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Comparative Analysis of Membership Functions in Fuzzy Logic Controllers for Robot Path Planning Optimization

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Abstract: Effective path planning is essential for autonomous mobile robots navigating unknown environments. Fuzzy Logic Controllers (FLCs) are well-suited for this task due to their robustness in handling uncertainty, vagueness, and nonlinearities. Among the core elements that influence FLC behaviour are membership functions (MFs), which define how sensory inputs are translated into fuzzy linguistic terms. Despite their importance, specific impact of different MF shapes on navigation performance remains underexplored. This study investigates the effect of three widely used MF types i.e., triangular, trapezoidal, and Gaussian on the traversal efficiency of a nonholonomic wheeled mobile robot operating in a static, obstacle filled environment. A series of simulations were conducted using MATLAB and CoppeliaSim, with traversal time serving as the primary performance metric. One-way ANOVA results ($F = 342.33$, $p < 0.001$) revealed statistically significant differences across MF types, with triangular MFs yielding the shortest average traversal time of 177.95 s, followed by trapezoidal with 179.08 s and Gaussian at 181.05 s. These findings highlight that MF shape significantly influences control responsiveness and path efficiency. By isolating MF type within a consistent rule base and simulation setup, this work provides baseline guidance for MF selection and sets the stage for future research involving hybrid MFs, real-world validation, and adaptive fuzzy systems.

Index Terms: Autonomous Mobile Robots, Path Planning, Fuzzy Logic Controller, Membership Functions, Fuzzy Controller Tuning

1. Introduction

Autonomous wheeled mobile robots (AWMR) have played an integral role in variety of fields including mining, health care, agricultural, surveillance and space exploration. These robots are designed to operate autonomously, smoothly traversing unmapped territories while avoiding obstacles. Four major components are very important for reliable autonomous navigation: path planning, perception, motion control and localization [1]. Path planning is particularly difficult among these because of uncertainty in the real world and incompleteness of sensory information. In order to meet such challenges, Fuzzy Logic Controllers (FLC) has been used for Robot Navigation since they offer robustness to imprecise data, linguistic reasoning based on rules as well as model-free control structure [2, 3]. FLCs mimic the way humans make decisions and allow seamless control reactions in different types of environments in real-time. However, their effectiveness is closely tied to the proper design of core components, especially Membership Functions (MFs), which define how sensor data is mapped into fuzzy sets [4].

MFs play a critical role in shaping the behaviour of fuzzy inference process. Improperly defined MFs can lead to poor robot decisions, longer traversal times, or failure to avoid obstacles. Although several studies have utilized various MF shapes specifically triangular, trapezoidal and Gaussian, limited research has systematically examined how different MF types affect overall navigation performance [5, 6, 7].

This study focuses on quantifying the impact of MF selection in FLC for path planning for a nonholonomic wheeled mobile robot. One-Factor Analysis of Variance was conducted to evaluate different MF types within a controlled simulation setting, using MATLAB and CoppeliaSim. The primary metric assessed was the duration it takes for the robot to move from starting point to designated target while successfully avoiding stationary obstacles. By comparing performance outcomes of each MF type, this study adds value to ongoing research aimed at enhancing fuzzy logic systems for greater robot autonomy and dependability.

2. Literature Review

Fuzzy Logic Controllers (FLCs) are widely used in mobile robot navigation because they're well-suited for dealing with uncertainty, sensor noise, and nonlinear system behavior. Since Zadeh first introduced fuzzy logic back in 1965, it's been applied in many complex environments especially in situations where building mathematical models is impractical [8]. A core component of FLCs is the Membership Function, which defines how input data from sensors is mapped to fuzzy sets. This mapping directly influences how the controller makes decisions and responds to different scenarios [9].

The design of Membership Functions plays a critical role in performance of fuzzy systems, and this has been emphasized in several studies[9,10,8]. Prokopowicz et al. [12] pointed out that the shape, range, and degree of overlap between MFs can significantly affect system behaviour especially in environments that are dynamic or unpredictable. In the context of robotic control, the most commonly used MF types include triangular, trapezoidal, and Gaussian functions [13].

Triangular and trapezoidal MFs are popular in real time systems because of their simple structure and low computational cost [6]. Their piecewise linear form makes them easy to implement, but it can also lead to abrupt shifts in output when conditions change. In contrast, Gaussian MFs provide smoother transitions due to their continuous curvature, which can enhance control stability. However, they come with a higher processing demand, which can be a consideration in resource-constrained systems. [14].

