

Article

Model Predictive Rear-Wheel Assist Control for Path Tracking of Autonomous Mobility Based on Steering Performance Degradation Monitoring

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Abstract

This study proposes a driver monitoring and active rear-wheel assist steering control scheme integrating Model Predictive Control (MPC) and Recursive Least Squares (RLS) to enhance path-following precision and facilitate seamless control authority distribution in autonomous mobility. Rather than attempting to directly measure internal physiological cognitive states, the proposed approach quantifies physical steering performance degradation by employing a dual RLS algorithm to estimate a Steering Performance Degradation Index, which systematically fuses temporal response delay and spatial tracking deviation. Based on this real-time index, an assist MPC dynamically computes the auxiliary rear-wheel steering angle by adapting its tracking input weights according to three candidate weighting functions: exponential, linear, and threshold-based. High-fidelity co-simulations in IPG CarMaker and MATLAB/Simulink are conducted under various velocities and road curvatures with systematic driver delays. The evaluation results demonstrate that the proposed assist controller effectively enhances path-tracking precision, reducing the maximum lateral error and yaw angle error by up to approximately 82.24% and 73.53%, respectively, compared to the unassisted delayed driver. These findings verify that the proposed steering control architecture successfully mitigates transient trajectory deviation during driver performance degradation, establishing a promising candidate fail-safe strategy for advanced automated driving systems.

Keywords: steering performance degradation index; autonomous mobility; steering control; path tracking; adaptive model predictive control; recursive least squares



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1. Introduction

Recently, with the rapid advancement of autonomous driving technology, the adoption of autonomous driving Level 2 to 2.5, where the system and the driver share driving initiative, is accelerating. At these levels, since the driver receives system assistance while still bearing final control responsibility, safe control cooperation and smooth takeover strategies are essential. In particular, driver distraction, drowsiness, or cognitive response delays due to aging pose significant threats to road traffic safety, substantially increasing accident risks by reducing the timeliness of steering and acceleration/deceleration. Existing driver state monitoring studies have mainly focused on detecting drowsiness and inattention

using gaze tracking via cameras, facial image analysis, or physiological signals. Furthermore, ADASs such as Lane Keeping Assist or Autonomous Emergency Braking provide necessary interventions; however, they often have limitations in real-time quantification of the driver's actual steering ability and projecting this directly into control algorithms, as they merely constrain vehicle behavior. Therefore, to minimize driver discomfort during sudden control transitions and ensure driving stability, an intelligent control strategy is required to evaluate the driver's state as a continuous index and flexibly adjust the system's intervention intensity accordingly. Rather than bypassing the driver's control loop with a direct trajectory-tracking autopilot, quantifying the driver's immediate performance can serve as a dynamic scaling factor for allocating control authority. This helps ensure that the system's corrective actions complement, rather than conflict with, the driver's steering input, thereby preserving driver authority during shared-driving scenarios.

Literature Review

Tang et al. proposed a cascaded structure that uses geometric MPC to calculate a target yaw rate and utilizes it as feedback. This approach overcomes the limitations of geometric model predictive control, which is only valid at low speeds, and introduces a vehicle side-slip compensator to improve tracking performance during high-speed driving [1]. Wang et al. presented an MPC path-tracking method that assumes a nonlinear vehicle model and uses a genetic algorithm instead of traditional quadratic programming-based optimization to directly handle nonlinearities, thereby improving the accuracy of a system integrated with steering and speed control [2]. Guo et al. proposed a technique to enhance MPC performance through data-driven model calibration, utilizing Kolmogorov-Arnold networks and Gaussian process regression to learn the vehicle's lateral force and dynamic error models and applying them as compensation terms to MPC, significantly reducing lateral tracking errors [3]. Yin et al. proposed a nonlinear MPC-based path-tracking control utilizing discrete preview points of the vehicle, securing high tracking accuracy in low-speed narrow road environments by setting the initial path using the Stanley method and solving nonlinear optimization problems [4]. Pang et al. demonstrated high precision and stability at various driving speeds through an MPC control strategy that sequentially linearizes the model along a reference trajectory using a 2-DOF geometric model and calculates control inputs through real-time quadratic programming [5]. Sun et al. constructed a 3-DOF model based on vehicle dynamics and path curvature prediction and proposed a composite MPC control system that improves trajectory tracking error by more than 20% compared to conventional MPC in high-speed straight and cornering situations by applying optimization weights including slip angle limits [6]. Chen et al. proposed a tube-based robust MPC to achieve robust path tracking despite uncertainties in the road friction coefficient, confirming excellent lateral tracking performance even in complex road environments [7]. Zhu et al. presented a method to increase control accuracy by analytically discretizing nonlinear MPC using orthogonal collocation and showed superior performance over fixed-length methods in various driving scenarios based on a 1-DOF dynamic model [8]. Chen et al. conducted a study to estimate tire cornering stiffness and vehicle state (velocity, angular velocity) by combining RLS with a variable forgetting factor and an adaptive iterative extended Kalman filter [9]. Du et al. proposed a dual Kalman structure combining RLS with an adaptive forgetting factor and a Kalman filter to estimate the mass change of an electric bus online, achieving an estimation error of less than 10% [10]. Nie et al. researched MPC path-tracking control using variable forgetting factor-RLS to compensate for the uncertainty of the road friction coefficient, improving tracking error by identifying the road surface condition in real-time [11]. Cai et al. proposed a technique for the joint estimation of tire cornering stiffness and vehicle state for 4WID electric vehicles,

improving RMSE by 30–50% compared to the existing Kalman filter [12]. Dixith et al. verified drowsiness detection performance by comparing a custom 5-layer CNN with a pre-trained MobileNetV2, achieving an accuracy of over 99% [13]. Salakapuri et al. proposed an integrated deep learning framework that simultaneously performs driver distraction and forward object detection (YOLOv7) [14]. Rahman et al. significantly improved the reliability of image-based fatigue detection through a two-stage structure combining Spatial Transformer Networks and ConvLSTM [15]. Jeong and Yim proposed an integrated MPC system for 4-wheel independent steering/4-wheel independent driving vehicles, improving tracking performance compared to existing MPC [16]. Xu et al. applied a fuzzy control-based Pure Pursuit algorithm for path tracking of agricultural machinery, maintaining a lateral deviation at the 3–5 cm level [17]. Lu et al. used a genetic algorithm to optimize the weighting matrix of an LQR controller for 4WS and proposed an adaptive LQR technique to ensure stability in both low and high-speed environments [18]. Previous research on driver state monitoring has demonstrated significant achievements in detecting distracted states through camera-based gaze tracking or physiological signal analysis. However, such sensor-based approaches, while capable of capturing the driver's physiological state, possess inherent limitations in directly quantifying and projecting the physical impact of cognitive decline onto real-time control algorithms. To address this challenge of translating estimated driver states into active control actions, shared steering control frameworks have been actively investigated. For instance, haptic shared steering control systems, such as the MPC-based symbiotic driving controller proposed by Rios Lazcano et al., have integrated cognitive preview driver models and neuromuscular dynamics to minimize steering torque conflicts on the front axle through adaptive authority allocation [19]. However, these front-wheel haptic blending methods inherently act on the same front-wheel steering actuator, which can still induce physical torque resistance and driver-vehicle conflicts under unexpected driver impairment. To address this limitation, our proposed framework decouples steering execution by strictly maintaining the driver's front-wheel steering input as an absolute equality constraint, while achieving compensatory path-following through active rear-wheel steering (RWS) based on real-time driver state monitoring. Furthermore, currently commercialized Advanced Driver Assistance Systems technologies, such as Lane Keeping Assist, exhibit discontinuous characteristics that intervene only when specific error thresholds are exceeded, this may induce abrupt disparities during the transfer of control between the driver and the system, potentially compromising driving stability. Directly applying a controller for automated trajectory tracking without assessing the human operator's immediate capability risks overriding driver-led steering authority, causing steering torque conflicts and high driver heterogeneity. Moreover, in this transition phase leading toward fully autonomous driving, incorporating an intermediate monitoring component is vital for facilitating a stable, seamless transition of control (takeover/control transition) and ensuring highly efficient driver-assist control. To establish a robust human-machine cooperative fail-safe framework, this study proposes an algorithm that utilizes vehicle dynamics model-based Model Predictive Control as a reference steering input to quantify the driver's actual driving capability in real time and integrates it with rear-wheel assisted steering control. Instead of relying solely on sensor data, an integrated Driving Performance Degradation Index was derived by quantifying the variability of steering errors through real-time comparison between the MPC-based reference steering input and the driver's actual input. This intermediate performance quantification enables a continuous and proportional assistance strategy, where the active rear-wheel steering intervention is dynamically scaled only to the extent of the driver's steering degradation. Consequently, the system aims to mitigate path deviation and yaw instability without interfering with the driver-led control authority. In this process, the Recursive Least Squares

(RLS) method and the forgetting factor theory were referenced and extended to design a framework that flexibly reflects both historical cumulative data and the latest emergent situations. Based on the index derived, an adaptive control strategy was established to dynamically vary the input weight of the auxiliary controller. By allowing the system to actively compensate through rear-wheel steering in proportion to the degree of the driver's performance degradation, the proposed method maintains driver-led driving authority while simultaneously improving path-following performance. Consequently, this approach realizes continuous and smooth distribution of control authority, enabling the system to intelligently intervene to prevent accidents by correcting the vehicle trajectory before it deviates, even in situations where cognitive response speed is significantly impaired, such as in the case of elderly or drowsy drivers.

The remainder of this paper is organized as follows. Section 2 describes the proposed steering performance degradation monitoring and assist rear wheel steering control algorithm, covering the development of the monitoring MPC for reference input generation, the quantification of driving indices using RLS, and the mathematical design of the adaptive assist controller. Section 3 presents the experimental environment and simulation scenarios conducted using CarMaker and MATLAB/Simulink, followed by a quantitative analysis of the performance evaluation results for each weighting model. Finally, Section 4 concludes the study by summarizing the key findings and suggesting directions for future research to enhance human-machine coordination.

The main contributions of this study are twofold:

- Real-time quantification of driving performance using an MPC-based reference standard: This study proposes a framework that numerically quantifies the physical impact of cognitive decline on vehicle control as a “Total steering performance degradation Index” by comparing MPC derived reference steering with actual driver input in real time.
- Establishment of a continuous control cooperation system through adaptive and predictive rear wheel steering: By designing an adaptive control strategy where rear wheel steering actively compensates in proportion to the driver's performance degradation, this approach realizes smooth distribution of control authority and maximizes path-following performance while maintaining driver-led steering initiative.

2. Steering Performance Degradation Monitoring and Assist Rear-Wheel Steering

Figure 1 shows the overall block diagram of the proposed system, which is divided into three core blocks: MPC for reference input calculation, monitoring index derivation, and the MPC for assist rear wheel angle derivation algorithm.

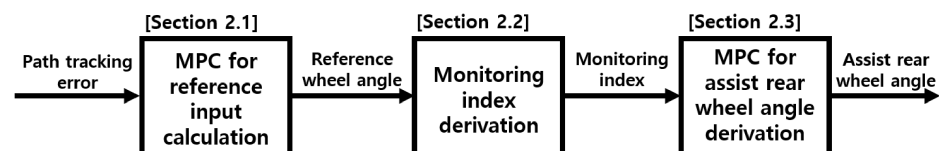


Figure 1. Overall block diagram for driver monitoring and rear wheel assist algorithm.

The first part (Section 2.1) is the stage of generating a reference front steering standard to evaluate the driver's current steering performance degradation. The monitoring MPC continuously calculates the reference front wheel angle required to minimize errors based on the vehicle error dynamics model and transmits it to the subsequent stage.

The second part (Section 2.2) is the process of quantifying steering performance degradation in real-time by comparing the reference front steering input derived by the

MPC with the actual driver's steering input. This section analyzes the driver's state from multiple perspectives through two RLS modules, which derive the driver deviation index and the driver response delay index.

The final part (Section 2.3) is the active assist control stage that corrects the actual behavior of the vehicle based on the derived driving indices. In this section, the Assist rear wheel derivation algorithm outputs an adaptive control input that dynamically varies the input weighting factor of the MPC according to the total steering performance degradation index.

2.1. Derivation of Reference Input

This section describes the process of calculating the reference input (front steering angle), which serves as a standard for monitoring the driver's driving state. To derive the reference front wheel angle, an error dynamics model is constructed based on the vehicle's center of mass, and based on this, a model predictive controller is designed to predict the future trajectory and calculate the reference control input. Figure 2 is the block diagram of the MPC for deriving the reference front wheel angle input.

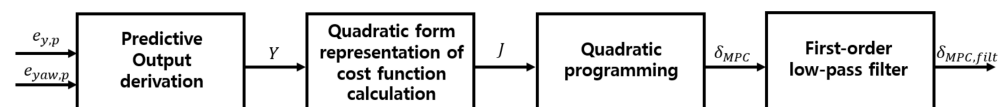


Figure 2. Block diagram for MPC for reference input derivation.

Here, $e_{y,p}$, $e_{yaw,p}$, Y , J and δ_{MPC} represent the lateral error at the preview point and yaw angle error at the preview point, predictive output, cost function expressed in quadratic form, reference front wheel angle output from the MPC, respectively.

2.1.1. Error Dynamics for Path Tracking

Figure 3 illustrates the geometric definitions of path-tracking errors, encompassing both the conventional errors at the center of gravity and the preview errors derived at a forward-looking point.

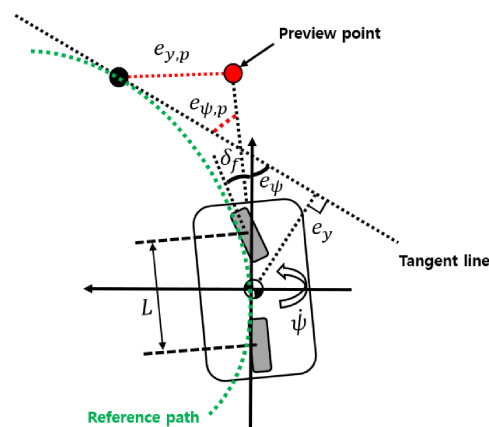


Figure 3. Defined control errors for path tracking.

Based on the path-tracking errors, a mathematical error model based on kinematic interpretation was derived. The equations below represent the corresponding mathematical error model using kinematic parameters and its state-space representation. In this study, it is assumed that the lateral and yaw angle errors at the preview point are geometrically equivalent to those at the center of mass with respect to the tangent line. Based on this similarity, utilizing preview point errors enables the vehicle to execute steering control that

preemptively reflects the geometric shape of the path. Equations (1)–(3) represent the error dynamics derived from Figure 3, and the corresponding state-space representation of the continuous-time error dynamics is expressed in Equation (4).

$$\dot{e}_y = v_x e_\psi \quad (1)$$

$$\dot{e}_\psi = \frac{v_x}{L} \delta_f - \dot{\psi}_{des} \quad (2)$$

$$\begin{bmatrix} \dot{e}_y \\ \dot{e}_\psi \end{bmatrix} = \begin{bmatrix} 0 & v_x \\ 0 & 0 \end{bmatrix} \begin{bmatrix} e_y \\ e_\psi \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{v_x}{L} \end{bmatrix} \delta_f + \begin{bmatrix} 0 \\ -1 \end{bmatrix} \dot{\psi}_{des} \quad (3)$$

$$\begin{aligned} \dot{e} &= A_e e + B_e u + F_e w \\ y &= C_e e \end{aligned} \quad (4)$$

Here e_y , e_ψ are the lateral error and yaw angle error for the path tracking of the autonomous vehicle, respectively, while v_x , $\dot{\psi}_{des}$, δ_f and L represent the vehicle's longitudinal velocity, desired yaw rate, front wheel angle, and wheelbase, respectively.

2.1.2. Discretization and Predictive Output Derivation

While the continuous-time model established above describes the physical behavior of the vehicle, a discretization process is essential to perform future state predictions in MPC. In this study, a discrete-time state-space model is constructed as follows.

$$e = x_d - x \quad (5)$$

The error is defined as in Equation (5), where x_d and x represent the desired state and the current state, respectively. To implement the real-time controller, the continuous-time model is converted into a discrete-time model using the sampling time Δt . By approximating the derivative term using the forward difference method as shown in Equation (6), the discrete-time error dynamics model can be derived as in Equation (7).

$$\text{Let, } \dot{e} = \frac{e_{k+1} - e_k}{\Delta t} = A_e e_k + B_e u_k + F_e w_e \quad (6)$$

$$\begin{aligned} e_{k+1} &= A_{e,d} e_k + B_{e,d} u_k + F_{e,d} w_k \\ y_k &= C_d e_k \end{aligned} \quad (7)$$

where

$$A_{e,d} = A_e \Delta t + I, \quad B_{e,d} = B_e \Delta t, \quad F_{e,d} = F_e \Delta t$$

The predictive model, which represents the future outputs during N the prediction steps, is derived in the form of a linear combination as follows.

$$Y = G e_k + L U + M u_k + F W + S w_{d,k} \quad (8)$$

In Equation (8), term $w_{d,k}$ is defined as the disturbance corresponding to the desired yaw rate $\dot{\psi}_{des}$. Equations (9) through (16) represent the matrices that constitute Equation (8).

$$Y = [y_{k+1} \ y_{k+2} \ \cdots \ y_{k+n}] \quad (9)$$

$$G = [C_d A_d \ C_d A_d^2 \ \cdots \ C_d A_d^n] \quad (10)$$

$$L = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ C_d B_{e,d} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ C_d A_{e,d}^{N-2} B_{e,d} & C_d A_{e,d}^{N-3} B_{e,d} & \cdots & 0 \end{bmatrix} \quad (11)$$

$$U = [u_{k+1} \ u_{k+2} \ \cdots \ u_{k+n}] \quad (12)$$

$$M = [C_d B_{e,d} \ C_d A_{e,d} B_{e,d} \ \cdots \ C_d A_{e,d}^{N-1} B_{e,d}] \quad (13)$$

$$F = \begin{bmatrix} 0 & 0 & \cdots & 0 \\ C_d F_{e,d} & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ C_d A_{e,d}^{N-2} F_{e,d} & C_d A_{e,d}^{N-3} F_{e,d} & \cdots & 0 \end{bmatrix} \quad (14)$$

$$W = [w_{k+1} \ w_{k+2} \ \cdots \ w_{k+n}] \quad (15)$$

$$S = [C_d F_d \ C_d A_d F_d \ \cdots \ C_d A_d^{N-1} F_d] \quad (16)$$

2.1.3. Cost Function Design and Quadratic Form Representation

To derive the optimal reference front wheel angle, the cost function J is designed as shown in Equation (17). Equations (18), (19), and (20) represent the output weighting matrix, the input difference matrix, and the input weighting matrix that constitute the cost function, respectively. The cost function is designed to minimize the predicted output Y and the control input U , consisting of terms for constraints on system output errors and the minimization of the rate of input changes.

$$J = Y^T Q^T Q Y + U^T D^T R D U \quad (17)$$

$$Q = \begin{bmatrix} \sqrt{q_1} & 0 & 0 & 0 \\ 0 & \sqrt{q_2} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \sqrt{q_n} \end{bmatrix}, q_i > 0 (i = 1, \cdots, n) \quad (18)$$

$$D = \begin{bmatrix} 1 & \cdots & -1 & 0 & 0 & 0 \\ 0 & 1 & \cdots & -1 & 0 & 0 \\ 0 & 0 & 1 & \cdots & -1 & 0 \\ 0 & 0 & 0 & \ddots & \cdots & \ddots \end{bmatrix} \quad (19)$$

$$R = \begin{bmatrix} r_1 & 0 & 0 & 0 \\ 0 & r_2 & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & r_n \end{bmatrix}, r_i \geq r_{min} > 0 \quad (20)$$

To obtain the optimal solution using the quadratic programming technique, the defined cost function expressed in quadratic form is given by Equation (21).

$$J = \frac{1}{2} U^T H U + v^T U \quad (21)$$

$$H = L^T Q^T Q L + D_d^T R_d D_d \quad (21a)$$

$$V = Q^T Q (G e_k + M u_k + F W + S w_{d,k}) \quad (21b)$$

$$v = L^T V \quad (21c)$$

2.1.4. Multiple Constraints Design

In this study, inequality and boundary constraints were applied to monitoring MPC algorithms. Considering physical limitations, constraints for the maximum steering angle of the wheel and the steering rate limit were designed. The designed boundary and inequality constraints are expressed as Equations (22) and (23), respectively.

$$\text{Boundary constraint} : \delta_{f,\min} \leq \delta_{f,n} \leq \delta_{f,\max}, (n = 1, 2, \dots, N) \quad (22)$$

$$\text{Inequality constraint} : -\dot{\delta}_{f,\max}\Delta t \leq \delta_{f,n+1} - \delta_{f,n} \leq \dot{\delta}_{f,\max}\Delta t, (n = 1, 2, \dots, N) \quad (23)$$

where $\delta_{f,\min}$ and $\delta_{f,\max}$ denote the lower and upper bounds of the front wheel steering angle, respectively. $\delta_{f,n}$ represents the front-wheel steering angle at the n -th step within the prediction horizon. $\dot{\delta}_{f,\max}$ is the maximum steering angular velocity (steering rate) reflecting the motor's bidirectional speed limits. Δt is the discretization of sampling time and n is the discrete-time index within the prediction horizon N .

