservative solutions.	[114]
Tube-Based MPC	Defines invariant tubes around the nominal trajectory to handle uncertainties.	Systematic approach to robustness, guarantees stability and performance.	Requires careful design of the invariant tubes, computational overhead.	[115]
Learning-Based MPC	Combines MPC with machine learning techniques.	Improved prediction accuracy, adaptability to changing environments.	Reliance on data quality and model complexity, potential for overfitting.	[116]

Table 2.3: Comparison of MPC for Autonomous Control Models (Table Continued).

Model	Description	Advantages	Disadvantages	References
Hierarchical MPC	Decomposes complex tasks into simpler subtasks, allowing for modular design.	Improved scalability, reduced computational complexity.	Coordination challenges between different levels of the hierarchy.	[117]
Distributed MPC	Enables coordination among multiple agents, suitable for cooperative systems.	Enhanced flexibility, distributed decision-making.	Communication overhead, synchronization issues.	[118]
MPC with Sequential Quadratic Programming (MPC-SQP)	Combines MPC with SQP to solve nonlinear optimization problems efficiently.	Improved computational efficiency for nonlinear systems, handles constraints effectively.	Requires careful initialization and tuning of the SQP algorithm.	[119]
Economic MPC	Focuses on optimizing economic performance objectives, such as minimizing energy consumption.	Improved economic efficiency, considers long-term objectives.	Potential for suboptimal control performance if not carefully designed.	[120]
Adaptive MPC	Adapts to changes in system dynamics and disturbances.	Improved robustness and performance in non-stationary environments.	Increased complexity, requires online identification of system parameters.	[121]
Economic MPC	Focuses on optimizing economic performance objectives, such as minimizing energy consumption or maximizing throughput.	Improved economic efficiency, considers long-term objectives.	Potential for suboptimal control performance if not carefully designed.	[120]

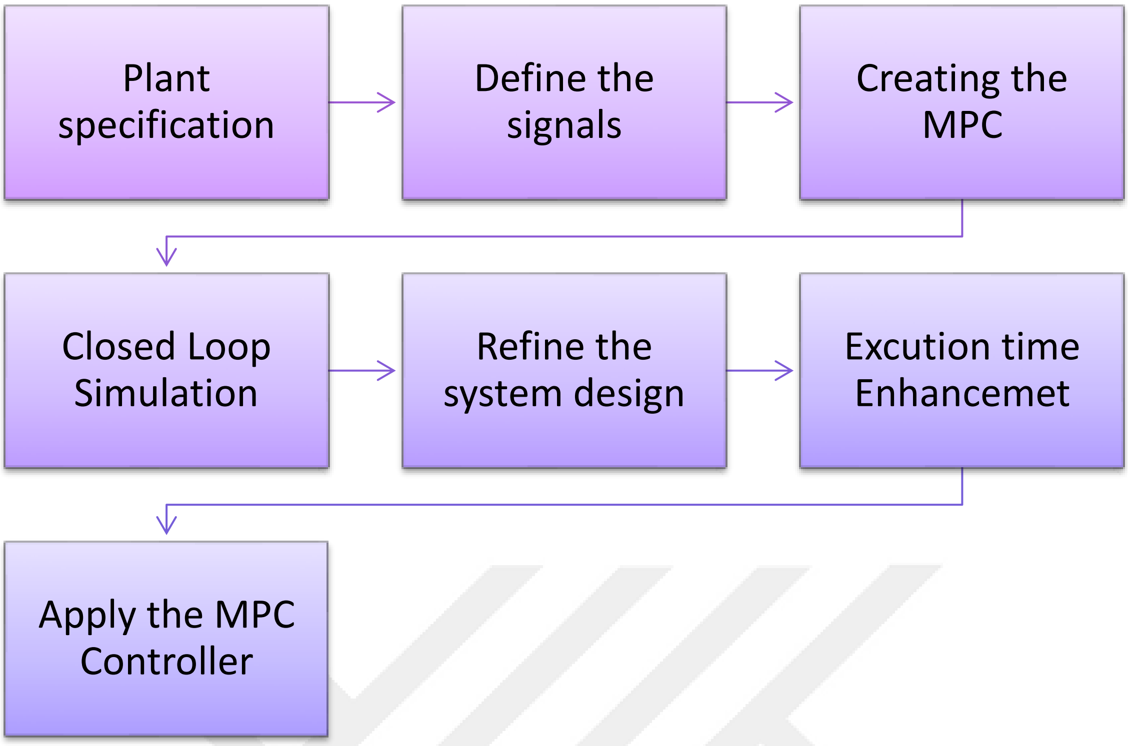

Figure 2.14: Workflow of the Model Predictive Control Design.

In this thesis, our objective is to control an autonomous vehicle so that it follows a particular reference path. To achieve this, a cost function should account for the deviation from the path, with smaller deviations yielding better results. Additionally, it is important to minimize the magnitude of the control inputs to ensure a comfortable experience for the passengers, as smaller steering angles generally lead to smoother outcomes. This is related to an optimization problem in control theory, where the trade-off between control performance and the aggressiveness of the inputs exists; therefore, the following cost function is defined:

$$J(x(t), U) = \sum_{j=t}^{t+T-1} \delta x_{j|t}^T Q \delta x_{j|t} + u_{j|t}^T R u_{j|t} \tag{2.19}$$

δx stands for the distance between the reference points and the predicted ones:

$$\delta x_{j|t} = x_{j|t,des} - x_{j|t} \tag{2.20}$$

u denotes the steering input. Firstly, the predictive model of the plant is needed. So, we will get δx.

While the central principle of MPC controller is the use of the plant model for the evolution future predicting of the model. In this study a simple kinematic bicycle model was used.

$$x_{dot} = v * \cos(\delta + \theta) \tag{2.21}$$

$$y\_dot = v * \sin(\delta + \theta) \tag{2.22}$$

$$x\_(t+1) = x\_t + x\_dot * \Delta t \tag{2.23}$$

$$y\_(t+1) = y\_t + y\_dot * \Delta t \tag{2.24}$$

$$\theta\_dot = v / R = v / (L/\sin(\delta)) = v * \sin(\delta)/L \tag{2.25}$$

$$\delta\_dot = \varphi \tag{2.26}$$

$$\delta\_(t+1) = \delta\_t + \delta\_dot * \Delta t \tag{2.27}$$

$$\theta\_(t+1) = \theta\_t + \theta\_dot * \Delta t \tag{2.28}$$

Where:

Table 2.4: Symbols Explanation and Functions.

Symbol	**function**
X	States of [x, y, θ, δ]
δ	Wheel steering angle
θ	Heading angle
U	Inputs [v, φ]
v	Velocity
φ	Steering rate

3. METHODOLOGY

To control an autonomous vehicle effectively, there are two major aspects to consider: lateral control and longitudinal control. Lateral control helps in keeping the vehicle aligned with the desired path, while longitudinal control is used for maintaining the speed and acceleration of the vehicle along the path. In this system presented here, we introduce a new hybrid controller, which is called the Model Predictive and Stanley-based controller (MPS). This control system combines two already established control techniques, namely Model Predictive Control and the Stanley controller. This embeds strengths from each technique to yield a better performance.

The model predictive control applies in the longitudinal control since it capitalizes on the strong capability of the model. Generally, MPC has been highly rated to be highly predictable and have great ability in constraint handling making one of the most trustable systems to manage vehicles speed when driving autonomously. Conversely, the Stanley controller provides lateral control on MPS. The Stanley controller is very efficient, especially in path-following issues, and was initially designed for high-performance applications such as racing cars. Combining these two control methods yields a highly efficient and reliable control system for autonomous vehicles, which is the MPS. (Figure 3.1) presents a simple block diagram of the proposed model.

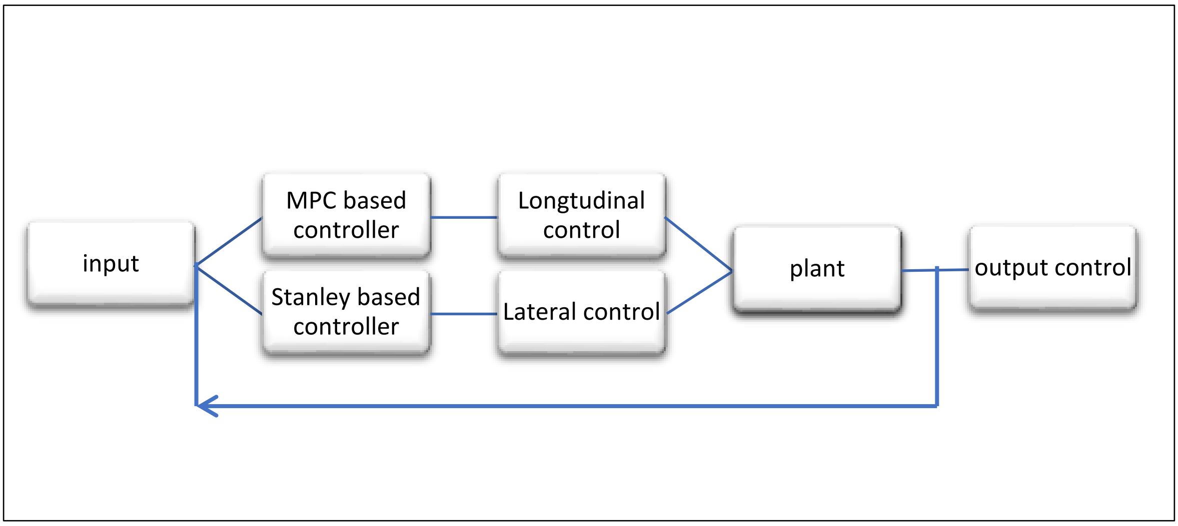

Figure 3.1: The General Block Diagram of the Proposed Model.

(Figure 3.2) presents a detailed block diagram that shows the structure of this hybrid control system. The two main inputs to the longitudinal and lateral controllers are shared: feedback from the vehicle, reference path data, and reference velocity. The integration ensures the collaboration between these two control models to maintain precise path following and smooth motion control. This means that the MPS uses the strengths of both MPC and the Stanley controller to provide a system appropriate to a wide variety of autonomous driving with much better accuracy and stability.

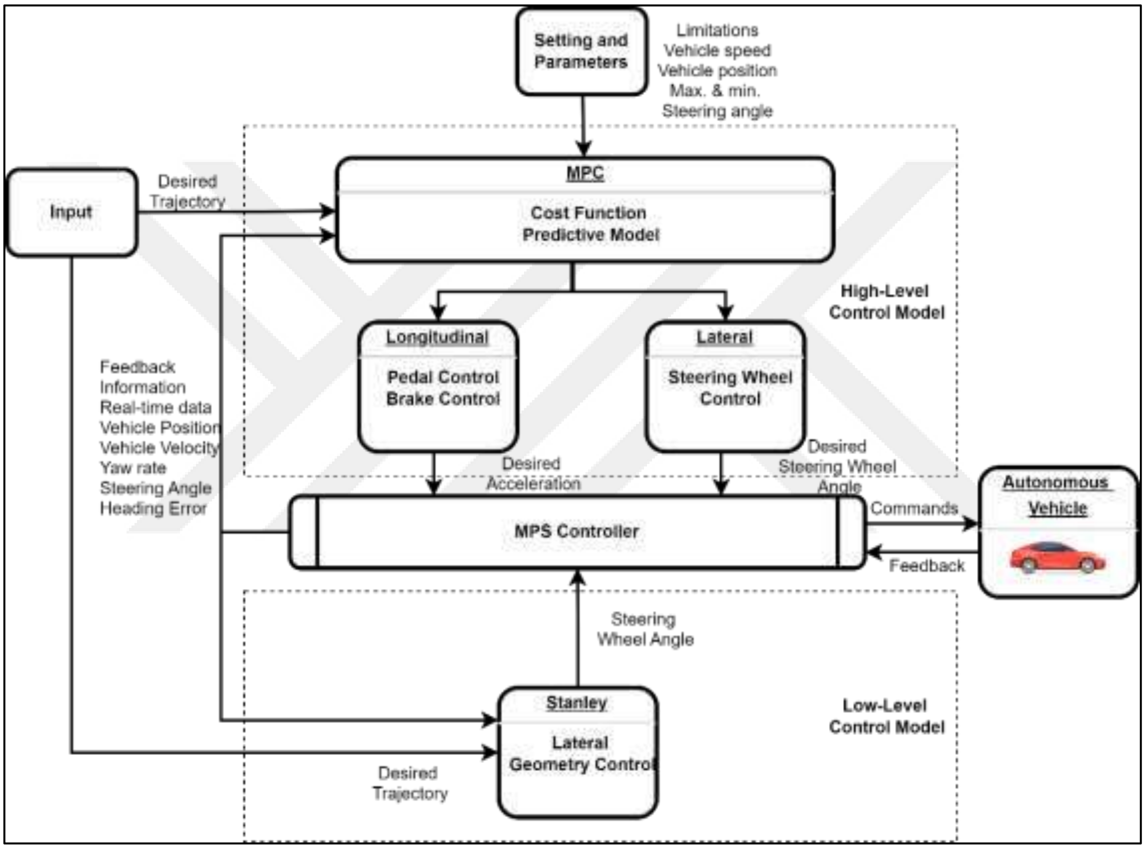

Figure 3.2: The Detailed Block Diagram of the Proposed System.

A combination of MPC and the Stanley controller can bring significant potential in enhancing the autonomous driving systems. Both controllers contribute different strengths and capabilities; therefore, integrating the two will result in greater robustness, improving overall control performance. This allows for the attainment of a more efficient and adaptive control framework by leveraging their complementary features.

