The focus of this study is the lateral control system of autonomous vehicles using steering control. The main objective is to ensure the vehicle consistently stays on the correct path. Existing methods remain limited, as they often assume ideal road conditions without obstacles or dynamic objects. To address this limitation, this study investigates steering angle control for autonomous vehicles in unstructured environments with potential obstacles. It specifically analyzes the application of a type-2 fuzzy logic controller (type-2 FLC) for steering control, using input values in the form of error and delta error. These values are calculated from the difference between the output generated and the steering angle measured by a pulse encoder mounted on the steering wheel. The type-2 FLC demonstrated high accuracy in obstacle avoidance tests: 1.54% (human), 4.28% (one car), 1.2% (two objects on the left), and 2.13% (two on the left, one on the right). In contrast, the PID controller produced higher error rates: 2.19%, 3.49%, 1.12%, and 3.49%, respectively. Full-route testing showed average forward-route errors of 8.87% for the type-2 FLC and 12.35% for the PID controller. On the return route, the type-2 FLC recorded a 4.52% error, while the PID controller showed 7.57%. Overall, the type-2 FLC achieved lower error rates and better accuracy than the PID controller, particularly in dynamic conditions. These results highlight the effectiveness of the type-2 FLC in enhancing autonomous vehicle performance and steering accuracy. Its low error values indicate superior path-tracking capabilities, effectively addressing the research objective

Keywords: autonomous vehicle, type-2 FLC, PID control, steering angle, membership function, maneuvers

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DESIGN AND OPTIMIZATION OF A TYPE-2 FUZZY LOGIC-BASED LATERAL CONTROL SYSTEM FOR ENHANCING TRAJECTORY STABILITY IN AUTONOMOUS VEHICLES

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1. Introduction

In the last decade, the rapid advancement of autonomous vehicle (AV) technologies has transformed the transportation sector, laying the groundwork for a new era of intelligent mobility. The concept of fully autonomous driving, defined as Society of Automotive Engineers (SAE) Level 5, where no human intervention is required under any circumstance, or known as a self-driving car [1, 2], has transitioned from a futuristic vision into a key research and industrial objective [3]. However, because of the complexity of the surroundings that exist in the actual world, the concept of complete autonomy continues to be a hard obstacle to overcome. Automated vehicles are required to precisely detect their surroundings and can follow planned trajectories, maintain lane positions, handle curves, avoid obstructions, and adjust dynamically to changing road and traffic situations thanks to the steering control system.

Advancements in autonomous vehicle technology have reached an important development in the automotive industry, where cars are no longer merely modes of transportation, but now can think and make decisions for themselves [4, 5]. To drive autonomously without human involvement, vehicles must be able to sense environmental variables, forecast the movement of nearby objects, and calculate the best route to their destination while avoiding both stationary and moving impediments [6].

In achieving the full automation of autonomous vehicles, a control system is needed in autonomous vehicles [7]. This control system consists of two parts, namely longitudinal and lateral controllers. The longitudinal controller is responsible for regulating the vehicle's travel speed, while the lateral controller directs the steering to keep the vehicle on the right track [8]. The lateral control system, or steering control, is one of the most important components to ensure that the car can perform maneuvers such as going straight, turning left, turning right, and avoiding collisions with other vehicles and objects around the car [9]. In autonomous vehicles, the control system method in steering is very much needed because autonomous vehicles do not have drivers who can control their movements directly [10].

Lateral control, attained through precise steering actions, allows an autonomous vehicle to follow specified paths, sustain lane alignment, and navigate complex road layouts. The effectiveness of lateral control is directly linked to the overall trajectory stability and road safety of autonomous systems [11, 12].

Conventional control strategies frequently encounter challenges in managing the significant uncertainty, nonlinearity, and variability inherent in real-world driving scenarios. Challenges include variations in road surface conditions, sensor noise, and unexpected disturbances [13, 14]. Traditionally, steering control has been addressed using classical control techniques, such as proportional-integral-derivative (PID) controllers, linear quadratic regulators (LQR), and model predictive control (MPC). These methods are mathematically rigorous and computationally efficient when the vehicle and environment models are well-defined and deterministic [14]. However, real-world driving is inherently nonlinear and filled with uncertainties, where precise mathematical modeling is often infeasible or unreliable. These conditions reduce the performance and robustness of traditional controllers, which are sensitive to unmodeled dynamics, parameter variations, and external disturbances [15, 16].

Fuzzy logic control is acknowledged as an effective method for addressing these challenges, given its ability to model imprecision and replicate human-like decision-making processes [17, 18]. Type-2 fuzzy logic systems (T2FLS) provide notable benefits compared to conventional type-1 systems by integrating an extra layer of uncertainty within their membership functions. This feature improves the robustness, adaptability, and fault tolerance of T2FLS under the uncertain and nonlinear conditions characteristic of autonomous driving environments [19–21]. In the realm of lateral control, steering systems employing type-2 fuzzy logic have demonstrated improved efficacy in maintaining vehicle stability and enabling seamless trajectory tracking. This is especially apparent in intricate maneuvers, such as curved path navigation, obstacle evasion, and abrupt lane changes [22]. The amalgamation of T2FLS with optimization methodologies improves the calibration of controller settings, enabling more adaptable and robust control responses.

The significance of lateral control in guaranteeing dependable and secure autonomous navigation is substantial. Furthermore, type-2 fuzzy logic has proven effective in addressing uncertainty and enhancing control resilience. Advancing steering control with type-2 fuzzy logic is essential in autonomous vehicle research.

Therefore, research on the development of lateral control for autonomous vehicles that utilize type-2 fuzzy logic and implement this algorithm in the steering control of the wheels is relevant to the advancement of autonomous vehicle technology towards smart vehicles.

2. Literature review and problem statement

Several studies have discussed steering control and the implementation of fuzzy logic in autonomous vehicles. In study [7], a hybrid controller is proposed, combining PID for speed and a linear quadratic regulator (LQR) with feedforward for steering to improve trajectory tracking in autonomous vehicles, especially on sharp curves. The system adjusts speed based on path curvature and significantly reduces lateral errors in simulations and real tests. However, the study is mostly simulation-based, with limited real-world testing using a simplified vehicle model. It does not include obstacle avoidance and relies solely on sensor data with fixed controller parameters.

[12] used a model predictive controller (MPC) for steering control in autonomous vehicles. The MPC optimizes control inputs to minimize trajectory deviation while considering vehicle dynamics and constraints. Simulations show that the MPC-based controller successfully guides the vehicle with minimal lateral error, demonstrating its potential for real-world autonomous driving applications. Nevertheless, this study was only implemented in simulation with a simplified vehicle model and without dynamic obstacles.

In [15], a robust PID steering controller was designed for highly automated driving, focusing on lateral motion control. The controller is developed using a parameter space approach, ensuring robustness against variations in vehicle dynamics. Both linear and nonlinear models of a midsized sedan are utilized, with experimental validation of the vehicle's longitudinal and lateral dynamics. Simulation results demonstrate the controller's effectiveness in guiding the vehicle along circular and curved trajectories, highlighting its potential for real-world autonomous driving applications. However, this study does not consider external factors, relies on fixed PID parameters, and is based solely on simulation.

The next research was conducted by [20], discussing the use of type-2 Fuzzy logic control and PI control in controlling the steering of autonomous vehicles. The primary control method employs type-2 fuzzy logic control, utilizing three inputs (distance, navigation, and speed), to produce an output in the form of a steering angle value. This output is then used as input for secondary control, namely PI control, which adjusts the position of the motor to realize the steering angle. During the trial, the researchers compared type-2 and type-1 fuzzy to determine the appropriate and optimal steering angle. The final results of this study indicate that type-2 fuzzy produces better and smoother control compared to Fuzzy type-1. At high speeds, type-2 fuzzy has better performance in controlling the steering angle, with smoother output and faster response. In addition, at close range to obstacles, type-2 Fuzzy produces a smaller steering angle, so that control is smoother and more responsive. These results indicate that type-2 fuzzy is superior in controlling autonomous vehicles, especially in maintaining user comfort and safety. However, this study only focuses on low-speed city vehicles with a restricted sensor range and does not consider environmental disturbances. It was also not compared with other methods, such as PID.

Further research was conducted by [22], who tested a Fuzzy logic system for autonomous vehicle steering control in a roundabout. The researchers used Bezier curves and parametric equations to generate trajectories, taking into account the geometry of the roundabout. A fuzzy logic controller was used for steering control, with inputs such as lateral error and steering angle error. In this study, two fuzzy controllers are designed for steering wheel position and one for angular velocity. The steering position controller has two inputs: lateral error (meters) and angular error (degrees). Lateral and angular errors are calculated using two consecutive differential global positioning system (DGPS) measurements. The inputs of the angular velocity controller are Distance to curve (meters) and Longitudinal velocity (kilometers per hour (km/h)). Distance to the curve is measured using the vehicle position and its point above the curve (circle). Triangular and trapezoidal membership functions are defined for the linguistic variables. In this study, a circular loop is designed to be passed by the autonomous vehicle. However, this study does not consider dynamic environmental factors, such as obstacles, and it depends on accurate sensor data. Furthermore, it was not compared with other control methods.

The next research was conducted by [23]. This research focuses on the development of a Fuzzy lane change control system on autonomous vehicles to perform overtaking maneuvers. This system uses a fuzzy controller that mimics human behavior and reactions when performing overtaking maneuvers. It combines high-precision GPS and wireless network information to track routes and calculate deviations from reference maps. The system checks various conditions before starting the overtaking maneuver, such as vehicle speed, availability of the left lane, and the distance required to perform the maneuver. Then it performs a lane change and tracks the overtaken vehicle until it can safely return to the right lane. This system uses a fuzzy logic controller and GPS guidance to control the vehicle's steering [23]. However, this study is limited by its reliance on simulations rather than real-world testing and its narrow focus on overtaking maneuvers involving two vehicles, neglecting more complex traffic scenarios.

The research conducted by [18] discusses the development and implementation of the Fuzzy PD PI controller for steering and speed control of autonomous guided vehicles (AGV). The aim of this study is to design a controller that is stable, robust, and suitable for real-time applications. The performance of the fuzzy controller is compared with the conventional PID controller. The fuzzy controller shows better performance in terms of tracking accuracy, steady state error, and robustness. In addition, this study also proposes a control structure for longitudinal and lateral control of the AGV [18]. Encoders are installed on all four wheels of the AGV to calculate the vehicle speed. Then there is also an encoder installed on the steering motor to measure the steering angle and steering angular velocity of the AGV. The results of this study indicate that the proposed fuzzy logic controller (FLC) scheme has better performance than the conventional PID scheme, especially in tracking accuracy and steady-state errors. Furthermore, the results of the study indicate that the designed FLC is resistant to load changes, coupling effects, operating point changes, and changes in road slope. Simultaneous operation of the longitudinal fuzzy logic controller (LOFC) and the lateral fuzzy logic controller (LAFC) shows that the designed uncoupled direct fuzzy controller is able to eliminate the implicit coupling effect, unlike the PID control. Simultaneous operation of the fuzzy driving controller (FDC), designed for the DC series motor-powered drive system, and the fuzzy braking controller (FBC), designed for the stepper motor-driven braking system, shows smooth speed tracking performance without jerking. However, this research is still being conducted on AGVs, and their movements are still limited.