To precisely reflect the physical boundaries of the human driver and the vehicle system within the CarMaker environment, the maximum steering wheel angle and the steering wheel angular velocity limit at the driver's steering interface were established at 630 deg and 500 deg/s, respectively. By incorporating the vehicle's specific steering gear ratio of 17.37 configured in the CarMaker vehicle model, these steering-wheel-side control parameters were mathematically converted into corresponding physical states at the tire level. Consequently, the boundary constraints for the road wheel steering angle were derived as ± 36.26 deg, and the road wheel angle rate limit was applied at ± 28.75 deg/s to define the physical actuator boundaries within the reference-generation MPC framework.

2.2. Steering Performance Degradation Index Derivation

This section describes the process of quantifying steering performance degradation by analyzing the relationship between the reference front steering input derived in Section 2.1 and the actual driver's steering input. Since the driver's steering behavior changes in real-time according to the road curvature and vehicle status, RLS is utilized to identify the overall driving tendency as well as short-term errors. An RLS algorithm with a forgetting factor was designed to sensitively reflect the latest driving status by adjusting the influence of past data.

The proposed system derives indices from two perspectives—steering deviation and steering time delay—to evaluate the driver's state from multiple angles.

- Driver deviation index: The squared value of the driver's steering error is normalized via RLS to output steering precision as an index.
- Driver response delay index: The timing at which the actual input is applied relative to the reference input is analyzed to estimate the time delay constant, which is then output as an index.

Figure 4 is a block diagram of the algorithm that outputs the monitoring index. The block diagram illustrates the systematic process of quantifying driving performance by analyzing the discrepancy between the driver's actual steering input and the reference steering calculated through MPC.

Here, e_{driver} is the steering angle deviation between the steering angle output from the monitoring MPC and the driver's steering input. $\hat{\tau}$ and $\hat{\gamma}$ represent the Driver response delay index and Driver deviation index output through RLS, respectively, and I_t is the total steering performance degradation index.

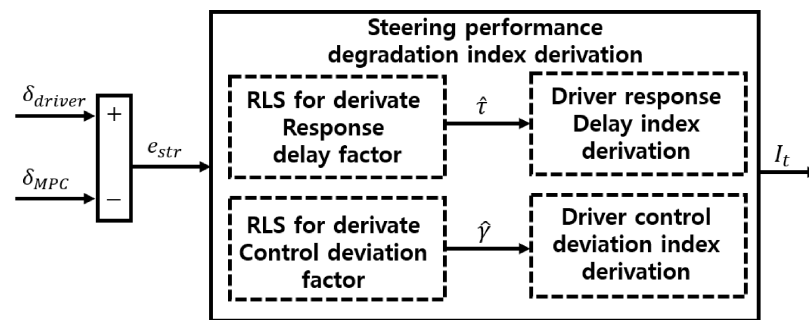


Figure 4. Block diagram for steering performance degradation index derivation.

2.2.1. RLS Algorithm with Forgetting Factor

Both index derivation modules basically share the same RLS update structure. The loss function to be optimized is defined as follows [20]:

$$V(\hat{\theta}, k) = \frac{1}{2} \sum_{i=1}^k \lambda^{k-i} (y_i - \phi_i^T \hat{\theta}_k)^2 \quad (0 < \lambda \leq 1) \quad (24)$$

The system's parameter estimate, gain, and covariance are designed to be updated in real-time, as shown in Equations (25)–(27):

$$\hat{\theta}_k = \hat{\theta}_{k-1} + L_k (y_k - \phi_k^T \hat{\theta}_{k-1}) \quad (25)$$

$$L_k = P_{k-1} \phi_k (\phi_k^T P_{k-1} \phi_k + \lambda)^{-1} \quad (26)$$

$$P_k = (I - L_k \phi_k^T) P_{k-1} \lambda^{-1} \quad (27)$$

where $V(\hat{\theta}, k)$ is the weighted least squares loss function to be minimized at time step k , $\hat{\theta}_k$ denotes the vector of estimated system parameters. y_k is the measured output at the current time step. ϕ_k represents the regression variable vector. λ is the forgetting factor ($0 < \lambda < 1$) that determines the weighting of past data relative to new observations. L_k is the estimator gain vector. P_k denotes the error covariance matrix.

2.2.2. Driver Control Deviation Index Derivation

The first RLS module derives an index based on the deviation between the driver's front wheel input angle and the reference front wheel angle input for MPC-based path tracking. The driver's steering deviation is defined as shown in Equation (28).

$$e_{str} = \delta_{driver} - \delta_{MPC} \quad (28)$$

δ_{driver} is the driver's front wheel angle (which is equivalent to δ_f but denoted as such to distinguish it from the MPC reference), and δ_{MPC} is the reference front wheel angle for MPC-based path tracking.

In the simulation environment, numerical fluctuations or spikes may occur in the calculated deviation due to the discrepancy between the MPC update period and the simulation sampling time. To ensure signal stability and suppress high-frequency noise, a first-order low-pass filter, implemented as an exponential moving average, is applied to the raw data before the RLS process:

$$y_k = \alpha u_k + (1 - \alpha) y_{k-1} \quad (29)$$

where y_k and y_{k-1} are the filtered outputs at the current and previous time steps, respectively, u_k is the raw steering deviation e_{str} and α is the smoothing factor ($0 < \alpha < 1$).

To quantify the magnitude variation of the steering error, the squared value of the driver's steering angle error is utilized as the input for the RLS, which quantifies the driver's macroscopic steering precision and directly represents the spatial steering deviation.

The regression model is established as follows: Here, y is the measured squared steering error, the regression variable ϕ is a constant, and the estimated parameter θ becomes the adjusted error factor $\hat{\gamma}$.

$$y = \phi\theta$$

$$\text{where, } y = e_{str}^2, \phi = 1, \theta = \hat{\gamma} \quad (30)$$

Finally, the Driver deviation index, ranging from 0 to 100, is calculated using the experimentally derived minimum value γ_{min} and maximum value γ_{max} of the error factor.

$$I_e = C_e \frac{\hat{\gamma} - \gamma_{min}}{\gamma_{max} - \gamma_{min}} \quad (31)$$

Here, the error factor represents the real-time steering error variability. The lower normalization limit is established at zero to represent an ideal, error-free path-following state. The upper limit is calibrated at eight; this maximum threshold is determined through preliminary simulation trials to reflect the critical boundary of steering deviation beyond which lateral lane departure becomes imminent under typical curved road scenarios. The scaling coefficient is set to one hundred to standardize the steering precision index within a percentage-based scale.

2.2.3. Driver Response Delay Index Derivation

The second RLS module estimates the physical time delay from the moment the driver perceives an external situation until the steering response is initiated, which represents the temporal phase lag of the driver. In this study, the driver's steering behavior is modeled as a first-order lag system relative to the optimal reference steering calculated by the MPC. The relationship between the reference steering input δ_{MPC} and the actual driver input δ_{driver} is expressed by the following first-order differential equation:

$$\hat{\tau}\dot{\delta}_{driver} + \delta_{driver} = \delta_{MPC} \quad (32)$$

To transform this physical model into a regression form for RLS estimation, the equation is rearranged to isolate the relationship between the steering discrepancy and the steering rate. This rearrangement allows the instantaneous deviation calculated as the difference between the MPC reference and the driver's input to be represented as a linear function of the steering angular velocity, Equation (32) can be rewritten as follows:

$$y = \phi\theta$$

$$\text{where, } y = \delta_{MPC} - \delta_{driver}, \phi = \dot{\delta}_{driver}, \theta = \hat{\tau} \quad (33)$$

In this model, y represents the steering error, the regression variable ϕ is the rate of change of the steering angle, and the estimated parameter θ is the time delay constant. Through this formulation, the RLS module estimates the physical time constant of the driver's steering system, which enables the real-time estimation of the extent to which a driver initiates steering later than a normal reaction speed can be estimated in real-time.

The derived time constant is normalized as follows and converted into the Driver response delay index.

$$I_d = C_d \frac{\hat{\tau} - \tau_{min}}{\tau_{max} - \tau_{min}} \quad (34)$$

The estimated time constant represents the temporal latency in the steering response. The minimum normalization threshold is set to zero to define the ideal case of immediate steering feedback with no cognitive delay. The maximum threshold is established at five to capture extreme driver impairment, such as severe distraction or micro-sleep, where driver-initiated steering actions are critically delayed. The scaling coefficient is defined as one hundred to project the normalized delay index onto a uniform percentage scale.

2.2.4. Total Steering Performance Degradation Index Derivation

The two previously derived indices are fused into one to comprehensively evaluate the driver's current driving performance. The total steering performance degradation index is defined as follows:

$$I_t = r_e I_e + r_d I_d \quad (35)$$

Here, I_t is the total steering performance degradation index, and r_e and r_d are parameters for determining the ratio of the indices derived earlier. The total steering performance degradation index starts at 0 and rises sharply if the driver's steering deviation increases or if the response is delayed due to fatigue. In particular, when a severe degradation in steering performance degradation occurs, such as in a drowsy driver scenario, the index increases; this serves as a key parameter for determining the intervention of the Assist rear wheel derivation algorithm, which will be described in the subsequent section.

Specifically, the weighting parameters for both indices are selected equally as zero point five, establishing an even fifty-fifty ratio. This equal allocation is grounded in the control principle that spatial steering accuracy and temporal reaction responsiveness are of equal and symmetrical significance to overall vehicle path-following stability. A deficiency in either dimension, i.e., whether a driver steers inaccurately despite a rapid response, or steers precisely but with an excessive delay, leads to an equivalent degradation in lateral lane-keeping performance. By assigning identical weights, the fused index provides a balanced and unbiased representation of the driver's overall impairment state, ensuring that neither spatial error nor temporal delay dominates the active intervention of the rear-wheel control algorithm.

2.3. MPC Weighting Factor Decision for Assist Rear Wheel Steering Derivation

This section describes the process of calculating the adaptive weighting factor that determines the intervention intensity of the assist rear-wheel steering controller using the previously derived total steering performance degradation index. In this process, the degree to which the system intervenes in driving is mathematically defined according to the driver's state. Figure 5 is a block diagram of the algorithm for deriving the assist rear-wheel steering angle.

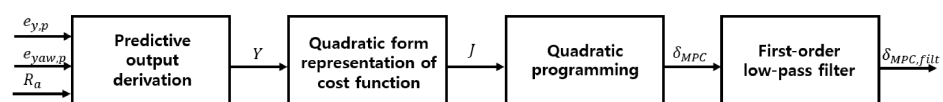


Figure 5. Block diagram for assist rear wheel steering derivation.

Here, R_a represents the input weighting factor of the MPC for deriving the assist rear-wheel angle.

Once the total steering performance degradation index is calculated, it must be converted into an input weighting factor within the objective function of the assist rear wheel steering MPC. The weighting factor determines the degree of system intervention and was designed in this study with safety as the highest priority.

The weighting function controls the interaction between the driver's state and the system's assistance, establishing an inversely proportional relationship between the steering performance degradation index and the weighting factor.

- Low-risk driving (Low index): In a state where the driver is following the path accurately. The system sets the weighting factor close to infinity, thereby deactivating rear wheel steering intervention and granting full control authority to the driver.
- High-risk driving (High index): As the total steering performance degradation index rises due to factors such as drowsiness or inattention, the system decreases the weighting factor. This reduction allows the MPC to more actively generate rear wheel steering inputs to minimize path tracking errors.

Index-Based Weighting Factor Decision

In this study, three types of weighting models are proposed, taking into account the driving situation and the rate of change of the total steering performance degradation index.

$$\text{Case 1 : } R_a = \frac{k_R}{I_t} e^{-(w_1 |\dot{e}|)} \quad (36)$$

This model is directly inversely proportional to the total steering performance degradation index. As the rate of change of the steering error increases, the system more sensitively reduces the weighting factor to perform intervention.

$$\text{Case 2 : } R_a = k_R e^{-(w_1 |\dot{e}| I_t)} \quad (37)$$

By utilizing the product of the index and the error change rate as an argument of the exponential function, this model performs auxiliary control that sharply reduces the weighting factor when both factors are simultaneously high.

$$\text{Case 3 : } R_a = k_R e^{-(w_1 |\dot{e}| + w_2 I_t)} \quad (38)$$

Here, the steering error rate is defined as the absolute time-derivative of the deviation between the driver's actual steering input and the MPC-derived reference steering angle, representing the physical responsiveness and rotational stability of the driver's control. This model is configured as an independent sum where distinct weights are assigned to the error change rate and the total steering performance degradation index, respectively. It determines the weighting factor by balanced reflecting both the total steering performance degradation index and the rate of change of the driver's deviation. To prevent the generation of overly aggressive control inputs under critical driving degradation, the proposed algorithm is designed to output a predefined minimum value if the calculated weighting factor falls below a certain threshold. This lower saturation mechanism effectively limits the corrective control effort, which prevents the assist rear-wheel steering controller from generating excessive steering inputs that could compromise vehicle stability. Additionally, the steering performance degradation index is standardized to operate within a range of 0% to 100%. To prevent numerical singularity and division-by-zero errors when the steering performance degradation index reaches 0% (representing the ideal alert state), the calculated weighting factor is strictly constrained by a predefined upper saturation limit of 80^5 . The selection of 80^5 as the maximum threshold was finalized through empirical tuning to properly regulate the active rear-wheel steering angle's path-following effort as

the index fluctuates dynamically between 0% and 100%. Under this saturation scheme, even if the degradation index reaches 0% or a value near 0%, the actual control weight used in the optimization is bounded by this maximum threshold. This cap mathematically acts as an implicit lower bound on the index denominator; it successfully suppresses rear-wheel intervention to a negligible, inactive state to preserve absolute driver initiative while preventing mathematical divergence or computational overflow in the real-time predictive solver. The control parameters including k_R , w_1 and w_2 are systematically selected through parametric simulations. The scale factor k_R , calibrates the baseline weight magnitude, while the sensitivity coefficients w_1 and w_2 are tuned to balance transient error responsiveness and steady-state control transition smoothness without chattering.

Furthermore, the baseline scaling factor k_R is established as an exceptionally large value to strictly govern the activation threshold of the assist controller. Under normal and alert driving conditions where both the total steering performance degradation index and the steering error rate are minimal, the exponential decay term in the proposed model approaches unity, causing the adaptive weighting factor R_a to be maximized. In the model predictive control framework, this massive weight represents a significant penalty on the rear-wheel control effort, which mathematically suppresses any active rear-wheel steering intervention to a negligible level. This configuration guarantees that the rear-wheel assist is virtually deactivated when the driver performs reliably, thereby eliminating any potential steering heterogeneity or control authority conflicts. Consequently, the alert human driver maintains full, uninterrupted control authority with zero sensory discomfort, and the assist system transitions to an active state only when a clear cognitive degradation is quantified.

2.4. Derivation of Assist Rear Wheel Angle

This section designs a rear wheel steering control algorithm to actively assist the vehicle's path-tracking performance when the driver's steering ability is degraded. This controller reflects the previously derived adaptive weighting factors and controls the rear-wheel angle in a direction that ensures driving stability without interfering with the driver's front wheel angle input.

2.4.1. Error Dynamics with Rear Wheel Steering

To design the assist controller, the existing front wheel angle-based bicycle model is extended to a form that includes rear-wheel steering input. When rear wheel steering is applied, the change in the vehicle's yaw rate is defined as follows.

$$\dot{\psi} = \frac{v_x}{L} (\delta_f - \delta_r) \quad (39)$$

Here, δ_r denotes the rear wheel steering angle. Based on this, the new state-space error dynamics equation is derived as follows.

$$\begin{bmatrix} \dot{e}_y \\ \dot{e}_\psi \end{bmatrix} = \begin{bmatrix} 0 & v_x \\ 0 & 0 \end{bmatrix} \begin{bmatrix} e_y \\ e_\psi \end{bmatrix} + \begin{bmatrix} 0 & 0 \\ \frac{v_x}{L} & -\frac{v_x}{L} \end{bmatrix} \begin{bmatrix} \delta_f \\ \delta_r \end{bmatrix} + \begin{bmatrix} 0 \\ -1 \end{bmatrix} \dot{\psi}_{des} \quad (40)$$

2.4.2. Difference Between Monitoring MPC and Assist Rear Wheel MPC

The assist controller proposed in this section is structurally similar to the monitoring MPC described previously, but it possesses the following two distinct differences:

- **Dynamic variation of input variables and weights:** While the monitoring MPC utilizes fixed input weighting factors, the MPC within the Assist rear wheel derivation algorithm applies the previously calculated adaptive weights to the objective function in real-time. This configuration enables control that minimizes rear-wheel interven-

tion when driving capability is sufficient and intensifies the intervention during hazardous situations.

