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Handling and Stability Analysis of an Autonomous Vehicle Using Model Predictive Control in a CarSim–Simulink Co-Simulation Environment

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Abstract

Cars are a prevalent mode of transportation for both people and goods, with B-class hatchbacks being particularly popular in Indonesia. However, road traffic crashes remain a major concern, contributing millions of deaths annually, primarily due to human error. Autonomous vehicles offer a promising solution to mitigate these issues by reducing reliance on human control. In particular, Level 3 autonomous vehicles enhance road safety, enable independent mobility, reduce traffic congestion, and allow drivers to engage in non-driving tasks. This study proposes an autonomous vehicle model that employs a trajectory tracking approach using Model Predictive Control (MPC), a robust and widely adopted control strategy in autonomous systems. A three-degree-of-freedom (3-DOF) vehicle dynamic model was developed and analyzed through co-simulation using CarSim and Simulink to evaluate its performance during a double-lane change maneuver. The simulation results demonstrate that the vehicle accurately follows the reference trajectory and exhibits excellent dynamic performance. The roll angle remained consistently low, ranging between 0.024 and 0.026 radians—well below the rollover threshold of 0.14 radians—demonstrating strong roll stability. The slip angle varied between –0.013 and 0.0135 radians, nearly 12 times lower than the critical limit, indicating optimal traction and directional control. Lateral acceleration ranged from –3.59 m/s^2 to 3.41 m/s^2, and yaw rate remained within –7.78°/s to 7.25°/s, both well within safe operational bounds. These findings confirm that the proposed MPC-based control framework enables precise path tracking, robust stability, and reliable handling performance in dynamic driving scenarios.

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1. Introduction

Cars are a primary mode of transport for people and goods, with hatchbacks, particularly B-class models such as Toyota Yaris and Honda Jazz, gaining popularity in Indonesia [1]. However, the rise in vehicle numbers also leads to safety concerns, as the World Health Organization reports approximately 1.35 million annual deaths from road traffic injuries, largely due to human error [2].

Autonomous vehicles (AVs) offer solutions for enhancing road safety and efficiency. SAE J3016 Level 3 autonomous vehicles provide some benefits, such as increased mobility, reduced congestion, and improved fuel efficiency [3]. Level 3 autonomous vehicles, also known as conditional automation, are mostly autonomous in specific conditions, such as highway driving, but still need a human driver to be present and ready to take over when the system encounters situations that it cannot manage. Path tracking is a crucial aspect of autonomous vehicle motion control that enables vehicles to follow predefined routes accurately. One of the trajectories used to simulate critical driving conditions is the double lane change, which directly impacts vehicle stability and handling performance.

Model Predictive Control (MPC) is a promising approach to trajectory tracking. By predicting future vehicle states, MPC optimizes control inputs in real time and manages nonlinear dynamics and constraints [4]. MPC is a powerful and flexible control strategy for autonomous driving that offers optimal performance while handling complex constraints. Despite its advantages, including real-time adaptation, optimality, and multi-objective optimization, challenges such as computational complexity and the requirement of a system model embedded in an MPC optimizer remain [5].

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Model Predictive Control is an optimization-based control strategy that is particularly well-suited for autonomous driving applications due to its ability to account for vehicle dynamics, constraints, and predictions over a future horizon. The effectiveness of MPC in ensuring vehicle stability, particularly in yaw and roll, has been assessed through co-simulation environments like CarSim and Simulink. For instance, Lin et al. illustrate the utilization of MPC for maintaining vehicle yaw stability and tracking specific paths by considering vehicle dynamics parameters such as front wheel angle and sideslip angle during path tracking [6]. Similarly, Guo et al. demonstrate an adaptive MPC approach that enhances calculation efficiency and control accuracy, showcasing faster response times in handling maneuvers such as J-turn and fishhook tests [7].

However, most existing studies are limited to high-level simulations or simplified models that do not fully incorporate complex interactions between vehicle dynamics and control constraints under rapid lane-changing scenarios, such as double lane change (DLC) maneuvers. There is still a lack of comprehensive evaluations that validate MPC's performance in simultaneously managing yaw and roll stability using high-fidelity co-simulation tools.

The novelty of this study lies in its integrated approach that combines MATLAB/Simulink and CarSim platforms to assess the effectiveness of MPC in path tracking and stability control during double lane change maneuvers. By utilizing co-simulation, this research provides more accurate and realistic assessments of MPC's control effectiveness, particularly in maintaining vehicle stability during dynamic lane-change conditions. Additionally, this study emphasizes the importance of accurate dynamic modeling to enhance the predictive capability of MPC and minimize the risks posed by modeling errors or unmodeled disturbances.