The method currently used still has weaknesses, such as complex calculations, then the method has not been tested on autonomous vehicles in real time even though autonomous vehicles need a fast response so all of this confirms that it is wise to conduct research on lateral control systems on autonomous vehicles based on type-2 fuzzy logic.

3. The aim and objectives of the study

The study aims to develop a steering control system based on a type-2 fuzzy logic controller (type-2 FLC) which will be applied to control the wheels using input values in the form of errors and delta errors. These values are calculated from the difference between the output generated and the steering angle measured by the pulse encoder installed on the steering wheel. So, this will allow to increase the effectiveness and stability in controlling the steering.

To achieve this aim, the following objective is accomplished:

– to conduct of type-2 FLC for implementation in controlling the steering of the autonomous vehicles;

– to optimize the parameters of the type-2 fuzzy logic controller using suitable optimization techniques for improved performance in trajectory tracking and obstacle avoidance.

4. Materials and methods

4. 1. Object and hypothesis of the study

The first object of this research is the autonomous vehicle lateral control system, especially the steering control system, which aims to maintain track stability so that the vehicle remains on the right track even when facing unstructured environmental conditions. While the second is: the application of the type-2 fuzzy logic controller in adjusting the steering angle based on the error value and delta error calculated from the difference in the actual steering angle (measured by the pulse encoder) and the target angle.

Then the main hypothesis of this research is: the implementation of type-2 fuzzy logic controller (FLC) in the lateral steering control system can improve the accuracy of trajectory tracking and stability of autonomous vehicles, especially in dynamic and unstructured environmental conditions, compared to conventional controllers such as PID.

Some assumptions used in this study are first, the vehicle is equipped with a sensor capable of measuring the steering angle in real-time via a pulse encoder. Second, the error and delta error values are sufficient to represent the deviation conditions of the vehicle from the desired path. Third, the obstacle objects in the test environment (such as humans, vehicles, or other objects) are considered detectable and their positions can be calculated in the control system. and the last is a test environment that represents a real-world situation even though on a limited scale (for example, a route from one faculty to another).

The simplifications adopted in this study include focusing only on lateral control (steering) without considering longitudinal control (such as acceleration and deceleration). then not consider other external factors such as weather conditions, road surfaces, or complex interactions with other road users. Only using two input parameters (error and delta error) as the basis for decision making in fuzzy control, which simplifies the complexity of the calculation compared to using other multi-inputs. And the testing was carried out in a limited route and semi-controlled environment (campus), not in real traffic.

4. 2. Research methods

This study was conducted using both simulation and real-time approaches. In the simulation, MATLAB software was used to evaluate the system's response under type-2 fuzzy logic and PID control. For the real-time implementation, sensors used in the autonomous vehicle included a real-time GPS and a camera mounted on the vehicle body. The camera captured road segmentation values, object distances, and object positions, while the GPS provided data on the vehicle's distance, angle, and intersection direction. All of these values were collected as inputs for the autonomous vehicle's controller. The experimental conditions considered both roads with and without obstacles, as the primary objective of this study is the lateral control of autonomous vehicles.

4. 3. Lateral control

Lateral control in autonomous vehicles is the ability of an autonomous system to control the movement of a vehicle horizontally, namely from side to side (left to right) along the road. This includes the ability of the car to maintain its position in the correct lane, handle bends or turns, and respond appropriately to surrounding situations such as traffic signs, road markings, surrounding vehicles, and obstacles in the vicinity. Through the modification of the steering angle, lateral control in autonomous vehicles achieves the goal of ensuring that the vehicle is aligned with a particular reference trajectory. In the realm of lateral control, the lateral error and the heading angle error are considered to be crucial components. The lateral error, denoted by the symbol e, represents the distance between the center of gravity of the vehicle and the reference path. On the other hand, the heading angle error, denoted by the symbol $e\theta$, represents the angular discrepancy between the vehicle's current orientation and the direction that it is expected to remain in. These faults are particularly important when it comes to the formulation of control systems that ensure a smooth and consistent trajectory adherence. A kinematic bicycle model is a mathematical representation that can be used to explicitly define the lateral control problem [16]:

$$\dot{x} = v\cos(\theta), \tag{1}$$

$$\dot{y} = v\sin(\theta), \tag{2}$$

$$\dot{\theta} = \frac{v}{L}\tan(\delta), \tag{3}$$

where x, y – the global coordinates of the vehicle, v – the longitudinal velocity, θ – the heading angle, L – the wheelbase length, and δ – the steering angle.

Previous studies have utilized a linear system model as a simplified approach to address the lateral control problem. Linear models often lacked sufficient accuracy in various instances, as demonstrated by the following examples. A reference path characterized by a small turning radius. As the steering angle increases, the modelling error becomes significant. Nonlinear system models provide a more accurate representation of vehicle dynamics compared to linear models, which justifies their use in this paper. The dynamics of an autonomous vehicle are illustrated in Fig. 1, with the positive direction of the X-axis oriented eastward and the positive direction of the Y-axis oriented northward. $P_0(X_0, Y_0)$ represents the midpoint of the vehicle's rear axle, while $P_1(X_1, Y_1)$ denotes the midpoint of the vehicle's front axle. L denotes the wheelbase length, φ represents the vehicle's heading angle, and θ indicates the front wheel steering angle. The state variable (X_0, Y_0, φ) or (X_1, Y_1, φ) can decide the vehicle's dynamics.

So, this equation represents the autonomous vehicle's lateral kinematic model [16]

$$\begin{bmatrix} \dot{X}_0 \\ \dot{Y}_0 \\ \dot{X}_1 \\ \dot{Y}_1 \\ \dot{\varphi} \end{bmatrix} = \begin{bmatrix} v\sin\varphi \\ v\cos\varphi \\ v\sin(\varphi+\theta) \\ v\cos(\varphi+\theta) \\ \dfrac{v\tan\theta}{L} \end{bmatrix}, \tag{4}$$

where v – the longitudinal velocity.

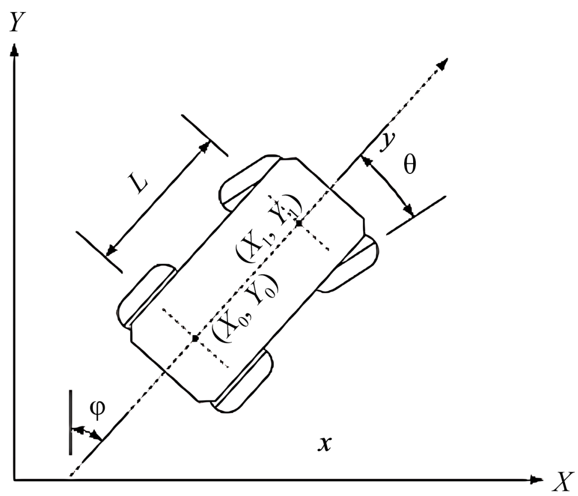


Fig. 1. The dynamics of an autonomous vehicle [16]

The autonomous vehicle is instructed to follow the local reference path, which is determined by the perceptual and decision-making system. The Cartesian coordinates x and y, which are specific to the vehicle's body, define the local reference route. The starting point of the coordinate system is the location where the vehicle's rear axle meets. In Fig. 2, the positive x-axis direction represents the vehicle's forward motion.

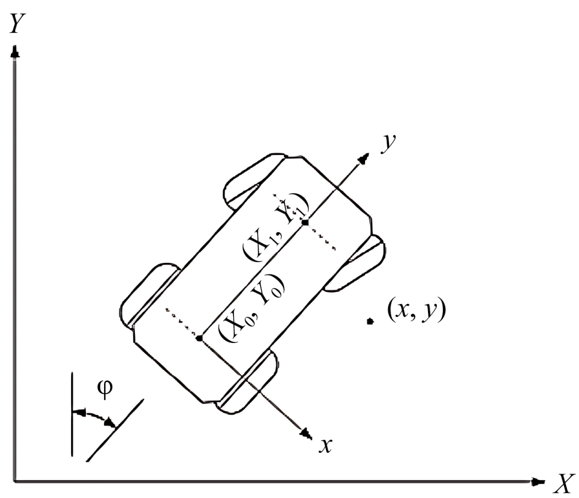


Fig. 2. The transformation between the local coordinates system and the geodetic coordinates [16]

The following equation shows the transformation of an arbitrary point's coordinates from the geodetic to the local system [16]

$$\begin{bmatrix} x \\ y \end{bmatrix} = R\begin{bmatrix} X \\ Y \end{bmatrix} + T, \tag{5}$$

where

$$R = \begin{bmatrix} \cos(-\varphi) & \sin(-\varphi) \\ -\sin(-\varphi) & \cos(-\varphi) \end{bmatrix}. \tag{6}$$

The matrix R is a 2D rotation matrix that performs a clockwise rotation by an angle φ (phi) in the Cartesian coordinate system. This matrix is commonly used to transform coordinates from one frame to another that is rotated by an angle φ concerning the original frame. Coordinates are transformed between different reference frames (e. g., from global to vehicle frame). Rotate velocity or steering vectors are used for trajectory tracking or control algorithms.

4. 4. Type-2 fuzzy logic control system

Type-2 fuzzy logic controller (FLC) is a development of type-1 FLC, which has a higher level of uncertainty. In Fig. 3, type-2 FLC allows input variables with uncertain values, which can be used to overcome uncertainty in the system. In the context of autonomous vehicles, type-2 FLC can be used to overcome uncertainty in decision-making based on input from sensors and other data sources. This allows the autonomous vehicle control system to be more adaptive to changes in road conditions and the surrounding environment. In type-2 FLC logic, each linguistic variable has a Footprint of Uncertainty (FoU), which reflects the range of uncertainty or ambiguity of the variable value. Type-2 FLC logic has better capabilities, even though it has heavier computation; the use of type-2 fuzzy intervals is easier to understand. The structure of a type-2 FLC control system is not significantly different from a type-1 FLC. Based on Fig. 3, there are several identical stages, including fuzzification, inference, and defuzzification. The main difference between the two control systems lies in the reduction stage. In this stage, the inference output is in the form of a type-2 FLC set, which is then converted into a type-1 set through the reduction process. After that, the output is defuzzified in the same manner as in a type-1 fuzzy system [20]. The type-2 FLC logic system has a general structure in Fig. 3 as follows.

