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Fuzzy logic in real-time decision making for autonomous drones

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A B S T R A C T

The rapid advancement of drone technology has expanded their applications across various sectors, necessitating robust real-time decision-making systems. Traditional algorithms often falter in dynamic and unpredictable environments. This paper introduces a fuzzy logic-based approach to enhance the decision-making capabilities of autonomous drones. Utilizing Monte Carlo simulations, the proposed model was evaluated through three distinct experiments involving 300, 600, and 950 scenarios respectively. The first experiment demonstrated an obstacle avoidance efficiency of 82.00%, an 8.00% reduction in energy consumption, a decision accuracy of 95.33%, and a mission success rate of 79.33%. The second experiment showed an avoidance efficiency of 82.50%, maintaining the energy consumption reduction at 8.00%, with a decision accuracy of 95.83% and a mission success rate of 78.33%. The third experiment achieved an avoidance efficiency of 82.11%, with an 8.00% reduction in energy consumption, a decision accuracy of 95.26%, and a mission success rate of 78.31%. These results highlight the superior performance of fuzzy logic in real-time decision-making for autonomous drones compared to traditional methods.

1. Introduction

The advent of self-driving drones represents a significant leap forward in the field of autonomous systems. These sophisticated devices are being utilized across a diverse array of applications, from delivery services and agricultural monitoring to search and rescue missions and surveillance operations. As the deployment of self-driving drones continues to expand, ensuring their safety and reliability becomes paramount, paralleling the safety expectations we hold for human pilots. Achieving this level of safety necessitates the development of advanced decision-making systems capable of real-time responsiveness (Merz et al., 2022; Mohsan et al., 2023). One of the most critical aspects of drone operation is the ability to make instantaneous decisions. The dynamic environments in which drones operate demand that they continuously process vast amounts of data and respond swiftly to changing conditions. Whether navigating through urban landscapes, avoiding unexpected obstacles, or adjusting to weather changes, the capacity for real-time decision-making is crucial. Failure to make immediate decisions can lead to significant risks, including collisions, mission failures, and even endangerment of human lives and property (Quamar et al., 2023). The motivation behind this research lies in the necessity to enhance the decision-making capabilities of self-driving drones. Traditional control systems often fall short in dealing with the complexities and uncertainties inherent in real-world scenarios. This research proposes the application of fuzzy logic as a solution to these challenges. Fuzzy logic, with its ability

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to handle imprecise information and mimic human reasoning, offers a promising approach to improve the adaptability and robustness of autonomous drones (Sana et al., 2023). Fuzzy logic is particularly suited for this research due to its strength in dealing with uncertainty and approximate reasoning. Unlike binary logic systems, fuzzy logic can process a range of values between true and false, enabling drones to make more nuanced decisions. This flexibility is essential for real-time applications where the environment can be unpredictable, and the drone must evaluate numerous variables simultaneously. By integrating fuzzy logic into the decision-making process, this research aims to develop a framework that enhances the safety and efficiency of self-driving drones, ensuring they can operate as reliably as human pilots in real-time scenarios (Pal & Mandal, 1991).

The paper is organized as follows: section 2 presents related work review, section 3 presents methodology, section 4 presents comparison between fuzzy and non-fuzzy approaches, section 5 presents results, section 6 presents discussion and section 7 presents conclusion.

2. Related Work

Fuzzy logic has gained significant traction in the realm of autonomous systems, particularly in enhancing decision-making capabilities for drones. Drones require robust real-time decision-making abilities to navigate complex environments and handle unpredictable situations effectively (Tsitses et al., 2024). Many papers in drone literature address the problem of decision making. But these methods still have some problems and can't be suitable for all the conditions (Sabo & Cohen, 2012). Talha et al. (2019) introduced a fuzzy logic-based auto-landing system for quadcopters, combining real-time position and velocity control to ensure safe and efficient landings. The system demonstrated improved efficiency and safety compared to traditional controllers, validated through simulations and practical testing on a quadcopter platform (Talha et al., 2019). Shcherban et al. (2020) developed a fuzzy logic-based method to decide whether to continue or terminate UAV flights, focusing on monitoring battery health using voltage, temperature, and wind conditions as input variables for decision-making. Wu et al. (2006) demonstrated that leveraging pipelining, parallelization, and advanced FPGA technology can significantly enhance the throughput of fuzzy processing systems. This adaptable and high-performance architecture is particularly beneficial for real-time decision-making in UAVs, meeting the demands of complex multi-criteria fuzzy processing. Sabo and Cohen (2012) introduced a fuzzy logic-based methodology for UAV motion planning, showing a 3% failure rate compared to 18% for artificial potential fields, highlighting its adaptability and reliability in real-time obstacle avoidance and target navigation. Validation through Monte Carlo testing confirmed the FLC's effectiveness, often matching optimal path results. Guimarães and Shiguemori (2019) demonstrated that a low-cost Multi sensor Data Fusion application using Hybrid Adaptive Computational Intelligence (HACI), combining Fuzzy C-Means Clustering (FCM) and Adaptive-Network-Based Fuzzy Inference System (ANFIS), significantly improves UAV positioning accuracy and outperforms Artificial Neural Networks and Regression Models in reducing error and computational burden. Aghdam et al. (2014) designed a UAV controller using FPGA to execute fuzzy logic, achieving 2GFLIPS performance at 125 MHz with potential scalability up to 8GFLIPS. It highlighted the importance of controlling UAV position, speed, and altitude using parallel pipelined FLC design and efficient resource usage. Wang et al. (2024) proposed a drone system with visual identification and tracking capabilities using DeepSORT and MobileNet models to reduce communication bandwidth demands. The system, validated in Real Flight simulation, achieved precise target tracking with significant performance improvements on the Jetson Xavier NX embedded platform. Tsitses et al. (2024) introduced a fuzzy logic-based autonomous ship deck landing system for fixed-wing UAVs, aiming to simplify landings on moving ships in challenging maritime conditions by relieving operators of the demanding task. The system comprises three interconnected subsystems (speed, lateral motion, and altitude), evaluated using MATLAB Fuzzy Toolbox.

