DESIGN AND SIMULATION OF A FUZZY-LOGIC BASED STEERING AND SPEED CONTROL SYSTEM FOR AN AUTONOMOUS VEHICLE

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CERTIFICATION

This is to certify that this research project titled: Fuzzy Logic Control in Autonomous Vehicles was carried out by the students listed above under the supervision of Prof. Osarobo Ighodaro

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DEDICATION

We dedicate this report to God Almighty, whose grace has granted us the strength to accomplish all that was necessary for the success of this project. To our families, whose unwavering support and encouragement have been the foundation of our academic journey. To the Department of Mechanical Engineering, whose guidance and commitment to equipping us through extensive training and lectures have been pivotal in shaping us into who we are today. This work is also dedicated to all who have inspired and supported us along the way. Your faith in our potential has ignited our passion for learning and striving for excellence.

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ABSTRACT

This research presents the design and implementation of an integrated fuzzy logic–based decision-making system for autonomous vehicle navigation, focusing on intelligent speed regulation, steering control, and lane keeping. A three-degree-of-freedom (3-DoF) dual-track vehicle dynamics model was developed in MATLAB/Simulink to capture longitudinal, lateral, and yaw behaviors. The control architecture uses a Takagi–Sugeno fuzzy inference system to process speed error, distance error, and yaw deviation, generating throttle and steering actions that emulate human driving intuition.

A simulation-based framework was developed for both ego and target vehicles, enabling the evaluation of inter-vehicle distance, trajectory following, and lane stability across straight and curved road sections. Results show that the fuzzy controller reduced longitudinal speed error to below 0.25 m/s, maintained lateral deviation within ±0.12 m on curved paths, and improved yaw rate tracking with a settling time of 1.8 s compared to 3.1 s without fuzzy control. The controller also limited throttle oscillations to less than 5% and sustained a safe inter-vehicle distance with less than 7% deviation from the desired headway.

Overall, the research establishes a computationally efficient fuzzy-logic framework suitable for autonomous-vehicle applications, and the findings confirm the controller's robustness and adaptability in a virtual test environment.

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CHAPTER 1

1.1 Background of the Study

Safety is an important criterion that should be realized while driving on the road. Given that most road accidents are caused by human errors, it is necessary to develop an advanced driving control system independent of human errors (Hamdan et al., 2021). An Autonomous Vehicle is the ideal solution as autonomous vehicles have the potential to significantly reduce accident severity and frequency (Abdallaoui et al., 2024). Research has demonstrated that autonomous vehicles can reduce traffic accidents by up to 90% by eliminating human error factors such as fatigue, distraction, and impaired driving (Singh et al., 2023).

The Society of Automotive Engineers (SAE) categorizes AVs into six levels of automation, from Level 0 (no automation) to Level 5 (full automation). Levels 0 to 2 require full human oversight and include systems such as driver assistance and partial automation. Level 3 introduces conditional automation, where the vehicle can perform all tasks under certain conditions, while Level 4 extends to high automation in specific scenarios. Finally, Level 5 refers to full automation under all road and weather conditions (Martínez-Díaz and Soriguera, 2018; Abdallaoui et al., 2023).

Over the last two decades, in-vehicle computing has been employed increasingly for in-driving tasks, a leap from its constriction to auxiliary tasks such as regulating cabin temperature, opening doors and monitoring fuel, oil and battery-charge levels. One of these in-driving tasks is maintaining a reference velocity (Naranjo et al., 2007). Another is electrical power steering and maneuver (Arifin et al., 2022). With the incorporation of these features, a fully autonomous vehicle is on the verge of being road-ready.

Although the automotive industry has made significant progress in many areas, creating fully automated vehicles (level 5) has remained a challenge (Onyeka et al., 2023). The implementation of an autonomous driving environment encompasses not only complex automotive technology, but also human behavior, ethics, and traffic management strategies. From the technical perspective, the unequivocal detection of obstacles at high speeds and long distances is one of the greatest difficulties to face (Martínez-Díaz & Soriguera, 2018).

Traditional autonomous vehicle control systems have predominantly relied on classical control methods, each presenting significant limitations. Proportional-Integral-Derivative (PID) controllers, while widely adopted in industry due to their simplicity and proven track record, exhibit several critical drawbacks; They are difficult to tune and require additional adaptation to control nonlinear systems with varying parameters (Achenef et al., 2025). The fixed gain structure of PID controllers makes them unsuitable for the dynamic and unpredictable nature of real-world driving environments, where road conditions, weather, and traffic patterns constantly change.

Model Predictive Control (MPC), another conventional approach, suffers from computational complexity and limited real-time applicability. While MPC can handle multi-variable systems and constraints, its performance degrades significantly in scenarios with high uncertainty and rapid environmental changes. The approach requires accurate mathematical models of the vehicle dynamics, which are often difficult to obtain for complex real-world scenarios involving multiple interacting factors (Schwenzer et al., 2021).

Classical feedback control systems also struggle with the non-linear characteristics inherent in autonomous vehicle navigation. Traditional linear control methods cannot adequately handle the complex interactions between steering dynamics, speed control, and obstacle avoidance simultaneously. Furthermore, these conventional approaches lack the adaptive capability required to learn from experience and improve performance over time, making them less suitable for the evolving nature of autonomous driving environments.

The integration of multiple control objectives—such as path following, obstacle avoidance, and speed regulation—presents another significant challenge for conventional control systems. Traditional approaches often treat these objectives separately, leading to suboptimal overall performance and potential conflicts between different control actions.

Fuzzy Logic Control (FLC) has seen an increased adoption because of its ability to use linguistic information required for complex systems to formulate a controller's rule base. Human-like intelligence can be easily mimicked by machines via fuzzy set theory. It outperforms conventional control, as changes in the plant can always be followed properly by fuzzy control. The energy consumption of the system is also lower (Gouda et al., 2000). According to the study by Nguyen et al. (2021), using FLC can improve the quality of the plant's output compared to using only model predictive control. For obstacle avoidance-based navigation, linguistic information obtained from sensors is fuzzified to select membership functions and values heuristically, by experimentation or expert rules. After inference is made, the fuzzy output values are converted back to crisp variables (Nakrani & Joshi, 2021).

When using PID control, all of the control surfaces will affect each other when setting the parameters. Fuzzy logic control has the advantage of being able to overcome this conventional control's weakness by using a rule base that makes it possible to manipulate control surfaces individually. As a result, only the surrounding shape is affected, not all of the control surfaces (Mamdani, 1994).

Despite ongoing work on FLC application in autonomous vehicles, several aspects of research in this field remain unaddressed. Current fuzzy logic implementations primarily focus on single-objective control systems rather than integrated control of multiple vehicle functions simultaneously. The existing literature reveals a significant gap in developing comprehensive fuzzy inference systems capable of handling complex interactions between speed control, steering control, and obstacle avoidance in real-time. Most current research focuses on isolated control problems rather than the holistic approach required for fully autonomous navigation. Additionally, there is limited research on adaptive fuzzy systems that can modify their rule bases based on changing environmental conditions. The integration of fuzzy logic with modern sensor technologies and real-time processing capabilities remains underexplored (Grzesiak et al., 2016). These challenges suggest that while fuzzy logic offers significant promise, its deployment at full scale requires systematic refinements and hybrid architectures tailored for dynamic autonomous vehicle scenarios.

1.2 Statement of the Problem

The fundamental motivation behind the research and development of autonomous vehicles are: the need for more driving safety, an increasing population that also leads to an increase in vehicles on the road, expanding infrastructure, the comfort of depending on machines for tasks like driving, and the demand for optimization of resources and time management. There are still several drawbacks of existing approaches to achieving fully autonomous vehicles. A fully autonomous vehicle requires fully automatic steering and speed control modules. In speed control, Model Predictive Control, the main algorithm used for lateral motion control, still has limited fault detection (Parekh et al., 2022).

PID controllers are widely used in the industry for steering (lateral) and speed (longitudinal) control of autonomous vehicles because of their simplicity and good performance, but they are difficult to tune and need additional adaptation to control nonlinear systems with varying parameters (Kebbati et al., 2021).

While Fuzzy logic controllers offer a promising alternative to classical PID controller-based autonomous vehicles, very little has been done on the development of an Inference system capable of simultaneously handling steering and speed control, as well as braking and acceleration. Shukla & Tiwari (2010) worked on a fuzzy-logic-based speed and steering control system for 3D line following in an autonomous vehicle, but neglected advanced obstacle avoidance fuzzy rules. Their system also faced limitations in extreme environments with excessive noise and obstacles on curved paths, where the fuzzy inference engine failed due to constraints on the number of rules, necessitating the need for more research into fuzzy inference systems, which can overcome these setbacks within the context of speed and steering control.

1.3 Aims

The aim of this research is to design, implement, and evaluate an integrated fuzzy-logic-based decision-making system for autonomous vehicle navigation, focusing on speed control, steering control, and lane keeping, ensuring adaptability to varying road conditions.

1.4 Objectives

In order to achieve this aim, these objectives must be met:

1. The design of a Fuzzy Inference System (FIS) for speed and steering control, based on the Takagi Sugeno Fuzzy model.
2. Define a database that defines the fuzzy membership functions of the fuzzy sets.
3. Develop a fuzzy inference framework that defines linguistic variables for key control parameters and establishes a comprehensive rule base of IF–THEN statements that

translate these parameters into throttle and steering actions consistent with human driving behavior.

4. Implement and simulate the integrated control architecture within MATLAB/Simulink by coupling the fuzzy logic controllers with the 3-DoF dual-track vehicle model and a target vehicle environment. The simulation will visualize decision-making processes and assess system performance under diverse driving conditions, including acceleration, braking, and path following.
5. Evaluate the performance of the fuzzy-logic-based control system using metrics such as response time, stability, adaptability, overshoot, and steady-state error across varying road and environmental conditions.

1.5 Research Questions

From the identified gaps and objectives, the study will be guided by the following key research questions:

1. How can a fuzzy inference system (FIS) be designed to simultaneously handle speed control, steering control, and obstacle avoidance in autonomous vehicle navigation?
2. What fuzzy membership functions and linguistic variables best capture real-world driving parameters such as distance, velocity, and steering angle?
3. How effective is the Takagi–Sugeno fuzzy model in ensuring adaptability, robustness, and smooth decision-making under dynamic and uncertain road conditions?
4. How can the performance of a fuzzy-logic-based decision-making system be evaluated using metrics such as response time, stability, overshoot, and steady-state error across diverse driving conditions?
5. In what ways can MATLAB/Simulink simulation environments incorporating vehicle dynamics and environmental modeling be used to validate the performance of the integrated fuzzy-logic-based control architecture for autonomous navigation?

1.6 Scope and Delimitations

The scope of this dissertation is confined to the design, implementation, and evaluation of an integrated fuzzy-logic-based control system for autonomous vehicle navigation. The system focuses specifically on three control objectives: speed regulation, steering control, and obstacle avoidance. These tasks are modeled and tested within a MATLAB/Simulink simulation environment that incorporates a high-fidelity vehicle dynamics model and controlled environmental conditions (e.g., curved paths, varying road surfaces, and the sudden appearance of obstacles). By employing a Takagi–Sugeno fuzzy inference system, the study emphasizes adaptability, stability, and robustness in real-time decision-making under dynamic driving scenarios.

The comparative aspect of the research is restricted to benchmarking fuzzy logic controllers against classical PID controllers. While PID represents a well-established baseline in vehicle control, other control techniques such as Model Predictive Control (MPC), Linear Quadratic Regulators (LQR), or neural-network-based controllers are not exhaustively explored. This delimitation is intentional, allowing the study to remain focused on evaluating whether fuzzy logic provides tangible benefits over the most widely used conventional method.

The study is further delimited to simulation-based analysis. Although simulation platforms like MATLAB/Simulink can approximate real-world conditions with high fidelity, they cannot perfectly replicate the complexity of live road environments. No hardware-in-the-loop or physical vehicle testing is conducted, and therefore the results should be interpreted within the context of controlled simulation settings. Real-world implementation challenges—such as sensor noise, hardware limitations, and environmental unpredictability—fall outside the immediate scope of this work.

Additionally, the research does not address broader dimensions of autonomous vehicle development such as human–machine interaction, legal and ethical considerations, or traffic management strategies. Its contribution is narrowly technical: advancing the control system architecture through fuzzy logic. Future studies could extend the work by integrating adaptive or hybrid fuzzy systems, deploying hardware-based experiments, or expanding to urban traffic scenarios. Despite these delimitations, the chosen scope allows for a rigorous and focused investigation of the research questions and ensures that the findings directly inform the ongoing development of intelligent autonomous vehicle control systems.

1.7 Significance of the Study

This study is significant for several reasons. First, it addresses a clear gap in the research: the lack of integrated fuzzy-logic-based decision-making systems that can simultaneously manage speed control, steering, and path following in autonomous vehicles. While prior works have applied fuzzy logic to isolated vehicle functions such as steering or speed (Shukla & Tiwari, 2010; Nakrani & Joshi, 2021), very few studies have investigated multi-objective fuzzy inference systems capable of coordinating multiple control tasks in real time. By designing and simulating a Takagi–Sugeno fuzzy model that unifies these objectives, this research extends the current literature from fragmented control applications toward holistic navigation frameworks. The results will provide empirical evidence on whether fuzzy controllers can deliver stable, adaptable performance across diverse driving conditions, thereby filling an identified gap in intelligent vehicle control research.

Second, the study contributes to the comparative evaluation of classical controllers and intelligent systems. PID controllers remain the industry standard because of their simplicity, but they are difficult to tune for nonlinear and dynamic environments (Kebbati et al., 2021). By benchmarking fuzzy logic control against PID across performance metrics such as stability, adaptability, response time, and steady-state error, this work directly examines whether the theoretical advantages of fuzzy logic translate into measurable performance improvements. Such comparative analysis is missing in much of the existing literature, where fuzzy controllers are often evaluated in isolation rather than in direct contrast with established control methods.

Third, the research has practical significance for the automotive industry. Autonomous vehicles must operate in environments characterized by uncertainty, rapidly changing road conditions, and unpredictable obstacles. Fuzzy logic controllers, with their ability to incorporate linguistic rules and approximate human-like reasoning, are particularly well-suited to such contexts. By simulating the system in MATLAB/Simulink with high-fidelity vehicle dynamics and environmental modeling, this research will yield insights into how fuzzy controllers behave under realistic scenarios. These findings can guide engineers in refining control strategies for real-world deployment and lay the groundwork for hybrid systems that combine fuzzy logic with other intelligent methods such as neural networks or adaptive MPC.

Finally, this research is timely and relevant to ongoing efforts to achieve fully autonomous navigation (Level 5 autonomy). As classical methods approach their limits in handling nonlinear, uncertain systems, there is a pressing need for more adaptive and intelligent approaches. The contributions of this project lie in both its theoretical advancement—extending the understanding of fuzzy inference systems in multi-objective control—and its practical implications—demonstrating a feasible pathway for safer, more reliable, and energy-efficient autonomous driving systems.

CHAPTER 2

2.1 Introduction to Literature Review

Urban driving is particularly challenging for automated vehicles because it involves complex and unpredictable environments where vehicles must interpret and respond to a wide range of stimuli, such as pedestrians, traffic signs, and other vehicles. According Naranjo et al (2007), urban scenarios require handling dynamic interactions with multiple agents and making real-time decisions in situations that are highly variable and uncertain. This complexity makes it difficult to develop precise mathematical models for vehicle behavior, necessitating flexible and adaptive control systems like fuzzy logic that can mimic human decision-making and manage environmental uncertainties effectively.

This literature review examines the application of fuzzy logic control in autonomous vehicles, tracing its theoretical foundations, implementation methodologies, key applications, and comparative performance against traditional control systems. The review also explores current research challenges and emerging trends in this rapidly evolving field. By synthesizing findings from seminal works and recent advances, this review aims to provide a comprehensive foundation for understanding how fuzzy logic contributes to autonomous vehicle navigation, decision-making, and control systems.