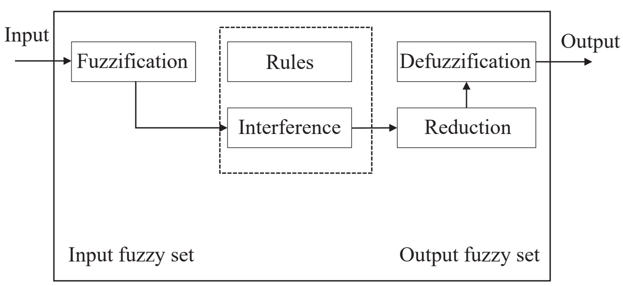


Fig. 3. Type-2 fuzzy logic structure

A fuzzy inference system (FIS) is a method of fuzzy logic that interprets input data and generates output data based on fuzzy rules. The Sugeno method is one type of FIS proposed by [24]. This method is used to develop a systematic approach for generating fuzzy rules from a set of input-output data. In this study, the Sugeno model is used because it is more suitable for the developed autonomous vehicle. The fuzzy rules commonly used in the Sugeno model follow the form of (7) as shown below

$$\text{IF}\left(x_1 \text{ is } A_1\right)\cap\left(x_2 \text{ is } A_2\right)\cap\left(x_3 \text{ is } A_3\right)\cap\ldots\cap\left(\left(x_n \text{ is } A_n\right)\right). \quad (7)$$

Then [Y is (x_1, x_2, ..., x_n)], where the variable *xn* represents the n-th input of the fuzzy system, while A_n refers to the n-th fuzzy set associated with each input. Meanwhile, Y denotes the output variable generated by the fuzzy system. The primary distinction between the Sugeno technique and the Mamdani method is that the output (consequent) of the Sugeno system is a constant or a linear equation, rather than a fuzzy set. The implementation of the Sugeno technique entails the formation of fuzzy sets, the establishment of the rule base, and the execution of the inference procedure on the rules to derive a valid output or conclusion. The Sugeno method employs a weighted average approach for defuzzification. Consequently, the Sugeno approach is extensively utilized in systems necessitating constant values, rendering it appropriate for implementation in autonomous vehicles [24].

The membership function of type-2 fuzzy logic is defined by the upper and lower membership functions. The upper membership function (UMF) is approximately the same as the membership function in type-1 fuzzy logic. In contrast, the lower membership function (LMF) in type-2 fuzzy logic provides a range within the membership function to handle higher levels of uncertainty. The LMF cannot exceed the UMF, indicating that the LMF reflects a degree of membership that is either lower than or equal to that of the UMF. The interval between the LMF and UMF is referred to as the footprint of uncertainty (FOU), which can be modified according to user specifications. Fig. 4 illustrates the UMF and the LMF, with the shaded area between them representing the FOU.

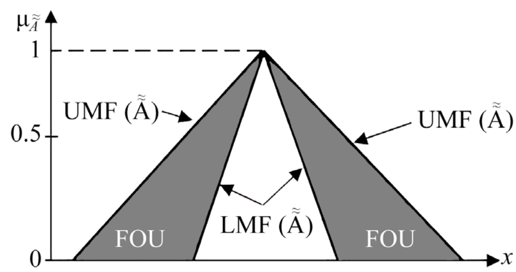


Fig. 4. Type-2 fuzzy membership function

Type-2 fuzzy logic defines membership functions through upper membership functions (UMF) and lower membership functions (LMF), thus forming a larger uncertainty spectrum due to its added parameter range. Type-2 fuzzy logic differs from type-1 fuzzy logic in that it assigns a fuzzy set for each degree of membership, thus accommodating higher levels of uncertainty, while type-1 fuzzy logic assigns one membership value for each input. Therefore, type-2 fuzzy logic has a smoother graph shape and control response, resulting in the process reaching stability more quickly. A type-2 fuzzy set A in the universe of discourse X is expressed as

$$\bar{A}=\left\{\left(\left(x\ ,u\right),\mu_{\bar{A}}\left(x\ ,u\right)\right)I_x \in J_x \sqsubseteq\left[0\ .1\right]\right\}, \quad (8)$$

where x – an element in the input space X, u – the secondary membership variable within the interval Jx, $\mu_{\bar{A}}\left(x,u\right)$ – the secondary membership function, which defines the degree of membership of u in the primary membership function. The UMF and LMF are denoted as:

$$\text{UMF}:\widetilde{\mu_{\tilde{A}}}\left(x\right), \quad (9)$$

$$LMF:\mu_{\tilde{A}}\left(x\right), \quad (10)$$

where the footprint of uncertainty (FOU) is the region between the UMF and LMF

$$FOU=U_{x\in X}\left[\mu_{\tilde{A}}\left(x\right),\tilde{\mu}_{\tilde{A}}\left(x\right)\right]. \quad (11)$$

UMF defines the upper boundary of the fuzzy set, similar to type-1 membership functions. LMF defines the lower boundary, restricting the possible membership degrees. FOU represents the uncertainty range, which allows the system to handle variability and imprecision in data. This structure makes type-2 fuzzy logic particularly useful in applications with prevalent uncertainty, such as autonomous vehicle control, robotics, and decision-making systems. Membership function curves have several forms such as triangular, trapezoidal, and custom membership functions. However, the triangular curve is the most frequently used. In Fig. 4, there is a membership function curve with FoU shading. The following are the upper and lower membership functions, represented by triangular curves.

Lower membership function ($\underline{\mu}^1(x)$) [25]

$$\underline{\mu}^1(x;a,b,c)=\begin{cases} 0,\ x\le a_i \text{ or } x\ge c_i, \\ \dfrac{x-a_i}{b_i-a_i},\ a_i<x<b_i, \\ \dfrac{c_i-x}{c_i-b_i},\ b_i<x<c_i, \\ 1,\ \ x=b_i. \end{cases} \tag{12}$$

Upper membership function $\left(\overline{\mu^1}(x)\right)$ [25]

$$\left(\overline{\mu^1}x;a,b,c\right)=\begin{cases} 0,\ x\le a_i \text{ or } x\ge c, \\ \dfrac{x-a_i}{b_i-a_i},\ a_i<x<b_i, \\ \dfrac{c_i-x}{c_i-b_i},\ b_i<x<c_i, \\ 1,\ x=b_i, \end{cases} \tag{13}$$

where $\left(\underline{\mu^1(x)}\right)$ – a lower membership function, i – an upper membership function, a – a lower bound of the fuzzy set, b – the peak value of the Fuzzy set, and c – an upper bound of the fuzzy set. At this stage, fuzzy rules are established to connect input and output variables. These rules are expressed in the form of "if the input condition is A and B, then the output is C". Logical operators, typically "AND", are used to link multiple input conditions. In type-2 fuzzy logic controllers (FLC), the process is more complex because the input has both lower and upper levels. In the inference system, this study uses the Sugeno method where only the input membership function is a type-2 fuzzy set while the output membership function is the same as the Sugeno method in fuzzy type-1. The inference system involves UMF and LMF in the process as seen in Fig. 5 below.

This method employs the minimum operation to ascertain the minimum membership value from the fuzzy sets linked to each rule. The outcome of this minimum operation is subsequently utilized as a contribution to the membership at the Fuzzy output level. The membership values are divided into two categories: upper and lower. The diagram in Fig. 6 illustrates the type-2 fuzzy inference process steps, where the minimum operation is applied to address uncertainty levels and provide a more conservative membership contribution.

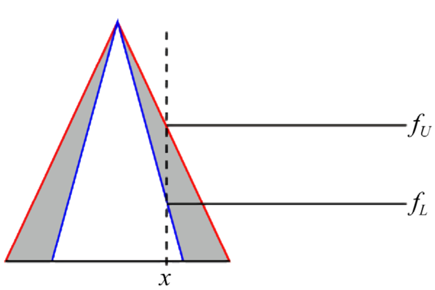


Fig. 5. Upper membership functions and lower membership functions in Fuzzy inference systems [25]

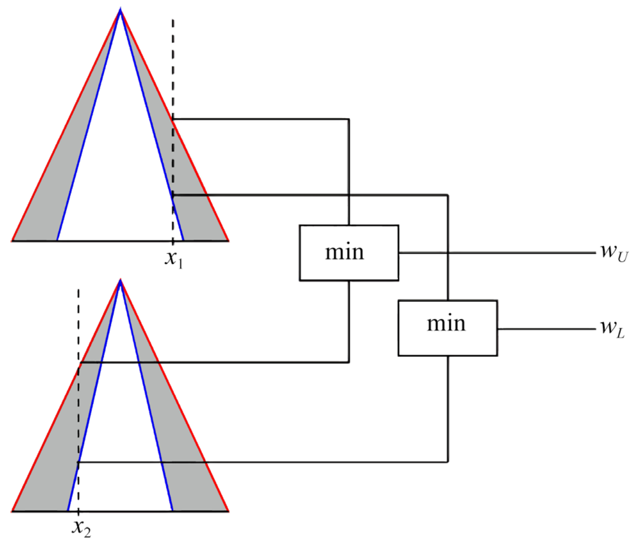


Fig. 6. Type-2 fuzzy inference process [25]

Based on the adopted approach, the upper and lower membership values can be calculated using the following formulas:

$$\underline{F}=\min\left(\underline{\mu}_{a_1}(x_1),\underline{\mu}_{a_2}(x_2),\ldots..\underline{\mu}_{a_n}(x_n)\right), \tag{14}$$

$$\overline{F}=\min\left(\overline{\mu_{a_1}}(x_1),\overline{\mu_{a_2}}(x_2),\ldots..\overline{\mu_{a_n}}(x_n)\right), \tag{15}$$

where $\underline{F}$ – the lower predicate value, $\overline{F}$ – the upper predicate value, $\underline{\mu_{A2}(xn)}$ – the lower membership degree in ted color on n-th input, $\overline{\mu_{A1}}(xn)$ – the upper membership degree in blue color on n-th. A key distinction between type-1 fuzzy logic and type-2 fuzzy logic systems resides in their reduction procedures. The simplification of type-2 fuzzy logic is a crucial procedure intended to enhance the output membership function of a type-2 fuzzy system, transforming it into a singular value prior to defuzzification. Unlike type-1 fuzzy logic, which employs a single membership function, type-2 fuzzy logic integrates an upper membership function (UMF) and a lower membership function (LMF), resulting in an interval-valued fuzzy output. The output of a type-2 fuzzy system is represented as a range of values, requiring reduction to transform this interval into a single numerical value for further analysis. Frequently employed reduction techniques include the centre of sets (COS) method, renowned for its processing efficiency; the Height Method, which emphasizes the apex values of the membership function; and the Karnik-Mendel (KM) algorithm, which adopts an iterative approach for enhanced precision. The selection of a reduction method depends on the complexity of the system and its computational demands. This reduction method improves the applicability of type-2 fuzzy logic systems, rendering them more appropriate for real-world scenarios necessitating decision-making grounded in fuzzy logic. In this study, the center of set (COS) method was used because its computation time is fast and effective. The COS method is written in the following equation

$$Y_{\text{CO}}(x)=\left[y_l,y_r\right], \tag{16}$$

where y_l – the lower limit on Y_{CO}, y_r – the upper limit on Y_{CO}, Y_{CO} – the center of the set method. Where the values of y_l and y_r can be formulated as follows:

$$y_l = \frac{\sum_{i=1}^{M} f_l^i y_l^i}{\sum_{i=1}^{M} f_l^i}, \quad (17)$$

$$y_r = \frac{\sum_{i=1}^{M} f_r^i y_r^i}{\sum_{i=1}^{M} f_r^i}, \quad (18)$$

where f_r^i shows the upper limit of membership degree of the i-th element; f_l^i shows the lower limit of membership degree of the i-th element; M – the number of elements; y_r^i – the upper limit of the i-th element, and y_l^i – the lower limit of the i-th element. The defuzzification process can vary depending on the method used in type-2 fuzzy theory. The output of type-2 fuzzy, which previously had a level of uncertainty, after being reduced using the COS method, is changed into a crisp value that can be used with the following formulation

$$y_r = \frac{y_l + y_r}{2}. \quad (19)$$

If to look at equation (19), it is possible to determine the reduction results using the COS method, where it is possible to obtain the average of the low limit and upper limit. This result will be converted to a crisp value that will be sent to the output.

