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Motorcycle Adaptive Cruise Control Using Model Predictive Control with Integrated Sensor Fusion

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ABSTRACT

Motorcycle safety remains a critical challenge due to the inherent instability and complex dynamics of two-wheeled vehicles, particularly in longitudinal control and car-following scenarios. This study addresses this challenge by developing a Motorcycle Adaptive Cruise Control (MACC) system based on Model Predictive Control (MPC), specifically tailored to motorcycle dynamics. The research contribution is the integration of longitudinal and lateral MPC control with a sensor fusion framework to manage speed regulation, safe following distance, and path-following under motorcycle-specific constraints. The proposed system employs MPC to predict future vehicle states and compute optimal acceleration and steering commands while respecting safety, comfort, and stability constraints. Radar- and vision-based sensor fusion is used to estimate relative distance, relative velocity, and lane geometry, providing reliable perception inputs for the controller. A comprehensive MATLAB/Simulink simulation framework is developed to evaluate system performance under straight-road, curved-road, and mixed-traffic scenarios, including lane changes and vehicle cut-ins. Simulation results demonstrate accurate velocity tracking, consistent maintenance of safe inter-vehicle distances, and stable path-following performance, with lateral deviations remaining below 0.5 m on straight segments and 1.2 m on curved paths. Longitudinal acceleration remains within predefined comfort limits, indicating smooth control behavior. The integrated controller adapts effectively to dynamic traffic conditions while maintaining safety margins. The findings confirm the feasibility of MPC-based MACC for motorcycles under simulated conditions. However, the results are limited to simulation-based validation, and real-world deployment will require further investigation of computational feasibility, sensor uncertainties, and experimental testing. This work contributes toward the development of scalable and reliable adaptive cruise control systems for motorcycle autonomy.

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1. Introduction

Electric motorcycles (EMs) are transforming today's transport and revolutionizing modern mobility by offering an eco-friendly alternative to traditional internal combustion engine motorcycles. They rely on electric powertrains, battery systems, and advanced control electronics to achieve efficient, quiet, and emission-free transportation [1]. Their development aligns with the global push toward sustainability, particularly in urban environments where noise and air pollution are pressing concerns. Unlike conventional motorcycles, electric variants integrate components such as battery management systems, power electronics, and energy-efficient electric motors designed to meet a wide spectrum of commuter and performance demands [2], [3]. These developments not only allow the achievement of environmental objectives but also result in the incorporation of advanced technologies that improve safety and general riding comfort [4], [5].

At the core of these intelligent systems lies Adaptive Cruise Control (ACC), an advanced driver assistance system (ADAS) originally developed for automobiles and now adapted for motorcycles [6], [7]. ACC automates the process of maintaining a safe following distance and consistent speed by sensing the environment and dynamically adjusting throttle and braking inputs [8], [9]. Employing radar, lidar, cameras, and ultrasonic sensors, ACC systems monitor the position and behavior of surrounding vehicles to make real-time control decisions [10], [11]. Radar systems, in particular, are highly valued for their robustness under varying weather and lighting conditions [12], [13]. Lidar sensors enhance spatial awareness by providing high-resolution three-dimensional environmental maps [14], while camera systems provide valuable visual data for lane detection, obstacle recognition, and traffic sign interpretation [15]. Ultrasonic sensors, although limited in range, are especially useful in low-speed urban scenarios, such as parking and close-quarter maneuvering [16], [17]. The synergy of these sensors, often through sensor fusion, creates a comprehensive perception framework essential for accurate and safe cruise control [18], [19].

The integration of these sensors into motorcycle specific ACC systems, which is known as Motorcycle Adaptive Cruise Control (MACC), presents a unique set of challenges due to the dynamic and unstable nature of two-wheeled vehicles [20], [21]. Unlike automobiles, motorcycles exhibit nonlinear behaviors including lean angles, variable rider posture, and higher sensitivity to external and environmental disturbances [22], [23]. Therefore, the development of reliable and effective MACC systems necessitates advanced control strategies capable of accounting for these complexities [24], [25]. Existing ACC and MACC studies have mainly adapted car-oriented control strategies and perception architectures to motorcycles, often with important limitations. Many works rely on PID-like longitudinal controllers and simplified linear models [26], [27]. which struggle to capture lean-angle-dependent stability and fast transients in motorcycle dynamics. Other approaches employ single-sensor configurations, typically radar-only, that are vulnerable to occlusions, false detections in curves, and limited lane-awareness [12], [21]. Several MACC prototypes are validated only in simplified conditions, such as constant-speed following or low-curvature roads [6], [9], leaving performance under realistic rider-induced disturbances and nonlinear responses insufficiently explored. These shortcomings motivate the need for a motorcycle-specific MACC framework that explicitly handles nonlinear dynamics and perception uncertainty rather than only extending existing automotive ACC strategies.

Historically, classical control approaches, particularly Proportional-Integral-Derivative (PID) controllers, have long been employed in cruise control systems due to their simplicity and effectiveness. PID controllers adjust vehicle speed by calculating the error between the desired and actual states and applying corrective measures. In motorcycles, PID controllers are often tuned to manage throttle and braking responses while preserving balance and rider comfort [26]. Despite their widespread use, PID systems may struggle in highly dynamic environments or when confronted with nonlinear vehicle responses [27].

To address these limitations, researchers have increasingly turned to Model Predictive Control (MPC), which leverages a model of the vehicle's future behavior to optimize control actions over a finite time horizon [28], [29]. MPC anticipates changes in the environment, such as traffic fluctuations or road curvature, and computes control inputs that minimize deviations from the desired trajectory [30], [31]. Its predictive capabilities make MPC well-suited for motorcycle applications, where rapid adjustments are necessary to maintain safety and stability [32].

However, applying MPC in MACC is not straightforward. Real-time implementation must consider limited on-board computation, short sampling times imposed by fast motorcycle dynamics, and uncertainties in the underlying vehicle model [24], [25]. At the same time, the perception system must cope with sensor latency and noise to provide reliable state estimates to the controller [13], [19]. This creates a coupled challenge: without robust perception, MPC may optimize on inaccurate information, whereas without predictive and constraint-handling control, the system may fail to exploit the full potential of sensor fusion in demanding maneuvers such as cut-ins, tight curves, and rapid speed changes [33], [34]. Therefore, an integrated design that jointly considers motorcycle dynamics, computational constraints, and multi-sensor perception is essential for achieving reliable MACC performance.

Intelligent control systems, including Fuzzy Logic Controllers (FLCs) and Reinforcement Learning (RL) algorithms, further advance the capabilities of MACC. Fuzzy logic introduces human-like reasoning to control systems, enabling accurate decisions under uncertainty. This is particularly beneficial in motorcycle applications, where precise numerical models may not fully capture real-world riding conditions [35], [36]. Fuzzy controllers interpret ambiguous or imprecise inputs, such as varying rider behavior or uneven road surfaces, and deliver smooth, adaptive control outputs [33], [37]. Reinforcement learning, on the other hand, allows systems to learn optimal control policies by interacting with the environment. Through continuous feedback, RL-based controllers can adapt and improve over time, even in unstructured or rapidly changing scenarios [38], [39]. These intelligent systems are pivotal in pushing MACC toward true autonomy.

Machine learning, especially deep learning, has also played a transformative role in modern ACC systems. Neural networks trained on large datasets can recognize complex patterns in sensor inputs and infer appropriate control outputs [13], [40]. In the context of ADAS, machine learning algorithms enhance functionalities such as object recognition, pedestrian detection, and traffic prediction [41], [42]. For motorcycles, the use of deep learning opens new possibilities for rider-assist features that account for context-aware decision-making and adaptive responses in congested or unpredictable environments [43], [34].

Another emerging advancement is Cooperative Adaptive Cruise Control (CACC), which expands traditional ACC by enabling communication between vehicles through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) technologies [44]. CACC allows groups of vehicles to coordinate their speed, acceleration, and braking patterns, promoting smoother traffic flow and reducing congestion [45]. Although still in early development stages for motorcycles, CACC shows promise in enhancing road safety and operational efficiency in urban mobility systems [46]. Cooperative frameworks could eventually support motorcycle platooning, improved intersection management, and shared data on road conditions [47], [48].

Robust control strategies remain an essential element in ensuring system reliability across a wide range of operating conditions [49]. These approaches are designed to tolerate model inaccuracies, external disturbances, and sensor noise [50]. For MACC, robust control ensures that safety margins are maintained even when the vehicle encounters slippery surfaces, sudden obstacles, or rapid changes in rider input [51]. Studies have shown that incorporating robust design principles leads to systems that are not only safer but also more adaptable to real-world conditions [52], [53].

Sensor fusion techniques are integral to the reliability and accuracy of MACC systems. By combining data from multiple sensors, such as radar, lidar, cameras, and ultrasonic devices, integrated with fusion algorithms, reduces uncertainty and produces a cohesive understanding of the vehicle's surroundings [54], [55]. This integrated perception system improves decision-making accuracy and supports features like autonomous emergency braking, lane-keeping assistance, and blind-spot monitoring [56]. As sensor technologies continue to evolve, so too will the fidelity and responsiveness of MACC and related ADAS functions.

Developing effective MACC systems involves more than just applying automotive technologies to motorcycles. It requires a deep understanding of motorcycle dynamics, rider behavior, and human-machine interaction [57], [58]. Adaptive control methods tailored for motorcycle-specific conditions must be sensitive to factors such as lean angle, road camber, and rider intent [59], [60]. Personalized ADAS features such as intelligent headlight orientation, posture-based braking assist, and rider monitoring are crucial to ensuring not just functionality, but also rider trust and comfort [61]. These innovations contribute to safer, more intuitive, and context-aware systems that better support the unique demands of motorcyclists. In this context, there is still a clear gap between current MACC implementations and the requirements of real-world motorcycle operation. Existing systems only partially address the combined effects of nonlinear dynamics, perception uncertainty, and real-time hardware limitations, especially when operating in complex traffic and curved-road scenarios [23], [62]. Consequently, there is a need for an integrated MACC architecture that couples a predictive, constraint-aware controller with a robust multi-sensor perception layer specifically tailored to motorcycles. Therefore, this study develops and evaluates a Motorcycle Adaptive Cruise Control system based on Model Predictive Control and integrated radar-vision sensor fusion, implemented and tested in realistic simulation scenarios. The research contribution is the formulation and assessment of an MPC-based MACC framework that (i) explicitly considers motorcycle-specific dynamic characteristics, (ii) leverages fused radar-camera perception to improve object detection and spacing control, and (iii) analyzes performance across representative highway and mixed-traffic conditions to evaluate real-time applicability on electric motorcycles. Such a unified approach has not been sufficiently addressed in prior motorcycle automation research.