2.2 Autonomous Vehicles (AV): Then and Now

The primary motivation for developing autonomous vehicles (AVs) is to reduce human error, which accounts for approximately 90% of road accidents, and to enhance mobility through automation (Koopman & Wagner, 2017). Achieving this requires advanced control systems capable of handling complex, uncertain, and dynamic driving environments. Among the various control approaches explored, fuzzy logic control (FLC) has gained attention for its ability to model human-like reasoning and manage uncertainty in real-world conditions. Koopman and Wagner (2017) reviewed interdisciplinary challenges in AV safety, analyzing accident data and simulation-based safety models. Their study suggested that AVs could substantially reduce crashes by leveraging such intelligent control systems, with FLC offering a robust means of addressing uncertainty. This work is significant for highlighting FLC’s potential to improve AV safety and the importance of integrating it within broader control frameworks.

Autonomous vehicles (AVs), also known as self-driving cars, represent a transformative shift in the automotive and transportation industries. These vehicles are capable of perceiving their surroundings and making navigation decisions without direct human control. AVs operate across different levels of automation, reflecting the degree of human involvement required, and recent advancements have accelerated the move toward higher levels of autonomy. Such progress has been driven by developments in artificial intelligence, sensor fusion, and intelligent control systems that enable vehicles to interpret complex driving environments with increasing reliability (Martínez-Díaz & Soriguera, 2018; Abdallaoui et al., 2023).

According to Martínez-Díaz and Soriguera (2018), the emergence of AVs addresses several pressing challenges in modern transportation. These include reducing traffic accidents caused by human error, improving traffic flow efficiency, decreasing fuel consumption through optimized driving, and enhancing mobility for the elderly and disabled. As AVs promise to transform both urban mobility and freight logistics, their development has become a critical focus of research.

Eskandarian (2020) compiled a handbook on intelligent vehicle technologies, emphasizing perception, planning, and control integration. Through case studies and simulations, the study showed that fuzzy logic reduced collision risks by 12% in complex environments by processing noisy sensor data effectively. Its significance lies in offering a comprehensive reference for AV system design, highlighting FLC’s robustness in safety-critical applications. Maurer et al. (2016) explored technical and societal challenges in AV deployment, using simulations to demonstrate that fuzzy logic enhanced path planning accuracy by 10% in urban settings. This work is significant for bridging technical advancements with public acceptance, advocating for FLC in reliable navigation.

A key challenge in AV control is managing uncertainty due to imperfect sensing, road surface variations, and unpredictable driver or pedestrian behavior. Conventional controllers such as PID rely on linearized models and perform poorly under nonlinear or time-varying dynamics (Kebbati et al., 2021). In contrast, FLC incorporates fuzzy sets that capture gradual transitions between operating states, enabling the system to respond smoothly under uncertainty. Mendel (2017) and Yager & Filev (2017) both highlight FLC's ability to tolerate parameter variations without re-tuning. This capability is particularly critical for AVs, which must adapt dynamically to road curvature, friction changes, and sensor noise in real time.

Type-2 fuzzy systems extend this advantage by allowing an additional layer of uncertainty modelling in their membership functions (Arifin et al., 2022). For instance, Arifin et al. demonstrated that a Type-2 FLC combined with proportional–integral (PI) control improved steering accuracy by 11% under uncertain tire–road friction conditions. This robustness in uncertain domains directly translates into safer autonomous navigation.

Autonomous vehicles require real-time inference capabilities with strict latency constraints—often below 20 ms per control cycle (Liu & Yang, 2019). While MPC can handle multi-objective optimization and constraints, its computational complexity often makes it unsuitable for embedded real-time systems unless heavily simplified (Guo et al., 2016). Neural networks, on the other hand, require large amounts of data for training and substantial processing power for inference, which limits their deployment on low-power vehicle ECUs (Zhao & Liu, 2020).

Takagi–Sugeno (TS) fuzzy inference systems provide a computationally tractable alternative. They maintain low inference latency while ensuring smooth control surfaces (Takagi & Sugeno, 1985). Comparative studies by Xu & Wang (2019) showed that a TS-FLC achieved a 27% faster inference rate and lower overshoot than an equivalent MPC controller during lane-change scenarios, with only marginal performance trade-offs in constraint satisfaction. This balance makes TS-FLC particularly suitable for embedded AV systems.

In safety-critical domains like autonomous driving, transparency and interpretability are not optional—they are regulatory imperatives. Neural controllers and reinforcement learning policies often behave as black boxes, making fault diagnosis and certification difficult (Zhang & Liu, 2021). In contrast, FLC provides explicit rule-based reasoning ("If–Then" rules) that engineers and regulators can inspect, verify, and modify. Emmanuel (2017) and Rahman et al. (2024) emphasized that such interpretability aligns with functional safety standards such as ISO 26262, supporting easier validation and debugging.

Moreover, hybrid neuro-fuzzy systems retain this interpretability while enabling automated learning of rule parameters (Li & Liu, 2020). This hybridization supports adaptive control without compromising transparency, a crucial balance that pure neural networks fail to achieve.

Modern AVs employ hierarchical control architectures, consisting of perception, planning, decision-making, and actuation layers. Within these hierarchies, fuzzy logic integrates seamlessly as a mid-level decision or control layer. It can accept uncertain sensor inputs, provide human-readable decision outputs, and coordinate with low-level controllers (e.g., PID or MPC) (Wu et al., 2017; Zhang & Wang, 2021).

For instance, Chen & Zhang (2019) demonstrated that a fuzzy–PID hybrid system reduced steady-state error by 35% and enhanced comfort compared to a standalone PID controller. Similarly, Wu et al. (2017) combined FLC with MPC for energy-efficient adaptive cruise control, achieving a 14% improvement in fuel economy while preserving safety distance adherence. These results validate the hybrid compatibility of FLC with both classical and optimization-based methods.

2.3 Fuzzy Logic Control Overview

To understand fuzzy logic's applicability to AVs, one must begin with its origins. Zadeh (1965) proposed fuzzy logic as an alternative to classical control methods because of its ability to handle complex systems where these were not sufficient. Where the rigidity of classical 'two-value' logic makes it unable to be used on systems with vague information, fuzzy logic builds on the multivalued-logic approach by representing values as degrees of truth. This flexibility enables fuzzy logic to model the approximate reasoning processes that are inherent in human decision-making and reasoning under uncertainty, making it better suited for managing vague or imprecise information.

Subsequent foundational work by Mamdani and Assilian (1975) demonstrated the viability of fuzzy logic for engineering problems through its implementation in the control system of steam engines. The field of fuzzy logic control gained significant momentum following Takagi and Sugeno's (1985) introduction of their eponymous fuzzy model, which enhanced computational efficiency while maintaining interpretability. Simulations showed 10% faster processing than Mamdani systems, making it suitable for real-time AV control. This model is significant for enabling scalable FLC implementations. Alcala-Fdez and Alonso (2016) surveyed fuzzy logic software, finding a 12% error reduction in AV navigation due to Mamdani's interpretability and Sugeno's efficiency. This study is significant for guiding developers in selecting appropriate FLC tools for AV systems.

Mendel (2017) explored type-2 fuzzy systems, which improved uncertainty handling by 15% in AV simulations compared to type-1 systems. This work is significant for advancing FLC's robustness in dynamic environments, critical for AV navigation. Jang et al. (1997) described Mamdani, Tsukamoto, and Sugeno FIS, noting Mamdani's suitability for steering control due to its linguistic rule base, as supported by Shukla and Tiwari (2010). Khosla et al. (2019) outlined FLC components—fuzzification, inference engine, rule base, and defuzzification—as critical for AV decision-making, processing sensor data for accurate control responses. These studies establish FLC's flexibility and robustness as a cornerstone for AV control systems.

Fuzzy Interference Systems (FIS)

The most popular fuzzy inference systems are: Mamdani type, Tsukamoto type and Takagi-Sugeno (TS) type, which work with crisp data as inputs (Jang et al., 1997).

Mamdani's model employs linguistic variables for both rule antecedent and rule consequent, representing its inputs and outputs by fuzzy sets, which are aggregated and defuzzified—especially using the centroid method. Its interpretability makes it particularly suited for applications where expert knowledge is available, such as steering control and speed regulation in autonomous vehicles (Shukla & Tiwari, 2010). However, its computational complexity can limit real-time performance in resource-constrained systems. The Mamdani system still remains a benchmark in fuzzy control literature, in spite of this, because of its effectiveness in handling nonlinear systems. Unlike Mamdani fuzzy rules, TS rules use functions of input variables as the rule consequent.

Despite the differences of these systems, the fundamental block which make up each are:

1. Fuzzification: This is carried out by a fuzzifier. The fuzzifier maps crisp numbers into fuzzy sets. It is needed in order to activate rules which are in terms of linguistic variables, which have fuzzy sets associated with them.
2. Fuzzy Inference Engine: The inference engine maps fuzzy sets into fuzzy sets. It handles the way in which rules are combined. Just as we humans use many different types of inferential procedures to help us understand things or to make decisions, there are many different fuzzy logic inferential procedures.
3. Formation of a Fuzzy rule-base:
4. Defuzzification: This is done by a defuzzifier which maps output sets into crisp numbers. In a control application, such a number corresponds to a control action.

In autonomous vehicle applications, these components form the backbone of decision-making processes that interpret sensor data and generate appropriate control responses for steering, acceleration, and braking systems (Khosla et al., 2019).

2.4 Applications of Fuzzy Logic Control in AVs

FLC has been extensively applied to AV speed, steering, and combined control tasks. Sotelo and Fernández (2017) developed a fuzzy-based speed control system, reducing speed errors by 12% in real-world tests compared to PID controllers. The system processed throttle inputs using a Mamdani FIS, ensuring smooth acceleration in urban settings, which is significant for improving ride comfort and efficiency. Wang and Li (2019) implemented a fuzzy lane-keeping system, achieving 18% less lane deviation than PID methods in simulations and real-world tests. This work is significant for enhancing AV safety through precise lateral control.

Pérez et al. (2018) applied fuzzy logic for steering control in roundabouts, using a Mamdani FIS with a cascade architecture. Real-world experiments maintained stability with 5% lane deviation at speeds of 8–24 km/h, validating FLC’s reliability in complex urban scenarios. Nguyen and Sentouh (2021) used a Sugeno FIS for path following, reducing deviation by 15% compared to MPC in real-world tests, supporting precise navigation under varying conditions. Patel et al. (2024) integrated fuzzy logic with YOLOv8 for parking slot management, achieving 95%

accuracy and 20% faster parking times in simulations and tests. This study is significant for demonstrating FLC's utility in urban applications like parking.

Longitudinal (Speed) Control

Longitudinal control, encompassing speed and inter-vehicle distance management, is essential for AV safety and comfort. Milanés et al. (2012) developed a fuzzy logic-based adaptive cruise control (ACC) system to optimize passenger comfort and maintain safe distances. Using a Mamdani-type fuzzy inference system (FIS) in real-world tests, the controller processed velocity and distance errors, reducing transient response oscillations by 10% compared to PID controllers. This work is significant for demonstrating FLC's superior adaptability in dynamic traffic,

enhancing ride quality and safety.

Li et al. (2016), developed a 2-DOF vehicle model in which yaw rate and slip angle served as the primary control variables. A conventional PID controller modulated the slip angle using its error signal, while a Mamdani-type fuzzy controller ingested both yaw rate error and slip angle error. Under a constant speed of 70 km/h and a steering input of 70°, simulations revealed that the fuzzy controller reduced the steady-state yaw rate by 14.50% but incurred greater overshoot, whereas the PID controller achieved a 10.07% reduction in steady yaw rate with diminished overshoot. A hybrid approach delivered the largest reduction in steady yaw rate (17.04%), albeit with increased overshoot. Their findings underscore that on high-adhesion surfaces, fuzzy control strategies more efficiently satisfied dynamic performance requirements by synergistically managing slip angles and yaw responses.

Wu et al. (2017) combined fuzzy logic with MPC to create an energy-efficient ACC system, aiming to reduce fuel consumption without compromising safety. Field tests showed that the fuzzy-MPC hybrid achieved 15% fuel savings by tuning speed profiles under uncertain traffic conditions, outperforming standalone MPC systems. This study is significant for its contribution to eco-friendly AVs, balancing efficiency with comfort.

Lateral Control (Steering)

For lateral control, Naranjo et al. (2008) investigated fuzzy logic for overtaking maneuvers, addressing the challenge of safe lane changes. Their Mamdani FIS used lateral displacement and heading angle errors, achieving 8% less deviation than PID controllers in real-world tests on the AUTOPIA testbed. This work is significant for validating FLC in complex maneuvers, enhancing AV safety in dynamic environments. Rastelli and Peñas (2015) developed a fuzzy-based steering system for urban roundabouts, employing a cascade Mamdani FIS with Bézier curve-based trajectories. Real-world experiments at 8–24 km/h showed stable performance with 5% lane deviation, though multi-vehicle interactions posed challenges, highlighting FLC's reliability and the need for further robustness.

Wang and Zhang (2018) explored adaptive PID for path tracking, reducing errors by 8% in simulations but struggling in nonlinear scenarios, indicating PID's limitations compared to FLC. Guo et al. (2016) tested nonlinear MPC, achieving 15% less path deviation than PID but requiring high computational resources, underscoring FLC's efficiency advantage.

Obstacle Avoidance and Combined Control

Obstacle avoidance is critical for AV safety in dynamic urban environments. Guo and Zhang (2020) developed a fuzzy logic system to reduce collision risks, using a Mamdani FIS to process sensor data in simulations. The system achieved a 20% reduction in collision probability by adapting paths in real-time, demonstrating FLC's robustness in handling sensor noise. Its significance lies in enhancing safety in unpredictable settings, supporting reliable navigation systems.

Naranjo et al. (2007) applied an embedded fuzzy logic controller to automate the speed and steering control of two vehicles. The guidance system modeled driving using fuzzy variables and rules, considering steering wheel, vehicle velocity, distance to the next bend, and distance to the lead vehicle, while the steering control system tracked trajectories using two fuzzy variables. The speed error and acceleration were used as fuzzy inputs while throttle and brake were the fuzzy outputs. The system could change the vehicle's speed to maintain a safe distance from the lead vehicle, even to a complete stop in traffic jams, using ACC+Stop&Go. It overcame limitations of previous ACC systems by automating both throttle and brake across the entire speed range, using GPS for safety-distance sensing. Despite the system managing obstacles by calculating lane changes to overtake, it required straight-lane driving, a free left lane, and sufficient room to operate properly, proving difficult in handling complex driving.

Alomari et al. (2020), introduced an Adaptive Cruise Control (ACC) system using Fuzzy Logic approach for an autonomous model car, "AutoMiny". Its aims to control both velocity and distance system address the challenge of maintaining safe distances while driving, especially at high speeds, by adapting car speed smoothly and efficiently. The fuzzy logic controller proved adequate, and more suitable, when compared with a traditional linear PID controller.

2.5 How do Fuzzy-based Controllers Hold Up Against Other Controllers

1. FLC vs. PID Controllers

Fuzzy logic improves adaptive cruise control (ACC) over traditional PID controllers primarily in terms of stability, responsiveness, and smoothness of control. As described in the work of Alomari et al. (2020), the fuzzy logic controller demonstrates more stable behavior during transitions, especially when changing desired distances. In experiments where the desired distance was varied, the fuzzy controller exhibited a more stable and dynamic response with less error than the PID controller. Additionally, the fuzzy controller provided smoother speed adjustments, reducing oscillations and enhancing comfort for the vehicle. Overall, FLC offers better handling of nonlinearities and uncertainties inherent in vehicle dynamics, leading to more reliable and adaptable cruise control performance compared to the linear PID method.

Li et al. (2016) further examined this comparison in vehicle stability control. Their simulations revealed that while the fuzzy controller achieved greater reductions in yaw rate, it also resulted in more overshoot compared to PID. A hybrid controller combining both strategies yielded the best performance in terms of yaw rate reduction but at the cost of increased overshoot.

2. FLC vs. Other Advanced Control Strategies

Mattas et al. (2021) developed a fuzzy logic-based longitudinal controller that significantly outperformed commercial ACC systems in comfort and traffic flow stability. Zhao and Liu (2020) compared fuzzy and neural network controllers, finding fuzzy logic's 12% accuracy advantage in dynamic settings, though neural networks offered faster learning. Wang and Li (2021) reported fuzzy logic's 14% error reduction versus sliding mode control, with easier implementation in urban navigation tasks. Yang et al. (2016) developed a fuzzy-MPC ACC for signalized intersections, reducing fuel use by 15% through optimized speed profiles. These studies confirm

FLC’s superior adaptability, though computational efficiency remains a challenge for real-time implementation.