4. 5. Experimental setup

This research aims to make autonomous vehicles able to navigate, such as moving straight and turning at intersections, and also to make autonomous vehicles adjust their position on the correct path stably.

To achieve this aim, this research was conducted by designing the process as listed in the flowchart in Fig. 7.

In Fig. 7, the process begins with initialization, destination setting, and path planning to determine both the global and local paths, as well as GPS and camera readings. It then continues with capturing camera data and obtaining the coordinates of the autonomous vehicle. The results from these sensor readings are converted into a steering angle, which serves as the input for the type-2 FLC. The output of type-2 FLC is PWM, which will move the steering so that the autonomous vehicle can move to avoid obstacles. if a roadblock is detected, a local path replanning process will occur to find another route. The coordinates continue to update during the journey from node to node until the current coordinates are the same as the destination coordinates; then the entire system will stop. The camera gets the road segmentation value, object distance, and object position using the YOLO V8 algorithm. At the same time, GPS gets the autonomous vehicle distance value, angles, and intersection directions. All of these values will be collected as input in the form of a steering angle value, which will then be used by the controller to stabilize the autonomous vehicle when maneuvering, such as moving straight and turning at intersections, ensuring it remains within its designated path.

In the design of type-2 FLC, the zero-order Sugeno method is used, with the input used in the form of error values (e) and delta error (Δe). Using 7 membership functions (MF), namely NL (Negative Large), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positive Small), PM (Positive Medium), and PL (Positive Large) as seen in Fig. 8. Then the output produced from type-2 FLC is in the form of a PWM (Pulse Width Modulation) value, which will be used by the steering motor. The output itself is divided into 7 variables, namely "Stop", "Slow", "Slightly Slow", "Normal", "Slightly Fast", "Fast", and "Very Fast" as seen in Fig. 9.

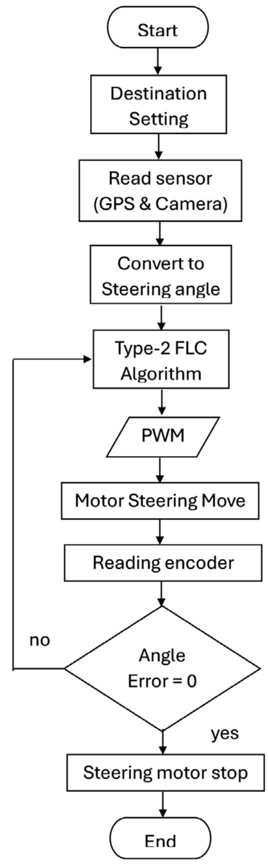


Fig. 7. Flowchart of steering control system design on autonomous vehicle

Fig. 8, 9 show the membership functions of the input and output of the Type-2 FLC.

Then, the block diagram of the steering control system that will be used in this study can be seen in Fig. 10.

Based on the closed-loop block diagram as seen in Fig. 10, the setpoint used is the steering angle value obtained from the sensor. Then the setpoint is subtracted from the actual angle value obtained from the encoder sensor reading on the steering motor. This subtraction yields the error value, and the delta error is then determined by subtracting the current error from the previous error. The obtained error and delta error values are used as inputs for the type-2 FLC. The output of the type-2 FLC is a pulse width modulation (PWM) value, which is used to control the steering motor and the steering motor rotates to reach the expected steering angle value, which is read through the encoder. This research utilizes a setpoint in the form of a steering angle value generated from sensor readings. The steering angle value will be used by type-2 FLC as a setpoint. The setpoint is then subtracted by the feedback from the pulse encoder, resulting in an error value, and the delta error is also calculated. These errors and delta error values serve as inputs for the type-2 FLC.

The implementation of the type-2 FLC-based controller in this study uses two inputs in the form of error and delta error values obtained from the difference between the steering angle value and the encoder reading on the steering motor. In this study, two types of testing will be carried out, namely simulation and real-time. Both tests aim to evaluate the performance of type-2 FLC in the lateral control of autonomous vehicles.

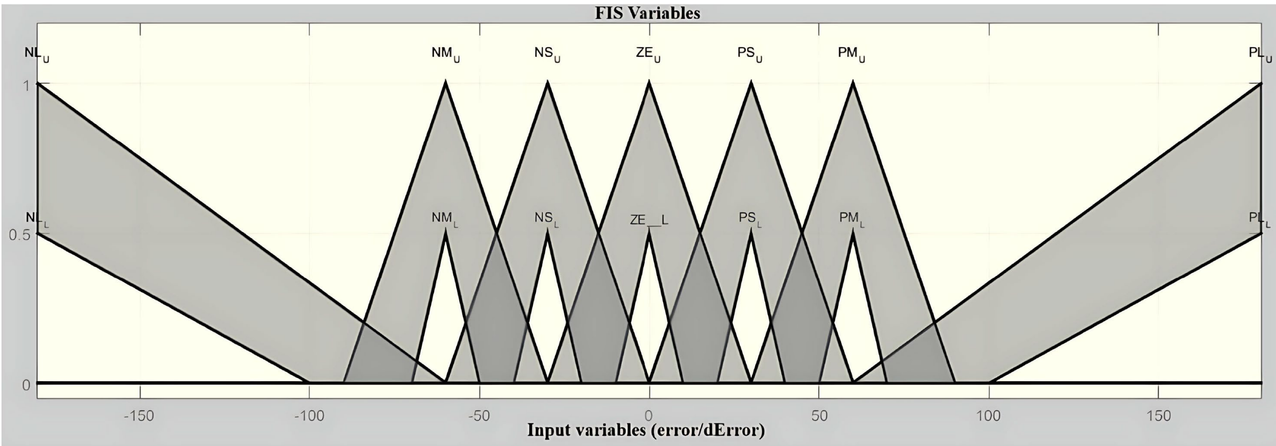


Fig. 8. Membership function type-2 FLC input

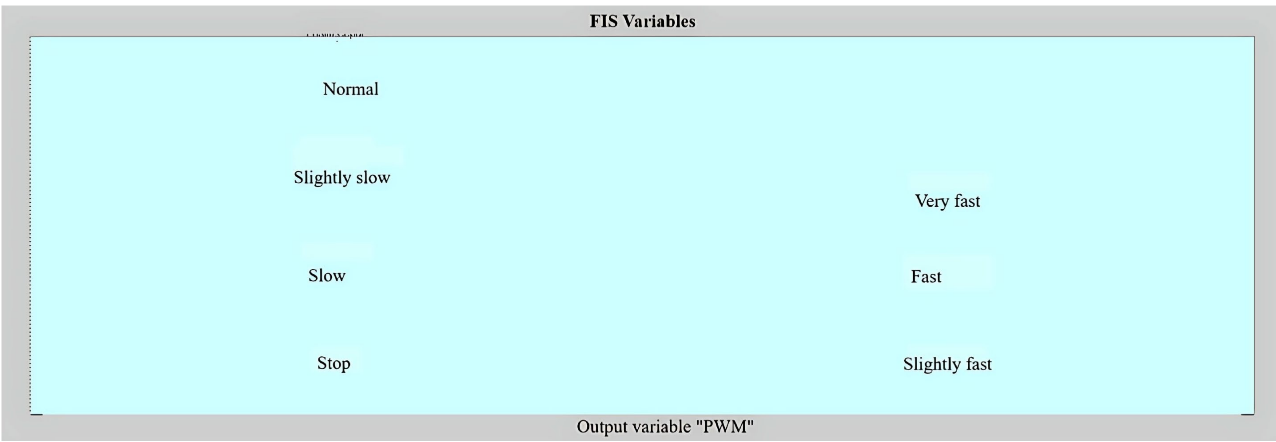


Fig. 9. Membership function type-2 FLC output

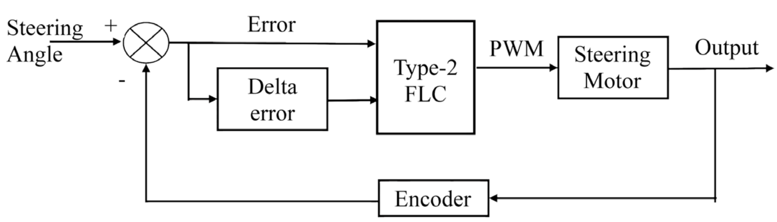


Fig. 10. Block diagram of steering control system on autonomous vehicle

The simulation testing aims to evaluate the stability level of two types of controllers, type-2 FLC and PID controller, which will be implemented to control the steering system. The purpose of this test is to compare the performance of both controllers in maintaining the stability of the steering system under various simulation conditions. The testing is conducted by considering several simulation scenarios, including sudden input changes, external disturbances, and speed variations. The data generated from this simulation will be analyzed to identify the ability of each controller to respond to the changes that occur and its ability to maintain system stability. Besides, the parameters of the type-2 FLC and PID controllers will be optimized using appropriate tuning methods to ensure optimal performance of each controller. The results of this testing will be used to compare the advantages and disadvantages of both controllers in controlling the steering system, as well as to provide recommendations regarding the use of the most appropriate controller in real applications. Real-time testing will be conducted at the Sriwijaya University, Inderalaya campus, to evaluate the stability level of two types of controllers, namely type-2 FLC and PID controller, in controlling the lateral movement of autonomous vehicles. The purpose of this test is to compare the performance of the two controllers in realistic control situations.

During testing, autonomous vehicles will be directed to follow a predetermined route and will face various road conditions that can be observed to see the performance of the control system. Autonomous vehicles must be able to maneuver, such as walking straight, turning at intersections, and avoiding obstacles. Then the autonomous vehicle must also be able to maintain its position to stay on track. Data will be collected directly from autonomous vehicles moving in a real environment to analyze the response and stability of the control system. The test route map that will be passed by the autonomous vehicle is as shown in Fig. 11 below.