Fuzzy logic control systems have been widely explored for tasks like obstacle avoidance and path planning in mobile robotics. For instance, Ahmad Fauzi et al. [15] used Membership Functions to translate proximity sensor data into steering adjustments, enabling smooth navigation in static environments highlighting the practical strengths of FLCs. Building on that, Nakrani and Joshi [16] combined expert knowledge with real-time sensor input to develop fuzzy navigation rules, showing that the structure of MFs can significantly influence controller's overall effectiveness.

Table 1. Summary of Membership Function Usage in FLC-Based Robot Navigation

Study	MF Types Used	Application Environment	Optimization Applied	Evaluation Metric	Remarks
Prokopowicz et al. [12]	Triangular, Trapezoidal	Obstacle Avoidance	None	Control smoothness	Not focused on MF impact individually
Ahmad Fauzi et al.[15]	Triangular	Static Indoor Environment	Manual Tuning	Collision avoidance	No comparative analysis of MF types
Nakrani & Joshi [16]	Trapezoidal	Indoor Mapping & Navigation	Heuristic Rule Design	Time to goal	MF type fixed; performance variation unexplored
Pham et al. [18]	Gaussian	Dynamic Navigation	Genetic Algorithm	Path optimality	MFs tuned indirectly via GA; interaction effects not studied
Reguii et al. [17]	Triangular, Gaussian	Unknown Terrain	Neuro-Fuzzy System	Path tracking error	Focused on learning; MF role not isolated
This Study	Triangular, Trapezoidal, Gaussian	Static Unknown Environment	Factorial Design	Traversal Time	Direct, comparative analysis of MF type effects

To further enhance MF performance, some researchers have turned to hybrid approaches. Techniques like neural networks [17], genetic algorithms [18], and reinforcement learning [19] have been used alongside fuzzy logic to optimize MF parameters and improve adaptive behaviour in complex environments. However, these approaches frequently add a great deal of complexity. Hewawasam et al. [1] noted that MF design is often overlooked or handled heuristically, leading to suboptimal performance and limited generalizability.

This research aims to experimentally compare different MF types under a controlled simulation environment. By isolating MF shape as a factor and measuring its impact on robot traversal time, the study provides empirical evidence on how MF selection influences fuzzy controller performance in static, unknown environments.

A review of studies as highlighted in table 1. shows that while various membership function (MF) types such as triangular, trapezoidal, and Gaussian are commonly used in fuzzy logic controllers for robot navigation, their individual impact on controller performance is rarely isolated or systematically evaluated. Most prior work either adopts a single MF type without comparison and evaluation metrics varied across the studies.

While this study focused on classical MF types triangular, trapezoidal, and Gaussian prior works have increasingly explored adaptive and learning-based approaches, such as neuro-fuzzy systems and metaheuristic MF tuning using techniques like genetic algorithms and reinforcement learning. These approaches allow MFs to dynamically evolve based on environmental feedback, improving adaptability in complex or time-varying settings [20]. However, such models introduce additional computation and design complexity, which was beyond the scope of this comparative analysis.

This study applies One Factor Analysis of Variance to directly assess and compare the impact of different MF types on traversal time, providing a focused contribution to understanding how MF shapes influence FLC performance in static, unknown environments.

3. Methodology

This study used a quantitative, simulation approach to assess how the shape of membership functions affects navigation efficiency of a nonholonomic wheeled mobile robot. The choice of triangular, Gaussian and trapezoidal membership functions was motivated by their prevalence in existing fuzzy control literature, and their differing geometric properties. Triangular and trapezoidal MFs are widely adopted due to their simplicity and ease of implementation in embedded systems, while Gaussian MFs offer smoother transitions beneficial for stability analysis. While other MF types such as sigmoid or generalized bell-shaped functions are also valid and commonly used, they often introduce additional tuning parameters.

To evaluate system performance, traversal time was used as the primary metric, with a One Factor Analysis of Variance applied for statistical analysis. The simulation environment was built using CoppeliaSim to model the robot and its surroundings, while MATLAB was used to develop and implement the fuzzy logic controller, real-world validations using physical robotic platforms were not conducted. Physical experimentation is crucial to verify the transferability of simulation results, especially in accounting for sensor noise, actuator delays, and hardware constraints. Future work will involve implementing the optimized fuzzy logic controller on an actual mobile robot

Traversal time was selected as the sole performance metric in this study because it provides a direct, quantifiable measure of the robot's navigation efficiency capturing cumulative effectiveness of sensory input processing, rule evaluation, and decision execution under each MF configuration. This approach is consistent with prior fuzzy controller research and offers a clear basis for comparing MF effects in a controlled setting. While other factors such as energy efficiency, motion smoothness, and safety margins are important, including them would introduce additional variables that could obscure the isolated influence of MF.

