Comparative Vehicle Stability Analysis of Indoor RC Vehicle Using Control Techniques

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ABSTRACT

Autonomous and robotic vehicle systems depend heavily on vehicle stability control to maintain performance, safety, and maneuverability under changing circumstances. Three popular control methods—Proportional-Integral-Derivative (PID), Linear Quadratic Regulator (LQR), and Model Predictive Control (MPC)—applied to an indoor robotic vehicle are compared in this work in order to compare stability control. Key vehicle factors such as mass, yaw inertia, centre of gravity (CG) distribution, and front and rear tire cornering stiffness are taken into account in the research to assess their impact on vehicle dynamics. Yaw rate, slip angle, steering angle, and velocity are all controlled by each control method, and tracking accuracy, response time, and control effort are used to evaluate performance. MPC uses predictive optimization for improved performance, LQR maximizes stability through state feedback, and PID control offers a straightforward yet efficient approach. Graphical depictions and simulation results show the advantages and disadvantages of each strategy for preserving vehicle stability. The results aid in the creation of effective control schemes for self-driving robotic cars, allowing for increased stability and versatility in practical applications.

Key words: Vehicle stability Control, Proportional- Integral-Derivative, Linear Quadratic Regulator, Model Predictive Control, Self driving robotic cars.

I. INTRODUCTION

A vehicle's stability is crucial for both performance and safety, especially while driving in hazardous situations like tight corners, slick roads, or fast maneuvers. The capacity of a vehicle to move in a controlled manner without losing traction, sliding, or flipping is known as vehicle stability.

Vehicle stability has significantly improved over the last few decades because to developments in control strategies and vehicle dynamics. In order to improve safety and guarantee stability in a range of driving situations, contemporary automobiles are outfitted with a number of active and passive control systems. This paper examines the various vehicle control techniques used for stability analysis, including model- based methods, feedback control strategies, and real-time adaptive algorithms. The main goal of vehicle control techniques for stability analysis is to assess and mitigate the risks of instability, such as over-steering or under- steering, loss of traction, and rollover accidents. These techniques are based on understanding the vehicle's dynamic response to external forces and implementing control algorithms that adjust parameters like steering, braking, and acceleration in real-time. The introduction of advanced driver assistance systems (ADAS) and electronic stability control (ESC) has greatly increased the accuracy and efficacy of these techniques. Additionally, covered is how improving control efficacy may be achieved through the use of simulation tools, vehicle modelling, and sensor integration. This study attempts to support continuing research efforts to create safer, more dependable vehicle systems by analyzing the most recent developments in vehicle stability control.

II. LITERATURE SURVEY

The study introduces a hybrid control approach that enables autonomous cars to execute stable and seamless lane-changing movements at high speeds by combining four-wheel steering (4WS) with model predictive control (MPC). To provide precise and reliable control of the rear-wheel steering angle, the suggested method integrates sliding mode control and employs a two-degree-of-freedom (2DOF) ideal model as the path- tracking response model. According to the testing results, the MPC-4WS hybrid controller reduces the maximum error with respect to the reference route by around 0.553 m, outperforming the standalone MPC controller in terms of path-tracking precision and stability. In high- speed situations, the hybrid control approach successfully increases the safety and agility of self-driving cars. [1]

A model predictive controller (MPC) for four- wheel steering (4WS) vehicles travelling at high speeds is presented in this work. The suggested controller transforms the dynamic stability area based on vehicle speed into restrictions on the vehicle states and is based on a three-degree-of-freedom vehicle dynamic model. Simulations on a double lane-change road in the CarSim- Simulink environment are used to verify the DSR-MPC controller's efficacy. The findings demonstrate that, particularly at high speeds where a conventional MPC controller is unable to keep the vehicle states inside the stability zone, the DSR-MPC controller may successfully improve vehicle stability without sacrificing route tracking performance. The report also explores how 4WS cars' greater steering capability under speed may lead to their widespread adoption in the future. [2]

For unmanned surface vehicles (USVs), this study suggests a hybrid heading control frame work that combines an enhanced Beetle Antennae Search–Particle Swarm Optimization–Simulated Annealing (BAS-PSO- SA) optimization algorithm with a variable domain fuzzy Proportional–Integral–Derivative (VUF-PID) controller. The main improvements include an asymmetric learning factor that strikes a compromise between local refinement and global exploration, a weighted adaptive optimization technique that minimizes parameter tuning iterations, and a self-tuning VUF mechanism that enhances disturbance rejection. When compared to traditional techniques, the suggested framework exhibits notable gains in control accuracy, dynamic responsiveness, and energy economy, satisfying the IMO heading control requirements.

Future developments to further advance autonomous navigation systems for intricate marine operations are also included in the paper, including FPGA acceleration and MPC-based time delay correction. [3]

The multi-model predictive control (MMPC) approach for a four-wheel-drive electric car with four hub motors is presented in this study. In a variety of driving situations, including emergency obstacle avoidance maneuvers, unexpected component failures, and dangerous external surroundings, the suggested control strategy is made to guarantee that the vehicle can swiftly meet the minimal safety criteria. Conventional control techniques may not be able to guarantee vehicle accuracy and stability due to the complicated nonlinear dynamics of electric cars, which lead to significant model uncertainties. To manage this, the MMPC technique integrates many model predictive controllers. Nonlinearities and uncertainties, enabling the car to be more effective in dangerous driving situations. The outcomes of the simulation validate that the suggested method is successful. [4]

The electronic stability control (ESC) system, a cutting-edge active safety technology for contemporary automobiles, is covered in the paper. ESC's control method successfully improves vehicle stability by combining logic gate and PID control. Logic gate control generates the PID parameters, and the PID technique outputs the wheel braking torque to maintain vehicle stability. This method speeds up calculation while reducing the computing process. The suggested control method may be utilized to drive the vehicle more steadily under a variety of circumstances, according to simulation data. Matlab/Simulink and Stateflow are used to build the control strategy model, while AMESIM is used to build the vehicle and hydraulic models. The AMESIM and Simulink interface is used to implement the combined simulation. {5}