It is one of the most advanced control models, and its overall predictive capability for a system's future behaviour over a finite time horizon can perform an optimization of performance by considering potential changes and disturbances beforehand. One of the key benefits of this controller MPC is that it deals very well with constraints and restrictions, so this controller is reliable in scenarios where there might be a risk to safety and stability during autonomous driving [122].

The Stanley controller represents a simple and effective approach developed for autonomous vehicles in general, and for solving the problems of lateral control in particular [123]. It thus primarily focuses on keeping alignment with the reference path through minimum lateral offset and corrections in the steering angle. The Stanley model calculates the steering wheel angle based on cross-track error (lateral distance from desired path) and the heading error, which is an angular difference between a direction of the vehicle and a target trajectory[124]. Despite its simplicity, Stanley controller has been very effective for path following operations in unmanned drive systems [125].

The combination of the two models allows the autonomous car driving systems to take advantage of the predictive aspect present and constraint management ability of MPC in longitudinal control, as well as the efficiency and simplicity of the Stanley control model in lateral control. This will further provide for the enhancement of the balance and robustness of the approach as well as greater precision and responsiveness in driving under varying conditions.

The combination of MPC with the Stanley controller is a complex method of controlling autonomous vehicles. This mixed model exploits the strengths of MPC in handling complex dynamics and constraints, and the Stanley model for accurate path following. By integrating these methods, a system has been developed that not only is robust but also extremely efficient for most control problems.

This integrated control approach can be organized in the following way:

i. High Level Control Tasks: A general function of an MPC control system is performed in the execution of tasks like path planning and decision-making. By predicting, taking into account vehicle dynamics, operational constraints, and road conditions, it determines the most feasible path. With this, the system will be able to predict future changes and adapt for safety and efficiency in traversing complex environments.

ii. Low Level Control Tasks: Stanley controller is employed for real-time path tracking. It is generally responsible for precise adjustment of a steering wheel depending on the cross-track error, or lateral deviations, and direction error, or heading differences. By specifying these real-time control tasks, the Stanley controller ensures that the vehicle follows the programmed path and makes its movements accurately.

This hierarchical structure allocates the activities between the two controllers, with the MPC performing strategic control considerations-optimizing the motion of the vehicle and keeping it within the constraints-and Stanley controller performing real-time operational corrections so critical for accurate path following. They complement one another to provide a complementary system balancing long-term planning versus real-time response for a better overall performance of autonomous driving systems.

Two-way communication among the two controllers, i.e., Stanley controller and Model Predictive Control, is the essence of performance of the hybrid system by dynamic communication and adaptation in the feedback loop. Here, MPC controller determines the optimal path and sends it to the Stanley controller, which provides accurate steering angle adjustments such that the vehicle follows the allotted path perfectly [126].

This closed-loop feedback creates a strong synergy between the two controllers by linking the system output to its input for continuous update and refinement. Real-time sensing is the centrepiece of this process. The Stanley controller collects and sends the latest feedback of the actual car state to the MPC controller. MPC accomplishes this, corrects the necessary deviations on the way, and sees to it that the predicted path will closely track the vehicle's actual dynamics. This feedback loop of information assists with ongoing refining of system performance and expanding the vehicle's responsiveness envelope.

Under trying situations, like poor road conditions, very tight corners, or intricate manoeuvres, that becomes even more vital. MPC is proactive; it utilizes its prediction capability to recourse the vehicle path based on actual constraints and environmental conditions [127], while the Stanley controller corrects the vehicle's alignment precisely to the new path offered by the former one [128]. The hybrid system is thus able to maintain control and stability even under bad or unfavourable conditions.

Via predictive optimization coupled with real-time corrective actions, the MPC and Stanley controllers constitute a robust, adaptive, and high-performance autonomous driving solution. Acting together, as they do, the vehicle stays on track while dynamically adjusting to the requirements of the real-world environment for improved safety and reliability in autonomous navigation.

For the validation of performance of these combined controllers, extensive tests will be implemented on a simulation and programmed basis. Testing will provide data on the efficiency and reliability in different conditions. The combined structure of the controllers forms a hierarchical control system MPS. It is a complex architecture that takes advantage of the virtues of both the controllers to deliver a precise and reacting control response in vehicle position terms.

In this layout, top-level decisions are made by the MPC controller that performs the core function of planning the best path possible through different predictive calculations and real-time data. Considering vehicle dynamics, operational constraints, and road conditions results in an optimum and practicable trajectory. The Stanley controller performs low-level tasks of real-time path tracking and makes instantaneous adjustments to the steering angle to maintain the vehicle aligned with the given trajectory.

This brings about considerable advantages in many aspects of driving scenarios. Further, the performance of MPS, combining the strengths of the two controllers, results in better path convergence: that is, the vehicle can track the intended trajectory closer without any occurrence of overshooting or corner-cutting, making navigation smooth and safe even in complicated or highly demanding situations.

The robustness and adaptability of the MPS controller make it adequate for wide scenarios, from urban driving to highway scenarios with challenging road conditions. (Figure 3.3) depicts an overview of the proposed MPS controller and summarizes the interaction flow between the high-level and low-level components of the architecture.

Extensive testing will be carried out in both simulated and on-road environments to further refine the MPS controller and demonstrate capability improvement in performance and reliability for the autonomous driving system. (Figure 3.3) presents the flow-chart of the proposed model (MPS controller).

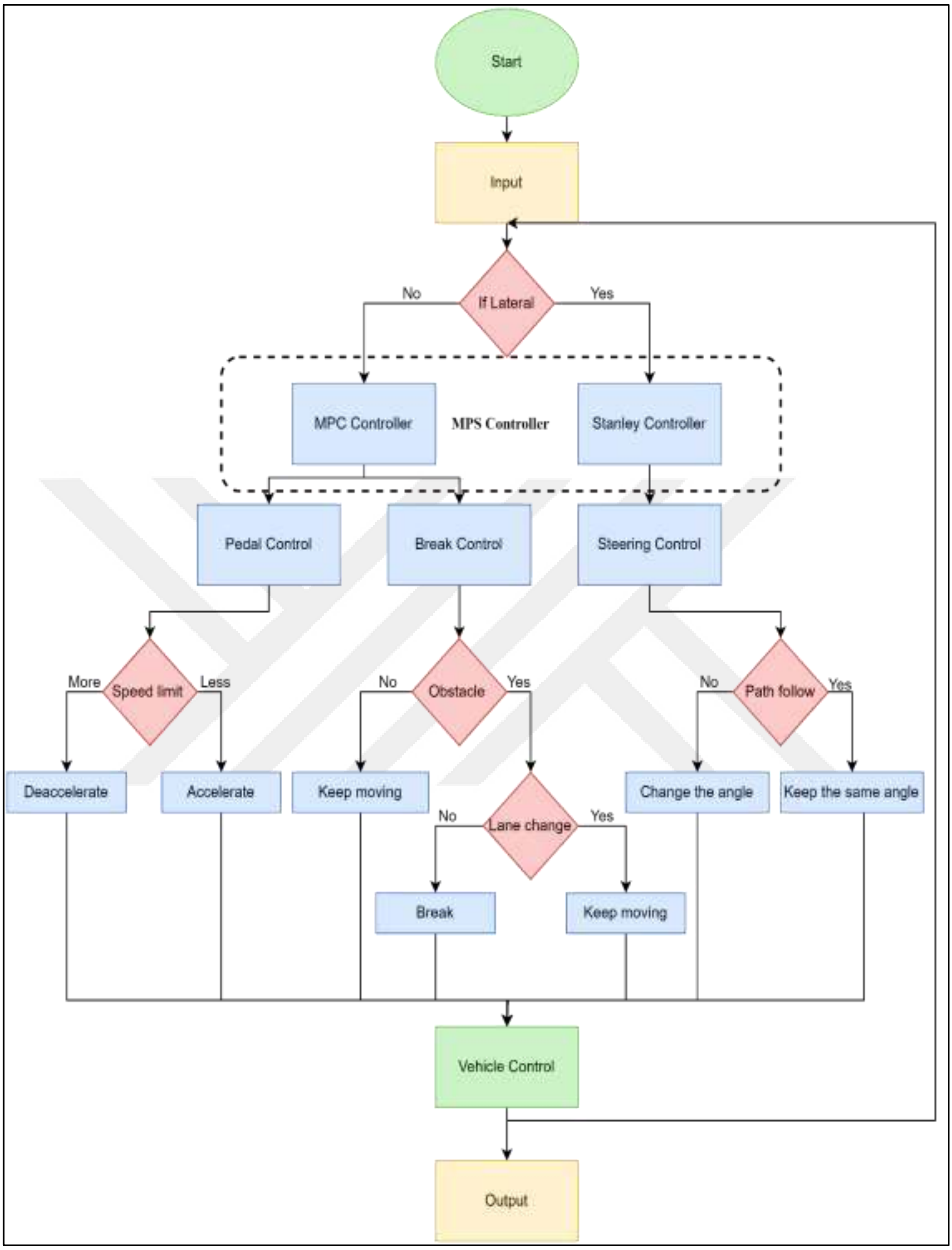

Figure 3.3: Flow Chart of the Proposed MPS Controller.

3.1 MATHEMATICAL MODEL

Mathematically, the two control models can be integrated: Model Predictive Control (MPC) and Stanley. The integration could be formalized in a hierarchical structure in which MPC is a high-level and Stanley is a low-level controller. In such a structure, each model does what it can do most effectively, resulting in a more efficient and effective overall controller.

High-Level Model: The MPC Algorithm At high level, the MPC algorithm is the strategic planner of the vehicle's trajectory. MPC's principal job is to make optimal the motion of the vehicle along a specified finite time horizon by solving at each time step a constrained optimization problem.

Low-Level Model: The Stanley controller, in the low level, must execute, in real time, the trajectory that the model predictive control algorithm provides. Its primary task is the steering angle adjustment of the vehicle to the provided path, with an adjustment to be performed on both the lateral and heading error.

That enables the system to use the MPC's predicting and optimization capabilities for long-term strategic planning and the Stanley controller's simplicity and efficiency for very fine, real-time path tracking.

3.1.1 Mathematical Integration

Mathematically, the integration can be represented as: The MPC output is the desired trajectory defined by waypoints and desired velocities along the planning horizon. The computed outputs are then passed on to the Stanley controller for computing real-time steering commands based on the trajectory's lateral offset and heading angle differences.

It enables a smooth information exchange and coordination between high-level trajectory planning and low-level path following. This hierarchical approach endows the system with enhanced capacity to handle complex dynamics with assured real-time response and hence is suitable for general autonomous driving situations.

$$\min U \sum_{k=0}^{N-1} \left\| x_k - x_{ref,k} \right\|^2 + \left\| u_k \right\|^2 \tag{3.1}$$

S.T.

$$xk + 1 = f(xk, uk),$$

$$h(xk, uk) \leq 0,$$

$$g(xk, uk) = 0,$$

$$x0 = xinitial$$

Where:

i. $U = [u_0, u_1, ..., u_{n-1}]$ is the vector of control inputs.

ii. x_k represents the state of the vehicle at the time step (k).

iii. $x_{ref,k}$ is the reference state at time step (k).

iv. $f(\cdot)$ denotes the dynamic model of the vehicle.

v. $h(\cdot)$ and $g(\cdot)$ are the inequality and equality constraints, respectively.

In the low-level model, the Stanley controller fine-tunes the steering angle by modifying both lateral and heading errors, to ensure that the vehicle stays aligned with the desired path.

$$\delta = \delta \text{feedforward} + \delta \text{feedback} \tag{3.2}$$

$$\delta = \arctan\left(\frac{k \cdot e\text{lat}}{v}\right) + \arctan\left(\frac{k\text{stanley}}{\alpha}\right) \tag{3.3}$$

The variables are defined as follows:

i. δ: The steering angle.

ii. elat: The lateral error, representing the distance between the vehicle and the reference path.

iii. α: The heading error, which is the difference between the desired heading and the vehicle's current heading.

iv. k: The vehicle gain.

v. kstanley: The gain parameter specific to the Stanley controller.

vi. v: The velocity of the vehicle.

The combined control input is derived by merging the outputs of both the MPC and Stanley controllers.

$$U = uMPC + uStanley \tag{3.4}$$

Where:

i. uMPC: The control input generated by the MPC controller.

ii. uStanley: The control input provided by the Stanley controller.

3.2 SIMULATION

3.2.1 Simulink-Based Simulation

A powertrain block is used to simulate the stresses, friction, and other elements of an automobile. To simulate the primary vehicle body, the system uses a dual track vehicle body block. It receives signals from the powertrain and sends its output to a 2D visualizer and the system's feedback. The Vehicle Body 3DOF block estimates the longitudinal, the lateral, and the yaw movements by using a rigid two axle vehicle body model [129]. This block takes into consideration both the steering and accelerating effects of the mass of the body, aerodynamic drag, or weight sharing between axles. (Figure 3.4) shows the Body forces system. (Figure 3.5) shows the system details of Model Predictive Control (MPC). The details of the Stanley control system are shown in (Figure 3.6), and (Figure 3.7) shows the proposed system, MPS, integrating the previous two controllers.

