TELKOMNIKA Telecommunication Computing Electronics and Control
Vol. 24, No. 2, April 2026, pp. 696~706
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i2.27167

Performance assessment of an adaptive model predictive control with torque braking for lane changes

Zulkarnain[1], Irwin Bizzy[1], Armin Sofijan[2], Mohd Hatta Mohammed Ariff[3]
[1]Department of Mechanical Engineering, Faculty of Engineering, Universitas Sriwijaya, Palembang, Indonesia
[2]Department of Electrical Engineering, Faculty of Engineering, Universitas Sriwijaya, Palembang, Indonesia
[3]Advanced Vehicle System, Malaysia Japan International Institute of Technology, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia

Article Info

Article history:

Received May 3, 2025
Revised Dec 30, 2025
Accepted Jan 30, 2026

Keywords:

Adaptive model predictive control
Autonomous vehicle
Braking torque
Lane change
Steering

ABSTRACT

The growing demand for autonomous vehicles requires robust control systems that can maintain safety during complex maneuvers like lane changes. However, a significant research gap exists in developing controllers that effectively manage the combined challenges of steering and braking across diverse and unpredictable driving conditions, such as varying speeds and low-friction road surfaces. This research addresses this gap by proposing and evaluating an adaptive model predictive control (MPC) system integrated with a torque braking distribution strategy. The key advantage of our adaptive method is its ability to continuously update its internal model in real-time, allowing it to anticipate and respond to changing road friction and vehicle dynamics more effectively than a static controller. In simulations of a lane change maneuver across speeds of 10-25 m/s and road friction levels from 0.3 (icy) to 1 (dry asphalt), the proposed system demonstrated a substantial performance improvement. The proposed framework demonstrated a 52.8% average reduction in lateral tracking error and enhanced stability by reducing the yaw rate by up to 41.8% on low-friction surfaces, compared to a non-adaptive MPC baseline. These results quantitatively confirm that our framework's synergistic coordination of steering and braking significantly enhances the safety, precision, and reliability of autonomous lane change maneuvers.

Corresponding Author:

Irwin Bizzy
Department of Mechanical Engineering, Faculty of Engineering, Universitas Sriwijaya
Jalan Raya Palembang Prabumulih Km 32, Ogan Ilir, Palembang, Indonesia
Email: irwin@ft.unsri.ac.id

1. INTRODUCTION

The study of autonomous vehicles has developed into a quickly expanding topic of study because to major industry and academic effort. Particularly in the last ten years, interest in this topic has significantly increased [1]-[4]. Autonomous vehicles have the ability to lessen the role that driver error and irresponsibility play in collisions between vehicles. A self-learning method for autonomous vehicles includes environment recognition, real-time localisation, course planning, and motion tracking. The path tracking control, which concentrates on the vehicle control in the lateral and longitudinal directions in order to follow a specified path or trajectory, is one of the key components of any autonomous vehicle [5]-[7]. Numerous renowned automakers have been performing research and advancing technology to produce smart autonomous vehicles [8]. Kang *et al*. [9], autonomous vehicle systems must be the requirements that they can know where they are, understand the goals they must achieve, and protect themselves from experiencing mishaps while traveling. Given the aforementioned requirements, it follows that the entire autonomous system should be composed of several modules and tasks to carry out, as shown in Figure 1 [6], [10].

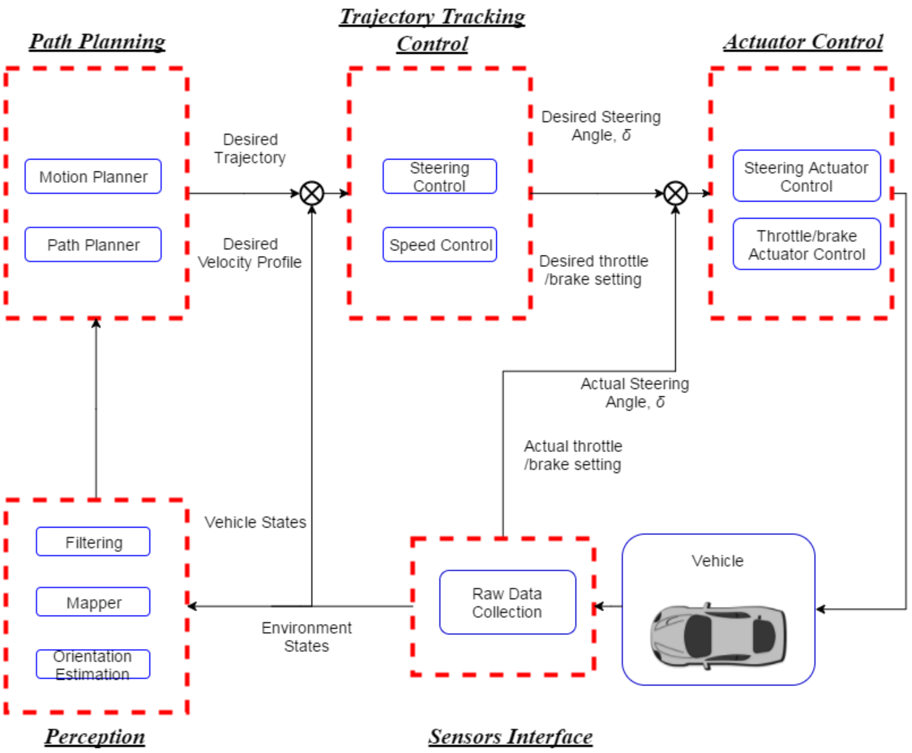


Figure 1. Schematic diagram of autonomous vehicle building components [10]

One of the control systems that is still being developed is path following. This control system's goal is to reduce the vehicle's lateral and heading errors relative to the predetermined course. The steering correction input is sent to the vehicle by the control system in order to accomplish this goal. The vehicle has three different types of actuators: the steering, throttle, and braking systems. The steering control's primary goal is to create a control strategy that can accurately estimate the path to the intended target. This control system also keeps the vehicle's directional stability while following the path [11]-[13]. The inclusion of model uncertainty and outside disturbances makes path following control for autonomous vehicles more challenging. Variations in the vehicle/environment parameters and the vehicle state may cause model uncertainties. The simulation stage is where control method is often implemented, with the controlled plant being modelled to produce simulated responses. The majority of these papers deal with non-linear or linear control techniques with linearized vehicle models. When using vehicle linear models, some vehicle-related effects are disregarded. Consequently, path tracking control may not always give outcomes that are satisfactory [14], [15].

