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Three-Axis Fuzzy Logic Attitude Control of a Tetrahedral Satellite with Adaptive Fuzzy Enhancement

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Abstract
This study presents the design and evaluation of a three-axis fuzzy-logic-based attitude controller for a tetrahedral satellite, along with an adaptive enhancement that adjusts controller parameters in real time. The proposed approach overcomes the limitations of conventional proportional derivative (PD) control by improving stability and robustness under nonlinear and uncertain operating conditions. Comparative simulations are performed to assess settling time, overshoot, control effort, and error indices. The results demonstrate that the designed fuzzy controller provides smoother stabilization and reduced overshoot compared with the PD baseline, while the adaptive mechanism further accelerates convergence and enhances energy efficiency. Overall, the study highlights the progression from classical PD to fuzzy and adaptive fuzzy control schemes, establishing a robust and efficient framework for multi-axis satellite attitude regulation.

Keywords: Tetrahedral satellite, fuzzy logic controller, adaptive fuzzy enhancement, nonlinear control, attitude control, three-axis stabilization, simulation.

1. Introduction

The attitude of a satellite defines its angular position and orientation with respect to a reference coordinate system, such as the Earth-centered inertial frame or another celestial reference. Maintaining an accurate attitude is fundamental to spacecraft operation since every subsystem including communication antennas, imaging sensors, and propulsion modules depends on correct orientation to function optimally. For instance, Earth-observation satellites must sustain precise pointing to capture high-resolution images, while communication satellites require continuous alignment with ground stations to ensure uninterrupted signal transmission. Any deviation from the intended orientation can cause significant degradation in mission performance, leading to data loss, misalignment of instruments, or inefficient energy utilization. Hence, achieving reliable three-axis attitude control is a critical requirement for both large and small spacecraft platforms.

Effective attitude control not only stabilizes the satellite during orbit but also enhances its ability to perform complex maneuvers, such as target tracking, orbit correction, and payload reorientation. Even slight inaccuracies in orientation may result in substantial mission failures when accumulated over time. For example, a small pointing drift can reduce the efficiency of solar panels and affect the energy budget, while vibration or oscillation in imaging satellites can blur captured data. These operational challenges become more pronounced in small-scale satellites and CubeSats, where the available space for sensors and actuators is minimal, and power resources are severely constrained. Therefore, designing compact and robust control algorithms capable of maintaining stability despite nonlinear dynamics, environmental disturbances, and hardware limitations is essential for modern satellite missions.

The design of an attitude control system (ACS) is complicated by the nonlinear nature of rotational dynamics and the coupling between the three rotational axes. External torques due to gravity gradients, magnetic fields, or solar radiation pressure can disturb the satellite, while modeling uncertainties and sensor noise further limit control precision. Under such conditions, linear controllers tend to perform poorly because they are derived under small-angle and nominal operating assumptions. These limitations motivate the use of more adaptive and intelligent control strategies that can maintain performance even when system parameters or environmental factors change over time.

Among conventional control schemes, the proportional-derivative (PD) controller is one of the most widely implemented methods for spacecraft attitude regulation due to its straightforward structure and ease of implementation. It produces control torque as a linear combination of the attitude error and angular velocity, providing quick response and acceptable stability for small deviations. However, PD control exhibits certain shortcomings. It is highly dependent on accurate gain tuning and assumes near-linear behavior of the system. When the spacecraft operates far from equilibrium or experiences strong nonlinear coupling effects, the PD controller may generate oscillations, large overshoot, or sluggish settling. Furthermore, it cannot adapt to parameter changes or actuator saturation, which often occur in small and flexible satellites. As a result, PD control alone is insufficient for missions that demand high precision and adaptability under variable dynamic conditions.

To address the inherent nonlinearity and uncertainty in satellite attitude control, researchers have explored a variety of intelligent control techniques, among which fuzzy logic control (FLC) has emerged as a promising alternative. Fuzzy controllers mimic human reasoning by transforming heuristic control knowledge into a set of linguistic rules. These rules establish relationships between inputs such as attitude error and angular rate, and the output control torque, without requiring a detailed mathematical model of the satellite. This makes FLCs inherently robust to modeling errors and environmental variations. They can also provide smoother control actions, reduced overshoot, and better damping characteristics compared with conventional linear controllers. Consequently, fuzzy logic has been successfully applied to many nonlinear systems, including robotics, automotive systems, and aerospace vehicles, making it an attractive candidate for satellite attitude stabilization.