In order to enhance overall vehicle performance and stability in emergency handling scenarios, the paper addresses the integration of electronic chassis control systems, particularly the Electronic Stability Control (ESC) and Continuous Damping Control (CDC) systems. A simulation environment and many integration methods that were created and evaluated are presented in the article. The findings demonstrate that the integrated chassis control system can perform better than ESC by itself as well as an algorithm that combines ESC and CDC. [6]

The significance of vehicle motion stability control (VMSC) and the impact of unstable zero dynamics on vehicle stability are covered in the paper. To increase motion stability, the authors suggest a cooperative control technique that employs a linear combination of sideslip angle and yaw rate as the control output. Even with some vehicle motion controllers engaged, the vehicle may begin to spin and slide sideways under certain circumstances, as shown by the study of the zero dynamics. The authors demonstrate the efficacy of their suggested approach with simulation and experimental data. [7]
The proposed time-varying control-dependent barrier function (CDBF) is more general than conventional control barrier functions (CBFs) because it considers invariant sets that can be both time- varying and control-dependent. The authors design a vehicle stability control algorithm that ensures the vehicle states are always kept within the time-varying and control- dependent lateral stability regions. The accuracy and efficacy of the proposed theory and control method are verified through simulation results of high-speed J-turn and double lane change maneuvers for an autonomous ground vehicle. [8]

In order to minimize noise and inaccuracies in Inertial Measurement Unit (IMU) data, the research proposes a technique for enhancing indoor vehicle navigation that combines digital filtering with Kalman filtering. Over a distance of 17 meters, the suggested method yields a maximum position error of just 1.1%, as opposed to 18% when utilizing the Kalman filter alone. The technique was evaluated both online and offline, and the outcomes show that it outperforms earlier methods in terms of less mistakes and less computing complexity, which qualifies it for real-time deployment. The study highlights the significance of improving position estimation for indoor navigation without the use of an extra position sensor and reducing IMU acceleration data inaccuracies. [9]

Through the use of Vehicle-to-Vehicle (V2V) communication—more especially, the DSRC protocol, which permits the exchange of alarm messages in the event of emergencies like accidents—this initiative seeks to link automobiles and avoid collisions. In order to address problems like traffic congestion and wasteful resource consumption in urban transportation,V2V and Vehicle-to-Infrastructure (V2I) technologies are essential parts of Intelligent Transportation Systems (ITS) and the Internet of Things (IoT). By tackling dynamic issues like traffic flow and congestion, V2V and V2I technologies are essential for increasing transportation efficiency.

While expanding infrastructure may be helpful, it is often expensive in terms of time and resources. However, applications based on data collected from vehicles, such as safety, traffic management, pollution monitoring, and tourism, can improve overall transport systems. Autonomous vehicles are controlled by the CARLA simulation platform, which converts ROS (Robot Operating System) commands for steer and speed values into CARLA-compatible throttle and steering data. While proportional gains are used for basic control, a PID controller provides a more reliable way to maintain desired vehicle speed. The vehicles in this project are connected within a 300-meter radius, and alert systems are triggered in case of emergencies. Low-latency message transfer, which is more effective than cellular or Wi-Fi connectivity, is made possible via V2V communication. These experiments' outcomes have been examined. Autonomous vehicles (AVs) are developing quickly and have a big chance to lower transportation expenses. According to estimates, AVs can save up to 1,40,000 INR a year per car, with a larger impact that might reach 2,80,000 INR when crash expenses are taken into account. Autonomous cars may eventually provide independent services to elderly people, children, and those with disabilities. [10]

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III. METHODOLOGY

Using the bicycle model, this paper develops a vehicle dynamics framework for analyzing steering reactions, yaw rate, slip angle, and velocity using state-space equations and nonlinear tire force models. Simulations demonstrate how front/rear stiffness ratios and inertial qualities determine stability thresholds and transient behaviors. It is demonstrated that critical parameters—mass, yaw inertia, CG location, and cornering stiffness—control under steer/over steer inclinations via the under steer gradient KKK. Vibration-dependent slip angles, yaw rate resonances, and nonlinear saturation effects are described numerically and confirmed by case studies showing handling changes caused by parameters. The approach quantifies the effects of design parameters on dynamic reactions under various operating situations, providing prediction tools for assessing stability margins and optimizing electronic stability control (ESC) systems. Based on the comparison of the data, we examine different control strategies including PID, LQR, and MPC to enhance the vehicle's stability control.

These are the input parameters,

PARAMETERS	**VALUES**
Mass (*m*)	1500
Yaw inertia (*Jz*)	2500
a/*b*	1.2/1.5
*Cα*1,*Cα*2	100000kN/rad,100000kN/rad

PID CONTROLL TECHNIQUE

The algorithm's three primary modes— proportional, integral, and derivative—are implied by the name Proportional-Integral-Derivative (PID) controller. The output signal is directly proportional to the controller input (in this case, the error signal) thanks to the proportional action. Here, the controller gain KP is the variable. An offset between the actual and ideal will always exist since a proportional controller lessens error but does not completely remove it. In order to remove this offset, integral mode is employed. The controller's TI, or integral time, is the variable in this case. Last but not least is the derivative mode, which predicts by examining the controlled variable's rate of change over time. Derivative action can be changed by varying the rate time, or TD.

$$u_t = K_P\left(e_t + \frac{1}{T_I}\int e_t\,dt + T_D\frac{de_t}{dt}\right)$$

We must discretize the preceding equation using the rectangular integration method to replace the integration term and the backward difference method to replace the derivative term in order to compare it with alternative approaches. In order to improve stability, maneuverability, and general safety, proportional-integral-derivative (PID) control is applied in vehicle dynamics. This study investigates the use of a PID controller to control important dt

vehicle parameters like steering responsiveness, yaw rate, and slip angle in response to inputs like mass, yaw inertia, center of gravity (CG) distribution, and the front and rear tires' cornering stiffness. In order to get the best handling performance, the system adjusts the PID gains to reduce departures from the intended vehicle behavior. According to simulation studies, PID-based steering control is effective at lowering instability and enhancing reaction to outside disturbances. The outcomes can be seen below.