To prevent any mathematical or naming overlap with the monitoring MPC, the assist MPC formulation is constructed using unique subscripts a . The objective function J_a for the assist controller is designed in the quadratic form to optimize the control input sequence U_a over the prediction horizon N :

$$J_a = \frac{1}{2} U_a^T H_a U_a + v_a^T U_a \quad (41)$$

where the Hessian matrix H_a and the linear coefficients vector v_a are formulated as follows:

$$H_a = L_a^T Q_a^T Q_a L_a + D_a^T R_a D_a \quad (42)$$

$$v_a = L_a^T V_a \quad (43)$$

$$V_a = Q_a^T Q_a (G_a e_{a,k} + M_a u_{a,k} + F_a W_a + S_a w_{d,a,k}) \quad (44)$$

Here, the matrices (L_a , Q_a , D_a , G_a , M_a , F_a , S_a) are defined identically to those used in the monitoring MPC for deriving the reference input. In this formulation, the optimization vector U_a is composed of pairs of front and rear wheel steering angles at each predictive step:

$$U_a = \begin{bmatrix} u_{a,k}^T & u_{a,k+1}^T & \cdots & u_{a,k+N-1}^T \end{bmatrix}^T \quad (45)$$

where $u_{a,k+1} = \begin{bmatrix} \delta_{f,k+1} & \delta_{r,k+1} \end{bmatrix}^T$

To govern this multi-input structure, the input weighting matrix R_a is configured diagonally by pairing a fixed front-wheel weight $r_{a,f}$ with the real-time adaptive rear-wheel weight R_a derived in Section 2.3:

$$R_a = \text{diag}(r_{a,f} R_a, r_{a,f} R_a, \cdots, r_{a,f} R_a), R_a \geq R_{\min} > 0 \quad (46)$$

To guarantee the mathematical stability of the controller and the existence of a unique global optimum at each sampling interval, the state weighting matrix is designed to be positive semi-definite ($Q_a \succcurlyeq 0$) and the input weighting matrix is configured to be strictly positive definite ($R_a \succ 0$) as shown in Equation (46). Since the adaptive rear-wheel weight is strictly bound from below by the predefined lower saturation limit, and the fixed front weight is positive, the diagonal weighting matrix remains positive definite ($R_a \succ 0$) under all operational conditions. Consequently, the Hessian matrix defined in the formulation is strictly positive definite ($H_a \succ 0$), which mathematically proves that the objective function is strictly convex. This strict convexity plays a vital role in constraint satisfaction and controller stability when the adaptive weighting factors vary rapidly during transient maneuvers. Because the optimization problem is formulated as a strictly convex quadratic programming problem, the optimization algorithm is guaranteed to converge to the unique globally optimal control input sequence within a finite number of solver iterations. Furthermore, the quadratic programming solver systematically handles the physical steering limits and steering rate boundaries as hard constraints. Even under sharp, rapid variations of the adaptive weight during sudden driver degradation, the strict convexity of the cost function prevents the optimization from yielding unbounded inputs, thereby securing mathematical convergence and physical steering stability simultaneously.

While both front and rear wheel steering angles are mathematically represented within the optimization input vector, the actual front-wheel elements are strictly restricted to the driver's real-time steering input via the equality constraint detailed in the subsequent

section. Under this control structure, the front-wheel steering angle is treated as a known parameter rather than a free optimization variable, ensuring that the driver's primary steering inputs are directly reflected on the front axle. This configuration guarantees that the model predictive controller only optimizes the active rear-wheel steering sequence to compensate for path-tracking errors, thereby fully preserving the driver's steering authority without any physical interference.

- **Driver input constraints:** Specific constraints are applied during the control optimization process. Whereas the monitoring MPC freely derives the reference front steering angle determined by the system, the Assist rear wheel derivation algorithm applies an equality constraint that fixes the actual steering input currently provided by the driver as the front-wheel input value. Rather than depriving the driver of steering authority by forcibly manipulating the front wheels, the system treats the driver's current input as a constant and compensates for path tracking errors by utilizing only the rear wheel steering angle as an optimization variable. The applied constraint is expressed in Equation (47):

$$\text{Equality constraint} : \delta_{MPC,f} = \delta_{driver} \quad (47)$$

Inequality and boundary constraints: To reflect the physical limitations of the rear wheel steering system, separate constraints are established for the rear-wheel angle. Equations (48) and (49) represent the inequality constraint and boundary constraint, respectively:

$$\text{Inequality constraint} : -\dot{\delta}_{r,max}\Delta t \leq \delta_{r,n+1} - \delta_r, \quad n \leq \dot{\delta}_{r,max}\Delta t \quad (48)$$

$$(n = 1, 2, \dots, N)$$

$$\text{Boundary constraint} : \delta_{r,min} \leq \delta_{r,n} \leq \delta_{r,max} \quad (n = 1, 2, \dots, N) \quad (49)$$

Consequently, this MPC maintains the driver as the primary subject of vehicle operation while implementing a control strategy that assists steering performance when dangerous situations arise.

3. Performance Evaluations

This section describes the experimental environment and scenarios for evaluating the performance of the proposed MPC-based degradation monitoring and rear-wheel assist steering control algorithm. The performance evaluation were conducted using the vehicle dynamics simulation software CarMaker (ver. 8.1.1) and the Matlab/Simulink (R2019a) environment with a simulation sampling time of 0.001 s. All simulation curves presented in this study were extracted directly from the original numerical data generated by CarMaker and MATLAB/Simulink without any manual post-processing. The observed numerical behaviors, such as locally jagged segments in certain control inputs and error curves, are a numerical characteristic resulting from the discrepancy between the MPC update period and the simulation sampling time of the CarMaker/Simulink environment. The steering error calculated between the MPC-derived reference steering angle and the driver's actual steering input was smoothed via a first-order low-pass filter and directly fed into the CarMaker simulation environment for closed-loop performance evaluation.

3.1. Performance Evaluation Environment and Parameters

The vehicle used in the experiment is based on the vehicle model provided by CarMaker, and its primary physical parameters of the vehicle are listed in Table 1.

Table 1. Vehicle Specifications.

Division	Value [Unit]
Mass	1.600 [kg]
Length between mass center and front axle	1.48 [m]
Length between mass center and rear axle	1.48 [m]
Wheel tread	1.614 [m]

To ensure the real-time computation of the algorithm, the parameters for the monitoring MPC and the MPC used in the assist rear wheel derivation algorithm were established independently. These parameters are summarized in Tables 2 and 3. The input weighting factor for the assist rear wheel derivation algorithm was applied adaptively, and the parameters governing this weighting factor are detailed in Table 4.

Table 2. MPC parameters for steering performance degradation monitoring.

Division	Value [Unit]
Weighting matrix for state	$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$
Weighting for input	15,500
Discretization time	0.1
Update period	0.1
Prediction step	10
Minimum steering angle	−36.26 [deg]
Maximum steering angle	36.26 [deg]
Minimum steering angle rate	−28.75 [deg/s]
Maximum steering angle rate	28.75 [deg/s]

Table 3. MPC parameters used for assist rear wheel angle derivation.

Division	Value
Weighting matrix for state	$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$
Weighting for input	Adaptive
Discretization time	0.01
Update period	0.01
Prediction step	10
Minimum steering angle	−36.26 [deg]
Maximum steering angle	36.26 [deg]
Minimum steering angle rate	−28.75 [deg/s]
Maximum steering angle rate	28.75 [deg/s]

Table 4. Adaptation of weighting factors for input parameters.

Division	Value
k_R	800,000
w_1 (Case 1)	30,000
w_1 (Case 2)	500
w_1 and w_2 (Case 3)	10,000 and 0.12
R_{max}	800,000

Furthermore, the RLS parameters for deriving the driver deviation index and the driver response delay index are summarized in Table 5 and Table 6, respectively.

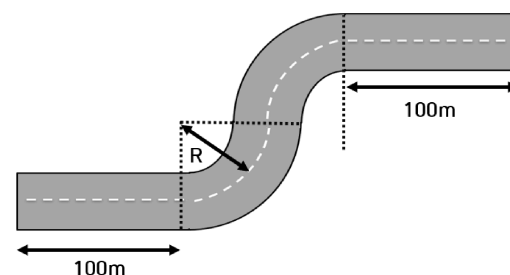
Table 5. RLS parameters used for driver deviation index.

Division	Value
Forgetting factor	0.9995
Initial covariance	0.1
Coefficient	100
(Driver deviation index)	
Maximum index	8
(Driver deviation index)	
Minimum index	0
(driver deviation index)	

Table 6. RLS parameters used for driver response delay index.

Division	Value
Forgetting factor	0.997
Initial covariance	0.1
Coefficient	100
(Driver response delay index)	
Maximum index	5
(Driver response delay index)	
Minimum index	0
(Driver response delay index)	

A schematic diagram of the S-curved road designed for the performance evaluation is shown in Figure 6, where the baseline road width is configured as 3.5 m.

**Figure 6.** Schematic of S-curved road.

To evaluate the tracking performance and robustness of the monitoring index under various conditions, the simulation scenarios are systematically divided into two main categories: (i) verification and sensitivity analysis of the driving impairment monitoring index (Scenarios 1 to 3), and (ii) path-tracking and assist control evaluation (Scenarios 4 to 7).

For the monitoring index verification, the vehicle is driven at a constant speed of 80 km/h on a continuous S-curve with a radius of curvature (R) of 100 m. The driver's reaction delay is replicated by adjusting the 'Reaction time' parameter within the CarMaker driver model, representing the temporal lag from the perception of a lateral path deviation to the physical initiation of steering. Furthermore, to evaluate the robustness of the monitoring index, the 'Tolerated Deviation' parameter of the driver model in CarMaker was systematically varied from 0.2 m to 1.0 m. This parameter defines the lateral error threshold before the driver model initiates corrective steering maneuvers, allowing for a comprehensive sensitivity analysis of the spatial deviation index.

For the assist control evaluation, the system is evaluated under cornering scenarios near handling limits. This includes variations in longitudinal velocities (50 km/h, 60 km/h, and 80 km/h) and sharper curves ($R = 50$ m and 100 m) under a driver reaction delay of

1.0 s. This 1 s delay interval is based on previous research evaluating drowsy drivers [21]. In Section 3.3, the evaluation of the path-following and vehicle stability performance under various cornering speeds and road curvatures (Scenarios 4 to 7), followed by an ablation study evaluating the contribution of each steering performance degradation index (Scenario 7).

The performance evaluation in this study is systematically structured into two stages to demonstrate both the monitoring fidelity and the active control capabilities of the proposed framework.

First, the driving impairment monitoring index verification (covering Scenarios 1 to 3) is conducted under completely unassisted driving conditions. In these scenarios, active rear-wheel steering intervention is deactivated, and the vehicle is steered solely by the human driver model in CarMaker under systematically varying reaction delays and tolerated deviation thresholds. This configuration isolates the vehicle's dynamic behavior, allowing for a rigorous sensitivity, linearity, and robustness analysis of the Recursive Least Squares based time constant and spatial deviation estimations without control loop feedback interference.

Second, path-tracking and active rear-wheel assist control performance is evaluated (covering Scenarios 4 to 7). To quantitatively demonstrate the efficacy, intervention timing, and tracking error reduction of the proposed adaptive weighting assist MPC under driver cognitive degradation, the vehicle's dynamic responses are compared and analyzed across six distinct control configurations:

- (1) CarMaker Driver (w/o RWS): A baseline scenario representing the unassisted driver, where path-following is performed solely by the front-wheel steering input of the human-like driver model under a critical reaction delay of 1.0 s, with no system assistance.
- (2) Autonomous MPC: An ideal, fully automated baseline where a front-wheel steering model predictive controller independently controls the vehicle to track the path, serving as the theoretical upper bound for path-following performance under perfect driving conditions.
- (3) w/ Assist (Case 1): The proposed active RWS assist control utilizing the index-based inversely proportional weighting model, where the RWS controller input weight is scaled dynamically in direct inverse proportion to the estimated total steering performance degradation index.
- (4) w/ Assist (Case 2): The proposed active RWS assist control utilizing the index–error rate product fusion weighting model, which triggers sharp and aggressive rear-wheel stabilization when both tracking deviation and the driver's steering error rate are simultaneously high.
- (5) w/ Assist (Case 3): The proposed active RWS assist control utilizing the independent sum weighting model, where independent weights are balanced and summed to generate a stabilized and smooth rear-wheel steering angle.
- (6) w/ Assist (Constant): A conventional active steering baseline operating with a fixed, non-adaptive rear-wheel steering input weight, representing standard non-cooperative co-driving systems.

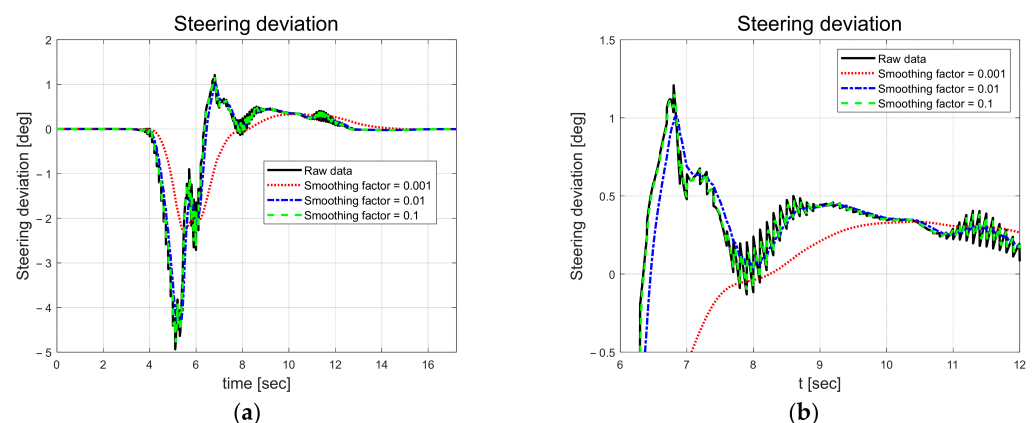
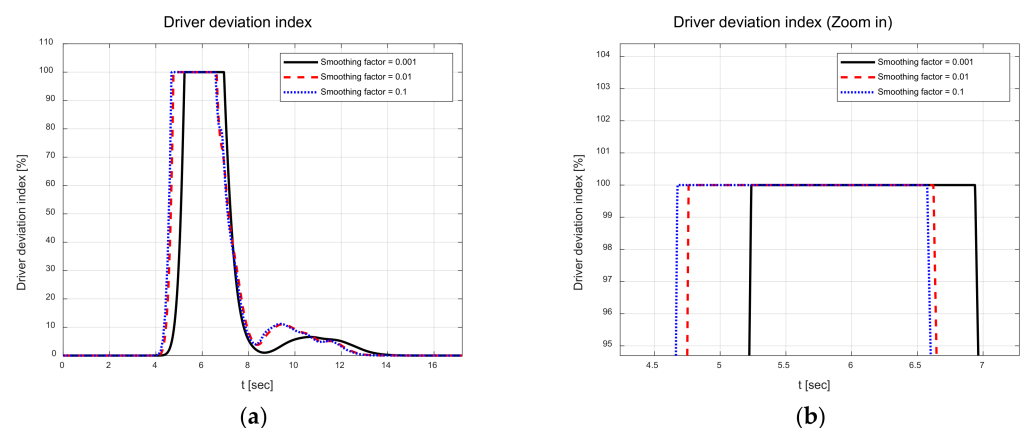
By comparing these six configurations under various longitudinal speeds and road curvatures, the real-time adaptability, human–machine conflict mitigation, and vehicle stability enhancement of the proposed integrated framework are comprehensively indicated. The specific parameters used to determine the adaptive weighting factors for each case are summarized in Table 7.

Table 7. Proposed adaptive weighting factor models for rear wheel assist steering.

Division	w/RWS (Case 1)	w/RWS (Case 2)	w/RWS (Case 3)
R_a	$R_a = \frac{k_R}{I_t} e^{-(w_1 \dot{e})}$	$R_a = k_R e^{-(w_1 \dot{e} I_t)}$	$R_a = k_R e^{-(w_1 \dot{e} + w_2 I_t)}$

3.1.1. Sensitivity Analysis of First-Order Low-Pass Filter

To systematically analyze the sensitivity of the pre-processing first-order low-pass filter, a series of closed-loop simulations were performed on a continuous S-curved road configured with a radius of curvature of 100 m. During the maneuvers, a critical response delay of 1.0 s was introduced to the driver model to induce significant trajectory deviations. Under this transient cornering scenario, the parametric impact of the filter coefficient, alpha, was evaluated by observing both the steering deviation and the resulting driver deviation index. Figure 7 illustrates the dynamic profiles of the filtered steering deviation under different configurations, while Figure 8 presents the corresponding real-time driver deviation index calculated via the recursive least squares estimation loop. Based on the comparative analysis of the transient response characteristics, signal delay, and noise attenuation in these profiles, the optimal filter coefficient, smoothing factor α , was determined. This selected value is subsequently utilized for all closed-loop performance evaluations to maintain a balanced relationship between estimation delay and signal smoothness.

**Figure 7.** Steering deviation: (a) Total; (b) Zoom in.**Figure 8.** Driver deviation index: (a) Total; (b) Zoom in.

An analysis of the filtered steering deviation in Figure 7 reveals distinct characteristics depending on the configured smoothing factor. When the smoothing factor is established at 0.1, the filtered signal yields a profile that is highly similar to the raw, unfiltered steering

deviation data. However, due to the discrepancy in the sampling time and the update period between the MPC and the human driver model, this configuration directly propagates high-frequency chattering and numerical oscillations into the subsequent estimation stage. Conversely, when the smoothing factor is set to low value of 0.001, the filter becomes overly damped as a result, the filtered output fails to track the overall transient trend and dynamic characteristics of the actual steering deviation command. In contrast, the smoothing factor configuration of 0.01 successfully strikes a balance. It maintains close tracking of the raw data's trajectory trend while suppressing the high-frequency chattering compared to the 0.1 configuration.

This trade-off between signal smoothness and time delay is further clarified by the real-time driver deviation index profiles shown in Figure 8. Under the highly responsive smoothing factor of 0.1, which tracks the raw data most closely, the normalized index reaches the maximum saturation threshold of 100% earliest at 4.676 s. Under the heavily damped smoothing factor of 0.001, the index propagation is delayed, reaching the 100% threshold latest at 5.237 s. When the proposed smoothing factor of 0.01 is applied, the driver deviation index reaches 100% at 4.76 s. Although this configuration introduces a minor phase lag compared to the 0.1 case, this transient latency is minimal and is judged to have a negligible impact on the performance and stability of the overall decision-making algorithm. Consequently, the optimal smoothing factor of 0.01 is systematically selected for all subsequent closed-loop performance evaluations.

To suppress high-frequency noise and ensure signal stability, a first-order low-pass filter is applied to the raw steering deviation data, with its key parameters in Table 8.

Table 8. Parameters for first-order low pass filter.

Division	Value
Smoothing factor	0.01

3.1.2. Quantitative Validation and Applicability of the Kinematic Vehicle Model

To validate the applicability of the simplified kinematic bicycle model with active rear-wheel steering utilized in the MPC formulation, a quantitative comparative evaluation was conducted against the high-fidelity CarMaker vehicle model. Although kinematic vehicle models are highly efficient for real-time control due to low computational complexity, they neglect tire slip dynamics and lateral force saturation under demanding cornering scenarios. To investigate and clarify the exact extent of the discrepancy and the resulting adverse impacts introduced by neglecting these dynamic effects under handling limits, open-loop sinusoidal steering tests were executed under out-of-phase front and rear road wheel steering commands. Specifically, at a longitudinal velocity of 50 km/h, a sinusoidal steering amplitude of 3 degrees was applied in counter-phase, whereas at 80 km/h, a sinusoidal steering amplitude of 2 degrees was applied in counter-phase to systematically evaluate the models under handling limit conditions. Figure 9 illustrates the comparison of the yaw rate and lateral acceleration profiles for both models under the 50 km/h cornering condition with a 3-degree steering amplitude. Figure 10 presents the corresponding yaw rate and lateral acceleration responses under the 80 km/h cornering condition with a 2-degree steering amplitude, demonstrating the quantitative correlation between the simplified kinematic representation and the high-fidelity dynamic vehicle model under handling limit conditions.

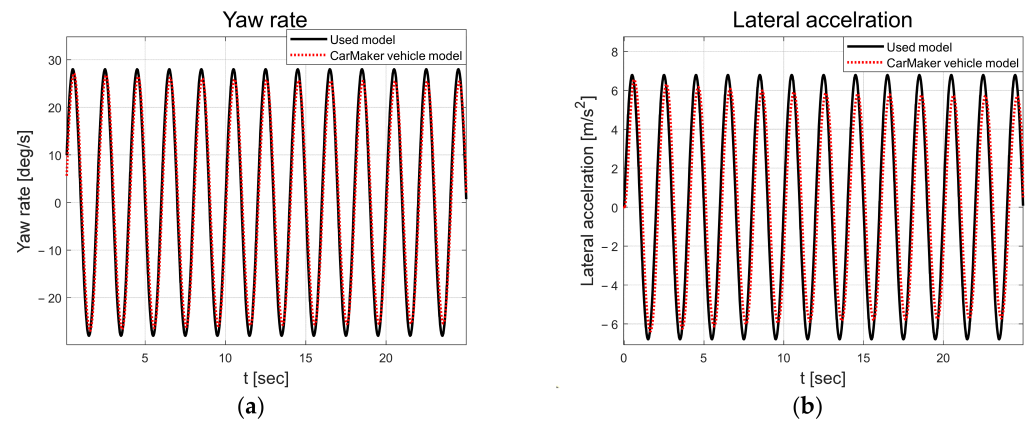


Figure 9. Yaw rate and lateral acceleration (50 kph): (a) Yaw rate; (b) Lateral acceleration.