Current methods such as those presented by Talha (2019) and Sabo and Cohen (2012) show improvements in specific scenarios like auto-landing and motion planning. However, these solutions may not comprehensively address the variability and unpredictability of diverse operational environments that drones encounter. The proposed research can focus on creating a more universally adaptable fuzzy logic system for real-time decision-making that can handle a broader range of environmental conditions. Shcherban and Ieremenko (2020) and Wang et al. (2024) focus on specific decision-making factors such as battery health or visual identification and tracking, respectively. There is a need for a more integrated approach that combines multiple critical factors (e.g., environmental conditions, battery status, obstacle detection) into a single fuzzy logic-based decision-making framework.

This paper integrates a wide array of sensors, including Obstacle Distance (OD), Battery Level (BL), Wind Speed (WS), Drone Velocity (DV), GPS, Altimeter, and Mission Control Interface. This comprehensive integration ensures robust real-time decision-making by considering multiple critical factors simultaneously. Where other Papers focus on specific sensor inputs or a limited number of variables, such as the fuzzy logic-based auto-landing system by Talha et al. (2019) and the UAV motion planning by Sabo and Cohen (2012), which may not address the full complexity of operational environments.

3. The Methodology and Design

This methodology outlines the approach taken to implement and evaluate the use of fuzzy logic in real-time decision-making for autonomous drones. The focus is on the design, development, and testing of a fuzzy logic-based system that enables drones to make decisions in dynamic and uncertain environments as shown in Fig. 1.

Fig. 1 shows the flowchart for the fuzzy logic-based decision-making system for autonomous drones.

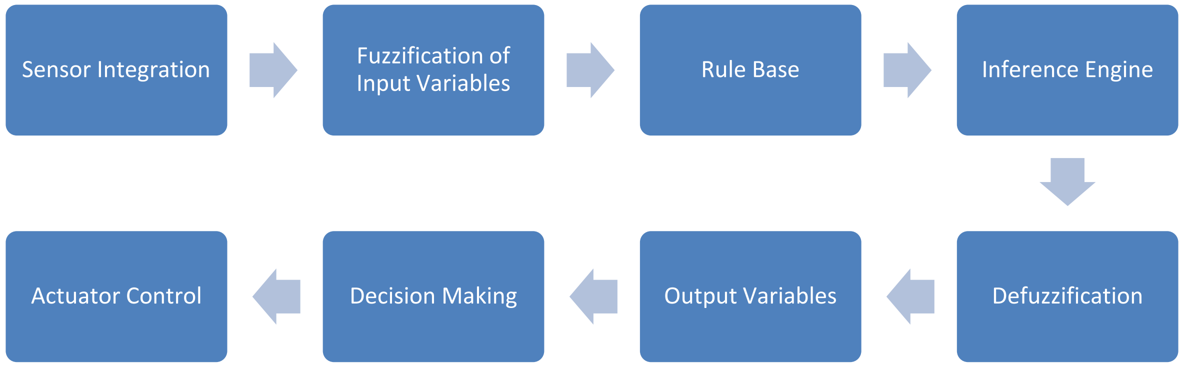

Fig. 1. Fuzzy Control System Design

3. Fuzzy Control System Design

The fuzzy control system for the autonomous drone consists of the following main components:

1. Sensors Integration:

   - Obstacle Distance (OD) Sensor: Measures the distance between the drone and obstacles.
   - Battery Level (BL) Sensor: Monitors the battery charge level.
   - Wind Speed (WS) Sensor: Measures the wind speed affecting the drone.
   - Drone Velocity (DV) Sensor: Tracks the drone's speed and direction.
   - GPS Sensor: Assesses the accuracy of the GPS signal.
   - Altimeter: Measures the altitude of the drone.
   - Mission Control Interface: Receives input on mission priority.