LQR Control Technique

The goal of optimal control theory is to run a dynamic system as cheaply as possible. The LQ problem is the situation in which a quadratic function describes the cost and a set of linear differential equations describes the dynamics of the system. The linear-quadratic regulator (LQR) provides the solution, which is one of the theory's primary conclusions.

A mathematical technique that optimizes a cost function with weighting factors required is used to determine the settings of a (regulatory) controller that governs a machine or process (such as an airplane or chemical reactor). A cost function is a function that, intuitively, represents some "cost" connected to an event or the values of one or more variables on a real number. The total of the variations of important measurements, such as altitude or process temperature, from their intended values is a common definition of the cost function. By using an algorithm, the controller settings that minimize unwanted deviations are found. The cost function may also take into account the size of the control action itself. It is also distinguished by the horizon, which is finite in reality but limitless in theory. Examine the system's discrete time state space model.

Finite horizon LQR
For a continuous-time linear system , define don't $\epsilon[t0,t1]$,described by: $\dot{x}=Ax+Bu$

With a quadratic cost function defined as: $J=x^T(t_1)F(t_1)x(t_1)+\int t_0 t_1(x^TQx+u^TRu+2x^TNu)dt$ the feedback control law that minimizes

the value of the cost is:

$u=-Kx$
where K is given by: $K=R-1(B^TP(t)+N^t)$

By minimizing a cost function that strikes a balance between control effort and system performance, the Linear Quadratic Regulator (LQR) approach is frequently employed in vehicle dynamics control to maximize stability and maneuverability. The center of gravity (CG) distribution between the front and rear axles, mass, yaw
$A^TP(t)+P(t)A-(P(t)B+N)R-1(B^TP(t)+N^T)+Q=-P(t)$
With boundary condition, $P(t\ )=F(t\ )$.
inertia, and the cornering stiffness of the front and rear 1 1
tires are among the important vehicle parameters taken into account by this method. While CG distribution influences load transmission and handling characteristics, mass and yaw inertia dictate the vehicle's resistance to changes in motion. Both front and rear tires' cornering stiffness affects lateral force production and has a direct effect on understeer or oversteer tendencies. In order to obtain the required vehicle response with the least amount of control effort, LQR control optimizes state feedback gains to manage yaw rate, slip angle, steering angle, and velocity. In order to get the ideal gain values, the method solves the Riccati equation and creates a cost function based on state variables and control input.

By integrating real-time feedback, LQR successfully improves vehicle stability by dynamically modifying steering input, reducing deviations brought on by disruptions like abrupt turns or uneven roads. The controlled parameters (velocity, steering angle, slip angle, and yaw rate) are graphically represented to show how LQR stabilizes the system in contrast to an uncontrolled situation. This control strategy ensures improved safety and ride comfort and is especially helpful in applications involving driverless vehicles and advanced driver-assistance systems (ADAS). The results of the simulation are displayed and tabulated.

MPC CONTROLL TECHNIQUE

Recessing horizon control, another name for
Model Predictive Control (MPC), is a control approach that provides appealing solutions for the control of constrained linear or nonlinear systems and, more recently, hybrid systems.

MPC is an optimal control technique in which a limited finite horizon optimal control problem for the plant's present state at each sample period is solved to determine the control action. For a predicted evolution of the system model across a finite horizon, the order of optimal control inputs is calculated. The system's state is then measured once more at the subsequent sampling time, but just the first component of the control sequence is used.

By adding input to the system, the so-called Receding Horizon Strategy (RHC) makes it possible to compensate for any modeling errors or systemic disruptions. Either a linear problem (LP) or a quadratic problem (QP) can be used to formulate the LMPC. The goal of both formulations is to minimize a cost function. In MPC, the system model is crucial. The optimal control of nonlinear and uncertain systems in both continuous and discrete time is made possible by do-mpc. The system model for the continuous example is determined by,

$\dot{x}(t)=f(x(t),u(t),z(t),p(t),ptv(t))$,

$y(t)=h(x(t),u(t),z(t),p(t),ptv(t))$, and for the discrete-time

case by $xk+1=f(xk,uk,zk,pk,ptv,k)$,

$yk=h(xk,uk,zk,pk,ptv,k)$.

Accordingly, the systems' states are provided by x(t), xk, the control inputs by u(t), uk, algebraic states by z(t), zk, (uncertain) parameters by p(t), pk, time- varying (but known) parameters by ptv(t), ptv,k, and measurements by y(t), yk.

For a continuous system, time is represented by t, and for a discrete system, time steps are represented by k.

Model Predictive Control (MPC), which forecasts future states and modifies control inputs accordingly, is a potent control technique used in vehicle dynamics to maximize stability, handling, and overall performance. Important vehicle factors like mass, yaw inertia, the distribution of center of gravity (CG) between the front and rear axles, and the cornering stiffness of the front and rear tires are all taken into account by this method. The vehicle's resistance to changes in motion is influenced by mass and yaw inertia, whereas stability and weight transfer are affected by CG distribution. Determining the lateral force generated for both the front and back tires, cornering stiffness affects the vehicle's propensity to understeer or oversteer.
In contrast to conventional controllers, MPC predicts future vehicle behavior by minimizing a cost function that strikes a compromise between tracking performance and control effort, and by solving an optimization problem over a constrained prediction horizon. To provide improved stability and responsiveness, MPC appropriately modifies the steering angle to control yaw rate, slip angle, and velocity by continually updating the control input based on real-time measurements. Visual depictions of these regulated parameters—velocity, steering angle, slip angle, and yaw rate—show how well MPC maintains vehicle stability in a range of driving scenarios. MPC's predictive nature makes it popular in applications for autonomous vehicles and advanced driver-assistance systems (ADAS). It provides better performance in dynamic conditions by instantly responding to driver inputs and road disturbances. Below is a display and tabulation of these simulation results.

RESULTS

There was a simulation of the several control methods. Prior to hardware implementation, the design's functionality, performance, and efficiency were to be confirmed. Values are tabulated after a wave-form analysis of the simulation's outcomes.

