Journal of Electronics and Electrical Engineering
https://ojs.wiserpub.com/index.php/JEEE

Research Article

Model Predictive Control-Based Lane Keeping Assist: Design, Validation, and Comparative Analysis for ADAS and Autonomous Driving

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Received: 30 October 2025; **Revised:** 12 January 2026; **Accepted:** 4 February 2026; **Published:** 2 March 2026

Abstract: Precise lateral control is a key challenge in the development of Advanced Driver-Assistance Systems (ADAS), particularly for Lane Keeping Assist (LKA) functionalities. This paper presents a Model Predictive Control (MPC) strategy tailored for LKA, designed to maintain the vehicle within its lane while ensuring stability and responsiveness. The controller leverages a dynamic vehicle model that integrates longitudinal, lateral, and yaw dynamics to realistically capture tire–road interactions and vehicle behavior. Through real-time optimization, the MPC predicts future vehicle states and computes an optimal control sequence that minimizes lateral deviation and heading error, while adhering to physical constraints such as steering limits and actuator saturation. The closed-loop stability of the system is theoretically validated using a Lyapunov-based approach. The proposed MPC controller is intended for integration within a modular ADAS architecture, alongside perception, lane detection, and longitudinal control modules. Simulation results using real-world trajectory data demonstrate the controller's effectiveness in delivering precise and robust lane keeping performance under varying driving conditions.

Keywords: Advanced Driver-Assistance Systems (ADAS), Lane Keeping Assist (LKA), Model Predictive Control (MPC)

1. Introduction

Advanced Driver-Assistance Systems (ADAS) and automated driving technologies are typically organized into a perception–planning–control architecture. This structure is designed to enhance both safety and comfort, while progressively enabling higher levels of autonomy. A number of recent books and surveys have explored this framework in depth, discussing not only the technical components such as sensing, estimation, control algorithms, and embedded execution but also the associated legal and verification challenges [1–4]. Within this architecture, two key closed-loop behaviors stand out: lateral control, which governs lane keeping and trajectory tracking, and longitudinal control, which manages cruise and car-following functions.

While learning-based components are increasingly integrated into modern control stacks, classical controllers particularly PID-based designs continue to serve as a reliable foundation in production systems [5]. Their enduring appeal lies in their transparency, ease of calibration, and well-understood behavior, which are critical in safety-sensitive automotive applications. Empirical studies involving both trucks and passenger vehicles have shown that PID-type controllers can deliver competitive performance in low-speed longitudinal control and platooning tasks, especially when

DOI: https://doi.org/10.37256/jeee.5120269046

the vehicle's actuation dynamics are properly identified and the control loops are structured in a nested fashion. In more complex scenarios, hybrid schemes that combine Model Predictive Control (MPC) with PID tuning have been proposed to handle constrained Multi-Input Multi-Output (MIMO) systems effectively [6–8].

Beyond conventional PID, adaptive and intelligent variants—such as neural network and Radial Basis Function (RBF)-based designs—continue to find practical use in engine and velocity control, highlighting their robustness and adaptability in real-world settings [9, 10]. For high-speed and evasive maneuvers, however, control strategies must integrate both longitudinal and lateral dynamics. Recent developments have introduced coordinated lane-change controllers capable of achieving collision avoidance at highway speeds. Robust and sliding-mode control approaches have also demonstrated improved disturbance rejection and reduced reliance on precise modeling, benefiting both path tracking and longitudinal control [11–13].

In parallel, the Stanley controller remains a widely used benchmark for nonlinear trajectory tracking, particularly in off-road conditions. Its formal stability guarantees and extensive field validation make it a common reference point for evaluating model-based MPC formulations [14]. MPC itself offers a principled framework for handling multi-objective trade-offs and hard constraints by optimizing control actions over a prediction horizon. In longitudinal control, MPC has been successfully applied to regulate inter-vehicle spacing and speed in platoons including merging and exiting maneuvers and to enhance energy efficiency in dual-motor electric vehicles, with both Hardware-in-the-Loop (HIL) and simulation studies supporting its real-time feasibility [15–17].

For lateral and path tracking, MPC complements classical controllers by incorporating preview capabilities, state and input constraints, and comfort metrics into a unified optimization framework. Recent innovations include horizon-varying MPC tuned via proximal policy optimization to adapt to varying curvature and speed [18]; Particle Swarm Optimization (PSO)-based MPC and other meta-heuristic methods for tuning weights and parameters [19, 20]; and cascaded discretization techniques with path preview to balance accuracy and latency within a single horizon [21]. Reinforcement learning–aided MPC has also emerged as a promising approach to compensate for modeling inaccuracies while preserving constraint handling [22]. Furthermore, data-driven MPC for steering reduces dependence on explicit vehicle and tire models, while maintaining the structural advantages of MPC [23]. Hybrid approaches that blend nominal calibrated models with learned low-dimensional residuals have shown strong performance in both simulation and real-world tests [24].

Selecting an appropriate predictive model and defining suitable constraints remain central challenges in the design of effective Model Predictive Control (MPC) systems. Surveys have cataloged the conditions under which various vehicle models such as kinematic bicycle, dynamic bicycle, or higher-Degree-of-Freedom (DOF) representations are most suitable for control synthesis, along with the implications these choices have on computational tractability and robustness [25]. While traditional constraints often focus on lateral position and yaw rate, recent benchmark problems and studies have expanded the scope to include body-attitude constraints, such as roll, pitch, and vertical forces. These considerations are especially relevant for vehicles equipped with four in-Wheel Motors (4-IWM), where precise torque distribution and body dynamics play a critical role. MPC designs that explicitly incorporate these constraints have demonstrated strong performance in competitive settings, with some winning community challenges. A journal extension further explores hierarchical strategies for torque and attitude allocation under such bounds [26].

Recent studies have increasingly explored the use of Artificial Intelligence (AI) and Machine Learning (ML) techniques in vehicle lateral control and Lane Keeping Assistance (LKA) systems to overcome modeling uncertainties and performance limitations of purely model-based approaches. In particular, Reinforcement Learning (RL) has been investigated for lateral control due to its ability to learn steering policies directly from interaction data and handle nonlinear vehicle dynamics under varying road conditions without relying on explicit models [27, 28]. However, purely learning-based controllers often lack formal stability and safety guarantees, which limits their applicability in safety-critical automotive systems. To address these limitations, hybrid control architectures combining ML with Model Predictive Control (MPC) have been proposed, where learning-based models are used to estimate uncertain dynamics or compensate for modeling errors, while MPC ensures constraint satisfaction and closed-loop stability [29].