This study focuses on investigating the effectiveness of MPC in improving vehicle stability and handling performance through co-simulation using MATLAB/Simulink and CarSim for clear model accuracy. These platforms allow realistic evaluations of vehicle dynamics and control strategies [8]. By leveraging these tools, this study aims to develop a robust MPC framework capable of not only accurately following desired trajectories but also offering optimal stability and handling.

2. Methods

2.1. Path tracking & model predictive control

Path tracking has gained significant attention in current research on autonomous vehicles. Accurately following a reference path is a fundamental aspect of the motion control system. However, current research often overlooks the integration of vehicle–steering systems. Model Predictive Control (MPC) is a popular method for managing autonomous vehicles; nevertheless, analyzing the stability of path-tracking systems using MPC remains challenging.

MPC relies on optimal control principles, utilizing a dynamic model to predict system behavior and refine predictions to make optimal control decisions. The state estimation problem involves analyzing past data and combining it with a model to determine the most likely current state, as illustrated in Figure 1. MPC encompasses various methods that generate control signals by minimizing an objective function. This results in controllers with a similar structure and high flexibility.

MPC offers many advantages, including broad applicability, user-friendliness, ease of implementation, transparent methodology, straightforward constraint handling, and utility for future reference tracking [4],[8].

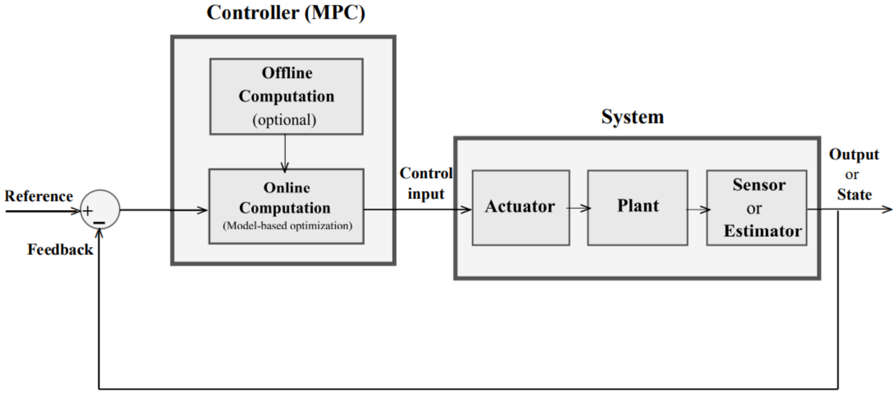

Figure 1. MPC general block diagram [9]

For Y(T +1)|T) and ΔU(T), which are the system output and input respectively, the model prediction equation for T sample time can be expressed as:

$$Y(T+1)|T) = \psi_t \xi(T) + \Theta_t \Delta U(T) \tag{1}$$

$$\psi_\xi = \begin{bmatrix} \overline{C_t}\overline{A_t} \\ \overline{C_t}\overline{A_t}^2 \\ \vdots \\ \overline{C_t}\overline{A_t}^{N_c} \\ \vdots \\ \overline{C_t}\overline{A_t}^{N_p} \end{bmatrix} \tag{2}$$

$$\Theta_\xi = \begin{bmatrix} \overline{C_t}\overline{B_t} & 0 & 0 & 0 \\ \overline{C_t}\overline{A_t}\,\overline{B_t} & \overline{C_t}\overline{B_t} & 0 & 0 \\ \vdots & \vdots & \vdots & \vdots \\ \overline{C_t}\,\overline{A_t}^{N_c-1}\,\overline{B_t} & \overline{C_t}\,\overline{A_t}^{N_c-2}\,\overline{B_t} & \dots & \overline{C_t}\overline{B_t} \\ \overline{C_t}\,\overline{A_t}^{N_c}\,\overline{B_t} & \overline{C_t}\,\overline{A_t}^{N_c-1}\,\overline{B_t} & \dots & \overline{C_t}\overline{A_t}\,\overline{B_t} \\ \vdots & \vdots & \vdots & \vdots \\ \overline{C_t}\,\overline{A_t}^{N_p-1}\,\overline{B_t} & \overline{C_t}\,\overline{A_t}^{N_p-2}\,\overline{B_t} & \dots & \overline{C_t}\,\overline{A_t}^{N_p-N_c-1}\,\overline{B_t} \end{bmatrix} \tag{3}$$

In Equation (3), ξ represents the system state vector. The matrices A_t, B_t, and C_t denote the state transition matrix, input matrix, and measurement matrix, respectively. The control horizon is represented by N_c, while N_p indicates the prediction horizon [10].