Nevertheless, standard fuzzy controllers have fixed membership functions and rule bases, which limit their ability to adapt dynamically to changes in operating conditions. To overcome this drawback, adaptive fuzzy logic controllers (AFLCs) have been introduced. These controllers integrate online learning or gain-tuning mechanisms that modify fuzzy parameters in real time based on the system's current state. In satellite control applications, adaptive fuzzy methods enable the controller to react swiftly to large initial errors, external torques, or disturbances by automatically adjusting its control gains. This results in faster stabilization, reduced steady-state error, and more efficient actuator operation. The self-tuning nature of adaptive fuzzy control ensures that the system remains stable even in uncertain and highly nonlinear environments, which is essential for autonomous spacecraft operation.

In summary, attitude control remains a core challenge in modern space missions, particularly as satellite systems become smaller, more autonomous, and required to perform increasingly complex tasks. The transition from traditional PD controllers to fuzzy logic and adaptive fuzzy frameworks represents a significant step toward achieving high-precision, robust, and intelligent spacecraft control. This research contributes to that progression by designing and evaluating a three-axis fuzzy logic attitude controller for a tetrahedral satellite and extending it through adaptive fuzzy enhancement. The developed system aims to achieve improved response, robustness, and efficiency across a range of operating conditions, offering a viable control strategy for future satellite missions.

2. Literature Review

Research on spacecraft attitude control has undergone remarkable evolution over the past few decades, driven by the growing need for precision, autonomy, and adaptability in satellite operations. Early spacecraft employed classical linear controllers, such as proportional-derivative (PD) and proportional-integral-derivative (PID) schemes, primarily due to their simplicity and low computational cost. These controllers perform adequately when the system dynamics remain near linear regions, but their limitations become evident when addressing nonlinearities, actuator constraints, or environmental disturbances such as gravity-gradient torque and magnetic field variations. As satellite missions became increasingly complex and miniaturized, the requirement for intelligent and adaptive control methods became more pressing.

Henry Travis (2020) presented a broad introduction to the fundamentals of satellite motion and attitude control. His study discussed the various natural forces acting on satellites, such as gravitational pull, atmospheric drag, and third-body perturbations, and how these forces influence orbital and attitude dynamics. He also introduced the classical orbital elements (COEs) that describe satellite trajectories and highlighted how perturbations, including the J_2 effect, modify these orbits over time. Furthermore, Travis explained how the direction cosine matrix and quaternion representations are employed to describe satellite orientation without encountering singularities. This foundational framework provides essential background for developing reliable control algorithms that ensure stable attitude regulation in space missions. [1]

Scott R. Starin et al. (2011) provided a detailed technical review of the Attitude Determination and Control System (ADCS), emphasizing its critical role in successful satellite missions. Their work systematically described how sensors and actuators work together to determine and control spacecraft orientation. The authors analyzed how environmental factors vary across orbital regions such as Low Earth Orbit (LEO) and Geostationary Orbit (GEO), showing that the availability and strength of magnetic and gravitational fields differ significantly between them. They concluded that robust attitude controllers must be designed to handle such environmental variability while ensuring precise pointing accuracy and stability throughout the satellite's mission lifespan. [2]

Yihe Shan et al. (2022) focused on comparing the performance of a conventional Proportional–Integral–Derivative (PID) controller with a Fuzzy PID controller for satellite attitude stabilization. The study developed the satellite's kinematic and dynamic models using the quaternion method, which eliminates singularities associated with Euler angles. Using reaction flywheels as actuators, they tested both control strategies through simulations. Results revealed that while the traditional PID controller achieved faster stabilization, the Fuzzy PID controller provided smoother control torque with reduced overshoot and better adaptability to parameter variations. The authors concluded that fuzzy logic integration enhances classical PID control by allowing self-tuning of gains, improving steady-state performance and overall system robustness. [3]

Suriya Thongchet et al. (2001) proposed a minimum-time fuzzy logic controller (FLC) for three-axis attitude control of satellites using bang-bang actuation. Their main objective was to achieve rapid attitude correction while minimizing thruster activations to preserve fuel and prolong actuator life. The fuzzy logic structure was designed using heuristic rule bases and triangular membership functions to determine the control torque. Simulation outcomes showed that their fuzzy-based approach achieved near-minimum-time convergence with significantly fewer on–off cycles compared to the conventional bang-bang controller. This work demonstrated the potential of fuzzy reasoning for achieving efficient and low-stress control in thruster-driven satellite systems. [4]