At a broader system level, distributed MPC is gaining traction for platooning applications. Open benchmarks now support standardized comparisons across heterogeneous and hybrid control methods, promoting reproducibility and fair evaluation across research efforts [30]. Meanwhile, adaptive MPC formulations that adjust weights or parameters in real time are proving effective in maintaining control performance across varying road geometries and vehicle speeds. Curvature-aware strategies, in particular, have shown promise in recent automotive case studies, where they help preserve stability and comfort under dynamic driving conditions [31, 32]. These approaches offer adaptability and robustness under complex scenarios. However, AI/ML methods are not yet acceptable in ISO 26262–compliant, and adaptive MPC requires stricted conditions for ADAS functions such as LKA because the standard certifies the development process and safety concept, not the algorithm itself. Consequently, this work focuses on Model Predictive Control (MPC), which provides explicit constraint handling and aligns with safety principles for industrial deployment. Table 1 details the comparison of different controllers for LKA applications, highlighting complexity, constraint handling, and suitability for ISO 26262–compliant development processes.

Table 1. Control methods

Controller Type	Complexity	Real-Time Feasibility	Constraint Handling	ISO 26262 Compliance	Industrial Applicability
PID	Low	High	Limited	well-established	Very High
LQR	Medium	High	Limited	certifiable	High
MPC	Medium-High	Good (with optimization)	Excellent	principles applied	High
Adaptive MPC	High	Moderate	Excellent	Under stricted conditions	Medium
AI/ML-based	Very High	Moderate-Low	Excellent	not certifiable yet	Low

The main contributions of this work are as follows: (i) the development of a Model Predictive Control (MPC)-based lateral controller tailored for Lane Keeping Assist (LKA) within an Advanced Driver Assistance System (ADAS) framework, leveraging a dynamic vehicle model with safety-oriented constraints; (ii) the seamless integration of the proposed controller into MUXLAB, an internal Capgemini platform for system control, representing a critical step toward real-world deployment; (iii) the implementation and validation of the controller using Hardware-in-the-Loop (HIL) testing to ensure robustness and reliability under realistic conditions; and (iv) the performance assessment based on client-provided test-run data, demonstrating the controller's capability to maintain precise lane tracking and its readiness for next-generation semi-autonomous applications. The remainder of this paper is organized as follows. Section 2 describes the vehicle model and the control problem formulation. Section 3 presents the design of the MPC controller with detailed mathematical formulation and stability analysis. Section 4 (Validation) contains validation results and experimental evaluation. Section 5 concludes the paper and discusses perspectives.

2. Problem statement and vehicle modeling

The control of autonomous and assisted driving systems fundamentally relies on accurate mathematical models capable of describing the physical interaction between the vehicle, its actuators, and the surrounding environment. Following the introduction, which highlighted the growing importance of robust trajectory tracking for Advanced Driver Assistance Systems (ADAS) and autonomous vehicles, this section focuses on establishing a physically consistent dynamic model of a four-wheel ground vehicle. This model serves as the foundation for the design of the predictive controller presented later in this paper.

The goal is to derive a dynamic representation that captures the essential longitudinal, lateral, and yaw dynamics relevant to trajectory tracking, while remaining computationally tractable for real-time Model Predictive Control (MPC). The modeling process begins with a general kinematic formulation, followed by a dynamic force-based analysis that incorporates tire-road interactions, longitudinal slip, and lateral coupling. The assumptions and simplifications applied at each stage are explicitly stated, as they form the physical and mathematical bridge between the real vehicle behavior and the control-oriented model.

2.1 *Vehicle model*

Consider a four-wheeled ground vehicle moving on a flat plane, represented by a global inertial frame Y and a body-fixed coordinate frame centered at the vehicle's Center of Gravity (CG). The pose of the vehicle in the inertial frame is described by its position (x, y) and yaw angle ψ. The translational velocity of the CG is denoted by v, which is decomposed into longitudinal and lateral components with respect to the body frame:

$$\begin{aligned} \dot{x} &= v_x \cos(\psi) - v_y \, sin(\psi) \\ \dot{y} &= v_x \sin(\psi) - v_y \, cos(\psi) \end{aligned} \tag{1}$$

Where v_x and v_y are the longitudinal and lateral velocity at the vehicle's CG. The yaw rate $\dot{\psi}$ relates to the rotational motion around the vertical z-axis, and its derivative describes the yaw acceleration.

The dynamic model is derived from Newton–Euler equations applied to the vehicle body. Considering longitudinal, lateral, and yaw motion in the plane, the equations of motion can be written as:

$$\begin{aligned} & m\left(\dot{v}_x - \dot{\psi} v_y\right) = \sum F_{x,i} - F_{aero} - F_{roll} \\ & m\left(\dot{v}_y + \dot{\psi} v_x\right) = \sum F_{y,i} \\ & I_z \ddot{\psi} = \sum M_{z,i} \end{aligned} \tag{2}$$

Where m is the vehicle mass, I_z is the yaw moment of inertia, $\sum F_{x,i}$ and $\sum F_{y,i}$ are the longitudinal and lateral titre force at wheel I, $F_{aero} = C_d v_x^2$ is the aerodynamic drag, and $F_{roll} = mgC_r$ is the roll resistance.

The summations run over all four wheels $\sum F_{x,i}$ and $\sum F_{y,i}$ and the yaw total moment are given as follow:

$$\begin{aligned} & \sum F_{x,i} = F_{x,fl} + F_{x,fr} + F_{x,rl} + F_{x,rr} \\ & \sum F_{y,i} = F_{y,fl} + F_{y,fr} + F_{y,rl} + F_{y,rr} \\ & \sum M_{z,i} = L_f\left(F_{y,fl} + F_{y,fr}\right) - L_r\left(F_{y,rl} + F_{y,rr}\right) + \frac{t_f}{2}\left(F_{x,fr} - F_{x,fl}\right) + \frac{t_r}{2}\left(F_{x,rr} + F_{x,rl}\right) \end{aligned} \tag{3}$$

Where L_f, L_r denote the distances from the CG to the front and rear axles, respectively, and tf, tr are the front and rear track widths, in $F_{x,i}$, fl, fr, rl, rr are front left, front right, rear left, rear right, respectively.