At the core of the simulation setup was Pioneer P3-DX, a widely adopted mobile robot platform in both academic and research settings. This robot features a differential drive system and supports integration with a broad range of sensors and peripherals. The modular design, robust mechanical structure, and compatibility with middleware such as the Robot Operating System (ROS), the P3-DX is well-suited for experiments in autonomous navigation, control algorithm development, and sensor fusion techniques [21].

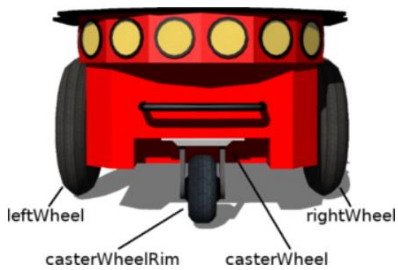


Fig. 1. Pioneer P3-DX platform

As illustrated in fig 1., the robot model used in this research was a unicycle mobile robot. Two actuators independently drive the wheels to control both orientation and motion [22].

A static environment was chosen to provides a stable and repeatable testbed that isolates the variable of interest in this case, the Membership Function. Dynamic environments with moving obstacles, time-varying noise, or sensor drift introduce multiple uncontrolled variables, this would obscure the attribution of observed effects solely to the MF type, violating the assumption of analysis in ANOVA.

CoppeliaSim simulation managed robot kinematics, sensor emulation, and environment modeling. The test arena was 5m × 5m square enclosure that confines the robot, ensuring consistent and repeatable experimental conditions as shown in figure 2. Within the enclosure, a structured maze composed of 5 cm thick walls, passage widths ranging from 30 to 50 cm, and wall heights of 20 cm introduces navigational complexity while remaining within the detection range of onboard sensors. Additionally, twelve cylindrical obstacles with 10 cm diameter and 15 cm were dispersed across the environment to emulate real world clutter and evaluate the robot's obstacle avoidance capabilities. The robot was initialized at the bottom left corner, necessitating autonomous path planning and maneuvering through a constrained environment. This setup provided a controlled, sensor rich scenario for assessing the performance of navigation algorithms in static, unknown domain.

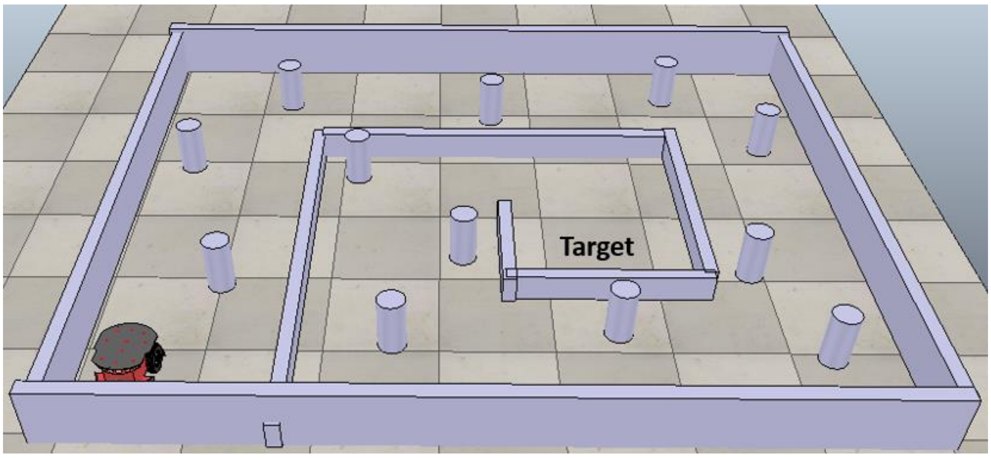


Fig. 2. Robot navigational field [23]

MATLAB was employed as the development platform for constructing the fuzzy logic system, defining rule sets, and implementing membership function shapes. Fuzzy logic path planning architecture was designed to process ultrasonic sensor data for real time obstacle proximity detection. The sensor outputs, initially in crisp form, were transformed into fuzzy linguistic variables "Low," "Medium," and "Big" through MFs, which served as core components of fuzzification process. Triangular, trapezoidal, and Gaussian MFs were utilized to map input distances to normalized membership degrees within the [0,1] range, quantifying the degree of set inclusion. Mamdani inference engine evaluated 27 fuzzy rules based on three sensor inputs of right, front and left to determine corresponding control actions for the left and right wheels ("Slow," "Moderate," "High"). The 27-rule Mamdani fuzzy inference system ensured consistency across MF types and isolated the influence of MF shape on controller performance. However, we acknowledge that MF shape may interact with rule complexity and specificity, especially in systems with simplified rule bases. The fuzzy inference utilized AND operator for rule aggregation, followed by center of gravity defuzzification to generate crisp output signals. MFs were essential to enabling context-aware, human-like navigation decisions.