2.2. Co-simulation

Co-simulation is an effective method for modeling and simulating complex systems by utilizing well-established simulation tools from various domains. It has been widely applied in engineering and computer science, although its impact on simulation accuracy and results is often not thoroughly analyzed.

MATLAB and Simulink are seamlessly integrated, enabling users to analyze, simulate, and modify models within either environment at any time. These platforms provide a broad range of tools for designing and testing control systems, making them highly suitable for developing algorithms for autonomous vehicle applications [11]. CarSim is a specialized software tool used to simulate 3D vehicle dynamics and visualize vehicle responses under a variety of driving conditions. It enables researchers to create detailed models of vehicle behavior and evaluate the performance of autonomous systems [12]. When used together, MATLAB/Simulink and CarSim provide a comprehensive framework for research and development in autonomous vehicle technology.

2.3. Vehicle dynamic model

This study employs a three-degree-of-freedom (3-DOF) vehicle dynamic model, as illustrated in Figure 2. The model effectively describes vehicle motion within a plane through three principal components: longitudinal, lateral, and yaw motion.

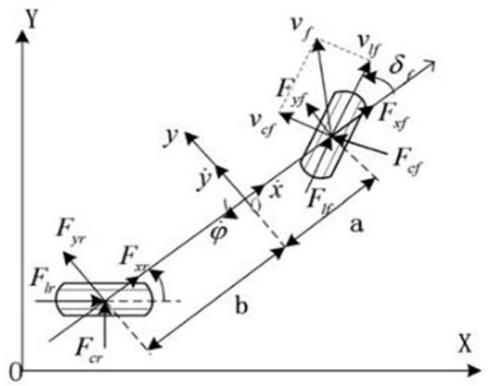

Figure 2. Three DOF vehicle dynamic model

Several simplified assumptions are made in the modeling process: longitudinal and lateral aerodynamic forces are neglected; only lateral dynamics are considered without any coupling between longitudinal and lateral tire forces; vehicle roll and pitch motions are disregarded; and the vehicle is assumed to use front-wheel steering only [13].

According to Newton's second law of motion, the longitudinal, lateral, and yaw dynamics of the vehicle can be expressed by the following equations:

$$m\ddot{x} = m\dot{y}\dot{\varphi} + 2F_{xf} + 2F_{xr} \tag{4}$$

$$m\ddot{y} = -m\dot{x}\dot{\varphi} + 2F_{yf} + 2F_{yr} \tag{5}$$

$$I_z\ddot{\emptyset} = 2aF_{yf} + 2bF_{yr} \tag{6}$$

Here, mmm is the vehicle mass, and I_z is the moment of inertia. The variables $\dot{x}$ and $\dot{y}$ represent longitudinal and lateral velocities, while $\ddot{x}$ and $\ddot{y}$ represent longitudinal and lateral accelerations. $\dot{\varphi}$ is the yaw rate, and $\ddot{\emptyset}$ is the yaw angular acceleration. F_{xf}, F_{xr}, F_{yf}, and F_{yr} denote the longitudinal and lateral forces on the front and rear wheels, respectively. These can be further defined as:

$$F_{xf} = F_{lf}cos\delta_f - F_{cf}sin\delta_f \tag{7}$$

$$F_{xr} = F_{lr}cos\delta_r - F_{cr}sin\delta_r \tag{8}$$

$$F_{yf} = F_{lf}sin\delta_f - F_{cf}cos\delta_f \tag{9}$$

$$F_{yr} = F_{lr}sin\delta_r - F_{cr}cos\delta_r \tag{10}$$

Here, δ_f and δ_r are the front and rear steering angles. The longitudinal and lateral tire forces are determined by the tire side-slip angle α\alphaα, and the respective longitudinal and lateral velocities (v_l and v_c), defined as:

$$\alpha = tan^{-1}\left(\frac{v_c}{v_l}\right) \tag{11}$$

$$v_c = v_y cos\delta - v_x sin\delta \tag{12}$$

$$v_l = v_y sin\delta - v_x cos\delta \tag{13}$$

Based on the relationship between speed and angular velocity, the transformation of longitudinal and lateral velocities at the front and rear tires is described by:

$$v_{yf} = \dot{y} + a\dot{\varphi} \tag{14}$$

$$V_{yr} = \dot{y} - b\dot{\varphi} \tag{15}$$

$$V_{xf} = \dot{x} \tag{16}$$

$$V_{yr} = \dot{x} \tag{17}$$

To simplify calculations, it is necessary to transform the vehicle's coordinate system velocities $\dot{X}$ and $\dot{Y}$ and φ, and the yaw angle ϕ, using the following equations:

$$\dot{Y} = \dot{x}sin\varphi - \dot{y}cos\varphi \tag{18}$$

$$\dot{X} = \dot{x}cos\varphi - \dot{y}sin\varphi \tag{19}$$

2.4. Vehicle stability and handling performance

In the context of autonomous vehicles, roll and slip angles are critical parameters related to vehicle dynamics and stability. The roll angle refers to the tilt of the vehicle's body around its longitudinal axis. This angle becomes particularly important during maneuvers such as cornering, braking, or driving on uneven surfaces. A significant roll angle can compromise vehicle stability, increasing the risk of rollover. Therefore, maintaining the roll angle within safe limits is essential to ensure passenger safety and effective vehicle handling [14]. Figure 3 illustrates the basic concept of vehicle motion.

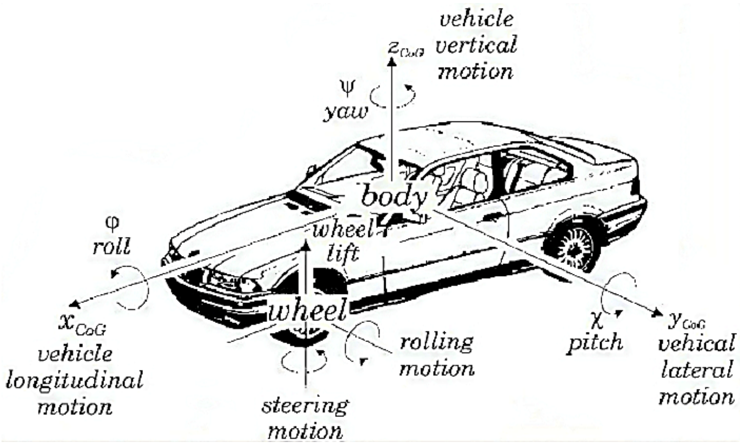

Figure 3. Vehicle motion [13]

The slip angle is defined as the angle between the direction in which the wheel is pointed and the actual direction of the vehicle's movement. It occurs when the vehicle turns and the tires experience lateral forces. While a small slip angle is normal during cornering, a large slip angle can result in loss of traction and instability [16]. Previous studies have suggested that the roll angle should not exceed 8° (0.14 rad), as exceeding this limit increases the likelihood of rollover [15]. Similarly, the slip angle should remain below 8.91° (0.156 rad) to maintain vehicle stability [17].

Lateral acceleration and yaw rate are also essential metrics for evaluating the handling and stability of autonomous vehicles. Lateral acceleration refers to the horizontal acceleration of the vehicle, especially during cornering, and indicates how quickly the vehicle can change direction. While high lateral acceleration suggests good handling characteristics, excessive values can cause a loss of traction or vehicle instability, increasing the risk of rollover [18], [19]. The yaw rate, defined as the rate at which a vehicle rotates about its vertical axis, indicates how quickly the vehicle is turning. High yaw rates may suggest aggressive turning behavior, which can lead to skidding if safety thresholds are exceeded. Autonomous vehicles use yaw rate data to make real-time adjustments to maintain stability during navigation [20]. According to industry standards, the acceptable range for lateral acceleration is between –13.73 m/s^2 and 9.81 m/s^2, which indicates good handling performance. For yaw rate, the acceptable range is between –35°/s and 35°/s [21].

2.5. Vehicle parameter and maneuver procedure

This study uses a B-class hatchback vehicle model from the CarSim database, as shown in Figure 4. The detailed parameters of the vehicle are provided in Table 1. The double-lane change (DLC) maneuver is a critical test procedure for evaluating autonomous vehicles because it replicates emergency or high-speed avoidance scenarios. The ISO 3888-2 standard specifies the parameters and setup for this maneuver, as shown in Figure 5. The procedure begins once the vehicle reaches the target speed. The driver accelerates and then releases the accelerator pedal. Subsequently, the driver turns the steering wheel to move into the left lane and then steers back to the right lane. During this maneuver, vehicles may exhibit different dynamic responses, including understeering due to tire force saturation in the front axle, oversteering during counter-steering maneuvers, or even rollover effects due to excessive lateral acceleration. These dynamics are especially critical in vehicles with a higher center of gravity. By simulating these responses, the DLC maneuver provides valuable insight into the agility and lateral stability of autonomous vehicles [22].