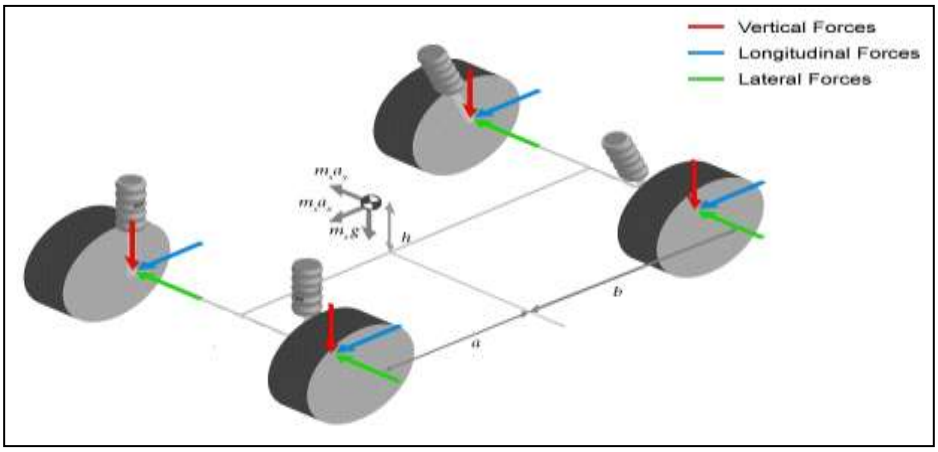

Figure 3.4: Vehicle Body Forces System.

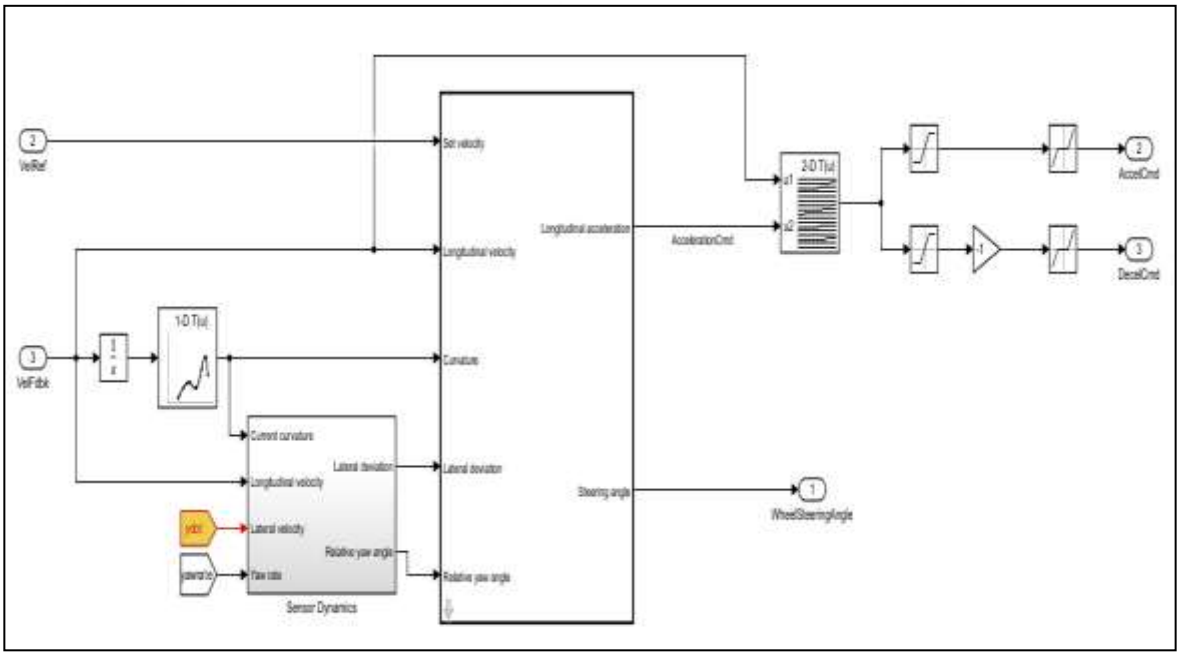

Figure 3.5: System Details of the MPC Model.

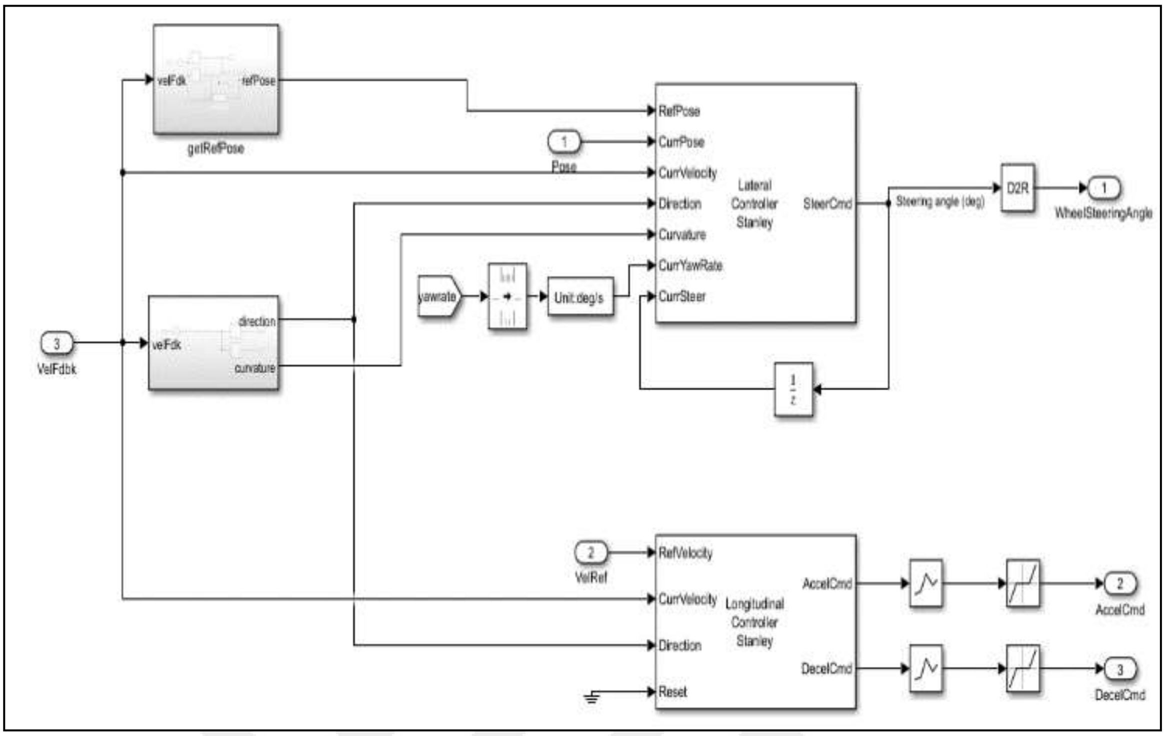

Figure 3.6: System Details of the Stanley Model.

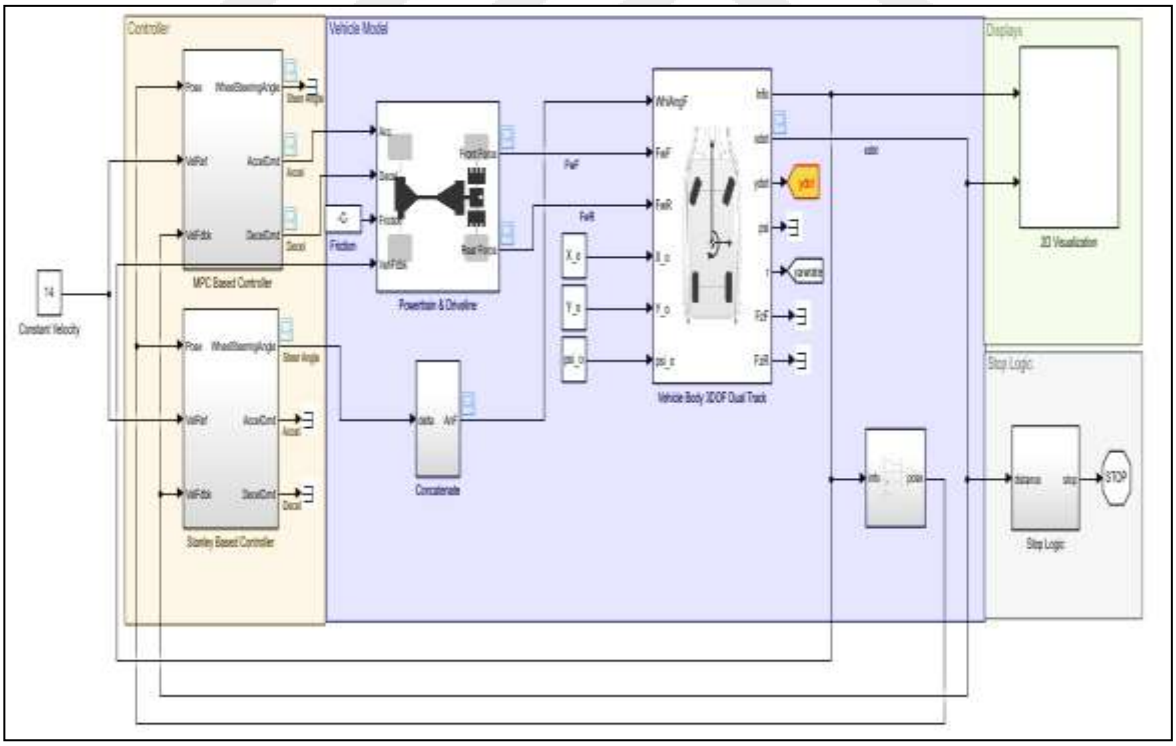

Figure 3.7: System Details of the MPS Model.

(Figure 3.7) shows the details of the proposed system. In the two main parts of the controllers, the upper part is the MPC longitudinal control part, and the lower one is the lateral part of the controller which is the Stanley lateral control part. Both controllers work in collaboration in one system to make a high-performance control system for autonomous vehicles.

3.2.2 Code-Based Simulation

The simulation environment of this study was developed using MATLAB software, which was helpful in building and testing the control systems and their surrounding environment. Equipped with versatile simulation tools, MATLAB allowed modelling and testing various situations ranging from simple autonomous vehicles to complex traffic conditions. In this process, the system was built piece by piece: first, a Model Predictive Control system was developed that initially used the car's brake and throttle controls. It was one effective way of managing the speed and braking of the vehicle to ensure response smoothness in changing driving conditions.

With the MPC system in place, the development of the Stanley controller was the next task. This controller should control the vehicle's steering angle. Consequently, the Stanley controller was utilized for tracking along the path to follow the reference trajectory precisely, with corrections on the vehicle's heading and steering using lateral and heading errors.

For generating the driving path in simulation, a spline function was utilized. Spline function will be more effective to develop smooth and continuous curves, which is the main purpose of developing realistic driving paths for autonomous vehicles. By choosing proper (x, y) coordinates, the interpolating features of the spline function connect these points with a smooth reference path. This technique provides realistic routes that the vehicle can take during the simulations smoothly, which is very important in the testing performance of the controllers.

In the test setup, the reference path used is shown in (Figure 3.8). In this figure, the blue line connects the chosen reference points, while the red line is the actual reference path adopted in running the simulations. This has been the same for all the experiments conducted with the autonomous controllers and hence serves as a common basis for testing and comparison. In this way, using this reference path allowed the performance of both MPC and Stanley controllers, and the hybrid system under different driving scenarios to be assessed accurately.

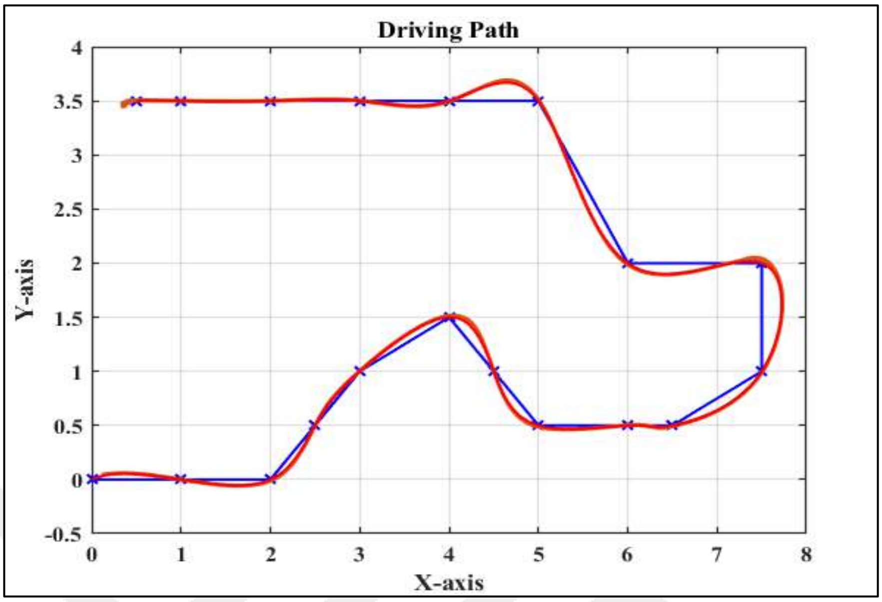

Figure 3.8: Reference Test Driving Path for the Models.

Several models were developed and implemented in this study to perform the evaluation of the proposed control system and comparisons with traditional controllers. First to be implemented was the MPS (Model Predictive Stanley-based) controller, and its results were carefully analysed and presented. Next, the Pure Pursuit controller was coded and tested under the same conditions and constraints to determine the effectiveness of path tracking. A PID controller has also been implemented and tested with the same reference path and simulation parameters, which allows a direct comparison between the performance of all three control strategies.

The kinematic bicycle model-Ackermann steering model is a commonly used model when simulating the behaviour of vehicles, which was used in this study. This model is considering a front-wheel-steering configuration, which means only the front wheels are steerable. It further assumes that there is no lateral slipping of the wheels, a usual approximation in vehicle simulations. The system was modelled with regard to maintain the characteristics that would occur in real life where the vehicle behaves as a rigid body, moving according to its steering angle and velocity.

The linear dynamic bicycle model can be used for continuous-time simulations of the system and enables the modelling of vehicle dynamics in a simplified but effective way. It has been chosen because it offers a good balance between computational efficiency and the accuracy of representing the vehicle's motion within autonomous driving simulation.