3.1 Fuzzy Logic Controller Configuration

A Mamdani Fuzzy Inference System (FIS) was developed to control the navigation of a nonholonomic mobile robot based on real-time obstacle detection.

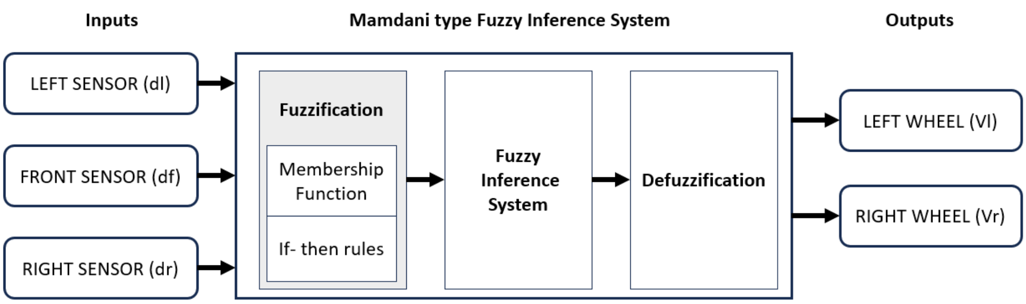


Fig. 3. Fuzzy logic controller [23]

As illustrated in Figure 3., the system received three input variables: the distances to obstacles from the left (dl), front (df), and right (dr) form ultrasonic sensors. These crisp input values were first processed through the fuzzification stage, where they were converted into fuzzy linguistic variables such as *Near*, *Medium*, and *Far*. This transformation was achieved using membership functions (MFs), which define the degree of where particular input belongs to a fuzzy set. To evaluate the influence of MF shape on system behavior. Following fuzzification, fuzzy inference engine applied a predefined set of *if-then* rules to determine the appropriate control action. These rules output fuzzy values for the left and right wheel velocities (Vl and Vr), were then passed through the defuzzification process to yield crisp outputs. The differential velocity between the two wheels adjusts the robot's steering behavior, allowing it to avoid obstacles while progressing toward its goal. This FIS-based control architecture enabled human-like decision-making in dynamic navigation tasks within static, unknown environments.

3.2 Experimental Design

The experimental design was structured to quantitatively assess the effect of membership function (MF) type on the performance of a fuzzy logic path planning system for a nonholonomic mobile robot. Independent variable in this study was the type of MF used during the fuzzification process, with three configurations under evaluation: Triangular, Trapezoidal, and Gaussian. Each MF type was applied using identical fuzzy rule sets and linguistic variables to maintain consistency across test conditions. The robot operates within a controlled 5m × 5m static simulation environment populated with fixed cylindrical and maze-like obstacles, with the same obstacle configuration and initial position used for all trials.

Ten separate simulation runs were conducted for every MF configuration in order to capture the statistical heterogeneity in robot behaviour brought on by small changes in sensor readings and dynamic interactions with the environment. The main performance metric in this study is the robot's average traversal time measured in seconds which reflects how long it takes to move from the starting point to the target. This metric gave a clear picture of how effective and responsive the navigation system was. The goal of the experiment was to understand how different Membership Function shapes influence the robot's decision making, particularly in terms of how well it avoided obstacles and chose efficient paths.

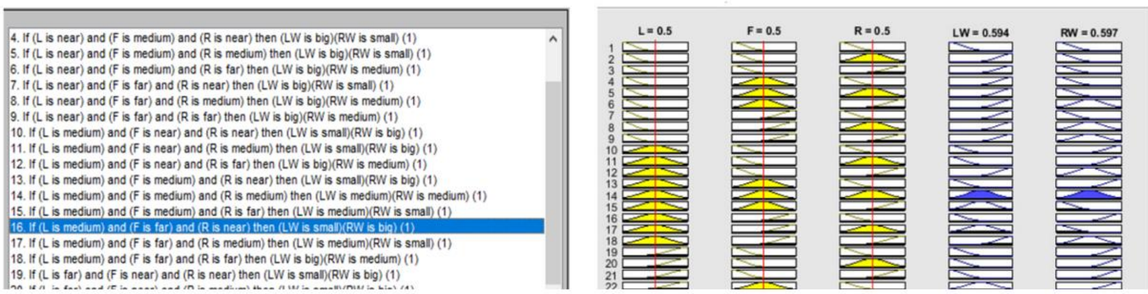
3.3 Evaluation Procedure

Evaluation was designed to closely examine how different types of Membership Functions (MFs) influence the performance of a fuzzy logic path planning system. To ensure consistent and repeatable results, each test run began with the robot positioned at the same starting point within a fixed, static simulation environment. The fuzzy inference system was configured in MATLAB using one of three MF types while keeping the fuzzy rules, input variables, and linguistic terms unchanged across all trials. Once configured, the fuzzy controller was integrated with the robot model in CoppeliaSim, which handled environmental interaction, sensor simulation, and the robot's motion dynamics.