Each wheel generates longitudinal and lateral forces that depend on slip ratio k_i and slip angle α_i. For small slip conditions (typical of nominal driving and trajectory tracking maneuvers), these forces can be approximated linearly as:

$$F_{x,i} = C_{x,i}k_i$$

$$F_{y,i} = -C_{y,i}\alpha_i \tag{4}$$

$$\alpha_i = \delta_i - \tan^{-1}\left(\frac{v_{y,i}}{v_{x,i}}\right)$$

Where $C_{x,i}$, $C_{y,i}$ are the longitudinal and cornering stiffness coefficient, respectively, δ_i is the steering angle of wheel i. These relations allow expressing the total tire forces as functions of the vehicle lateral and yaw velocity and the control input as steering angle δ.

2.2 *Problem statement*

To develop a model predictive controller, the nonlinear model presented in (3)-(4) will be linearized with the following assumption, these assumptions are made for calculating in the control horizon for solving the optimization problem. For each prediction horizon we assume that

- The longitudinal velocity is constant, namely: $\mathbf{v_x}=\mathbf{v_0}$
- Negligible load transfer between wheels
- The cornering stiffness coefficient of two front wheel are similar, similarly to rear wheels.

Under these conditions, the linearized equation of motion can be presented as following

$$\dot{v}_y = -\frac{2\left(C_{y,f} \vdash C_{y,r}\right)}{mv_0}v_y - \left(v_0 + \frac{2\left(C_{y,f}L_f - C_{y,r}L_r\right)}{mv_0}\right)\dot{\psi} + \frac{2C_{y,f}}{m}\delta$$

$$\ddot{\psi} = -\frac{2\left(L_fC_{y,f} - L_rC_{y,r}\right)}{I_zv_0}v_y - \frac{2\left(L_f^2C_{y,f} + L_r^2C_{y,r}\right)}{I_zv_0}\dot{\psi} + \frac{2L_rC_{,y,f}}{I_z}\delta \tag{5}$$

The corresponding lateral displacement dynamics are obtained by the following equation

$$y = v_y + v_0\psi \tag{6}$$

The above equation (5)-(6) collectively presents the coupled lateral-yaw motion of the four-wheels vehicle.

Now let us define the state vector X and the controller u as following:

$$X = [y, v_y, \psi, \dot{\psi}]^T\ ;\ u = \delta \tag{7}$$

Based on (5) and (7) we can rewrite the dynamic equation of the vehicle as following:

$$\dot{X} = AX + Bu \tag{8}$$

Where matrices A and B, based on (5) are given as follows:

$$A = \begin{bmatrix} 0 & 1 & v_0 & 0 \\ 0 & -\frac{2(C_{y,f}+C_{y,r})}{mv_0} & 0 & -\left(v_0 + \frac{2(C_{y,f}L_f - C_{y,r}L_r)}{mv_0}\right) \\ 0 & 0 & 0 & 1 \\ 0 & -\frac{2(L_f C_{y,f} - L_r C_{y,r})}{I_z v_0} & 0 & -\frac{2\left(L_f^2 C_{y,f} + L_r^2 C_{y,r}\right)}{I_z v_0} \end{bmatrix}; \; B = \begin{bmatrix} 0 \\ \frac{2C_{y,f}}{m} \\ 0 \\ \frac{2L_r C_{,y,f}}{I_z} \end{bmatrix} \tag{9}$$

For discrete-time implementation, with the MPC, this model is discretized with sampling time T_s as:

$$\begin{aligned} X_{k+1} &= A_d X_k + B_d u_k \\ A_d = e^{AT_s}; \; B_d &= \int_0^{T_s} {}^{At} Bt \end{aligned} \tag{10}$$

Where T_s represents the sampling period. The preceding development provides a completely dynamic model suitable for MPC design. To proceed with the development of controllers in the next section, we introduce the following assumption, which will be instrumental in the formulation.

Assumption 1: The vehicle's vertical dynamics and roll dynamics are disregarded in the modeling process. The system is treated as operating in a planar motion framework, where pitch, roll, and heave effects are assumed to have negligible influence on the lateral and longitudinal behavior.

Assumption 2: The longitudinal velocity of the vehicle is assumed to be precisely known at all times and remains constant throughout the prediction horizon. This implies that variations in speed due to acceleration or braking are not considered within the scope of the lateral control model.

Assumption 3: The relationship between tire forces and slip angles is assumed to be linearized around small slip angles. This means that nonlinear effects associated with large slip angles or tire saturation are excluded from the model representation.

Assumption 4: Changes in vertical load distribution among the four wheels are assumed to be negligible. The normal loads on the tires are considered constant, and load transfer effects due to lateral acceleration or suspension dynamics are ignored.

Assumption 5: The steering actuation is assumed to be symmetric across the front axle, such that both front wheels receive identical steering angles. Consequently, the front axle is modeled as a single equivalent steering input without accounting for individual wheel steering variations.

Assumption 6: External environmental influences such as aerodynamic disturbances, wind gusts, road gradient, and surface irregularities are assumed absent. The vehicle is considered to operate on a flat and uniform road surface under ideal conditions.

3. Control design

The control strategy developed in this section focuses on achieving precise lateral trajectory tracking for a four-wheel vehicle, based on the dynamic model and assumptions outlined in Section 2. The controller is designed to produce steering commands that minimize both lateral and heading errors, while adhering to physical constraints such as steering limits and tire force capabilities. To address this challenge, we employ a Model Predictive Control (MPC) approach. MPC optimizes control inputs over a finite prediction horizon using the vehicle's dynamic model, allowing it to anticipate future states and enforce system constraints explicitly. Its ability to handle multi-variable interactions and constraints makes it particularly well-suited for vehicle control applications. The following subsections present the formulation of the MPC optimization problem, the design of the cost function, the structure of the real-time control loop, and a stability analysis demonstrating asymptotic convergence of the tracking errors.