2. MACC System Development Framework

MACC system design includes a design process with software and control algorithms cooperating to enable intelligent decision-making. System architecture is applied through front radar sensors, multi-purpose cameras, and ultrasonic sensors to monitor the surroundings of the motorcycle and execute optimal control actions. The Model Predictive Control (MPC) algorithm is the central tool in this framework, dynamically adjusting speed and spacing according to real-time environmental parameters and conditions, ensuring a safe and efficient operation.

The overall research procedure is summarised in the MACC system development flow shown in Fig. 1. Vehicle and environmental data are first collected from GPS, multi-purpose camera, ultrasonic sensors, and radar. These signals are then passed to the planning, decision, and control unit, which selects the current driving condition (ramp, curve, or straight segment) and the appropriate control mode (distance control or speed control). Finally, the actuator control layer applies the computed brake and drive commands using the brake system model and engine/drive model. In this framework, vehicle and environmental information is sequentially sensed, processed by the control unit, and executed through the actuator layer to realise the MACC functionality.

2.1. System Architecture and Components

The MACC system is an intelligent framework composed of three integrated components: sensors, a control unit, and actuators, which work together to enhance rider safety and stability. Overall architecture of the system is represented in Fig. 1. Sensors like radar, lidar, and cameras serve as the system's perceptual layer, which continuously monitors the riding environment. They capture critical data on relative speed, distance to nearby vehicles, and lane geometry, providing the foundational input for decision-making. This sensory layer enables the system to perceive and interpret dynamic traffic conditions in real time.

Functioning as the system's computational core, the control unit processes sensor data in real time using sophisticated algorithms. It evaluates parameters such as acceleration, motorcycle dynamics, and the relative position of surrounding vehicles to compute precise throttle and braking adjustments.

This intelligent processing ensures optimal actions, whether maintaining a driver-set speed or adjusting to maintain a safe following distance.

Actuators form the system execution mechanism, translating control-unit commands into physical actions. During braking interventions or speed adjustments, the actuators interface directly with the motorcycle's throttle and braking systems. This closed-loop interaction between sensing, control, and actuation ensures stable and responsive system behaviour while maintaining rider comfort and safety. For system simulation, a MATLAB Simulink model was developed with dynamic interactions between the MACC system and outside parameters such as traffic and road conditions. The model constantly optimizes ACC performance in diverse conditions, checking its responsiveness and adaptability.

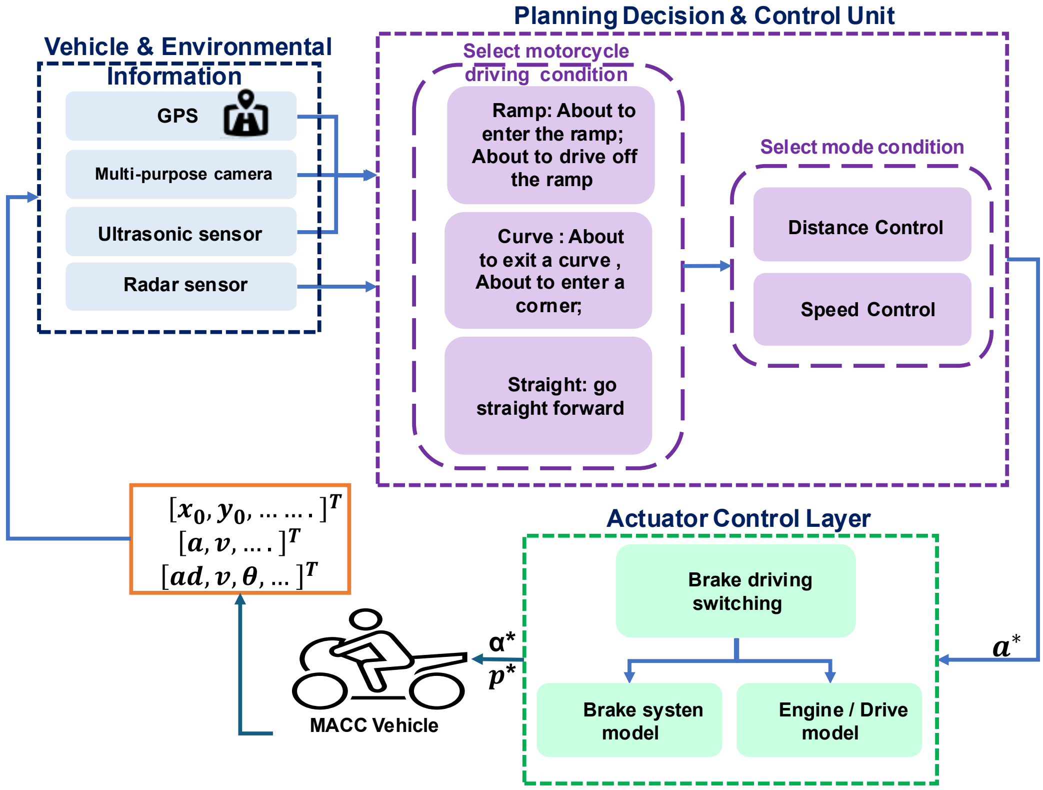

Fig. 1. System architecture and components block diagram

2.2. ACC System Control Architecture with Adaptability to Multiple Working Conditions

Adaptive Cruise Control (ACC), as an active safety system, is able to autonomously adjust the brake and acceleration of a vehicle. The system is activated using a button on the steering wheel and can be deactivated by braking input from the driver or another specific button. The primary role of the ACC system is continuous monitoring of surrounding vehicles and road objects to ensure safe and comfortable driving.

Driver-customisable settings, such as following distance, speed mode (e.g., economy or comfort mode), and integration with road-related information, including speed limits, curvature, and accident zones, are employed to dynamically determine vehicle speed. A comprehensive simulation of the ACC system is implemented in the MATLAB Simulink platform, incorporating detailed dynamic couplings within and outside the system. The simulation framework allows systematic evaluation of ACC performance under varying traffic and road conditions.

2.3. Model Predictive Control Method (MPC) For Enhancing Vehicle Safety

The motorcycle-based ACC system enhances riding safety and comfort by automatically adjusting speed and maintaining a safe distance from the preceding vehicle. A radar sensor measures the relative distance D_{rel} and relative velocity V_{rel} to the lead vehicle. Based on real-time data, the control logic switches between two operating modes, as illustrated in Fig. 2.

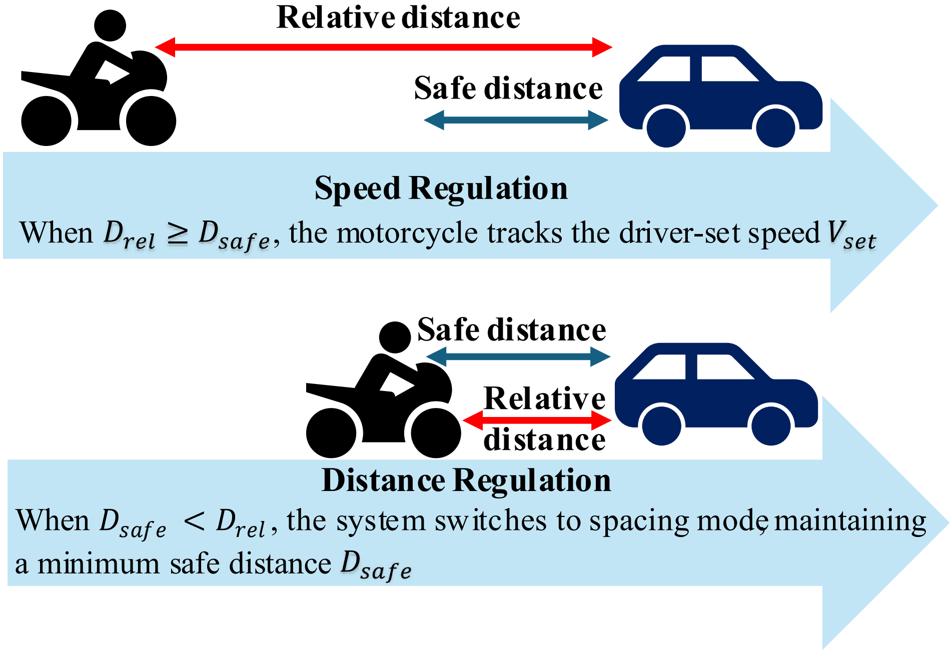

Fig. 2. Modes for adaptive cruise control

In speed regulation mode, the motorcycle travels at a speed set by the driver, denoted as V_{set}. The ACC system aims to maintain this driver-set velocity unless safety constraints necessitate a switch to another mode. When the relative distance D_{rel} is greater than or equal to the safe distance D_{safe}, the motorcycle tracks and maintains the velocity V_{set}. In distance control mode, when the motorcycle approaches the lead vehicle too closely, the ACC system shifts to spacing control mode. The primary objective here is to maintain a safe following distance D_{safe} from the lead vehicle, ensuring collision avoidance and comfortable spacing. If the measured distance D_{rel} becomes less than D_{safe}, the system transitions into this spacing mode.

For the mode-switching logic, the ACC system continuously evaluates the appropriate operating mode using real-time inputs from the radar sensor. The decision-making process follows clear rules to ensure safety and performance. If the relative distance $D_{rel} \geq D_{safe}$, the system activates speed control mode, prioritizing the maintenance of V_{set}. On the other hand, if $D_{safe} < D_{rel}$ the spacing control mode becomes active to maintain a safe buffer from the lead vehicle. These rules allow the ACC system to dynamically adapt based on the driving environment. The system switches seamlessly between the two control modes according to the movement of the lead vehicle and radar feedback. This real-time mode switching is required to ensure both a constant cruising speed and a safe following distance, especially under varying traffic conditions.

2.4. Simulation Setup

A Simulink model simulates the lead vehicle and motorcycle dynamics. The lead car's acceleration follows a sine wave to emulate realistic driving fluctuations. The ACC System block generates acceleration commands for the motorcycle in response.