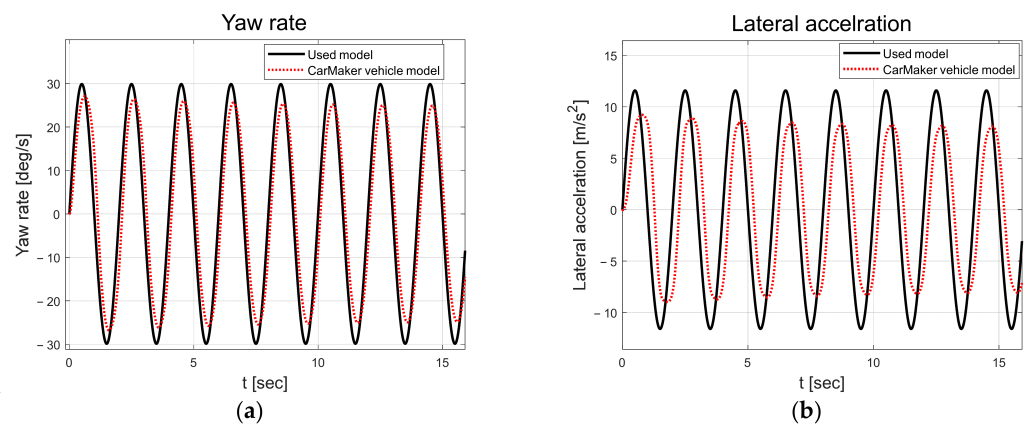


Figure 10. Yaw rate and lateral acceleration (80 kph) (a) Yaw rate; (b) Lateral acceleration.

An analysis of these profiles indicates that although numerical discrepancies exist, both models yield highly consistent transient trends across the evaluated states. Quantitatively, under the 80 km/h cornering condition with a 2-degree steering amplitude, the maximum offsets between the used model (Equation (40)) and the CarMaker representation are 4.98 deg/s for the yaw rate and 3.49 m/s² for the lateral acceleration. Under the 50 km/h cornering condition with a 3-degree steering amplitude, the maximum offsets are approximately 6.79 m/s² for the lateral acceleration and 2.61 deg/s for the yaw rate. To provide a comprehensive statistical comparison, the detailed transient metrics of the two models over the 10 s evaluation interval are summarized in Table 9.

Table 9. Quantitative validation metrics of the kinematic bicycle model against CarMaker representation.

Speed [km/h]	Physical Parameter	Model Type	Min/Maximum Value	Mean Value	Root-Mean-Square Error
50	Lateral acceleration [m/s ²]	Used model Equation (40)	−6.7901/6.7901	0.0000	1.9258
		CarMaker vehicle	−6.3796/6.5618	0.0344	
	Yaw rate [deg/s]	Used model Equation (40)	−28.0119/28.0119	0.0000	3.6440
		CarMaker vehicle	−26.9749/27.1467	0.0688	

Table 9. Cont.

Speed [km/h]	Physical Parameter	Model Type	Min/Maximum Value	Mean Value	Root-Mean-Square Error
80	Lateral acceleration [m/s ²]	Used model Equation (40)	−11.5885/11.5885	0.0000	5.5526
		CarMaker vehicle	−8.9619/9.2161	0.1855	
	Yaw rate [deg/s]	Used model Equation (40)	−29.8797/29.8797	0.0000	7.1562

Notably, the mean values of both the lateral acceleration and yaw rate responses for the used model (Equation (40)) are calculated to be close to zero. This zero-mean characteristic mathematically demonstrates that the transient model discrepancies are highly symmetric and balanced over the transient cornering cycle. In other words, although the neglected tire slip dynamics and lateral force saturation introduce localized transient peaks, they conceptually do not introduce cumulative directional drifts. This symmetric and unbiased nature of the model mismatch indicates that utilizing the low-complexity kinematic bicycle model for real-time predictive control is applicable.

3.2. Verification of Driver Ability Monitoring Index

3.2.1. Estimation of Time Constants for Quantification

In this subsection, a systematic evaluation is presented to demonstrate the stand-alone estimation fidelity, tracking responsiveness, and parametric sensitivity of the proposed RLS-based driver response delay estimator. To establish a baseline and analyze the unassisted system dynamics, all evaluations are conducted under a completely open-loop driving condition where active rear-wheel steering assist is deactivated ($R_a \rightarrow \infty$), forcing the vehicle to be steered solely by the driver model in CarMaker. Operating at a speed of 80 km/h on an S-curved road with a radius of curvature of 100 m, the performance of the estimator is analyzed by systematically increasing the driver's reaction delay from 0.2 s to 1.0 s in increments of 0.2 s. Figure 11 illustrates the spatial path-following trajectories of the vehicle, comparing the overall global trajectory with magnified views of the critical curved zones. Figure 12 details the corresponding steering control inputs and the tire level, presenting the driver's steering wheel angle and the resulting front road wheel angle, respectively. The transient dynamic response of the vehicle is captured in Figure 13, which displays the yaw rate profile and the longitudinal and lateral velocity histories. Figure 14 depicts the path-tracking accuracy at the vehicle's center of mass, showing the resulting lateral position error and yaw angle error under each delay condition. Finally, Figure 15 illustrates the real-time quantification performance of the RLS identification module, presenting both the transient time-history curves of the estimated steering time constant and the regression analysis indicating the proportional sensitivity relationship between the estimated time constant and the driver's actual reaction delay.

RT denotes the driver's reaction time. As the reaction time parameter configured in the CarMaker driver model increases, the driver's steering initiation is delayed, clearly indicating that the magnitude by which the vehicle deviates from the target trajectory becomes larger.

When a delay in the driver's reaction time occurs and steering initiation is delayed, the corresponding behavioral changes in the steering wheel angle and road wheel angle clearly show a direct physical correlation. If steering application is delayed while the vehicle already possesses a trajectory deviation or enters a curve, a larger steering input is

instantaneously required for path recovery, thereby resulting in a significantly increased steering angle magnitude. Furthermore, this sharply amplified steering input directly affects the vehicle's cornering dynamics, showing that the yaw rate representing the rate of change of the vehicle's heading also increases proportionally. In accordance with these steering delays and behavioral changes, it can be confirmed that both lateral error and yaw angle error exhibit distinct differences between conditions within the transient state specifically as the vehicle enters or exits the curved segments.

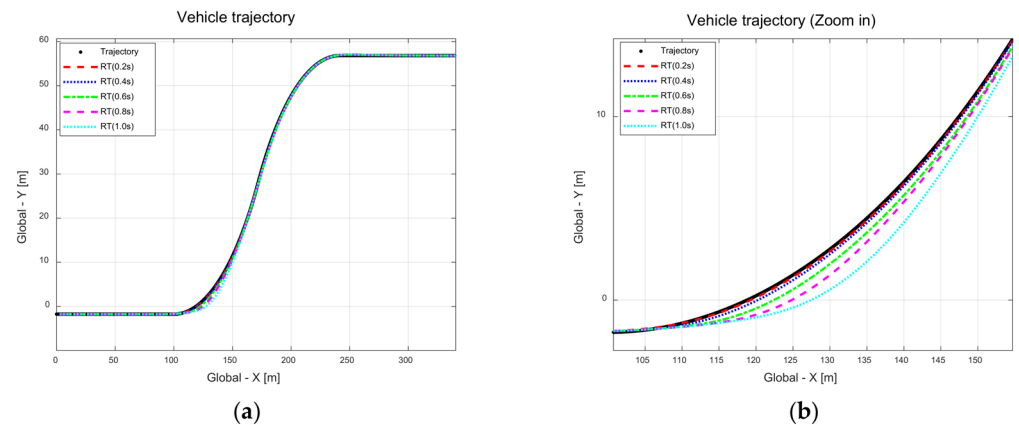


Figure 11. Vehicle trajectory: (a) Total; (b) Zoom in.

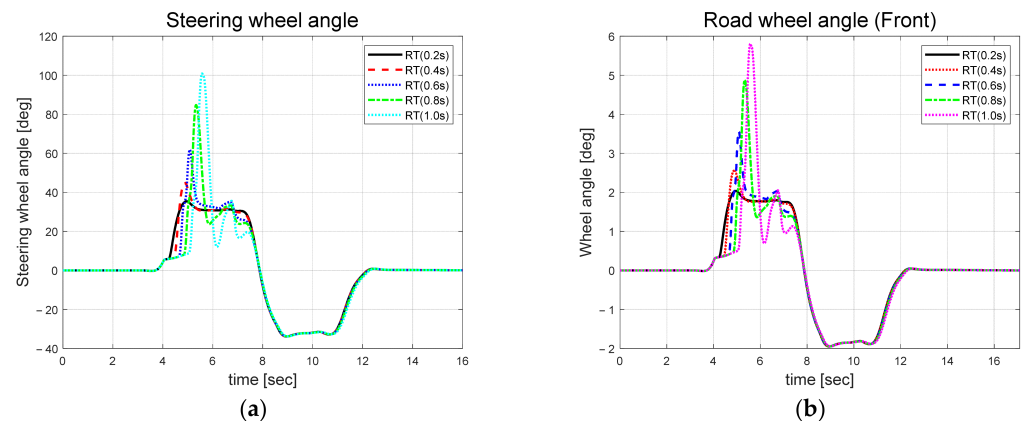


Figure 12. Wheel angle: (a) Steering wheel angle; (b) Road wheel angle (Front).

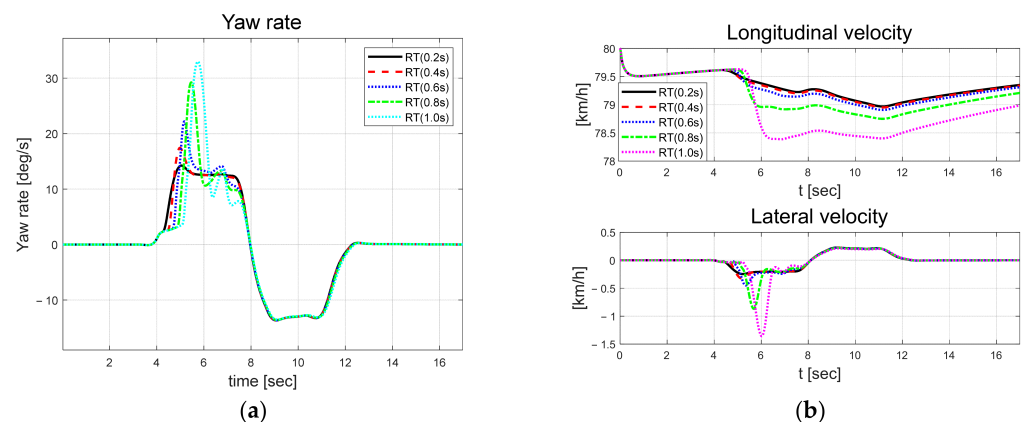


Figure 13. Vehicle dynamic states: (a) yaw rate; (b) Longitudinal/lateral velocity.

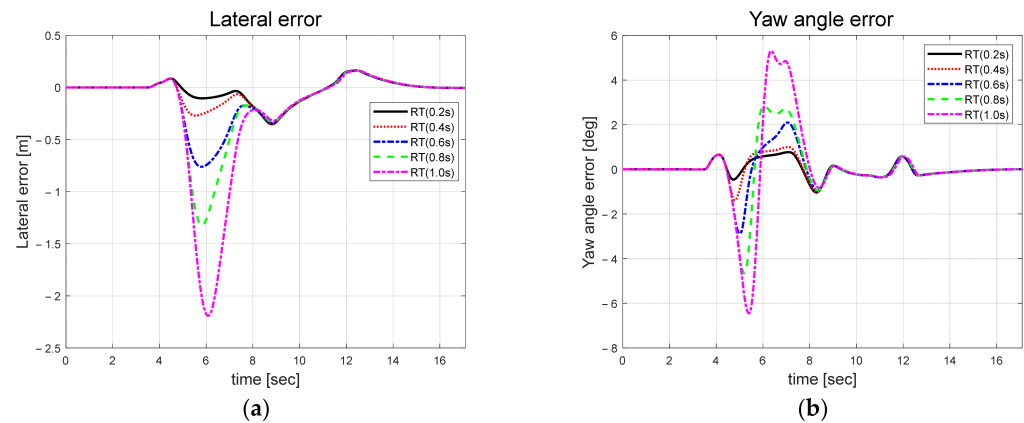


Figure 14. Path error (mass center): (a) Lateral error; (b) Yaw angle error.

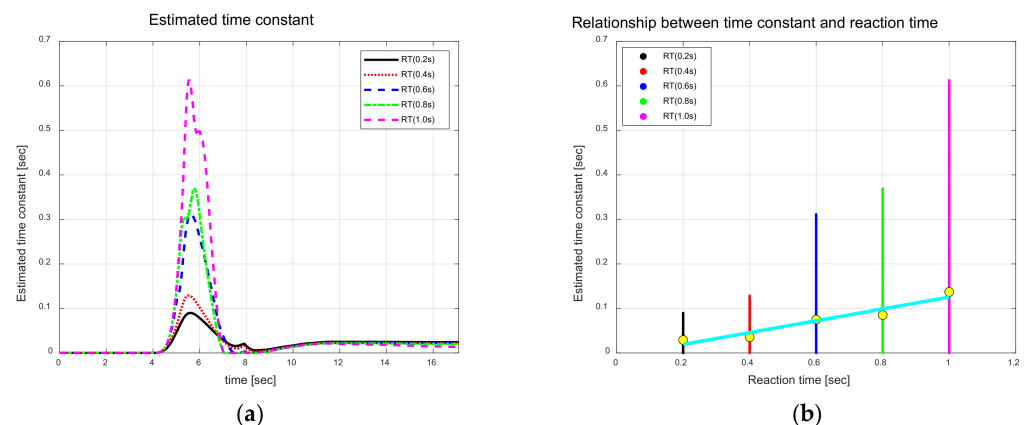


Figure 15. Estimated time constant: (a) Estimated time constant-reaction time; (b) Relationship between time constant and reaction time.

Based on the RMS (Root Mean Square) values calculated during the performance evaluation for each reaction time condition (0.2 s, 0.4 s, 0.6 s, 0.8 s, and 1.0 s), it can be clearly observed that as the reaction time increases, the RMS values of the estimated time constant progressively increase in an upward linear trend, measuring 0.0291 at 0.2 s, 0.0355 at 0.4 s, 0.0750 at 0.6 s, 0.0852 at 0.8 s, and 0.1371 at 1.0 s, respectively. A first-order linear fit (represented by the light blue line) was performed on these RMS values (marked in yellow), yielding a regression slope of 0.1328. This quantitatively indicates the sensitivity characteristics of the estimated parameter. It should be clarified that because the RLS estimator approximates the driver's transport delay utilizing a first-order lag model, the estimated time constant does not directly equal the absolute physical reaction delay in seconds. Instead, it functions as a highly sensitive and proportional delay-related indicator, suggesting that the magnitude and amplitude of the estimated parameter respond systematically to the relative severity of the reaction delay.

3.2.2. Estimation of Driver Deviation Index for Quantification

In this subsection, a systematic evaluation is presented to demonstrate the stand-alone estimation fidelity, tracking responsiveness, and parametric sensitivity of the proposed RLS-based driver deviation index.

To systematically analyze the vehicle's dynamic behavior and the corresponding estimation performance under varying spatial tracking thresholds (Tolerated Deviation), a comprehensive set of simulation curves is illustrated in Figures 16–20. Specifically, Figure 16 depicts the vehicle's spatial trajectories, comparing the overall global path with detailed magnified views at curve entries, transitions, and straight-line recovery zones. Figure 17

details the control inputs at both the steering wheel and front road wheel levels, revealing the amplitude changes under different tolerance limits. Figure 18 captures the vehicle's transient dynamic states, displaying the slow-swaying patterns in both the yaw rate and velocity profiles. Figure 19 presents the path-tracking errors at the vehicle's center of mass, illustrating the resulting lateral error and yaw angle error. Finally, Figure 20 showcases the real-time performance of the proposed RLS-based monitoring module, presenting the continuous steering deviation and its mathematically standardized driver deviation index.

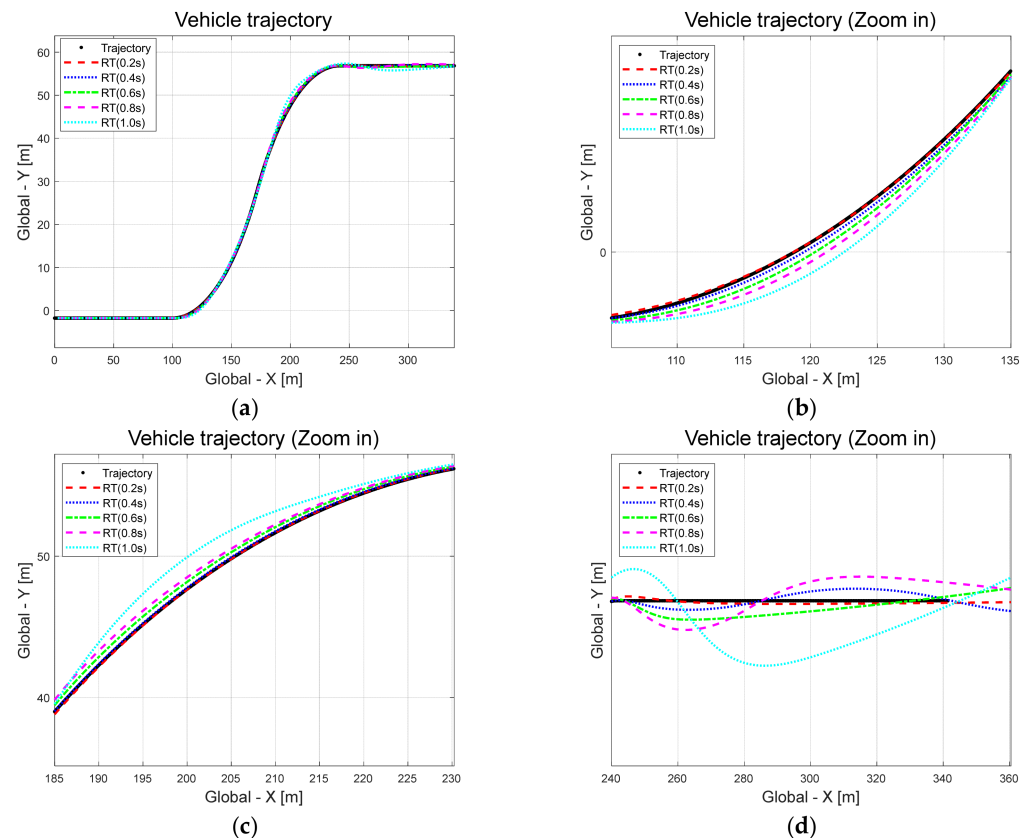


Figure 16. Vehicle trajectory: (a) Total; (b) Zoom in (X: 105–135 m); (c) Zoom in (X: 185–230 m); (d) Zoom in (X: 240–360 m).