3.1 *Control architecture*

The control of autonomous vehicles is generally divided into two main components: longitudinal control and lateral control. These two aspects must be coordinated to ensure smooth, safe, and efficient driving behavior.

The overall vehicle control system for Lane Keeping Assist (LKAS) is based on a modular architecture composed of several interconnected functional blocks. The control diagram shown in Figure 1 structures all the information flows and control actions necessary for the system to function correctly. It includes the following elements:

• Reference Generator: This module provides the trajectory and speed commands to be followed. The lateral trajectory can be derived from map data, perception sensors (cameras, LiDAR), or a trajectory planner. The longitudinal reference speed is also generated here, although it is assumed to be constant in this study.

• Speed Controller: This block is responsible for regulating the vehicle's longitudinal speed. It receives the speed command from the reference generator and acts on the accelerator or braking system to maintain the desired speed. This controller was developed and validated in previous work [9, 10]. In this study, the speed control system is not redesigned; instead, the existing controller is used as is to provide a constant speed to the system.

• MPC Controller for LKAS: This module forms the core of the lateral control system. It receives the reference trajectory and the vehicle's current state, and calculates the optimal steering angle at any given time. The controller is based on a Model Predictive Control (MPC) approach, which allows it to take into account the vehicle's physical constraints while optimizing trajectory tracking.

• Vehicle Model: This block represents the vehicle's actual dynamics. It provides the necessary measurements to the controller (lateral position, speed, yaw angle, etc.) via onboard sensors. It also receives commands from the speed and steering controllers.

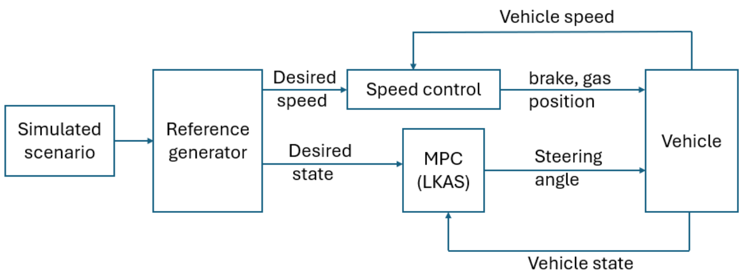

Figure 1. Control architecture

3.2 *Control design*

MPC control offers a powerful and flexible approach to regulating constrained dynamic systems. In this study, MPC allows us to predict the vehicle's future behavior over a finite time horizon and to calculate, at each instant, an optimal sequence of control actions, while respecting the vehicle's physical and dynamic constraints.

Let's define the cost function for the MPC controller as follows:

$$J = \sum_{i=0}^{N_p} \left(X_{d,i} - X_i\right)^T Q \left(X_{d,i} - X_i\right) + \sum_{i=0}^{N_c} u_i^T R u_i \tag{11}$$

Where, N_p is the number of predictive steps in the predictive horizon, N_c is the number of control steps in the control horizon, $X_{d,i}$ is the desired state vector at the i-th step, X_i is the state vector at the ith step defined by (10), the matrices Q and R are weights defining the compromise between tracking accuracy and control effort (they are positive). The control $U(t) = \begin{bmatrix} u_1 & \cdots & u_{N_c} \end{bmatrix}^T$ is calculated by solving the optimization problem at each time t as follows:

$$U(t) = \min \left(\sum_{i=0}^{N_p} \left(X_{d,i} - X_i\right)^T Q \left(X_{d,i} - X_i\right) + \sum_{i=0}^{N_c} u_i^T R u_i \right) \tag{12}$$

3.3 *Stability analysis*

To guarantee the stability of the closed-loop system, a candidate quadratic Lyapunov function is introduced as a function of the $E = X_d - X$ as following:

$$V(E) = E^T P E \tag{13}$$

Consider the discrete time error: $E_k = X_{,k} - X_k$, hence based on (10) one has:

$$E_{k+1} = A_d E_k + B_d \left(u_d - u_k\right) \tag{14}$$

Where u_d denote the steady-state input that maintains the reference trajectory invariant. This input represents the ideal control value, although it is not known a priori. The objective of the control design is to demonstrate that the applied control will converge to u_d in finite time. To analyze the stability of the proposed approach, we introduce an auxiliary feedback law that facilitates the convergence proof. As follows:

$$\widetilde{u} = u_d - u_k = K E_k \tag{15}$$

which represents the implicit linear feedback used by MPC near equilibrium (and exactly equal to the LQR law when constraints are inactive). Now based on (13)-(15) one has:

$$\begin{aligned} E_{k+1} &= \left(A_d + B_d K\right) E_k \\ V(E_k) &= \ E_k{}^T P E_k \\ V(E_{k+1}) &= \ E_k{}^T \left[\left(A_d + B_d K\right)^T P \left(A_d + B_d K\right) \right] E_k \end{aligned} \tag{16}$$

Then one can derive:

$$\Delta V = V(E_{k+1}) - V(E_k) = \ E_k{}^T \left[\left(A_d + B_d K\right)^T P \left(A_d + B_d K\right) - P \right] E_k \tag{17}$$

Let us now consider the MPC stage cost $l(E_k, \widetilde{u}) = E_k{}^T Q E_k + \widetilde{u}^T R \widetilde{u}$. Now if the matrices Q and R is design so that the following LMI is feasible:

$$(A_d + B_d K)^T P (A_d + B_d K) - P + Q + K^T R K \leq 0 \tag{18}$$

Then one can derive that:

$$\Delta V \leq - l(E_k, \widetilde{u}) = -\left(E_k{}^T Q E_k + \widetilde{u}^T R \widetilde{u} \right) < 0 \tag{19}$$

This condition guarantees that the Lyapunov function $V(E)$ stricly decreases and, moreover, decrease by at leaset the stage cost then the stability and performance guarantees of the control system can be established.

The LMI (18) is dedicated to calculating the matrices Q and R for the controller. To ensure closed-loop convergence of the error E_k in (16), we first select a stabilizing feedback K such that the linearized closed-loop matrix satisfies $A_d + B_d K \leq -a_e I$, which guarantees the decay of E_k under the imposed convergence rate. Using this determined K, we impose an analogous convergence condition on the Lyapunov matrix P consistent with
$V(E_k) = E_k{}^T P E_k$ and solve the LMI (18), subject to $P \geq$, $Q \geq 0$, and $R \geq 0$. This procedure yields Q and R that are consistent with the prescribed convergence rate and the chosen Lyapunov structure; detailed numerical values are omitted due to confidentiality.