The sample time T_s is set to 0.1 seconds, and the simulation runs for a total duration of 80 seconds. This value provides a compromise between capturing the dominant longitudinal dynamics (time constant 0.5 s in (1)) and keeping the computation feasible for real-time implementation, with several control updates occurring within each dynamic time constant. The initial conditions are as follows: the lead vehicle is positioned at 50 meters with a velocity of 25 m/s, while the motorcycle starts at 10 meters with a velocity of 20 m/s. These conditions represent a realistic highway-following scenario requiring speed adaptation and distance regulation. The relationship between acceleration and velocity is modeled using the transfer function in (1):

$$G = \frac{1}{s(0.5s + 1)} \tag{1}$$

This first-order-plus-integrator model is a standard approximation for longitudinal vehicle dynamics and captures the main behaviour of throttle/brake action on the velocity while avoiding unnecessary model complexity. The ACC system is implemented using the Adaptive Cruise Control System block in Simulink. It receives the driver-set velocity V_{set}, the desired time gap T_{gap}, the current motorcycle velocity $V_{motorcycle}$, and radar-measured inputs including the relative distance D_{rel} and the relative velocity V_{rel}. The output of the block is the desired acceleration for the motorcycle. The safe distance D_{safe} is dynamically calculated based on the ego motorcycle's velocity using (2):

$$D_{safe} = D_{default} + T_{gap} \times V_{ego} \tag{2}$$

Here, $D_{default}$ is the default standstill spacing, and T_{gap} is the desired time gap. For the simulation, T_{gap} is set to 1.4 seconds and $D_{default}$ is 10 meters. These values are consistent with typical time-headway and standstill distances used in production ACC systems and provide a balance between safety and traffic efficiency. The driver-set speed V_{set} is specified as 30 m/s. In order to enforce physical vehicle limits, the acceleration of the motorcycle is restricted between –3 m/s² and 2 m/s². Deceleration stronger than –3 m/s² and acceleration above 2 m/s² are generally perceived as uncomfortable for riders in normal driving; therefore, these bounds approximate practical comfort and safety limits. These limits are for physical realism and the safety of the motorcycle response. The Adaptive Cruise Control System block in Simulink is also to the same effect; to ensure a common reference, the same parameters should be used for the simulations; if not, the block configurations should be updated.

3. Implementing Path-Following Control with Model Predictive Control

The Path-Following Control (PFC) system utilizes an adaptive Model Predictive Control (MPC) strategy to determine optimal control actions. It dynamically adjusts both the longitudinal acceleration and front steering angle of the motorcycle to maintain adherence to the desired path while satisfying a set of predefined constraints. These constraints include safe following distance, velocity limits, and permissible ranges for acceleration and steering angles. Fig. 3 shows the high-level PFC block, where set velocity, longitudinal velocity, curvature, lateral deviation, and relative yaw angle enter as inputs, and the MPC outputs the commanded longitudinal acceleration and steering angle.

As illustrated in Fig. 3, the PFC block integrates the functionalities of the Lane Keeping Assist System (LKAS) and Adaptive Cruise Control (ACC) system into a unified controller. This integrated structure enables the controller to manage complex driving scenarios by leveraging the strengths of both lateral and longitudinal control components. This integrated system enhances driving safety and rider comfort by simultaneously managing lane-centering through LKAS and dynamic speed regulation via ACC. While LKAS ensures the motorcycle remains centered within the lane, including straight paths and curves, ACC dynamically adapts the vehicle's speed to maintain a safe distance from a lead vehicle under varying traffic conditions.

3.1. Mathematical Modelling of Path-Following Dynamics

In this path-following control approach, we integrate two state-space models: one for lane-keeping control and another for adaptive cruise control (ACC). By integrating these models, we have an integrated control strategy that addresses both the longitudinal and lateral dynamics of the vehicle. The longitudinal dynamics in (3) illustrate how the ACC Model regulates the longitudinal motion of the motorcycle. Its input is longitudinal acceleration in (m/s²), and its output is longitudinal velocity in (m/s). A time constant (τ) is used in the model to represent the delay in acceleration response:

$$A_{ACC} = \begin{bmatrix} -\frac{1}{\tau} & 1 \\ 0 & 0 \end{bmatrix}, \quad B_{ACC} = \begin{bmatrix} \frac{1}{\tau} \\ 0 \end{bmatrix}, \quad C_{ACC} = \begin{bmatrix} 0 & 1 \end{bmatrix}, \quad D_{ACC} = 0 \tag{3}$$

For the lateral dynamics, the lane-keeping model handles lateral velocity and yaw dynamics. The input is the steering angle in (radians), and the outputs are lateral velocity (m/s) and yaw rate (rad/s). The state-space representation is given in (4):

$$A_{Line} = \begin{bmatrix} \frac{-2(C_F + C_R)}{mV_x} & \frac{-2(C_F L_F - C_R L_R)}{I_Z V_x - V_x} \\ \frac{-2(C_F L_F - C_R L_R)}{mV_x} & \frac{-2\left(C_F {L_F}^2 - C_R {L_R}^2\right)}{I_Z V_x} \end{bmatrix}, \quad B_{Line} = 2C_F \begin{bmatrix} \frac{1}{m} \\ \frac{L_F}{I_Z} \end{bmatrix} \tag{4}$$

$$C_{Line} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad D_{Line} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

In the motorcycle dynamics model V_x represents the longitudinal velocity of the motorcycle. This velocity begins at an initial condition and is updated in real-time according to the longitudinal velocity input signal during the simulation. The total mass of the vehicle is denoted by m, and I_z symbolizes the yaw moment of inertia, which plays a critical role in the vehicle's rotational dynamics. The parameters L_F and L_R represent the longitudinal distances from the center of gravity to the front and rear tires, respectively, with L_F corresponding to the front tires and L_R to the rear tires. The cornering stiffness of the front tires is denoted by C_F, while C_R represents the cornering stiffness of the rear tires. These stiffness parameters are essential in defining the lateral forces generated by the tires during cornering maneuvers, significantly influencing the vehicle's handling characteristics.

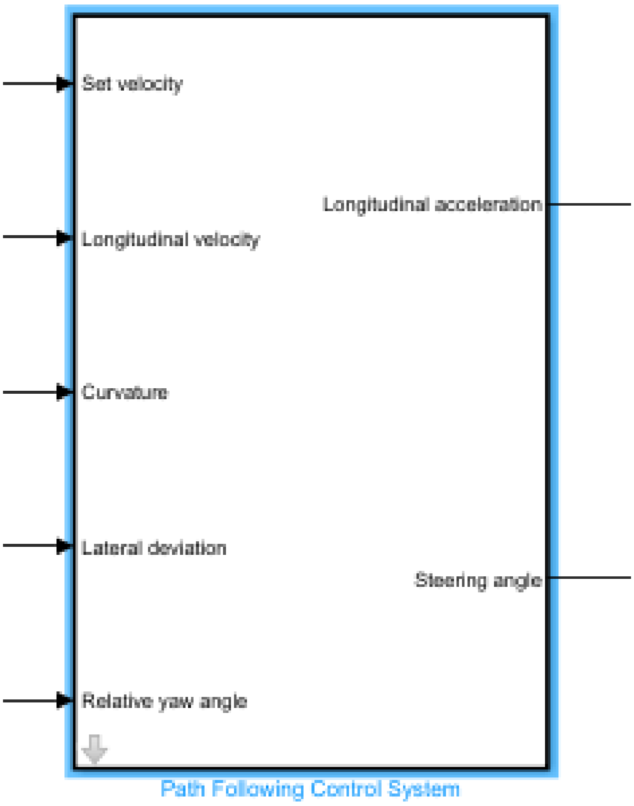

Fig. 3. Path-following control simulink block diagram

We merge both models to create a comprehensive path-following predictive model. The full state-space model is formed by combining the two subsystems as shown in (5):

$$A = \begin{bmatrix} A_{ACC} & 0 \\ 0 & A_L \end{bmatrix}, \quad B = \begin{bmatrix} B_{ACC} & 0 \\ 0 & B_L \end{bmatrix}, \quad C = \begin{bmatrix} C_{ACC} & 0 \\ 0 & C_L \end{bmatrix}, \\ D = \begin{bmatrix} D_{ACC} & 0 \\ 0 & D_L \end{bmatrix} \tag{5}$$

This integration supports a predictive control scheme capable of managing both lateral and longitudinal movements concurrently.

3.2. MPC Cost Function and Constraints

The MPC controller is formulated to minimise a quadratic cost function over a prediction horizon N_p as shown in (6):

$$J = \sum_{k=0}^{N_p} (\| e_v(k) \|_{Q_v}^2 + \| e_d(k) \|_{Q_d}^2 + \| \Delta\delta(k) \|_{R_\delta}^2 + \| \Delta a(k) \|_{R_a}^2) \tag{6}$$

where e_v is the longitudinal velocity tracking error, e_d is the spacing or path-deviation error, $\Delta\delta$ is the change in steering angle, and Δa is the change in longitudinal acceleration. The weighting matrices Q_v and Q_d prioritise accurate speed and path tracking, while R_δ and R_a penalise aggressive steering and acceleration changes. Since Δa is proportional to jerk, the last term explicitly reduces high-frequency throttle and brake actions, improving rider comfort. The optimisation is subject to actuator and comfort constraints, as well as a lateral-acceleration constraint to avoid exceeding the stable lean-angle range of the motorcycle, as shown in (7):

$$a_{\min} \le a(k) \le a_{\max}, | \Delta a(k) | \le \Delta a_{\max}, | \delta(k) | \le \delta_{\max}, \\ a_y(k) = \frac{V_x(k)^2}{R(k)} \le a_{y,\max} = g\tan(\varphi_{\max}), \tag{7}$$

where V_x is the longitudinal speed, $R(k)$ is the instantaneous curvature radius, $g$is gravitational acceleration, and $\varphi_{\max}$is the maximum allowable lean angle. By enforcing this bound, the controller prevents path-following commands that would require excessive lean and hence risk loss of stability during cornering. The prediction model used in the MPC corresponds to the combined longitudinal and lateral state-space model defined in (3)-(5).

3.3. Simulation and Validation

The simulation framework begins with the integration of the path-following control system into a comprehensive motorcycle dynamics model, as illustrated in Fig. 4. This model incorporates both longitudinal and lateral control aspects while accounting for the complex interactions between vehicle kinematics and environmental factors to ensure realistic simulation results. Fig. 4 provides the detailed Simulink implementation, in which the MPC-based controller drives the motorcycle model and receives feedback on pose, wheel forces, and yaw rate. It shows how the MPC-based controller, the powertrain and driveline, and the 3-DOF motorcycle body model are interconnected: the controller outputs steering angle and longitudinal acceleration, the motorcycle model returns pose and velocities, and these states are fed back into the controller and used to compute performance indicators such as path deviation and inter-vehicle distance.