The integration of various sensors in autonomous drones, such as the Obstacle Distance (OD) Sensor, Battery Level (BL) Sensor, Wind Speed (WS) Sensor, Drone Velocity (DV) Sensor, GPS Sensor, Altimeter, and Mission Control Interface, is essential for enhancing their real-time decision-making capabilities. The utilization of these sensors, combined with fuzzy logic, provides a robust framework for autonomous navigation and mission execution. Combining these sensors with a fuzzy logic-based decision-making system significantly enhances the drone's autonomous capabilities. Fuzzy logic excels at handling imprecise and variable data, making it ideal for processing the continuous inputs from these sensors. The benefits include:

- Adaptive Decision Making: Fuzzy logic allows the drone to interpret and react to complex environmental conditions, enhancing its ability to adapt to dynamic situations.
- Robust Performance: The integrated sensor data enables the drone to maintain robust performance even in unpredictable environments.
- Increased Autonomy: By leveraging sensor inputs

2. Fuzzification:

To design a fuzzy logic system using the Mamdani method for real-time decision-making in autonomous drones, we define a set of rules based on the fuzzified input variables. The goal is to create rules that govern the drone's behavior in different scenarios. Here are the fuzzified input variables as shown in figures 2,3,4,5,6,7, 8 respectively:

The fuzzy inputs, linguistic values, and variables are designed to provide a comprehensive and adaptable framework for real-time decision-making in autonomous drones. Each input and its corresponding values were selected based on their relevance to critical aspects of drone operation, ensuring that the system can effectively manage the complexity and uncertainty of dynamic environments. This approach allows the drone to perform optimally, balancing safety, efficiency, and mission success.

- Obstacle Distance (OD): Very Close, Close, Medium, Far, Very Far
- Battery Level (BL): Low, Medium, High
- Wind Speed (WS): Low, Medium, High
- Drone Velocity (DV): Slow, Moderate, Fast
- GPS Accuracy (GA): Low, Medium, High
- Altitude (A): Low, Medium, High
- Mission Priority (MP): Low, Medium, High

The Mamdani model is used for interpretability, flexibility, and proven effectiveness in handling the uncertainty of real-world environments. The selected fuzzy variables and their linguistic values are tailored to address the critical aspects of drone operation, such as navigation, power management, stability, and mission prioritization. By integrating these elements into a fuzzy logic framework, the drone can make informed, adaptive decisions in real-time, enhancing its autonomy and operational reliability.