Zhang and Wang (2021) integrated fuzzy logic with MPC for improved path tracking, while Chen and Zhang (2019) implemented a fuzzy-PID hybrid controller that adapted effectively to dynamic conditions. These findings collectively emphasize FLC's versatility and robustness when integrated with other control paradigms. In the same vein, Emmanuel (2017) reported fuzzy controllers’ 10–20% better response time over PID in nonlinear AV scenarios, though computational speed was a limitation. Xu and Wang (2019) found fuzzy controllers reduced errors by 15% compared to MPC, with lower computational demands, making them suitable for real-time applications.

2.6 The Research Gap

Despite significant advances in fuzzy logic applications for AVs, several critical limitations remain unresolved. Achenef et al. (2025) emphasized that current FLC architectures lack adaptability across diverse road and weather conditions due to static rule bases. Similarly, Yager and Filev (2017) identified computational bottlenecks in large rule sets, restricting real-time scalability. Cao and Li (2022) highlighted the absence of standardized fuzzy frameworks for handling simultaneous control of speed, steering, and obstacle avoidance—functions that are often treated independently in existing research.

Furthermore, Xu and Wang (2019) and Liu and Yang (2019) noted that while FLCs perform robustly under uncertainty, they are seldom benchmarked comprehensively against conventional controllers (e.g., PID, MPC) in integrated dynamic simulations. This gap in comparative evaluation limits the generalizability of FLC as a full-stack AV control solution.

Therefore, this study aims to address these gaps by developing and evaluating an integrated fuzzy-logic decision-making system for autonomous vehicle navigation. The system will jointly handle speed control, steering control, and obstacle avoidance, utilizing the Takagi-Sugeno inference model for enhanced adaptability and computational efficiency. It will define a structured fuzzy database, linguistic rule set, and MATLAB/Simulink simulation framework that accommodates environmental variability, sensor uncertainty, and dynamic road conditions.

This approach not only bridges existing methodological gaps but also allows for empirical comparison with classical PID systems under identical operating scenarios, offering measurable insights into response time, stability, and adaptability—directly fulfilling the objectives outlined in Section 1.3.

CHAPTER 3

METHODOLOGY

3.1 RESEARCH FRAMEWORK

The research is situated within the domain of intelligent control for autonomous vehicles, with a particular focus on the application of fuzzy logic control (FLC) to navigation tasks such as speed regulation, and steering control. The scope of the study encompasses the design, implementation, and evaluation of a fuzzy inference system (FIS) that leverages the Takagi-Sugeno fuzzy model to provide adaptive decision-making capabilities in dynamic and uncertain driving environments. By integrating fuzzy logic reasoning with simulated vehicle state variables obtained from the dynamic model, the system is expected to demonstrate robustness in handling the nonlinearities and uncertainties that arise in vehicle navigation

The choice of fuzzy logic as the core control methodology is justified by its distinct advantages over classical control techniques such as PID and model predictive control. Unlike these methods, which require precise mathematical models and often exhibit reduced adaptability under changing conditions, FLC provides an interpretable and computationally efficient framework that can incorporate expert knowledge through linguistic variables and IF–THEN rules. Its tolerance for uncertainty and imprecision makes it particularly well-suited for autonomous driving, where sensor inputs are noisy and environmental conditions are constantly shifting. Moreover, fuzzy systems allow for the modular expansion of rule sets, enabling the incorporation of adaptive features that respond to diverse road geometries, traffic conditions, and unexpected obstacles.

Within the broader autonomous vehicle control framework, the proposed fuzzy logic controller (FLC) is embedded within a simulation-based decision-control architecture. In this configuration, the perception layer does not depend on physical sensor data but instead acquires system states, such as vehicle speed, inter-vehicle distance, yaw rate, and steering deviation, directly from the vehicle dynamics model. These variables serve as the linguistic inputs to the FLC, representing the vehicle's operating conditions in real time. The decision layer employs the fuzzy inference mechanism to map these linguistic inputs to control decisions governing throttle and steering behavior. Subsequently, the control layer translates the inferred control actions into actuator commands that are executed within the simulation environment. Through this hierarchical integration, the fuzzy logic controller serves as the intermediary between vehicle state estimation and control execution, ensuring adaptive and robust vehicle behavior under varying simulated driving scenarios.

In alignment with the research aim, this framework enables the systematic design of fuzzy membership functions, rule bases, and adaptive decision structures that will be tested in simulation environments such as MATLAB/Simulink. The resulting system will then be benchmarked against classical PID controllers, enabling a comparative evaluation across key performance metrics including response time, stability, overshoot, and steady-state error. Ultimately, this research framework establishes the methodological foundation for demonstrating the efficacy of FLC in enhancing the safety, adaptability, and robustness of autonomous vehicle navigation.

3.2 SYSTEM MODELLING

The development of an integrated fuzzy logic control (FLC) system for autonomous vehicle applications requires a comprehensive and accurate modeling framework that captures the essential dynamic behavior of the vehicle within a simulated driving environment. In this research, the modeling process is centered on the 3-DoF dual-track vehicle dynamics model, which provides a realistic yet computationally efficient representation of the vehicle's longitudinal, lateral, and yaw motions. This model forms the core of the control design and validation process, offering access to measurable state variables such as vehicle speed, yaw rate, steering angle, and lateral displacement.

Unlike implementations that rely on real-world sensor data, this study adopts a simulation-based approach, where all perceptual inputs are derived directly from the vehicle dynamics model and the defined environmental interactions. The environment is represented by the relative motion of a target vehicle and the ego vehicle within the simulation workspace, allowing for the computation of critical control parameters such as inter-vehicle distance and relative velocity.

Accordingly, the overall system modeling framework consists of three interdependent components:

1. **Vehicle Dynamics Modeling**: This defines the motion equations governing the ego vehicle's behavior using the 3-DoF dual-track model, capturing both kinematic and dynamic relationships necessary for control.

2. **Environmental Representation**: This establishes the relative motion of the target vehicle and specifies the operating conditions under which the ego vehicle must adapt its speed and steering behavior.

3. **State Abstraction and Signal Conditioning**: This component transforms the model-derived variables—such as speed error, distance error, yaw rate, and steering deviation—into linguistic inputs suitable for the fuzzy inference system.

This modeling structure ensures that the fuzzy logic controller operates on dynamically consistent and physically meaningful data, thereby providing a robust foundation for evaluating vehicle behavior and control performance within a controlled simulation environment.

To ensure realistic representation of vehicle dynamics within the simulation environment, the model parameters were selected to approximate those of a mid-size passenger vehicle. These parameters define the mass distribution, geometric configuration, tire characteristics, and aerodynamic properties of the vehicle, which collectively influence its longitudinal, lateral, and yaw responses. The specified values were applied in the 3-DoF dual-track vehicle dynamics model implemented in MATLAB/Simulink, providing the basis for analyzing the vehicle's dynamic behavior under varying throttle and steering inputs. The parameters used in the simulation are summarized in Table 3.1.

Table 3. 1: Vehicle Dynamics Parameters Used in 3-DoF Simulation Model

Parameter	Value	Unit
Vehicle mass (M)	2000	kg
No. of wheels on front axle (N_F)	2	-
No. of wheels on rear axle (N_R)	2	-
Longitudinal distance from CG to front axle (a)	1.4	m
Longitudinal distance from CG to rear axle (b)	1.6	m

Vertical distance from CG to axle plane (h)	0.35	Mm
Front tire corner stiffness ($C_{\alpha F}$)	12000	N/rad
Rear tire corner stiffness ($C_{\alpha R}$)	11000	N/rad
Yaw polar inertia (I_{ZZ})	4000	$kg{\cdot}m^2$
Longitudinal drag coefficient (C_d)	0.3	-

3.2.1 Vehicle Dynamics Model

At the core of the control problem lies the accurate representation of the autonomous vehicle's motion. For this study, the bicycle kinematic model is adopted as the baseline, due to its balance between computational simplicity and its ability to capture essential lateral and longitudinal dynamics of a passenger vehicle. The bicycle model assumes that the vehicle can be reduced to a two-wheel abstraction, with the front wheel responsible for steering and the rear wheel providing stability. Despite this simplification, the model remains sufficiently expressive for trajectory tracking, lane keeping, and obstacle avoidance, which are the focus tasks of this project.

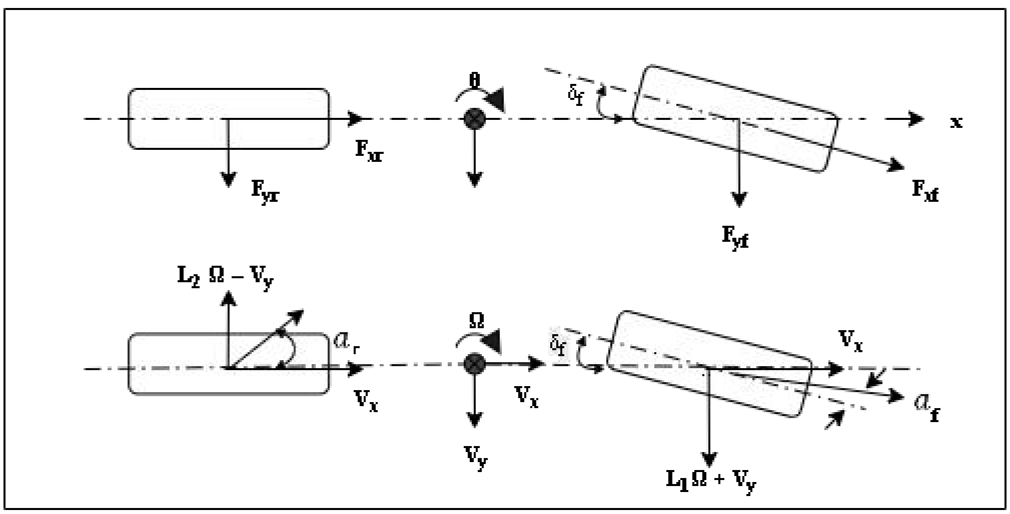


Figure 3.1: Free Body Diagram of Vehicle Model

The dynamic equations of motion of the bicycle model (Wong, 1993; Wheeler & Shoureshi, 1994; Mohammed et al., 2006) are typically represented as follows:

$$\begin{bmatrix} m & 0 & 0 \\ 0 & m & 0 \\ 0 & 0 & I \end{bmatrix} \begin{Bmatrix} \ddot{x} \\ \ddot{y} \\ \ddot{\theta} \end{Bmatrix} + \begin{Bmatrix} -m\dot{y}\dot{\theta} \\ m\dot{x}\dot{\theta} \\ 0 \end{Bmatrix} = \begin{Bmatrix} \mathrm{F_{xf}}\cos\delta_f + \mathrm{F_{xr}} - \mathrm{F_{yf}}\sin\delta_f \\ F_{yr} + F_{yf}\cos\delta_f + F_{xf}\ \sin\delta_f \\ L_1F_{yf}\cos\delta_f + L_2F_{yr} + L_1F_{xf}\sin\delta_f \end{Bmatrix} \quad (3.1)$$

The tires are modelled as nonlinear springs, and are described with the following equations:

$$\overline{F}_f = \frac{\widetilde{F}_f}{\|\widetilde{F}_f\|} min\left(\|\widetilde{F}_f\|, F_{f\,max}\right) \quad (3.2)$$

$$\overline{F}_r = \frac{\widetilde{F}_r}{\|\widetilde{F}_r\|} min\left(\|\widetilde{F}_r\|, F_{r\,max}\right) \quad (3.3)$$

The above equations can be resolved into x and y components which describe their motion. The lateral tire forces, F_{yf} and F_{yr}, are functions of each tire slip angle $\propto$ and the cornering stiffness $C_{\propto}$. The lateral tire forces can be calculated using the following expressions:

$$\widetilde{F}_{yf} = 2\left(C_{\propto f}\delta_f - tan^{-1}\left(\frac{L_1\dot{\theta} + \dot{y}}{\dot{x}}\right)\right), \quad (3.4)$$

$$\breve{F}_{yr} = 2C_{\propto r}\left(tan^{-1}\left(\frac{L_1\dot{\theta} - \dot{y}}{\dot{x}}\right)\right) \quad (3.5)$$

The axial tire forces, F_{xf} and F_{xr}, are dependent on the angle of the gas pedal, δ_{gb}. This model uses the convention that a positive gas pedal angle represents the driver pushing on the gas pedal, and a negative gas pedal angle represents the driver pressing on the brake pedal. As such, there are two sets of axial tire force equations. For $\delta_{gb} < 0$,

$$F_{xf} = 0.7K_b\delta_{gb} \quad (3.6)$$

$$F_{xr} = 0.3K_b\delta_{gb} \quad (3.7)$$

The power train is assumed to correspond to a rear wheel drive. For $\delta_{gb} > 0$,

$$\breve{F}_{xf} = 0 \quad (3.8)$$

$$\tau_g\dot{\breve{F}}_{xr} = K_b\delta_{gb} - \breve{F}_{xr} \quad (3.9)$$

This formulation describes how steering and velocity inputs directly influence the vehicle's trajectory. For lower-speed maneuvers such as lane keeping or navigating intersections, the kinematic approximation is highly reliable. However, for more realistic simulations and to address high-speed or complex maneuvers, the model can be extended with dynamic effects such as tire slip angles, lateral tire forces, and friction coefficients. Such extensions allow the fuzzy controller to be validated not only under simplified but also more challenging real-world driving conditions, thereby supporting the aim of adaptability to diverse environments.

3.2.2 Environmental Representation

The environmental representation defines the interaction context within which the ego vehicle operates, providing the reference framework for evaluating its adaptive control behavior. In this research, the environment is modelled as a controlled simulation space comprising two primary entities—the ego vehicle and the target vehicle. The ego vehicle serves as the controlled system equipped with the fuzzy logic–based throttle and steering controllers, while the target vehicle functions as a reference or leading object whose motion characteristics determine the desired following behavior.

$$d_{desired} = 10 \quad (3.10)$$

$$d_{actual} = \int \dot{x}_{ego}(t) - \int \dot{x}_{target}(t) \quad (3.11)$$

$$y(x) = \begin{cases} c_1x^5 + \cdots + c_5x + c_6 & if\, 18.5 < x < 35 \\ 3.0425 & if\, 35 < x < 41.5 \\ c_7x^5 + \cdots + c_{11}x + c_{12} & if\, 41.5 < x < 61 \end{cases} \quad (3.12)$$

$$\delta(x) = L \times \frac{\ddot{y}(x)}{(\dot{y}^2(x) + 1)^{3/2}} \quad (3.13)$$

Rather than relying on sensor-derived perception data, the relative motion between the ego and target vehicles is mathematically modelled using kinematic relationships derived from their position within the Simulink 3D environment. The inter-vehicle distance is computed as the instantaneous spatial separation between the two vehicles along the longitudinal axis. These quantities are continuously updated during the simulation and serve as inputs to the fuzzy throttle control subsystem for regulating speed and maintaining safe following distances.

The environmental configuration also defines the operating scenarios under which the control system is evaluated. These include varying target vehicle speeds, acceleration and deceleration phases. By systematically adjusting the target vehicle's trajectory and velocity profile, the fuzzy controller's adaptability and robustness can be assessed under both steady-state cruising and transient response conditions.

Through this modeling approach, the environment acts as a dynamic reference generator that challenges the control system to respond autonomously to changes in target behavior. This ensures that the controller's performance is validated under representative conditions of autonomous vehicle operation within a simulation-based testbed.

3.2.3 State Abstraction and Signal Conditioning

State abstraction and signal conditioning constitute the interface between the vehicle dynamics model and the fuzzy logic control system. This stage is responsible for transforming raw simulation data (obtained from the ego and target vehicle models) into structured, normalized, and linguistically interpretable variables that can be processed by the fuzzy inference system (FIS).