4. Validation

Following the theoretical development of the Model Predictive Control (MPC) strategy for the Lane Keeping Assist System (LKAS), a numerical validation phase is essential to assess its performance in a simulated environment that closely reflects real-world driving conditions. This step is crucial for verifying the controller's robustness, stability, and efficiency across various scenarios, including trajectory changes, sharp curves, and dynamic disturbances.

To achieve this, the validation relies on a Hardware-in-the-Loop (HIL) setup that integrates the MPC-based LKAS controller with a high-fidelity vehicle dynamics model. This configuration enables real-time execution of the control algorithm on embedded hardware while interacting with a simulated environment, ensuring that timing constraints and computational limitations are properly evaluated. The HIL approach provides a more realistic assessment compared to pure software simulations, as it bridges the gap between theoretical design and practical implementation. The overall architecture of this validation platform is illustrated in Figure 2, which depicts the MUXLAB-based HIL setup developed for this work.

The simulation architecture, depicted in Figure 1 of Section 3, incorporates the key functional blocks introduced earlier: the reference trajectory generator, MPC controller, speed controller, and vehicle dynamics model. This closed-loop setup enables comprehensive testing of the controller by capturing the interactions between subsystems.

To demonstrate the effectiveness of the proposed MPC-based LKAS controller and provide a fair comparison with a conventional approach, two validation scenarios are considered. In both cases, the performance of our developed controller is evaluated against a baseline PID controller, as described in reference [5]. The first scenario involves lane-keeping at a constant longitudinal speed, allowing us to assess the controllers under steady-state conditions. The second scenario introduces a time-varying speed profile, which tests the adaptability and robustness of both controllers under dynamic driving conditions. These complementary experiments provide a comprehensive evaluation of tracking accuracy, stability, and responsiveness across different operating regimes.

Figure 3 compares the lane-keeping performance of the proposed MPC controller (left) and the PID controller (right) presented in [5] under a constant-speed scenario. The results clearly indicate that the MPC achieves superior tracking accuracy, maintaining a trajectory that closely follows the reference path with smooth transitions. In contrast, the PID controller exhibits noticeable deviations, particularly in curved sections, which highlights its limited capability to handle predictive control requirements.

Figure 4 presents the tracking error profiles for both controllers. The MPC demonstrates a consistently low and stable error throughout the maneuver, confirming its robustness and precision. Conversely, the PID controller produces highly fluctuating errors, which corroborates the trajectory deviations observed in Figure 3. These oscillations indicate that the PID struggles to maintain stability under the given conditions, resulting in degraded lane-keeping performance.

Figure 5 illustrates the steering control signals generated by the two controllers. The MPC provides smooth and gradual steering angle adjustments, which are essential for vehicle stability and passenger comfort. On the other hand, the PID controller exhibits abrupt changes in the control signal, resembling a bang-bang behavior. Such aggressive actuation not only compromises tracking performance but could also lead to increased mechanical stress on steering components in real-world applications.

Figure 2. Workstation with MuxLab bench in operation: embedded model and supervision

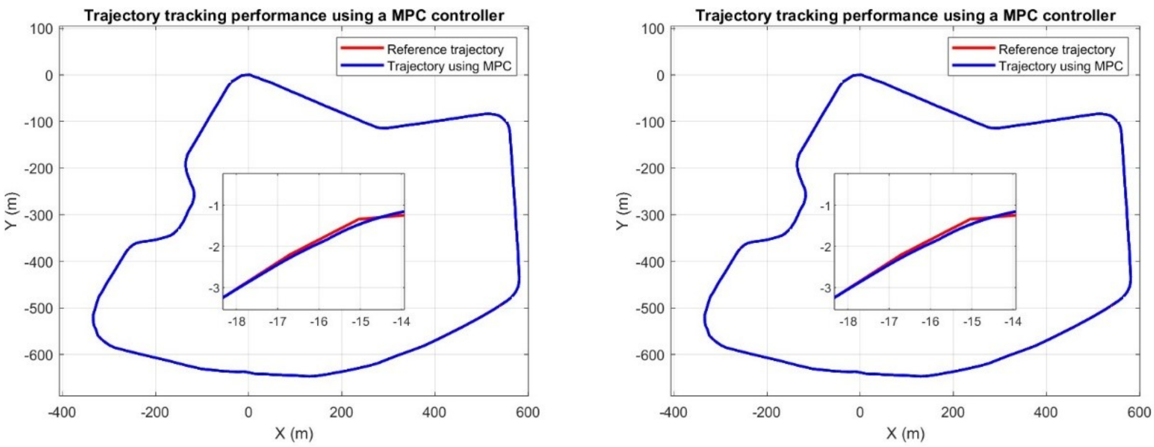

Figure 3. Constant speed trajectory tracking performance with MPC (left) and PID (right)