The developed Simulink model, as shown in Fig. 5, enables extensive testing of the control strategy's effectiveness and robustness across various driving scenarios. These simulations evaluate system performance under a range of conditions, including straight segments of highway, curved roads, varying densities of traffic, and different road geometries. Key performance parameters are continually monitored during simulations, with particular focus on the accuracy of trajectory tracking, path deviation, time response to dynamic environment changes, and adherence to safety constraints like maintaining appropriate following distances. Fig. 5 illustrates this setup: the lead-car block generates position and velocity, the yellow ACC subsystem computes the desired longitudinal acceleration based on V_{set}, T_{gap}, D_{rel}, and V_{rel}, and the motorcycle block applies this acceleration to update its position and speed.

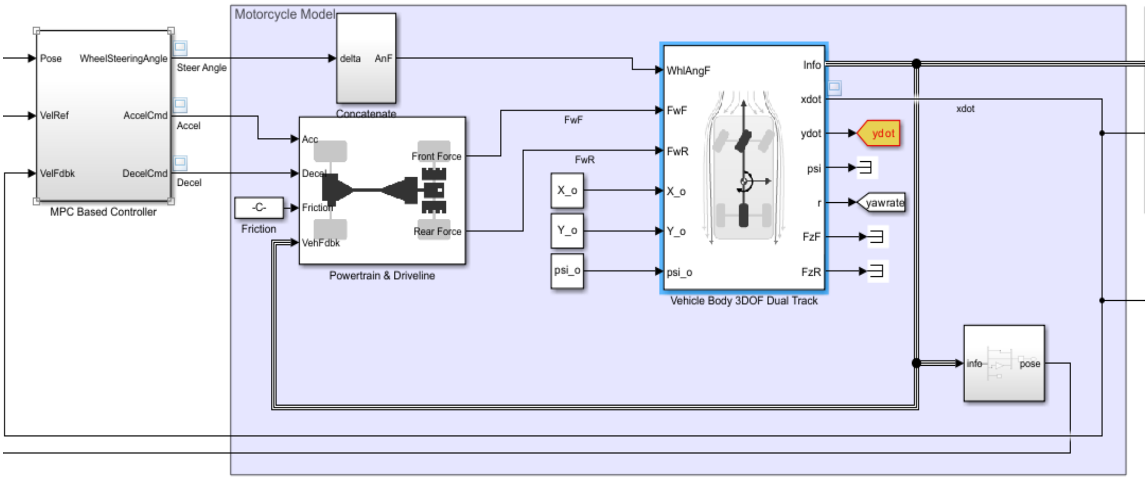

Fig. 4. Simulink diagram for path-following control with MPC

Validation procedures involve comparing simulation results with empirical data collected from real-world driving scenarios. This comparison verifies the simulation framework's accuracy in replicating actual driving conditions and assesses the control strategy's effectiveness. Additional sensitivity analyses examine system robustness by introducing perturbations to critical parameters, including vehicle dynamics, sensor noise characteristics, and environmental variables. These tests evaluate the system's resilience and adaptability under various operational conditions. Following successful validation, the path-following control system becomes a candidate for further refinement and potential real-world implementation. Future development efforts may focus on enhancing system capabilities through improved control algorithms and integration of additional sensor modalities to expand operational applicability across broader driving scenarios.

The Motorcycle Adaptive Cruise Control (MACC) system simulation employs a virtual model incorporating Model Predictive Control (MPC) functionality, as depicted in Fig. 5. This model accurately represents the MACC system by capturing the essential dynamic relationships and interactions. The Simulink implementation includes multiple cooperating components and subsystems that collectively realize the complete MACC functionality. The simulation framework also provides fundamental equations governing system behavior, establishing a theoretical basis for understanding system dynamics. Detailed parameter specifications for the MPC-controlled MACC system are included to precisely define its operational characteristics.

3.4. Sensor Fusion Integrated With Model Predictive Control

The integrated system architecture is presented in Fig. 6, showing the complete integration of all components. The system enhances driving safety and comfort through dynamic speed adjustment in response to road conditions and surrounding vehicle behavior. Unlike conventional cruise control systems that maintain fixed speeds, the Adaptive Cruise Control (ACC) system can automatically decelerate when detecting slower-moving preceding vehicles, thereby maintaining safe following distances. Critical to ACC operation is the accurate determination of lane curvature and the identification of the immediate preceding vehicle. The implemented solution combines two key subsystems: a sensor fusion system and an adaptive cruise control system.

Sensor data from radar and vision systems are combined to generate a reliable representation of the surrounding environment. In the INPUT stage, raw detections are collected. In the TUNNING stage, sensor measurements are fused using a state estimator. In the OUTPUT stage, the fused object states are provided to the MPC-based ACC and path-following controllers.

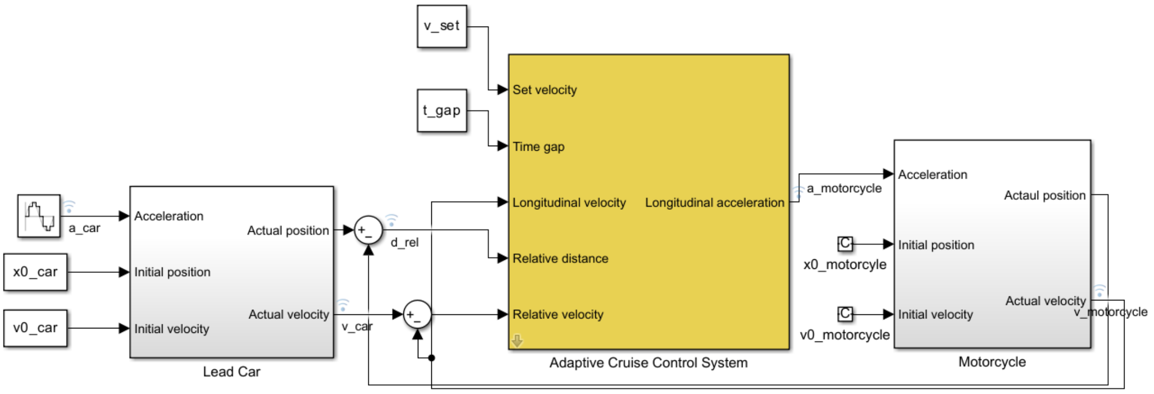

Fig. 5. Simulink system for MPC

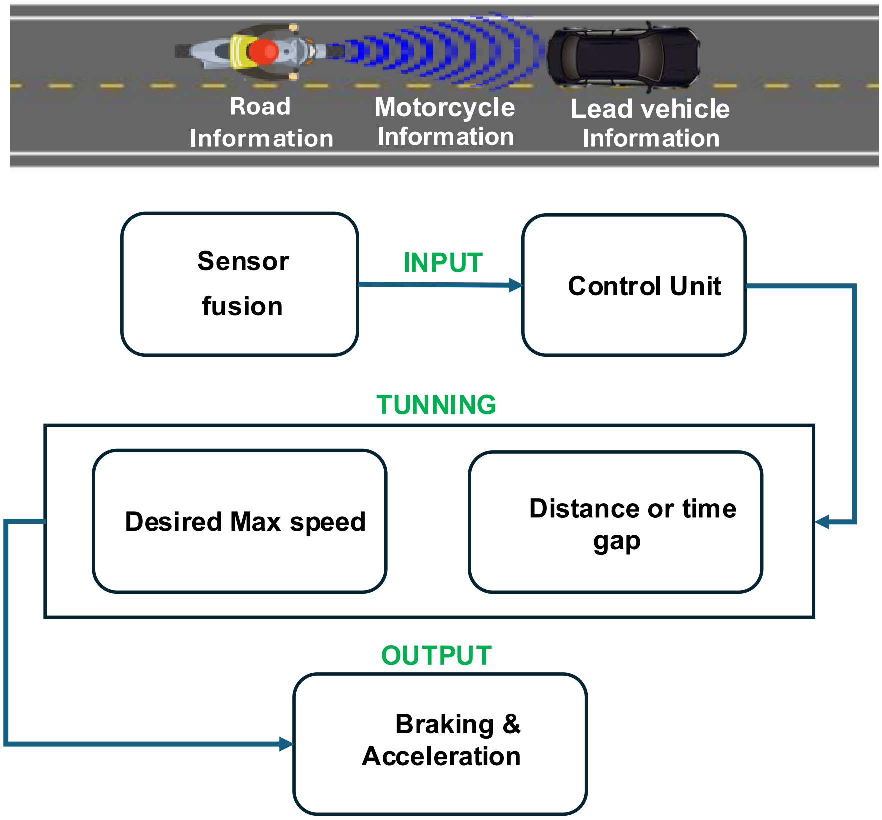

Fig. 6. Sensor fusion integrated with model predictive control

The sensor fusion system integrates data from both vision and radar sensors to create a comprehensive understanding of the driving environment, enabling effective ACC response to dynamic road conditions and other vehicles' actions. This sensor fusion enhances lead-vehicle tracking and lane estimation, particularly under curved roads and dynamic traffic scenarios. The integration of sensor fusion with MPC improves system robustness and control performance, supporting safe and adaptive motorcycle operation.

Table 1 presents the geometric, mass, and suspension parameters used in the motorcycle dynamics model, adapted from the reference [62]. These parameters are essential for accurate simulation of vehicle response during both path-following and ACC control operations.

Table 1. Parameters for motorcycle modelling [62]

Geometry and mass			Front and rear suspensions		
Parameter	**Value**	**Unit**	**Parameter**	**Value**	**Unit**
Wheelbase	1459.5	mm	K_{sf}	16	kN/m
Rake	23.7	deg	C_{sf}	0.74	$kN \cdot s/m$
Front trail (positive)	112	mm	Front stroke	150	mm
Front wheel radius	316	mm	K_{sr}	80	kN/m
Rear wheel radius	316	mm	C_{sr}	2.34	$kN \cdot s/m$
Rider mass	70	kg	Rear stroke	57	mm
Sprung mass (with rider)	228.6	kg	K_{tf}	180	kN/m
Front unsprung mass	15	kg	K_{tr}	180	kN/m
Rear unsprung mass	18	kg			

The control system implementation involved evaluation and selection of appropriate control strategies, with the MPC-based controller chosen for its dynamic adaptation capabilities. Testing was conducted using a closed-loop Simulink model (Fig. 5) with synthetic data generated by the Automated Driving Toolbox, creating realistic scenarios including varying road curvatures and vehicle maneuvers. Practical implementation considerations included configuration of software-in-the-loop (SIL) simulation settings with automatic code generation for the control algorithm, enabling comprehensive system validation in a simulated environment.