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.0	
SLIP ANGLE	0.0	0.0	0.00	0.00	0.00	0.00	0.00	0.00	-2.0	

Table-1a-Silp angle value of input parameters

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.0	
YAW RATE	0.0	0.0	0.00	0.00	0.00	0.00	0.00	0.00	-1.49	

Table-1b-Yaw rate value of input parameters

TIME	0	1	2	3	4	5				
VELOCITY	15	16	17.5	18	19	19.8				

Table-1c-Velocity value of input parameters

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.0	
STEERING ANGLE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-14	

Table-1d-Steering angle value of input parameters

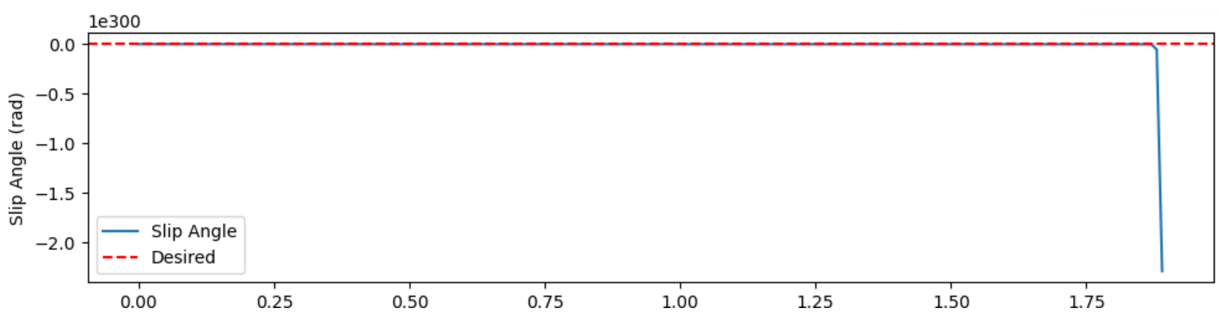

Fig-1-a –Slip VS Time

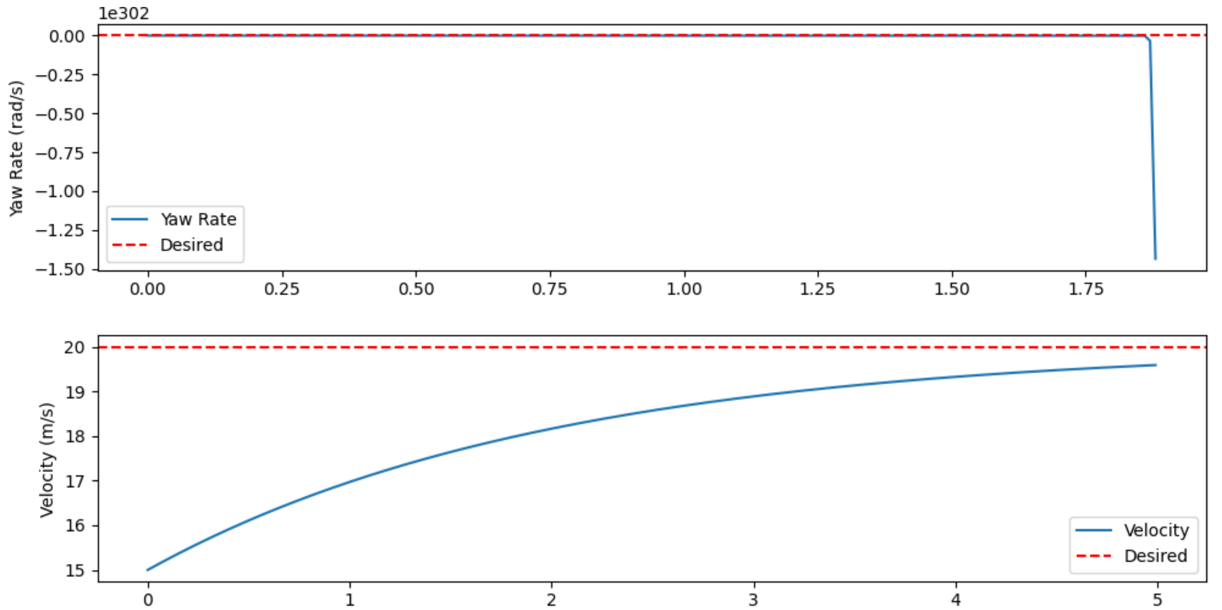

Fig-1-b –Yaw rate Vs Time & 1 c Velocity Vs Time

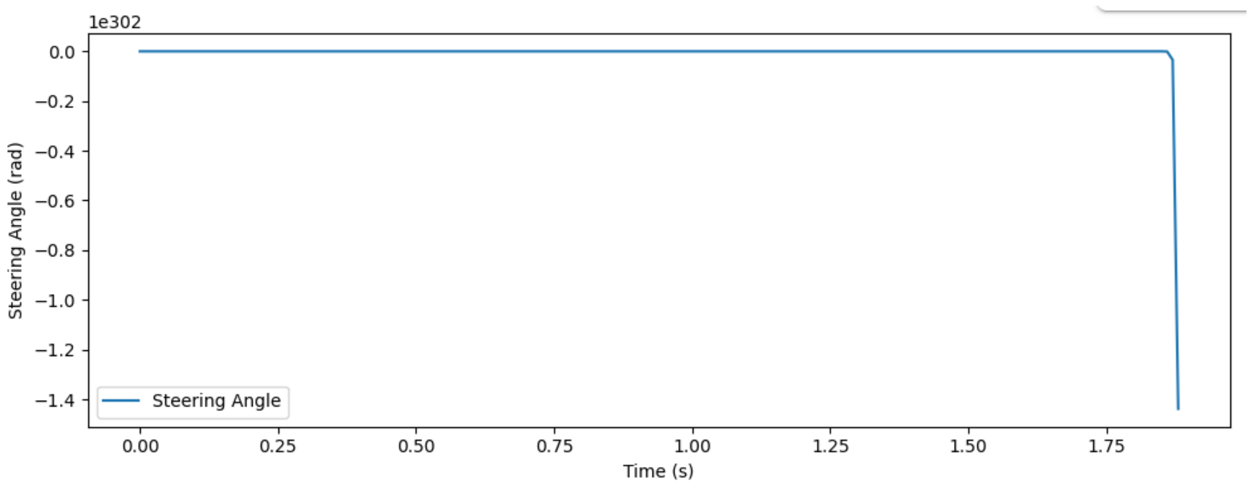

Fig-1-d–Steering angle Vs Time

PID

The values obtained by using PID control technique for indoor autonomous technique and the graphs are showed in below.