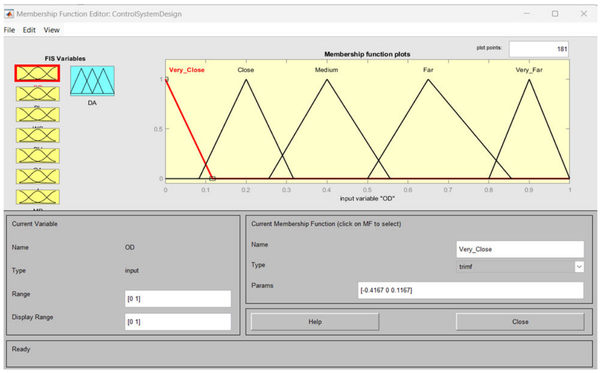

Fig. 2. Membership Function Editor for OD

Fig. 3. Membership Function Editor for BL

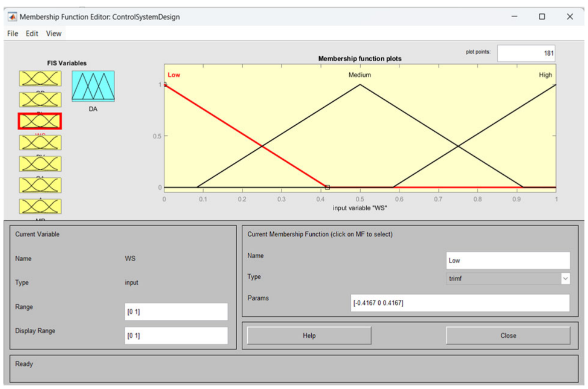

Fig. 4. Membership Function Editor for WS

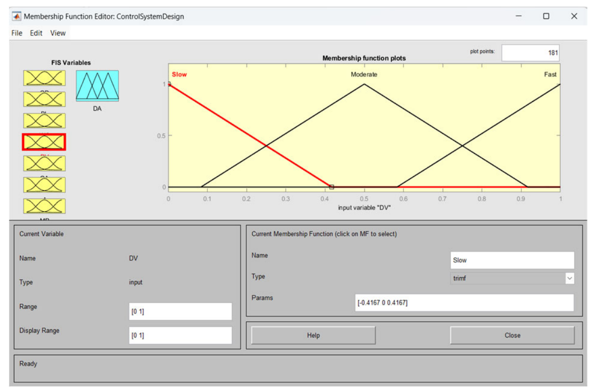

Fig. 5. Membership Function Editor for DV

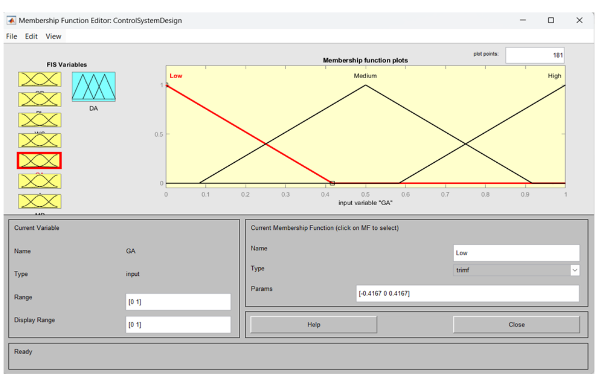

Fig. 6. Membership Function Editor for GA

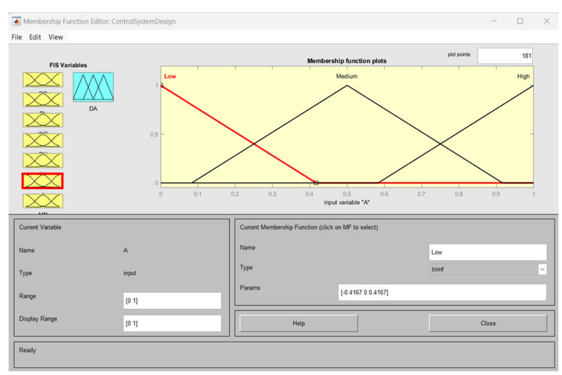

Fig. 7. Membership Function Editor for A

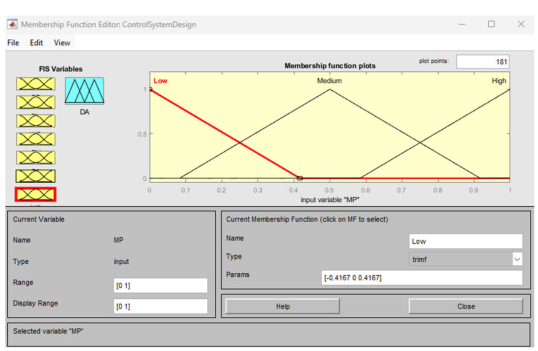

Fig. 8. Membership Function Editor for MP

The output variables we are interested in could be the drone's action, such as changing velocity, adjusting altitude, or making navigational adjustments. For simplicity in this paper, let's define the output as Drone Action (DA): Decrease Velocity, Maintain Velocity, Increase Velocity, Adjust Altitude, Change Path.

3. Rule Base:

Fig. 9 shows the if-then rules that relate fuzzy input sets to desired output actions. In designing our fuzzy logic system, we strategically curated a large rule base initially containing up to 3645 rules. Recognizing that this set includes redundancies and some rules that may not realistically occur, we focused on extracting the most crucial rules applicable to real-world scenarios. This selection process ensured that our system prioritizes practical and plausible decision-making contexts, enhancing the drone's operational adaptability, safety, and efficiency across diverse environmental conditions and mission priorities. By focusing on these key rules, the fuzzy control system remains effective, manageable, and capable of handling the dynamic and uncertain conditions faced by autonomous drones