The vehicle dynamics and performance can be represented by the following parameters in the simulation:

i. Wheelbase: 2.5 m - distance between the vehicle's front and rear axles, it is an important parameter to assess turning radius and handling performance.

ii. Steering dynamics time constant: 0.27 s - time constant of the response of the vehicle against a steering input.

iii. Width: 0.724 m - width of the vehicle, which will be a factor in the stability and turning radius of the overall vehicle.

iv. Steering limit: 30°, which is the maximum angle at which the front wheels can steer. This constraint keeps the simulation within practical limits of common vehicle handling.

v. Velocity range: -5 to 10 km/h, providing for reverse and forward motion of the vehicle. This provides a realistic setting for the testing of the control systems under various driving conditions, from low-speed manoeuvers to higher-speed driving.

The above parameters have been selected with utmost care to make the conditions as close to reality as possible. It will be also easy to bring the results from the simulation to real-life applications in autonomous driving. All the models were compared and analysed regarding the strengths and weaknesses of every control approach, providing a complete overview about their performance under different driving conditions.

4. RESULTS AND DISCUSSION

4.1 SIMULINK-BASED RESULTS FOR MPS

It consists of a combination of straight and curved lines, hence enabling us to see the capabilities of the car in tracking. In the tracking of an autonomous car over a given road, the Stanley control of the steering algorithm is used. This method consists of two steps: one is finding the steering angle depending on the deviation from the desired heading angle. The phase and magnitude of the steering angle are calculated with the following equations: The sign of the deviation between intended and present heading angles - indicating left or right direction the vehicle has to steer - determines the phase in the Stanley steering angle. The magnitude of this error forms a steering angle, which is further constrained to practical limits and amplified by a proportional gain factor. Magnitude and phase control together provide the vehicle with the stability and mobility it needs to successfully follow the intended course. (Figure 4.1) shows both phase and magnitude of the MPS model. The magnitude of the steering wheel for sharp curves is 0.58 degrees; when the path is straight, it is almost zero degrees. The phase flips with turning the steering wheel left and right.

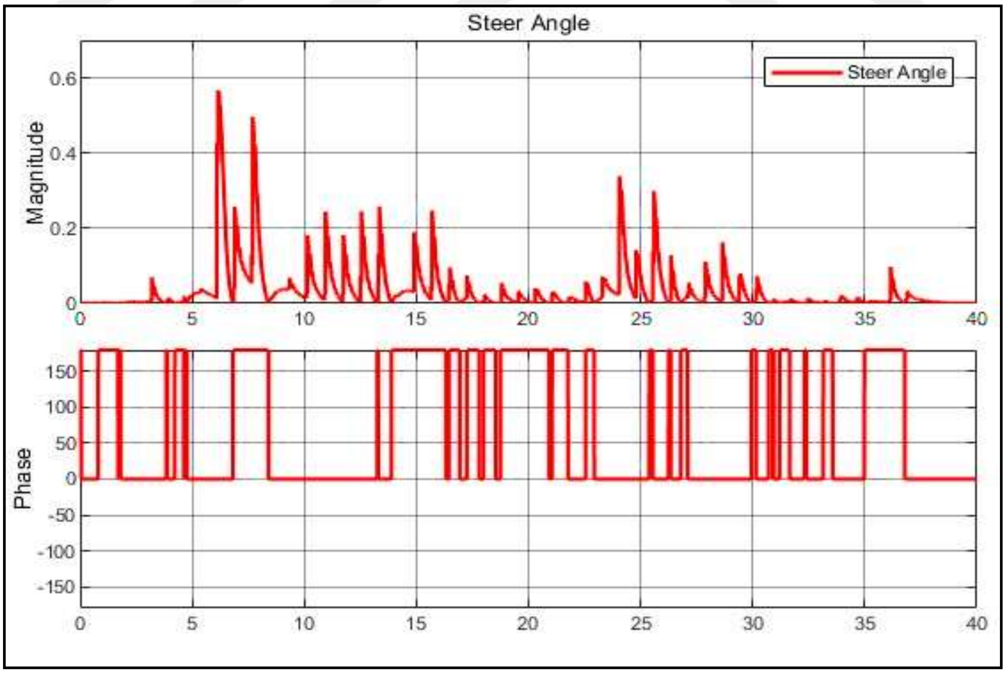

Figure 4.1: MPS Steering Angle Both Phase and Magnitude.

(Figure 4.2) depicts the change in the front wheel's angle against simulation time. This plot is depicting how the system is dealing with the curve on the street and how the vehicle is performing to change its direction accordingly. (Figure 4.3) represents the rate at which change of the system's state variables (commonly indicated by "x") over time. This figure is the basis for prediction of the future states of the system. It is also crucially needed for understanding its dynamic behaviour. The "xdot" graph shows the derivative of the state of the variables concerning time. It gives information on every state variable concerning how it changes over time. Mathematically, xdot = dx/dt, where t is the time and x is the vector of state variables. Table 4.1 is the parameters of the vehicle's plotter in the system.

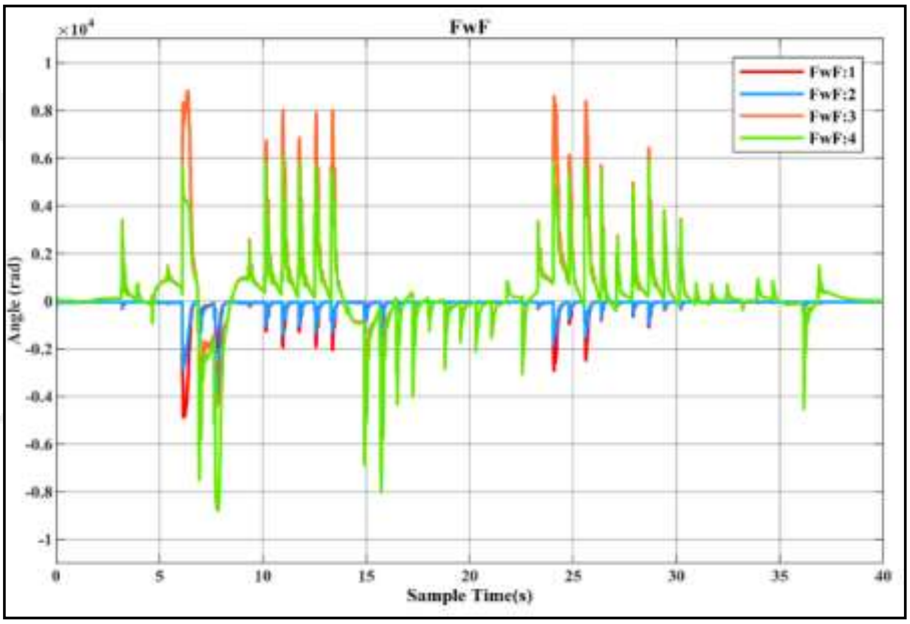

Figure 4.2: Forward Vehicle’s Front Wheels Angle Changing.

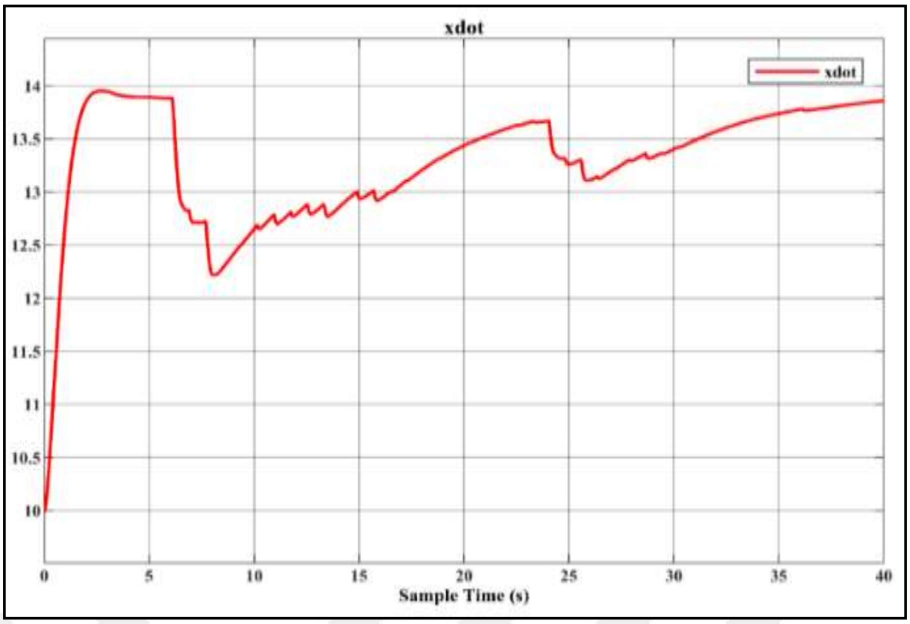

Figure 4.3: Changing of the System's State Variables ("x") Over Time.

Table 4.1: Vehicle’s Plotter Parameters.

Vehicle (xy) Plotter	Amount
Distance to front axle from CG, a [m]:	2
Distance to rear axle from CG, b [m]:	2
Track width, w [m]:	2
Distance to figure borders, [m]:	10
Path buffer sample size, []:	1024
Velocity vector scaling, [m*s/m]:	5
Tire force vector scaling, [m/N]:	1000
Plot update rate, [s]:	0.2

From (Figure 4.4), the red dots represent the desired path, and the circles represent the AV movement. It is obvious that the vehicle is tracking the desired path precisely. The maximum off track of the vehicle is less than half a meter, which is an acceptable value. This is because the width of the street is more than double the vehicle's width, which is two meters. Table

4.2 shows the statistics of both desired and actual paths. It can be seen from this table that the system is controlling the vehicle in a very good shape, with the statistics of the results having low errors as in (Figure 4.5).

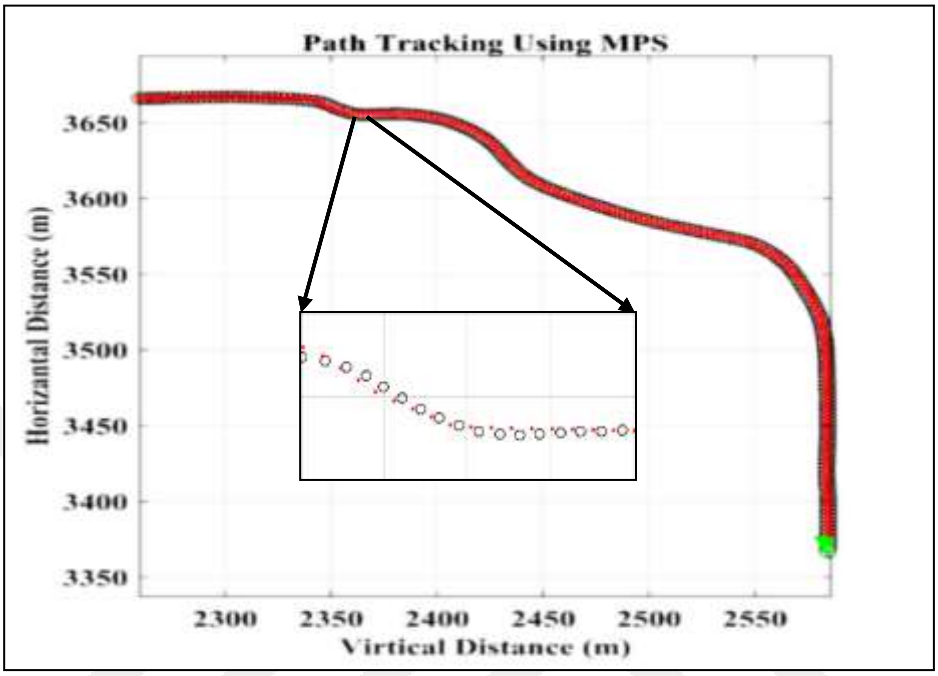

Figure 4.4: Autonomous Vehicle Path Following Using MPS Controller.

Table 4.2: Desired and Actual Path Data Statistics.

Path Data	**Desired Path (.)**		**Actual Path (o)**	
	X	**Y**	**X**	**Y**
Min.	2260	3367	2260	3369
Max.	2585	3667	2585	3667
Mean	2302	3647	2302	3647
Median	2260	3666	2260	3666
Mode	2260	3666	2260	3666
STD	97.42	55.61	97.24	55.13
Range	324.7	300.1	325.2	298.3

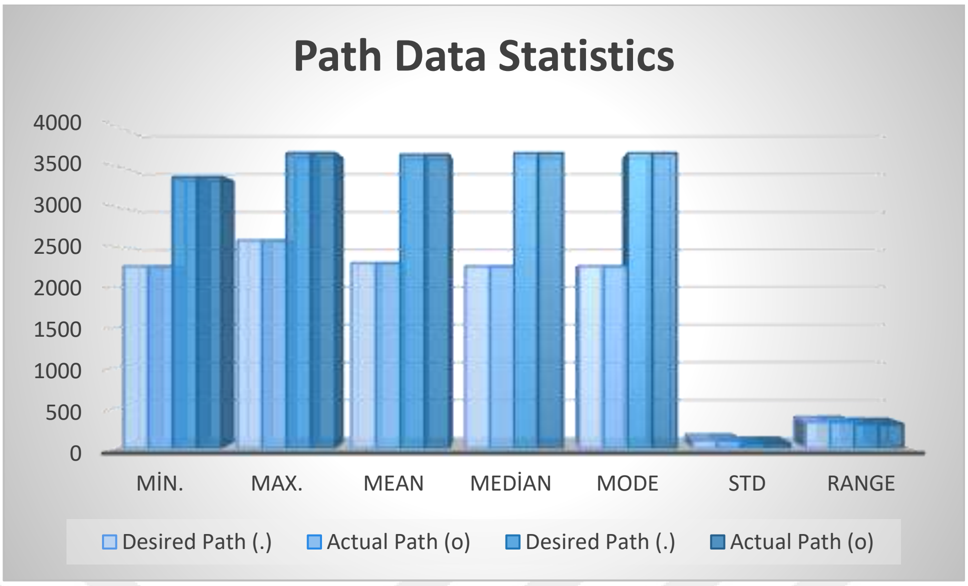

Figure 4.5: Path Data Statistics of Both Desired and Actual Paths**.**

4.2 CODE-BASED RESULTS FOR MPS

The established driving trajectory contains straight lines and road curves to represent various real road scenarios. Different scenarios have been used to test the reliability of the proposed model and to conclude whether it can be deployed in real-world application. We first consider a path tracking scenario, wherein there is a certain path that is fed to the system that the autonomous vehicle needs to follow. For performance and robustness assurance of the MPS method and for comparison, three different models have been used in this study.