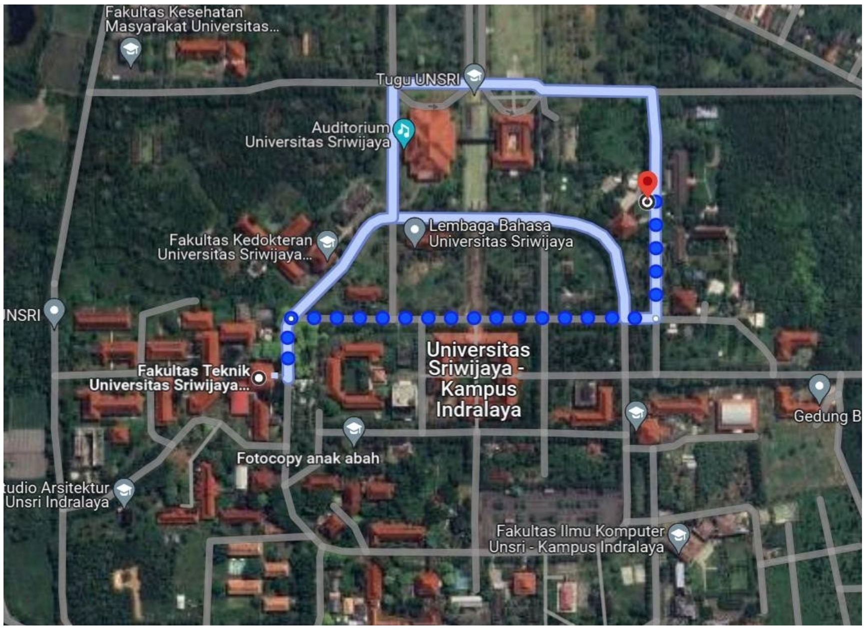


Fig. 11. Testing route

The testing route for the real-time implementation, as shown in Fig. 11, takes place at Universitas Sriwijaya, from the Faculty of Engineering to the Main Rectorate.

5. Type-2 FLC performance results

5. 1. Type-2 FLC for implementation in controlling the steering of the autonomous vehicles

This section discusses the comparison between type-2 FLC and PID for steering control on autonomous vehicles in maneuvering, such as turning at intersections and moving to maintain their position. This section discusses system testing, both in simulation and real-time testing, as well as analysis of the results obtained to see the performance of the two control methods in the implementation of the system that has been created.

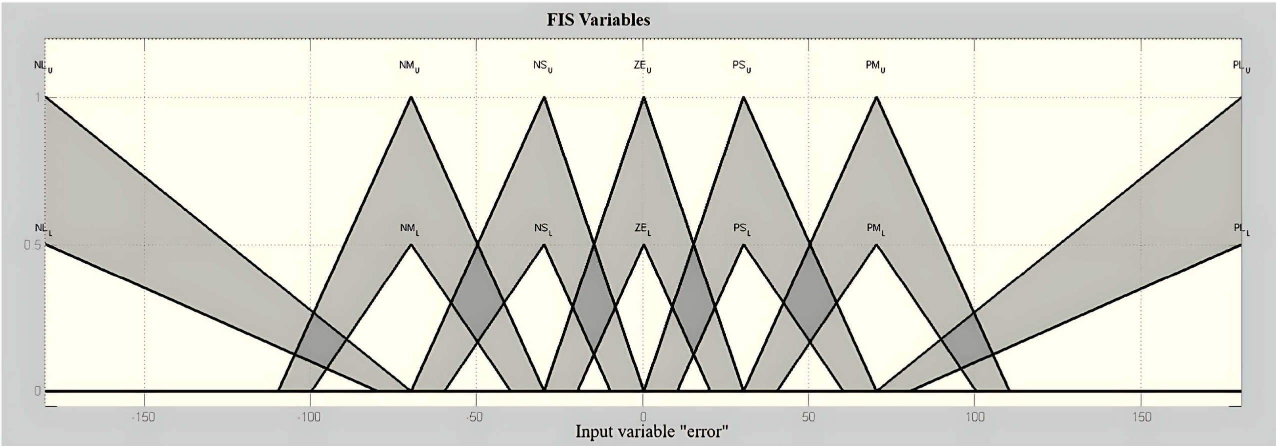
This type-2 FLC system uses the Sugeno method as a secondary controller to control the steering of the autonomous vehicle. This system is designed to help the car maneuver, such as when turning at an intersection and maintaining its position in its lane. The following are the membership functions that will be tested in this study. This type-2 FLC system uses the Sugeno method as a secondary controller to control the steering of the autonomous vehicle. This system is designed to help the car maneuver, such as when turning at an intersection and maintaining its position in its lane. The following are the membership functions that will be tested in this study. The curve shown in Fig. 12 is a curve of the variable error value and delta error of the steering angle, which can be calculated using (12), (13) that obtained as in Table 1.

Table 1 contains the membership function parameters that are used as input for errors and delta errors such as negative large, negative medium, negative small, zero, positive small, positive medium and positive large.

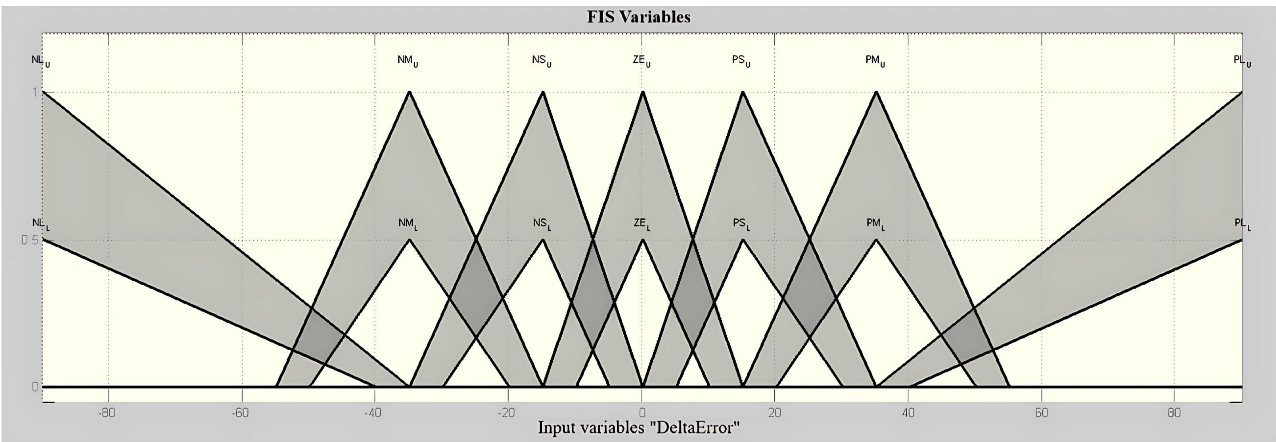
Table 1 and Fig. 12 are representations of the membership function of each input tested in this study. This system uses input in the form of error values and delta errors from the difference between the steering angle values obtained from the output of the sensor and the steering encoder value. The membership function used consists of seven categories: NL (Negative Large), NM (Negative Medium), NS (Negative Small), Z (Zero), PS (Positive Small), PM (Positive Medium), and PL (Positive Large). Positive is the area where the error value indicates that the steering wheel must be directed to the right, resulting in the expected output of rightward steering movement. Conversely, negative is the area where the error value indicates that the steering wheel must be directed to the left, leading to the expected output of leftward steering movement. While zero is the area where the error value is almost zero, so that the steering wheel is conditioned to run straight with very small corrections.

The fuzzification stage in this study aims to determine the membership function value of the given input. The input data used for the angle error is 45 and 90, with a delta error value of 45. The results of the fuzzification process for the upper and lower error variable set and the upper and lower delta error are PS (Positive Small). The results of this fuzzification process show that the values produced are determined by the predetermined membership function. Then continued with the stage of determining the fuzzy rules, which aim to obtain the desired output. In this study, there is one output variable, namely PWM (pulse width modulation). This study uses input variables with 7 membership functions. Then, from these various conditions, a rule of 49 was created as in Table 2 below.

Based on the fuzzy rules in Table 2, the output of the type-2 FLC system is the PWM value used to drive and control the steering motor with seven membership functions: NB (Negative Big), NM (Negative Medium), NS (Negative Small), Z (Zero), PS (Positive Small), PM (Positive Medium), and PB (Positive Big). PB indicates the need for cars steering for high speed in reaching a distant target position, while NB is the opposite for the opposite direction. PM requires a medium rotation speed, not too fast or slow, while NM is the opposite. PS requires low speed for close targets, and NS is the opposite for the opposite direction. Zero indicates the need for car steering for very slow speed approaching a target position that is very close to the setpoint value 0. In this study, the fuzzy inference system Sugeno zero order method is used in determining the produced output value. The output values in this study can be seen in Table 3.



a



b

Fig. 12. Membership function input: *a* — error; *b* — delta error

Table 1

Membership function error and delta error steering angle

Error			Delta error		
Member	Upper	Lower	Member	Upper	Lower
Negative Large	[–180, –180, –70, 1]	[–180, –180, –80, 0.5]	Negative Large	[–120, –90, –35, 1]	[–100, 90, –40, 0.5]
Negative Medium	[–110, –70, 30, 1]	[–100, –70, –40, 0.5]	Negative Medium	[–55, –35, 15, 1]	[–50, –35, –20, 0.5]
Negative Small	[–70, –30, 0, 1]	[–60, –30, 10, 0.5]	Negative Small	[–35, –15, 0, 1]	[–30, –15, –5, 0]
Zero	[–30, 0, 30, 1]	[–20, 0, 20, 0.5]	Zero	[–15, 0, 15, 1]	[–10, 0, 10, 0.5]
Positive Small	[0, 30, 70, 1]	[10, 30, 60, 0.5]	Positive Small	[0, 15, 35, 1]	[5, 15, 30, 0.5]
Positive Medium	[30, 70, 110, 1]	[40, 70, 100, 0.5]	Positive Medium	[15, 35, 55, 1]	[20, 35, 50, 0.5]
Positive Large	[70, 180, 240, 1]	[80, 180, 210, 0.5]	Positive Large	[35, 90, 120, 1]	[40, 90, 100, 0.5]

Table 2

Type-2 FLC rule base

ΔErr / *Err*	NL	NM	NS	ZE	PS	PM	PL
NL	NB	NB	NB	NB	NS	NS	NS
NM	NB	NM	NM	NM	NS	NS	NS
NS	NM	NS	NS	NS	NS	NS	NS
ZE	Z	Z	Z	Z	Z	Z	Z
PS	PS	PS	PS	PS	PS	PS	PM
PM	PS	PS	PS	PM	PM	PM	PB
PL	PS	PS	PS	PB	PB	PB	PB

Table 3

Type-2 FLC rule base

Membership function	PWM value
Negative Big	–230
Negative Medium	–150
Negative Small	–70
Zero	0
Positive Small	70
Positive Medium	150
Positive Big	230

The type-2 FLC used in this study requires a reduction stage where equations 17 and 18 describe the center set reduction technique used. Defuzzification is the last step that produces one value that will be output. Then, in this defuzzification step, a direct average is used, similar to equation 18, where the difference between the upper and lower reduction results is added together, and the results are divided.

5. 2. Type-2 FLC for simulation and real-time testing

Then the next stage is to simulate the type-2 FLC that has been designed. This test aims to evaluate the output value of the type-2 FLC that has been designed and will test the comparison of type-2 FLC and PID controller. The results of this simulation are analyzed to evaluate how the system responds to changes in input, including how quickly and accurately the system reaches the desired output. This simulation will compare type-2 fuzzy with seven members and PID control to test the system's response to a setpoint value of 90 as seen in Fig. 13.