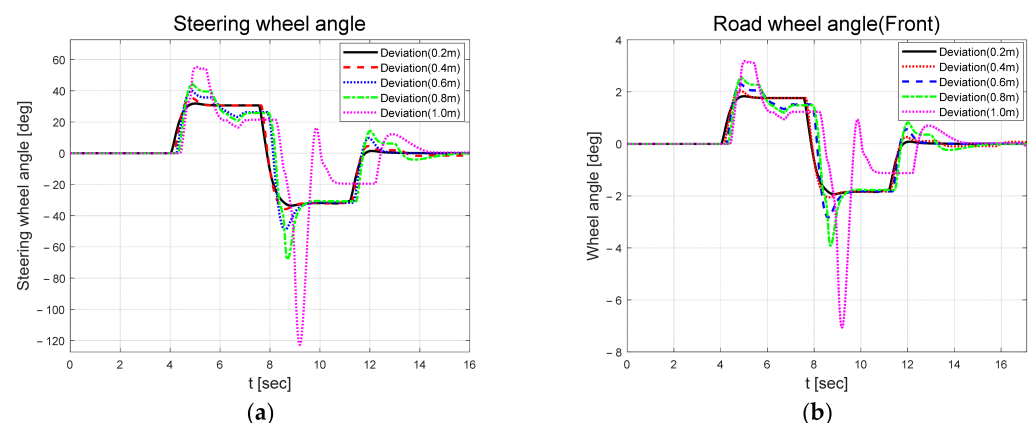


Figure 17. Wheel angle: (a) Steering wheel angle; (b) Road wheel angle (Front).

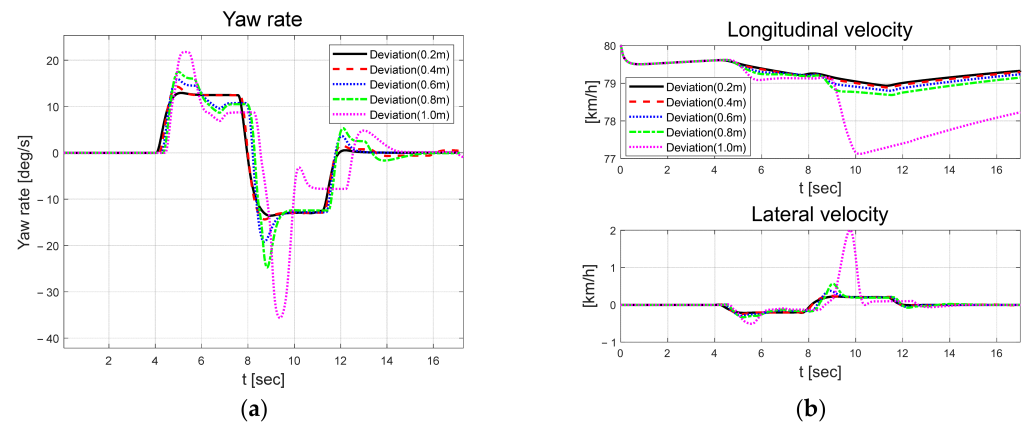


Figure 18. Vehicle dynamic states: (a) Yaw rate; (b) Longitudinal/lateral velocity.

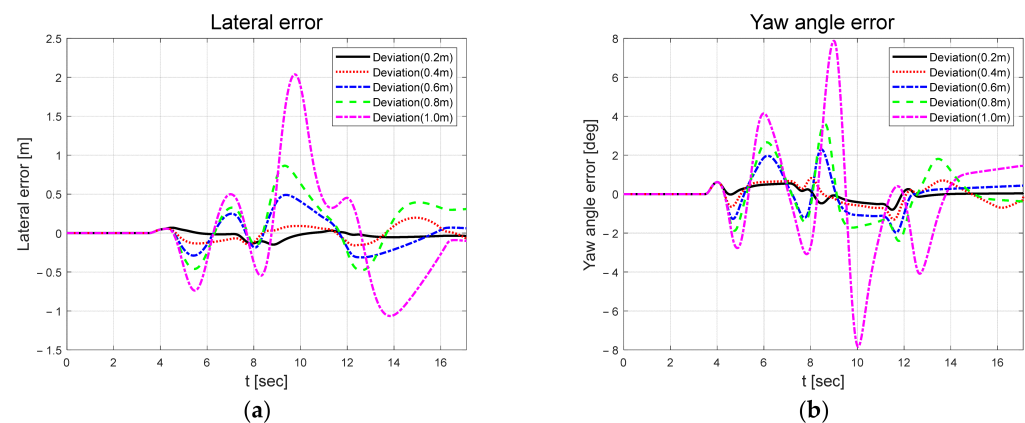


Figure 19. Path error (mass center): (a) Lateral error; (b) Yaw angle error.

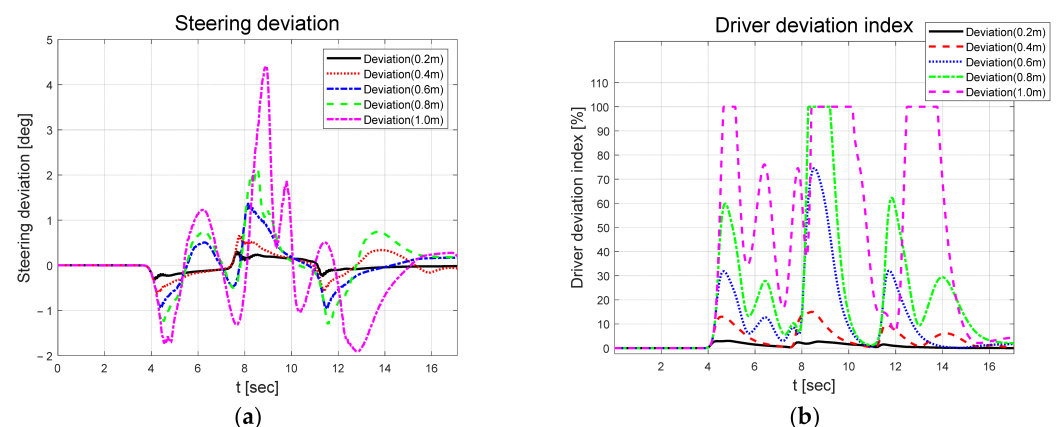


Figure 20. Steering deviation and its normalized index: (a) Steering deviation; (b) Driver deviation index.

Figure 16b illustrates the zoomed-in vehicle trajectory within the first curve entry transient section ($105 \text{ m} \leq X \leq 135 \text{ m}$). It is observed that larger tolerated deviation thresholds lead to significantly wider deviations from the target reference centerline. Because corrective steering is delayed until the lateral error violates the inflated threshold, the vehicle fails to respond in a timely manner to the initial curve entry, pushing the trajectory outward. A highly consistent tracking degradation is also observed in the second curve transition section ($185 \text{ m} \leq X \leq 230 \text{ m}$), as shown in Figure 16c, where the peak transient path deviation scales in direct proportion to the configured error tolerance limit. Furthermore, Figure 16d highlights the vehicle's dynamic behavior during the straight-line segment

after exiting the curved section ($240 \text{ m} \leq X \leq 360 \text{ m}$). Under high tolerated deviation configurations, the driver model exhibits unstable, large-amplitude trajectory oscillations. Since the driver model ignores small path-tracking errors during straight cruising until they exceed the tolerance limit, it repeatedly applies delayed yet aggressively amplified steering corrections. This discrete and delayed steering pattern prevents the vehicle from smoothly stabilizing and instead forces it to traverse the straight road with continuous, large-amplitude lateral oscillations.

In Figure 17, the steering wheel angle and front road wheel angle show a clear difference depending on the tolerance limit. When the tolerance is small (0.2 m and 0.4 m), the steering inputs are stable. The driver makes small, frequent corrections, so oscillations are minimal. However, from 0.6 m and especially at 1.0 m, the steering inputs become much larger. Because the driver ignores the path error until it exceeds the set limit, the driver initiates steering late and subsequently applies significant force to recover. This causes the steering angle to oscillate at a low frequency but with a very large amplitude, rather than showing fast or rapid oscillations. This slow, large swaying behavior directly affects the vehicle states in Figure 18. The yaw rate in Figure 18a sways slowly with a large amplitude at the 1.0 m condition, closely matching the driver's steering pattern. In Figure 18b, this slow swaying also causes a clear, visible difference in both the longitudinal and lateral velocities under the 1.0 m condition compared to the stable, tighter tolerance cases. Consequently, the tracking errors in Figure 15 follow the same slow-swaying pattern. While the errors remain small and flat at 0.2 m and 0.4 m, they sway slowly with a large amplitude under the 1.0 m condition. Because the driver corrects the path late, the vehicle deviates widely from the target centerline, especially when entering and exiting the curves, leading to much larger lateral and yaw angle errors.

As shown in Figure 20a, the steering deviation exhibits significant amplification within the transient states, specifically during the entry and exit of the curved road segments. Under wider spatial tolerance thresholds, the driver model's steering initiation is delayed. If the steering correction is postponed while the vehicle is already negotiating a curve, a much larger steering wheel input is instantaneously demanded to recover the target path, which directly results in a drastically increased steering deviation magnitude and a larger wave amplitude.

This physical error propagation is directly reflected in the driver deviation index shown in Figure 20b. As the tracking error escalates due to the delayed steering corrective actions, the monitoring index dynamically yields larger values. Notably, under the 0.8 m Tolerated Deviation configuration, the driver deviation index rapidly increases and reaches the critical limit of 100% at the inflection point of the S-curve. Furthermore, under the extreme 1.0 m configuration, the severe tracking failure causes the index to saturate at 100% across all three sequential curves along the evaluation path. This quantitative behavior demonstrates that the proposed RLS framework can reliably standardize and translate spatial driving degradation into a clear, bounded index (0–100) to adjust the cooperative rear-wheel control authority.

3.2.3. Sensitivity Analysis of Weighting Factors

To systematically investigate the control characteristics of the proposed adaptive framework, a numerical sensitivity analysis ($\partial R_a / \partial I_t$) was conducted for all three proposed adaptive weighting formulations (Case 1, Case 2, and Case 3) under varying steering error rates ($|\dot{e}| = 10^{-6} \text{ rad/s}$, 10^{-5} rad/s and 10^{-4} rad/s). Figures 21–23 illustrate the sensitivity curves across the full range of the driving capability index in subplot (a), with corresponding magnified views near the initial transient region in subplot (b).

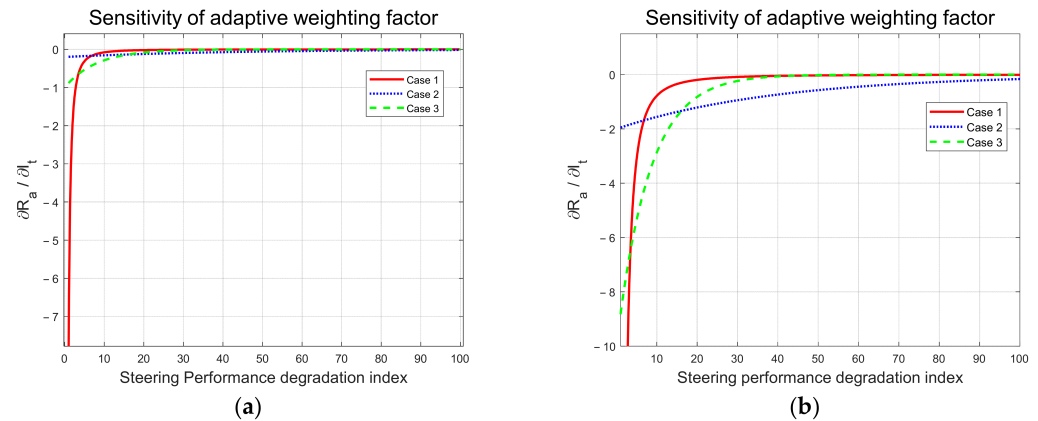


Figure 21. Sensitivity of adaptive weighting factors under a low steering error rate: (a) Total; (b) Zoom in.

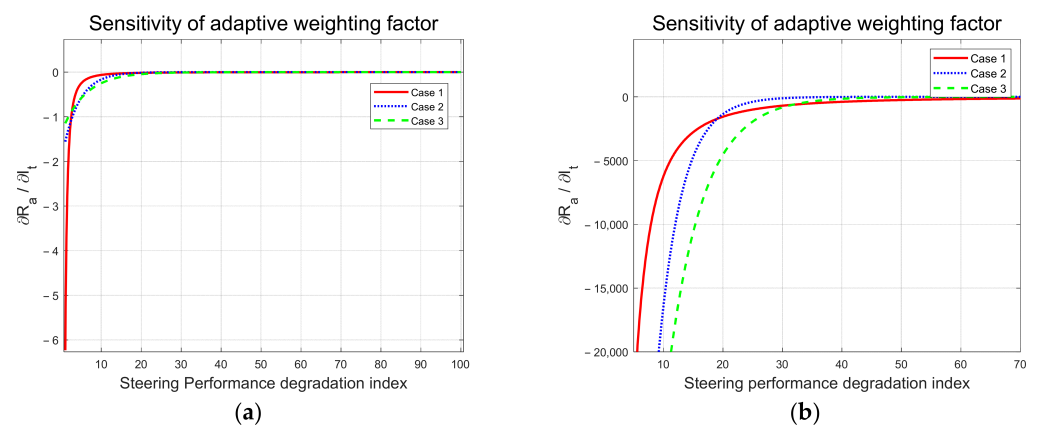


Figure 22. Sensitivity of adaptive weighting factors under a moderate steering error rate: (a) Total; (b) Zoom in.

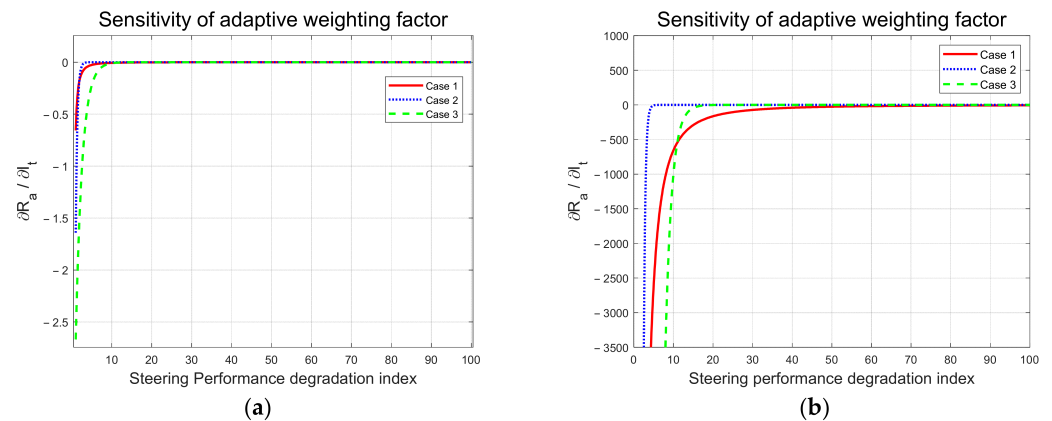


Figure 23. Sensitivity of adaptive weighting factors under a high steering error rate: (a) Total; (b) Zoom in.

These figures demonstrate that each proposed case possesses distinct sensitivity decay rates and control authority allocation behaviors depending on the physical nature of the driver's steering inputs:

Low Steering Error Rate (Figure 21): Under an extremely low steering error rate, Case 1 exhibits the fastest sensitivity attenuation (the gradient $\partial R_a / \partial I_t$ rapidly decays to zero) as I_t increases, followed by Case 3, while Case 2 shows the slowest decay rate. This highlights that Case 1 is mathematically dominated by the driving index regardless of the error rate

magnitude, making it highly effective for quietly detecting steady-state path deviations, whereas Case 2 remains inactive due to the lack of dynamic steering excitation.

Moderate Steering Error Rate (Figure 22): When the steering error rate increases to a moderate level, the sensitivity decay speed (the rate at which $\partial R_a / \partial I_t$ approaches zero) shifts to the order of Case 2, Case 3, and Case 1. Although Case 1 exhibits a steeper initial gradient in the ultra-low index region, Case 2 shows the sharpest and most aggressive decay toward zero as I_t accumulates. Nevertheless, until I_t reaches approximately 19%, Case 1 maintains a lower sensitivity magnitude (remains closest to zero) compared to the other cases, indicating its high responsiveness in the early stages of impairment.

High Steering Error Rate (Figure 23): Under a highly dynamic steering error rate, the decay speed follows the order of Case 2, Case 3, and Case 1. In the initial phase below $I_t = 2\%$, Case 1 remains closest to zero, showing the lowest sensitivity magnitude. However, beyond the 2% threshold, Case 2 exhibits the most rapid decay. Case 3, owing to its hybrid formulation, eventually intersects Case 1 around $I_t = 19\%$ and converges closer to zero thereafter.

Consequently, these comparative sensitivity curves mathematically demonstrate the unique design purposes of the proposed weighting suite: Case 1 acts as a driving index-dominant formulation with the highest sensitivity dominance with respect to I_t , making it suitable for slow-drift scenarios. Conversely, Case 2 acts as an error rate-dominant formulation with the highest sensitivity dominance with respect to the steering error rate $|\dot{e}|$, which is optimal for suppressing sudden, high-frequency physical steering instability. Finally, Case 3 serves as a balanced hybrid formulation that effectively blends these opposing characteristics to secure stable, non-chattering control authority across both steady-state and highly dynamic steering maneuvers.

3.3. Assist Rear Wheel Steering Algorithm Performance Evaluation

3.3.1. Algorithm Performance Evaluation Under Low Speed and S-Curve Road with Time Delay (50 km/h, $R = 100$ m, 1 s Delay)

To rigorously evaluate the real-time control efficacy, path-following precision, and steering workload mitigation of the proposed active rear-wheel assist framework under low-speed cornering conditions with driver cognitive delay, a series of closed-loop simulations was executed. The resulting vehicle states, actuator control inputs, and driving risk indices are comprehensively plotted in Figures 24–28. Specifically, Figure 24 presents the vehicle's spatial trajectories, comparing the overall global path with localized magnified views around the critical curved entry and apex zones. Figure 25 details the physical steering control inputs at the actuator level, depicting the front road wheel angle and the active rear road wheel angle, respectively, under each control configuration. The transient dynamic response of the vehicle chassis is captured in Figure 26, which displays the yaw rate profile and the corresponding longitudinal and lateral velocity histories. Figure 27 illustrates the spatial tracking accuracy at the vehicle's center of mass, showing the resulting lateral position error and yaw angle error. Finally, Figure 28 quantitatively compares the steering performance degradation, illustrating both the continuous time-history of the total steering performance degradation index and its cumulative integration over the entire maneuver to demonstrate the overall reduction in driving risk.

First, the path-tracking performance was analyzed using the vehicle trajectories in Figure 24 and the center of mass tracking errors in Figure 27. To ensure readability, all numerical values from the raw simulation data are rounded to two decimal places. Without any system assistance, the delayed human driver (Manual driving) exhibits severe path deviation, resulting in a maximum lateral error of 1.76 m and a maximum yaw angle error of 9.03 deg. In contrast, the fully automated baseline (Autonomous driving) maintains a

stable trajectory, yielding a maximum lateral error of only 0.13 m and a yaw angle error of 0.81 deg.