The code provides a way of running one model at a time, or we could just run them all in sequence. The point is that with this design, there would be the possibility to reduce some overhead from the beginning by making comparisons as accurate as possible. To run every single model, we are expected to first decide on several general and model-specific simulation settings before running. These simulation settings are put in Table 4.3 together with all parameters of our models.

Table 4.3: Parameters Setting of All Model's Simulation.

Parameter Type	**Value**	**Control Model**
Simulation time	30 s	All
Simulation time step	0.002	All
Reference velocity	30 Km/h	All
Control Frequency	100 Hz	All
Input delay	0.05 s	All
Steering limit	30 degrees	All
Steer rate	280 degrees	All
Steering steady state error	1 degree	All
Noise measurement	0.5 degree	MPS
Horizon steps	15	MPS
Look ahead distance	6 m	Pure Pursuit
KP	0.3	PID
KI	0	PID
KD	1.5	PID

First, the PID controller will be applied, especially the PD feedback control system, in the autonomous vehicle. The main reason for choosing it is that the PD feedback controller makes the system response smoother and reduces the undesired overshoots. These characteristics are indispensable to keep the driving stable. (Figure 4.6) indicates that the use of the PID controller enables the vehicle's trajectory to remain on the prescribed path; however, it is not optimally placed. This model has defects at some points in time, which allows the vehicle to deviate from the track, particularly at curvilinear sections. This form of failure is a serious drawback for the system. Moreover, (Figure 4.7) shows a huge difference between the desired and actualized steering commands. The blue line represents the desired command, while the orange line represents the actualized command. This difference makes the system unstable and impairs the performance of the vehicle. Also, (Figure 4.8) shows a large error associated with latitude error. All these put together make PID a doubtful control system for an autonomous vehicle.

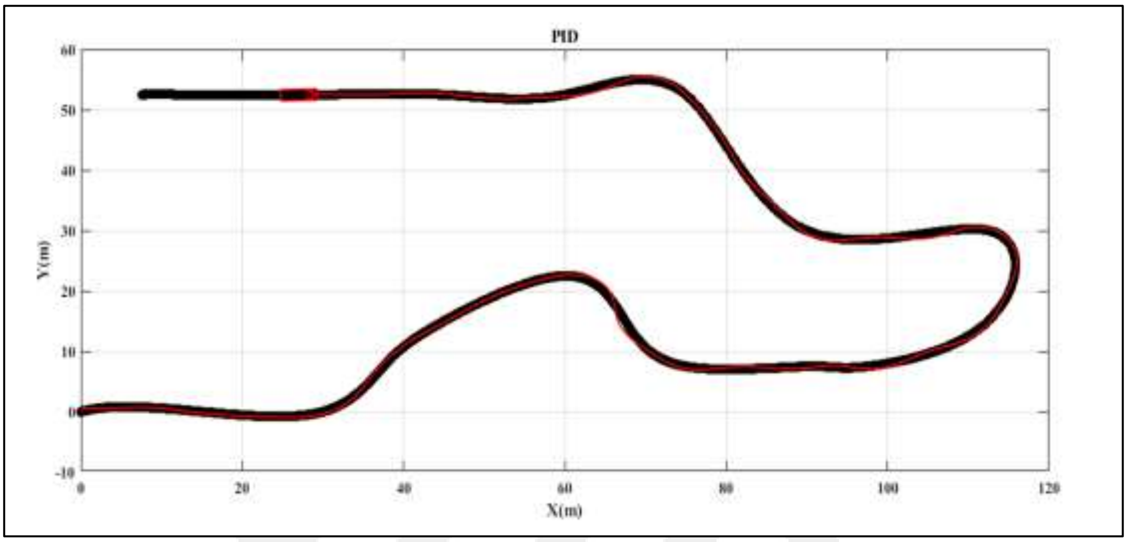

Figure 4.6: PID Controller Simulation.

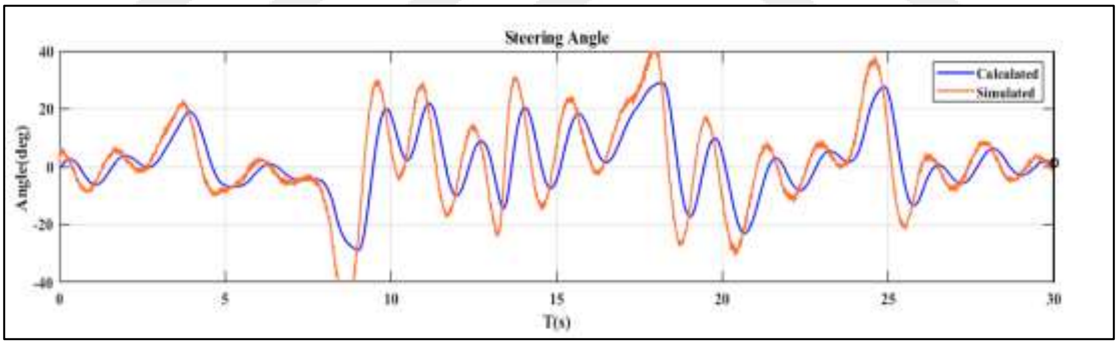

Figure 4.7: PID Controller Steering Angle Simulation.

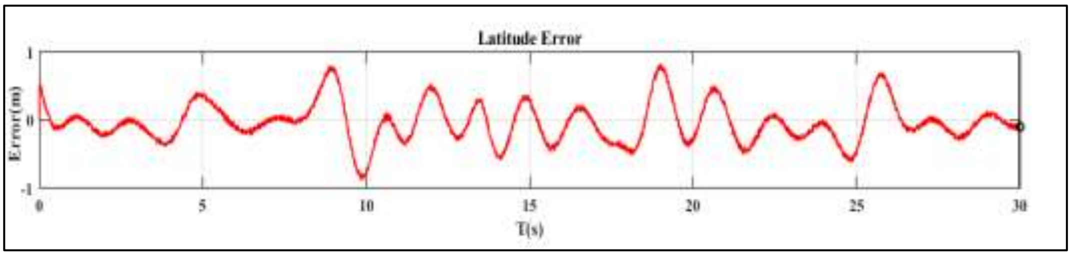

Figure 4.8: PID Controller Vehicle's Latitude Error.

Secondly, the vehicle was subjected to the Pure Pursuit controller. Results from this model indicate it has various good points but equally shares some quite negative points in terms of the vehicle's performance. From (Figure 4.9), one can easily see that the vehicle went off path for more than one time, precisely on the curves at the second 7 and the second 17 respectively. That is the undesired output for self-driving vehicles and may create some unsafe situations in the real-world. Besides, (Figure 4.10) shows that there is a shift between the actual line and the desired line in the steering wheel angle. Also, the latitude error is jumped over one, as shown in (Figure 4.11), which makes the controller unstable and unreliable.

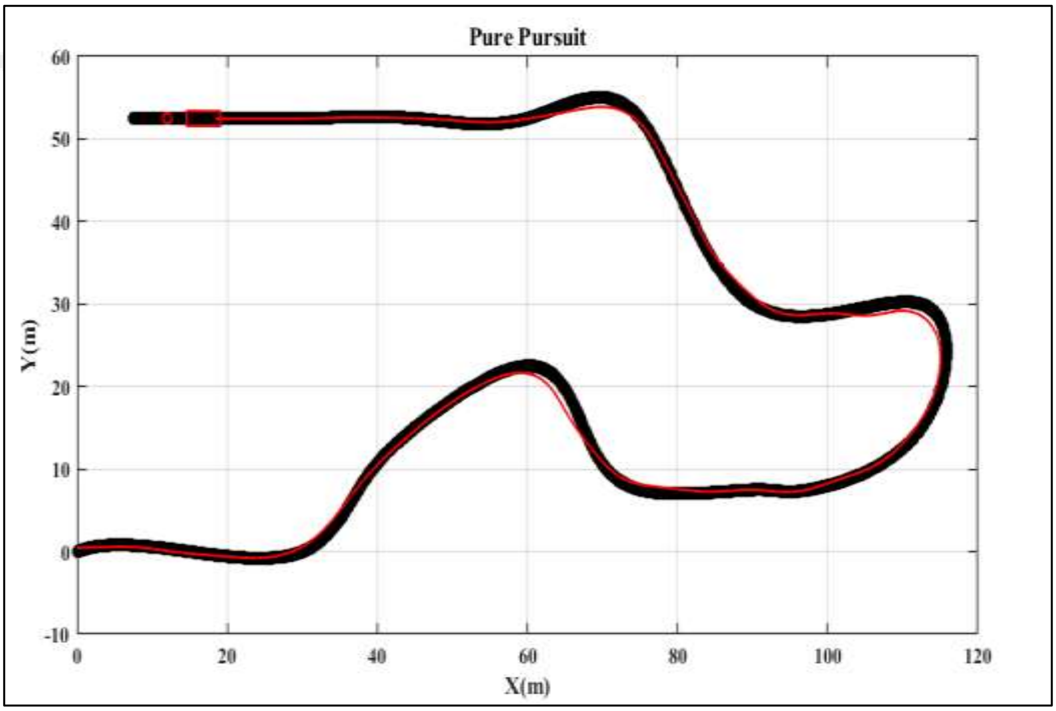

Figure 4.9: Pure Pursuit Controller Simulation.

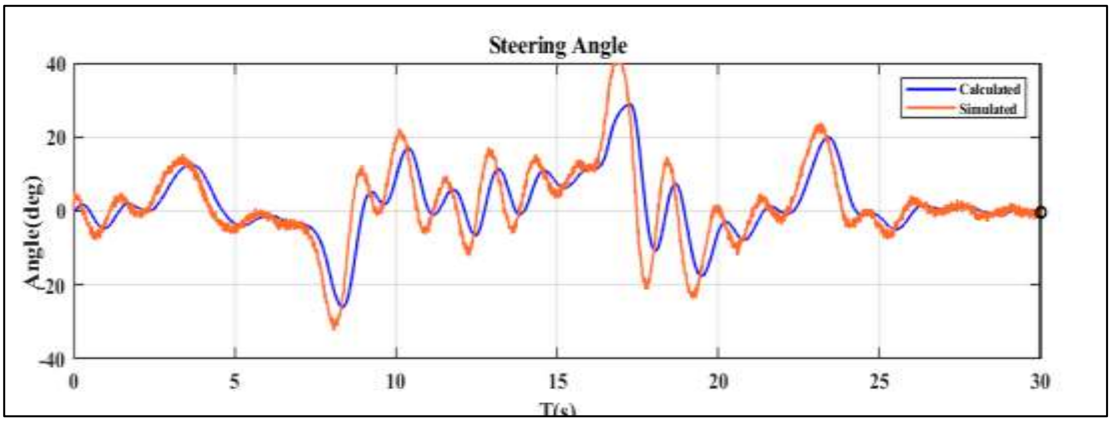

Figure 4.10: Pure Pursuit Model Steering Angle Simulation.

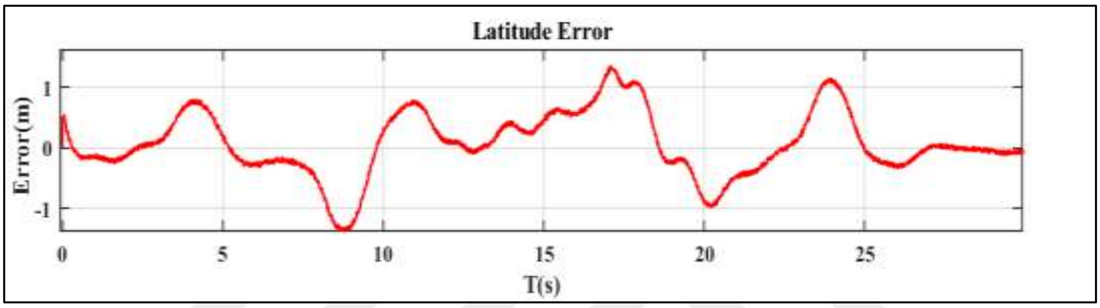

Figure 4.11: Pure Pursuit Controller Vehicle's Latitude Error.

In this stage, the proposed system is implemented, which is the MPS controller on the self-driving vehicle and obtained the results shown below in (Figures 4.12, 4.13, and 4.14). (Figure 4.12) manifests that the MPS model gives very high accuracy to the vehicle to follow the desired pathway with low hesitation. In that respect, it lets the vehicle to keep the intended velocity while keeping the performances in stability. Observing the figure, the red rectangle will be our vehicle, while the reference path is the black line that the vehicle goes on and the red one, on the other side, simulates the motion path of a vehicle. It also points out the horizon steps from the MPS in green circles. It can be realized from the red line that the vehicle did not move out of its trajectory, and it approximately remained in the middle of the path. In other words, this can be considered as a success of the MPS where one of its goals is to keep the vehicle on the right track even at sharp turns.