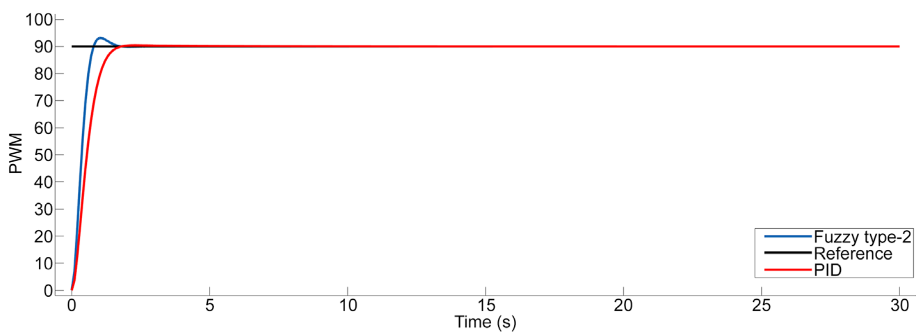


Fig. 13. Type-2 FLC and PID control simulation test results

The simulation results can be seen in Table 4, where type-2 FLC has advantages compared to PID only in the steady state error and overshoot parameters that outperform type-2 FLC. This comparison can be seen in Table 4.

Table 4 shows the simulation results of using the type-2 FLC and PID, with parameters such as rise time, settling time, peak time, overshoot, and steady-state error.

Real-time testing of the type-2 FLC on autonomous vehicles begins by comparing the performance of the controller using 5 and 7 membership functions. The purpose of this test is to determine the most optimal type-2 FLC configuration in controlling the steering system of the autonomous vehicle. After determining the best configuration, the results will be used to compare the performance of type-2 FLC with PID control. The steering angle value of the wheel is the pulse value generated each time the steering wheel rotates. The steering wheel can rotate up to 720 degrees to the left but only rotate up to 540 degrees to the right. Due to this difference, the steering angle value for rotation to the left is also set at 540 degrees. The steering wheel and the connected encoder have a gear ratio of 1 : 2, with the larger gear on the encoder. The encoder used has a value of 360 ppr (pulses per revolution), which means that one full rotation of the encoder produces 360 pulses. Therefore, the steering wheel rotation value that is read should be 540 degrees to the left and 540 degrees to the right. However, due to the different gear ratios, the values read on the encoder are 270 degrees to the right and left. Thus, the steering wheel rotation range is 0 to 540 degrees, with the midpoint at 270 degrees. The rotation value is then limited in the program so that the steering wheel limit is 0 to 540 degrees.

The route used in this test starts from the front of the Electrical Engineering Department and ends at the turn in front of the Mining Engineering Department. This route was chosen to evaluate the effectiveness and accuracy of steering control in real environmental conditions, so as to ensure the type-2 FLC configuration that provides the best results in navigation and maneuvering of the autonomous vehicle. Fig. 14 shows the route that will be taken in this test.

Table 4

Simulation results

Parameter	Type-2 FLC	PID
Rise Time	0.5074 s	0.9056 s
Settling Time	1.3388 s	1.4549 s
Peak Time	1 s	2.3 s
Overshoot	3.5117%	0.5361%
Steady State Error	-0.0150	-2.1491×10^{-6}

Fig. 14. Type-2 FLC configuration comparison test route

Following a comparative test between type-2 FLC with 5 and 7 membership functions, the results revealed that the type-2 FLC configuration with 7 membership functions performed better. Type-2 FLC with 7 membership functions demonstrated a quicker and smoother response than the 5 membership functions configuration. During testing, type-2 FLC with 7 membership functions was able to control the steering system of the autonomous vehicle with higher precision, resulting in more stable maneuvers without significant overshoot. In contrast, type-2 FLC with 5 membership functions still overshoots, which indicates instability in steering control. Therefore, the Type-2 FLC configuration with 7 membership functions was chosen as the most optimal configuration for controlling the steering of the autonomous vehicle before proceeding to the comparison stage with PID control. These results indicate that increasing the number of memberships in type-2 FLC can improve the accuracy and responsiveness of the steering control system in autonomous vehicles. The results of the comparison graph can be seen in Fig. 15 below.

Fig. 15 shows that type-2 FLC with 7 membership functions is better in following the given setpoint response compared to 5 membership functions. However, both are still less able to follow the setpoint response when turning at a large angle.

It was necessary to conduct comparative testing between type-2 FLC and PID control in obstacle avoidance to evaluate the efficiency of both controllers when confronted with difficult circumstances. For the purpose of this test, the autonomous vehicle will be required to go through three different obstacle scenarios. To get around the first obstacle, which is a pedestrian on the left side of the road, the driver of the vehicle must shift the steering wheel to the right to avoid the pedestrian. The second obstacle is a parked car on the left, while the third obstacle is two parked cars, one on the left and one on the right, which require more complex maneuvers to be passed safely. In this experiment, the PID constants were used, which were tuned by trial and error as in Table 5 below, and the route used in this test can be seen in Fig. 16.

Table 6 shows the obstacle avoidance capability of the type-2 FLC and PID, including the type of obstacle and the camera view.

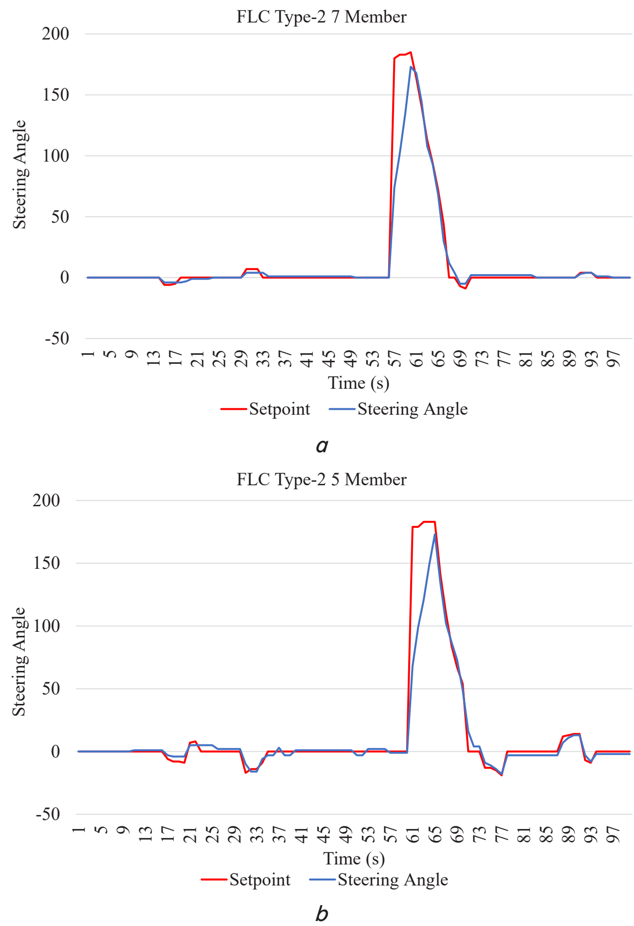


Fig. 15. Type-2 FLC configuration test results:
a — 7 membership function; *b* — 5 membership function