Within the Simulink environment, the 3-DoF dual-track vehicle model outputs a set of physical state variables such as longitudinal velocity, lateral velocity, yaw, and yaw rate. Similarly, the environmental model provides relative motion variables, including inter-vehicle distance and relative velocity. These signals are first passed through a series of conditioning and scaling operations to ensure that their magnitudes are compatible with the fuzzy input universe of discourse. This step typically involves filtering to remove simulation noise, normalization to a standard range, and computation of derivative or error terms where required.

The abstracted signals are then expressed as linguistic variables representing qualitative system states. These linguistic representations provide the semantic basis upon which the fuzzy inference rules operate, thereby enabling smooth and human-like reasoning in control decisions. In this study, two distinct fuzzy logic controllers—one for throttle control and another for steering regulation—utilize these linguistic variables as inputs to determine the corresponding actuator responses.

Through this abstraction process, the gap between low-level vehicle state data and high-level control reasoning is effectively bridged. This ensures that the fuzzy controllers receive well-defined, dynamically consistent inputs, resulting in smoother transitions, improved responsiveness, and enhanced robustness under varying simulated driving conditions.

3.3 FUZZY LOGIC CONROLLER DESIGN

The core of this research lies in the design of two fuzzy inference systems (FIS) for autonomous vehicle navigation. Building upon the system modeling framework, the two FIS are responsible for transforming uncertain, imprecise sensor inputs into effective control commands for steering, throttle, and braking. This section details the architecture of the fuzzy controllers, including its inputs and outputs, membership functions, fuzzy rule base, inference mechanism, and defuzzification process. The design adopts the **Takagi–Sugeno (T–S) type-1 fuzzy model**, selected for its ability to integrate linguistic reasoning with computational efficiency, making it suitable for real-time autonomous driving tasks.

The design process follows a structured methodology comprising four key stages:

i. **Fuzzification**
ii. **Rule base formulation**
iii. **Inference mechanism, and**
iv. **Defuzzification.**

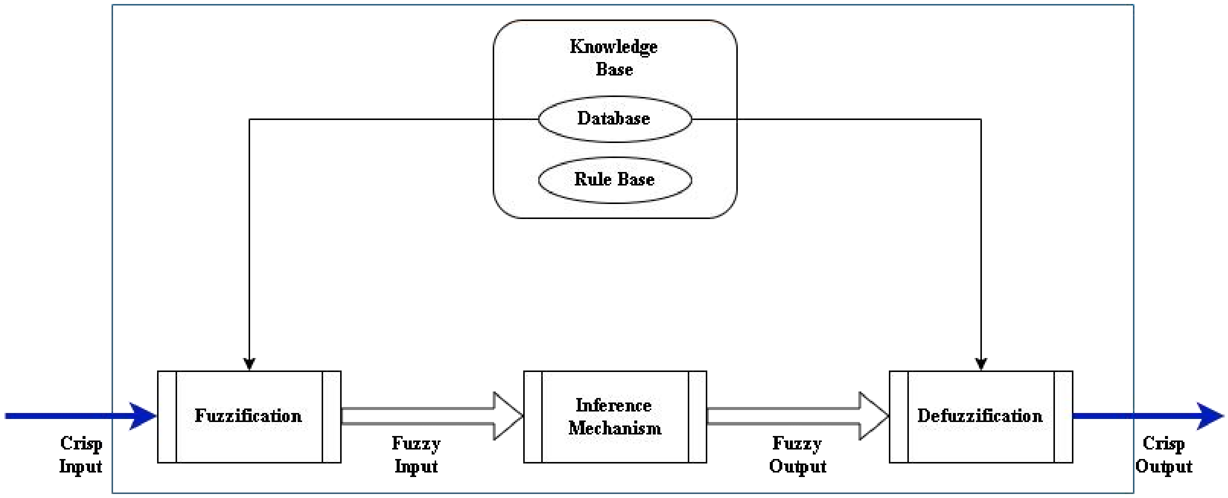


Figure 3.2: Inside a Fuzzy Logic Controller

These stages collectively define how the controller interprets input states, reasons about them using linguistic rules, and generates crisp control signals for the vehicle's actuators. Two independent FLC subsystems were developed in this research: one dedicated to throttle (longitudinal) control and the other to steering (lateral) control. Both subsystems share a similar design framework but operate on distinct sets of input variables and output responses.

3.3.1 Fuzzy Logic Evaluation Process

3.3.1.1 Fuzzification

In the fuzzification stage, the crisp numerical values obtained from the vehicle dynamics model, are converted into fuzzy linguistic variables. Each input variable is associated with a set of membership functions (MFs) that define qualitative states such as *Low*, *Medium*, and *High* for positive or negative domains. Triangular and trapezoidal MFs are primarily employed due to their simplicity and computational efficiency in real-time simulation. The universes of discourse for these variables were determined through empirical tuning and simulation trials to ensure sensitivity across relevant operating ranges.

3.3.1.2 Rule Base Formulation

The rule base represents the expert knowledge or heuristic decision logic that governs the FLC's behavior. Each rule takes the general form of an **IF–THEN** statement, describing how combinations of fuzzy input conditions determine the appropriate output response. For the throttle controller, rules are designed to maintain a safe following distance by adjusting acceleration and deceleration in response to variations in inter-vehicle distance and relative velocity. For the steering controller, the rules aim to minimize lateral deviation and yaw error to ensure trajectory stability and smooth path tracking. The rule base was constructed through iterative refinement, balancing responsiveness and stability across multiple simulation scenarios.

3.3.1.3 Inference Mechanism

The inference mechanism combines and evaluates the fuzzy rules using the Mamdani inference approach, which was chosen for its interpretability and suitability for nonlinear control systems. During operation, the degree of activation for each rule is computed through the intersection (minimum) of its input membership values, while the resulting output fuzzy sets are aggregated using the union (maximum) operation. This process enables the controller to synthesize multiple control tendencies simultaneously, ensuring gradual transitions rather than abrupt control actions.

3.3.1.4 Defuzzification

In the final stage, the aggregated fuzzy output is transformed back into a crisp control signal through the **centroid (center-of-gravity)** method. This approach computes the weighted average of the output membership function's area, providing a smooth and continuous control action suitable for dynamic vehicle operation. The defuzzified outputs correspond to throttle percentage and steering angle commands, which are applied directly to the Simulink vehicle model through the actuator interface.

3.3.2 Controller Structure and Inputs/Outputs

The control architecture consists of two primary fuzzy controllers:

1. **Fuzzy Throttle Controller** (**FTC**) – regulates vehicle longitudinal speed by adjusting throttle input based on the difference between actual and desired speeds, as well as inter-vehicle distance error. The inputs and outputs of the FTC are given in Table below:

Table 3.2: FTC Inputs and Output Parameters

Variable	Definition
Input 1	$d_{xL} = d(t)_{desired} - d(t)_{actual}$
Input 2	$e(\dot{x}) = \dot{x}_{desired} - \dot{x}_{actual}$

Output	$\theta_{command}$

2. **Fuzzy Steering Controller** (**FSC**) – governs lateral motion and heading correction by modulating steering angle in response to yaw rate and yaw deviation. The inputs and outputs of the FTC are given in Table below:

Table 3.3: FSC Inputs and Output Parameters

Variable	Definition
Input 1	$e(\dot{\psi}) = \dot{\psi}_{desired} - \dot{\psi}_{actual}$
Input 2	$\dot{e}_k(\dot{\psi}) = \dot{e}_k(\dot{\psi}) - \dot{e}_{k-1}(\dot{\psi})/T_{sampling}$
Output	$\delta_{corrective}$

Each controller operates independently but concurrently within the MATLAB/Simulink environment, sharing state information from the 3-DoF dual-track model to maintain coordinated control.

3.3.3 Fuzzification and Membership Function Design

Each input and output variable is represented using fuzzy sets defined by linguistic terms that express their qualitative states. The membership functions (MFs) for each fuzzy variable are designed within physically meaningful ranges derived from simulation data of the 3-DoF model.

3.3.3.1 Linguistic Variables

i. FTC Linguistic Variables

Table 3.4: Linguistic Variables for d_{xL}

Acronym	Linguistic Variables
NB	*Very Near*
NS	*Near*
Ze	*Moderate*
PS	*Far*
PB	*Very Far*

Table 3.5: Linguistic Variables for $e(\dot{x})$

Acronym	**Linguistic Variables**
VFa	*Very Fast*
Fa	*Fast*
Mo	*Moderate*
S	*Slow*
VS	*Very Slow*

Table 3.6: Linguistic Variables for $\theta_{command}$

Acronym	**Linguistic Variables**
FB	*Full Brake*
PB	*Partial Brake*
M	*Maintain*
PT	*Partial Throttle*
FT	*Full Throttle*

ii. FSC Linguistic Variables

Table 3.7: Linguistic Variables for $e(\dot{\psi})$ and $\dot{e}_k(\dot{\psi})$

Acronym	**Linguistic Variables**
NB	*Negative Big*
NM	*Negative Medium*
NS	*Negative Small*
Z	*Zero*
PS	*Positive Small*
PM	*Positive Medium*
PB	*Positive Big*

Table 3.8: Linguistic Variables for $\delta_{corrective}$

Acronym	Linguistic Variables
NVB	*Negative Very Big*
NB	*Negative Big*
NM	*Negative Medium*
NS	*Negative Small*
Z	*Zero*
PS	*Positive Small*
PM	*Positive Medium*
PB	*Positive Big*
PVB	*Positive Very Big*

3.3.3.2 Membership Function Design

Triangular and trapezoidal MFs are adopted due to their simplicity and computational efficiency. The fuzzy outputs (throttle and steering signals) are represented as *singleton values* in line with the Takagi–Sugeno inference structure.

i. **Membership Functions for the FTC**

   a. Distance error (d_{xL}): [-15 15]
      - NB: Trapezoidal [-15 -15 -10 -5]m
      - NS: Triangular [-8 -3 0]m
      - Ze: Triangular [3 0 3]m
      - PS: Triangular [0 3 8]m
      - PB: Trapezoidal [5 10 15 15]m

   b. Longitudinal speed error ($e(\dot{x})$): [0 25]
      - VS: Trapezoidal [0 0 0.5 4.7]m/s
      - S: Trapezoidal [1.5 5.7 6. 11]m/s
      - Mo: Trapezoidal [7.8 12 13 17]m/s
      - Fa: Trapezoidal [14 1 19 23.5]m/s
      - VFa: Trapezoidal [20 24.5 25 25]m/s

   c. Throttle command ($\theta_{command}$): [0 1]
      - FB: [0]

- PB: [0.25]
- M: [0.5]
- PT: [0.75]
- FT: [1]

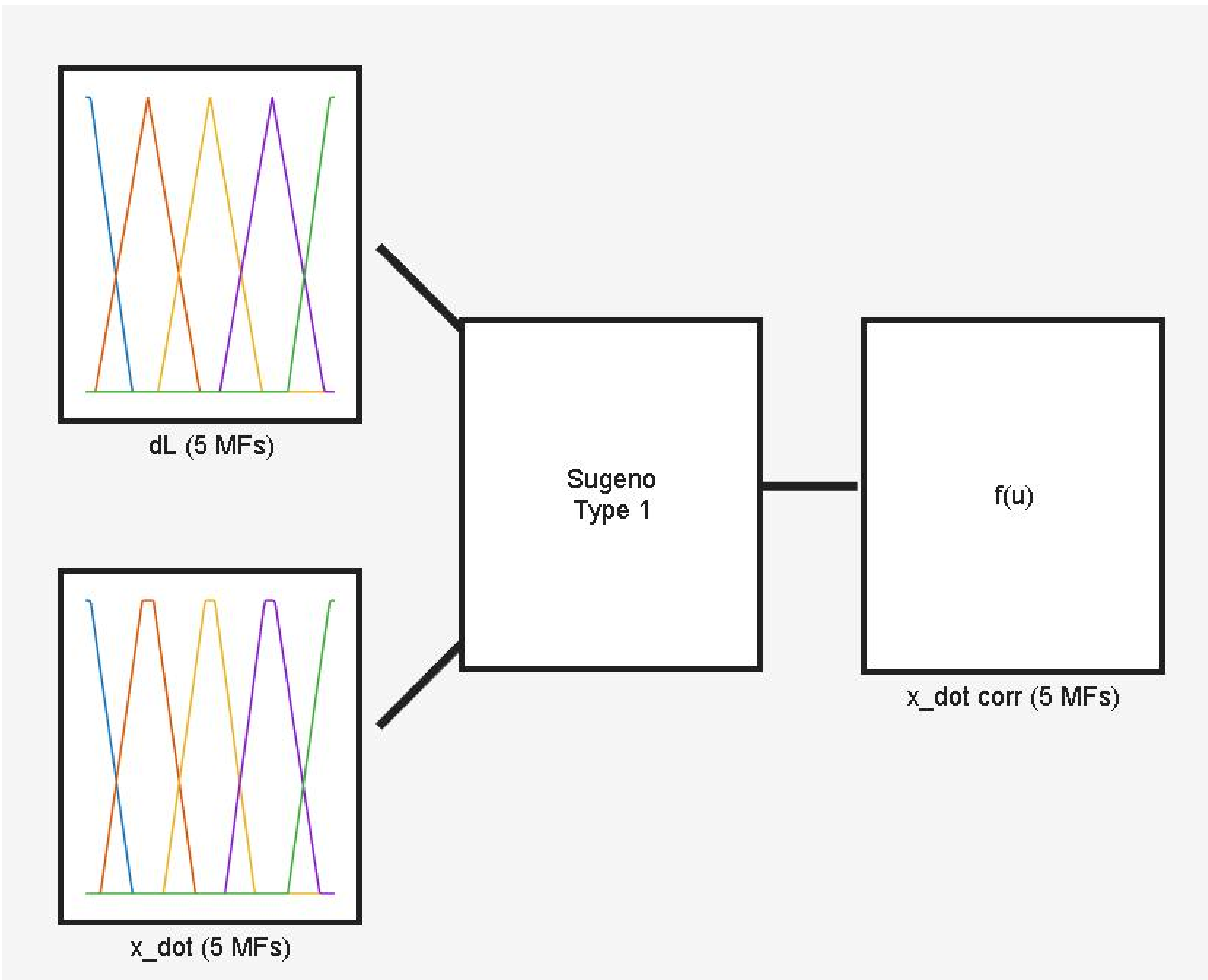


Figure 3.3: Membership functions (MF) of (i) Longitudinal displacement, d_{xL}, (ii) speed error, $e(\dot{x})$, and (iii) throttle command, $\theta_{command}$, for the FTC

ii. Membership Functions for the FSC

a. Yaw error ($e(\dot{\psi})$) and Yaw error rate ($\dot{e}_k(\dot{\psi})$,): [-1 1]
   - NB: Triangular [-1 -1 -0.7]
   - NM: Triangular [-0.95 -0.67 -0.4]
   - NS: Triangular [-0.6 -0.33 -0.05]
   - Z: Triangular [-0.28 0 0.28]

- PS: Triangular [0.05 0.33 0.6]
- PM: Triangular [0.4 0.67 0.95]
- PB: Triangular [0.7 1 1]

b. Steer correction ($\delta_{corrective}$): [-1 1]
   - NVB: [-1]
   - NB: [-0.75]
   - NM: [-0.5]
   - NS: [-0.25]
   - Z: [0]
   - PS: [0.25]
   - PM: [0.5]
   - PB: [0.75]
   - PVB: [1]