Theoretically, an autonomous vehicle ought to be able to recover from significant disturbances without assistance from a person. In a geometric/kinematic form of controller called the geometric controller is used for those purposes. The configuration and deployment of geometric/kinematic controllers is straightforward. But according to earlier studies, this kind of controllers may require adequate tuning to operate effectively, and a tuned controller might only operate with a specific kind of trajectory and speed range [10], [16]-[18]. Additionally, the majority of geometric/kinematic controllers, including the Stanley controller, are incapable of handling sharp corners. Therefore, a suggestion for improvement is made to incorporate a dynamic vehicle that will modify the controller's settings in accordance with road circumstances [19], [20].

Several references contain a common way to develop the control law. Researchers [21], [22] detailed the application of the linear quadratic regulator (LQR) controller in route tracking control with dynamic feedback. However, the controller struggled because there was no path feedback. A feed forward term of steering angle to zero steady state error was added to the original technique. Since the look-ahead distance is still absent and the controller can only be reactive, the outcome was still worse. The ideal preview method suggested by [23], [24] in at least three articles can be used to solve this issue. Adaptive controllers are developed for use in systems that require strong robustness against specific disturbance and uncertainty models. The development and evaluation of adaptive trajectory tracking control have been documented in reference [25]. A reference signal with linear velocity and angle is used by this controller. The reference signal is complemented with an adaptive parameter update law to prevent drift parameters. Although this concept is being implemented on a mobile robot that rides a unicycle, it can be adjusted to work on a vehicle that has single point control. Adaptive rule was added to the back-stepping kinematic/dynamic theory that employed [26], [27]. It aims to assist a mobile robot with unidentified features.

In this study, a dynamic controller along with a torque controller were proposed. There are several notable adaptive controllers available, each of which can address a distinct component of the operating environment for a vehicle. An adaptive controller investigation on slippery road conditions was done [28]. Another adaptive controller used in the vehicle for unidentified skidding is also covered in [28]. To stabilize yaw on the front and rear wheels, research is conducted. An adaptive law that adjusts cornering stiffness by tracking the dynamic wheel sideslip angle eliminates the effect of wheel-road sliding on slick roads. Position tracking control system for an autonomous vehicle is the main goal of this study.

2. METHOD

A non-holonomic system can be categorized as an autonomous vehicle. The term "holonomic system" describes the relationship between the total number of four degrees of freedom (DOF), for the dynamic system and the controllable DOF. The controllable DOF of a non-holonomic system was less than the total DOF. According to [6], [29], a typical vehicle is regarded as non-holonomic because it has a total of four DOF, including motion in the two Cartesian coordinates of direction and heading, but only two DOF that can be controlled: the longitudinal (forward and backward) and lateral directions (bounded steering input).

The majority of studies on path tracking controllers use kinematic vehicle modelling as shown in Figure 2. Due of its simplicity and crucial relevance to explain the motion of the vehicle, this model is commonly utilized. The position and orientation of the vehicle with regard to its local axis and the global axes, are described using this model. For this, a straightforward kinematic model is frequently employed, as shown in Figure 3. Local (x-y) and global (X-Y) axes are used to define the vehicle, v represents the vehicle's longitudinal velocity, θ is its heading in relation to the local coordinates, and ψ is its orientation in relation to the global coordinates [6].

$$\begin{aligned} \begin{bmatrix} v_X \\ v_Y \end{bmatrix} &= \begin{bmatrix} \cos\psi & -\sin\psi \\ \sin\psi & \cos\psi \end{bmatrix} \begin{bmatrix} v_x \\ v_y \end{bmatrix} \\ v_x &= v\cos\theta \\ v_y &= v\sin\theta \end{aligned} \tag{2}$$

The dynamic vehicle model takes into account external and internal forces, energy or momentum within the system to describe the motion of the vehicle in terms of its position, velocity, and acceleration as shown Figure 3. This model takes into account the mass of the vehicle body as well as tire forces (1) and (2).

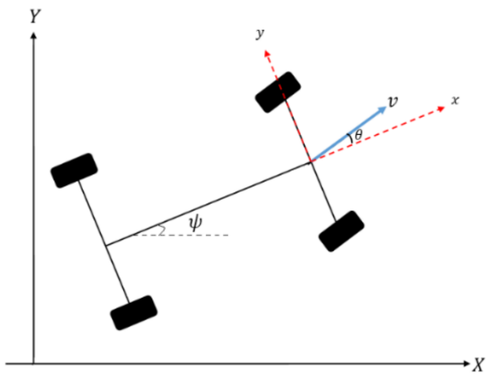


Figure 2. Full vehicle in kinematic model

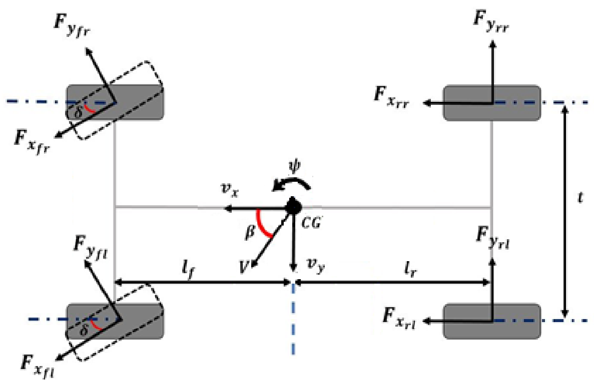


Figure 3. 7DOF Autonomous vehicle model

$$\begin{pmatrix} \sum M_{zij} + [-F_{yrr} - F_{yrl}]l_r \\ + \begin{bmatrix} F_{xfl} \sin\delta + F_{yfl}\cos\delta \\ +F_{xfr}\sin\delta + F_{yfr}\cos\delta \end{bmatrix} l_f \\ + \begin{bmatrix} F_{xfr}\ \cos\delta - F_{xfl}\cos\delta \\ +F_{yfl}\sin\delta - F_{yfr}\sin\delta - F_{xrl} + F_{xrr} \end{bmatrix} \frac{t}{2} \end{pmatrix} = I_{z,CG}\ddot{\psi} \quad (2)$$