- If OD is Very Close and BL is Low and WS is High and DV is Fast and GA is Low and A is High and MP is High, then DA is Decrease Velocity.
- If OD is Close and BL is Medium and WS is Medium and DV is Moderate and GA is Medium and A is Medium and MP is Medium, then DA is Maintain Velocity.
- If OD is Medium and BL is High and WS is Low and DV is Slow and GA is High and A is Low and MP is Low, then DA is Increase Velocity.
- If OD is Far and BL is Low and WS is High and DV is Moderate and GA is Low and A is Medium and MP is High, then DA is Adjust Altitude.
- If OD is Very Far and BL is Medium and WS is Medium and DV is Fast and GA is Medium and A is High and MP is Medium, then DA is Change Path.
- If OD is Very Close and BL is Medium and WS is High and DV is Moderate and GA is Medium and A is Low and MP is High, then DA is Decrease Velocity.
- If OD is Close and BL is High and WS is Low and DV is Slow and GA is High and A is Medium and MP is Medium, then DA is Maintain Velocity.
- If OD is Medium and BL is Low and WS is Medium and DV is Fast and GA is Low and A is High and MP is Low, then DA is Increase Velocity.
- If OD is Far and BL is Medium and WS is Low and DV is Slow and GA is Medium and A is Low and MP is High, then DA is Adjust Altitude.
- If OD is Very Far and BL is High and WS is High and DV is Moderate and GA is High and A is Medium and MP is Medium, then DA is Change Path.
- If OD is Very Close and BL is Low and WS is Medium and DV is Fast and GA is High and A is Low and MP is Medium, then DA is Decrease Velocity.
- If OD is Close and BL is Low and WS is Low and DV is Moderate and GA is Low and A is Medium and MP is Low, then DA is Maintain Velocity.
- If OD is Medium and BL is Medium and WS is High and DV is Slow and GA is Medium and A is High and MP is High, then DA is Increase Velocity.
- If OD is Far and BL is High and WS is Medium and DV is Fast and GA is High and A is Low and MP is Medium, then DA is Adjust Altitude.
- If OD is Very Far and BL is Low and WS is Low and DV is Moderate and GA is Medium and A is High and MP is Low, then DA is Change Path.
- If OD is Very Close and BL is High and WS is High and DV is Slow and GA is Low and A is Medium and MP is Medium, then DA is Decrease Velocity.
- If OD is Close and BL is Medium and WS is Low and DV is Fast and GA is High and A is Low and MP is High, then DA is Maintain Velocity.
- If OD is Medium and BL is Low and WS is High and DV is Moderate and GA is Medium and A is High and MP is Medium, then DA is Increase Velocity.
- If OD is Far and BL is High and WS is High and DV is Slow and GA is Low and A is Medium and MP is Low, then DA is Adjust Altitude.
- If OD is Very Far and BL is Medium and WS is Medium and DV is Fast and GA is Medium and A is Low and MP is Medium, then DA is Change Path.

These rules provide a comprehensive rule base using the Mamdani method for a fuzzy logic system aimed at enhancing real-time decision-making in autonomous drones.

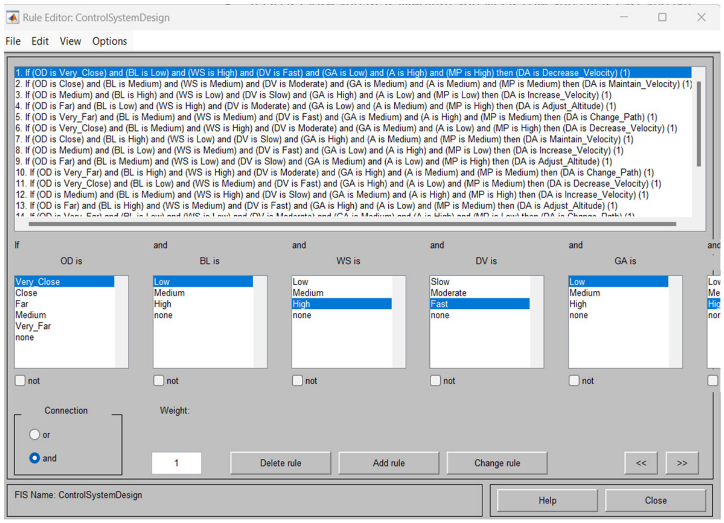

Fig. 9. Rule Editor for Control System Design

4. Inference Engine:

Within the fuzzy control system, the Inference Engine assumes the critical role of deciphering the fuzzy rules and formulating decisions grounded in the prevailing state of the drone and its surroundings. It undertakes this task by assimilating fuzzy inputs obtained from the fuzzification stage and subsequently employing predefined fuzzy rules to yield fuzzy outputs. This involves the application of rules to the fuzzified inputs, thereby generating fuzzy outputs, and the amalgamation of multiple rules while computing the degree of truth associated with each output as shown in Fig. 10.

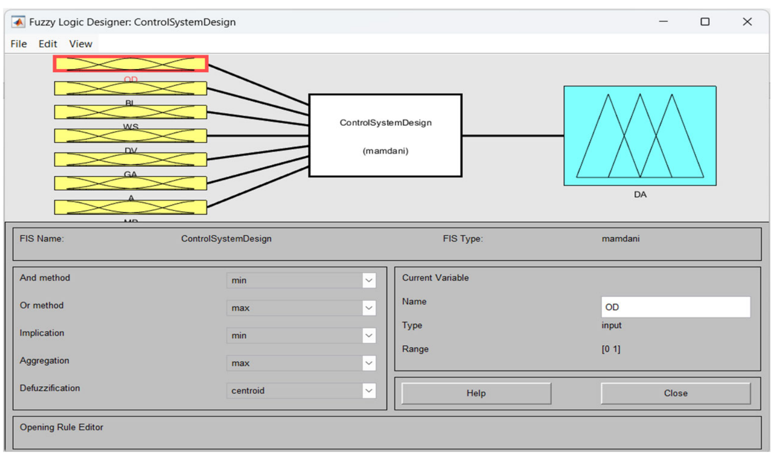

Fig. 10. Inference Engine for Control System Design

5. Defuzzification:

Is the process of converting fuzzy output values, which represent linguistic variables, into crisp, actionable control signals that can be applied to the drone's actuators? These crisp values provide clear instructions for the drone's movement and behavior.