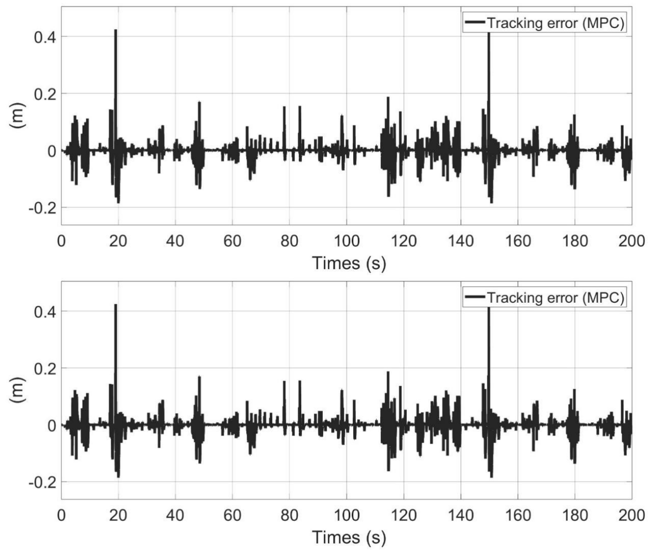

Figure 4. Constant speed trajectory tracking error with MPC and PID

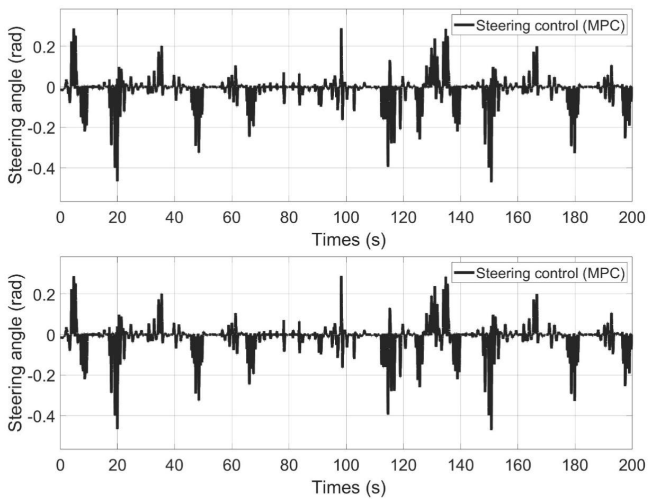

Figure 5. Steering control angle given by MPC and PID

After analyzing the constant-speed case, it is essential to evaluate the controller's performance under more dynamic conditions. To this end, a second validation scenario is introduced, where the vehicle follows a time-varying speed profile. This experiment aims to assess the adaptability and robustness of the proposed MPC controller compared to the PID baseline when subjected to changing longitudinal dynamics. By examining trajectory tracking accuracy, error behavior, and control signal characteristics under these conditions, we can provide a comprehensive comparison of both controllers across different operating regimes

Figure 6 compares the lane-keeping performance of the proposed MPC controller (left) and the PID controller (right) under a time-varying speed profile. Similar to the constant-speed case, the MPC maintains smooth and accurate trajectory tracking, closely following the reference path despite changes in longitudinal dynamics. In contrast, the PID controller exhibits larger deviations and less stability, particularly during speed transitions, confirming its limited adaptability to dynamic conditions.

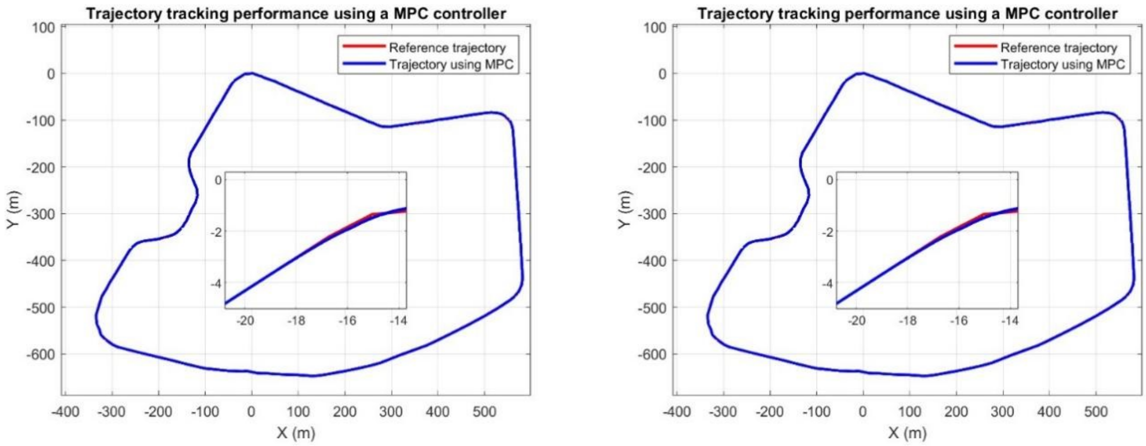

Figure 6. Time-varying speed trajectory tracking performance with MPC (left) and PID (right)

Figure 7 presents the tracking error profiles for both controllers under the time-varying speed scenario. The MPC achieves consistently low error values with minimal fluctuations, demonstrating its robustness against varying operating conditions. Conversely, the PID controller shows significant oscillations and higher error peaks, which align with the trajectory deviations observed in Figure 6. These results reinforce the superior performance of MPC in maintaining lane-keeping accuracy under dynamic speed variations.

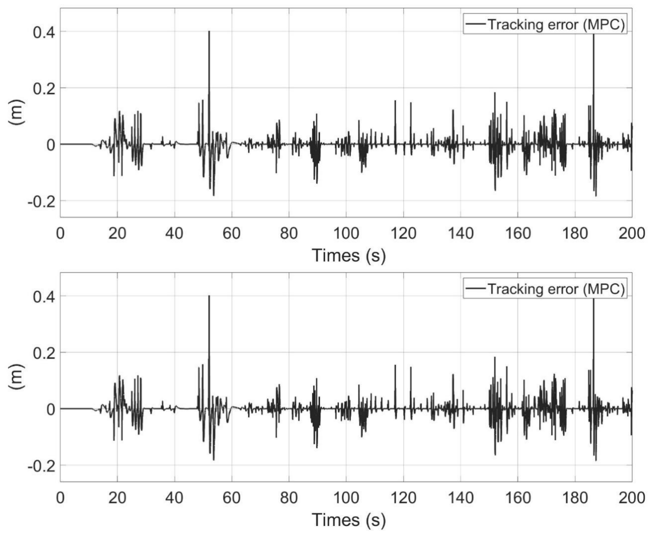

Figure 7. Time-varying speed trajectory tracking error with MPC and PID

Figure 8 illustrates the steering control signals generated by the two controllers. The MPC continues to provide smooth and gradual steering angle adjustments, ensuring stability and comfort even during speed changes. On the other hand, the PID controller exhibits abrupt variations in the control signal, resembling a bang-bang behavior similar to the previous scenario. Such aggressive actuation compromises control quality and could lead to mechanical stress in practical implementations.