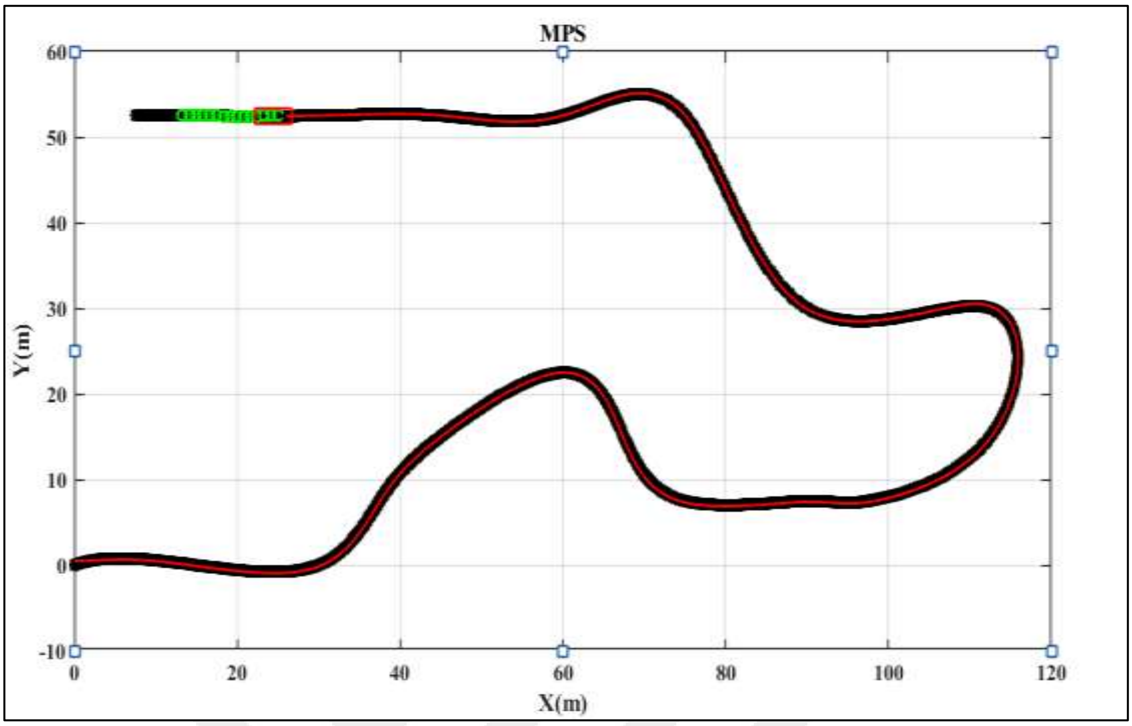

Figure 4.12: MPS Control Model Simulation.

(Figure 4.13) shows two types of steering angle commands. First line is the blue line, represents calculated steering wheel angle commands, which are perfect ways of steering movement, as the system can measure them while the driving path is already known, and the vehicle parameters are available. It is used to view the difference between what real commands should be, which will be in orange color and those that are desired, which will be in blue. That gives evidence of the excellent performance regarding commands on the angle of the steering wheel through the model MPS, the desired trajectory with tints of deviation within the sharps at every path bend-but all this has been known to be well within expectation in autonomous systems. The second is the fact that the weakness of MPS relies on the high number of steering wheel angle commands and must be decreased in subsequent studies due to leading to high computations.

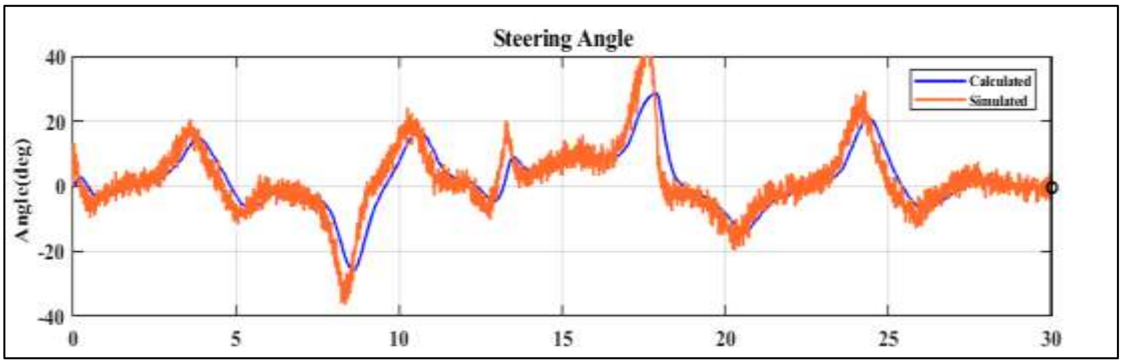

Figure 4.13: MPS Model Steering Angle Simulation.

From (Figure 4.14) it is possible to notice the latitude error curve of the MPS model performance in this simulation. The first notable aspect is the very low rate of error; practically close to zero, except for the very start until it corrects the direction. Additionally, at the second (17) the curve went down which is normal, as the vehicle passed through the hardest curve in the driving path. Generally, the maximum error was 0.5m, which falls within a very acceptable error, and the minimum about zero, which indicates there is no shift, and it is just a perfect indication of the stability of the model.

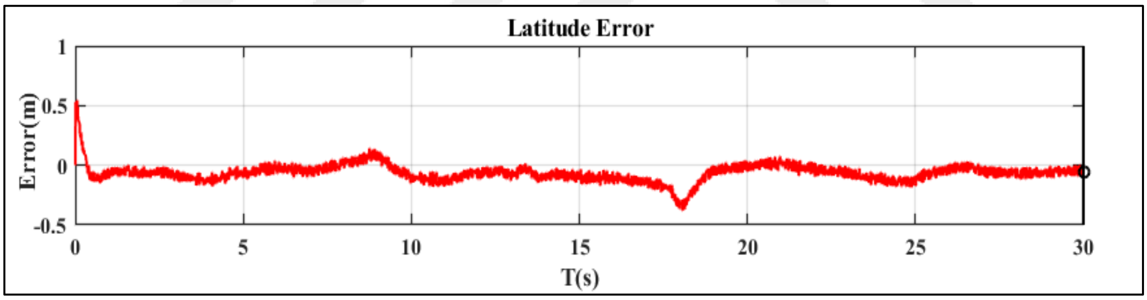

Figure 4.14: MPS Model Vehicle's Latitude Error.

As in the end, all the three models have been done to depict the differences that occurred among the three: how they looked and differences. The MPS model has a red line, green indicates the Pure Pursuit model and blue colour used for PID model. (Figure 4.15) gives black colour dotted line at the bottom for reference path of all system. MPS represents the best of the path following models presented here, as it follows the desired path without the vehicle deviating from the road. Another observation that can be made with this figure is the amount of distance travelled by each model. While Pure Pursuit model has travelled the furthest of all three models, this does not necessarily make Pure Pursuit any better. This is because of its nature of not sticking to the right track at every bend, thus it covers less distance because of its inefficiency. On the contrary, PID model has the least distance travelled in the different models. That is because of the sharp curves it makes at the path bends and its gradual coming back to the correct path.

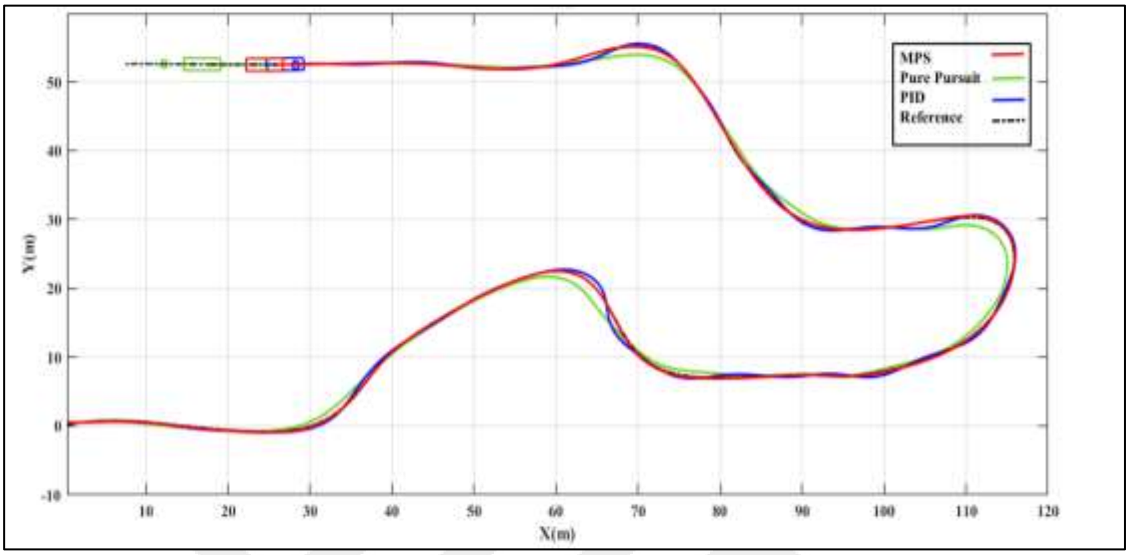

Figure 4.15: Simulation of All Models MPS, Pure Pursuit, and PID.

(Figure 4.16) shows all systems' steering angles together. This figure shows almost identical performances for all models until the 7th second of the simulation, where the first curve is on the path. Then, each system has its own performance as explained previously.

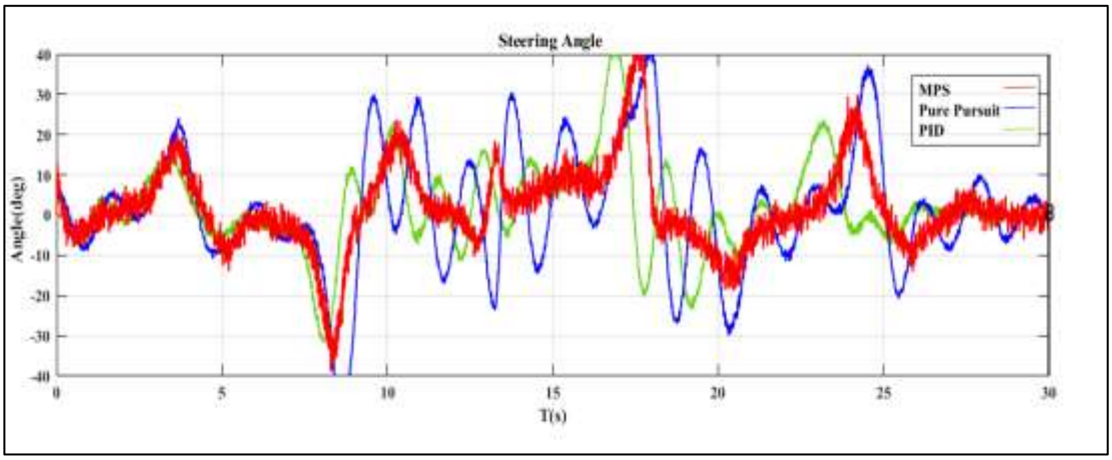

Figure 4.16: Steering Wheel Angle of All Models MPS, Pure Pursuit, and PID.

In addition, a track-following error comparison is done to test the MPS controller robustness of. The new control model outperforms two classic controllers: the PID and the Pure Pursuit controller. This requires calculating the car traveling inaccuracy through the same path. The same tracking path was shared in all the experiments, as well as having all the parameters set at the same value. We modelled the three models and obtained the results depicted in (Figures 4.15 and 4.16). Low error rates mean MPS outperforms them both.

Lastly, the MPS model is compared with the MPC and Stanley controllers. (Figure 4.17) shows the results of comparing all three models. MPS performs better than the other two models in both following the path accurately and taking less time. The vehicle using MPS travels a little longer distance than the other two models. It is less hesitant in the movement of the steering wheel, meaning it has more stability.

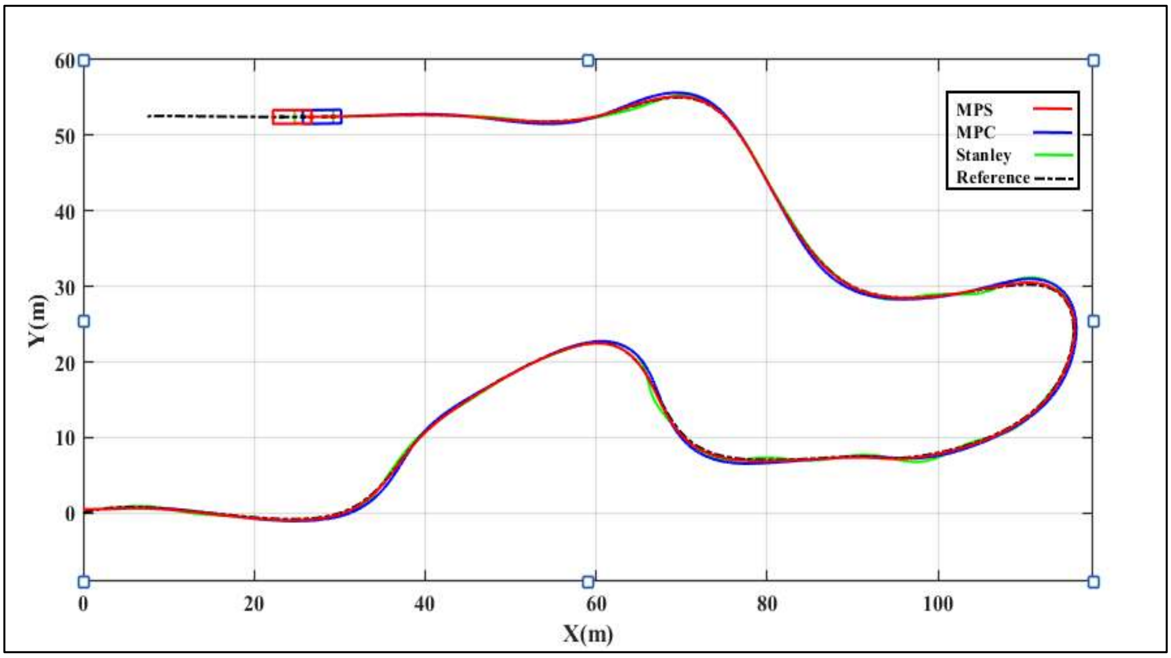

Figure 4.17: Simulation of Three Models MPS, MPC, and Stanley.