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.0	
SLIP ANGLE	0.0	0.0	0.00	0.00	0.00	0.00	0.00	0.00	2.5	

Table-2a-Silp angle value using PID control technique

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.0	
YAW RATE	0.0	0.0	0.00	0.00	0.00	0.00	0.00	0.00	2.0	

Table-2b-Yaw rate value using PID control technique

TIME	0	1	1.5	2	2.5	3	4	4.2	5	
VELOCITY	15	16	17.5	18	18.5	19	19.8	20	20.4	

Table-2c-Velocity value using PID control technique

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	2.0	
STEERING ANGLE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-6	

Table-2d-Steering angle value using PID control technique

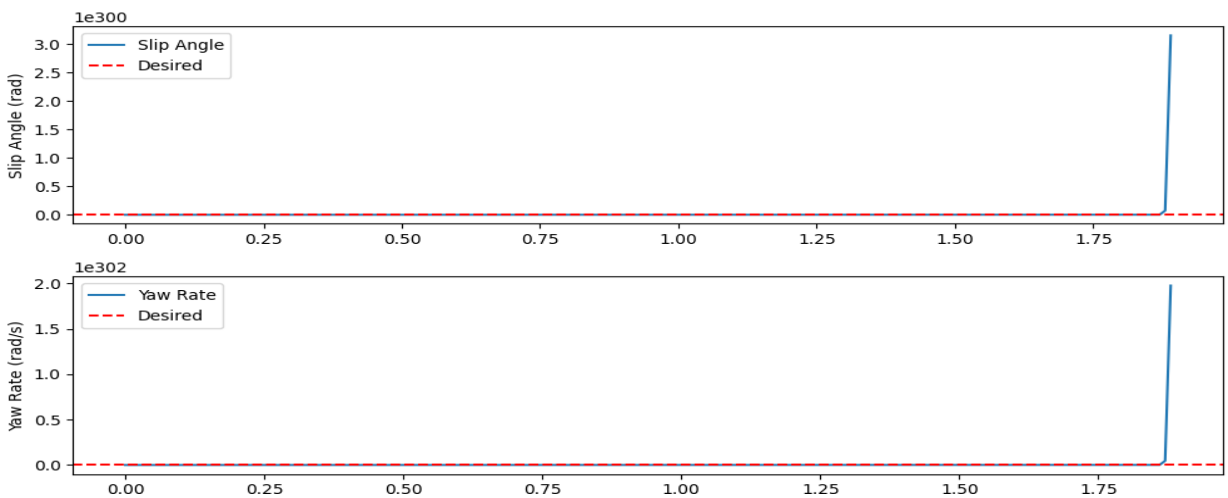

Fig- 2(a) &2(b)- Slip rate Vs Time & Yaw rate Vs Time

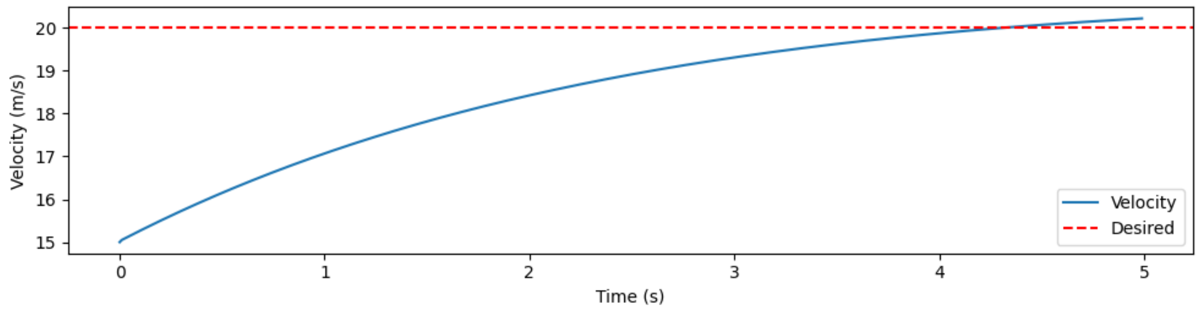

Fig- 2(c)- Velocity Vs Time

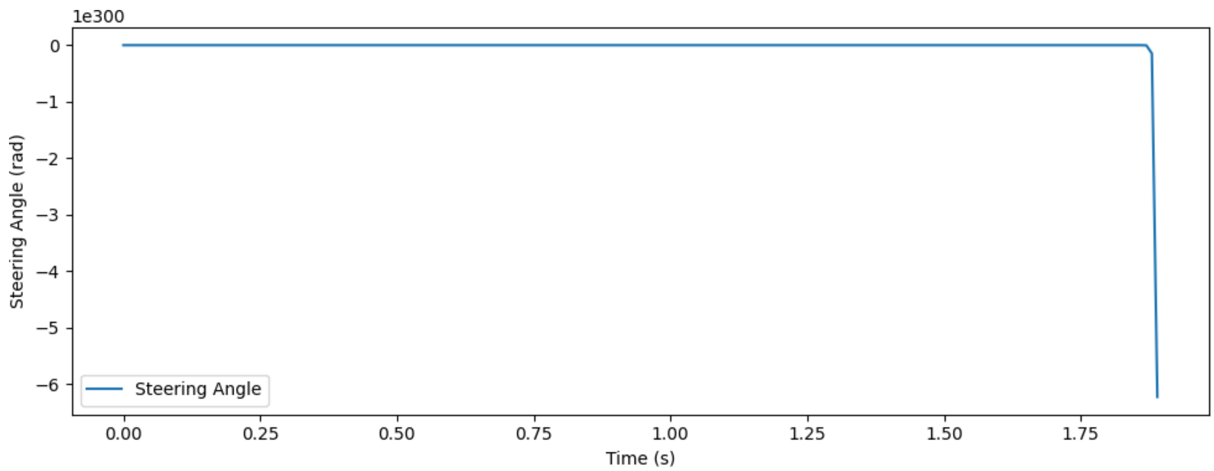

Fig- 2(d) – Streeing angle Vs Time

Above figure 2(a),2(b),2(c),2(d) infers the comparative analysis desired value with slip angle ,yaw rate, velocity and steering angle respectively.