The ACC system dynamically adjusts motorcycle speed based on real-time road conditions and preceding vehicle behavior. While the driver sets the desired speed, the system can automatically reduce speed when encountering slower vehicles. Accurate determination of lane curvature and identification of the lead vehicle are critical functions, particularly given the potential for vehicles to enter or exit the lane. The sensor fusion system shown in Fig. 6 combines data from complementary sensors: vision systems offer lateral position information and lane marking detection for the vehicle position within the lane, while radar sensors offer precise range and range rate measurements for distance and relative speed estimation. This combined data enhances tracking precision for vehicles and lane geometry even in difficult conditions.

The MPC controller facilitates advanced control capabilities for an improved reaction to abrupt environmental change. Considering future states and system constraints, the MPC approach guarantees adequate safety distance while facilitating rapid maneuvers by other cars. Development difficulties included accurate relative position and velocity estimation, which were addressed by sensor fusion techniques utilizing a combination of vision and radar signals. Lane detection and tracking rely to a great extent on vision sensors for estimating lateral position. The MPC controller's constraint-handling and predictive capabilities proved particularly beneficial in responding safely to aggressive maneuvers such as sudden lane changes by other vehicles. The integration of sensor fusion with MPC-based ACC control has demonstrated performance improvements in curved road navigation and dynamic traffic conditions. This technological foundation supports the ongoing development of more autonomous and reliable motorcycle control systems.

4. Results and Discussion

4.1. Longitudinal Control Performance

The simulation results demonstrate the controller's effectiveness in maintaining both the desired velocity set by the driver and a safe following distance from the lead vehicle across various driving conditions. As shown in Fig. 7, during the initial 3-second phase, the motorcycle exhibits rapid acceleration to reach the target velocity. The steep acceleration curve confirms the controller's responsive handling of driver inputs.

Between 3 and 13 seconds in Fig. 8, the system demonstrates adaptive behavior as the lead vehicle initiates gradual deceleration. The motorcycle correspondingly adjusts its speed while maintaining a safe inter-vehicle distance, as shown in Fig. 9. During this phase, the inter-vehicle gap consistently remains above the computed safe distance threshold, confirming correct switching between speed and distance regulation modes.

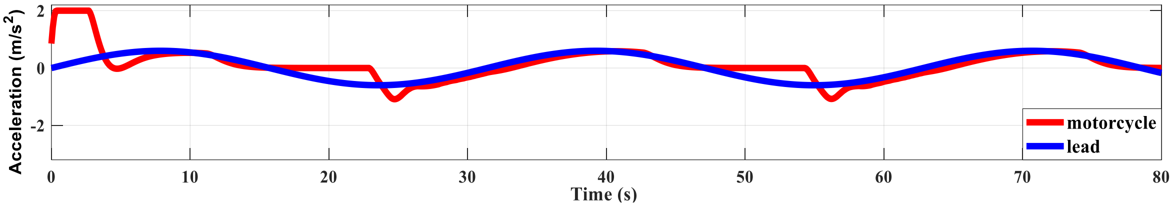

Fig. 7. Acceleration of vehicle using MPC

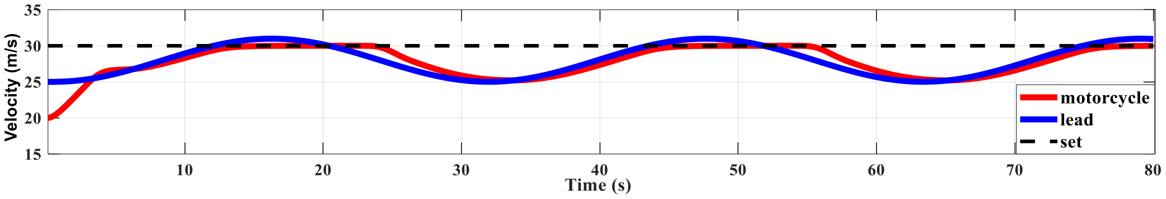

Fig. 8. Velocity of vehicle using MPC

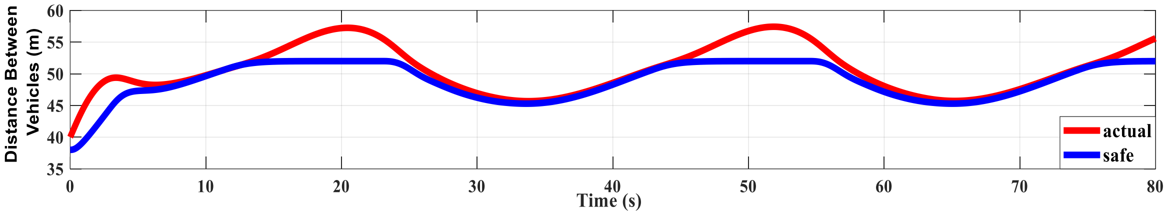

Fig. 9. Distance between two vehicles using MPC

From 13 to 25 seconds, the motorcycle sustains the rider-defined speed while responding to further deceleration of the lead vehicle. The decreasing gap between vehicles in Fig. 9 illustrates the controller's ability to regulate proximity without violating safety constraints. The period between 25 and 45 seconds highlights the controller's robustness under fluctuating lead-vehicle speeds, as reflected in the stable velocity and distance profiles shown in Fig. 7, Fig. 8, Fig. 9. Between 45 and 56 seconds, with adequate spacing available, the controller prioritizes maintaining the set velocity (refer to Fig. 8). The subsequent phase (56-76 seconds) replicates the earlier pattern of speed adjustments, with the system consistently maintaining proper following distances (refer to Fig. 9).

Throughout the entire simulation, the MPC-based controller ensures that the real gap between the motorcycle and the lead always exceeds the predetermined safe distance, while acceleration remains within the comfort bounds of -3 m/s^2 to 2 m/s^2. When this gap is ample, the controller gives priority to maintaining the velocity set by the rider. This behaviour showcases the controller's success in striking a balance between safety and adherence to the desired speed. The simulation analysis indicates that the MPC-based controller efficiently regulates the motorcycle's speed and distance in relation to the lead vehicle. Through dynamic adjustments of acceleration and deceleration rates, the controller preserves both a secure following distance and the velocity set by the rider, thereby ensuring optimal performance across diverse driving scenarios. Although similar velocity-tracking behavior has been reported in car-based MPC ACC studies, the presented results address motorcycle-specific challenges, including tighter safety margins, higher sensitivity to acceleration changes, and stronger coupling between longitudinal control and rider comfort. This distinction underlines the novelty of applying MPC-based ACC to two-wheeled platforms.

4.2. Path-Following Performance

The path-tracking performance of the MPC controller was evaluated through comprehensive simulations. Fig. 10 presents the mesh plot of the 2-D lookup table correlating acceleration and velocity with throttle position, providing valuable insight into the controller's decision-making process. The actual path-following performance is demonstrated in Fig. 11, which shows the motorcycle's trajectory relative to the reference path generated from a skidpad track configuration.

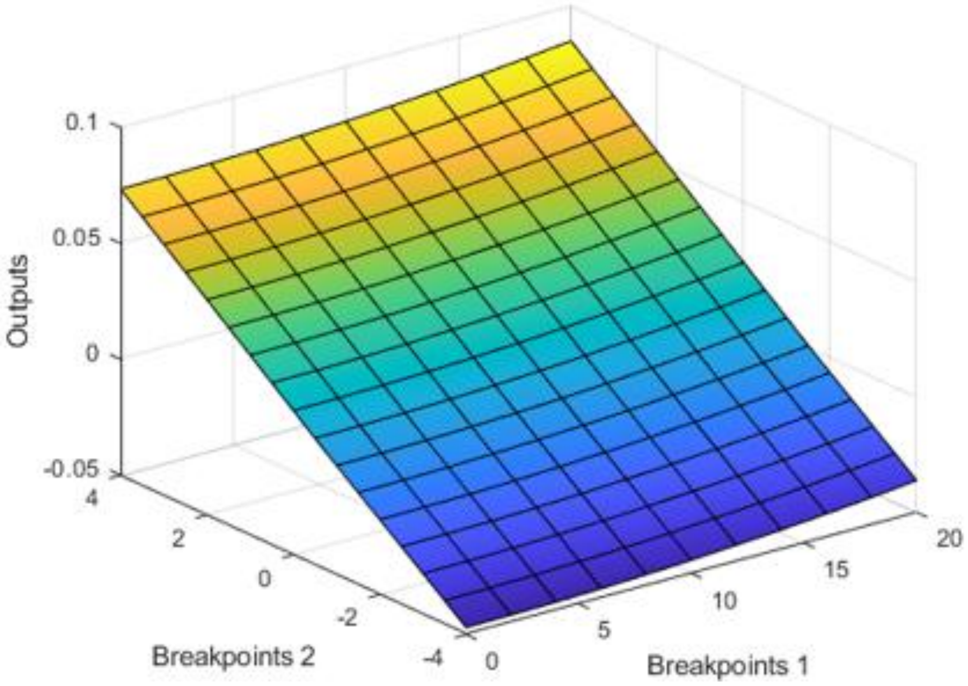

Fig. 10. Mesh plot of 2-D lookup table for acceleration and velocity

The system achieved excellent tracking accuracy, maintaining deviations within 0.5 meters during straight segments and 1.2 meters in curved sections. These deviation limits are consistent with reported bounds in autonomous vehicle literature and are particularly notable given the inherent instability and lean-dependent dynamics of motorcycles. These results meet the stringent requirements for autonomous vehicle path following. The implementation of MPC successfully controlled both lateral and longitudinal vehicle dynamics throughout complex manoeuvres, as evidenced by the precise trajectory following shown in Fig. 11. The MPC formulation enables simultaneous consideration of lateral and longitudinal dynamics, allowing the controller to respect steering, acceleration, and stability constraints during complex maneuvers. Unlike car-based MPC path-following studies, the controller here operates under lean-sensitive constraints, making direct numerical comparison insufficient and reinforcing the motorcycle-specific contribution of this work.

MPC's effectiveness stems from its optimization-based approach, which solves a constrained optimization problem at each time step to determine optimal control inputs. This enables real-time adjustments while respecting the vehicle's dynamic constraints. The simulation results confirm the controller's ability to maintain both trajectory accuracy and safety margins under various operating conditions. While the MPC approach demonstrated excellent path-tracking performance, it does present computational challenges. The need to solve optimization problems in real-time requires careful consideration of the available onboard computational resources. This trade-off between performance and computational demand represents an important implementation consideration for practical applications.