In the context of an autonomous drone, defuzzification is crucial for translating the fuzzy outputs generated by the inference engine into precise control commands. This step enables the drone to navigate, adjust altitude, change speed, or alter direction based on the fuzzy logic decisions made earlier as shown in figure 11.

In this paper, the Centroid Method is used for defuzzification. This method calculates the center of the area under the curve representing the fuzzy set and returns this value as the crisp output (Sivanandam et al., 2015). The centroid method computes the crisp output Z using the following formula (Sivanandam et al., 2015):

$$z = \frac{\int_{all\ z} z.\mu(z)dz}{\int_{all\ z} \mu(z)dz} \tag{1}$$

where $\mu(z)$ is the membership function of the output fuzzy set, and z represents the output variable.

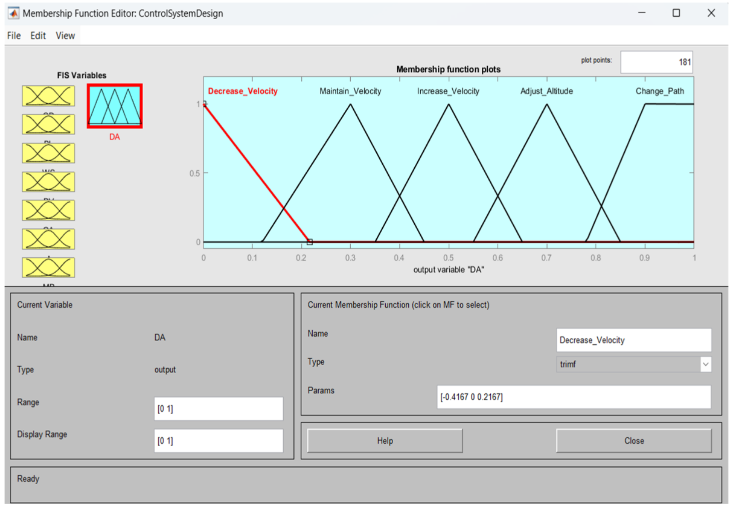

Fig. 11. The output membership function for Control System Design

6. Decision Making

Decision-making is a critical component that guides the drone's actions based on real-time sensor data and environmental conditions collected and model output.

7. Actuator Control:

Actuator control plays a pivotal role in converting the precise decisions generated by the fuzzy control system into tangible movements executed by the drone. It serves as the interface between the control system's commands and the physical actions required for navigation and stability. Two prominent examples of actuators are motor controllers and the flight control system. Motor controllers regulate motor speeds, facilitating throttle adjustments and changes in direction essential for maneuvering the drone through the air. On the other hand, the flight control system oversees the broader aspects of flight, ensuring stability and navigating the drone safely through its environment. Together, these actuators translate the abstract instructions from the control system into tangible movements, enabling the drone to carry out its tasks effectively and autonomously.

Fig. 12 shows the Rule Viewer displays each rule's contribution to the final decision, based on the current inputs such as Obstacle Distance (OD), Battery Level (BL), Wind Speed (WS), Drone Velocity (DV), GPS Accuracy (GA), Altitude (A), and Mission Priority (MP). By adjusting these inputs, you can observe how the fuzzy rules activate and combine to produce a specific output, such as the drone's action to decrease velocity, maintain velocity, increase velocity, adjust altitude, or change path. This tool is invaluable for debugging and refining the rule base, ensuring that the drone's behavior aligns with the designed fuzzy logic.