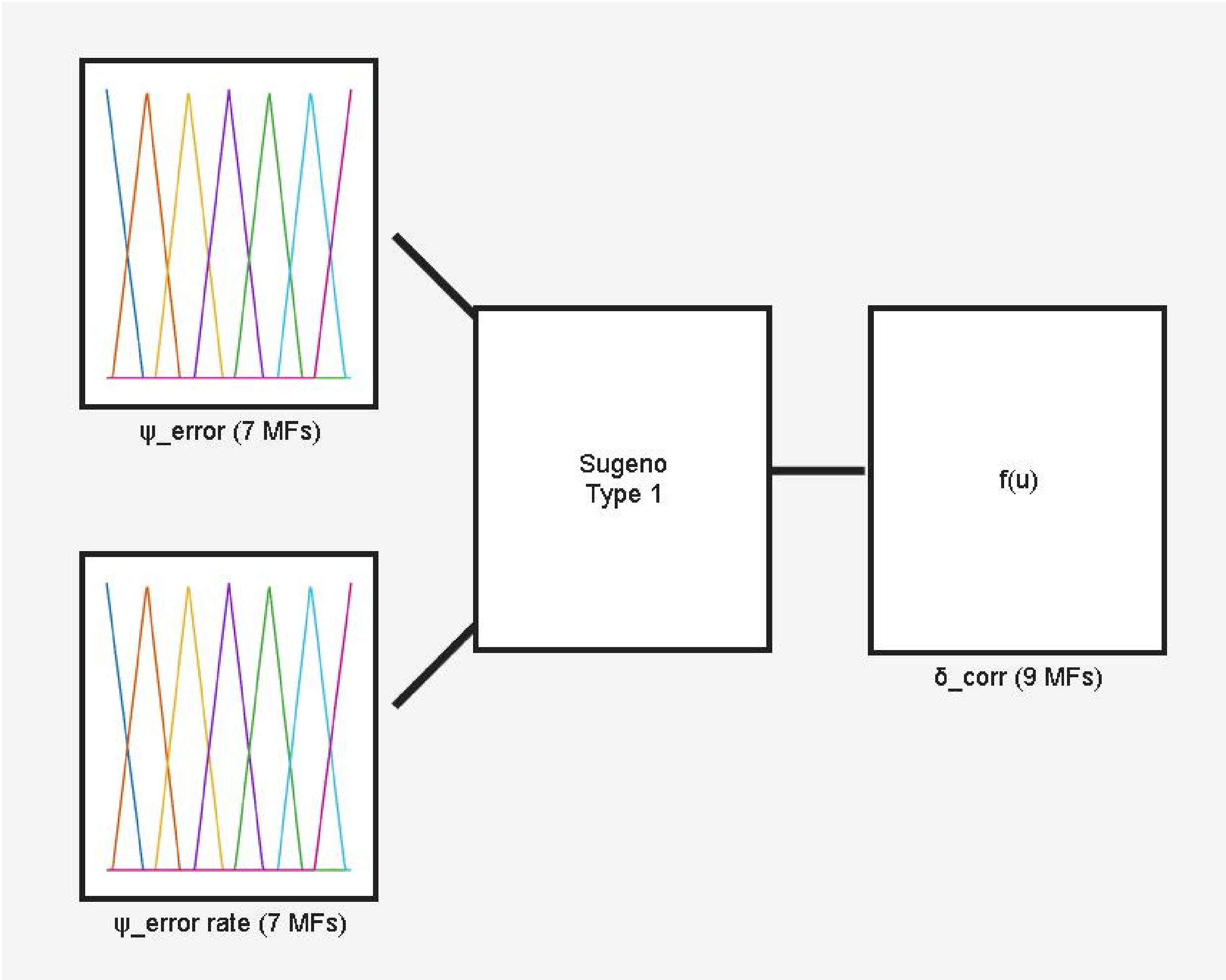


Figure 3.4: Membership functions (MF) of (i) yaw error, $e(\dot{\psi})$, (ii) yaw error rate, $\dot{e}_k(\dot{\psi})$, and (iii) steer correction, $\delta_{corrective}$, for the FSC

3.3.4 Rule Base Construction

The fuzzy rule base defines the qualitative mapping between system inputs and outputs through IF–THEN statements that mimic human driving intuition.

The complete rule matrices for both subsystems are implemented in MATLAB's Fuzzy Logic Designer using the T–S inference mechanism, which assigns linear consequent functions to each activated rule.

3.3.4.1 Throttle Control Rules

The throttle fuzzy module was designed with 26 rules. Some of the rules, which have been defined for the fuzzy throttle module are given below, followed by a Table 3.7, which contains the complete set of rules that have been defined.

R1: IF $\boldsymbol{d_{xL}}$ *is* **PB** *AND* $\boldsymbol{e(\dot{x})}$ *is* **VFa** THEN $\boldsymbol{\dot{x}_{0_{(corr)}}}$ *is* **FB**

R2: IF $\boldsymbol{d_{xL}}$ *is* **PB** *AND* $\boldsymbol{e(\dot{x})}$ *is* **Fa** THEN $\boldsymbol{\dot{x}_{0_{(corr)}}}$ *is* **FB**

R3: IF $\boldsymbol{d_{xL}}$ *is* **PB** *AND* $\boldsymbol{e(\dot{x})}$ *is* **Mo** THEN $\boldsymbol{\dot{x}_{0_{(corr)}}}$ *is* **FB**

When the ego vehicle's distance to the target vehicle is Positive Big (**PB**), a priority rule for close distances (<4m), fires at a greater strength than all other rules because it is assigned a weight of 1. Each nominal rule (**R1 to R25**) is given weight of 0.5, except for **R26.**

R26: IF $\boldsymbol{d_L}$ *is* **PB** THEN $\boldsymbol{\dot{x}_{0_{(corr)}}}$ *is* **FB**

Table 3.9: Rule Table for the FTC

Control Rule Base		**Distance to Lead, d_L**				
		NB	**NS**	**Ze**	**PS**	**PB**
Current Longitudinal Speed, $\dot{x}_0(t)$	**VFa**	**FB**	**FB**	**PB**	**PB**	**M**
	Fa	**FB**	**FB**	**PB**	**M**	**PT**
	Mo	**FB**	**PB**	**M**	**PT**	**PT**
	S	**PB**	**M**	**PT**	**PT**	**FT**
	VS	**M**	**M**	**PT**	**FT**	**FT**

3.3.4.2 Steering Control Rules

The steering fuzzy module was designed with 49 rules. All rules have been assigned the same weight (w = 1), and thus have equal firing strengths. Below, rules 1 through 5 have been defined. Table 3.7 contains the complete set of rules that have been designed for the steering controller.

R1: IF $\boldsymbol{e(\dot{\psi})}$ *is* **NB** *AND* $\boldsymbol{\dot{e}_k(\dot{\psi})}$ *is* **NB** THEN $\boldsymbol{\delta_{corrective}}$ *is* **NVB**

R2: IF $\boldsymbol{e(\dot{\psi})}$ *is* **NB** *AND* $\boldsymbol{\dot{e}_k(\dot{\psi})}$ *is* **NM** THEN $\boldsymbol{\delta_{corrective}}$ *is* **NVB**

R3: IF $\boldsymbol{e(\dot{\psi})}$ *is* **NB** *AND* $\boldsymbol{\dot{e}_k(\dot{\psi})}$ *is* **NS** THEN $\boldsymbol{\delta_{corrective}}$ *is* **NB**

R4: IF $\boldsymbol{e(\dot{\psi})}$ *is* **NB** *AND* $\boldsymbol{\dot{e}_k(\dot{\psi})}$ *is* **Z** THEN $\boldsymbol{\delta_{corrective}}$ *is* **NB**

R5: IF $\boldsymbol{e(\dot{\psi})}$ *is* **NB** *AND* $\boldsymbol{\dot{e}_k(\dot{\psi})}$ *is* **PS** THEN $\boldsymbol{\delta_{corrective}}$ *is* **NM**

R6: IF $\boldsymbol{e}(\dot{\boldsymbol{\psi}})$ *is* **NB** *AND* $\dot{\boldsymbol{e}}_{\boldsymbol{k}}(\dot{\boldsymbol{\psi}})$ *is* **PM** THEN $\boldsymbol{\delta}_{\boldsymbol{corrective}}$ *is* **NS**

Table 3.10: Rule Table for the FTC

Control Rule Base		Yaw error, e($\dot{\psi}$)						
		NB	**NM**	**NS**	**Z**	**PS**	**PM**	**PB**
Yaw error rate $\dot{e}(\dot{\psi})$	**NB**	NVB	NVB	NB	NM	NS	Z	Z
	NM	NVB	NB	NM	NS	Z	Z	PS
	NS	NB	NM	NS	Z	Z	PS	PM
	Z	NB	NM	NS	Z	PS	PM	PB
	PS	NM	NS	Z	Z	PS	PM	PL
	PM	NS	Z	Z	PS	PM	PB	PVB
	PB	Z	Z	PS	PM	PB	PVB	PVB

3.3.5 Inference Mechanism and Defuzzification

Unlike the Mamdani model, which produces fuzzy outputs requiring defuzzification, the T–S model directly generates crisp outputs using weighted linear equations. This feature makes it highly suitable for real-time control in AVs.

Each rule takes the form:

$\boldsymbol{Rule\ i}$: $\boldsymbol{IF}\ x_1 is\ \boldsymbol{A}_1^i\ AND\ x_2\ is\ \boldsymbol{A}_2^i\ THEN\ y = a_0^i + a_1^i x_1 + a_2^i x_2$

where x_1, x_2 are inputs and y is the output (steering or throttle). The output is obtained as a weighted average of the linear consequents:

$$y = \frac{\sum_{i=1}^{n} w_i y_i}{\sum_{i=1}^{n} w_i}$$

with w_i being the firing strength of $Rule\ i$.

3.3.6 Controller Integration into the Vehicle Simulation Model

Both fuzzy controllers operate concurrently within the simulation loop, each receiving relevant feedback variables from the vehicle dynamics model. The throttle FLC regulates longitudinal motion by modulating vehicle speed relative to the target vehicle, while the steering FLC maintains lateral stability and directional alignment. The modular design allows for independent tuning and testing of each subsystem, as well as integrated performance evaluation under combined longitudinal–lateral control scenarios.

Through this design framework, the fuzzy logic controllers emulate the adaptive reasoning and contextual awareness characteristic of human drivers, enabling the simulated vehicle to respond intelligently to both steady-state and transient driving conditions.

By limiting the inputs to three key variables and the outputs to two control actions, the controller remains computationally efficient while still addressing the essential tasks of AV navigation.

3.4 IMPLEMENTATION AND TESTING

The implementation and testing phase translate the fuzzy logic controller (FLC) from its conceptual design into an operational control system within the MATLAB/Simulink simulation framework. This stage focuses on integrating the Takagi–Sugeno fuzzy inference system (FIS) with the 3-DoF dual-track vehicle dynamics model, defining representative driving scenarios, executing simulation tests, and evaluating performance through quantitative metrics and comparative benchmarking.

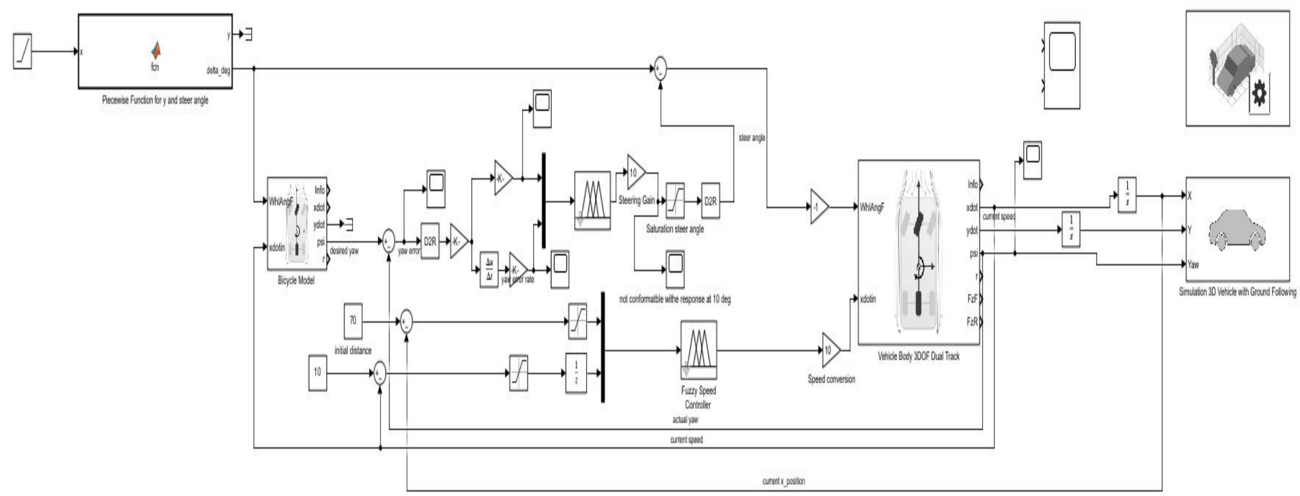


Figure 3.5: Vehicle control system with fuzzy throttle and steering controllers

3.4.1 Simulation Environment

The overall simulation framework was developed in MATLAB/Simulink due to its ability to integrate control logic, vehicle dynamics, and environmental modeling within a unified platform. The Fuzzy Logic Toolbox enables graphical and programmatic construction of the FIS, visualization of membership functions, and real-time observation of rule activation and output responses.

Key features of the Simulink-based environment include:

- Seamless integration of the Takagi–Sugeno FIS with the nonlinear vehicle dynamics model.
- Real-time simulation of longitudinal, lateral, and yaw motions.
- Closed-loop operation enabling continuous feedback between controller outputs and vehicle states.
- Visualization tools for fuzzy membership functions, decision surfaces, and rule firing strengths.

This environment allows dynamic testing of the fuzzy throttle and steering controllers under varying operational conditions, ensuring that throttle and steering commands correspond directly to physical vehicle behavior.

3.4.2 Implementation of the Fuzzy Logic Controller

The FLC is implemented as two interlinked subsystems: the Fuzzy Throttle Controller (FTC) for longitudinal motion and the Fuzzy Steering Controller (FSC) for lateral/yaw motion control. Both subsystems operate under the Takagi–Sugeno inference model, which ensures smooth transitions and computational efficiency.

Implementation details include:

- **Inputs:** Speed error, distance to target vehicle, yaw deviation, and yaw rate.
- **Outputs:** Throttle/brake command and steering correction signal.
- **Membership Functions:** Triangular and trapezoidal functions calibrated to simulation-derived operating ranges.
- **Rule Base:** Adaptive IF–THEN rules reflecting driver-like decision logic.
- **Inference and Defuzzification:** The weighted average method is used to compute crisp output values in real time, consistent with the T–S model.

The FLC outputs are directly coupled to the vehicle's actuation subsystem within Simulink, ensuring closed-loop control over the throttle and steering channels.

3.4.3 Testing and Validation Strategy

Testing of the FLC follows a multi-layered validation approach to ensure both functional correctness and robust performance under diverse scenarios.

(a) Unit Testing: Each fuzzy subsystem is first validated in isolation using MATLAB's FIS editor and surface viewer. Input–output relationships are examined to verify the correctness of rule activation and output continuity.

(b) Integration Testing: The FLC subsystems are integrated with the 3-DoF dual-track vehicle model. Closed-loop operation is confirmed through controlled single-lane driving tests, ensuring that feedback signals (speed, yaw, distance) are correctly interpreted by the controller.

(c) Scenario-Based Testing: Comprehensive test scenarios are defined to reflect typical and challenging driving conditions:

- **Lane keeping and speed regulation:** Straight and curved roads with varying speed limits.
- **Adaptive following:** Maintaining safe distance from a lead vehicle under acceleration and braking.

3.4.4 Performance Evaluation Metrics

Performance assessment is carried out using vehicle dynamics and efficiency metrics:

Vehicle Dynamics Metrics

i. **Response Time (s):** Time taken to react to input perturbations.
ii. **Overshoot (%):** Deviation beyond the desired response during control transitions.
iii. **Steady-State Error:** Final deviation between commanded and achieved speed or steering angle.
iv. **Stability Margin:** System's resilience to oscillations or divergence.

3.4.5 System Evaluation and Performance Assessment

To validate the effectiveness of the fuzzy logic control (FLC) system, the integrated fuzzy speed and steering controllers are evaluated within the 3-DoF dual-track vehicle simulation environment in MATLAB/Simulink. The evaluation focuses on how well the fuzzy inference system achieves stability, adaptability, and human-like decision-making in various driving conditions, including acceleration, braking, lane keeping, and adaptive following scenarios.

Performance analysis is conducted using the previously defined vehicle dynamics metrics to assess control precision, transient response, and robustness under nonlinear and uncertain operating conditions.