$$\begin{aligned} F_{xrr} + F_{xrl} + F_{xfl}\cos\delta + F_{yfl}\sin\delta + F_{xfr}\ \cos\delta + F_{yfr}\sin\delta &= m_b a_x \\ F_{yrr} + F_{yrl} - F_{xfl}\sin\delta - F_{xfr}\sin\delta + F_{yfl}\cos\delta + F_{yfr}\cos\delta &= m_b a_y \end{aligned} \quad (3)$$

Researchers have introduced and employed a variety of tire models. However, Pacejka tire model has also been widely employed in addition to linier estimation of tire response. This non-linear, semi-empirical tire model can replicate the forces produced by the tires. Function P may represent Fx, Fy, or Mz in (3), where B, C, D, Sh, and Sv stand for the function's stiffness factor, shape factor, peak value, curvature factor, horizontal shift, and vertical shift, respectively. Using the Calspan tire formula, researchers can delve into a wealth of additional insights and findings related to tire performance and behavior [30], [31]. This model uses a polynomial formulation of a saturation function, $f()$, to estimate the normalized lateral and longitudinal forces, F_x and F_y, respectively. The tyre vertical force, F_z, the coefficient of friction for the road surface, the lateral stiffness coefficient, Ks, the modified longitudinal stiffness coefficient, $K'c$, the constant for the tyre camber angle, Y, and the tire camber angle, must all be known in order to use this model. The normalized lateral and longitudinal forces can be calculated using (3).

$$\begin{aligned} P(F_z, \alpha, \sigma) &= D\sin(C\arctan(B\phi)) + S_v \\ \frac{F_y}{\mu F_z} &= \frac{f(\sigma)K_s\tan\alpha}{\sqrt{{K_s}^2\tan^2\alpha + K_c' s^2}} + Y_\gamma\gamma \\ \frac{F_x}{\mu F_z} &= \frac{f(\sigma)K_c' s}{\sqrt{{K_s}^2\tan^2\alpha + K_c' s^2}} \end{aligned} \quad (4)$$

2.1. Controller development

The location monitoring system of an autonomous vehicle will be given a new control structure. This calls for the use of two basic subsystem control strategies: steering control to track lateral motion and speed control to track longitudinal motion. Without the use of a path planning module, the vehicle is directed to follow a pre-defined trajectory by the steering control system. Position tracking control will focus on lateral and longitudinal motion control, with little or no attention paid to vertical vehicle motions. As a result, this thesis won't discuss suspension control.

Figure 4 outlines the core elements for autonomous vehicle control, focusing on steering and braking torque. Reference inputs from higher-level controllers include desired lateral position and yaw angle. The state estimator uses sensor data to estimate lateral position and yaw angle. The adaptive model predictive control (MPC) system employs adaptation laws to adjust control parameters and dynamic models in response to changing conditions. Computed braking torque and steering angle are then sent to the vehicle's control systems. A feedback loop compares actual state with reference inputs, enabling real-time adjustments.

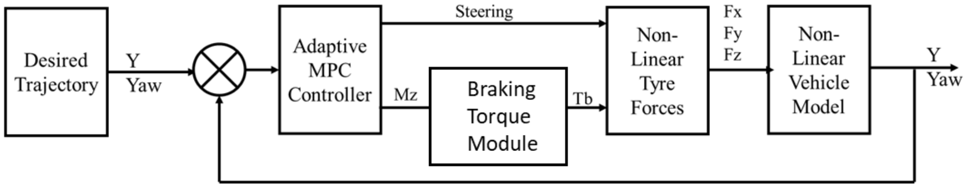


Figure 4. The application of an adaptive (MPC) system in an autonomous car

A multi-step prediction control law is adopted by the adaptive MPC controller, which corrects faults with feedback while repeatedly optimizing. The adaptive MPC controller optimizes stability and performance while having positive effects on controls, high robustness, and better balancing of control objectives and handling restrictions of the system. These benefits are crucial factors to take into account while creating automatic trajectory tracking controllers for use with autonomous vehicles. Trajectory tracking is used to drive the car toward the middle of the road by controlling the steering wheel [19]. State-space modelling is used in the adaptive MPC controller's vehicle plant model. This state-space model can be a closed-loop property-analysis and has various advantages for handling multivariable systems. In (5) illustrates how a time-invariant linear equation (LTI) can be used to characterize the system to be controlled in this scenario as a discrete-time state-space model.

$$\left.\begin{aligned} x(k+1) &= A_d x(k) + B_d u(k) \\ y(k) &= C_d\, x(k) \end{aligned}\right\} \\ \left.\begin{aligned} x(k+1) &= \bar{x} + A(x(k) - \bar{x}) + B(u(k) - \bar{u}) \\ y(k) &= \bar{y} + C(x(k) - \bar{x}) \end{aligned}\right\} \tag{5}$$

The state-space model on the compact form is represented by (4). Where $u(k)$, $x(k)$, and $y(k)$ are, respectively, the control input, state variable, and prediction output of step k. The yaw, yaw rate, and global lateral position arrange the vehicle state in (5). The wheel steering angle and yaw moment serve as the control input. The (6) is expressing the approximate dynamics of a system using a first-order Taylor series expansion around the nominal state and control input. It's a linearization that allows for local analysis of the system's behavior.

$$\left.\dot{x} = f(x_0, u_0) + \underbrace{\left[\left|\frac{\partial f}{\partial x}\right|_{x_0,u_0}\right]}_{J(x)}(x - x_0) + \underbrace{\left[\left|\frac{\partial f}{\partial u}\right|_{x_0,u_0}\right]}_{J(u)}(u - u_0)\right\} \tag{6}$$

The steering and yaw moment inputs to the vehicle model will be calculated using the adaptive MPC that has been composed and constructed. The goal of this control input is to steer the vehicle along the predetermined course. The amount of lateral position and heading error is what determines how accurately the vehicle follows the defined trajectory. The adaptive MPC controller makes use of a cost function to do this. The cost function is a quadratic program (QP) with minimized optimal control input and the desired error functions [30], [32].