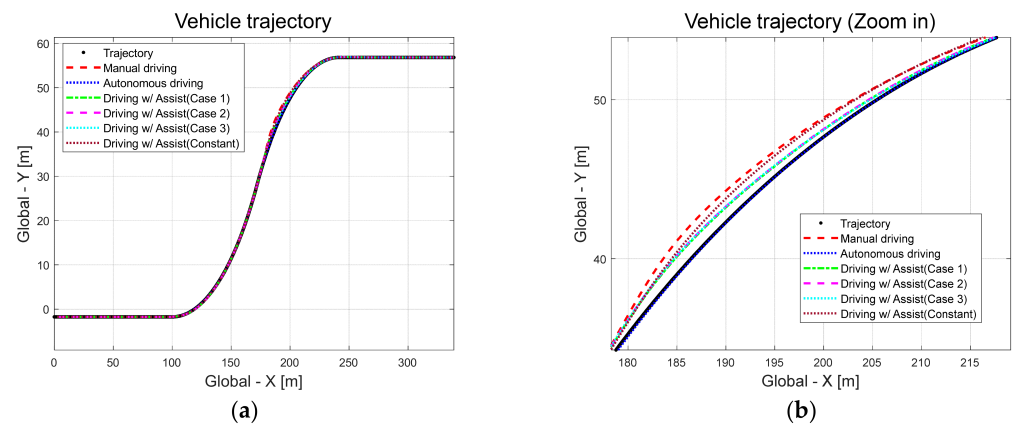


Figure 24. Vehicle trajectory: (a) Total; (b) Zoom in.

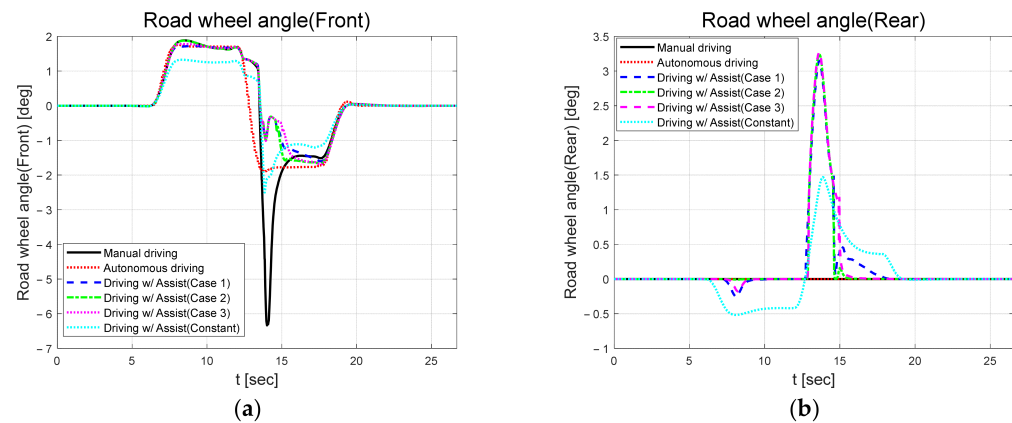


Figure 25. Wheel angle: (a) Road wheel angle (Front); (b) Road wheel angle (Rear).

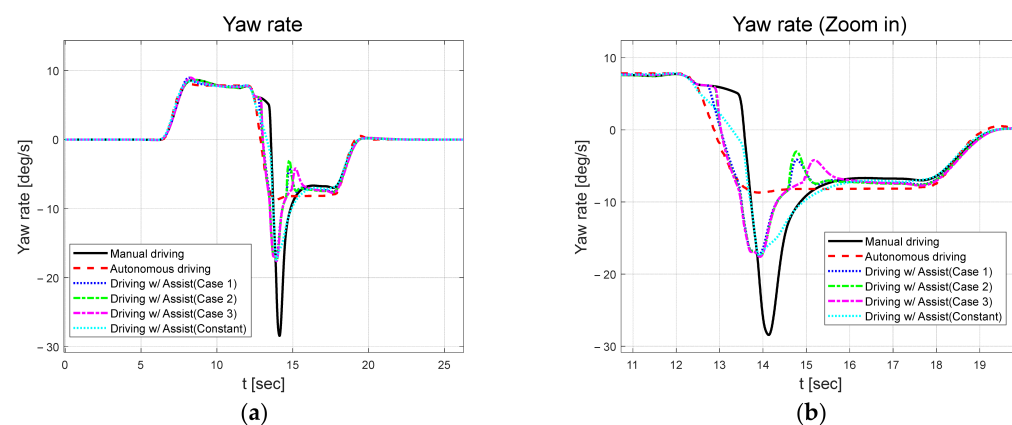


Figure 26. Vehicle yaw rate: (a) Total; (b) Zoom in.

When the proposed adaptive weighting assist controllers are activated, tracking performance is significantly improved considerably:

- Driving w/ Assist (Case 1): The maximum lateral error is reduced to 0.91 m (an approximately 48.30% reduction compared to the unassisted driver), and the maximum yaw angle error is reduced to 2.39 deg (an approximately 73.53% reduction).
- Driving w/ Assist (Case 2): The maximum lateral error is limited to 0.96 m (an approximately 45.45% reduction), and the maximum yaw angle error is limited to 2.57 deg (an approximately 71.54% reduction).

- Driving w/ Assist (Case 3): The maximum lateral error is limited to 0.97 m (an approximately 44.89% reduction), and the maximum yaw angle error is limited to 2.57 deg (an approximately 71.54% reduction).
- Driving w/ Assist (Constant): The unadaptive baseline achieves a maximum lateral error of 1.26 m (an approximately 28.41% reduction) and a maximum yaw angle error of 5.03 deg (an approximately 44.29% reduction), showing the lowest assist performance among the active steering cases.

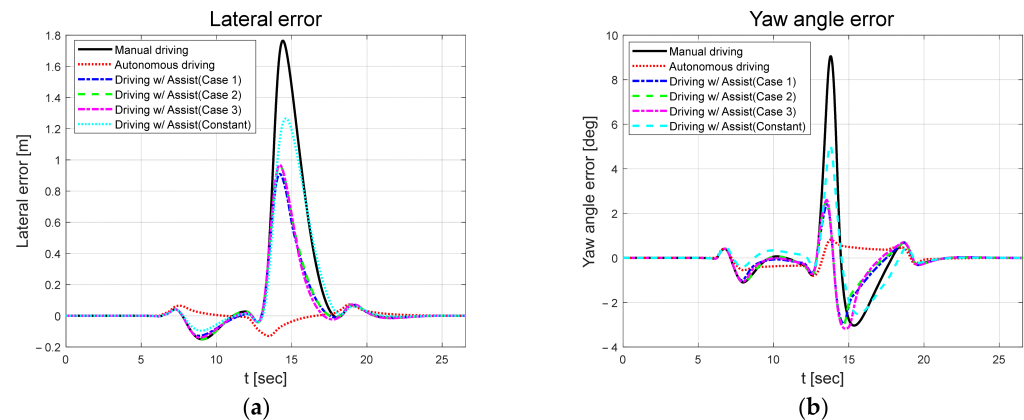


Figure 27. Path error (mass center): (a) Lateral error; (b) Yaw angle error.

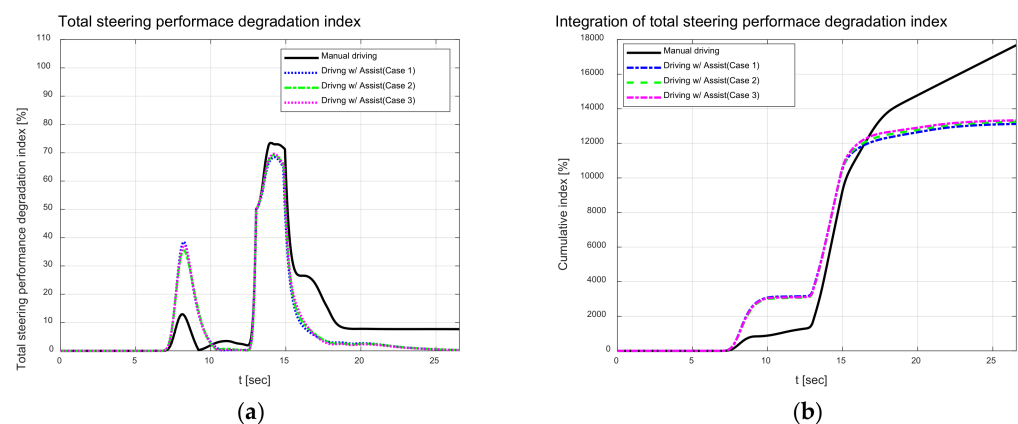


Figure 28. Comparison of steering performance degradation: (a) Total steering performance degradation index; (b) Integration of total steering performance degradation index.

Second, the physical correlation between the steering inputs (Figure 25) and the vehicle dynamic states (Figure 26) was evaluated. Under the unassisted Driver condition, both the front road wheel angle and the vehicle yaw rate responses are delayed due to the cognitive reaction delay. Once steering is initiated late, the driver is forced to apply an abruptly large front-wheel steering angle to recover the path, which in turn induces a substantial overshoot in the vehicle's yaw rate response.

Under the proposed w/ Assist (Cases 1, 2, and 3) configurations, the assist system actively generates prompt rear road wheel steering inputs (Figure 25b) that respond faster than the driver's delayed actions. By introducing this early steering, the assist control prevents vehicle trajectory deviation and substantially reduces the peak yaw rate overshoot compared to the unassisted driver, while keeping the overall vehicle velocity profile stable.

However, the w/ Assist (Constant) configuration exhibits highly unstable transient behavior. Although the constant assist model reduces the driver's steering burden during normal steady-state driving, it fails to stabilize the vehicle when the front wheels must turn rapidly to negotiate curves or recover from deviations. Because the rear-wheel weight-

ing factor is fixed as a static constant, the system cannot dynamically adjust its control authority. Consequently, the rear wheels cannot generate a larger, necessary corrective steering angle during critical emergency situations, leading to significant instabilities in the vehicle's yaw rate, lateral error, and yaw angle error. This comparative analysis highlights that the advantage of the proposed adaptive strategy does not lie in ensuring absolute tracking accuracy under all conceivable conditions, but rather in its ability to balance tracking precision with appropriate, context-dependent intervention. While a highly active constant-weight controller can be calibrated to achieve superior tracking accuracy under specific dynamic conditions, it does so through continuous, non-adaptive intervention that overrides the driver's steering authority and introduces control conflict during normal driving intervals. The adaptive strategy successfully resolves this trade-off by dynamically scaling the rear-wheel assistance, providing fail-safe support during driver degradation while remaining transparent to preserve driver authority during normal intervals.

Figure 28 presents the performance comparison of the driving impairment evaluation, showing: (a) the real-time integrated performance degradation index and (b) the integration of the integrated steering performance degradation index. Specifically, the cumulative steering performance degradation index is obtained via continuous-time numerical integration of the real-time index using the integrator block in MATLAB/Simulink, rather than direct discrete sample accumulation. In this analysis, the evaluation is performed by comparing only the unassisted driver and the adaptive assist configurations, while the Autonomous and Constant assist configurations are intentionally excluded due to the following control-loop characteristics:

First, the Autonomous MPC configuration is excluded because it represents a fully automated driving system with no human driver in the loop, making a direct comparison of a human-centric driving impairment index physically and structurally invalid.

Second, the w/ Assist (Constant) configuration is excluded because the static rear-wheel steering intervention continuously assists the vehicle dynamics even during normal driving intervals where the driver operates perfectly. This continuous non-adaptive intervention alters the baseline steering relationship, causing the monitoring module to output an index value that is artificially higher than the driver's actual impairment level.

In Figure 28a, the integrated steering performance degradation index of the driving w/ Assist cases exhibits a transient increase compared to the unassisted Driver at approximately the 7 s mark. This phenomenon is caused by the closed-loop steering interaction between the human driver and the assist controller. During this interval, the CarMaker driver model naturally steering-compensates for path deviations with some tracking errors. As the active rear-wheel steering intervenes to assist the vehicle's cornering, it reduces the steering workload on the driver's side, leading to a decrease in the driver's front-wheel steering angle. Consequently, this reduction in the driver's physical steering input temporarily widens the difference between the driver's input and the ideal reference steering command from the monitoring MPC, resulting in a momentary rise in the calculated steering performance degradation index.

At approximately the 13 s mark, where the 1.0 s driver cognitive reaction delay severely affects path-following, the steering performance degradation index across all evaluated cases rapidly exceeds 60% due to the delayed corrective actions.

However, once the active rear-wheel assist actively intervenes to stabilize the vehicle and bring it back to the normal tracking trajectory, the path-tracking error is quickly resolved. As a result, the integrated steering performance degradation index for the w/ Assist cases decreases at a significantly faster rate compared to the unassisted Driver, demonstrating that the proposed adaptive weighting framework effectively suppresses the accumulation of driving risk loads during critical cognitive delay lapses.

After the transient tracking errors are resolved during steady-state straight cruising, particularly in the case of a driver performing manual driving, the steering performance degradation index does not completely converge to absolute zero but remains sustained at a baseline of approximately 10%. This corresponds to the numerically sustained state of the RLS estimation module under steady-state driving conditions. Because the driver's steering angle and steering angular velocity exhibit virtually zero variation during straight cruising, the regression variables within the RLS estimator lack sufficient dynamic excitation to refresh the parameter updates. Under these zero-steering-rate conditions, the parameter identification process within the RLS algorithm stagnates, preventing the estimated time delay constant from being driven completely to zero and causing the index to sustain a minor residual offset. This sustained index baseline remains at a level that does not introduce control chattering or steering heterogeneity.

3.3.2. Algorithm Performance Evaluation Under High Speed and S-Curve Road with Time Delay (80 km/h, $R = 100$ m, 1 s Delay)

To rigorously evaluate the control effectiveness, high-speed handling limits, and active path-correction performance of the proposed active rear-wheel steering assist framework under severe driver cognitive impairment, closed-loop simulation trials were conducted at a high cornering speed of 80 km/h.

The resulting vehicle states, actuator control inputs, and steering performance indices are comprehensively illustrated in Figures 29–33. Specifically, Figure 29 depicts the vehicle's spatial trajectories on the continuous S-curve road, comparing the global driving path with localized magnified views near the critical high-speed curved zones. Figure 30 details the physical steering control inputs executed at the road wheel level, illustrating the front road wheel angle and the active rear road wheel angle, respectively. The transient dynamic response of the vehicle chassis under high lateral acceleration is captured in Figure 31, displaying the vehicle yaw rate profile and the longitudinal and lateral velocity histories. Figure 32 presents the path-tracking errors relative to the vehicle's center of mass, showing the resulting lateral position error and yaw angle error. Finally, Figure 33 quantitatively evaluates the fail-safe performance by comparing the steering performance degradation, illustrating both the continuous time-history of the integrated steering performance degradation index and its cumulative time-integration over the entire maneuver to demonstrate the overall reduction in driving risk.

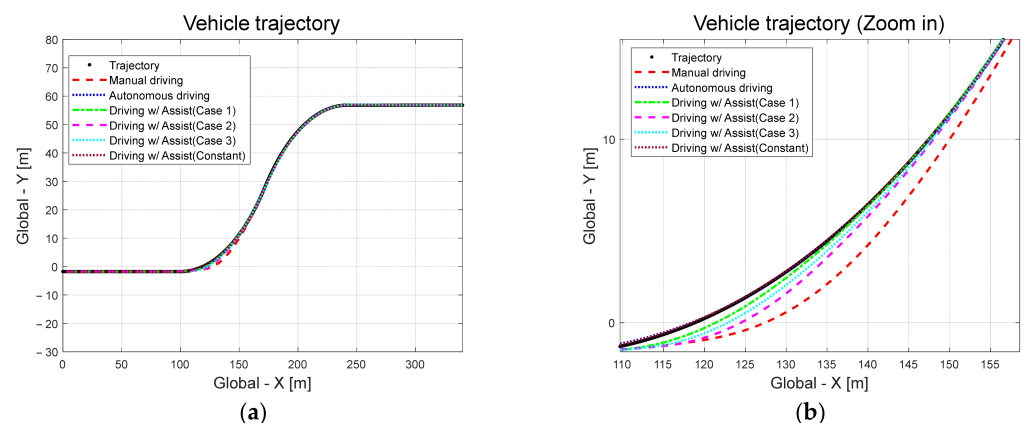


Figure 29. Vehicle trajectory: (a) Total; (b) Zoom in.

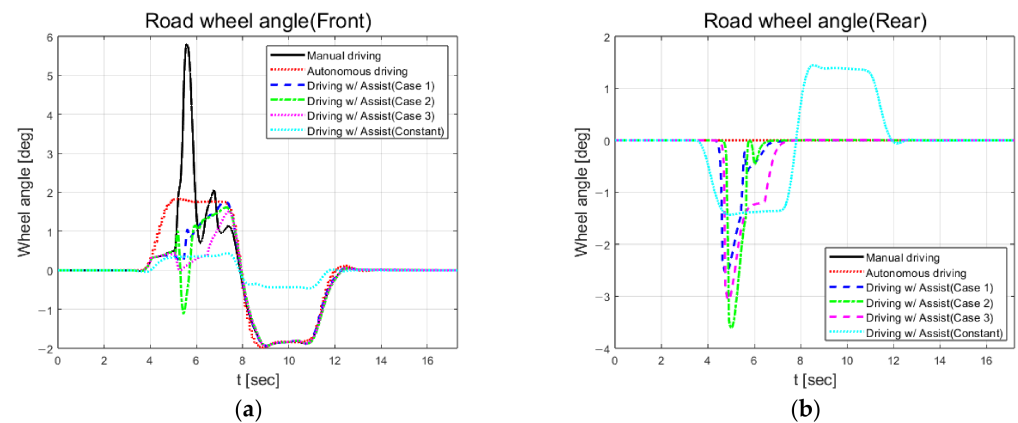


Figure 30. Wheel angle: (a) Road wheel angle (Front); (b) Road wheel angle (Rear).

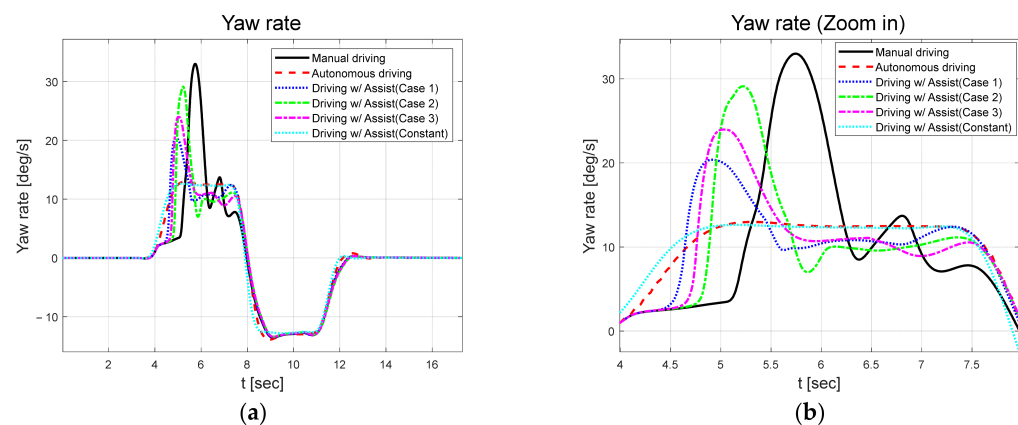


Figure 31. Vehicle yaw rate: (a) Total; (b) Zoom in.