4.3. Integrated Sensor Fusion System

The development and result of the MATLAB Simulink model designed for Adaptive Cruise Control (ACC) using sensor fusion are intended to validate the performance of the ACC system under various driving conditions, focusing on how sensor fusion enhances the system's decision-making. The simulation model comprises two core subsystems, which are the ACC with Sensor Fusion and the Vehicle Scenario subsystem. This model integrates the first simulation, which uses Model Predictive Control, with the second simulation, which is Path-Following Control. The ACC with sensor fusion subsystem manages the motorcycle's longitudinal acceleration using a model predictive control, while the vehicle scenarios subsystem simulates the motorcycle's motion and the surrounding environment. These help in incorporating synthetic data generation for radar and vision sensors that feed into the control subsystem.

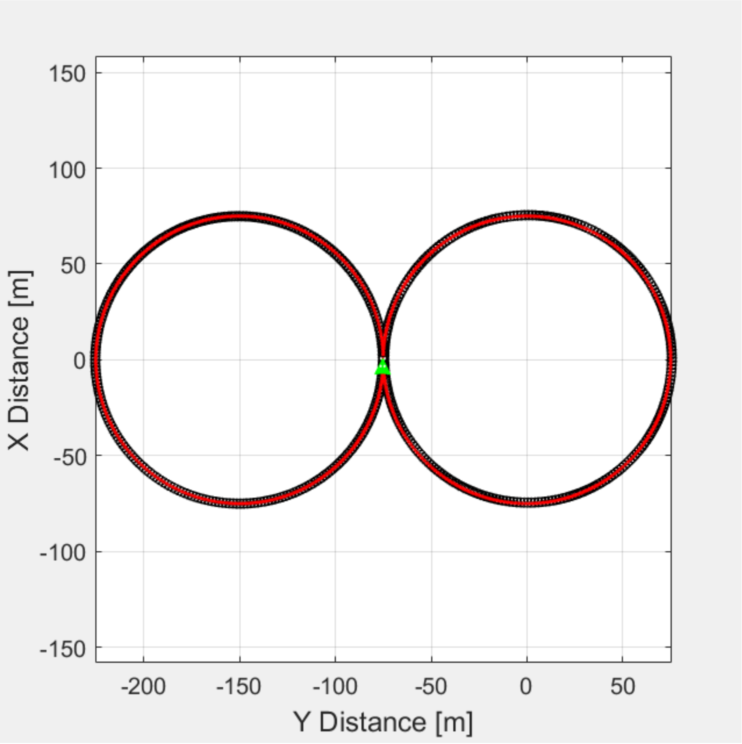

Fig. 11. Motorcycle position using path-following with MPC

The simulation parameters were initialized with a sample time of 0.1 seconds, and the road curvature was set to 760 meters to ensure accurate real-world scenario representation. The vehicle dynamics modeling incorporated comprehensive parameters, including a total mass of 228.6 kg, yaw moment of inertia, and detailed tire characteristics. These parameters were essential for creating realistic motorcycle behavior in the simulation environment. The control system utilized Model Predictive Control with carefully tuned gains for velocity error, spacing error, and relative velocity to ensure optimal performance.

The simulation results demonstrate the system's capability to handle complex traffic scenarios. As shown in Fig. 12, the velocity profile exhibits smooth transitions during both acceleration and deceleration phases. Initially, the motorcycle accelerates to 20 m/s. Since the first vehicle is far ahead, the driver must accelerate to 22 m/s to activate the ACC. From 11 to 20 seconds, another car cuts into the lane, becoming the new lead car. The motorcycle slows down to keep a safe distance. This action is controlled by information from the sensor and enhanced by MPC integrated with sensor fusion. From 20 to 34 seconds, as the car in front changes lanes, the motorcycle accelerates again to reach the initial set speed.

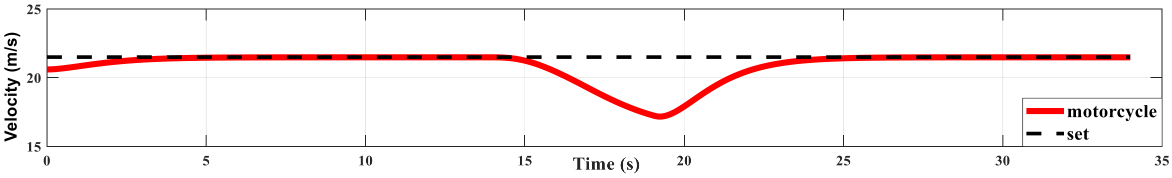

Fig. 12. Velocity of motorcycle with sensor fusion

Fig. 13 illustrates the system's ability to maintain safe following distances, with the actual gap consistently remaining above the calculated safe distance threshold. The acceleration profile in Fig. 14 confirms the system's ability to provide comfortable riding conditions, with all acceleration values remaining within comfortable limits for motorcycle operation, indicating implicitly low jerk behavior even though jerk is not explicitly measured.

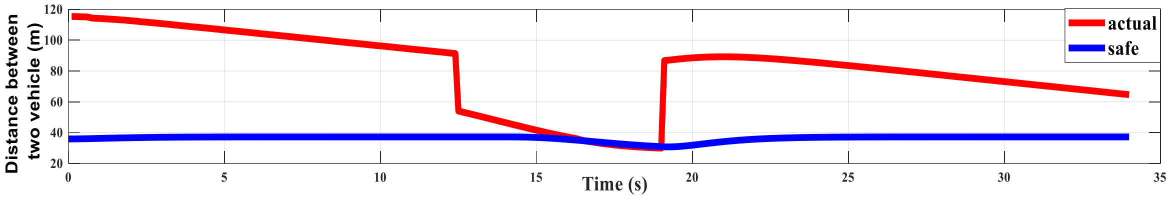

Fig. 13. Distance between two vehicle using sensor fusion

The vehicle coordinate view in Fig. 15 provides a comprehensive spatial visualization of the motorcycle's position relative to other vehicles and road geometry, demonstrating the effectiveness of the sensor fusion implementation. The integrated sensor fusion system successfully combines data from multiple sensor modalities to enhance decision-making capabilities. This integration allows for robust performance in challenging scenarios such as vehicle cut-ins and lane changes. The system demonstrates particular effectiveness in maintaining smooth speed transitions while ensuring safety margins are respected, as evidenced by the consistent maintenance of appropriate following distances throughout all test scenarios.

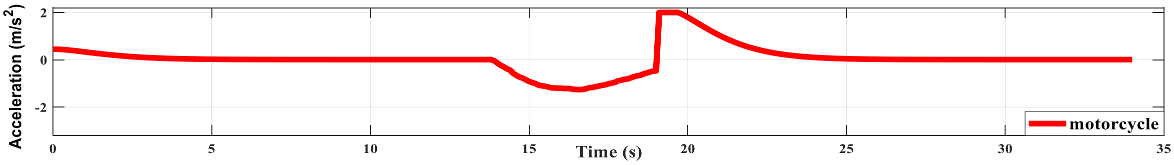

Fig. 14. Acceleration of motorcycle using sensor fusion

4.4. Validation And Future Directions

The performance of the MACC system was thoroughly tested and evaluated in various driving environments (straight-line, with curve, and mixed traffic) through different simulations in MATLAB Simulink®. Performance metrics such as trajectory deviation, response latency, and compliance with safety constraints were systematically monitored throughout the testing process. Although the available validation was conducted with simulated data, real-world experimental testing will be involved in future development to further validate the performance of the controller. Simulation results will be compared with real motorcycle behavior to enhance the reliability and operational confidence of the system. The primary limitation of this study is its reliance on simulated data and synthetic sensor models. Real-world effects such as sensor misalignment, actuator delays, and unmodeled disturbances are not fully captured. Additionally, the computational feasibility of MPC on resource-constrained embedded platforms is assumed but not experimentally verified.

Sensitivity analyses were performed to assess the system's robustness against parameter variations, including sensor noise, model uncertainties, and environmental disturbances. These tests confirmed the control system's adaptability and resilience under varying conditions. The successful application of the MPC-based path following controller establishes a solid base for real-life applications in autonomous motorcycle cases. Compared with prior MPC-based ACC studies focused on four-wheeled vehicles, the present work addresses additional challenges inherent to motorcycles, such as tighter stability margins, rider comfort sensitivity, and integrated lateral–longitudinal control. While absolute tracking errors may appear similar, the operating constraints and control objectives differ fundamentally. Future research directions will concentrate on three key areas: the implementation of hardware-in-the-loop (HIL) testing to narrow the gap between simulation and physical systems, the real-time computational efficiency optimization for improving the controller performance, and the multimodal sensor fusion development for advancing the environmental perception and decision making. These advancements will further strengthen the system's applicability in complex, real-world riding scenarios.

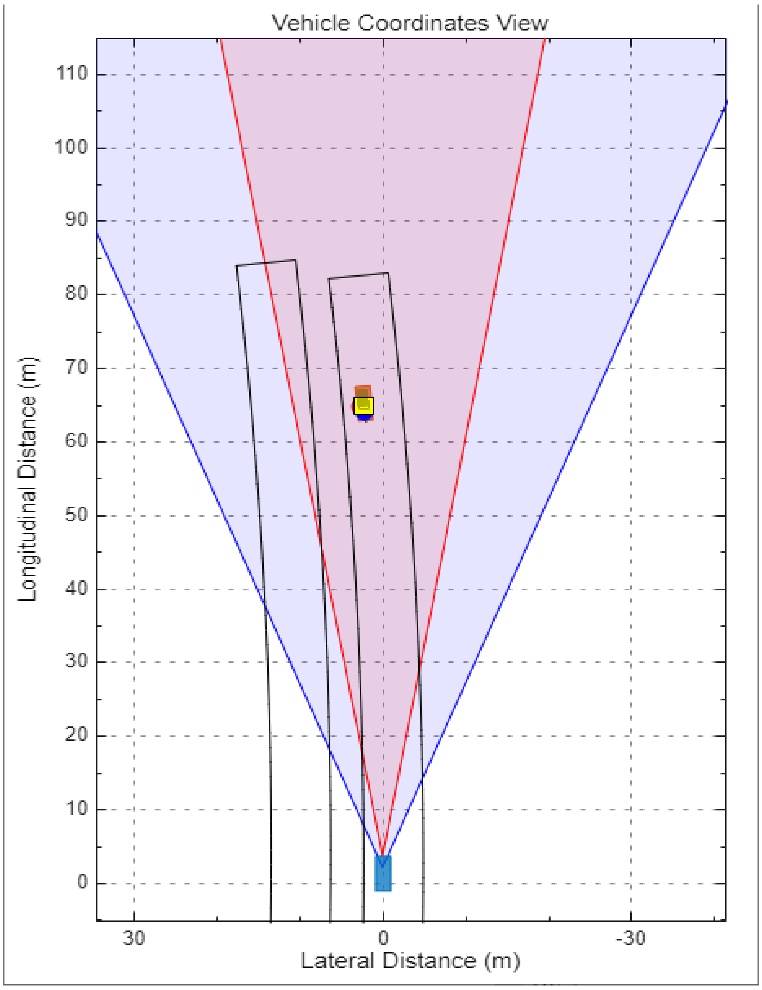

Fig. 15. Vehicle coordinate's view with sensor fusion in Simulink

5. Conclusion

The design of adaptive cruise control systems for motorcycles must address unique challenges related to two-wheeled vehicle dynamics, stability constraints, perception reliability, and integrated control strategies. This study demonstrates that an MPC-based control framework, combined with sensor fusion, can effectively manage longitudinal speed regulation and lateral path-following for motorcycles under diverse simulated traffic scenarios. Simulation results show consistent maintenance of safe inter-vehicle distances, smooth acceleration profiles within comfort limits, and accurate path tracking with lateral deviations remaining within 0.5 m on straight paths and 1.2 m on curved sections, highlighting the feasibility of the proposed approach for motorcycle applications.