The adaptive MPC must satisfy the objective and constraints of (8). Its design is challenging due to the vehicle's non-holonomic nature. The tracking accuracy is governed by the cost function's first term, while its second and third terms regulate control effort aggressiveness. The controller must then compute the optimal steering and yaw moment that jointly minimize this cost function while adhering to all defined constraints. A recursive least squares (RLS) estimator updates cornering stiffness parameters online, directly linking the Adaptive MPC to the vehicle's dynamic state. The core adaptation mechanism is realized through an RLS algorithm, which recursively updates the estimation of critical parameters the tire-road friction coefficient (μ) at each timestep (k) via the update (7).

$$\begin{aligned} \varepsilon(\mathrm{k}) &= \mathrm{y}(\mathrm{k}) - \varphi^{T}(\mathrm{k})\hat{\theta}(\mathrm{k}-1) \\ \mathrm{K}(\mathrm{k}) &= \frac{\mathrm{P}(\mathrm{k}-1)\varphi(\mathrm{k})}{(\lambda + \varphi^{T}(\mathrm{k})\mathrm{P}(\mathrm{k}-1)\varphi(\mathrm{k})} \\ \hat{\theta}(\mathrm{k}) &= \hat{\theta}(\mathrm{k}-1) + \mathrm{K}(\mathrm{k})\varepsilon(\mathrm{k}) \\ (\mathrm{k}) &= (1/\lambda)[\mathrm{P}(\mathrm{k}-1) - \mathrm{K}(\mathrm{k})\varphi^{T}(\mathrm{k})\mathrm{P}(\mathrm{k}-1)] \end{aligned} \tag{7}$$

Key parameters are now explicitly provided, including a prediction horizon of 20 steps, control horizon of 5, and empirically tuned weighting matrices (Q, R and S) optimized for path-tracking, with a 50 ms sampling time. The road friction coefficient (μ) is intrinsically embedded in the calculation of the nonlinear tire forces, which form the foundation of (4). Specifically, in (8), the self-aligning moment (Mz) is a direct function of the lateral tire forces (Fy).

$$\begin{gathered} J\big(\xi(t), u(t), \Delta u(t)\big) = \begin{array}{c} \sum_{i=1}^{H_p} \|y(k+i|k) - r(k+i|k)\|_Q^2 + \\ \sum_{i=1}^{H_c}(\|\Delta u(k+i-1)\|_R^2 + \|u(k+i-1\|_S^2) \end{array} \\ \delta_{min} \le \delta \le \delta_{max} \\ M_{z,min} \le M_z \le M_{z,max} \\ y = \begin{bmatrix} v_y\ \psi\ \dot{\psi}\ Y \end{bmatrix} \\ u = [\delta\ M_z] \end{gathered} \tag{8}$$

2.2. Longitudinal tyre forces

Braking torque generates longitudinal tire forces, enabling vehicle control. The required torque is derived from the yaw moment needed to maintain stability, a common stability control method. These forces originate at the tire-road contact patch and must obey the friction circle law to prevent traction loss. Standard formulas can calculate lateral and longitudinal forces, and algorithms can optimize torque distribution per tire for trajectory tracking. The braking module stabilizes the vehicle during sharp turns while preventing excessive lateral acceleration. According to the algorithm described in [33], the braking torque utilized to determine the longitudinal tire forces is estimated. The braking torques of a tire were calculated using (8).

$$\left.\begin{array}{ll} Tbfl = \frac{|M_z|R_w}{sin(\,tan^{-1}(\frac{l_w}{l_f}-\delta_f)\sqrt{l_f^2+l_w^2}} & M_z > 0, \quad \alpha_f - \alpha_r \leq 0 \\ Tbfr = \frac{|M_z|R_w}{sin(\,tan^{-1}(\frac{l_w}{l_f}-\delta_f)\sqrt{l_f^2+l_w^2}} & M_z < 0, \quad \alpha_f - \alpha_r \leq 0 \\ Tbrl = \frac{|M_z|R_w}{sin(\,tan^{-1}(\frac{l_w}{l_r}-\delta_f)\sqrt{l_f^2+l_w^2}} & M_z > 0, \quad \alpha_f - \alpha_r > 0 \\ Tbrr = \frac{|M_z|R_w}{sin(\,tan^{-1}(\frac{l_w}{l_r}-\delta_f)\sqrt{l_f^2+l_w^2}} & M_z < 0, \quad \alpha_f - \alpha_r > 0 \end{array}\right\} \tag{9}$$

2.3. Trajectory model

This specific coordinate point denotes a precise geographical location, either in terms of latitude and longitude or vice versa, to accurately delineate the path of the road. As the vehicle undergoes the maneuver, its real-time position on the global axis is compared with this coordinate, enabling the computation of lateral and heading errors. To evaluate the controllers, this study employs four distinct road trajectory models, as depicted in Figure 5. These trajectory is designated based on the specific characteristics and contours of the roads, with some conforming to the lane change trajectories outlined in the research papers by [34], [35]. The selection of this specific trajectory is highly intentional. It is not a random path but a condensed representation of a common yet complex driving task that, when performed at the limits of vehicle dynamics, becomes a primary safety-critical scenario. Testing this allows engineers to ensure that a vehicle can handle both everyday driving and emergency situations effectively.