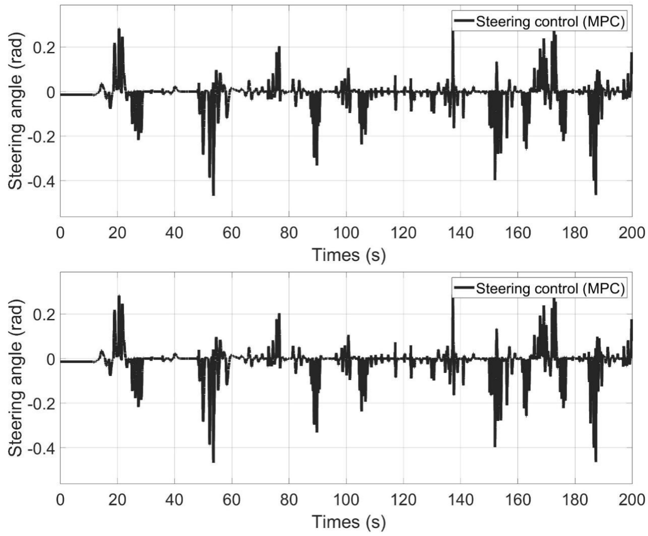

Figure 8. Steering control angle given by MPC and PID

The validation results presented in this paper confirm the superior performance of the proposed MPC-based Lane Keeping Assist System compared to a conventional PID controller. Across both constant-speed and time-varying speed scenarios, the MPC consistently achieved smoother and more accurate trajectory tracking, minimized tracking errors, and generated control signals with gradual transitions. These characteristics not only enhance lane-keeping precision but also improve vehicle stability and passenger comfort. In contrast, the PID controller exhibited larger deviations, fluctuating errors, and abrupt steering actions, which compromise overall control quality. The findings demonstrate that the MPC approach is well-suited for advanced driver assistance systems, offering robustness and adaptability under diverse driving conditions.

5. Conclusions

In this study, a Model Predictive Control (MPC)-based controller for Lane Keeping Assist (LKAS) systems was developed and validated within the framework of Advanced Driver Assistance Systems (ADAS). The controller was designed to ensure accurate lateral trajectory tracking under continuous longitudinal speed conditions while respecting vehicle dynamic constraints. Leveraging its predictive capability, the MPC approach optimizes control actions and anticipates system changes, ensuring stability as confirmed through Lyapunov-based analysis. The validation phase, using real GPS trajectory data as a reference, demonstrated the controller's effectiveness in achieving precise lane tracking with generally low dynamic errors, even in regions of complex curvature. Furthermore, comparative evaluations against a conventional PID controller confirmed the superior performance of the proposed MPC approach, delivering smoother trajectory tracking, reduced error fluctuations, and more stable control signals. Although localized error increases were observed when the vehicle speed was not adapted to road geometry, these results establish the MPC controller as a robust foundation for LKAS and represent a significant step toward safer, more intelligent, and increasingly autonomous driving systems.

Conflicts of interest

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

[1] S. C, S. P, M. Raj, and S. Raj, "Advanced driver assistance system (ADAS) in autonomous vehicles: a complete analysis," In Proc. 8th International Conference on Communication and Electronics Systems, Coimbatore, India, Jun. 1-3, 2023, pp. 1501-1505. https://doi.org/10.1109/ICCES57224.2023.10192617.

[2] L. Joseph and A. K. Mondal, Eds., *Autonomous Driving and Advanced Driver-Assistance Systems (ADAS): Applications, Development, Legal Issues, and Testing*. Boca Raton, FL, USA: CRC Press, 2021.

[3] A. Khodayari, A. Ghaffari, S. Ameli, and J. Flahatgar, "A historical review on lateral and longitudinal control of autonomous vehicle motions," In Proc. International Conference on Mechanical and Electrical Technology, Singapore, Sep. 10-12, 2010, pp. 421-429. https://doi.org/10.1109/ICMET.2010.5598396.

[4] C. V. Samak, T. V. Samak, and S. Kandhasamy, "Control strategies for autonomous vehicles," in *Autonomous Driving and Advanced Driver-Assistance Systems (ADAS)*, Boca Raton, FL, USA: CRC Press, 2021, pp. 45-67. https://doi.org/10.1201/9781003048381-3.

[5] A. Awathe and T. Varunjikar, "Closed-loop modeling of a quintic trajectory planning and PID motion control system," In Proc. IEEE International Conference on Intelligent Transportation Systems, Bilbao, Spain, Sep. 24-28, 2023, pp. 1713-1720. https://doi.org/10.1109/ITSC57777.2023.10421821.

[6] M. Marcano, J. A. Matute, R. Lattarulo, E. Martí, and J. Pérez, "Low speed longitudinal control algorithms for automated vehicles in simulation and real platforms," *Journal of Advanced Transportation*, vol. 2018, no. 1, 2018. https://doi.org/10.1155/2018/7615123.

[7] A. Aboelhassan, M. Abdelgeliel, E. E. Zakzouk, and M. Galea, "Design and implementation of model predictive control based PID controller for industrial applications," *Energies*, vol. 13, no. 24, p. 6594, 2020. https://doi.org/10.3390/en13246594.

[8] M. Marcano, J. A. Matute, R. Lattarulo, E. Martí, and J. Pérez, "Low speed longitudinal control algorithms for automated vehicles in simulation and real platforms," *Complexity*, vol. 2018, no. 1, 2018. https://doi.org/10.1155/2018/7615123.

[9] Q. T. Dam, "Adaptive neural network-based PID controller design for velocity control of an internal combustion engine using back propagation technique," *Journal of Electronic and Electric Engineering*, vol. 3, no. 2, pp. 613-630, 2024. https://doi.org/10.37256/jeee.3220245581.

[10] Q. T. Dam and F. Haidar, "Adaptive PID controller design for velocity control of a hydrogen internal combustion engines using RBF neural networks," *Engineering Perspective*, vol. 5, no. 1, pp. 41-48, 2025. https://doi.org/10.29228/eng.pers.76280.

[11] S. Zhang, X. Liu, G. Deng, J. Ou, E. Yang, S. Yang, et al., "Longitudinal and lateral control strategies for automatic lane change to avoid collision in vehicle high-speed driving," *Sensors*, vol. 23, no. 11, p. 5301, 2023. https://doi.org/10.3390/s23115301.

[12] K. Oh and J. Seo, "Development of a sliding-mode-control-based path-tracking algorithm with model-free adaptive feedback action for autonomous vehicles," *Sensors*, vol. 23, no. 1, p. 405, 2023. https://doi.org/10.3390/s23010405.