Figure 4. CarSim B-Class hatchback

Table1. CarSim B-Class hatchback vehicle parameters

Parameter	Value
Vehicle Mass (kg)	1110
Roll Inertia (kgm^2)	440.6
Pitch Inertia (kgm^2)	1343.1
Yaw Inertia (kgm^2)	1343.1
Distance of CG to Front Axle (m)	1.04
Distance of CG to Rear Axle (m)	1.56
Front Steering Damping Coefficient (Ns/m)	4.5
Wheelbase Length (m)	2.6
Width (m)	1.695
Height (m)	1.535

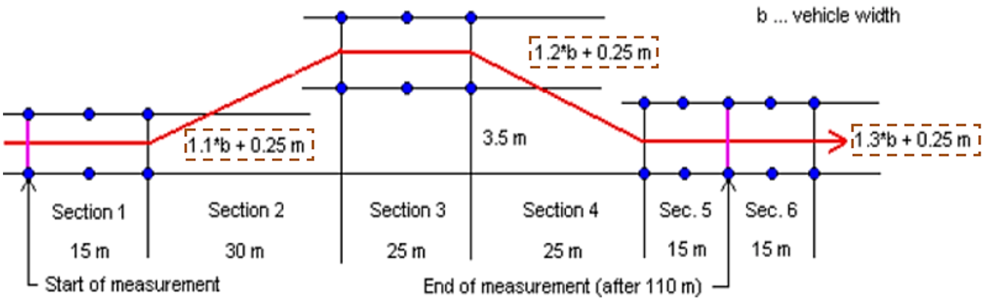

Figure 5. Double lane change trajectory as defined by ISO3888-2

The Driving Scenario Designer used in this study incorporates three main components. First, the road elements are defined, including their width and length. Second, the actors—in this case, the vehicle—are placed into the simulation. Third, sensors are added to monitor these actors. In this study, the sensors are configured to record the vehicle's lateral position and yaw angle. Once the scenario setup is complete, it is exported to Simulink, where the models are further integrated and refined into a unified co-simulation environment with CarSim.

The target vehicle speed was selected based on regulations from the Indonesian Ministry of Transportation, which specifies a minimum speed of 60 km/h and a maximum of 100 km/h on toll roads, with a limit of 80 km/h for inner-city toll roads [23]. Therefore, the target speed in this study was set at 80 km/h, representing the maximum allowed speed on inner-city toll roads.

2.6. Trajectory tracking model

The path trajectory was created in MATLAB using the Driving Scenario Designer from the Automated Driving Toolbox. This trajectory serves as a reference input for the Model Predictive Control (MPC) controller, enabling it to accurately track the desired path and successfully perform the double-lane change maneuver. The driving scenario design and the co-simulation model used in this study are illustrated in Figures 6 and 7, respectively.