The tracking error calculation has been carried out over the main controllers used in this thesis and the proposed model MPS. From (Figure 4.18), it can be noticed that the MPS has better performance compared to the other methods, MPC and Stanley, especially in terms of obtaining a smaller tracking error for the vehicle. Different speeds have been used in this test, ranging from 10 to 60 Km/h, as shown in Table 4.4 below.

Table 4.4: Three Models Tracking Error Results with Various Speeds.

Vehicle Speed (Km/h)	MPC model	Stanley model	MPS model
10	2	1	0.95
15	1.9	0.8	0.76
20	1.8	0.7	0.69
25	0.9	0.7	0.63
30	0.4	0.5	0.38
35	0.2	0.4	0.29
40	0.3	0.3	0.3
45	0.35	0.33	0.29
50	0.37	0.31	0.26
55	0.38	0.29	0.25
60	0.5	0.35	0.3

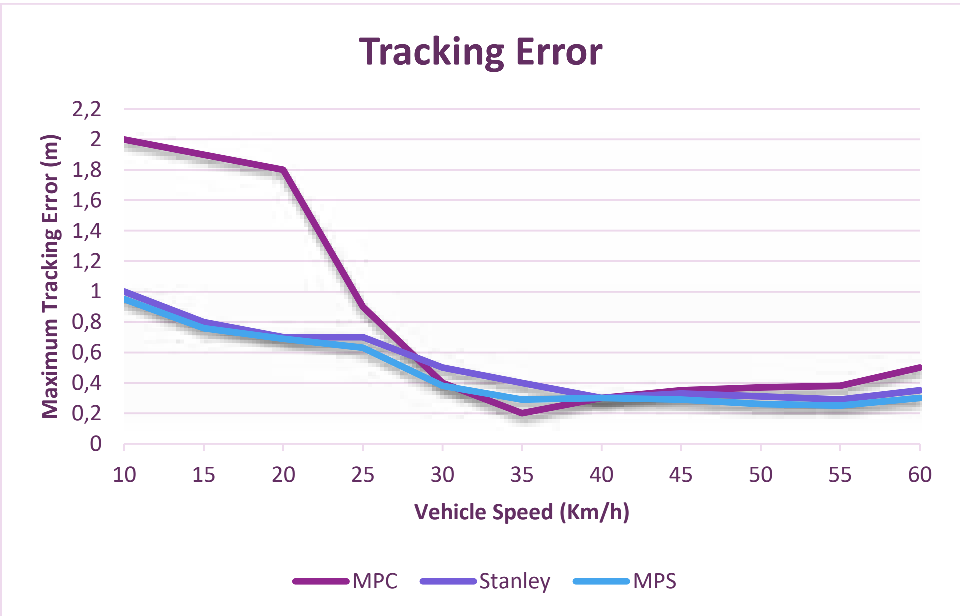

Figure 4.18: Comparison Among Different Controllers Tracking Error.

5. CONCLUSIONS

The novelty of this research is the proposal of a hybrid controller in which two traditional control methods are combined: the Stanley controller and Model Predictive Control, MPC, for the sake of improving autonomous vehicle performance. This newly introduced controller, called the MPS model, aims to achieve accurate path-following with adaptive adjustment of the motion of the vehicle, making use of the best aspects of both the Stanley and MPC approaches. The MPS model tries to strike a balance between the computational ease of the Stanley controller and the advanced predictive capabilities of MPC by combining these approaches, thus being an effective and reliable way of control for self-driving cars.

Architecture for the controller of MPS makes different parts play different and distinctive roles. The longitudinal control that mainly involves the speed and acceleration will be performed by an effective optimization MPC component, given its strong capability to do decisions with time horizon constraints in future states of the vehicle. In using only, the longitudinal part of the MPC, the computational complexity becomes very much reduced compared to using MPC for lateral control. On the other hand, lateral control-management of steering and direction-is done by the Stanley controller, which is a simpler yet effective algorithm that minimizes path-following errors due to its geometric approach. The division of labour capitalizes on the strengths of both controllers in the creation of an efficient, highly effective system.

Implementation of the MPS model shows great improvements compared to the existing controllers. The proposed method had a speedier processing of data and higher path-following precision than the standalone MPC and Stanley controller, while the MPS model was benchmarked to perform better in stability and performance, with reduced lateral error, when compared with some commonly used controllers like PID and Pure Pursuit. It is especially suited for real-time applications in autonomous driving because of its ability to deliver these benefits with a minimum of computational overhead.

The study not only details the mathematical formulation of the MPS model but also tests its effectiveness through simulations and comparisons with other control systems. Results show that the MPS model outperforms the earlier models in the minimum tracking error and vehicle stability under a wide range of driving conditions.

5.1 CHAPTER SUMMARY

Chapter one: This chapter presents an overview of autonomous vehicles, Model Predictive Control, motivation for research, thesis objectives, and the problem statement. The game-changing factor in transportation is now autonomous vehicles with advanced technologies. Yet, they face challenges with environmental uncertainties and regulatory issues. Model Predictive Control is a strong control strategy for trajectory tracking and obstacle avoidance, though its computational complexity remains a challenge for real-time applications. This work is motivated by the weaknesses that various control strategies face due to a dynamic and uncertain environment. Therefore, the goal of the thesis was to improve MPC frameworks so that the performance and adaptability in real-time applications for autonomous systems become much better. Investigation into current limitations, developing a superior MPC framework, and simulation validation can provide potential research toward increasing the reliability and efficiency of the AV control system to fill major gaps in the existing approaches.

Chapter two: The chapter covers the basics, levels of automation, state-of-the-art development, and types of controllers used in autonomous vehicles. It also introduces a historical and technological context of autonomous systems, classifying different levels of automation from Level 0, No Automation, to Level 5, Full Automation, each characterizing advancement in the stages of technological sophistication and independence. State of the art summarizes recent advances in the sensor systems, decision-making algorithms, and real-world deployment that address scalability and reliability issues. It compares different control models, simplicity of the PID Control Model, path following ability by the Pure Pursuit Control Model, accuracy by Stanley Controller, and multivariable handling ability by the Model Predictive Controller despite being computationally demanding. By incorporating these elements, the chapter provides a solid foundation for comprehending how autonomous vehicle operations are conducted and sets the stage for further analysis and creativity in the thesis.

Chapter three: The chapter herein comprises the MPS methodology for autonomous vehicle systems and simulation and coding information, e.g., design and development of the MPS framework with emphasis on mathematical modelling, optimization problem formulation, and constraint handling techniques in customizing MPC to real time and alleviating issues of computational efficiency and environmental uncertainties. The simulation chapter presents the tools, platforms, and situations utilised in confirming the performance of the controller in terms of tracking trajectories and avoiding obstacles through dynamic decisions. It therefore gives the relative strengths and weaknesses of the controller. In the implementation chapter, the focus shall be the realization of the MPS framework by means of using programming languages, libraries, and algorithms; further, code optimizations for runtime execution are also considered as well as integration issues with simulation environments. Together, the chapter is a comprehensive account of the methodological, simulation, and implementation efforts underpinning the thesis, while setting the stage for results and analysis to be discussed in later chapters.

Chapter four: The discussion and result carried out in this chapter are done based on simulation and programming terms, mirroring the way the developed MPS framework is carried out. Simulation outcomes from Simulink and other software will be analysed to discuss the applicability of the framework in trajectory tracking, obstacle avoidance, and decision-making in dynamical circumstances, with the focus on highlighting such critical performance metrics as accuracy, computational efficiency, and robustness. The chapter analyzes the results in relation to research objectives, comparing actual performance with theoretical expectations and benchmarks available while elaborating on strengths, weaknesses, and areas of improvement. Implementation issues and possible solutions are also addressed, thus comprehensively evaluating the MPS framework while laying the foundation for conclusions and recommendations for potential improvements.

Chapter five: The aim of this chapter is to summarize the key results obtained during this thesis, outline the research contributions, and point out further works. This has been a successful development and validation of the MPS framework concerning real-time computation challenges within an autonomous vehicle system using both simulation and coding implementations. Contribution to the development of technology in autonomous vehicles through optimization of control strategy for practical applicability. Future work will be devoted to the integration of the MPS framework with more complex environmental models, including machine learning techniques to enhance decision-making and testing of the MPS framework on real-world autonomous vehicle prototypes, to extend the impact and applicability of the research to remaining open challenges in the field.

5.2 CONTRIBUTIONS OF THESIS

In the context of autonomous vehicle control systems, the contributions of the thesis are stated in more detail below.

i. Design of a New Hybrid Controller by Merging Vehicle Kinematics

This research utilizes vehicle kinematics to develop a novel hybrid controller, incorporating the best aspects of the Stanley controller and Model Predictive Control, MPC, for path-following applications. In this paper, an approach is proposed where most of the work will be focused on kinematics rather than complex dynamic modelling, ensuring that this controller is computationally efficient and capable of achieving high levels of accuracy in tracking a reference path. This innovative design meets the critical challenges found in autonomous driving: stability and minimal tracking error, even when faced with dynamic or challenging environments.

ii. Integration of Stanley Controller into MPC with Task Division

The Stanley controller is integrated into the MPC framework, where every controller has unique duties depending on their ability to create a strong and effective control system. Longitudinal control-MPC is responsible for the speed and acceleration of the vehicle through its predictability and optimization over a horizon time. The Stanley controller, however, controls the lateral control involved in steering and directional adjustment due to its simplicity and effectiveness in eliminating lateral errors. This division of labour enables a proper balance between computation efficiency and control performance so that the system can become suitable for real-time autonomous driving applications.

iii. Introduction of Unique Combination of Two Well-Known Controllers

This is the first research representing two of the most widely recognized controllers: Stanley and MPC, combined for the first time into one hybrid system for autonomous vehicles. While both controllers have been used individually in the field, their combination into one in a framework is virgin. This combination will effectively enable the hybrid controller to tap into the strengths of predictive optimization from the MPC while leveraging the simplicity and reliability of the Stanley controller, hence making the system more flexible and powerful than would controller in operation.

iv. Presentation of a Mathematical Model for the Proposed Controller

The paper presents the mathematical formulation of the hybrid controller developed in detail. It includes an elaborative explanation of how two controllers will be integrated, the sharing of responsibilities, and how the system calculates control actions. The mathematical model forms a basis for understanding the operations of the controller and analysing its performance; thus, it is highly useful for researchers and engineers working in the domain of autonomous vehicle systems.

v. Implementation and Validation of the Proposed Controller

This study presents an experimental validation of the proposed hybrid controller along with benchmarking its performance against existing systems. Experimental results show that the MPS model offers improved performance in terms of path-following accuracy, vehicle stability, and computational load. It offers measurable improvements over other control systems, including solo MPC, Stanley, PID, and Pure Pursuit controllers, thus confirming its efficacy and usability. These promising outcomes allow the MPS model to have the potential of setting new standards for autonomous vehicle control.

5.3 FUTURE WORK

Looking ahead, we have ambitious plans to refine the MPS model to really test its mettle and utility. The use of more advanced AI techniques within the MPS architecture is one promising direction for future research. With the integration of AI, the controller would be able to deal with constraints in a much more elegant and dynamic way, such that it is able to generalize to very complex and unexpected driving scenarios. Thus, this would facilitate the development of control strategies that, apart from being smarter, also learn and improve with experience to continue optimizing an autonomous vehicle's performance. Next, in addition to all of the above developments, a very significant step forward is the verification of the MPS model in real-world conditions by implementing it on an actual autonomous vehicle.

This phase of testing is highly needed to bridge the gap between theoretically achieved improvement and practical applications. It would offer very valuable insights into the performance of the controller under real driving conditions, including road, traffic flow, and climatic conditions. This will not only confirm the robustness and reliability of the MPS model but also identify areas of improvement and optimization needed. For this purpose, the research team would like to contribute considerably to the advancement of next-generation autonomous driving systems. This should be reflected in unprecedented precision, stability, and adaptability for these systems to be ever closer to the fully autonomous vehicle capable of negotiating complex traffic with safety and efficiency without any human intervention. Integration of AI and real-world testing forms a critical phase of transformation of the theoretical promise of the MPS model into a practical, impactful solution for the cause of autonomous mobility.