R. N. Prasanna Kumar et al. (2006) developed an intelligent rule-based fuzzy control strategy for the attitude regulation of a spin-stabilized microsatellite operating in Low Earth Orbit. Their design utilized magnetic torquers and a magnetometer to generate control torques through interaction with the Earth's magnetic field. The authors argued that the nonlinearity and time-varying nature of the geomagnetic field require nontraditional, adaptive control strategies. Their simulation studies indicated that the proposed fuzzy controller achieved faster detumbling and enhanced stability when compared to the conventional B-dot controller, proving that fuzzy logic can offer robust control even under unpredictable environmental conditions. [5]

Sobutyeh Rezanezhad (2014) presented a fuzzy on–off control algorithm aimed at reducing fuel consumption and increasing system longevity in satellite attitude control. The controller was designed using the Takagi–Sugeno (T–S) fuzzy model, combined with the Particle Swarm Optimization (PSO) algorithm to fine-tune membership function parameters. The research addressed common issues of limit cycles and chattering in conventional on–off controllers. Simulation results showed that the optimized fuzzy controller significantly reduced oscillations and improved attitude stability while minimizing fuel usage. This approach demonstrated the benefits of combining fuzzy logic with optimization algorithms for achieving high-performance and energy-efficient satellite control. [6]

P. N. Achebe et al. (2025) introduced an Adaptive Proportional–Derivative (APD) controller for the yaw-axis attitude control system of a microsatellite. Their motivation stemmed from the limitations of classical PID controllers, which often suffer from high overshoot and sensitivity to parameter variations. The authors designed transfer function models for the amplifier, actuator, and satellite dynamics, and then implemented the APD controller using MATLAB/Simulink. Their simulation results showed that the adaptive control scheme achieved shorter settling times, smoother transients, and zero steady-state error compared to traditional PID-based methods. The study highlighted how adaptive gain mechanisms can enhance classical controllers, providing better accuracy and robustness for small satellite missions. [7]

Sohaib Aslam et al. (2024) explored the integration of deep learning with fuzzy control by developing a Deep-Learning-Based Fuzzy Model Predictive Control (D-FMPC) strategy for small satellites with limited computational capacity. The authors recognized that standard Fuzzy Model Predictive Control (FMPC) methods, while effective, impose high computational loads. To mitigate this, they trained a neural network to emulate the FMPC behavior, resulting in a system that delivers similar control precision with significantly reduced computation time. Their results demonstrated that D-FMPC maintained desired pointing accuracy and transient smoothness while operating efficiently, offering a practical solution for small satellite platforms constrained by onboard processing resources. [8]

Henrique Daitx et al. (2016) focused on the experimental implementation of attitude and position control on an air-bearing testbed. Their study combined both attitude and translational control using a Combined Attitude and Position Controller (CAPC) driven by a PD algorithm. Reaction wheels were employed for attitude control, while an air blower provided translational motion on a frictionless surface. The results validated that PD control could achieve basic orientation accuracy; however, the study also emphasized that advanced control methods are necessary for missions demanding higher precision. This experimental setup provided a valuable platform for verifying new algorithms under realistic conditions before in-orbit deployment. [9]

Overall, the reviewed studies reveal a steady evolution from traditional control approaches toward more intelligent and adaptive strategies. Early research concentrated on classical PD and PID schemes for their simplicity, whereas recent developments focus on fuzzy logic and hybrid adaptive systems capable of handling nonlinearities and uncertainties. Integrating techniques such as optimization algorithms and deep learning has further enhanced performance, leading to adaptive controllers with improved efficiency and robustness. Building upon these advancements, the present study develops a three-axis Adaptive Fuzzy Logic Controller (AFLC) for a tetrahedral satellite, aimed at achieving faster stabilization, reduced overshoot, and lower control effort compared with conventional and non-adaptive fuzzy methods.

3. Methodology

The methodology of this research focuses on developing, simulating, and analyzing multiple attitude control strategies for a tetrahedral satellite using MATLAB. The study compares three control architectures: a classical Proportional–Derivative (PD) controller, a Fuzzy Logic Controller (FLC), and an Adaptive Fuzzy Logic Controller (AFLC). Each controller is tested under identical conditions to evaluate performance based on transient and steady-state response parameters. The key stages of this methodology include the formulation of satellite dynamics, controller design, and performance assessment through simulation.