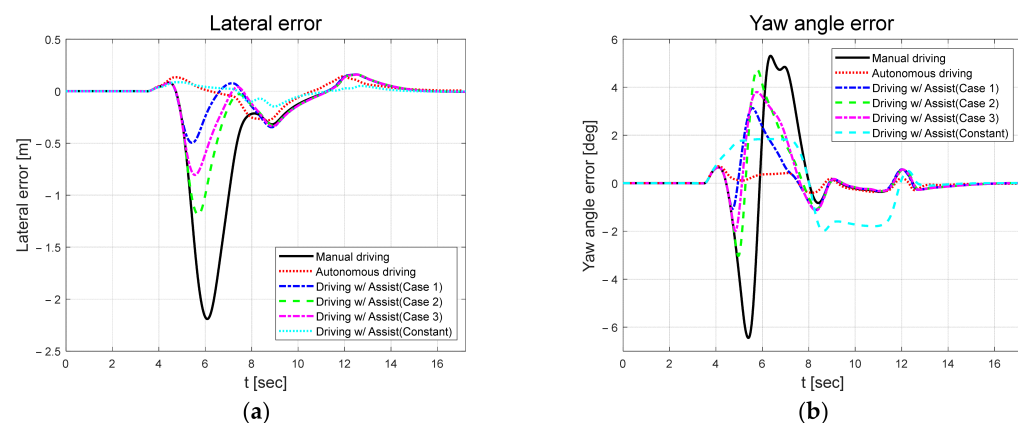


Figure 32. Path error (mass center): (a) Lateral error; (b) Yaw angle error.

Figures 29–32 show the vehicle's path-tracking and steering control results on the high-speed S-curve road under a critical 1.0 s driver delay. To ensure readability, all numerical values from the raw simulation data are rounded to two decimal places.

First, the tracking performance was analyzed quantitatively using the lateral and yaw angle errors shown in Figure 32. Without active steering assistance, the unassisted Driver deviates significantly from the centerline, resulting in a maximum lateral error of 2.19 m and a maximum yaw angle error of 6.45 deg.

In contrast, the Autonomous controller keeps the tracking stable, yielding a maximum lateral error of 0.28 m and a yaw angle error of 0.71 deg.

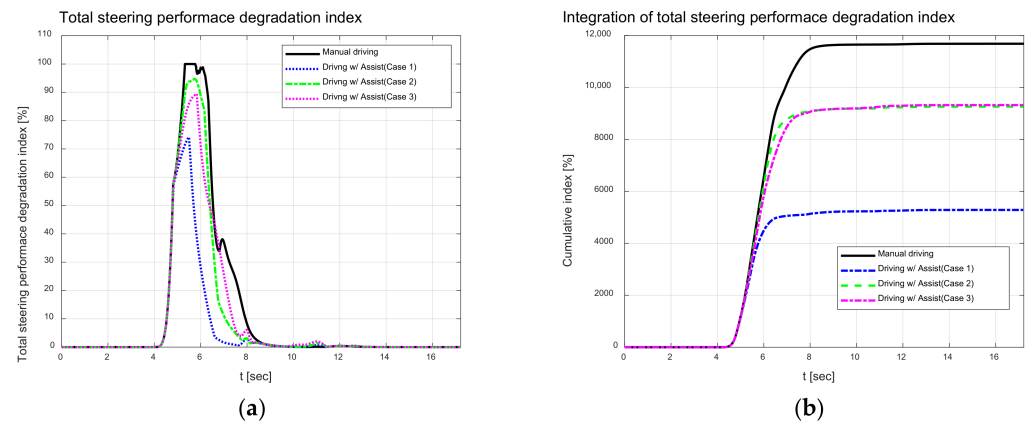


Figure 33. Comparison of steering performance degradation: (a) Integrated steering performance degradation index; (b) Integration of integrated steering performance degradation index.

When active rear-wheel steering (RWS) is applied, the tracking errors are successfully reduced across all cases compared to the unassisted driver:

- Driving w/ Assist (Case 1): The maximum lateral error is reduced to 0.49 m (an approximately 77.63% reduction), and the maximum yaw angle error is reduced to 3.13 deg (an approximately 51.47% reduction).
- Driving w/ Assist (Case 2): The maximum lateral error is limited to 1.19 m (an approximately 45.66% reduction), and the maximum yaw angle error is limited to 4.72 deg (an approximately 26.82% reduction).
- Driving w/ Assist (Case 3): The maximum lateral error is limited to 0.80 m (an approximately 63.47% reduction), and the maximum yaw angle error is limited to 3.80 deg (an approximately 41.09% reduction).
- Driving w/ Assist (Constant): The constant weight model achieves a maximum lateral error of 0.15 m (an approximately 93.15% reduction) and a maximum yaw angle error of 2.00 deg (an approximately 68.99% reduction).

Second, the dynamic correlation between steering inputs (Figure 30) and vehicle yaw rate responses (Figure 31) was evaluated. Under the unassisted Driver condition, the front road wheel angle and vehicle yaw rate responses are severely delayed. Because the driver model starts steering late, it must apply an abruptly large front road wheel angle to recover the trajectory, which causes a late but substantially large overshoot in the vehicle's yaw rate.

On the other hand, the proposed adaptive weighting configurations (Cases 1, 2, and 3) significantly reduce the driver's steering angle workload compared to the unassisted driver. More importantly, the driving w/ Assist (Constant) configuration achieves the highest path-tracking accuracy (0.15 m lateral error) because of its preemptive steering characteristics. Under the Constant configuration, even when the front road wheel angle remains completely unactuated due to the driver's delay, the rear road wheel angle actively steers first to guide the vehicle's heading. This early rear steering moment prevents the vehicle from drifting outward before the driver's delayed corrective action begins. However, it is crucial to note that this superior tracking accuracy under severe transient cornering is achieved through continuous, non-adaptive intervention. While the constant-weight model minimizes path deviations under these extreme high-speed conditions, its fixed control weight is anticipated to cause persistent, unadaptive overriding of the steering loop even during normal, perfect driving intervals, which conceptually compromises driver steering authority. The proposed adaptive weighting strategies (Cases 1, 2, and 3) resolve this trade-off by dynamically scaling the rear-wheel assist, sacrificing a small margin of absolute tracking accuracy to preserve driver control authority and minimize potential human-machine conflict during steady-state cruising.

Additionally, a clear physical trend was observed in the transition speed and peak magnitude of the vehicle yaw rate response (Figure 31a). The vehicle's yaw rate response transitioned and reacted quickest under w/ Assist (Constant), followed by Autonomous driving, Driving w/ Assist (Case 1), Driving w/ Assist (Case 3), Driving w/ Assist (Case 2), and finally the unassisted Driver. This sequence reveals correlation: a slower transition in the yaw rate response leads to a larger peak yaw rate magnitude during transient cornering, verifying that prompt active steering intervention is key to suppressing excessive cornering dynamics.

In Figure 33a, the integrated steering performance degradation index begins to increase from approximately the 4.0 s mark across all evaluated configurations.

- For the unassisted Driver, the index reaches 100% at 5.3 s, maintains a high value of above 90% until 6.3 s, and finally drops below 10% at 7.9 s as the vehicle stabilizes.
- For w/ Assist (Case 1), the index reaches a peak of 73.88% at 5.5 s and then decreases sharply, dropping below 10% at 6.4 s.
- For w/ Assist (Case 2), the index stays above 90% starting from 5.3 s, falls below 90% at 5.9 s, and reduces below 10% at 7.1 s.
- For w/ Assist (Case 3), the index reaches 85% at 5.5 s, reaches its peak of 89.29% at 5.8 s, and decreases gradually to drop below 10% at 7.4 s.

Rather than judging the superiority of each model solely by the magnitude or timing of these index values, the physical characteristics of the rear road wheel steering angle must be examined. Comparing the RWS inputs shows that Case 1 initiates RWS intervention the earliest, while Case 2 generates the largest and Case 3 generates the smoothest steering angle outputs among the adaptive models.

Finally, Figure 33b presents the cumulative risk load by integrating the steering performance degradation index over the entire path. This cumulative evaluation metric is computed by applying continuous-time numerical integration via a dedicated integrator block in MATLAB/Simulink. The unassisted Driver records the highest cumulative index of 11,684.30. The proposed adaptive weighting models successfully reduce this cumulative value to 5286.98 for Case 1 (the lowest total), 9264.89 for Case 2, and 9322.54 for Case 3, quantitatively demonstrating their effectiveness in mitigating overall driving risk.

3.3.3. Algorithm Performance Evaluation Under Low Speed and S-Curve Road with Time Delay (60 km/h, $R = 50$ m, 1 s Delay)

To rigorously evaluate the control effectiveness, handling limits, and stabilization performance of the proposed active rear-wheel assist framework under a sharper cornering geometry with severe driver delay, closed-loop simulation trials were conducted on a tight S-curve road with a radius of curvature of 50 m at a speed of 60 km/h.

The resulting vehicle states, actuator control inputs, and driving risk indices are comprehensively plotted in Figures 34–38. Specifically, Figure 34 illustrates the spatial path-following trajectories of the vehicle, comparing the overall global driving path with magnified views highlighting the entry and transient transition zones of the sharp curve. Figure 35 details the physical steering control inputs executed at the road wheel level, presenting the front road wheel angle and the active rear road wheel steering assist angle, respectively. The transient dynamic response of the vehicle chassis under high lateral acceleration is captured in Figure 36, which displays the yaw rate profile and the corresponding longitudinal and lateral velocity histories. Figure 37 depicts the spatial tracking accuracy at the vehicle's center of mass, showing the resulting lateral position error and yaw angle error under each control configuration. Finally, Figure 38 quantitatively evaluates the steering performance degradation, presenting both the continuous time-history of the integrated

steering performance degradation index and its cumulative time-integration over the entire maneuver to demonstrate the overall reduction in driving risk.

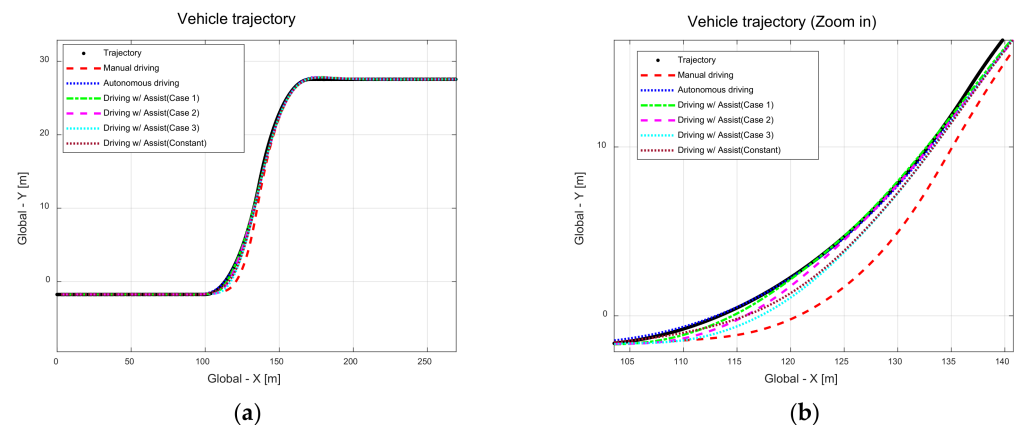


Figure 34. Vehicle trajectory: (a) Total; (b) Zoom in.

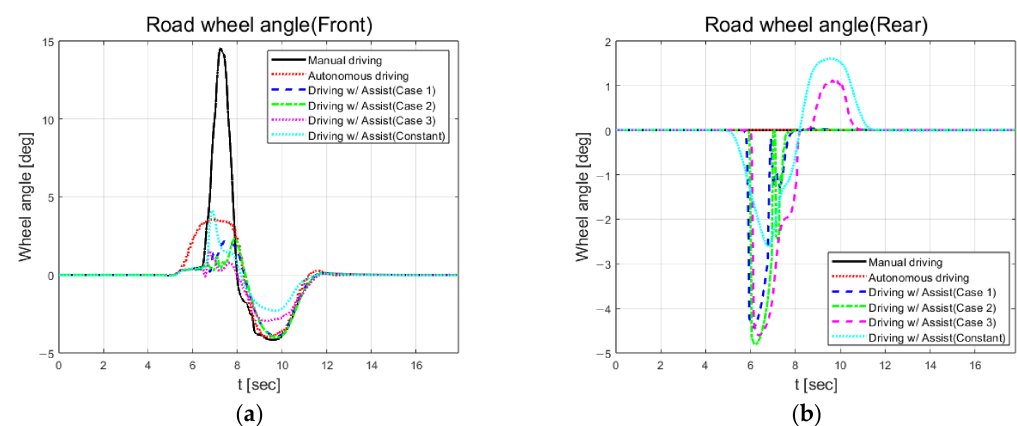


Figure 35. Wheel angle: (a) Road wheel angle (Front); (b) Road wheel angle (Rear).

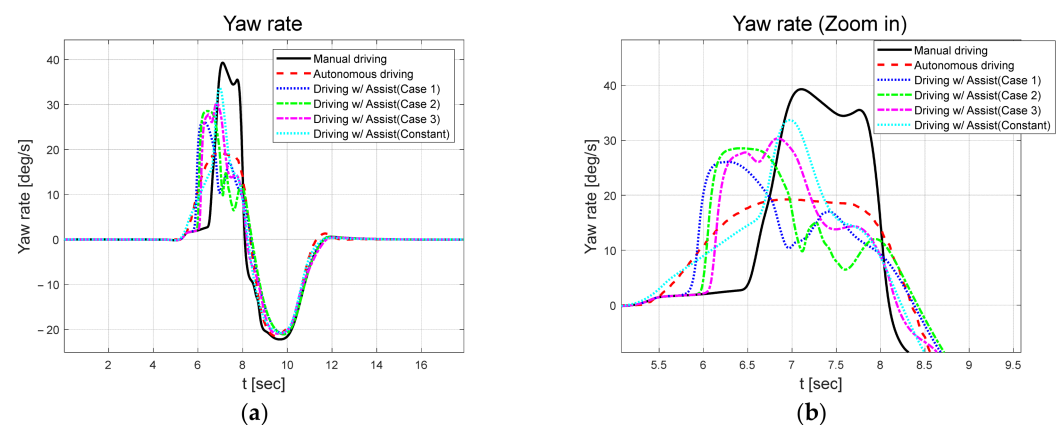


Figure 36. Vehicle yaw rate: (a) Total; (b) Zoom in.

First, the vehicle's tracking performance was evaluated using the trajectories in Figure 34 and the tracking errors in Figure 37. To ensure readability, all numerical values from the raw simulation data are rounded to two decimal places. Without steering assistance, the delayed human driver (Manual driving) exhibits considerable path deviation, resulting in a maximum lateral error of 2.59 m and a maximum yaw angle error of 10.63 deg. In contrast, the fully automated baseline (Autonomous driving) maintains most precise tracking, yielding a maximum lateral error of 0.39 m and a yaw angle error of 1.67 deg.

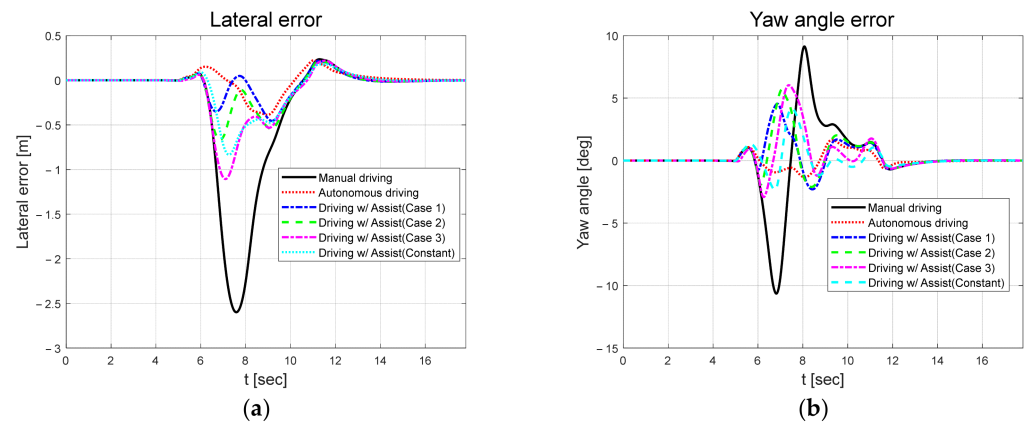


Figure 37. Path error (mass center): (a) Lateral error; (b) Yaw angle error.

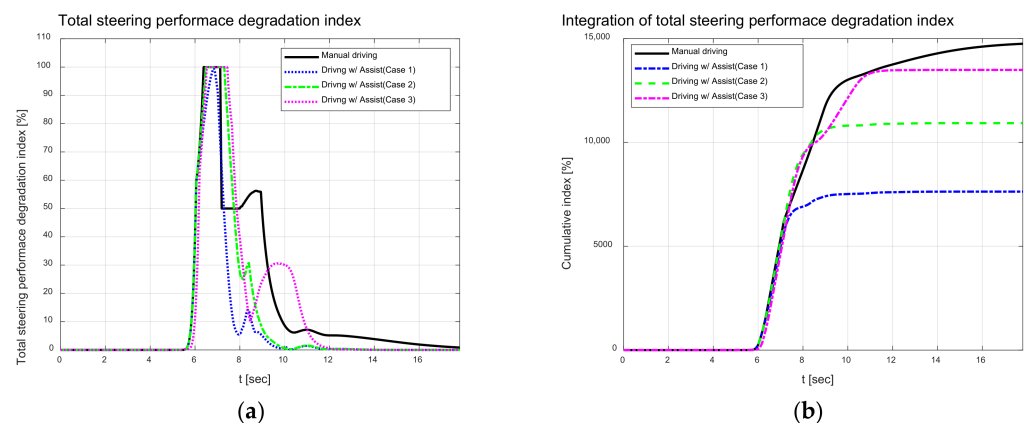


Figure 38. Comparison of steering performance degradation: (a) Integrated steering performance degradation index; (b) Integration of integrated steering performance degradation index.

When the active steering assist systems are applied, tracking errors are significantly reduced compared to the unassisted driver:

- Driving w/ Assist (Case 1): The maximum lateral error is reduced to 0.46 m (an approximately 82.24% reduction compared to the unassisted driver), and the maximum yaw angle error is limited to 4.55 deg (an approximately 57.20% reduction).
- Driving w/ Assist (Case 2): The maximum lateral error is limited to 0.67 m (an approximately 74.13% reduction), and the maximum yaw angle error is limited to 5.70 deg (an approximately 46.38% reduction).
- Driving w/ Assist (Case 3): The maximum lateral error is limited to 1.11 m (an approximately 57.14% reduction), and the maximum yaw angle error is limited to 6.03 deg (an approximately 43.27% reduction).
- Driving w/ Assist (Constant): The constant weight model achieves a maximum lateral error of 0.83 m (an approximately 67.95% reduction) and a maximum yaw angle error of 4.18 deg (an approximately 60.68% reduction).

Second, the correlation between the steering inputs (Figure 31) and the vehicle's yaw rate responses (Figure 32a) was analyzed. Under the unassisted Driver condition, the front road wheel angle reaches a substantial peak of 14.55 deg because the delayed steering initiation forces the driver to steer aggressively to recover the path. In contrast, under the proposed active rear steering configurations, the front road wheel angle is dramatically reduced to 2.13 deg for Case 1, 2.33 deg for Case 2, and 1.55 deg for Case 3. This quantitative reduction clearly demonstrates that the real-time rear road wheel steering (Figure 31b)

preemptively guides the vehicle, successfully unburdening the driver's steering effort during critical transient cornering.

Additionally, a clear physical relationship was observed in the timing and magnitude of the vehicle yaw rate response. The activation speed of the vehicle yaw rate was quickest under driving w/ Assist (Constant), followed by Autonomous driving, driving w/ Assist (Case 1), driving w/ Assist (Case 2), driving w/ Assist (Case 3), and finally the unassisted Driver. This sequence reveals that as the yaw rate response is delayed, the corresponding peak yaw rate magnitude during transient cornering becomes proportionally larger due to the delayed correction. This comparison highlights that although the constant-weight controller reacts quickest and achieves a smaller peak yaw angle error (4.18 deg) under this severe tight cornering geometry, it does so through aggressive, non-adaptive intervention. This persistent intervention is expected to override driver steering inputs even during straight cruising, conceptually causing control conflicts. The proposed adaptive strategies successfully re-solve this trade-off by dynamically scaling assistance in proportion to driver degradation, maintaining a balanced compromise between tracking precision and driver authority.