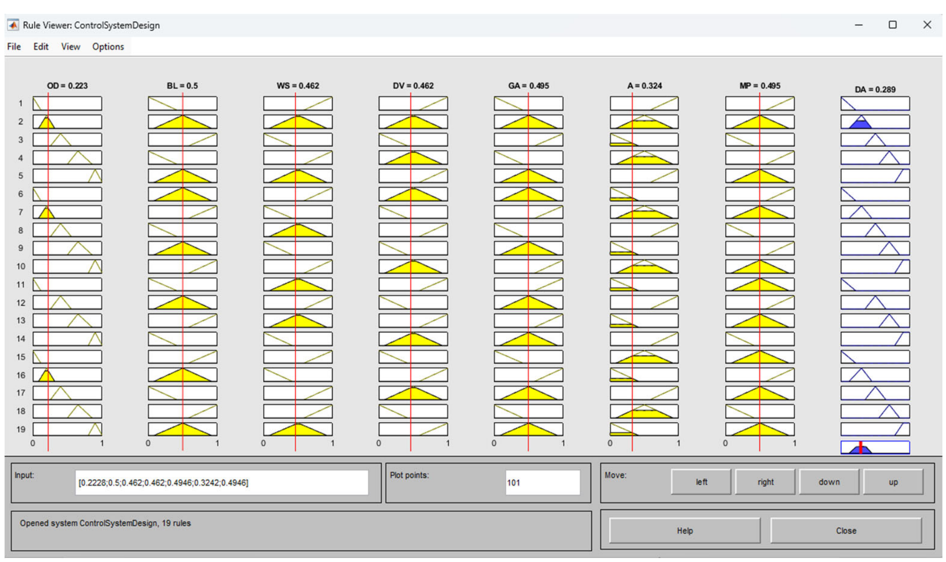

Fig. 12. The Rule viewer for Control System Design

Fig. 13 shows the Surface Viewer provides a graphical representation of the output surface of the fuzzy inference system (FIS) with respect to two input variables. This three-dimensional plot helps in understanding how changes in input variables influence the output of the control system. For instance, in the context of an autonomous drone, the Surface Viewer can illustrate how varying levels of Obstacle Distance (OD) and Battery Level (BL) affect the drone's Decision Action (DA). By examining these surfaces, researchers can gain insights into the interaction between inputs and how the FIS rules translate these into control actions. The Surface Viewer is particularly useful for validating the control system's performance and ensuring that it behaves as expected under different combinations of input conditions, thereby facilitating optimization and fine-tuning of the fuzzy control logic.

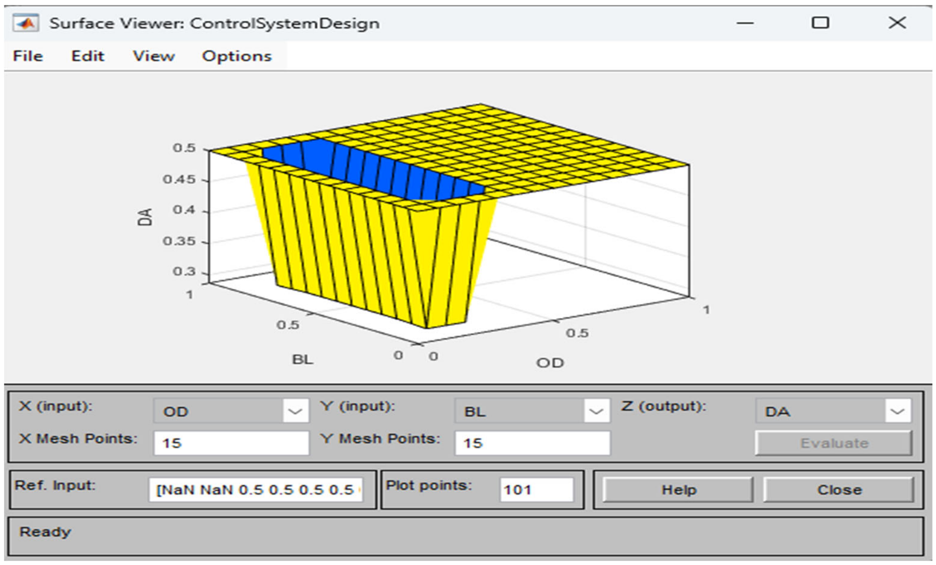

Fig. 13. The Surface viewer for Control System Design

4. Evaluation

To provide a comprehensive evaluation of the performance of the fuzzy logic-based decision-making system for autonomous drones we use the following metrics measurement,

Obstacle avoidance efficiency which it measures how effectively the drone can detect and avoid obstacles in its path using fuzzy logic as the following formula

$$\text{Avoidance Efficiency} = \left(\frac{\text{Number of Avoided Obstacles}}{\textit{Total Numbers of Obstacles}}\right) \times 100 \tag{2}$$

Energy consumption reduction which it evaluates how the fuzzy logic decision-making system impacts the drone's energy usage as following.