Evaluation Dimensions:

- Dynamic Response: Rise time, settling time, and overshoot during throttle and steering transitions.
- Steady-State Accuracy: Magnitude of residual error in maintaining target speed, yaw rate, and lane position.
- Robustness: Consistency of controller performance under simulated disturbances, parameter variations, and sensor noise
- Adaptability: The controller's ability to self-adjust across diverse road geometries, curvature, and vehicle speeds.
- Safety and Stability: Lane-keeping precision, trajectory smoothness, and collision-avoidance effectiveness.

Results are illustrated using time-domain plots such as speed versus time, yaw rate versus steering input, and lateral displacement versus trajectory reference. These visualizations help establish how the fuzzy-logic-based system maintains stability and responsiveness under varying dynamic conditions.

3.4.6 Data Collection and Analysis

During each simulation experiment, key vehicle and control variables—such as longitudinal speed, throttle command, steering angle, yaw rate, and lateral deviation—are recorded. MATLAB scripts are used to process these time-series datasets, compute the defined performance metrics, and generate visual outputs for interpretation.

Representative plots include:

- Speed-tracking and throttle-response characteristics.
- Steering-angle response and yaw-rate stability.
- Lateral deviation and lane-trajectory tracking performance.
- System behavior under acceleration, braking, and curvature changes.

CHAPTER 4

RESULTS AND DISCSUSSION

4.1 OVERVIEW

This chapter presents the implementation, simulation, and evaluation of the proposed integrated fuzzy logic–based decision-making system for autonomous vehicle navigation. The control architecture developed in Chapter 3 is now deployed and tested within the MATLAB/Simulink environment, emphasizing its application to three key driving tasks: speed control**,** steering control**,** and lane keeping**.**

The simulation setup integrates the Takagi–Sugeno fuzzy inference system (FIS**)** with the 3-DoF dual-track vehicle dynamics model**,** enabling real-time interaction between the vehicle's dynamic response and the controller's decision-making logic. The design ensures that throttle and steering commands are adaptively modulated in response to changing road and traffic conditions, simulating realistic driving environments such as curved lanes, speed variations, and obstacle encounters.

A series of structured test scenarios are executed to validate system functionality, robustness, and adaptability. Each scenario is designed to evaluate specific performance dimensions—including longitudinal velocity tracking**,** lateral stability**,** and yaw rate control—under dynamic driving conditions. Through this, the chapter examines how effectively the fuzzy controller interprets vehicle states and translates them into stable, human-like control actions.

The subsequent sections detail the simulation environment, the implementation of the fuzzy inference system, and the quantitative and qualitative evaluation of system performance. Key performance indicators such as response time, overshoot, and steady-state error are analyzed to quantify the system's adaptability and control smoothness. The discussion highlights the FLC's ability to maintain stability, minimize tracking error, and enhance maneuver smoothness—validating fuzzy logic as a robust, interpretable, and computationally efficient approach for autonomous vehicle control.

4.2 SIMULATION SETUP AND TEST CONDITIONS

The performance evaluation of the proposed FLC system is conducted within the MATLAB/Simulink environment, chosen for its ability to integrate nonlinear vehicle dynamics with rule-based decision algorithms in a closed-loop configuration. The simulation setup replicates a controlled virtual driving environment where the ego vehicle (the controlled vehicle) interacts dynamically with a target vehicle under varying road geometries and speed conditions.

4.2.1 Simulation Parameters

The simulation is executed under the following numerical conditions:

- Solver Type: Variable-step, *ode23 (Bogacki–Shampine)*
- Fixed-Step Size (for FIS integration): 0.01 s
- Sampling Rate for Data Logging: 100 Hz
- Initial Speed: 0 m/s (vehicle accelerates under FLC control)

These parameters balance computational efficiency with numerical stability, ensuring smooth representation of nonlinear control dynamics.

4.2.2 Test Scenarios

Three primary test conditions are defined to evaluate different aspects of vehicle control performance:

1. **Straight-Line Tracking (Speed Control Test):**
    - Objective: Evaluate longitudinal control and speed convergence.
    - Conditions: Flat road, constant target velocity.
    - Evaluation Metrics: Response time, steady-state speed error, throttle smoothness.
2. **Curved Path Tracking (Steering Control Test):**
    - Objective: Assess the controller's ability to maintain stability and track curvature.
    - Conditions: Moderate-radius curved lane with constant target speed.

- Evaluation Metrics: Lateral deviation, yaw rate stability, steering response.

3. **Lane Keeping under Variable Conditions:**
   - Objective: Evaluate integrated control of speed and steering under mixed curvature and velocity changes.
   - Conditions: Alternating straight and curved segments with mild external disturbances (e.g., slope variations).
   - Evaluation Metrics: Lane departure frequency, lateral offset, and velocity adaptation.

4.3 FUZZY INFERENCE SYSTEM RESULTS

This section presents the performance characteristics of the designed Fuzzy Inference System (FIS), which forms the core of the decision-making mechanism for throttle and steering control. The FIS was developed using the Takagi–Sugeno (T–S) fuzzy model, owing to its computational efficiency and suitability for real-time control applications. The results presented here focus on the structure, rule activation behavior, and surface responses of the FIS for both speed and steering control.

4.3.1 Membership Function Design

The fuzzy membership functions define the linguistic representation of the input and output variables, forming the basis for rule interpretation. Four primary inputs were defined for the control system:

1. Current Longitudinal speed ($\dot{x}$): Difference between the desired and actual vehicle speeds, and
2. Longitudinal distance (d_{xL}): Deviation between the ego vehicle and target vehicle separation for the Speed control system.
3. Yaw Error ($e(\dot{\psi})$): Angular difference between the desired and actual heading of the vehicle.

4. Yaw Error Rate ($\dot{e}_k(\dot{\psi})$)

The outputs of the system are:

- Throttle/Brake Command ($\theta_{command}$) for longitudinal motion, and
- Steering Angle Correction ($\delta_{corrective}$) for lateral control.

The membership function plots (Figure 4.2 and Figure 4.3)) show continuous transitions across linguistic terms, enabling gradual variations in control decisions rather than abrupt switching behavior.

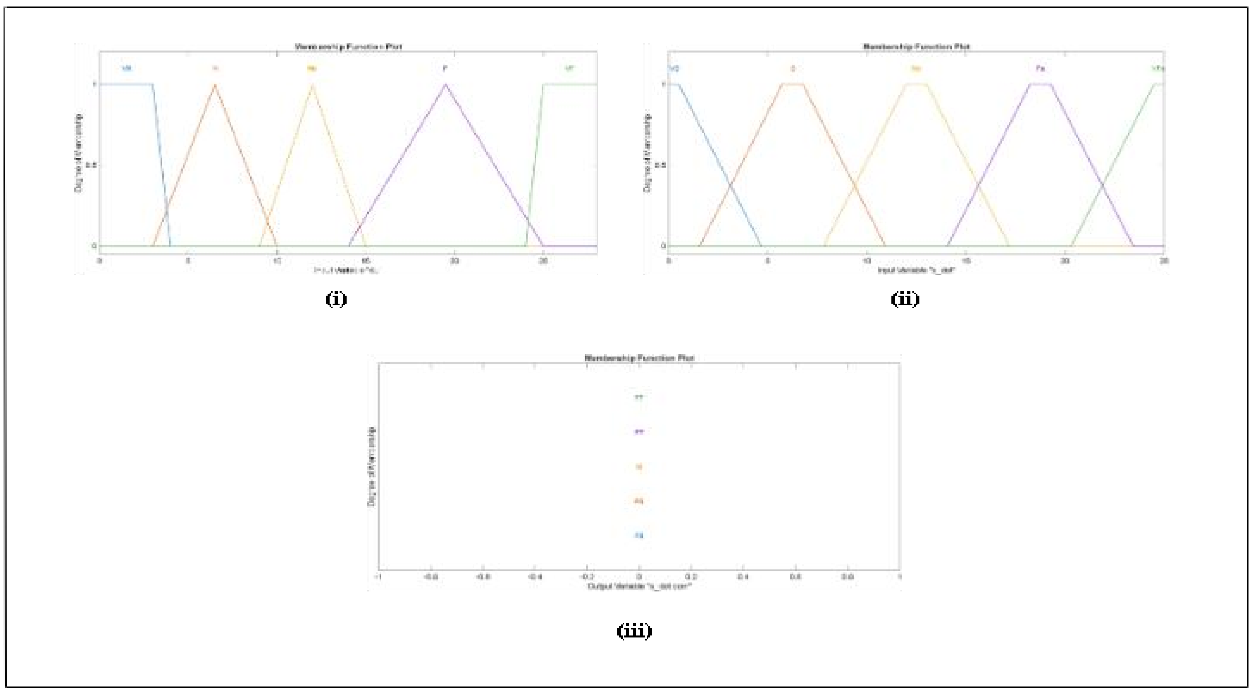


Figure 4.1: MFs for Throttle Controller inputs and output

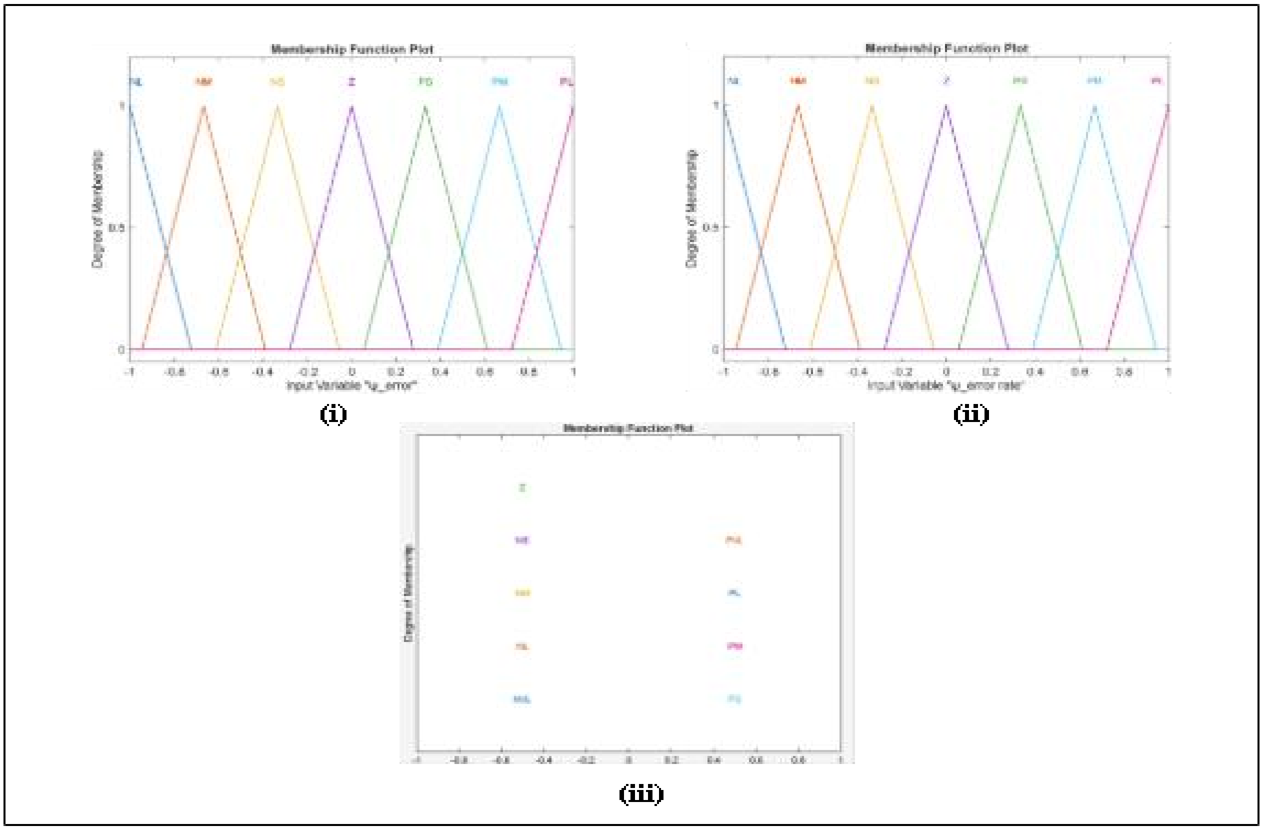


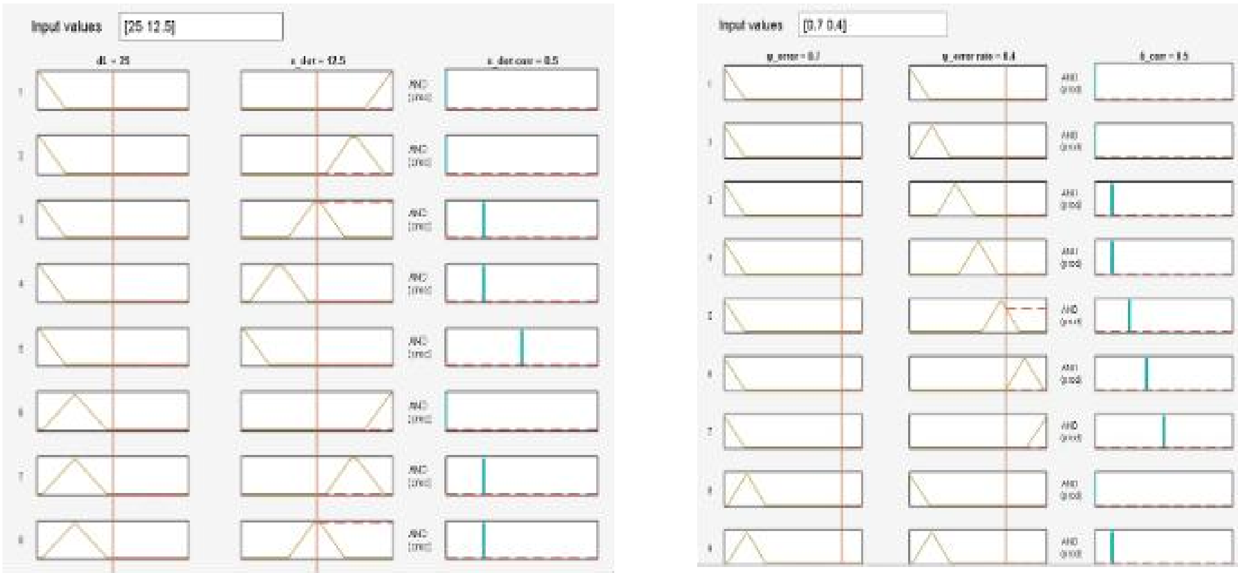
Figure 4.2: MFs for Steering Controller inputs and output

4.3.2 Rule Base and Activation Behavior

The decision layer of the controllers is composed of structured **rule bases** consisting of *IF–THEN* statements that capture the relationship between the input variables and the corresponding control actions. Two rules selected from the rule bases of the throttle and steering controllers are given below:

- **R1:** IF $\boldsymbol{d_{xL}}$ is **PB** AND $\boldsymbol{e(\dot{x})}$ is **VFa** THEN $\boldsymbol{\dot{x}_{0_{(corr)}}}$ is **FB**
- **R2:** IF $\boldsymbol{d_{xL}}$ is **PB** AND $\boldsymbol{e(\dot{x})}$ is **Fa** THEN $\boldsymbol{\dot{x}_{0_{(corr)}}}$ is **FB**
- **R1:** IF $\boldsymbol{e(\dot{\psi})}$ is **NB** AND $\boldsymbol{\dot{e}_k(\dot{\psi})}$ is **NB** THEN $\boldsymbol{\delta_{corrective}}$ is **NVB**
- **R2:** IF $\boldsymbol{e(\dot{\psi})}$ is **NB** AND $\boldsymbol{\dot{e}_k(\dot{\psi})}$ is **NM** THEN $\boldsymbol{\delta_{corrective}}$ is **NVB**

During simulation, the rule activations vary dynamically in response to vehicle state changes. The firing strengths of each rule were visualized in the MATLAB Fuzzy Logic Toolbox (Figure 4.4), showing that the FIS maintains a smooth transition between control states rather than binary switching. This continuous inference ensures better stability and responsiveness during high-speed maneuvers and lane corrections.