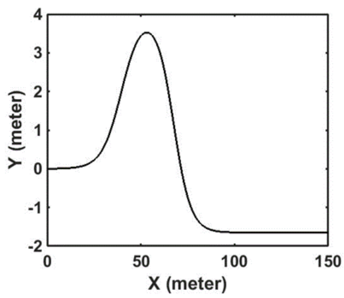


Figure 5. Lane change trajectory for controller testing

3. RESULT AND DISCUSSIONS

A high-fidelity vehicle dynamics model was implemented in the simulation to accurately capture the nonlinear behavior of the autonomous vehicle. The core of this model relies on the critical physical parameters detailed in Table 1, which define key properties such as mass distribution, inertia, and tire characteristics.

The comparative performance of the proposed adaptive MPC integrated with torque braking distribution versus a baseline solely adaptive MPC is presented in Figure 6. The evaluation uses a double-lane-change maneuver at a speed of 15 m/s on a surface with a friction coefficient (μ) of 0.6. Figures 6(a) and (b) illustrate the trajectory tracking and lateral error, respectively. The results confirm that the integrated controller delivers superior tracking accuracy and stability. A key demonstration of this advantage occurs at $t = 5.9$ seconds, where the torque braking distribution proactively corrects the vehicle's path, as seen in the trajectory (Figure 6(c)) and the corresponding dip in lateral error (Figure 6(d)). This corrective action is a direct application of direct yaw moment control, a well-established stabilization method for critical maneuvers by [36]. The improved performance stems from the coordinated reduction of lateral error through synergistic steering and braking, a principle supported by recent studies on integrated chassis control [20]. The braking torque responses for the front-left (TbFL) and front-right (TbFR) wheels are shown in Figures 6(e) and (f). The front-left wheel applies higher corrective torque, peaking at approximately 6 Nm, while the front-right wheel shows moderated peaks between 3-4.5 Nm. This differential torque generation creates the necessary yaw moment for stabilization. The magnitude and timing of this intervention align with findings from hardware-in-the-loop (HIL) tests on direct yaw control (DYC) systems, which report similar torque differentials for effective lateral error correction during lane changes [12]. Furthermore, the 52.8% average reduction in lateral error achieved by our method represents a significant improvement over the performance benchmarks reported for non-integrated adaptive MPC controllers in similar scenarios [12]. While simulation results are promising, the real-world efficacy of such torque-vectoring strategies has been validated in experimental autonomous vehicles, confirming their critical role in maintaining stability under low-friction conditions [37].

Table 1 The vehicle parameters were used in simulation

Symbol	Parameter	Value	Unit
m	Vehicle mass	2032	kg
l_f	Front axle to CoG	1.26	m
l_r	Rear axle to CoG	1.90	m
I_z	Mass inertia	6286	kg/m^2
C_f	Front tire cornering stiffness	40200	N/rad
C_r	Front tire cornering stiffness	62800	N/rad
I_ω	Wheel moment of inertia	2.1	kgm^2
R_ω	Wheel radius	0.3	m
l_w	Vehicle track width	1.53	m
g	Gravitational acceleration	9.81	m/s^2

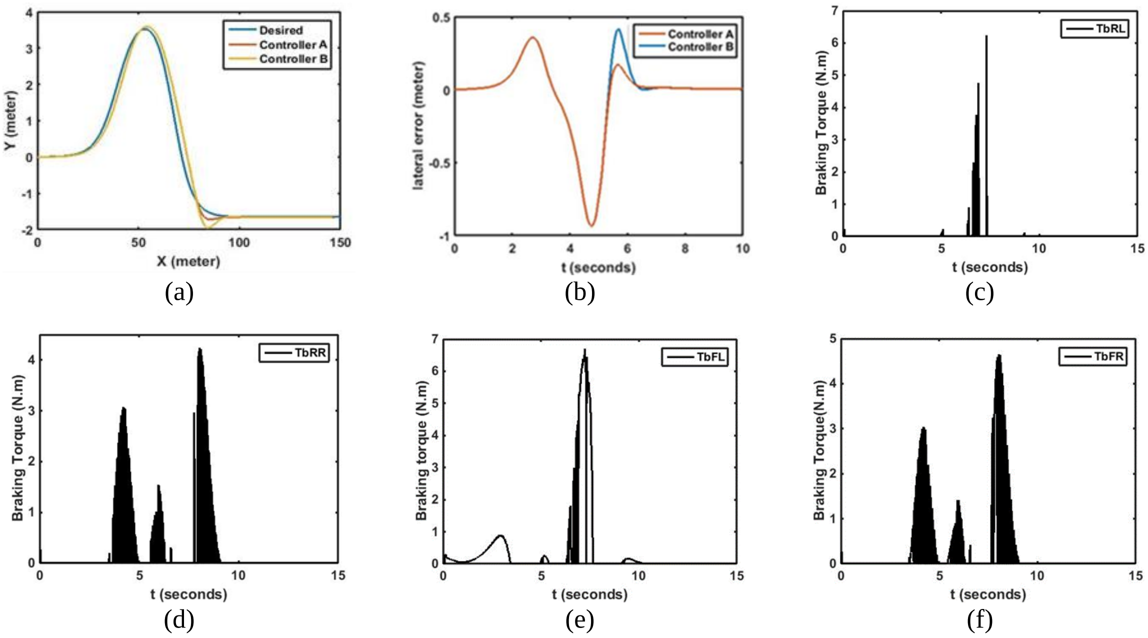
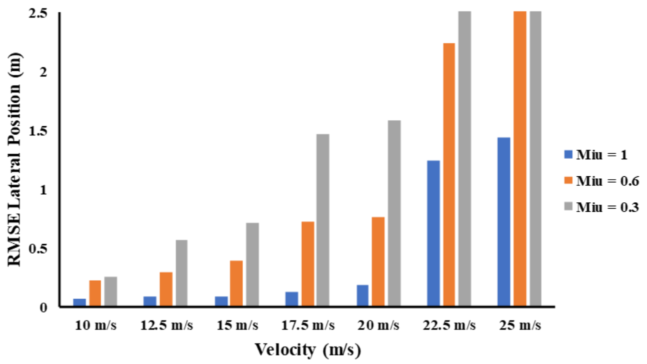