The main contribution of this work lies in the integration of longitudinal and lateral MPC control with a sensor fusion framework tailored to motorcycle dynamics, rather than in absolute performance improvements over car-based ACC systems. By accounting for tighter stability margins and two-wheeled handling characteristics, the proposed system advances the state of the art in motorcycle adaptive cruise control and provides a scalable control architecture applicable to other two-wheeled platforms. The conclusions of this study are limited by the simulation-based validation framework. While the results indicate robust performance under modeled conditions, real-world factors such as sensor misalignment, actuator delays, environmental disturbances, and sensor failures are not fully captured. No claims are made regarding compliance with autonomous vehicle certification standards, and experimental validation is required before real-world deployment. The computational demands of MPC remain a key implementation challenge. Although a sampling time of 0.1 s was shown to be sufficient in simulation, real-time deployment on resource-constrained motorcycle embedded systems will require further optimization of prediction horizons, solver efficiency, and hardware integration.

Future work will focus on hardware-in-the-loop and on-road experimental validation, optimization of real-time computational performance, and systematic extension of the sensor fusion framework to include additional perception sources and fault-tolerant mechanisms. These efforts aim to bridge the gap between simulation and real-world deployment, and to support the development of reliable, scalable, and rider-centric adaptive cruise control systems for next-generation motorcycles.

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References

[1] J. V. Mierlo *et al.*, “Beyond the state of the art of electric vehicles: A fact-based paper of the current and prospective electric vehicle technologies,” *World Electric Vehicle Journal*, vol. 12, no. 1, p. 20, 2021, https://doi.org/10.3390/wevj12010020.

[2] D. D. Tran, M. Vafaeipour, M. El Baghdadi, R. Barrero, J. Van Mierlo, and O. Hegazy, “Thorough state-of-the-art analysis of electric and hybrid vehicle powertrains: Topologies and integrated energy management strategies,” *Renewable and Sustainable Energy Reviews*, vol. 119, p. 109596, 2020, https://doi.org/10.1016/j.rser.2019.109596.

[3] S. Madichetty, S. Mishra, and M. Basu, “New trends in electric motors and selection for electric vehicle propulsion systems,” *IET Electrical Systems in Transportation*, vol. 11, no. 3, pp. 186-199, 2021, https://doi.org/10.1049/els2.12018.

[4] A. Ait-Moula, E. Riahi, and T. Serre, “Effect of advanced rider assistance system on powered two wheelers crashes,” *Heliyon*, vol. 10, no. 4, p. e26031, 2024, https://doi.org/10.1016/j.heliyon.2024.e26031.

[5] M. Aleksa, A. Schaub, I. Erdelean, S. Wittmann, A. Soteropoulos, and A. Fürdös, “Impact analysis of Advanced Driver Assistance Systems (ADAS) regarding road safety – computing reduction potentials,” *European Transport Research Review*, vol. 16, no. 39, 2024, https://doi.org/10.1186/s12544-024-00654-0.

[6] D. Huang, J. Ou, E. Yang, J. Lin, and Y. Zhang, “Research on a Multimode Adaptive Cruise Control Strategy with Emergency Lane-Changing Function,” *World Electric Vehicle Journal*, vol. 14, no. 7, p. 189, 2023, https://doi.org/10.3390/wevj14070189.

[7] D. Mohammed and B. Horváth, “Comparative Analysis of Following Distances in Different Adaptive Cruise Control Systems at Steady Speeds,” *World Electric Vehicle Journal*, vol. 15, no. 3, p. 116, 2024, https://doi.org/10.3390/wevj15030116.

[8] J. Zhang and T. Wang, “Design of adaptive cruise control strategy for EREV considering driving behavior,” *Frontiers in Mechanical Engineering*, vol. 10, 2024, https://doi.org/10.3389/fmech.2024.1408277.

[9] H. Wang, X. Wang, Y. Peng, X. Lou, and J. Lee, "An investigation of ADAS testing scenarios based on vehicle-to-powered two-wheeler accidents occurring in a county-level district in China," *Transportation Safety and Environment*, vol. 6, no. 4, 2024, https://doi.org/10.1093/tse/tdae013.

[10] G. Pai *et al.*, "Frequency and Quality of Exposure to Adaptive Cruise Control and Impact on Trust, Workload, and Mental Models," *Accident Analysis & Prevention*, vol. 190, p. 107130, 2023, https://doi.org/10.1016/j.aap.2023.107130.

[11] C. Huang, D. He, X. Wen, and S. Yan, "Beyond adaptive cruise control and lane centering control: drivers' mental model of and trust in emerging ADAS technologies," *Frontiers in Psychology*, vol. 14, 2023, https://doi.org/10.3389/fpsyg.2023.1236062.

[12] D. Wu *et al.*, "Multi-objective dynamic coordinated Adaptive Cruise Control for intelligent electric vehicle with sensors fusion," *Mechanical Systems and Signal Processing*, vol. 209, p. 111125, 2024, https://doi.org/10.1016/j.ymssp.2024.111125.

[13] Y. Zhuang *et al.*, "Multi-sensor integrated navigation/positioning systems using data fusion: From analytics-based to learning-based approaches," *Information Fusion*, vol. 95, pp. 62-90, 2023, https://doi.org/10.1016/j.inffus.2023.01.025.

[14] J. Zhou, "Academic Journal of Science and Technology A Review of LiDAR sensor Technologies for Perception in Automated Driving," *Academic Journal of Science and Technology*, vol. 3, no. 3, pp. 255-261, 2022, https://doi.org/10.54097/ajst.v3i3.2993.

[15] Z. Dai, Z. Guan, Q. Chen, Y. Xu, and F. Sun, "Enhanced Object Detection in Autonomous Vehicles through LiDAR—Camera Sensor Fusion," *World Electric Vehicle Journal*, vol. 15, no. 7, p. 297, 2024, https://doi.org/10.3390/wevj15070297.

[16] R. Alika, E. M. Mellouli, and E. H. Tissir, "Adaptive Cruise Control of the Autonomous Vehicle Based on Sliding Mode Controller Using Arduino and Ultrasonic Sensor," *Journal of Robotics and Control (JRC)*, vol. 5, no. 1, pp. 301-311, 2024, https://doi.org/10.18196/jrc.v5i1.20519.

[17] R. Stiawan, A. Kusumadjati, N. S. Aminah, M. Djamal, and S. Viridi, "An Ultrasonic Sensor System for Vehicle Detection Application," *Journal of Physics: Conference Series*, 2019, https://doi.org/10.1088/1742-6596/1204/1/012017.

[18] M. A. Shinde, M. R. B. Agrewale, and Y. K. Bhateshvar, "Development of sensor data fusion for obstacle detection for electric mini tractor," *Materials Today: Proceedings*, vol. 72, pp. 1206-1211, 2023, https://doi.org/10.1016/j.matpr.2022.09.284.

[19] J. Park, B. K. Thota, and K. Somashekar, "Sensor-Fused Nighttime System for Enhanced Pedestrian Detection in ADAS and Autonomous Vehicles," *Sensors*, vol. 24, no. 14, p. 4755, 2024, https://doi.org/10.3390/s24144755.

[20] V. M. Patel, "Sensor Fusion: The Backbone of Modern ADAS Systems," *International Journal of Research in Computer Applications and Information Technology*, vol. 8, no. 1, pp. 3066-3080, 2025, https://doi.org/10.34218/IJRCAIT_08_01_221.

[21] S. Favelli, M. Xie, and A. Tonoli, "Sensor Fusion Method for Object Detection and Distance Estimation in Assisted Driving Applications," *Sensors*, vol. 24, no. 24, p. 7895, 2024, https://doi.org/10.3390/s24247895.

[22] A. Martini, G. Bellani, and C. Fragassa, "Numerical assessment of a new hydro-pneumatic suspension system for motorcycles," *International Journal of Automotive and Mechanical Engineering*, vol. 15, no. 2, pp. 5308-5325, 2018, https://doi.org/10.15282/ijame.15.2.2018.12.0409.

[23] Z. Yang, R. He, S. Zhang, and J. Wu, "Research on adaptive cruise control algorithm considering road conditions," *IET Intelligent Transport Systems*, vol. 15, no. 12, pp. 1478-1493, 2021, https://doi.org/10.1049/itr2.12108.

[24] H. Mu, L. Li, M. Mei, and Y. Zhao, "A Hierarchical Control Scheme for Adaptive Cruise Control System Based on Model Predictive Control," *Actuators*, vol. 12, no. 6, p. 249, 2023, https://doi.org/10.3390/act12060249.

[25] S. K. El-Baklish, A. Kouvelas, and M. A. Makridis, "Driving towards stability and efficiency: A variable time gap strategy for Adaptive Cruise Control," *Transportation Research Part C: Emerging Technologies*, vol. 174, p. 105074, 2025, https://doi.org/10.1016/j.trc.2025.105074.

[26] A. Turan, "PID controller design with a new method based on proportional gain for cruise control system," *Journal of Radiation Research and Applied Sciences*, vol. 17, no. 1, p. 100810, 2024, https://doi.org/10.1016/j.jrras.2023.100810.

[27] O. Z. Zhao, V. R. Aparow, Z. M. Jawi, and K. A. A. Kassim, "Forward Collision Prevention System for Two-wheeler Bike Using Berkeley Algorithm-Based PID Control," *Journal of the Society of Automotive Engineers Malaysia*, vol. 6, no. 1, pp. 46-64, 2022, https://jsaem.my/index.php/journal/article/view/211.