In each simulation run, the robot's traversal time, the duration it took to reach the target was recorded. To ensure reliable and statistically meaningful results, this process was repeated ten times for each type of Membership Function (MF), all under identical experimental conditions. The collected traversal times were then analysed using a one-way ANOVA to determine whether the type of MF has a statistically significant effect on navigation efficiency. To maintain the validity of the experiment, key factors were held constant across all trials, the environment remains static, the robot's dynamics were uniform, and the sensor data was consistent and dependable.

4. Results and Discussion

This section presents and discusses the key findings derived from experimental analysis, focusing on how variations in MFs influenced system performance. Statistical analyses using ANOVA and post-hoc tests were used to validate the differences observed. The discussion further contextualizes these findings with reference to existing literature, offering insights into their practical implications and contributions. Ten runs of the same conditions were used to test each MF configuration.



a b

Fig. 4. (a) Fuzzy Logic set rules (b) the rule viewer

In fig 4 a fuzzy inference system (FIS) interface in MATLAB's Fuzzy Logic Designer is shown. It visualizes the rule evaluation and output computation for a specific input condition. Fig 4(a) displays the list of fuzzy rules and in Panel 4(b) shows a graphical summary of input membership values, Rule activations highlighted yellow regions and output aggregation and defuzzification. The plot in figure 5 confirms that the FLC behaves logically and safely by modulating velocity based on perceived side distances. The plateau at the center shows a region of confidence for high-speed navigation, while the slopes reflect adaptive deceleration when obstacles are nearby.

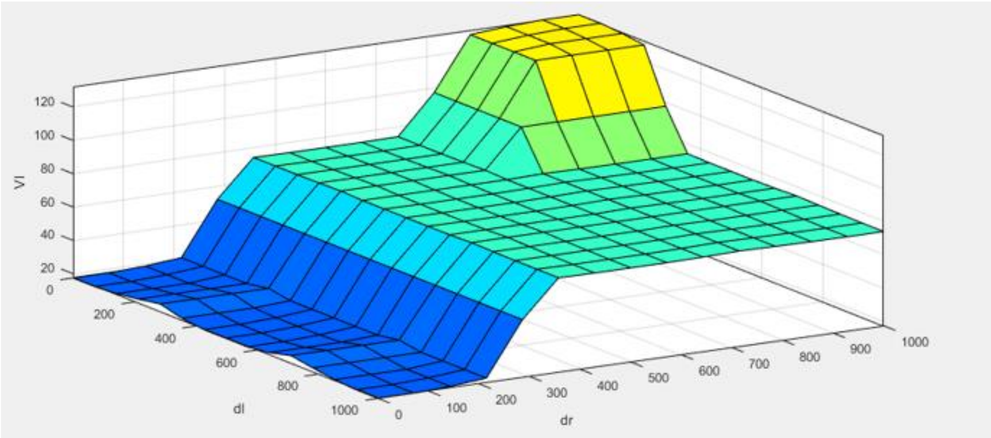


Fig. 5. Surface view of the fuzzy model Vl

Table 2. Traversal Time (in seconds) 10 Trials per MF Type

Mf Type	T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	Mean	Std Dev
Triangular	177.4	178.1	177.9	178.5	177.6	177.8	178.0	178.3	177.7	178.2	177.95	0.30
Trapezoidal	178.9	179.2	178.8	179.0	178.7	179.1	179.3	179.0	178.6	179.2	179.08	0.23
Gaussian	181.1	180.8	181.3	180.9	181.2	181.0	180.7	181.4	180.9	181.2	181.05	0.22

Figure 6. is a line plot showing the values of each membership function across the ten test points (T1 to T10) as in table 2. Each line helps visualize how consistent or varied the measurements were for each type. Standard deviation of 0.22 s shows that there was consistency in gaussian MFs.