Figure 6. Simulation results: (a) path tracking at a speed of 15 m/s in the double lane change (BLC) maneuver trajectory with friction surface 0.6, (b) lateral error using adaptive MPC integrated with torque braking distribution (controller A) compared to MPC (controller B), (c) rear left braking torque, (d) rear right braking torque, (e) front left braking torque, and (f) front right braking torque

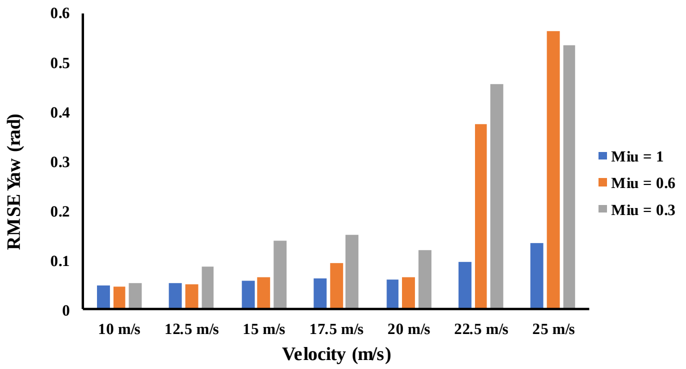
3.1. Yaw and lateral error with varying speed and surface friction

In order to evaluate the control performance under various road conditions and vehicle speeds, a root mean square error (RMSE) analysis was conducted for both yaw angle and lateral position. The results, as illustrated in Figure 7, compare the RMSE values at different velocities for three distinct road friction coefficients (μ =1, 0.6, and 0.3). This comparison provides a clear understanding of how tire–road interaction affects the accuracy and stability of vehicle motion control at increasing velocities**.**

The Figure 7(a) shows RMSE of yaw angle (rad) and the Figure 7(b) shows RMSE of lateral position for three road friction coefficients (μ = 1, 0.6, 0.3). For low-to-moderate speeds (10–20 m/s) RMSE values remain small for all μ, with the best performance at μ = 1 and progressively worse errors as μ decreases. Above ~22.5 m/s the errors rise sharply—yaw RMSE increases markedly and lateral-position RMSE exhibits a dramatic jump—especially for μ = 0.6 and μ = 0.3, indicating loss of tracking accuracy at high speed and low friction. This trend suggests tyre force saturation and stronger nonlinear tyre dynamics (and likely model mismatch) at high speeds and low μ, which the current controller cannot fully compensate. Practically, the results imply the control design requires either gain scheduling or adaptive/robust control, improved tire/vehicle modeling (or friction estimation), and possibly higher control bandwidth or actuator authority to maintain stability and tracking at high speeds and low-friction conditions.



(a)



(b)

Figure 7. RMSE of lateral error and yaw rate across a lane change scenario at various velocities: (a) friction $\mu = 0.6$ and (b) friction $\mu = 0.3$

4. CONCLUSION

This study proposed and validated a novel integrated control framework, combining adaptive MPC with a proactive torque braking distribution strategy, to enhance autonomous vehicle safety during lane change maneuvers. The primary scientific contribution is the synergistic, real-time coordination of steering and braking within a unified predictive optimization loop. Quantitative simulation results across diverse speeds (10-25 m/s) and friction levels (μ = 0.3 to 1.0) confirm the framework's efficacy. The adaptive MPC demonstrated a 52.8% average reduction in lateral tracking error and improved stability by reducing yaw rate by up to 41.8% on low-friction surfaces, compared to a non-adaptive baseline. These improvements are attributed to the controller's ability to update critical parameters in real-time and proactively generate stabilizing yaw moments. However, performance limitations were observed at very high speeds (>22.5 m/s) on low-friction roads. The primary limitation of this work is its reliance on simulation-based validation. Future work must therefore address uncertainties from model simplifications and unmodeled hardware effects through experimental validation using HIL systems and prototype vehicle testing.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Zulkarnain	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Irwin Bizzy		✓				✓		✓	✓	✓	✓	✓		
Armin Sofijan	✓		✓	✓			✓			✓	✓		✓	✓
Mohd Hatta Mohammed Ariff		✓		✓	✓	✓		✓		✓		✓		✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

[1] R. Chen, "A Comprehensive Analysis of PID Control Applications in Automation Systems: Current Trends and Future Directions," *Highlights in Science, Engineering and Technology*, vol. 97, pp. 126–132, 2024, doi: 10.54097/6q4xxg69.

[2] S. Abdallaoui, A. Kribèche, and E.-H. Aglzim, "Comparative Study of MPC and PID Controllers in Autonomous Vehicle Application BT- Advances in Automation, Mechanical and Design Engineering," M. A. Laribi, G. Carbone, and Z. Jiang, Eds., Cham: Springer International Publishing, 2023, pp. 133–144.

[3] D. Urbaniak, S. Damsgaard, W. Zhang, J. Rosell, R. Suarez, and M. Suppa, "Distributed Control for Collaborative Robotic Systems Using 5G Edge Computing," *IEEE Access*, vol. PP, p. 1, Jan. 2024, doi: 10.1109/ACCESS.2024.3475584.

[4] Z. A. Leman, I. Thamrin, N. P. E. Utami, S. A. Permana, and M. B. Pamungkas, "Mobile robots with differential drive with PD pose control utilizing kinematics model," in *AIP Conference Proceedings*, 2024, p. 50066.