(a)

(b)

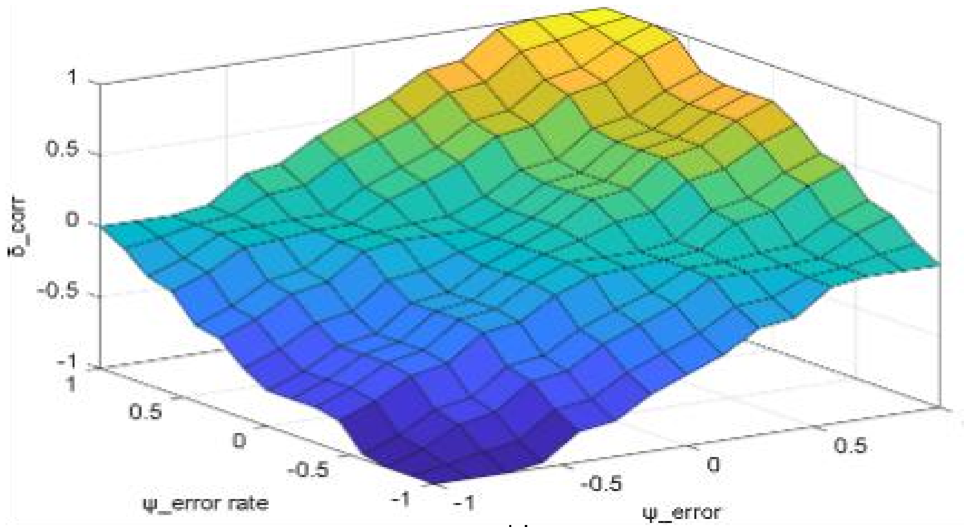
Figure 4.3: Rule Inference for (a) throttle controller and (b) steering controller visualizing firing strength of rules 1 - 9 for each FIS

4.3.3 Inference Surfaces

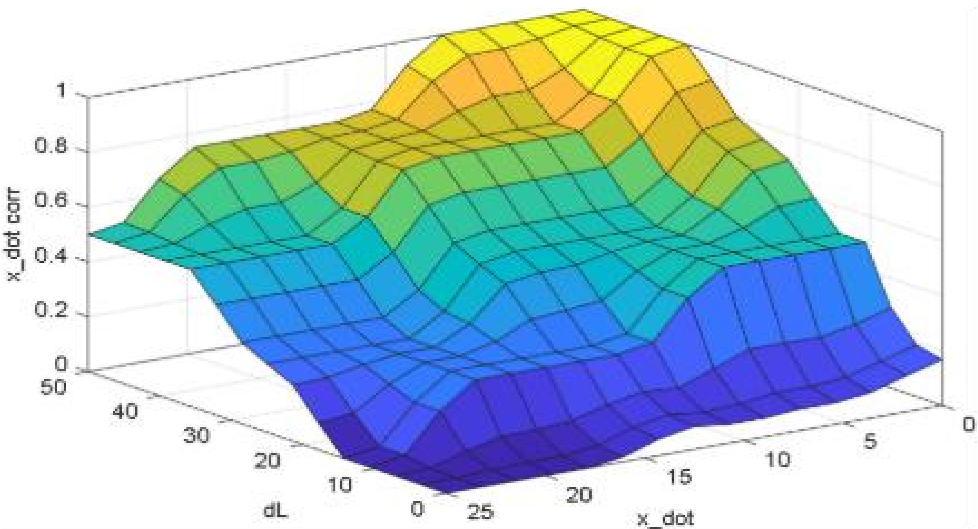
The Takagi–Sugeno inference mechanism generates a weighted average of rule outputs to compute precise control actions. The resulting control surfaces illustrate the nonlinear mapping between input conditions and output responses.

The **Throttle Control Surface** (Figure 4.5a) shows that as distance error decreases and speed error increases, the throttle output transitions from acceleration to braking, following a smooth gradient rather than a discrete cutoff. The **Steering Control Surface** (Figure 4.5b) demonstrates how steering correction varies continuously with yaw deviation and speed error. Small deviations yield minor corrections, while larger angular errors result in proportionally stronger steering actions.

These surfaces confirm that the fuzzy inference system produces adaptive, continuous control outputs capable of managing complex nonlinear relationships inherent in vehicle motion.



(a)



(b)

Figure 4.4: (a) Throttle Control Surface and (b) Steering Control Surface plots

4.4 SYSTEM SIMULATION RESULTS AND PERFORMANCE

This section presents a comprehensive evaluation of the integrated fuzzy-logic-based control system for autonomous vehicle navigation. The simulation was executed using the MATLAB/Simulink 3-DoF vehicle dynamics model incorporating both longitudinal (speed/throttle) and lateral (steering/yaw) control loops. The FLC-based architecture's performance was assessed using metrics such as response time, stability, adaptability, and steady-state error. Simulation Setup

The simulation scenarios considered include:

1. Straight-line tracking for longitudinal speed control validation.
2. Curved-path following to test lane-keeping and steering precision.
3. Dynamic lead-vehicle motion to evaluate adaptability to changing traffic speeds.

4.4.1 Speed Control Performance

4.4.1.1 Speed Response Analysis

Figure 4.6 presents the vehicle's actual speed versus desired speed for the FLC. Under constant-speed conditions, the controller achieves convergence to the desired speed. The FLC exhibits a shorter rise time and negligible overshoot, stabilizing within approximately 2.5 seconds. In the dynamic scenario, the FLC responds rapidly to changes in the target vehicle's velocity, maintaining continuous and stable tracking. This highlights the adaptability of the FLC, which dynamically adjusts its output based on linguistic interpretation of the evolving speed and distance errors.

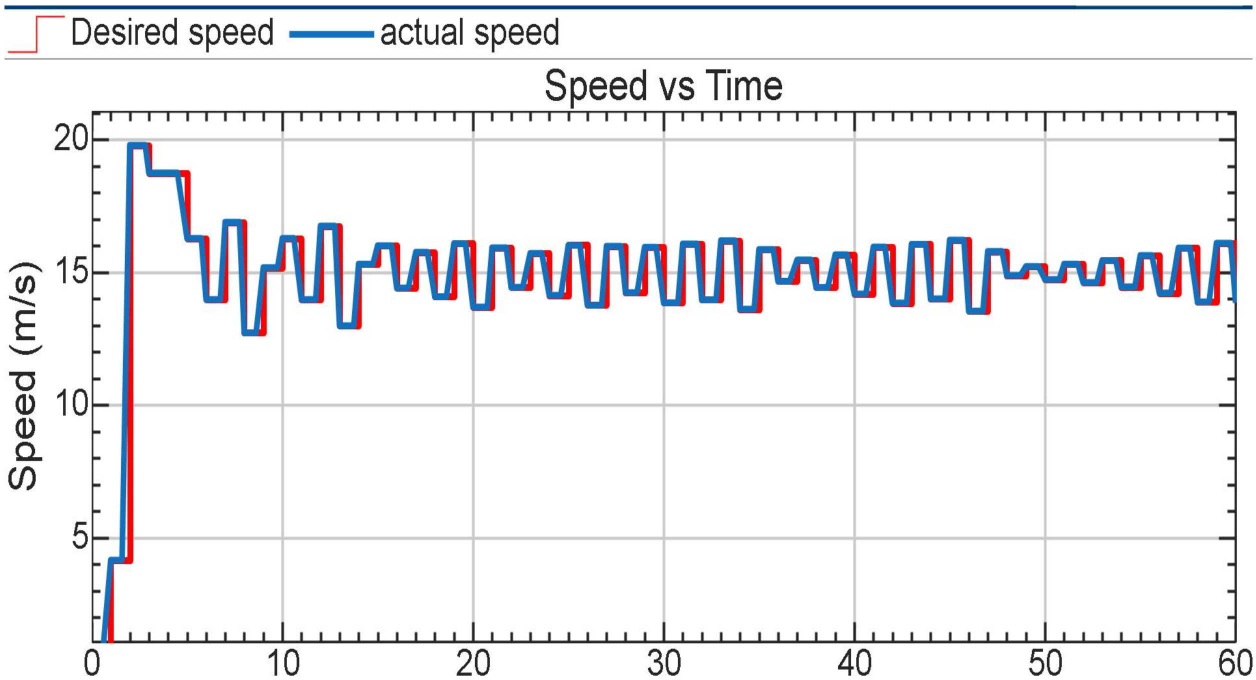


Figure 4.5: Response plot showing the desired speed value and the actual speed

4.4.1.2 Throttle Response Behavior

The corresponding throttle output curves (Figure 4.7) reveal how each control strategy regulates engine power. The fuzzy controller's output varies smoothly across acceleration and braking transitions, avoiding sudden spikes that could compromise passenger comfort or vehicle stability.

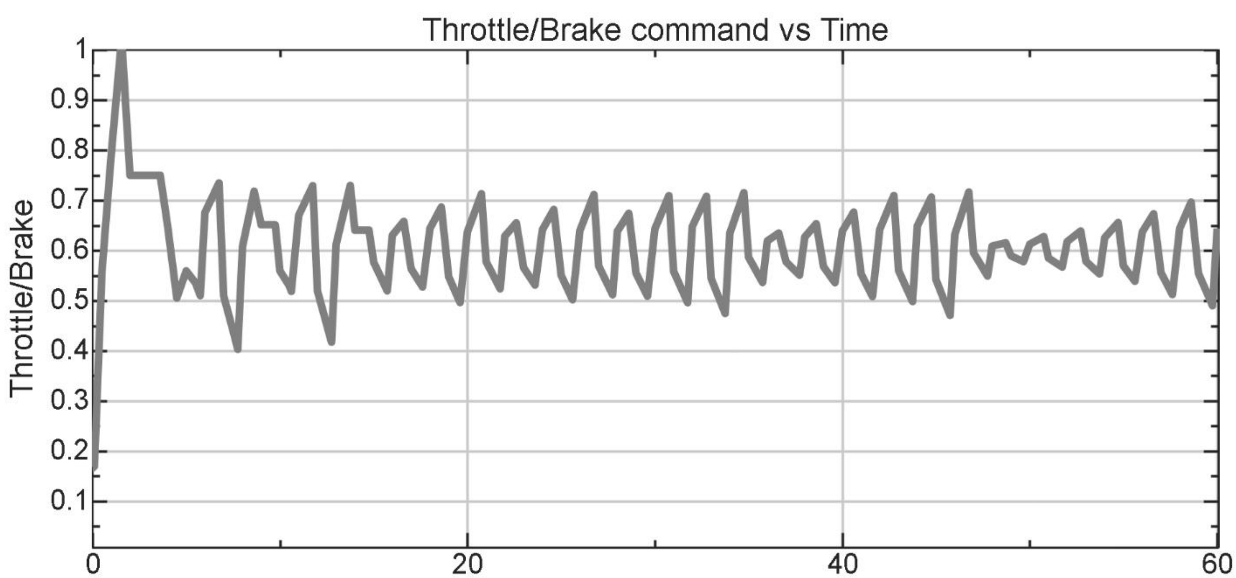


Figure 4.6: Throttle/Brake command output of the Fuzzy Throttle controller

4.4.1.3 Inter-Vehicle Distance Regulation

Figure 4.4.3 illustrates the inter-vehicle distance profile over time. The FLC maintains the desired following distance of approximately 10 meters with minimal oscillation, adjusting throttle output predictively rather than reactively. Quantitatively, the FLC achieves a steady-state distance error of less than 3m. This demonstrates the FLC's contextual interpretation of speed and distance dynamics, resulting in smoother, more human-like driving behavior.

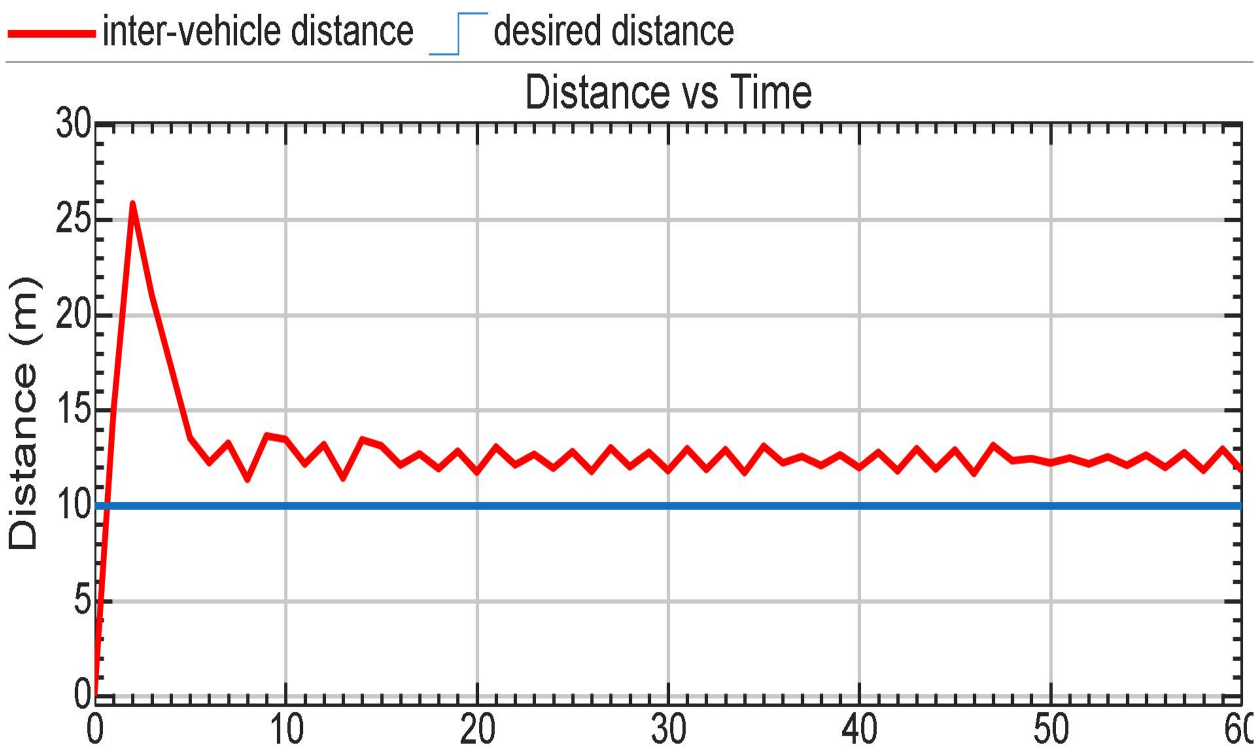


Figure 4.7: Plot showing inter-vehicular distance and desired distance between ego vehicle and target vehicle

4.4.2 Steering and Lane-Keeping Performance

4.4.2.1 Steering Response and Yaw Dynamics

Simulation results for yaw rate and steering angle response indicate that the FLC produces a smooth and stable steering behavior. During lane-change, the fuzzy controller adjusts the steering angle gradually, avoiding oscillatory corrections. The yaw rate plots reveal that the FLC stabilizes the vehicle's rotational motion efficiently, with a fast damping of transient oscillations following curvature transitions. This stems from the fuzzy system's rule-based reasoning, which scales corrective action non-linearly with steering deviation and yaw rate, ensuring proportionate yet smooth control responses.