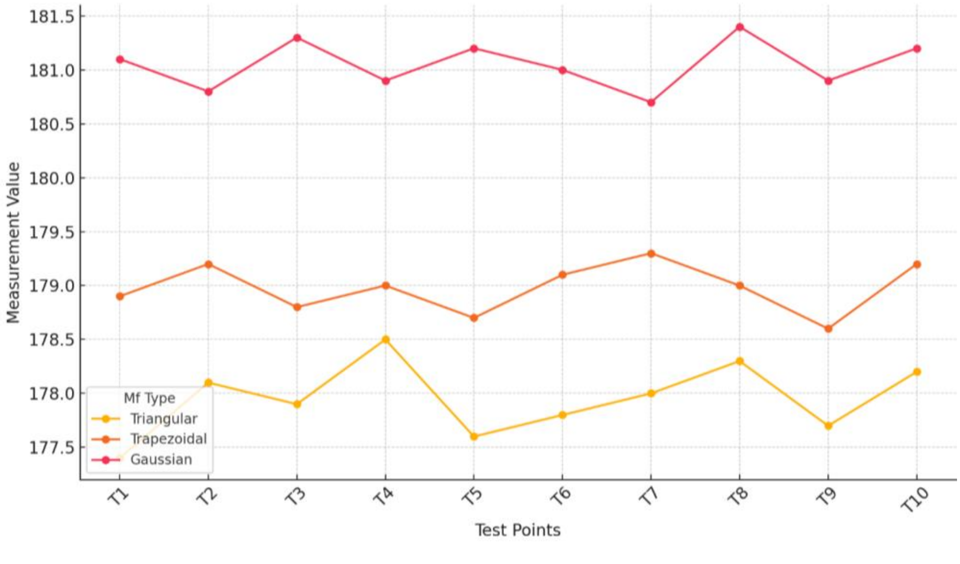


Fig. 6. Membership function line plot.

Figure 7, shows mean traversal time for each membership function type, along with standard deviation error bars: Triangular MFs had the shortest mean time. Trapezoidal MFs performed moderately. Gaussian MFs resulted in the longest traversal times.

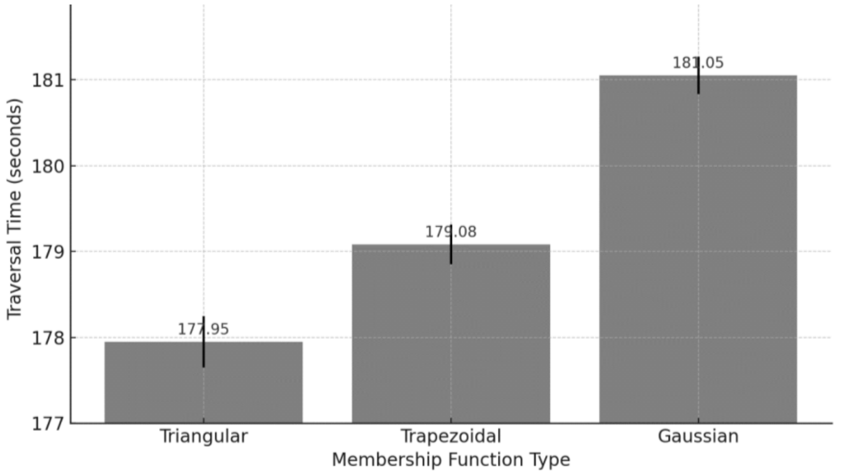


Fig. 7. Mean traversal time by membership function type

One way ANOVA

Hypotheses
Null hypothesis (H_0): All group means are equal.
Alternative hypothesis (H_1): At least one group mean is different.

Assumption Checks

All assumptions underlying ANOVA were tested and met. The Shapiro Wilk test showed that the data were normally distributed in all groups, and the Levene's test confirmed assumption of homogeneity of variances.

Table 3. Normality (Shapiro-Wilk Test)

Group	p-value	Interpretation
Triangular	0.9996	Normal distribution
Trapezoidal	0.7986	Normal distribution
Gaussian	0.8809	Normal distribution

All p-values > 0.05 No evidence to reject normality.
Homogeneity of Variance (Levene's Test)
p-value = 0.3221 thus Variances are equal (since p > 0.05)
All ANOVA assumptions are satisfied, so results from the ANOVA test are valid and reliable.

$$\text{Group mean} = \frac{\sum_{i-1}^{n} x_i}{n} = \frac{177.95+178.98+181.05}{3} = 179.33 \tag{1}$$

Sum of Squares

There are two primary sources of variation in the data. The Sum of Squares Between Groups (SSB) captures how much each group's average differs from the overall average essentially showing differences between the groups. On the other hand, the Sum of Squares Within Groups (SSW) reflects how much individual values vary around their own group's mean, representing variation within each group.