[5] I. L. H. Alsammak, M. A. Mahmoud, H. Aris, M. AlKilabi, and M. N. Mahdi, "The Use of Swarms of Unmanned Aerial Vehicles in Mitigating Area Coverage Challenges of Forest-Fire-Extinguishing Activities: A Systematic Literature Review," *Forests*, vol. 13, no. 5, p. 811, 2022, doi: 10.3390/f13050811.

[6] N. Hafizah, K. Hudha, H. Zamzuri, and V. Rau, "Adaptive modified Stanley controller with fuzzy supervisory system for trajectory tracking of an autonomous armoured vehicle," *Robotics and Autonomous Systems*, vol. 105, pp. 94–111, 2018, doi: 10.1016/j.robot.2018.03.006.

[7] Z. Leman, M. Ariff, H. Zamzuri, R. Mohd Azizi Abdul, and F. Yakub, "Gain Scheduling Model Predictive Path Tracking Controller for Autonomous Vehicle on Highway Scenario.," in *Lecture Notes in Mechanical Engineering: Proceedings of the 6th International Conference and Exhibition on Sustainable Energy and Advanced Materials*, Singapore: Springer Nature, 2020, pp. 461–472, doi: 10.1007/978-981-15-4481-1_44.

[8] S. Li, D. Li, H. Wang, Y. Jiang, and G. Cui, "Combined Steering and Braking Collision Avoidance Control Method Based on Model Predictive Control," *International Journal of Automotive Technology*, vol. 25, no. 3, pp. 553–563, 2024, doi: 10.1007/s12239-024-00044-4.

[9] N. Kang, Y. Han, and L. Liu, "Robust integrated control of autonomous vehicles path tracking with fault-tolerant yaw stability control," *Transactions of the Institute of Measurement and Control*, p. 01423312251330765, May 2025, doi: 10.1177/01423312251330765.

[10] N. Hafizah, A. Hairi, K. Hudha, and Z. Abdul, "Modelling and Control Strategies in Path Tracking Control for Autonomous Ground Vehicles : A Review of State of the Art and Challenges," *Journal Intelligent Robot System*, vol. 86, pp. 225–254, 2017, doi: 10.1007/s10846-016-0442-0.

[11] K. Liu, J. Gong, S. Chen, Y. Zhang, and H. Chen, "Model predictive stabilization control of high-speed autonomous ground vehicles considering the effect of road topography," *Applied Sciences (Switzerland)*, vol. 8, no. 5, 2018, doi: 10.3390/app8050822.

[12] P. Raksincharoensak, S. Daisuke, and M. Lidberg, "Direct yaw moment control for enhancing handling quality of lightweight electric vehicles with large load-to-curb weight ratio," *Applied Sciences (Switzerland)*, vol. 9, no. 6, 2019, doi: 10.3390/app9061151.

[13] X. V. Wang and L. Wang, "A literature survey of the robotic technologies during the COVID-19 pandemic," *Journal of*