[13] F. Zhang-qi, J. Hao-bin, W. Qi-zhi, H. Yang-ke, O. Abiodun Oluwaleke, "Model-free adaptive sliding mode control for intelligent vehicle longitudinal dynamics," *Advances in Mechanical Engineering*, vol. 14, no. 7, pp. 1-14, 2022. https://doi.org/10.1177/16878132221110131.

[14] G. M. Hoffmann, C. J. Tomlin, M. Montemerlo and S. Thrun, "Autonomous automobile trajectory tracking for off-road driving: controller design, experimental validation and racing," In Proc. American Control Conference, New York, NY, USA, Jul. 9-13, 2007, pp. 2296-2301. https://doi.org/10.1109/ACC.2007.4282788.

[15] A. Kazemi, I. Sharifi, and H. A. Talebi, "Longitudinal and lateral control of vehicle platoons using Laguerre-based and robust MPC with merge and exit maneuvers," *Control Engineering Practice*, vol. 142, p. 105737, 2024. https://doi.org/10.1016/j.conengprac.2023.105737.

[16] S. Graffione, C. Bersani, R. Sacile and E. Zero, "Model predictive control of a vehicle platoon," In Proc. IEEE 15th International Conference of System of Systems Engineering, Budapest, Hungary, Jun. 2-4, 2020, pp. 513-518. https://doi.org/10.1109/SoSE50414.2020.9130541.

[17] H. He, M. Han, W. Liu, J. Cao, M. Shi, N. Zhou, "MPC-based longitudinal control strategy considering energy consumption for a dual-motor electric vehicle," *Energy*, vol. 253, p. 124004, 2022. https://doi.org/10.1016/j.energy.2022.124004.

[18] Z. Chen, J. Lai, P. Li, O. I. Awad, and Y. Zhu, " Prediction Horizon-Varying Model Predictive Control (MPC) for Autonomous Vehicle Control," *Electronics*, vol. 13, no. 8, p. 1442, 2024. https://doi.org/10.3390/electronics13081442.

[19] D. M. M. Eldesouky, T. H. Abdelaziz, and A. E. Mohamed, "Path tracking of autonomous vehicles with model predictive control (MPC) optimized with particle swarm optimization (PSO)," SAE Technical Paper, 2025-01-8036, 2025. https://doi.org/10.4271/2025-01-8036.

[20] X. Tang, L. Shi, B. Wang, and A. Cheng, "Weight adaptive path tracking control for autonomous vehicles based on PSO-BP neural network," *Sensors*, vol. 23, no. 1, p. 412, 2023. https://doi.org/10.3390/s23010412.

[21] G. Zhu, H. Jie, Z. Zheng, and W. Hong, "MPC-based lateral motion control for autonomous vehicles through serially cascaded discretization method considering path preview," *International Journal of Control, Automation and Systems*, vol. 22, pp. 1666-1679, 2024. https://doi.org/10.1007/s12555-023-0008-4.

[22] M. Jia, M. Tao, M. Xu, P. Zhang, J. Qiu, G. Bergsieker, et al., "RL-MPC: reinforcement learning aided model predictive controller for autonomous vehicle lateral control," SAE Technical Paper, 2024-01-2565, 2024. https://doi.org/10.4271/2024-01-2565.

[23] J. Zhang, A. Kong, Y. Tang, Z. Lv, L. Guo, P. Hang, "Application of data-driven model predictive control for autonomous vehicle steering," *arXiv*, 2024. https://doi.org/10.48550/arXiv.2407.08401.

[24] Y. Li, C. Huang, D. Yang, W. Liu, and J. Li, "Learning-based MPC for autonomous driving using a low dimensional residual model," In Proc. 2025 IEEE International Conference on Robotics and Automation (ICRA), Atlanta, GA, USA, May 19-23, 2024. https://doi.org/10.1109/ICRA55743.2025.11128642.

[25] L. Jin, S. Zhao, and N. Xu, "A survey of vehicle dynamics models for autonomous driving," SAE Technical Paper, 2024-01-2325, 2024. https://doi.org/10.4271/2024-01-2325.

[26] H. Chu, Z. Li, Q. Kang, X. Liu, B. Gao, and H. Chen, "Predictive motion control considering body attitude constraints for four in-wheel motor vehicles," *Unmanned Systems*, vol. 13, no. 6, pp. 1713-1728, 2023. https://doi.org/10.1142/S2301385025430034.

[27] G. S. Aiswarya, M. Mariah, R. Katragadda, and R. Makam, "Control of self-driving cars using reinforcement learning," In Proc. IEEE International Conference on Electronics, Computing and Communication Technologies, Bangalore, India, Jul. 14-16, 2023, pp. 1-6. https://doi.org/10.1109/CONECCT57959.2023.10234763.

[28] Y. Lin, J. McPhee, and N. L. Azad, "Comparison of deep reinforcement learning and model predictive control for adaptive cruise control," *IEEE Transactions on Intelligent Vehicles*, vol. 6, no. 2, pp. 221-231, 2021. https://doi.org/10.1109/TIV.2020.301294.

[29] J. Kabzan, L. Hewing, A. Liniger, and M. N. Zeilinger, "Learning-based model predictive control for autonomous racing," *IEEE Robotics and Automation Letters*, vol. 4, no. 4, pp. 3363-3370, 2019. https://doi.org/10.1109/LRA.2019.2926677.

[30] S. Mallick, A. Dabiri, and B. De Schutter, "A comparison benchmark for distributed hybrid MPC control methods: distributed vehicle platooning," *arXiv*, 2024. https://doi.org/10.48550/arXiv.2401.09878.

[31] Y. Li, G. Dong, J. Wang, M. Li, Z. Wang, Q. Wang, et al., "Trajectory tracking control of intelligent vehicles based on integrated MPC with fuzzy adaptive weighting," *International Journal of Automotive Technology*, vol. 26, pp. 1819-1830, 2025. https://doi.org/10.1007/s12239-025-00253-5.

[32] Zulkarnain, M. H. M. Ariff, and H. Zamzuri, "Adaptive model predictive controller (MPC) hybrid with braking torque distribution for trajectory tracking on autonomous vehicle: a review," *AIP Conference Proceedings*, vol. 2689, no. 1, p. 070052, 2023. https://doi.org/10.1063/5.0115441.