LQR

The values obtained by using LQR control technique for indoor autonomous vehicle and the graphs are showed in below.

TIME	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.1
SLIP ANGLE	0	0	0	0	0	0	0	0	0	0.9

Table-3a-Silp angle value using LQR control technique

TIME	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.2
YAW RATE	0	0	0	0	0	0	0	0	0	0.19

Table-3b-Yaw rate value using LQR control technique

TIME	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.2
VELOCITY	0	0	0	0	0	0	0	0	0	1

Table-3c-Velocity value using LQR control technique

TIME	0.0	0.5	1.0	1.5	2.0	2.5	3.0	3.5	4.0	4.2
STEERING ANGLE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.98

Table-3d-Streering angle value using LQR control technique

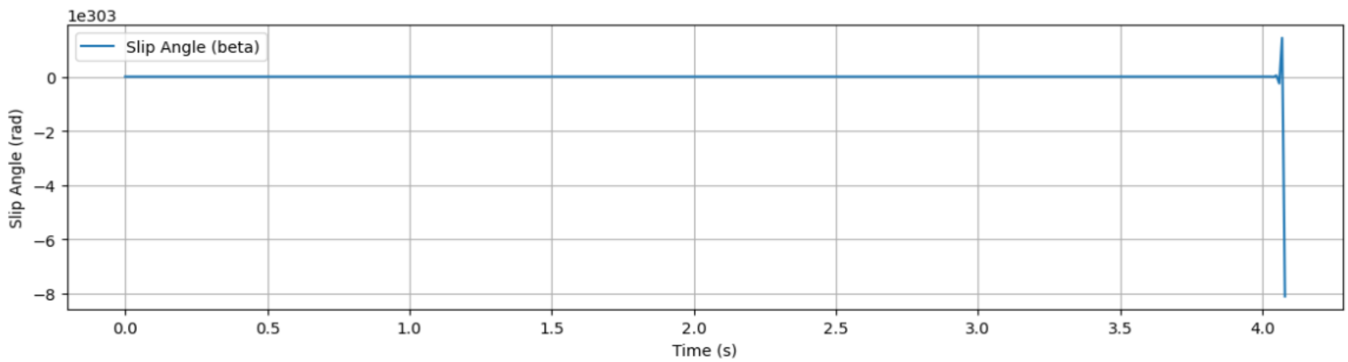

Fig- 3(a) – Slip angle Vs Time

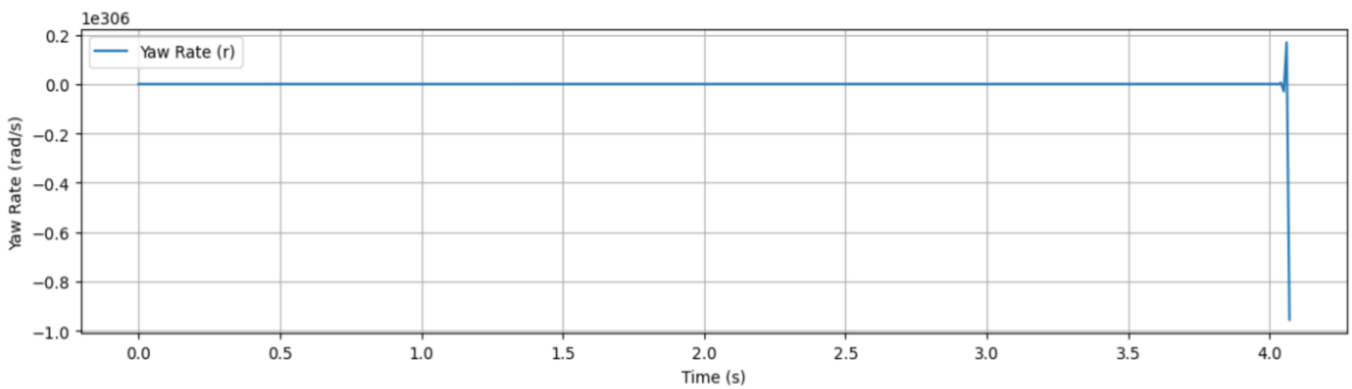

Fig- 3(b) – Yaw rate Vs Time

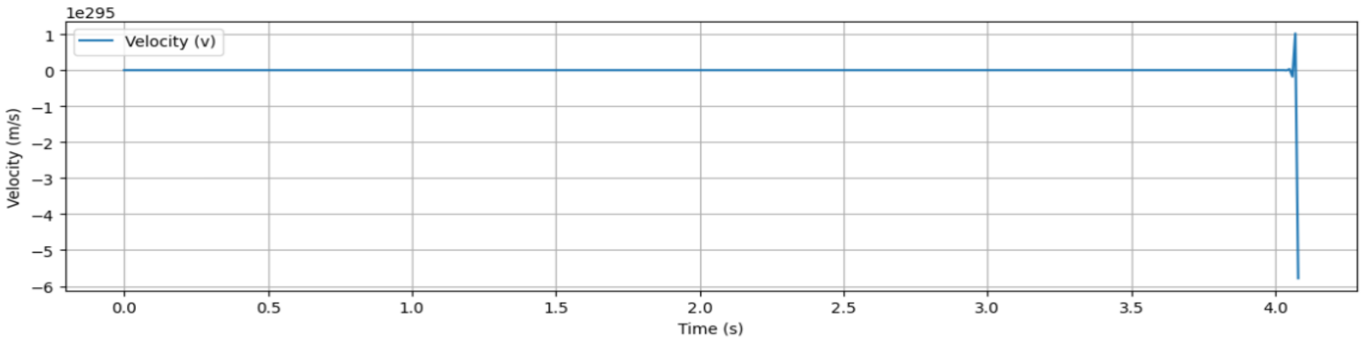

Fig- 3(c) – Velocity Vs Time

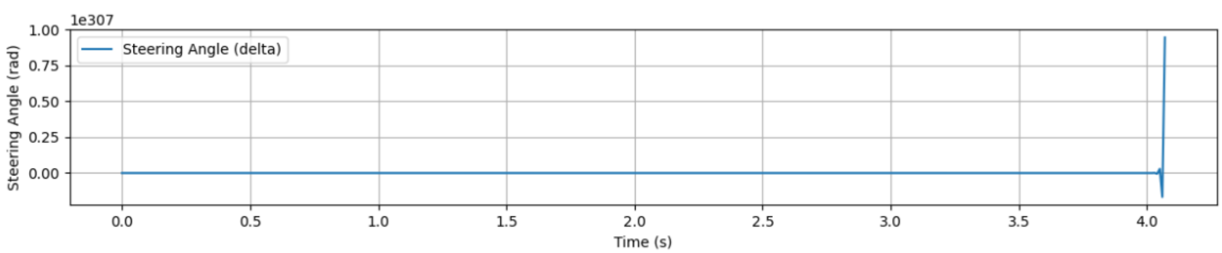

Fig- 3(d) – Streeing angle Vs Time

Above figure 3(a),3(b),3(c),3(d) infers the comparative analysis desired value with slip angle ,yaw rate, velocity and steering angle respectively.

MPC

The values obtained by using MPC control technique for indoor autonomous vehicle and the graphs are showed in below.

TIME	0.00	0.25	0.50	0.75	1.00	1.25	1.50	1.75	1.98	
SLIP ANGLE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.18	

Table-4a-Silp angle value using MPC control technique

TIME	0.0	0.25	0.50	0.75	1.00	1.25	1.50	1.75	1.98	
YAW RATE	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.2	