[28] K. Ma, H. Shi, C. Ma, Z. Huang, Q. Wang, and X. Li, "Development, Calibration, and validation of a Novel nonlinear Car-Following Model: Multivariate piecewise linear approach for adaptive cruise control vehicles," *Transportation Research Part E: Logistics and Transportation Review*, vol. 199, p. 104031, 2025, https://doi.org/10.1016/j.tre.2025.104031.

[29] J. Li, Q. Yi, P. Zhu, J. Hu, and S. Yi, "Data-driven co-optimization method of eco-adaptive cruise control for plug-in hybrid electric vehicles considering risky driving behaviors," *Applied Energy*, vol. 392, p. 126039, 2025, https://doi.org/10.1016/j.apenergy.2025.126039.

[30] K. Yeneneh, M. Walle, and T. Mamo, "Traffic dynamics in cooperative adaptive cruise control (CACC) vehicle platoons: Analyzing congestion and merge behaviors," *Physica A: Statistical Mechanics and its Applications*, vol. 673, p. 130724, 2025, https://doi.org/10.1016/j.physa.2025.130724.

[31] M. Abdullah, M. A. S. Zainuddin, S. Ahmad, and J. A. Rossiter, "Performance Comparison Between Centralized and Hierarchical Predictive Functional Control for Adaptive Cruise Control Application," *International Journal of Automotive and Mechanical Engineering*, vol. 20, no. 4, pp. 10808-10820, 2023, https://doi.org/10.15282/ijame.20.4.2023.01.0836.

[32] S. I. B. S. Abdullah, M. A. S. Zainuddin, M. Abdullah, and K. A. Tofrowaih, "Analysis of a Simplified Predictive Function Control Formulation Using First Order Transfer Function for Adaptive Cruise Control," *International Journal of Automotive and Mechanical Engineering*, vol. 21, no. 3, pp. 11641-11651, 2024, https://doi.org/10.15282/ijame.21.3.2024.15.0898.

[33] Z. Mehraban, A. Y Zadeh, H. Khayyam, R. Mallipeddi, and A. Jamali, "Fuzzy adaptive cruise control with model predictive control responding to dynamic traffic conditions for automated driving," *Engineering Applications of Artificial Intelligence*, vol. 136, p. 109008, 2024, https://doi.org/10.1016/j.engappai.2024.109008.

[34] A. Thakur and S. K. Mishra, "An in-depth evaluation of deep learning-enabled adaptive approaches for detecting obstacles using sensor-fused data in autonomous vehicles," *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108550, 2024, https://doi.org/10.1016/j.engappai.2024.108550.

[35] M. Mohamed, S. F. Toha, M. A. Rahman, and Moh. Khairudin, "Smart IoT Energy Optimisation and Localisation Monitoring for E-Bike Sharing," *IIUM Engineering Journal*, vol. 26, no. 2, pp. 305-325, 2025, https://doi.org/10.31436/iiumej.v26i2.3448.

[36] P. Aungkulanon, W. Atthirawong, and P. Luangpaiboon, "Fuzzy Analytical Hierarchy Process for Strategic Decision Making in Electric Vehicle Adoption," *Sustainability*, vol. 15, no. 8, p. 7003, 2023, https://doi.org/10.3390/su15087003.

[37] A. Mazouzi, N. Hadroug, W. Alayed, A. Hafaifa, A. Iratni, and A. Kouzou, "Comprehensive optimization of fuzzy logic-based energy management system for fuel-cell hybrid electric vehicle using genetic algorithm," *International Journal of Hydrogen Energy*, vol. 81, pp. 889-905, 2024, https://doi.org/10.1016/j.ijhydene.2024.07.237.

[38] Z. Yang, Z. Zheng, J. Kim, and H. Rakha, "Eco-cooperative adaptive cruise control for platoons in mixed traffic using single-agent and multi-agent reinforcement learning," *Transportation Research Part D: Transport and Environment*, vol. 142, p. 104658, 2025, https://doi.org/10.1016/j.trd.2025.104658.

[39] B. D. Evans, H. W. Jordaan, and H. A. Engelbrecht, "Safe reinforcement learning for high-speed autonomous racing," *Cognitive Robotics*, vol. 3, pp. 107-126, 2023, https://doi.org/10.1016/j.cogr.2023.04.002.

[40] M. Soori, B. Arezoo, and R. Dastres, "Artificial intelligence, machine learning and deep learning in advanced robotics, a review," *Cognitive Robotics*, vol. 3, pp. 54-70, 2023, https://doi.org/10.1016/j.cogr.2023.04.001.

[41] Y. Dai, D. Kim, and K. Lee, "An Advanced Approach to Object Detection and Tracking in Robotics and Autonomous Vehicles Using YOLOv8 and LiDAR Data Fusion," *Electronics*, vol. 13, no. 12, p. 2250, 2024, https://doi.org/10.3390/electronics13122250.

[42] A. Ess, K. Schindler, B. Leibe, and L. Van Gool, "Object detection and tracking for autonomous navigation in dynamic environments," *International Journal of Robotics Research*, vol. 29, no. 14, pp. 1707-1725, 2010, https://doi.org/10.1177/0278364910365417.

[43] S. Veluchamy, K. M. Mahesh, A. Pon Bharathi, and P. T. Sheeba, "DeepDrive: A braking decision making approach using optimized GAN and Deep CNN for advanced driver assistance systems," *Engineering Applications of Artificial Intelligence*, vol. 123, p. 106111, 2023, https://doi.org/10.1016/j.engappai.2023.106111.

[44] S. A. Yusuf, A. Khan, and R. Souissi, "Vehicle-to-everything (V2X) in the autonomous vehicles domain – A technical review of communication, sensor, and AI technologies for road user safety," *Transportation Research Interdisciplinary Perspectives*, vol. 23, p. 100980, 2024, https://doi.org/10.1016/j.trip.2023.100980.

[45] N. M. M. Noor, S. F. Toha, M. Abdullah, S. Ahmad, and M. A. Rahman, "Regenerative Braking System (RBS) MOSFET Switching-Based Drive Cycle for an Electric Motorcycle," *IIUM Engineering Journal*, vol. 26, no. 2, pp. 286-304, 2025, https://doi.org/10.31436/iiumej.v26i2.3413.

[46] H. Zhang, Z. Zhang, and J. Liang, "Dynamic driving intention recognition of vehicles with different driving styles of surrounding vehicles," *IET Intelligent Transport Systems*, vol. 16, no. 5, pp. 571-585, 2022, https://doi.org/10.1049/itr2.12158.

[47] C. Desjardins and B. Chaib-draa, "Cooperative Adaptive Cruise Control: A Reinforcement Learning Approach," *IEEE Transactions on Intelligent Transportation Systems*, vol. 12, no. 4, pp. 1248-1260, 2011, https://doi.org/10.1109/TITS.2011.2157145.

[48] R. Al-Hindawi and T. Alhadidi, "Evaluation and optimization of adaptive cruise control in autonomous vehicles using the car learning to act simulator: A performance evaluation under various weather conditions," *Sustainable Futures*, vol. 9, p. 100707, 2025, https://doi.org/10.1016/j.sftr.2025.100707.

[49] Z. Zhu *et al.*, "Research on Robust Control of Intelligent Vehicle Adaptive Cruise," *World Electric Vehicle Journal*, vol. 14, no. 10, p. 268, 2023, https://doi.org/10.3390/wevj14100268.

[50] H. S. Qi, "Robust responsibility-sensitive safety: Noise disturbed adaptive cruise control," *Systems & Control Letters*, vol. 196, p. 106021, 2025, https://doi.org/10.1016/j.sysconle.2025.106021.

[51] M. Sadaf *et al.*, "Connected and Automated Vehicles: Infrastructure, Applications, Security, Critical Challenges, and Future Aspects," *Technologies*, vol. 11, no. 5, p. 117, 2023, https://doi.org/10.3390/technologies11050117.

[52] Y. Zhang and J. Song, "Model-Free Robust Backstepping Adaptive Cruise Control," *International Journal of Aerospace Engineering*, vol. 2023, no. 1, pp. 1-17, 2023, https://doi.org/10.1155/2023/8839650.

[53] B. Yang *et al.*, "Research and application of UAV-based hyperspectral remote sensing for smart city construction," *Cognitive Robotics*, vol. 2, pp. 255-266, 2022, https://doi.org/10.1016/j.cogr.2022.12.002.

[54] E. Füssl *et al.*, "Methodological development of a specific tool for assessing acceptability of assistive systems of powered two-wheeler-riders," *IET Intelligent Transport Systems*, vol. 9, no. 1, pp. 12-21, 2015, https://doi.org/10.1049/iet-its.2014.0026.

[55] O. Tengilimoglu, O. Carsten, and Z. Wadud, "Implications of automated vehicles for physical road environment: A comprehensive review," *Transportation Research Part E: Logistics and Transportation Review*, vol. 169, p. 102989, 2023, https://doi.org/10.1016/j.tre.2022.102989.

[56] W. Hao, "Review on lane detection and related methods," *Cognitive Robotics*, vol. 3, pp. 135-141, 2023, https://doi.org/10.1016/j.cogr.2023.05.004.

[57] J. A. Mandujano-Granillo *et al.*, "Human–Machine Interfaces: A Review for Autonomous Electric Vehicles," *IEEE Access*, vol. 12, pp. 121635-121658, 2024, https://doi.org/10.1109/ACCESS.2024.3450439.

[58] M. Kyriakidis *et al.*, “A human factors perspective on automated driving,” *Theoretical Issues in Ergonomics Science*, vol. 20, no. 3, pp. 223-249, 2019, https://doi.org/10.1080/1463922X.2017.1293187.

[59] M. Nylin, J. Johansson Westberg, and J. Lundberg, “Reduced autonomy workspace (RAW)—an interaction design approach for human-automation cooperation,” *Cognition, Technology & Work*, vol. 24, no. 2, pp. 261-273, 2022, https://doi.org/10.1007/s10111-022-00695-2.

[60] M. R. Endsley, “From Here to Autonomy: Lessons Learned from Human-Automation Research,” *Human Factors: The Journal of the Human Factors and Ergonomics Society*, vol. 59, no. 1, pp. 5-27, 2017, https://doi.org/10.1177/0018720816681350.

[61] J. Antony and S. Manikandan, “Expanding vision-based ADAS for non-structured environments,” *IET Intelligent Transport Systems*, vol. 14, no. 6, pp. 620-627, 2020, https://doi.org/10.1049/iet-its.2019.0530.

[62] Y. Mei, R. Wang, R. Ding, and Y. Jiang, “Classification evolution, control strategy innovation, and future challenges of vehicle suspension systems: A Review,” *Actuators*, vol. 14, no. 10, p. 485, 2025, https://doi.org/10.3390/act14100485.