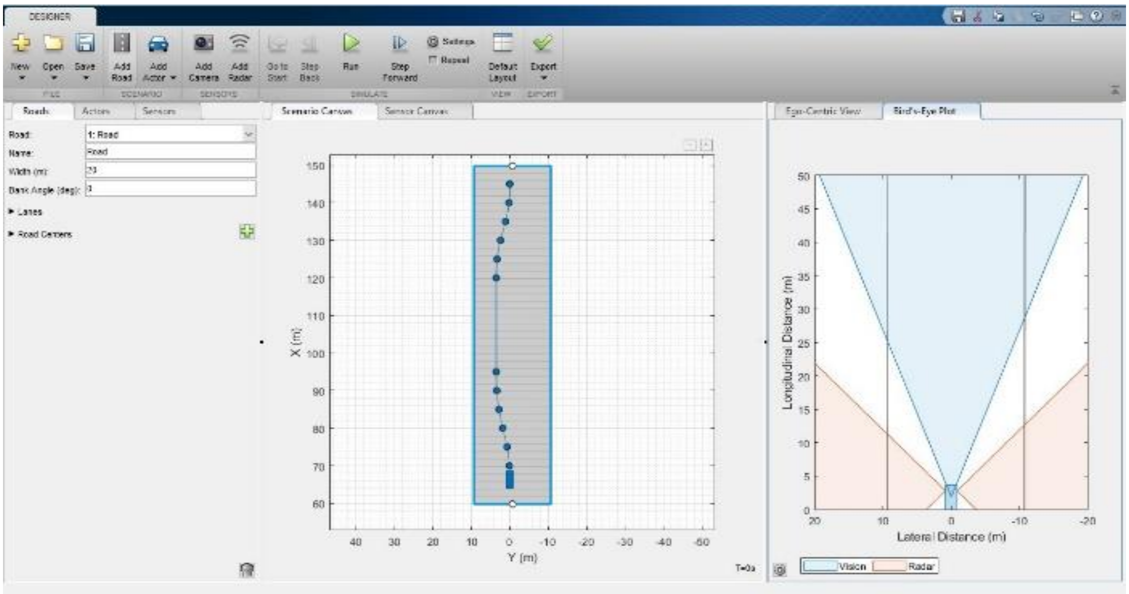

Figure 6. Trajectory driving scenario design

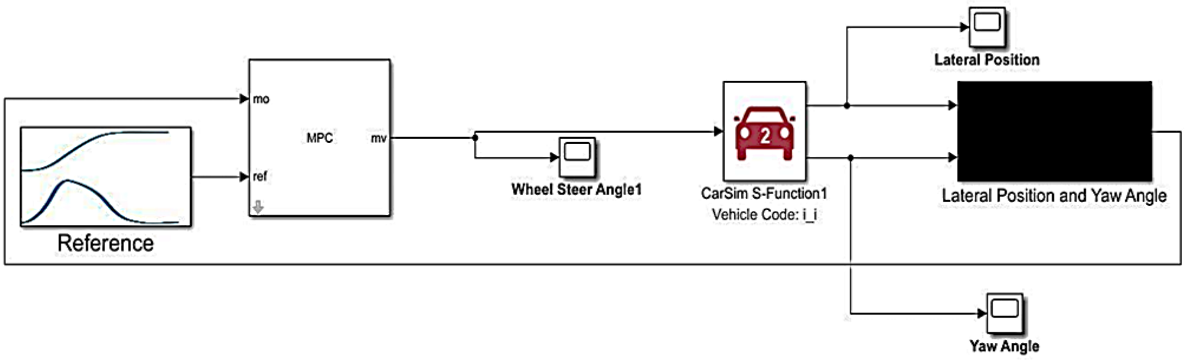

Figure 7. Carsim-Simulink block diagram model

3. Results and Discussion

3.1. Lateral tracking

As the primary objective of this research is to develop an autonomous vehicle capable of tracking a trajectory using Model Predictive Control (MPC), it is essential to compare the target lateral position with the vehicle's actual lateral position. The results show that the target trajectory and the autonomous vehicle exhibit similar patterns, indicating that the proposed vehicle model effectively tracks the path and performs the double-lane change maneuver.

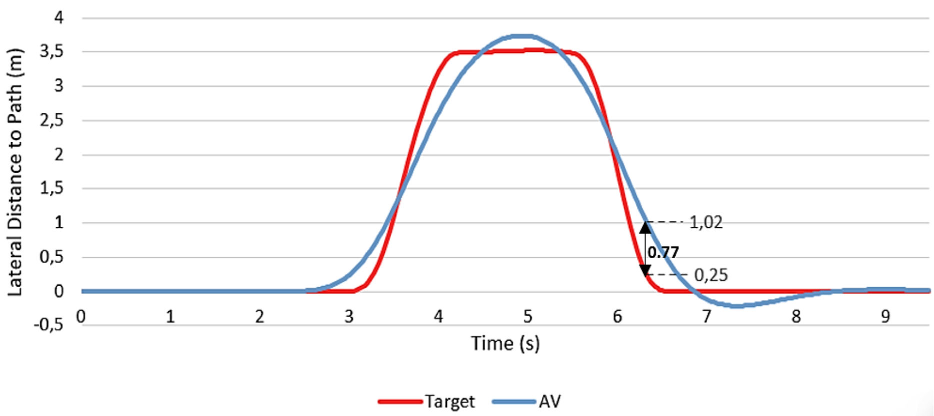

Figure 8. Lateral tracking graph

Although some deviation in the lateral position of the autonomous vehicle is observed compared to the target trajectory, the deviation is minimal and remains within acceptable limits, as illustrated in Figure 8. According to ISO 3888-2, the double-lane change procedure allows a lateral path width tolerance of 1.1b+0.25 m, where b is the vehicle width. For a vehicle width of 1.695 m, this results in a total tolerance of 2.1145 m, with a lateral tolerance of approximately 1.057 m on each side.