Table-4b-Yaw rate value using MPC control technique

TIME	0	1	2	3	4	5				
VELOCITY	15	15	15	15	15	15				

Table-4c-Velocity value using MPC control technique

TIME	0	1	2	3	4	5				
STEERING ANGLE	0.0	0.0	0.0	0.0	0.0	0.0				

Table-4d-Steering angle value using MPC control technique

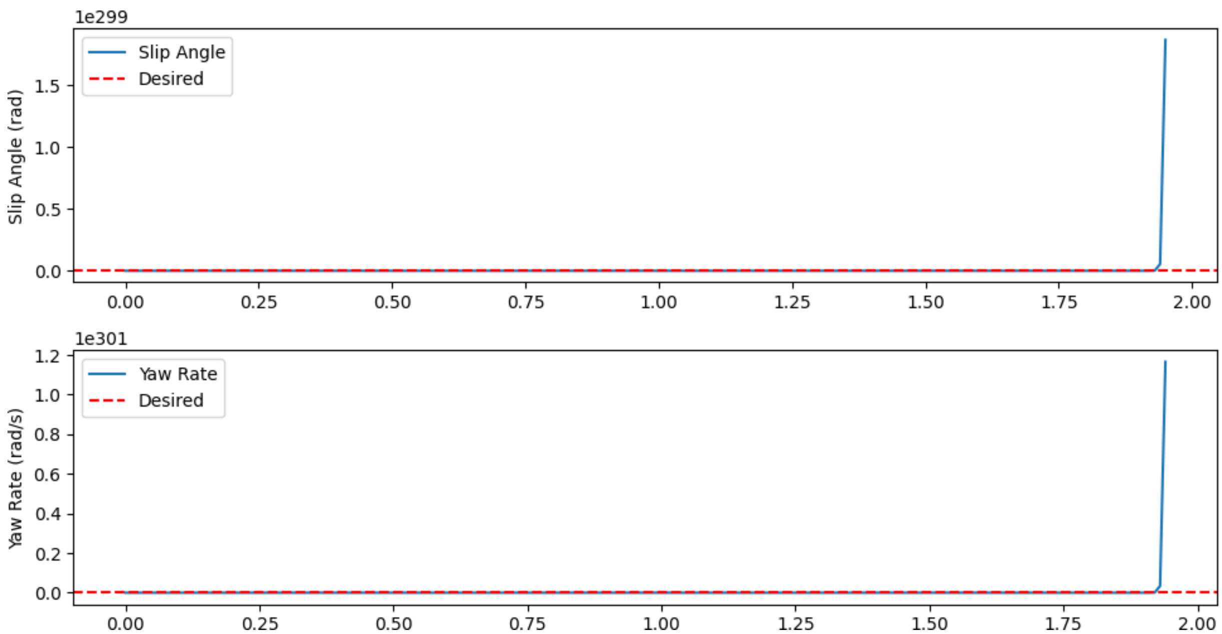

Fig- 4(a) &4(b)- Slip rate Vs Time & Yaw rate Vs Time

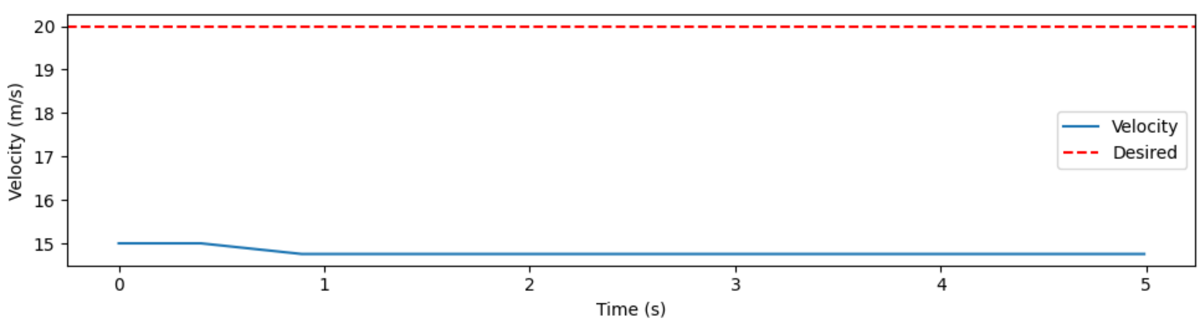

Fig- 4(c) – Velocity Vs Time

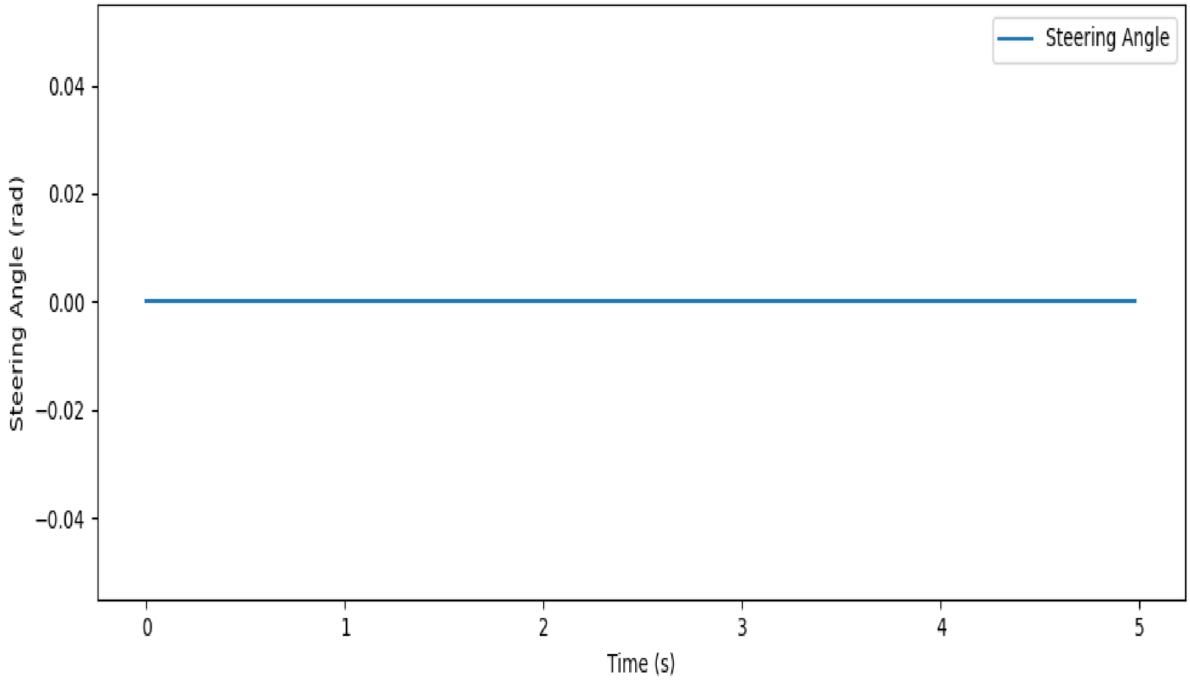

Fig- 4(d) – Steering angle Vs Time

Above figure 4(a),4(b),4(c),4(d) infers the comparative analysis desired value with slip angle ,yaw rate, velocity and steering angle respectively.

IV. CONCLUSION

The advantages and disadvantages of each method are highlighted by the comparison of PID, LQR, and MPC strategies for vehicle stability control in an indoor robotic vehicle. Despite being straightforward and simple to use, PID control has limits when it comes to managing intricate dynamics and outside disturbances. By minimizing a quadratic cost function, LQR improves stability and optimal state feedback, which increases its efficacy in attaining smooth and efficient control. By predicting future states and dynamically modifying control inputs, MPC—which makes use of predictive optimization—performs better, improving stability and