Manufacturing Systems, vol. 60, no. December 2020, pp. 823–836, 2021, doi: 10.1016/j.jmsy.2021.02.005.
[14] D. H. Watzenig, *Automated Driving Safer and More Efficient Future Driving*, First Edit. Switzerland: Sringer, 2017.
[15] S. De Sorniotti, A. Barber, P. Pinto, "Path Tracking for Automated Driving: A Tutorial on Control System Formulations and Ongoing Research," in *Automated Driving: Safer and More Efficient Future Driving*, First., M. D. Watzenig, Ed., Switzerland: Springer, 2016, ch. Fifth, pp. 1–620, doi: 10.1007/978-3-319-31895-0.
[16] S. Park, T. Oh, J. Kim, and J. Yoo, "Robust Path-Tracking Control for Autonomous Vehicles: A Model-Reference-Adaptive-Control-Based Integrated Chassis Control Strategy," 2025, doi: 10.3390/app152312387.
[17] M. Elbanhawi, M. Simic, and R. Jazar, "Improved manoeuvring of autonomous passenger vehicles: Simulations and field results," *Journal of Vibration and Control*, vol. 23, no. November, pp. 1–36, 2015, doi: 10.1177/1077546315605666.
[18] H. Andersen, Z. J. Chong, Y. H. Eng, S. Pendleton, and M. H. Ang, "Geometric path tracking algorithm for autonomous driving in pedestrian environment," *IEEE/ASME International Conference on Advanced Intelligent Mechatronics, AIM*, vol. 2016–Septe, pp. 1669–1674, 2016, doi: 10.1109/AIM.2016.7577010.
[19] L. Ni, A. Gupta, P. Falcone, and L. Johannesson, "Vehicle Lateral Motion Control with Performance and Safety Guarantees," *IFAC-PapersOnLine*, vol. 49, no. 11, pp. 285–290, 2016, doi: 10.1016/j.ifacol.2016.08.043.
[20] C. Jing, H. Shu, Y. Song, and C. Guo, "Hierarchical Control of Yaw Stability and Energy Efficiency for Distributed Drive Electric Vehicles," *International Journal of Automotive Technology*, vol. 22, no. 5, pp. 1169–1188, 2021, doi: 10.1007/s12239-021-0104-5.
[21] L. F. P. Oliveira, A. P. Moreira, and M. F. Silva, "Advances in forest robotics: A state-of-the-art survey," *Robotics*, vol. 10, no. 2, pp. 1–20, 2021, doi: 10.3390/robotics10020053.
[22] R. Wang, H. Zhang, and J. Wang, "Linear parameter-varying controller design for four-wheel independently actuated electric ground vehicles with active steering systems," *IEEE Transactions on Control Systems Technology*, vol. 22, no. 4, pp. 1281–1296, 2014, doi: 10.1109/TCST.2013.2278237.
[23] X. Wang, M. Fu, Y. Yang, and H. Ma, "Lateral Control of Autonomous Vehicles Based on Fuzzy Logic," *Control Engineering Practice*, pp. 237–242, 2013.
[24] T. M. Howard, R. A. Knepper, and A. Kelly, "Constrained optimization path following of wheeled robots in natural terrain," *Springer Tracts in Advanced Robotics*, vol. 39, pp. 343–352, 2008, doi: 10.1007/978-3-540-77457-0_32.
[25] J. Meng, H. Xiao, L. Jiang, Z. Hu, L. Jiang, and N. Jiang, "Adaptive Model Predictive Control for Mobile Robots with Localization Fluctuation Estimation," 2023, doi: 10.3390/s23052501.
[26] T. Wu, M. Cai, and X. Miao, "Adaptive Sliding Mode Trajectory Tracking Control of Mobile Robots," in *2024 8th International Workshop on Control Engineering and Advanced Algorithms (IWCEAA)*, 2024, pp. 24–28, doi: 10.1109/IWCEAA63616.2024.10823984.
[27] J. Zhang, C. Wang, and Y. Wu, "Adaptive neural network control for nonholonomic systems with partial/full or without state constraints," *Journal of the Franklin Institute*, vol. 360, no. 14, pp. 10633–10655, 2023, doi: https://doi.org/10.1016/j.jfranklin.2023.08.004.
[28] E. Lucet, R. Lenain, and C. Grand, "Control Engineering Practice Dynamic path tracking control of a vehicle on slippery terrain," *Control Engineering Practice*, vol. 42, pp. 60–73, 2015, doi: 10.1016/j.conengprac.2015.05.008.
[29] C. Katrakazas, M. Quddus, W. Chen, and L. Deka, "Real-time motion planning methods for autonomous on-road driving : State-of-the-art and future research directions," *Transportation Research Part C*, vol. 60, no. 2015, pp. 416–442, 2015, doi: 10.1016/j.trc.2015.09.011.
[30] M. Nagai, "Study on integrated control of active front steer angle and direct yaw moment," *JSAE Review*, vol. 23, no. 3, pp. 309–315, Jul. 2002, doi: 10.1016/S0389-4304(02)00189-3.
[31] P. Falcone, H. E. Tseng, and F. Borrelli, "MPC-based yaw and lateral stabilisation via active front steering and braking," *Vehicle System Dynamics*, vol. 46, no. September 2014, pp. 611–628, 2008, doi: 10.1080/00423110802018297.
[32] R. Hayashi, J. Isogai, P. Raksincharoensak, and M. Nagai, "Autonomous collision avoidance system by combined control of steering and braking using geometrically optimised vehicular trajectory," *Vehicle System Dynamics*, vol. 50, pp. 151–168, 2012, doi: 10.1080/00423114.2012.672748.
[33] P. Falcone, F. Borrelli, J. Asgari, H. E. Tseng, and D. Hrovat, "Predictive Active Steering Control for Autonomous Vehicle Systems," vol. 15, no. 3, pp. 566–580, 2007.
[34] P. Falcone, F. Borrelli, J. Asgari, and D. Hrovat, "Predictive Control Approach to Autonomous Vehicle Steering," in *Proceedings of the 2006 American Control Conference*, Minneapolis: IEEE, 2006, pp. 4670–4675, doi: 10.1109/ACC.2006.1657458.
[35] P. Falcone and F. Borrelli, "A model predictive control approach for combined braking and steering in autonomous vehicles," in *Proceedings of the IEEE 2007 Mediterranean Conference on Control & Automation (MED'07)*, 2007, pp. 1–6, doi: 10.1109/MED.2007.4433694.
[36] S. Ding, L. Liu, and W. X. Zheng, "Sliding Mode Direct Yaw-Moment Control Design for In-Wheel Electric Vehicles," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 8, pp. 6752–6762, 2017, doi: 10.1109/TIE.2017.2682024.
[37] R. Attia, R. Orjuela, and M. Basset, "Combined longitudinal and lateral control for automated vehicle guidance," vol. 3114, 2014, doi: 10.1080/00423114.2013.874563.

BIOGRAPHIES OF AUTHORS

Zulkarnain received the B.Eng. degree in Mechanical Engineering from Universitas Sriwijaya, Indonesia, in 2004, the M.Eng. degree from Universiti Kebangsaan Malaysia in 2011, and the Ph.D. degree from Universiti Teknologi Malaysia in 2021. His research interests include control systems, autonomous vehicle systems, and intelligent transportation technologies. His expertise focuses on the modeling, analysis, and design of control algorithms for autonomous vehicle navigation, motion planning, and system integration, aiming to improve safety, efficiency, and decision-making in intelligent mobility systems. He can be contacted at email: zulkarnain@ft.unsri.ac.id.

Irwin Bizzy earned his Bachelor's degree in Mechanical Engineering from Sriwijaya University in 1990, followed by a Master's degree from the Bandung Institute of Technology (Institut Teknologi Bandung) in 1992. He obtained his Doctorate (Ph.D.) in Mechanical Engineering from Sriwijaya University in 2019. His expertise lies in energy systems, thermal sciences, and energy conversion technologies. He is currently a Professor in the field of Mechanical Engineering, with a focus on the development and optimization of efficient, sustainable energy systems. He can be contacted at email: irwin@ft.unsri.ac.id.

Armin Sofijan received the Bachelor's degree in Electrical Engineering from Sriwijaya University, Indonesia. He earned his Master's degree from the Universitas Sriwijaya, and completed his Doctoral degree in Electrical Engineering at Sriwijaya University. His area of expertise is power systems, energy systems, thermal engineering, and energy conversion technologies. He can be contacted at email: a_sofijan@ft.unsri.ac.id.

Mohd Hatta Mohammed Ariff is an expert in control engineering and vehicle dynamics. His expertise includes the development and application of advanced control systems for automotive technologies, particularly focusing on autonomous vehicles. He specializes in vehicle dynamics, system modeling, and the integration of artificial intelligence to enhance vehicle performance and safety. His research also covers the optimization of motion control strategies and the design of innovative engineering solutions for complex automotive systems. He can be contacted at email: mohdhatta.kl@utm.my.