3.1 Satellite Dynamics Modeling

The first stage involves creating a mathematical model that accurately represents the satellite’s rotational motion. The satellite is modeled as a rigid, symmetric body with equal moments of inertia about its principal axes. The attitude of the satellite is described using Euler angles - roll (ϕ), pitch (θ), and yaw (ψ)

which define its orientation with respect to an inertial reference frame. This dynamic model forms the foundation for simulating the behavior of the satellite when different control torques are applied.

(a) Moment of Inertia

The distribution of mass within the satellite determines its resistance to rotational acceleration, quantified through the moment of inertia. For a symmetric tetrahedral satellite, the inertia matrix is represented as:

$$I = \begin{bmatrix} I_x & 0 & 0 \\ 0 & I_y & 0 \\ 0 & 0 & I_z \end{bmatrix} \quad (1)$$

Where I_x, I_y, I_z represent the principal moments of inertia along the respective axes, measured in $kg \cdot m^2$.

(b) Euler's Rotational Dynamics

The rotational motion of a rigid body in space is governed by Euler's equation, which relates angular momentum and external torques:

$$I\dot{\omega} + \omega \times (I\omega) = T \quad (2)$$

Here, ω is the angular velocity vector, T is the applied control torque vector, and the cross-product term accounts for gyroscopic coupling among the rotational axes. This nonlinear relationship highlights how motion in one axis can influence others, an important consideration for multi-axis attitude control.

(c) Euler Angle Kinematics

The transformation between body-frame angular velocities and time derivatives of Euler angles is expressed through the kinematic equations:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi/\cos\theta & \cos\phi/\cos\theta \end{bmatrix} \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \quad (3)$$

These relationships enable conversion between angular velocity data and the time-varying attitude of the satellite, allowing real-time simulation of orientation evolution.

3.2 Fuzzy Inference System (FIS) Design

The Fuzzy Inference System (FIS) forms the core of the proposed fuzzy logic controller. It determines the control torque required to stabilize the satellite based on two input variables - attitude error and angular rate error and one output variable control torque (τ). A Mamdani-type fuzzy system is employed, using triangular membership functions for simplicity and real-time compatibility.

(a) Fuzzification

In this step, crisp numerical inputs (error and rate) are transformed into fuzzy linguistic variables using membership functions defined by:

$$\mu_{\{A_i\}}(x) = \begin{cases} 0, & x \le a_i \\ \frac{x-a_i}{b_i-a_i}, & a_i < x \le b_i \\ \frac{c_i-x}{c_i-b_i}, & b_i < x \le c_i \\ 0, & x > c_i \end{cases} \quad (4)$$

Where a_i, b_i, c_i define the base and peak points of each triangular function. This step effectively maps the inputs into linguistic terms such as Negative (N), Zero (Z), and Positive (P).

(b) Fuzzy Rule Base

The rule base defines the control logic in the form of if–then statements:

$$R_k : \text{IF } e \text{ is } A_i \text{ AND } \dot{e} \text{ is } B_j\text{, THEN } \tau \text{ is } C_{ij}. \quad (5)$$

Each rule connects combinations of input conditions to an appropriate control torque output. With three membership functions per input, a total of nine rules govern the system's behavior, ensuring smooth nonlinear mapping between inputs and output torque.

(c) Inference Mechanism

The Mamdani max–min method is used for fuzzy inference, combining the activated rules through aggregation:

$$\mu_{C'}(z) = \max_k \left[\min\left(\mu_{A_i}(e), \mu_{B_j}(\dot{e}), \mu_{C_{ij}}(z)\right)\right] \quad (6)$$

This step determines how individual rule outputs are combined to form the overall fuzzy output set.

(d) Defuzzification (Centroid Method)

To generate a crisp control signal from the fuzzy output, the centroid method is used:

$$\tau = \frac{\int z\, \mu_{C'}(z)\, dz}{\int \mu_{C'}(z)\, dz} \quad (7)$$

This yields a continuous control torque suitable for real-time attitude correction.

3.3 Design and Implementation of Fuzzy Logic Controller

The fuzzy logic controller (FLC) is implemented in MATLAB using custom scripts. The FLC uses the defined rule base and membership functions to compute control torques for each axis. The input errors in roll, pitch, and yaw are fed into the FIS, which outputs the required torque signals. These torques are then substituted into Euler's dynamic equation to simulate the rotational response of the satellite.