Table 5

Obstacle route PID constant

Parameters	Value
Kp_stir	1.5486
Ki_stir	0.001
Kd_stir	3.1673

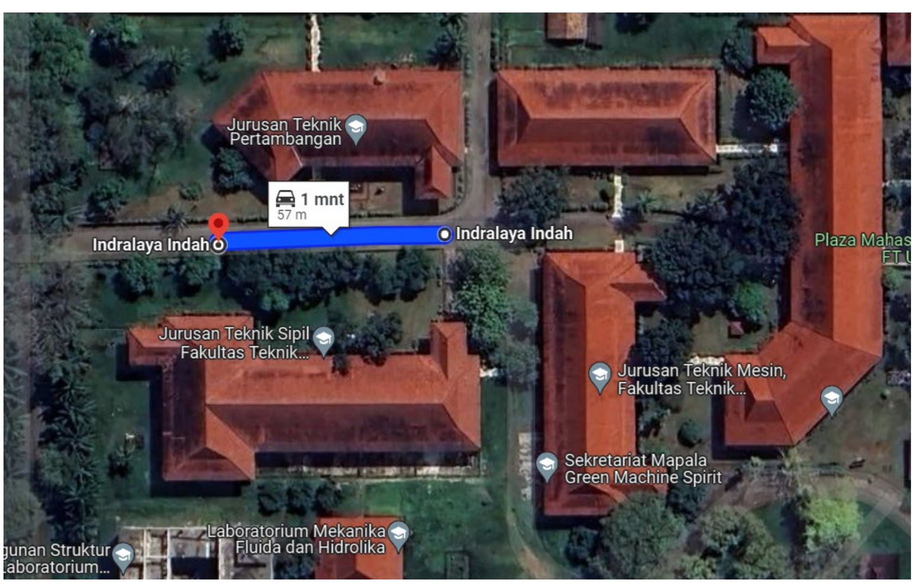


Fig. 16. Obstacle avoidance test route

Table 6

Obstacle avoidance

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<tr><th>No.</th><th colspan="2">Obstacle</th></tr>
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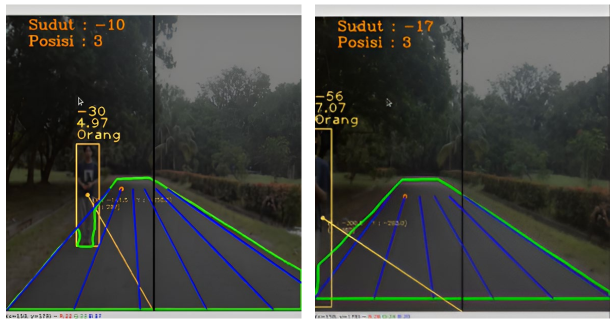
<tr><td rowspan="4">1</td><td colspan="2">Human</td></tr>
<tr><td>Camera result</td><td>
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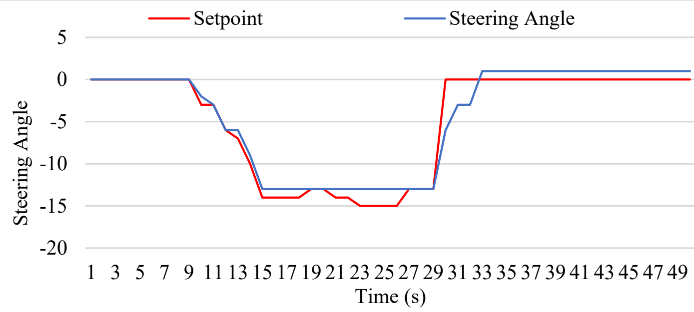
<tr><td>Type-2 FLC</td><td>
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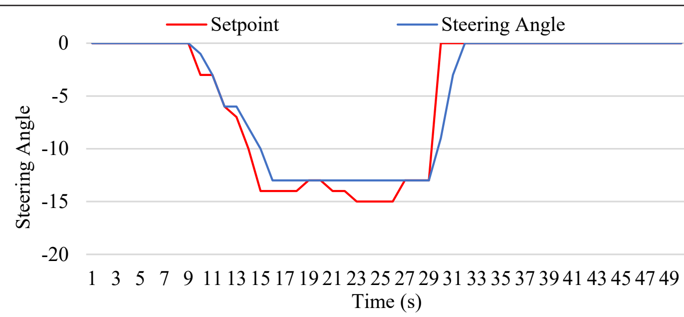
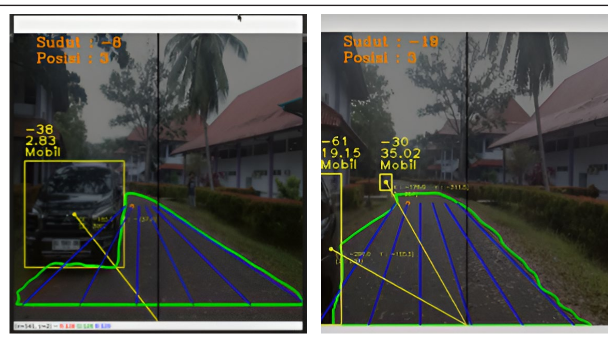
<tr><td>PID</td><td>
</td></tr>
<tr><td rowspan="3">2</td><td colspan="2">1 car</td></tr>
<tr><td>Camera result</td><td>
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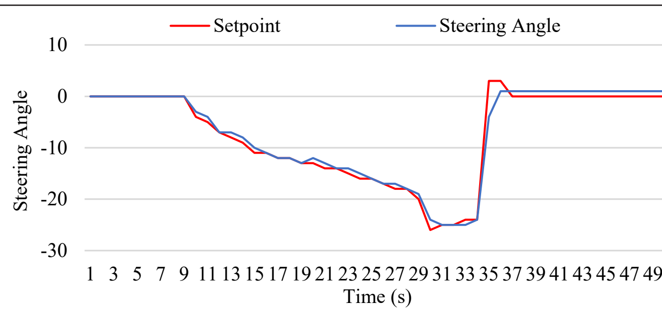
<tr><td>Type-2 FLC</td><td>
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Continuation of Table 6

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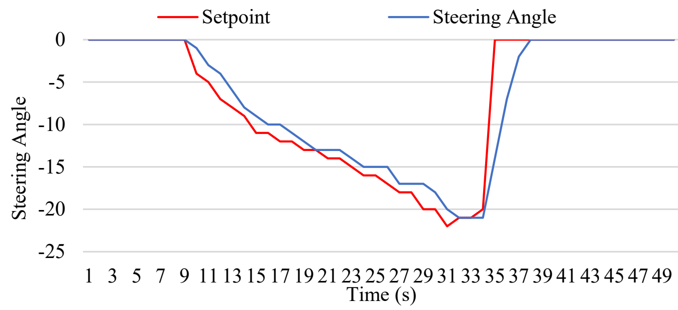
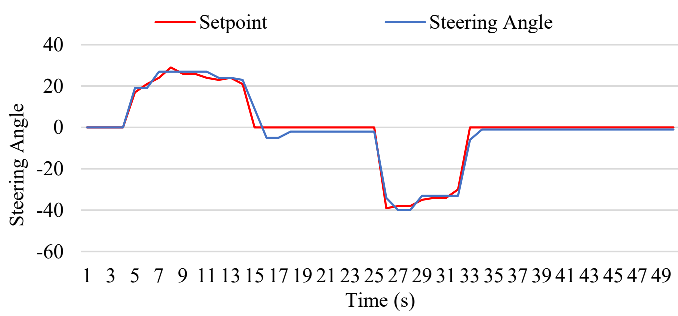
<tr><td>2</td><td>PID</td><td>
</td></tr>
<tr><td rowspan="4">3</td><td colspan="2">2 cars on the left side of the road</td></tr>
<tr><td>Camera result</td><td></td></tr>
<tr><td>Type-2 FLC</td><td>
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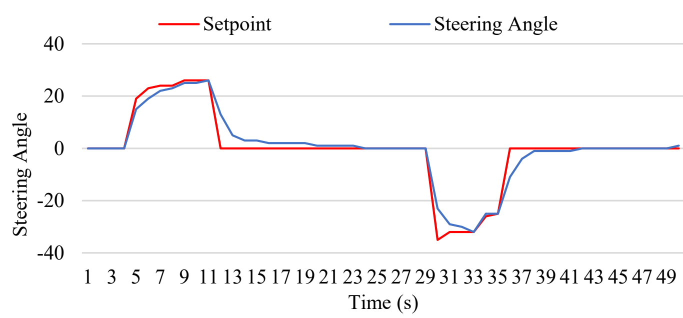
<tr><td>PID</td><td>
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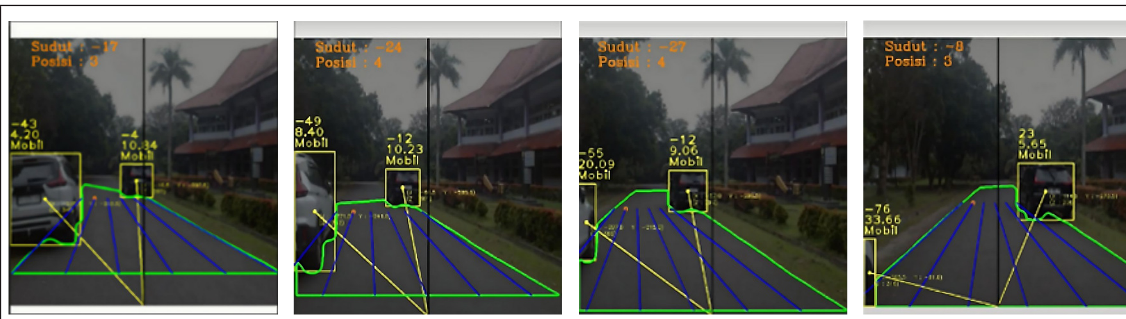
<tr><td>Camera result</td><td></td></tr>
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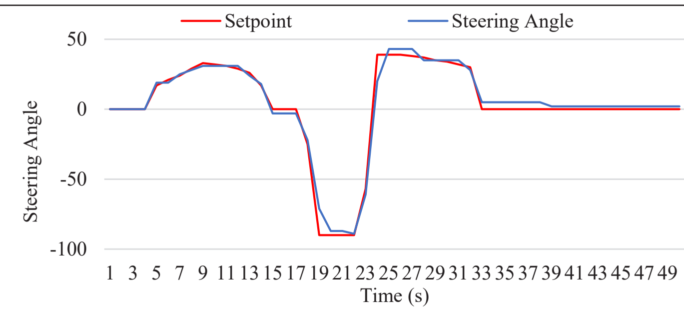
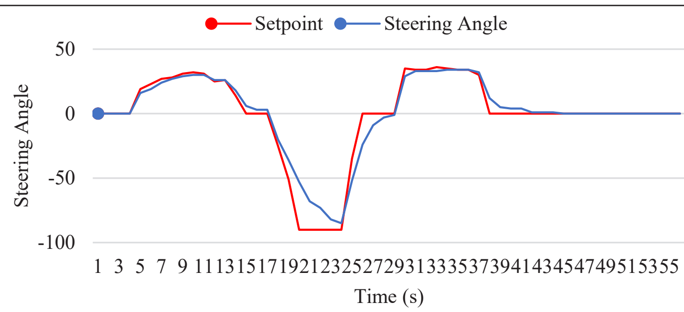
Continuation of Table 6

1	2	
4	Type-2 FLC	
	PID	

The comparative test of type-2 FLC and PID control performance on the autonomous vehicle steering system was conducted by passing through a route from the front of the Electrical Engineering Department to the front of the Faculty of Engineering building, then back to the front of the Electrical Engineering Department. On this route, there are three broken turns at the intersections that the autonomous vehicle will pass. The route shown in Fig. 17 is the one that will be followed.

The controller receives input from camera readings using the YOLOv8 method, where the results of these camera readings provide the car's position value on the mapped path and detect the presence of obstacles. The parameters for the vehicle turning at an intersection are based on the detection of intersections from the camera and the distance of the intersection obtained from GPS. However, this setpoint is influenced by actual conditions on the road, such as the presence of passing vehicles or those parked on the side of the road, which affect the camera readings. This test aims to evaluate the effectiveness and accuracy of type-2 FLC compared to PID control in controlling the steering system of an autonomous vehicle in various dynamic road conditions. In this experiment, the PID constants were used, which were tuned by trial and error as in the following Table 7.

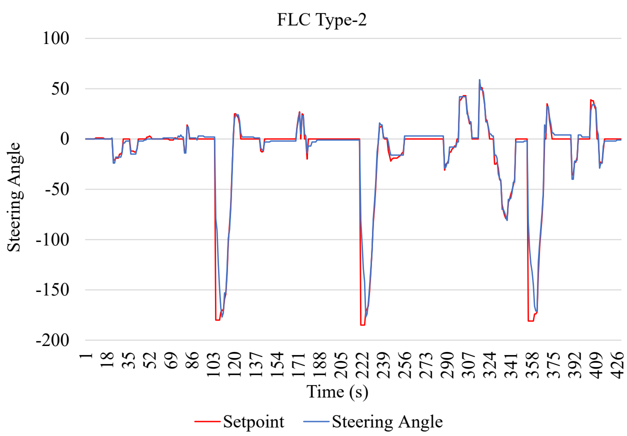
The performance of the type-2 FLC and PID controllers can be seen in Fig. 18 for the first route test from the front of the Electrical Engineering Department to the front of the Faculty of Engineering building. In Fig. 18, the x-axis is time, and the y-axis is the steering angle. then given a set point value that causes each controller to show its response for the type-2 FLC in Fig. 18, *a* while the PID controller in Fig. 18, *b*.

Fig. 17. Type-2 FLC and PID control performance test route

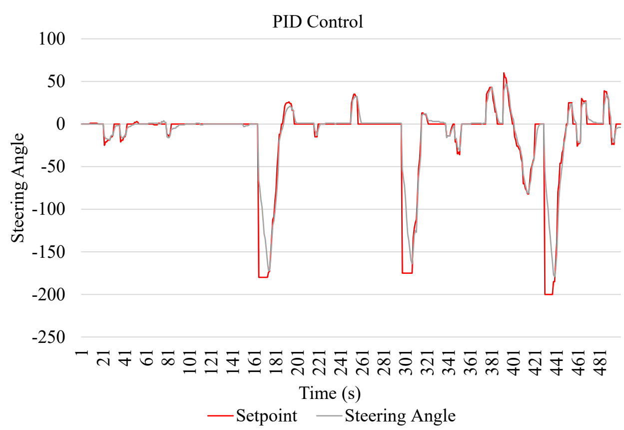
Table 7

PID constants on the full route

Parameters	Value
Kp_stir	1.9134
Ki_stir	0.001
Kd_stir	3.6672



a



b

Fig. 18. Controller performance results on the first route: *a* – type-2 FLC; *b* – PID control

Fig. 19 shows the results for the return route, from the Faculty of Engineering building back to the front of the Electrical Engineering Department.