V. FUTURE SCOPE

flexibility in a range of scenarios. According to simulation results, MPC performs exceptionally well in predicting adaptability and constraint handling, while LQR provides superior stability and PID is appropriate for simple applications. The results indicate that system requirements determine which control approach is best, with MPC being the most reliable for sophisticated autonomous car applications. Future research could examine hybrid control strategies are LQR +MPC that combine the benefits of these methods for increased efficiency and stability.

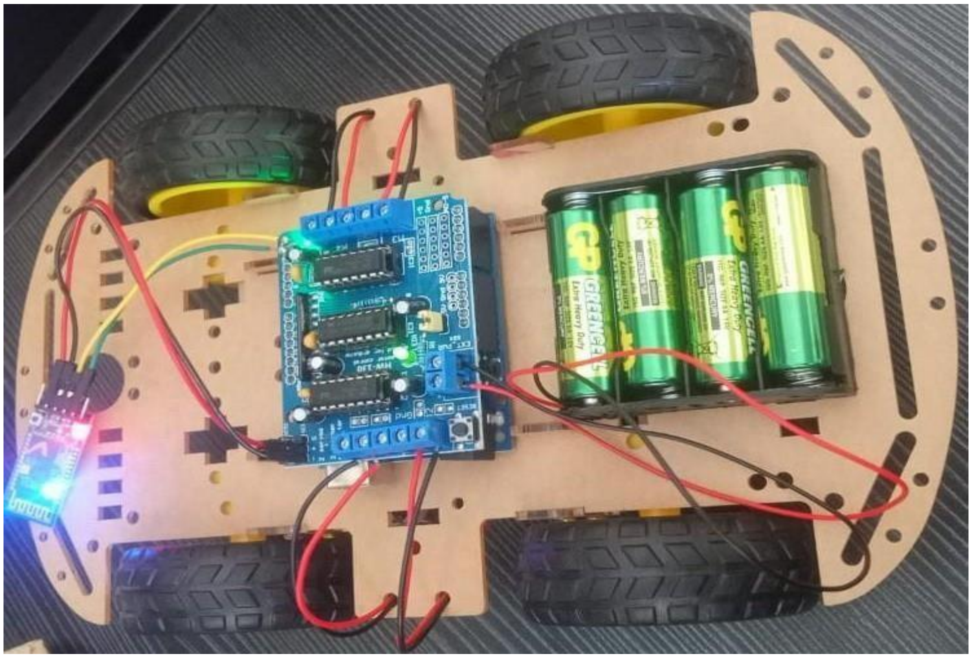

Fig-5- RC vehicle

The vehicle stability which has been analyzed in this paper via simulation is under development in real-time as shown above figure 5. Further the vehicle is to be tested two different terrains and these results analyzed to ensure the suitable vehicle stability. A novel algorithm is to be proposed to improve the vehicle stability and performance.

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