- Baseline Energy Consumption: Measure the average energy consumption of the drone during a typical flight without fuzzy logic.
- Fuzzy Logic Energy Consumption: Measure the energy consumption during flights with the fuzzy logic system enabled.
- Reduction Calculation: Calculate the percentage reduction in energy consumption using the formula:

$$\text{Energy Consumption Reduction} = \left(\frac{\text{Baseline Energy} - \text{Fuzzy Logic Energy}}{\text{Baseline Energy}}\right) \times 100 \tag{3}$$

Decision Accuracy which measures the accuracy of the decisions made by the fuzzy logic system in real-time scenarios.

$$\text{Decision Accuracy} = \left(\frac{\text{Number of Correct Decisions}}{\textit{Total Numbers of Decisions}}\right) \times 100 \tag{4}$$

Mission Success Rate which evaluates the success rate of the drone in completing its missions using the fuzzy logic system.

$$\text{Mission Success Rate} = \left(\frac{\text{Number of Successful Missions}}{\textit{Total Numbers of}\ \text{Missions}}\right) \times 100 \tag{5}$$

5. Simulation results

Monte Carlo simulation was employed to evaluate the proposed model through three distinct experiments as shown in figure 14. The first experiment utilized a dataset of 300 scenarios, where 246 out of 300 obstacles were avoided, resulting in an avoidance efficiency of 82.00%. The baseline energy consumption was 1250 units, while the energy consumption with fuzzy logic was 1150 units, leading to an 8.00% reduction. Out of 300 decisions, 286 were correct, achieving a decision accuracy of 95.33%, and 238 out of 300 missions were successful, yielding a mission success rate of 79.33%. The second experiment, with 600 scenarios, had 495 obstacles avoided out of 600, resulting in an avoidance efficiency of 82.50%. The energy consumption reduction remained at 8.00%, with 575 correct decisions out of 600, leading to a decision accuracy of 95.83%, and 470 successful missions out of 600, producing a mission success rate of 78.33%. The third experiment, using 950 scenarios, showed 780 avoided obstacles out of 950, achieving an avoidance efficiency of 82.11%. The energy consumption reduction was consistently 8.00%, with 905 correct decisions out of 950, resulting in a decision accuracy of 95.26%, and 744 successful missions out of 950, leading to a mission success rate of 78.31%.

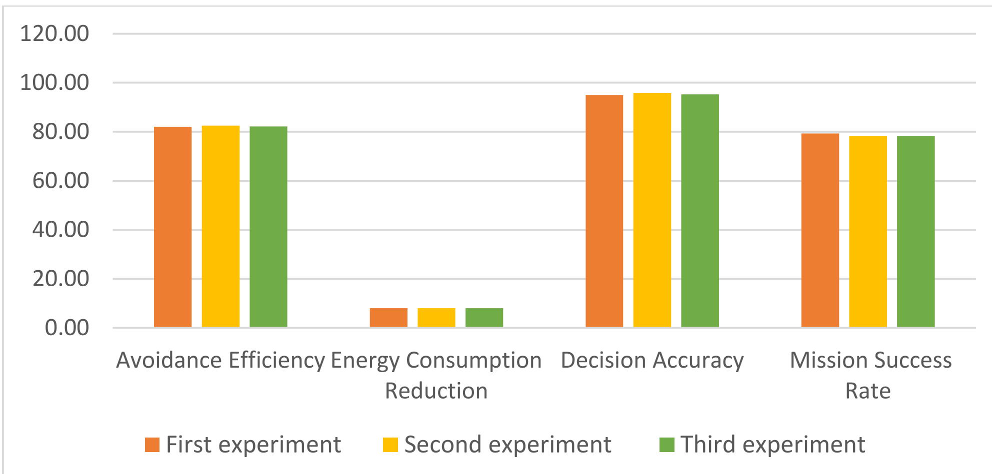

Fig. 14. Evaluation of model Performance

6. Discussion

Based on the results from the Monte Carlo simulations conducted through three distinct experiments, it is evident that the proposed Fuzzy Logic Decision Making model for autonomous drones consistently demonstrates high performance across various metrics. The avoidance efficiency remained above 82% in all scenarios, indicating the model's robust capability in detecting and avoiding obstacles. Energy consumption was reduced by 8.00% in all experiments, showcasing the model's efficiency in conserving energy. Decision accuracy was remarkably high, exceeding 95% in each experiment, which highlights the model's precision in real-time decision-making. Furthermore, the mission success rate remained consistently around 78%, proving the model's reliability in completing missions successfully. These results affirm that the Fuzzy Logic Decision Making model significantly enhances the performance and efficiency of autonomous drones.

7. Conclusion

The integration of fuzzy logic into real-time decision-making systems for autonomous drones has demonstrated significant improvements in performance metrics across various experimental scenarios. The Monte Carlo simulations revealed that fuzzy logic enhances obstacle avoidance efficiency, reduces energy consumption by 8.00%, and achieves high decision accuracy and mission success rates. The consistent performance across different experimental setups underscores the robustness and reliability of fuzzy logic in dynamic environments. Future research should focus on further refining fuzzy logic models and expanding their applicability to enhance the operational capabilities of autonomous drones, ultimately contributing to safer and more efficient autonomous systems.

Acknowledgement

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