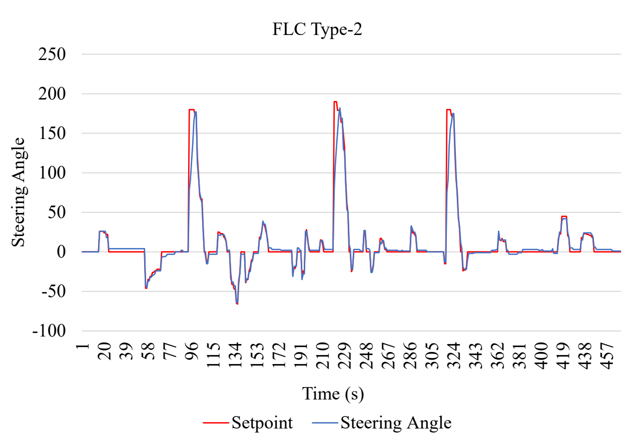
Fig. 18, 19 show that the performance of the type-2 FLC is superior to that of the PID control on both routes.

6. Discussion of results: the performance of type-2 FLC on steering control in autonomous vehicles

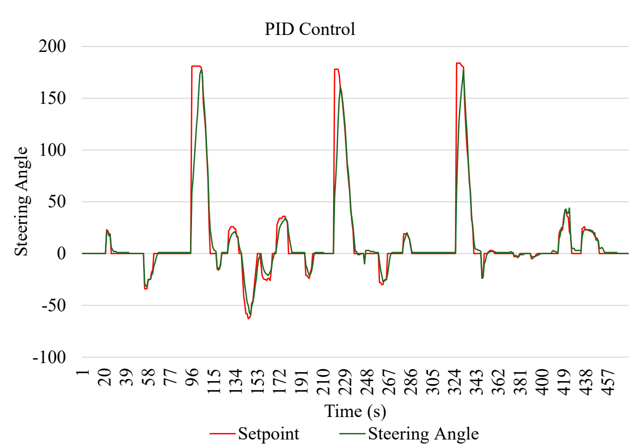
This research is compared with PID, which has been widely used and is still a mainstay. This chapter discusses the comparison.

Based on the aim of this study, Table 4 presents a comparison between the type-2 FLC and PID control in the simulation test. The results show that the type-2 FLC demonstrates superior performance in several key parameters. The rise time for the type-2 FLC is 0.5074 seconds, which is faster than that of the PID control, at 0.9056 seconds. The settling time for the type-2 FLC is 1.3388 seconds, slightly quicker than the PID control's 1.4549 seconds. Additionally, the peak time for the type-2 FLC is 1 second, significantly shorter than the PID control, which reaches its peak at 2.3 seconds. In terms of overshoot, the type-2 FLC records a value of 3.5117%, which is higher than the PID control's 0.5361%. However, it is important to note that the steady-state error for the type-2 FLC is –0.0150, while the PID control records a much larger error of $-2.1491 \cdot 10^{6}$. Although the PID control shows a smaller overshoot, the type-2 FLC exhibits a faster and more efficient response in reaching the setpoint, with shorter peaks and settling times. These results highlight the effectiveness of the type-2 FLC in improving the dynamic performance of autonomous vehicle control systems.

Meanwhile, in the case of real-time testing, as shown in Fig. 15, the average error generated by the type-2 FLC in the comparison test of 5- and 7-membership-function configurations indicates that the type-2 FLC with 7 membership functions has a smaller error value compared to the 5-membership-function configuration, especially in situations requiring fast and dynamic responses. Type-2 FLC with 7 membership functions recorded an average error percentage of 4.97%, whereas type-2 FLC with 5 membership functions recorded an average error percentage of 7.71%. Both figures are statistically significant. When compared to type-2 FLC with 5 membership functions, which has a tendency to experience more overshoot, this demonstrates that type-2 FLC with 7 membership functions is more effective in maintaining accuracy during obstacle avoidance maneuvers due to its increased number of membership functions.



a



b

Fig. 19. Controller performance results on the second route: *a* – type-2 FLC; *b* – PID Control

The test results in Table 6 show that the type-2 FLC has an advantage in responding quickly to obstacles that appear suddenly. In the first obstacle scenario, the type-2 FLC successfully avoided the pedestrian quickly and accurately, moving the steering wheel to the right with a fast response and without experiencing significant overshoot. For the second obstacle, the type-2 FLC was also able to avoid parked cars with efficient and rapid maneuvers. In the third and fourth, more complex obstacle scenarios, the type-2 FLC demonstrated good ability to navigate between two parked cars, although its response became slightly less smooth compared to the previous scenarios.

On the other hand, the PID controller produced a smoother response in all obstacle avoidance scenarios, but with slower response times than the type-2 FLC. In the first obstacle, PID control managed to avoid the pedestrian smoothly, but it took a bit longer to move the steering wheel to the right. For the second obstacle, PID control also successfully avoided the parked cars, but again, it took longer to turn. In the third and fourth obstacle scenarios, PID control was stable enough to navigate between two parked cars, but it took longer to complete the maneuver.

While the type-2 FLC excels in quick, dynamic responses like obstacle avoidance, the PID control is smoother and more stable, but slower. The optimal controller for obstacle avoidance in autonomous vehicles depends on balancing response speed and maneuver smoothness. In the second obstacle scenario, PID control avoided the parked cars effectively but responded slowly. In the third and fourth obstacle scenarios, PID control navigated between two parked cars with good stability, but took longer to finish the maneuver.

The average error generated by the type-2 FLC in avoiding the pedestrian (first obstacle) was 1.54%, in avoiding one parked car (second obstacle) was 4.28%, in avoiding two parked cars on the left (third obstacle) was 1.2%, and in avoiding two parked cars on the left and one on the right (fourth obstacle) was 2.13%. The PID controller exhibited average errors of 2.19%, 3.49%, 1.12%, and 3.49% for the corresponding cases, respectively. The results demonstrate that the type-2 FLC excels in obstacle avoidance with reduced error relative to the PID controller, despite the latter yielding a smoother response.

Fig. 18, 19, *a, b* are the results of the performance comparison test of the type-2 FLC and PID controller on the steering control of the autonomous vehicle. The results show that type-2 FLC has a faster response than the PID controller, especially in conditions that require the autonomous vehicle to maneuver quickly, such as turning at intersections. Because type-2 FLC can quickly change the direction of the steering, the car is better able to handle sudden changes in the road it's taking. The PID controller, on the other hand, has a slower response speed than the type-2 FLC but a smoother reaction. Although the PID controller shows slower performance, the smoothness of its response helps in maintaining steering stability, especially in straighter road conditions that do not require fast maneuvers. In addition, the PID controller has a better ability to overcome small steady-state errors, such as ± 4% value, thanks to the integral components in its controller.

On the other hand, type-2 FLC faces limitations in overcoming small steady-state errors due to the number and types of rules used in the fuzzy system. Although type-2 FLC is more responsive in dynamic conditions, its inability to eliminate small steady-state errors is a weakness that needs to be considered. The average error from the comparison of the performance of type-2 FLC and PID control on the autonomous vehicle steering system, which was tested by passing through a route from the front of the Electrical Engineering Department to the front of the Faculty of Engineering building, showed that type-2 FLC had an average error percentage of 8.87%, while PID control recorded an average error percentage of 12.35%. Then on the reverse route, namely from the front of the Faculty of Engineering building to the front of the Electrical Engineering Department, type-2 FLC recorded an average error percentage of 4.52%, while PID control recorded an average error percentage of 7.57%. These results indicate that type-2 FLC is more accurate in maintaining lanes and maneuvering than PID control throughout the test route. Overall, type-2 FLC is more suitable for conditions that require fast and dynamic responses, such as turns at intersections. Meanwhile, the PID controller is superior in maintaining stability and smoothness of response, as well as in overcoming small steady state errors. Both controllers have their own advantages and disadvantages, so the best choice depends on the desired performance priority in the Autonomous vehicle application.

Additional study is needed to address many constraints, even if the suggested type-2 FLC shows improved lateral control performance for autonomous vehicles by using steering control to keep their trajectories stable. There are some of these restrictions. This technique relies on precise sensor readings, such as those from pulse encoders used to measure steering angles. However, in real-world applications, sensor interference or failure can affect performance. Therefore, proper calibration is required for each vehicle platform, which limits plug-and-play applications. In addition, the current implementation has been tested within a limited range of input values to identify errors and delta errors. Whether the controller is still effective when working outside of this range, particularly in emergencies or at high speeds, requires further evaluation. It is possible to build a more robust framework for autonomous driving control in the future by expanding the current system to incorporate longitudinal control and decision-making. Improving environmental awareness and path tracking precision can be achieved by enhancing the perception system through the use of sensor fusion, which includes technologies like cameras, LIDAR, and GPS. Improving real-time adaptation and performance in uncertain contexts could be achieved through the creation of adaptive type-2 FLC or hybrid controllers that combine fuzzy logic with reinforcement learning or model predictive control.

Further development has several further challenges, including mathematically, real-time optimization of type-2 FLC parameters causes a significant computational burden. Experimentally, safe and repeatable testing in multiple real-world dynamic scenarios will require larger and more expensive planning and infrastructure.

Therefore, solving these challenges will be crucial for the continued advancement of intelligent lateral control systems and their practical implementation in real-world autonomous vehicle applications.

7. Conclusions

1. The implementation of type-2 fuzzy logic was successfully applied to autonomous as seen in the simulation test with the following parameters: the rise time for type-2 FLC is 0.5074 seconds, which is faster than the PID control, which is 0.9056 seconds. The settling time for type-2 FLC is 1.3388 seconds, slightly faster than the PID control, which is 1.4549 seconds. In addition, the peak time for type-2 FLC is 1 second, much shorter than the PID control, which peaks at 2.3 seconds. In terms of overshoot, type-2 FLC recorded

a value of 3.5117%, which is higher than the PID control, which is 0.5361%. Other test results show that type-2 FLC as the advantage of responding quickly to obstacles such as pedestrians who suddenly appear, parked cars, two parked cars. The type-2 fuzzy controller is able to move the steering wheel with a fast response and without experiencing significant overshoot.

2. The results demonstrate that type-2 FLC outperforms the PID control in terms of effectiveness and stability. Type-2 FLC recorded an average error percentage of 4.52% in obstacle avoidance and full route scenarios, while PID control recorded an average error percentage of 7.57%. PID control excels in handling small steady state errors and is good at handling errors that are not too large. The trial in the environment of Sriwijaya University, Indralaya Campus showed that Type-2 FLC is able to control autonomous vehicles more accurately and responsively than PID control. In obstacle avoidance and full route scenarios, type-2 FLC shows superior performance with a lower average error. However, because the road conditions in the Sriwijaya University environment do not have road markings, the setpoint value of the steering control system becomes less accurate and jumps.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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