3.2. Vehicle stability analysis

This study emphasizes the importance of maintaining the vehicle's roll angle as close to zero degrees as possible for optimal stability. During the lane-change maneuver, the measured roll angles consistently range between 0.024 and 0.026 radians, as shown in Figure 9. These values indicate that the vehicle demonstrates a commendable ability to maintain stability under dynamic conditions. The slight deviation from zero suggests that the vehicle's design and control algorithms are effective in managing lateral forces.

When compared with the critical rollover threshold of 0.14 radians, it is evident that the vehicle maintains a substantial safety margin. This is especially relevant for autonomous vehicles, which are expected to navigate complex driving scenarios with minimal human intervention. The ability to maintain such a narrow roll angle range during dynamic maneuvers highlights the effectiveness of the control algorithms in predicting and mitigating potential instability.

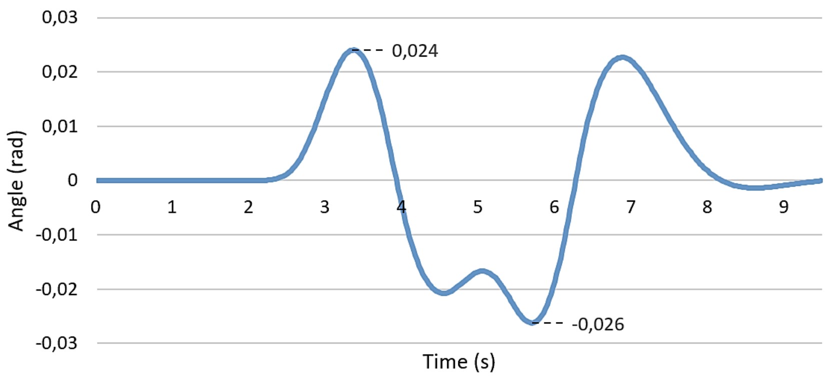

Figure 9. Roll angle graph

The analysis of the slip angle further supports the vehicle's stability. The slip angle should not exceed 0.156 radians, as exceeding this limit may lead to vehicle instability due to a loss of traction. The proposed autonomous vehicle maintains a slip angle ranging from –0.013 radians to 0.0135 radians, as shown in Figure 10. This range is well within the safe limit and is approximately 12 times smaller than the critical threshold. These results indicate excellent traction control, suggesting that the vehicle effectively maintains grip and stability throughout the maneuver. Overall, the low slip angles confirm that the vehicle is designed to handle dynamic driving conditions safely and reliably.

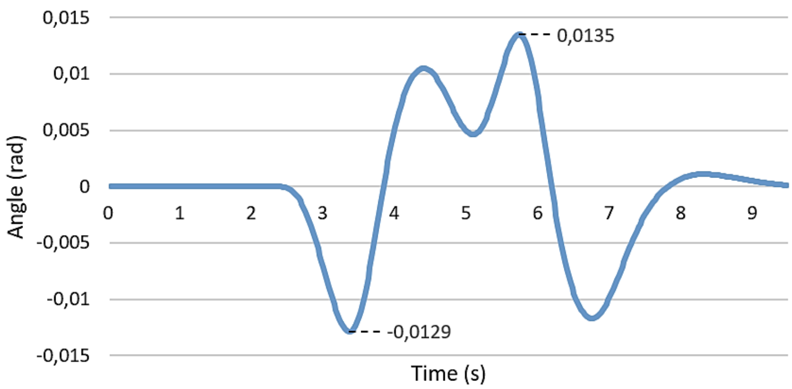

Figure 10. Slip angle graph

The evaluation of both the roll angle and slip angle confirms that the proposed autonomous vehicle exhibits strong stability control and remains well within safe thresholds for both parameters.

3.3. Vehicle handling performance analysis

The vehicle's handling performance was further evaluated through the analysis of lateral acceleration and yaw rate. The results show a minimum lateral acceleration of –3.59 m/s^2 and a maximum of 3.41 m/s^2, as illustrated in Figure 11. These values are well below the typical limits for lateral acceleration in vehicles, indicating that the proposed model demonstrates excellent handling performance.

The relatively low lateral acceleration values imply that the vehicle can change direction and navigate turns with a high degree of stability and control. Negative lateral acceleration during deceleration maneuvers indicates the vehicle's ability to maintain grip and avoid skidding. Conversely, positive acceleration during cornering reflects responsive handling without generating excessive lateral forces that could compromise stability.

By maintaining safe acceleration limits, the proposed autonomous vehicle not only enhances passenger comfort but also significantly reduces the risk of losing control during maneuvers. These findings support the vehicle's capability for safe and efficient operation under real-world driving conditions, contributing to the broader goal of advancing autonomous driving technologies.