Sum of squares between groups (SSB)

$$SSB = n.\sum_{j-1}^{k}(\bar{x}_j - \bar{x}_{grand})^2 \tag{2}$$

Where
$n = number\ of\ samples\ per\ group(10)$
$\bar{x}_j = mean\ of\ group\ j$
$\bar{x}_{grand} = grand\ mean$
Sum of squares within groups (SSW)

$$SSW = \sum_{j-1}^{k}\sum_{i-1}^{n}(x_{ij} - \bar{x}_j)^2 \tag{3}$$

Calculated SSB (Between Groups) was 49.85. (Variation due to difference between group means) and SSW (Within Groups) was 1.97 (Variation within each group)

$$SST_{total} = SSB + SSW = 49.853 + 1.966 = 51.819 \tag{4}$$

Degree of freedom

$$df_{between} = k - 1 = 3 - 1 = 2$$
$$df_{within} = N - k = 30 - 3 = 27$$
$$df_{total} = N - 1 = 30 - 1 = 29$$

Where
$k = 3(\ traingular, trapizoidal, gaussian)$
$n = 10\ trial\ per\ group$
$N = 30\ total\ observations\ (\ 3\ group\ x\ 10\ trails)$

Mean Squares.

Mean Squares (MS) are the averages of the Sum of Squares (SS), calculated by dividing each by its respective degrees of freedom (df). The MS between represents the variation caused by differences in membership function (MF) types—essentially the variation between group means. The MS within captures the variation within each MF group, often considered random error. These two values are compared to assess how much variability is due to group differences versus random variation, forming the basis of the F-statistic in ANOVA.

$$MS_{between} = \frac{SSB}{df_{between}} = \frac{49.85}{2} = 24.93 \tag{5}$$

$$MS_{within} = \frac{SSW}{df_{within}} = \frac{1.97}{27} = 0.0728 \tag{6}$$

The F-statistic in ANOVA indicates how much of the overall variation in the data can be attributed to differences between the group averages, compared to the variation that exists within each group. It helps determine whether the group differences are statistically meaningful.

$$F = \frac{variance\ between\ groups}{variance\ within\ goups} = \frac{MS_{between}}{MS_{within}} = \frac{24.926}{0.0728} = 342.33 \tag{7}$$

Table 4. One-Way ANOVA Summary

Source of variation	Sum of squares (SS)	Degree of freedom (df)	Mean square (MS)	F-statistic	p-value
Between groups	49.853	2	24.926	324.33	< 0.001
Within groups	1.966	27	0.0728		
Total	51.819	29			

A one-way analysis of variance (ANOVA) was performed to evaluate the effect of membership functions type on output values across three groups. The analysis revealed a statistically significant difference in mean values among the MF types, $F(2, 27) = 342.33$, $p < 0.001$.

These findings suggest that the output values are statistically significantly impacted by the kind of membership function used. Tukey's HSD post hoc test was used to compare the traversal times between the three-membership function types

Table 5. Tukey HSD post hoc analysis

Group 1	Group 2	Mean diff	p-adj	lower	Upper	Reject
Gaussian	Trapezoidal	2.07	0.001	1.83	2.31	True
Gaussian	Triangular	3.10	0.001	2.86	3.34	True
Trapezoidal	Triangular	1.03	0.001	0.79	1.27	True

The results of the Tukey HSD post hoc analysis indicate that all pairwise comparisons among the membership function types were statistically significant ($p < 0.05$). The results clearly show that the shape of the Membership Function has a significant effect on the robot's traversal time. Among the tested configurations, Gaussian MFs resulted in the longest average traversal times, followed by Trapezoidal MFs, while Triangular MFs consistently delivered the shortest and therefore most efficient performance.

These findings provide strong statistical evidence that MF shape plays a critical role in navigation efficiency. Specifically, the sharper transitions of triangular MFs appear to enable faster decision-making. Gaussian MFs, though more refined, slowed the system's responsiveness due to their exponential formulation, our preliminary profiling in MATLAB showed only a marginal increase in time compared to triangular MFs. We acknowledge that quantifying computational cost more precisely across MF types is a valuable direction for future research particularly for real-time or embedded applications.

The results of this study highlight the significant influence that the choice of Membership Function (MF) has on the performance of a fuzzy logic controller (FLC) used in navigating a nonholonomic wheeled mobile robot through a static, unknown environment. Through controlled testing and statistical evaluation, noticeable differences in traversal time were observed across the three MF type.

Effect Size (η^2)

The effect size for ANOVA was calculated using eta squared (η^2), which quantifies the proportion of variance in the dependent variable of traversal time explained by the independent variable that is MF type.

$$\eta^2 = \frac{SS_{between}}{SS_{total}} = \frac{49.853}{51.819} = 0.962 \quad (8)$$

This means that approximately 96.2% of the variance in traversal time is explained by the MF type, indicating a very large effect size according to Cohen's conventions.