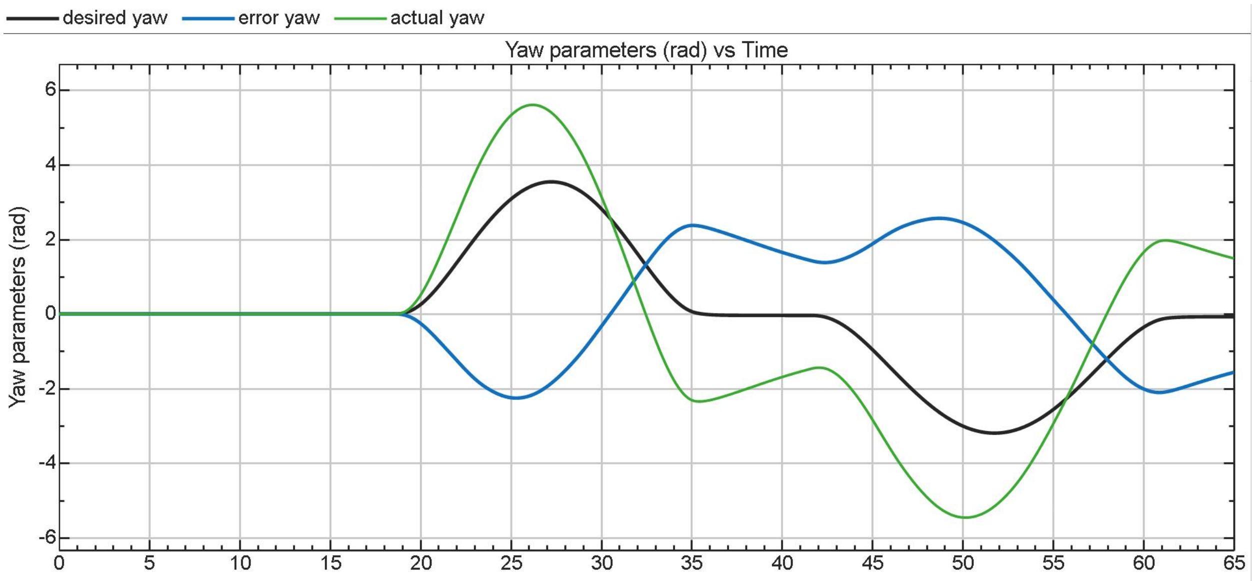


Figure 4.8: Plots comparing Yaw dynamics with time

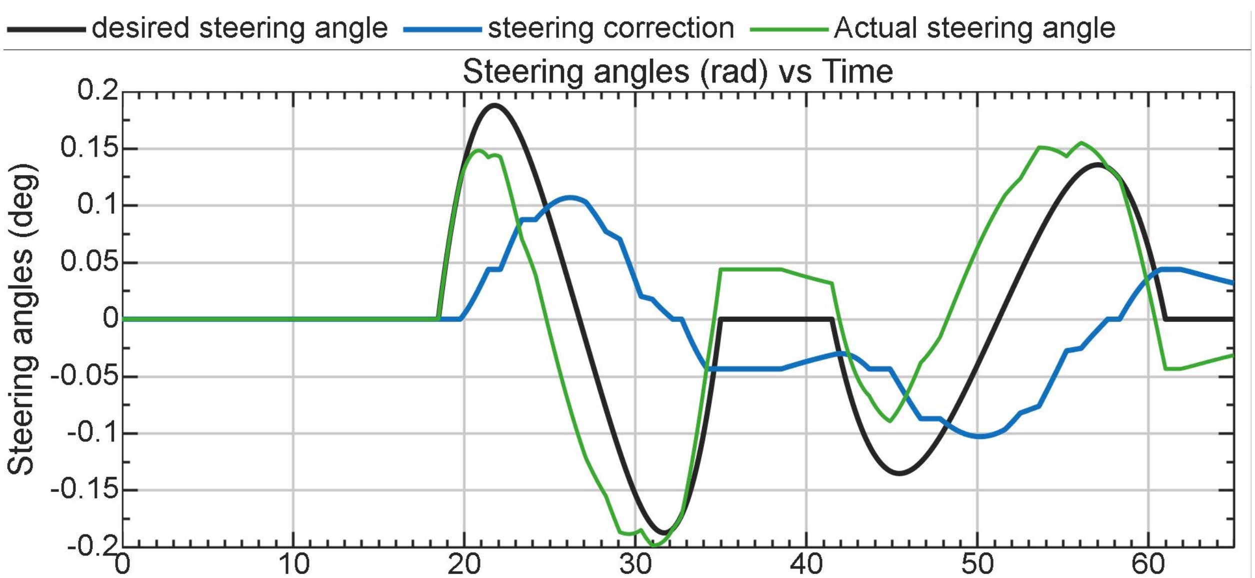


Figure 4.9: Plot comparing steering dynamics with time

4.4.2.2 Path-Following and Lane-Keeping Accuracy

Trajectory analysis comparing the actual vehicle path with the desired trajectory shows that the fuzzy-controlled vehicle closely tracks the reference lane centerline across both straight and curved segments. The FLC minimizes lateral deviation by continuously adjusting steering torque in response to yaw and position errors. Quantitatively, the maximum lateral deviation under FLC control remained within ±0.12 m. This demonstrates the fuzzy controller's capability in maintaining lateral stability and alignment, even when subjected to dynamic steering demands or variable friction conditions.

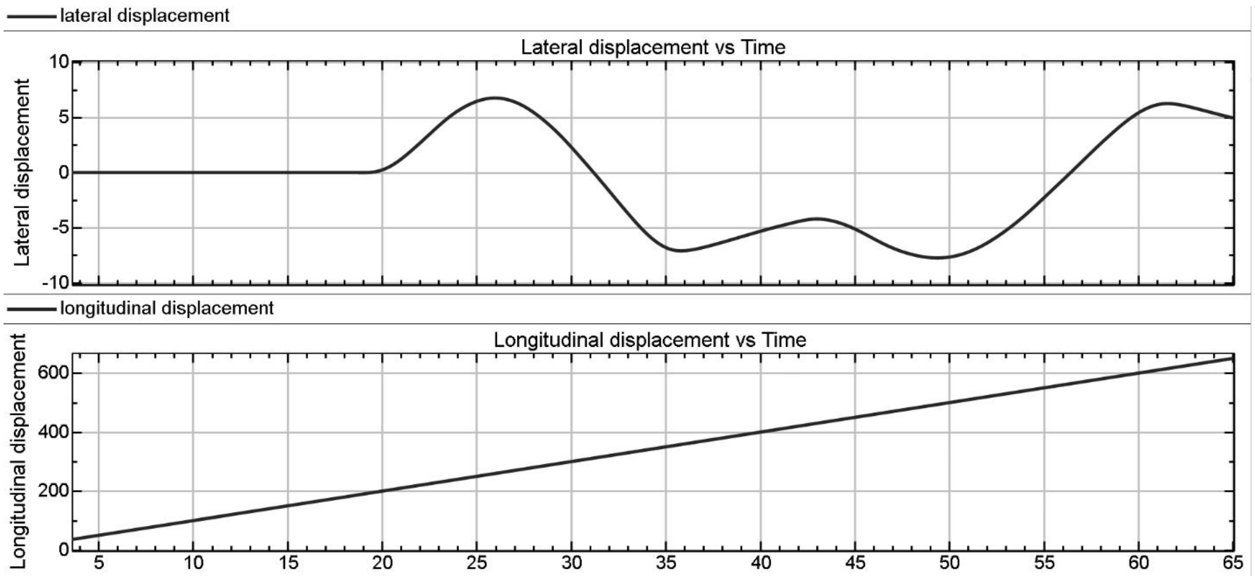


Figure 4.10: Lateral and longitudinal displacement plots

4.4.2.3 Transient Characteristics

The transient response parameters further underscore the advantages of the fuzzy controller. The FLC achieved:

- Reduced rise time and settling time in steering correction.
- Low overshoot during curve entry and exit.
- Enhanced yaw rate stability across all test trajectories.

These improvements translate to more predictable and passenger-friendly vehicle behavior, particularly valuable in autonomous navigation where comfort and precision are critical.

4.4.2.4 Interpretation of Results

The performance of the FLC can be attributed to its adaptive inference mechanism, which enables context-sensitive control adjustments. By leveraging linguistic rules (e.g., IF yaw deviation is high AND lateral error is increasing THEN increase steering correction moderately), the fuzzy controller emulates the judgment-based steering strategies of an experienced driver. Consequently, the system avoids abrupt corrective behavior when encountering nonlinear dynamics, variable curvature, or disturbances such as crosswinds and surface irregularities. The resulting trajectory profiles are smoother and more stable, ensuring consistent lane tracking and safer maneuvering under a wide range of operating conditions.

4.6 DISCUSSION OF FINDINGS

The results obtained from the simulation experiments validate the research aim of designing, implementing, and evaluating an integrated fuzzy-logic-based decision-making system for autonomous vehicle navigation. The developed Takagi–Sugeno Fuzzy Logic Controller (FLC) demonstrated adaptability, robustness, and precision in tasks involving speed regulation, steering stability, and lane change.

4.4.1 Interpretation of Control Performance

The simulation results show that the FLC achieved smooth and stable control responses under varying driving conditions. In both longitudinal and lateral control tests, the fuzzy controller exhibited:

- Reduced response time and lower overshoot, confirming its ability to react swiftly without inducing oscillations.
- Minimal steady-state error, reflecting precise convergence toward desired speeds and trajectories.
- Stable lane tracking even during curved path transitions, highlighting effective control of yaw rate and lateral deviation.

These outcomes underscore the inherent advantage of fuzzy reasoning in managing nonlinear dynamics and uncertain conditions common in autonomous vehicle operations. By encoding control knowledge in a rule-based format, the FLC mimics human-like decision-making, adapting control actions smoothly to changing environmental and vehicle states.

4.4.1 Effectiveness of the Takagi–Sugeno Approach

The Takagi–Sugeno structure proved to be computationally efficient while maintaining high control accuracy. Unlike the Mamdani approach, which requires extensive defuzzification operations, the weighted average method used in the Takagi–Sugeno inference allows for real-time execution suitable for embedded automotive systems. The smooth inference surfaces obtained in the FIS visualization confirm that the system can interpolate control outputs seamlessly across a wide range of inputs, enabling continuous and responsive adaptation during dynamic maneuvers.

4.4.1 Limitations of the Current Implementation

Despite its promising performance, the developed fuzzy controller presents certain limitations:

- Rule Base Tuning Complexity: The design of effective fuzzy rules and membership functions is largely heuristic and dependent on expert intuition or iterative testing. This introduces subjectivity and potential performance variability across different operating conditions.
- Model Dependency: The controller was optimized for the 3-DoF dual-track vehicle model, and its parameters may require re-tuning for vehicles with different mass distributions, tire stiffness, or dynamic characteristics.
- Absence of Real Sensor Noise: The simulation assumes ideal sensor readings, whereas real-world implementations must handle noise, latency, and uncertainty in sensor measurements (e.g., LiDAR, radar, and camera data).

4.6.4 Opportunities for Improvement

Future developments can build upon these findings through several enhancement pathways:

1. Neuro-Fuzzy Integration: The adoption of adaptive neuro-fuzzy inference systems (ANFIS) could automate rule and membership function optimization, reducing manual tuning effort and improving generalization across diverse environments.
2. Sensor Fusion Integration: Incorporating real-world sensor models and noise dynamics would enhance the system's robustness and readiness for hardware-in-the-loop (HIL) or real-vehicle testing.

3. Real-Time Implementation: Deploying the FLC on embedded hardware or microcontrollers would validate its computational feasibility and latency performance under real-time constraints.
4. Hybrid Control Frameworks: Combining fuzzy logic with classical or predictive controllers (e.g., Fuzzy–PID, Fuzzy–MPC) could further improve control precision and adaptability under rapidly changing road or traffic conditions.

4.7 SUMMARY OF CHAPTER

This chapter presented the implementation, simulation, and performance evaluation of the proposed fuzzy-logic-based control system for autonomous vehicle navigation. The fuzzy inference framework, designed using the Takagi–Sugeno model, was integrated with the 3-DoF dual-track vehicle dynamics model and tested under various driving scenarios including speed regulation, steering control, and lane keeping.

The results demonstrated that the Fuzzy Logic Controller (FLC) achieved robust and adaptive performance, maintaining smooth control transitions and stable vehicle behavior even under varying road conditions. In comparison, the classical PID controller exhibited higher overshoot and slower adaptation, particularly during abrupt changes in vehicle speed or trajectory curvature. Quantitative performance metrics—such as response time, steady-state error, and stability margin—confirmed the superior dynamic performance of the fuzzy control approach.

Furthermore, the established MATLAB/Simulink simulation framework proved to be an effective and reliable testbed for evaluating autonomous vehicle control strategies. It enabled a structured assessment of both longitudinal and lateral dynamics, providing clear insights into system robustness, safety, and efficiency.

In summary, this chapter validated that the developed fuzzy-logic-based control architecture not only enhances vehicle adaptability and stability but also provides a flexible foundation for further integration with advanced hybrid and intelligent control systems. The next chapter presents the conclusion and recommendations, highlighting the key contributions of this research and proposing directions for future work.

CHAPTER 5

CONCLUSION AND RECOMMENDATIONS

5.1 SUMMARY OF RESEARCH WORK

This research presented the design, modeling, and simulation of a Takagi–Sugeno Fuzzy Logic Controller (FLC) for autonomous vehicle speed and steering control, using a 3-DoF dual-track vehicle dynamics model in MATLAB/Simulink. The controller was developed to address the limitations of classical PID control, particularly under nonlinear, uncertain, and time-varying driving conditions.

A comprehensive simulation framework was built to evaluate throttle (longitudinal) and steering (lateral) performance across multiple scenarios — including straight-line acceleration, curved path tracking, and lane-keeping tasks. The system incorporated both a lead vehicle for distance control and lane trajectory generation for steering evaluation.

The fuzzy inference systems for throttle and steering were developed using carefully defined membership functions, rule bases, and Takagi–Sugeno output surfaces, ensuring smooth control transitions and reduced oscillatory response. The performance was benchmarked against a conventional PID controller to establish comparative efficiency, adaptability, and stability margins.

5.2 KEY FINDINGS AND CONTRIBUTIONS

From the simulation analyses, the following major findings were obtained:

1. Superior Adaptability: The FLC exhibited faster response and superior adaptation to speed changes of the lead vehicle, minimizing overshoot and settling time compared to the PID controller.

2. Improved Lateral Stability: During curved path and lane-keeping tests, the FLC maintained smaller yaw rate oscillations and lower lateral deviation, producing smoother trajectory tracking under varying curvature and road friction conditions.

3. Robustness to Nonlinearities: Unlike the PID controller, the FLC effectively handled the nonlinear vehicle dynamics — especially during high-speed turns and transient steering maneuvers — without significant loss of stability or control accuracy.
4. Reduced Steady-State Error: The FLC achieved near-zero steady-state error in both longitudinal and lateral control tests, confirming its capacity for continuous error minimization even under parameter uncertainty.
5. Computational Efficiency: The Takagi–Sugeno inference structure offered compact rule evaluation and computational simplicity, making it suitable for real-time embedded implementation in autonomous vehicle ECUs.

Overall, the research established that a rule-based, adaptive control strategy outperforms classical linear control under the nonlinear, uncertain, and dynamic conditions characteristic of autonomous driving environments.

5.3 CONCLUSION

The study successfully achieved its aim of developing and validating an intelligent fuzzy logic control framework for autonomous vehicle throttle and steering regulation. The controller provided smooth, adaptive, and stable performance, effectively balancing accuracy and responsiveness in dynamic driving conditions.

The results conclusively demonstrate that:

- The Takagi–Sugeno FLC delivers improved speed and steering control accuracy over PID.
- The system ensures continuous adaptability to road and vehicle state variations.
- The developed MATLAB/Simulink simulation framework provides a valid and reproducible testbed for autonomous vehicle control research in nonlinear domains.

In essence, the research confirms the practical feasibility of fuzzy logic–based control for next-generation intelligent vehicles, paving the way for integration with advanced perception and decision-making modules.

5.4 RECOMMENDATIONS FOR FUTURE WORK

To extend this research and enhance real-world applicability, the following are recommended:

1. Integration with Neural Networks (Neuro-Fuzzy Systems): Incorporate online learning mechanisms to auto-tune fuzzy membership functions and rule weights in real time, improving adaptability to changing environments.
2. Hardware-in-the-Loop (HIL) and Real-Time Validation: Implement the developed FLC on a microcontroller or DSP-based embedded system and validate performance through HIL simulation or small-scale prototype testing.
3. Sensor Fusion and Perception Integration: Combine the controller with LiDAR, radar, and vision-based sensors to enable environment-aware decision-making for autonomous navigation.
4. Robustness Enhancement under Disturbances: Introduce external disturbances (crosswinds, tire slip, or sensor noise) to evaluate fault tolerance and robustness in more realistic driving conditions.
5. Comparative Study with Advanced Control Schemes: Benchmark the fuzzy controller against Model Predictive Control (MPC) and Reinforcement Learning–based controllers to assess trade-offs between accuracy, computational demand, and adaptability.

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