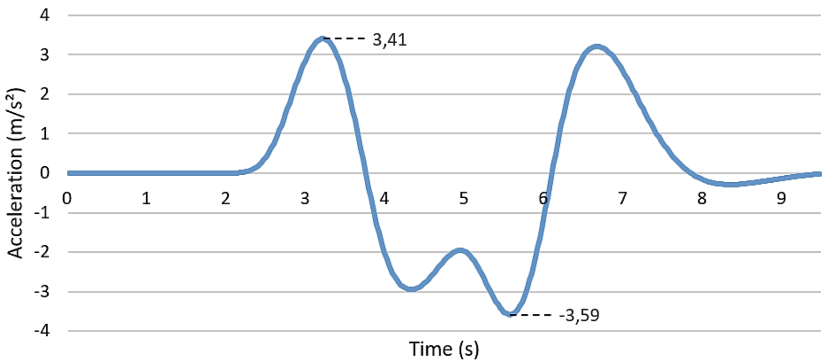

Figure 11. Lateral acceleration graph

Yaw rate analysis is another critical metric for evaluating the handling performance of the proposed autonomous vehicle. Ideally, the yaw rate should remain within the range of –35°/s to 35°/s, as values outside this range may indicate poor handling behavior. According to the data presented in Figure 12, the yaw rate for the proposed vehicle ranges from –7.78°/s to 7.25°/s, which is well within the acceptable limits and significantly below the maximum threshold. These results confirm that the vehicle maintains stable handling during dynamic maneuvers such as a double-lane change.

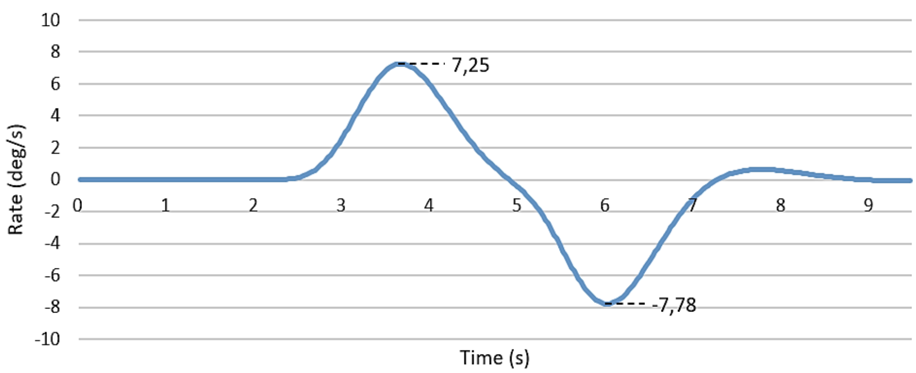

Figure 12. Yaw rate graph

Overall, the comprehensive evaluation of lateral acceleration and yaw rate confirms that the proposed vehicle model exhibits effective handling performance, making it a reliable and safe option for navigation in dynamic driving environments.

4. Conclusions

This study successfully developed and evaluated an autonomous vehicle model equipped with Model Predictive Control (MPC) for trajectory tracking and dynamic maneuvering. The simulation results, obtained through co-simulation using MATLAB/Simulink and CarSim, confirm that the proposed model exhibits excellent stability and handling performance during double-lane change maneuvers. The roll angle remained consistently low and significantly below the rollover threshold of 0.14 radians, demonstrating strong roll stability. Similarly, the slip angle was well within safe limits, with values nearly 12 times lower than the critical threshold, indicating that the vehicle maintained optimal traction and directional control throughout the maneuvers. Furthermore, the lateral acceleration values ranged between –3.59 m/s^2 and 3.41 m/s^2, confirming that the vehicle can navigate turns and directional changes without compromising passenger comfort or vehicle control. The yaw rate also remained within the safe range of –35°/s to 35°/s, reflecting the model's ability to perform rapid directional changes without sacrificing stability. In summary, the integration of MPC with a co-simulation environment enabled accurate trajectory tracking, effective stability control, and reliable handling under dynamic driving conditions. These findings affirm the potential of the proposed control framework for practical implementation in autonomous vehicle systems. For future research, efforts could be directed toward enhancing the vehicle's adaptability in more complex traffic environments. Integrating vehicle-to-everything (V2X) communication technologies may further improve situational awareness, enabling real-time adjustments based on surrounding vehicles, infrastructure, and road conditions. This advancement could significantly elevate the safety, responsiveness, and overall efficiency of autonomous driving systems.

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