A one-way ANOVA revealed a substantial F-statistic ($F = 342.33$, $p < 0.001$), confirming that the variation in traversal times is statistically significant and strongly linked to the MF type. Further insight was gained through a Tukey HSD post hoc test, which confirmed that all pairwise differences between MF types were statistically significant ($p < 0.001$), solidifying the performance ranking among them.

Triangular MF yielded the lowest mean traversal time (177.95 s) among the investigated MFs, followed by the Trapezoidal (179.08 s) and Gaussian (181.05 s) MFs. According to these results, the robot can react more forcefully to sensory input when membership transitions are sharper and simpler, like those in triangular MFs. Conversely, although while Gaussian MFs provide smoother transitions and are better at handling uncertainty in theory, they might result in overlapping fuzzy zones that cause the robot to take longer to make decisions, which lengthens the traversal time. This result is consistent with earlier studies (Prokopowicz et al., 2017; Nakrani & Joshi, 2022), which recognized that MF form can affect controller output but did not provide a quantitative, cross-type comparison. By isolating MF type as the experimental factor using One-Factor Analysis of Variance, this study fills a gap in fuzzy controller design literature and provides actionable guidance for practitioners.

These findings have practical implications for the design of real time fuzzy navigation systems, especially in resource-constrained robotic platforms where computational simplicity and responsiveness are prioritized. The results clearly show that the shape of the Membership Function has a significant effect on the robot's traversal time. These findings provide strong statistical evidence that MF shape plays a critical role in navigation efficiency

Although traversal time was the primary evaluation metric, qualitative observations indicated that triangular MFs led to slightly more abrupt steering adjustments, while Gaussian MFs produced smoother but slower turns. This suggests a potential trade-off between speed and motion smoothness, which future studies could quantify using additional metrics like number of oscillations, path smoothness, or energy efficiency.

Consistent performance patterns highlight the robustness and repeatability of the MF effects. These results not only validate previously observed tendencies in MF behavior but also elevate them with rigorous statistical analysis, thereby offering reproducible evidence for MF shape selection.

The findings here serve as a practical design baseline for researchers seeking real-time responsiveness in constrained robotic platforms. They also lay the groundwork for integrating MF shape as an optimization variable within broader multi-objective controller tuning frameworks.

5. Conclusion

This study examined how different membership function shapes including triangular, trapezoidal, and Gaussian affect the performance of a FLC for autonomous navigation of a nonholonomic wheeled mobile robot in static, unknown environments. Through simulations and statistical analysis using one-way ANOVA and Tukey's HSD test, we confirmed that MF shape has a significant impact on traversal time, with triangular MFs producing the fastest and most responsive navigation.

The findings demonstrate that simpler, sharper MFs enable quicker transitions in fuzzy inference, resulting in more efficient control behaviour. This insight is valuable for real-time robotic systems where responsiveness and low computational load are crucial. In addition to statistical validation, this study contributes theoretical understanding by linking MF transition profiles with decision-making speed and rule activation.

While 27-rule Mamdani inference system was held constant across all MF types, future work should explore how MF shape interacts with rule base complexity and granularity to influence control precision and interpretability. The exclusive use of simulations provided a controlled environment to isolate MF effects; however, real-world validation is essential. As such, deploying the controller on physical robot platforms under varying terrains, sensor noise, and dynamic conditions is a recommended. Further investigations should address several promising directions:

- Benchmark FLCs against traditional controllers like PID and MPC to contextualize the benefits of fuzzy reasoning.
- Incorporate dynamic obstacles and real-time map updates to test controller adaptability under uncertainty.
- Experiment with hybrid MFs (e.g., triangular for side sensors, Gaussian for front) to improve both reactivity and smoothness.
- Introduce additional performance metrics such as path smoothness, energy efficiency, and steering stability.
- Leverage neuro-fuzzy models or metaheuristic optimization (e.g., PSO, GA) for automatic MF tuning.

By isolating MF shape within a controlled framework, this study lays a strong foundation for principled MF selection in FLCs moving beyond heuristic choices. This study focused on the effect of MF shapes on navigation performance, using fixed parameters for each type. However, we did not explore the impact of internal MF parameter variations such as overlap degree or spread, which are known to influence FLC responsiveness and accuracy.

This study utilized a single robot model (Pioneer P3-DX) in a static simulated environment. While the results provide important insights into fuzzy logic controller optimization, they may not directly generalize to robots with different locomotion dynamics or to more complex or dynamic real-world terrains. Future work will extend the framework to other platforms and environmental conditions to validate scalability and robustness

This work not only confirms known effects of MF shape on fuzzy controller behavior but also advances understanding by isolating MF shape, proposing hybrid configurations, and offering a foundation for future optimization studies.

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