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APPENDIX A

APPLYING THE CONTROLLERS ON A CIRCLE PATH

A.1 CIRCLE PATH TRACKING DESIGN

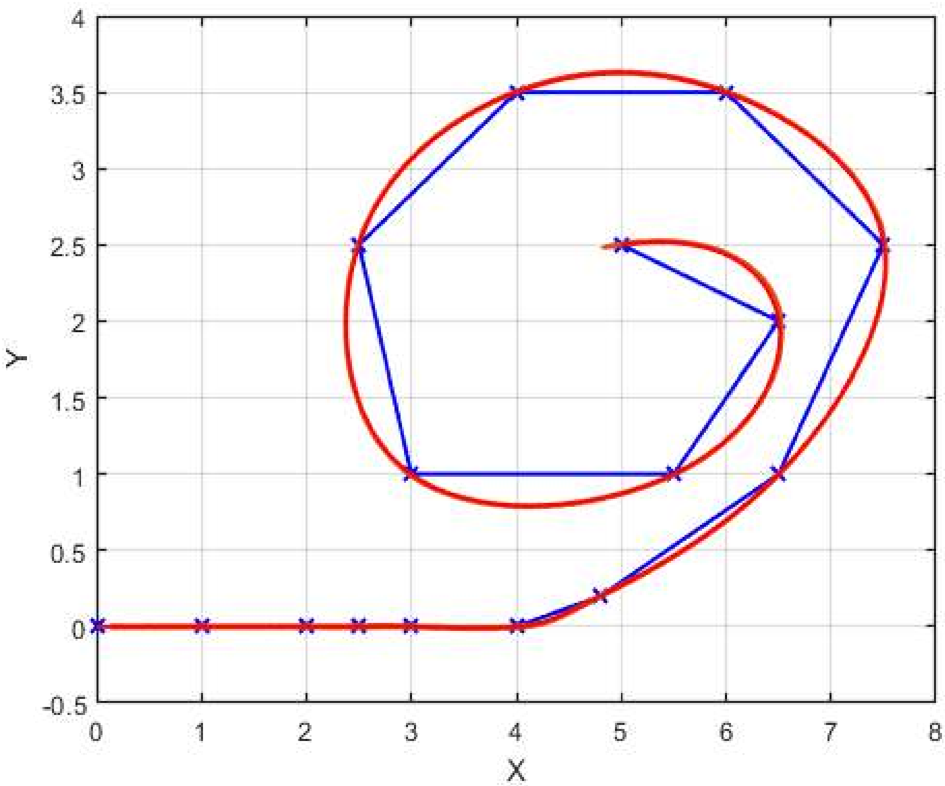

Figure A.1: Circle Path Tracking Design.

A.2 APPLYING MPS ON CIRCLE PATH TRACK

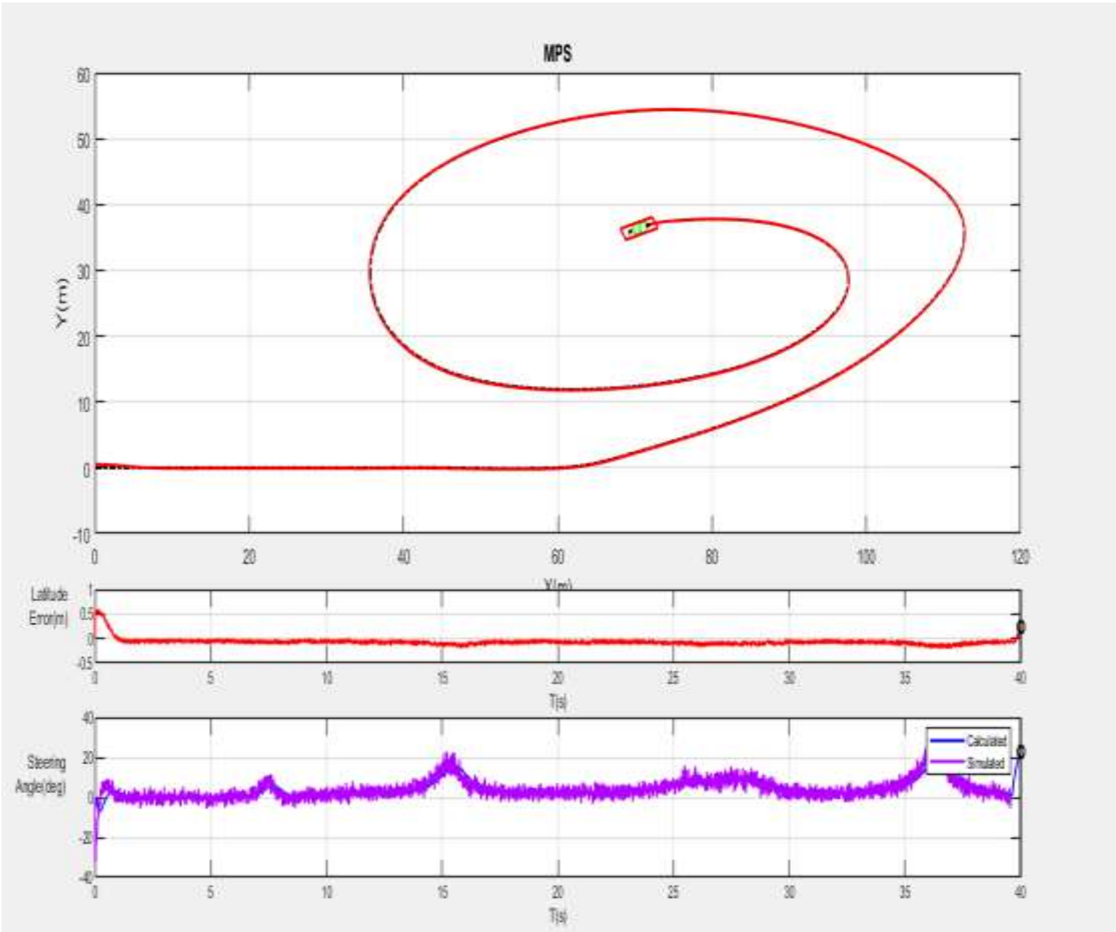

Figure A.2: Applying the MPS Controller on a Circle Path Track.

A.3 APPLYING PURE-PURSUIT ON CIRCLE PATH TRACK

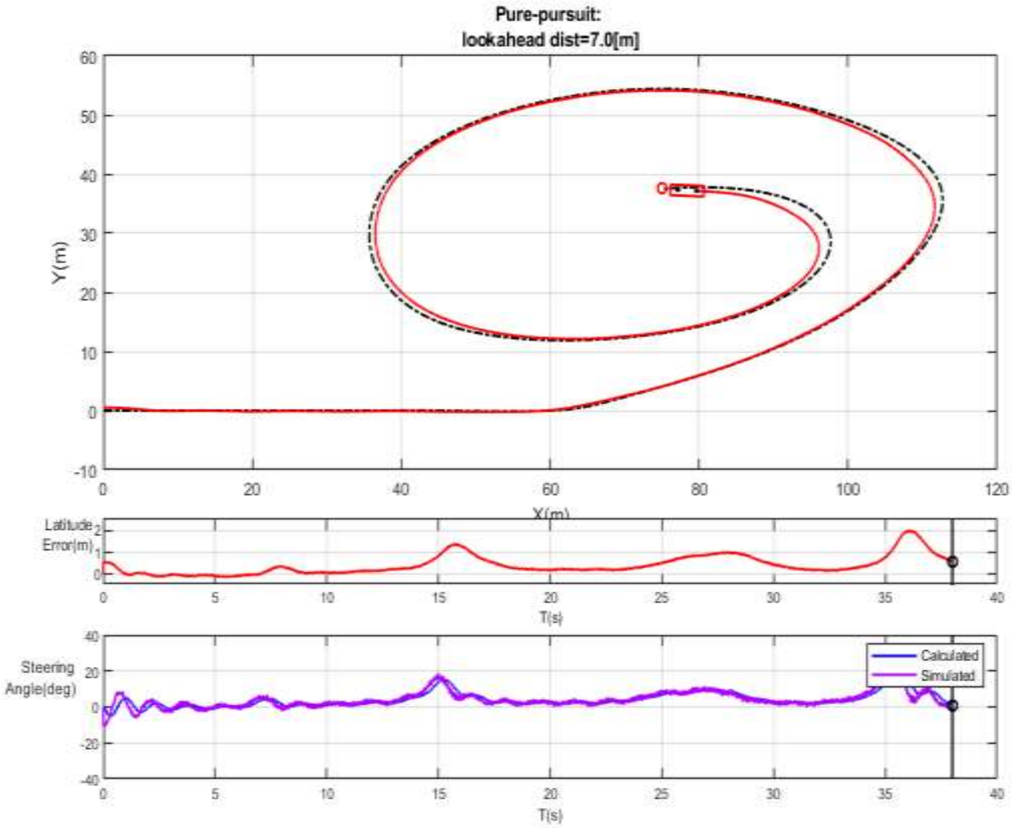

Figure A.3: Applying the Pure-Pursuit Controller on a Circle Path Track.

A.4 APPLYING PID ON CIRCLE PATH TRACK

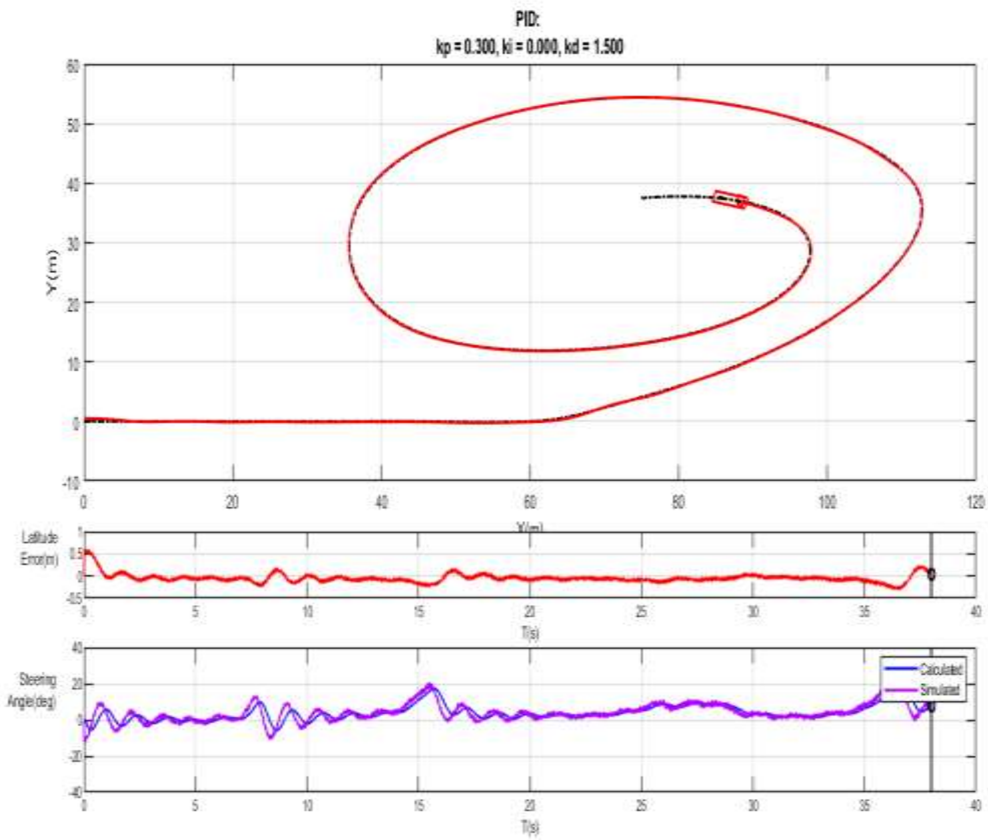

Figure A.4: Applying the PID Controller on a Circle Path Track.

A.5 APPLYING MPC ON CIRCLE PATH TRACK

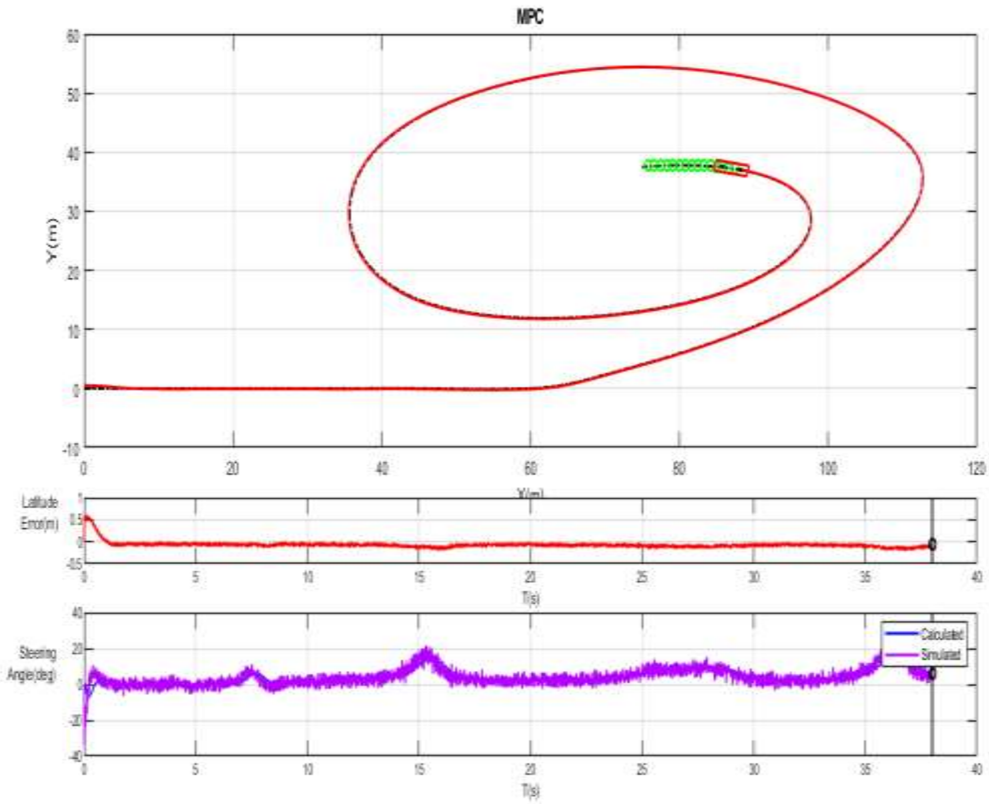

Figure A.5: Applying the MPC Controller on a Circle Path Track.