Finally, a distinct control interaction was observed at the inflection point of the S-curve as the vehicle transitions between curves. Around this inflection section, the active rear road wheel angle for Case 1 and Case 2 quickly approaches nearly 0 deg. However, for Case 3, the rear road wheel steering continues to actively assist the vehicle's yaw moment throughout the curve transition. Because the rear wheels maintain this continuous steering support, the required front road wheel steering angle for Case 3 remains relatively smaller compared to Case 1 and Case 2.

In Figure 38a, the integrated steering performance degradation index begins to increase from approximately the 5.5 s mark across all evaluated configurations. Every configuration eventually reaches the maximum saturation level of 100%. Specifically, the Driver, Case 1, and Case 2 configurations reach the 100% saturation limit at 6.1 s, while Case 3 reaches 100% at 6.2 s.

Thereafter, the index values begin to decrease from the 100% peak at different elapsed times, showing a downward trend starting at 8.9 s for the unassisted Driver, approximately 6.84 s for Case 1, 7.30 s for Case 2, and 7.44 s for Case 3.

Notably, Case 3 exhibits a unique transient trend around the 8.3 s mark, where the index first drops to 9.98%, suddenly rises back up to 30.56%, and then declines again. While Case 1 and Case 2 also experience secondary index rises, their peaks are restricted to values of 14.07% and 30.83%, respectively.

This prominent jump in Case 3's index is caused by the smooth control characteristics of its weighting model. In Case 3, the rear road wheel steering angle decreases in a highly stable and gradual manner compared to the other adaptive cases. Because of this steady rear-wheel support, the driver's front-wheel steering workload is successfully reduced, which decreases the driver's corrective steering input. However, because there is still a remaining steering deviation between the driver's reduced input and the ideal reference command from the monitoring MPC, this unresolved error temporarily drives the calculated index upward.

Finally, Figure 38b presents the cumulative risk load by integrating the steering performance degradation index over the entire evaluation path. Specifically, the cumulative steering performance degradation index is obtained via continuous-time numerical integration of the real-time index using the integrator block in MATLAB/Simulink. The unassisted Driver records the highest cumulative index of 14,752.6. The proposed adaptive weighting models successfully reduced this cumulative value to 7632.08 for Case 1 (the lowest total), 10,929.7 for Case 2, and 13,493.2 for Case 3.

This evaluation confirms the distinct control features of each adaptive weighting model:

- Case 1 initiates rear-wheel assist intervention the earliest, yielding the lowest cumulative index sum.
- Case 2 outputs the largest instantaneous rear road wheel steering angle during critical peak error states to provide sharp correction.
- Case 3 generates the smoothest rear road wheel steering curve. Although Case 3 reduces the index by a smaller margin compared to Case 1 and Case 2, it delivers the most stable and continuous assist behavior with the highest steering smoothness.

3.3.4. Control Complementarity and Stand-Alone Index Analysis

To systematically investigate the performance boundaries of the stand-alone indicators, a comparative evaluation was conducted by isolating the Driver Deviation Index and the Driver Response Delay Index under the three adaptive weighting mechanisms (Cases 1, 2, and 3). The resulting closed-loop vehicle trajectories, steering inputs, dynamic states, tracking errors, and index characteristics are comprehensively illustrated in Figures 39–43. Specifically, Figure 39 presents the vehicle's spatial trajectories, comparing the global path-following performance of the stand-alone deviation-based and stand-alone delay-based control configurations. Figure 40 details the corresponding front and rear road wheel angles under each stand-alone control configuration. Figure 41 displays the vehicle chassis' transient dynamic responses, capturing the yaw rate and longitudinal/lateral velocity histories. Figure 42 illustrates the path-tracking accuracy at the vehicle's center of mass, showing the resulting lateral position error and yaw angle error under each stand-alone configuration. Finally, Figure 43 showcases the time histories of the individual steering performance degradation indices.

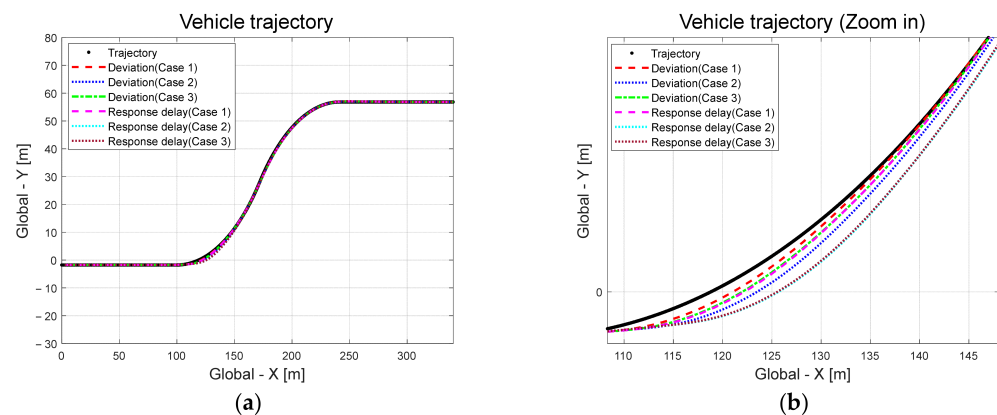


Figure 39. Vehicle trajectory: (a) Total; (b) Zoom in.

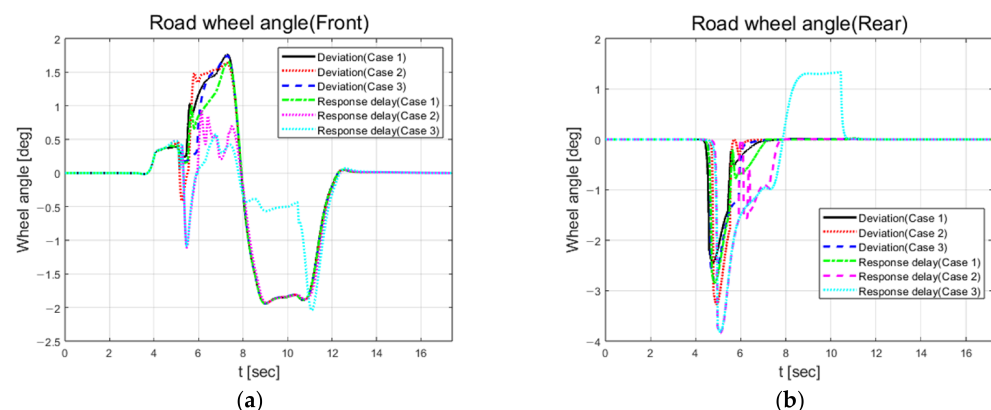


Figure 40. Wheel angle: (a) Road wheel angle (Front); (b) Road wheel angle (Rear).

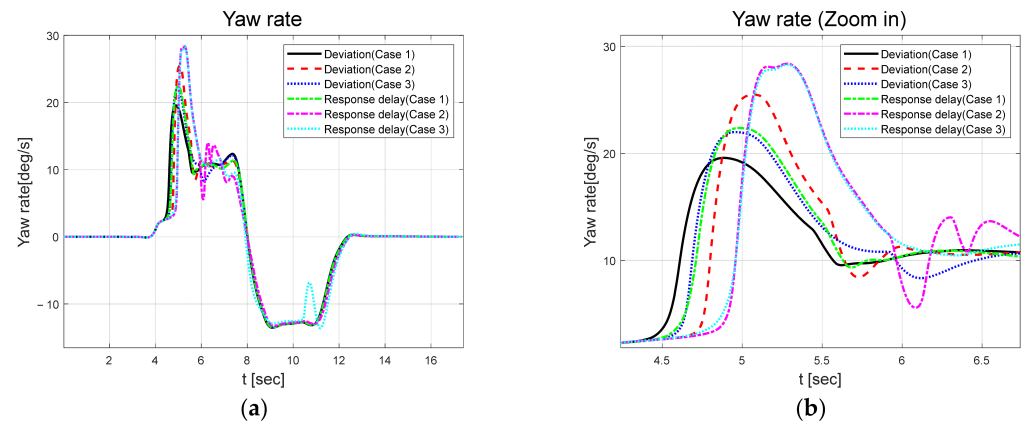


Figure 41. Vehicle dynamic states: (a) Yaw rate; (b) Longitudinal/lateral velocity.

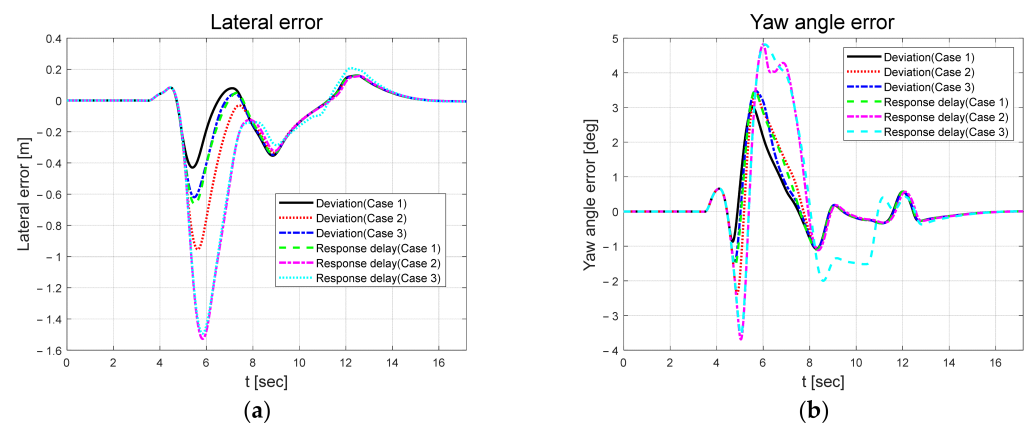


Figure 42. Path error (mass center): (a) Lateral error; (b) Yaw angle error.

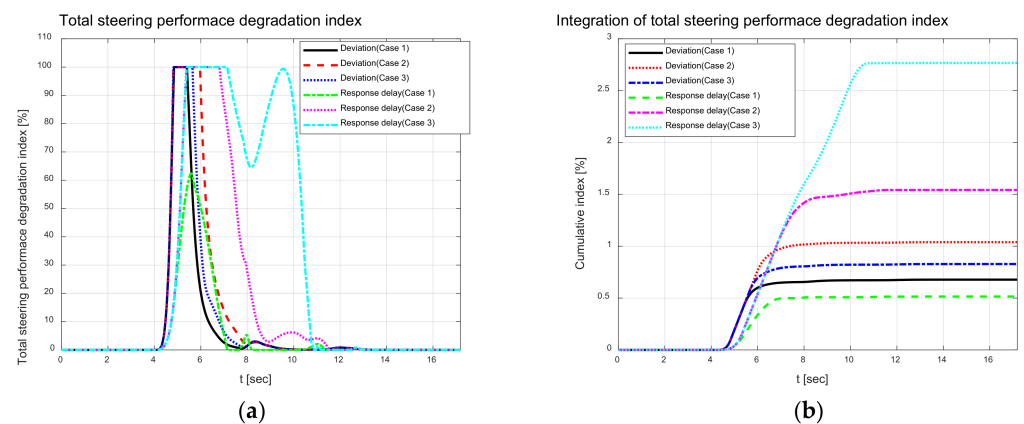


Figure 43. Comparison of steering performance degradation: (a) Integrated steering performance degradation index; (b) Integration of integrated steering performance degradation index.

To evaluate the individual control contribution of each monitoring index, simulation trials were conducted by applying the driver deviation index and the driver response delay index independently to the active rear steering assist controller. Figures 39–43 show the comparative results, where the first three configurations represent the deviation-based assist (Deviation Cases 1, 2, and 3) and the next three represent the response delay-based assist (Response Delay Cases 1, 2, and 3) under a constant 1.0 s driver delay.

First, the activation sensitivity and timing of the vehicle yaw rate response shown in Figure 41a exhibit distinct characteristics under each stand-alone index:

- Under the driver deviation index configurations, the vehicle yaw rate reacts and transitions quickest under Case 1, followed by Case 3, and then Case 2.
- Under the driver response delay index configurations, Case 1 demonstrates the fastest yaw rate response, while Case 2 and Case 3 exhibit highly similar reaction timing.

Second, this reaction timing directly translates to the path-tracking precision in Figure 42:

- Maximum Lateral Error: Under deviation-based assist, the maximum lateral errors are limited to 0.43 m for Case 1, 0.95 m for Case 2, and 0.62 m for Case 3. In contrast, the response delay-based assist yields larger deviations, measuring 0.66 m for Case 1, 1.53 m for Case 2, and 1.49 m for Case 3.
- Maximum Yaw Angle Error: The deviation configurations achieve tighter boundaries of 3.00 deg for Case 1, 3.47 deg for Case 2, and 3.49 deg for Case 3. The response delay configurations exhibit larger errors, measuring 3.48 deg for Case 1, 4.81 deg for Case 2, and 4.81 deg for Case 3.

The primary physical reason for this performance gap is the different response characteristics of the steering performance degradation indexes shown in Figure 43. The driver deviation index responds much faster to the curve entry than the driver response delay index. Because the driver deviation index is calculated directly from the spatial tracking error amplitude, it rises immediately as the vehicle approaches the curve. Conversely, the driver response delay index, which estimates the steering time constant via RLS, requires a finite convergence time to identify the steering delay. Due to this estimation delay, the response delay-based rear steering generates the yaw-assisting rotational force later, leading to a larger, delayed peak in the vehicle's yaw rate and consequently larger path-following errors.

Notably, in Response Delay Case 2 and Case 3, an unstable, large-amplitude swaying behavior is observed in the vehicle's motion after negotiating the first corner. Because the index output is delayed in Case 2 and Case 3, the assist system fails to intervene during the initial curve entry. Once the delayed index eventually rises, the assist controller abruptly applies an excessively large corrective rear steering angle to compensate for the massive, accumulated errors. This delayed, aggressive rear steering input conflicts with the driver's late steering input, causing a control overshoot that triggers continuous swaying in both the wheel angles and the vehicle dynamic states.

This comparative evaluation supports the necessity of fusing the two indexes into the total steering performance degradation index due to their clear theoretical complementarity:

- Theoretical advantage of the driver response delay index (Direct Assessment of Cognitive Impairment): While the driver deviation index only reacts after a spatial tracking error has physically occurred on the road, the driver response delay index directly quantifies the driver's internal cognitive and reaction time delay by estimating the steering lag. In the integrated system, this index allows the vehicle to explicitly identify whether a trajectory error is caused by a temporary, non-critical driver maneuver or a genuine cognitive impairment such as drowsiness or fatigue. By identifying the physical reaction delay, the assist controller can scale its control authority more appropriately.
- Theoretical advantage of the driver deviation index (Robustness to Zero-Steering-Rate States): The response delay estimation model relies heavily on the steering angular velocity. When the driver's steering rate approaches zero during steady cornering or straight cruising, the RLS estimation of the time delay constant can exhibit numerical chattering and fluctuations. In contrast, the driver deviation index is derived from the squared steering error using a constant regression variable. This formulation

establishes a continuous and highly stable index baseline that represents absolute steering accuracy regardless of steering speed, preventing sudden weight fluctuations and keeping the active rear steering smoothly bounded.

4. Conclusions

In this study, a driver monitoring and active rear-wheel assist steering control scheme integrating MPC and RLS is proposed to enhance the safety of autonomous mobility and facilitate stable auxiliary steering support during hazardous situations. The proposed algorithm derives reference front wheel angle inputs in real-time through a monitoring MPC based on a vehicle error dynamics model and quantifies spatial steering deviation and temporal response delay by comparing these with the actual inputs from the driver. Specifically, two RLS modules were designed to estimate the driver's steering capability from multiple perspectives, and an adaptive control strategy was established to dynamically vary the input weighting factors of the assist controller based on the derived total steering performance degradation index.

The MPC within the active rear-wheel assist control algorithm maintains the driver's front wheel angle input as an equality constraint while supplementing degraded steering performance with the rear wheels according to adaptive weights; this approach respects driver-led driving authority while improving path-following performance. Performance evaluation results on S-curved roads under various velocities and road curvatures using IPG CarMaker and MATLAB/Simulink demonstrated that for a driver experiencing cognitive response delay, the maximum lateral error and maximum yaw angle error were reduced by up to approximately 82.24% and 73.53%, respectively, compared to the unassisted baseline. Although the conventional constant-weight assist configuration can yield tighter path-tracking precision under specific dynamic conditions by continuously utilizing rear-wheel steering effort, its persistent, non-adaptive intervention is anticipated to impose an unnecessary adaptation burden on the human driver and increase control energy consumption. In contrast, the proposed adaptive control strategy dynamically scales the rear-wheel assistance in proportion to the estimated steering performance degradation, mitigating human-machine control interference and reducing energetic control effort while preserving the driver's steering authority during normal intervals.

Furthermore, the system exhibited differentiated control characteristics in terms of responsiveness, instantaneous correction power, and control stability depending on the adaptive weighting model used (Case 1, 2, or 3), verifying its potential as a promising candidate fail-safe steering strategy for advanced automated driving systems.

Although the optimal method for deriving the steering performance degradation index and the most suitable adaptive weighting model may vary depending on driving conditions and environments, a high-level decision logic for real-time mode selection is currently beyond the scope of this study. While this study analyzed the three weighting cases independently, future actual driving environments will require an integrated decision algorithm capable of dynamically switching to the most appropriate control strategy based on individual driver characteristics and the specific type of hazardous situation. In addition, to further enhance the robustness of the reference standard under varying road conditions, future research will investigate an adaptive input weighting design for monitoring MPC. While the current reference controller utilizes a low-complexity geometric bicycle model to minimize real-time computational load and avoid reliance on highly uncertain dynamic parameters (such as cornering stiffness under transient friction states), this kinematic simplification can introduce model mismatch under high-lateral acceleration scenarios. To compensate for these neglected dynamic effects including lateral tire force saturation and vehicle sideslip without increasing the online computational overhead, the adaptive

input weighting scheme will be developed to dynamically adjust the controller's input weights based on longitudinal velocity, and path curvature. This control strategy will allow the simplified geometric model to partially mitigate dynamic discrepancies and reliably derive an optimal and physically feasible reference wheel angle across diverse driving scenarios. While the reference steering input utilized in this study is determined through a systematic trial-and-error calibration process to serve as a reasonable control baseline, future research will focus on developing an adaptive reference-generation model capable of dynamically adjusting to both internal driver state transitions and external environmental changes to achieve highly adaptive driver monitoring. Furthermore, because securing high model reliability (low model uncertainty) is critical for facilitating stable and accurate auxiliary steering intervention, future research will also plan to derive the reference steering inputs utilizing highly reliable, high-fidelity vehicle dynamic models or adaptive and advanced control architectures. Future work will focus on developing a driving capability index that integrates human-vehicle harmony to minimize any sense of disparity experienced by drivers during rear-wheel control interventions. Additionally, future research will encompass experimental validation under diverse environmental and operational factors including variations in road friction, external wind gusts, and steering disturbances utilizing Hardware-in-the-Loop and Driver-in-the-Loop simulation setups to robustly evaluate the system's real-time feasibility and practical efficacy. Furthermore, this research will be extended to formulate intelligent auxiliary control strategies tailored to critical driving scenarios. By utilizing the quantified driving indices, the system will be designed to enhance safe and seamless shifts of control authority between the human and the controller, thereby establishing a fail-safe framework for advanced automated driving systems.

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Abbreviations

RLS	Recursive Least Squares
MPC	Model Predictive Control

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