The FLC's control law is expressed as:

$$\tau_f = f(e, \dot{e}) \quad (8)$$

where τ_f represents the fuzzy torque output and f(·) denotes the nonlinear mapping defined by the inference system. This controller is especially effective for handling nonlinearities and disturbances that conventional linear controllers cannot easily manage.

3.4 Design and Implementation of PD Controller

To provide a baseline comparison, a classical **Proportional–Derivative (PD)** controller is implemented. It produces control torque proportional to the attitude error and its rate of change:

$$\tau = K_p e + K_d \dot{e} \quad (9)$$

Here, K_p and K_d are proportional and derivative gain matrices, respectively. While PD control is computationally simple and responsive under nominal conditions, it lacks adaptability. Its effectiveness diminishes when nonlinear coupling or large disturbances are present, making it suitable mainly for benchmark purposes in this study.

3.5 Design and Implementation of Adaptive Fuzzy Logic Controller

To enhance flexibility and adaptability, an **Adaptive Fuzzy Logic Controller** (AFLC) is designed by integrating online gain adjustment within the fuzzy control structure. The adaptive mechanism modifies scaling factors for the input and output variables in real time, based on the magnitude of the instantaneous attitude error and rate error. This allows the controller to apply stronger corrective torques during large deviations and finer corrections near equilibrium.

The AFLC control law is expressed as:

$$\tau = K_u \cdot \mathrm{FIS}(K_e e, K_{de} \dot{e}) \quad (10)$$

where K_e, K_{de}, K_u are adaptive gain coefficients that evolve according to the current error state. These gains are computed using adaptive scaling equations such as:

$$K_e = K_{e0}(1 + \alpha|e|) \quad (11)$$

$$K_{de} = K_{de0}(1 + \alpha|\dot{e}|) \quad (12)$$

$$K_u = K_{u0}(1 + \alpha|e|) \quad (13)$$

Here, α is the adaptation rate constant, and the subscript '0' denotes the nominal gain value. This adaptive structure allows the fuzzy controller to continuously adjust its response, leading to faster stabilization and reduced steady-state error.

3.6 Performance Evaluation Metrics

To quantitatively assess and compare the PD, FLC, and AFLC controllers, several performance metrics are computed:

- **Settling Time (T_s):** Measures how quickly the attitude error remains within ±2% of the final value.
- **Peak Overshoot (M_p):** Indicates the maximum deviation from the desired attitude during transient response.

$$M_p = \theta_{peak} - \theta_{ref} \quad (14)$$

- **Integral Absolute Error (IAE):** Represents the total magnitude of error over the entire simulation duration.

$$IAE = \int_0^T |e(t)|\, dt \quad (15)$$

- **Integral Squared Error (ISE):** Penalizes large deviations by integrating the square of the error signal.

$$ISE = \int_0^T e^2(t)\, dt \quad (16)$$

- **Root Mean Square Torque ($\tau_{(rms)}$):** Reflects actuator energy usage and smoothness of control action.

$$\tau_{rms} = \sqrt{\frac{1}{T}\int_0^T \tau^2(t)\, dt} \quad (17)$$

Together, these metrics provide a comprehensive evaluation of response speed, precision, and energy efficiency across all three controllers.

4. Simulation Setup

This section describes the configuration of the simulation environment, satellite parameters, controller settings, and data collection procedures used to evaluate the performance of the PD, Fuzzy Logic, and Adaptive Fuzzy Logic controllers. All simulations are performed using the same dynamic model and solver conditions to ensure consistent comparison across the three control strategies.

4.1 Simulation Environment and Tools

All simulations are conducted using MATLAB R2025a along with the Fuzzy Logic Designer Toolbox for the design and tuning of fuzzy inference systems. The dynamic equations of motion, control algorithms, and adaptive mechanisms are implemented using MATLAB scripts and Simulink models. A variable-step ODE45 solver is selected for numerical integration because of its accuracy and stability in handling nonlinear systems. The simulation runs for a total duration of 100 s with a sampling time of 0.1 s, ensuring sufficient temporal resolution for capturing transient and steady-state responses. All simulation scripts are executed on a standard workstation running MATLAB under default computational settings.

4.2 Satellite Model Parameters

The satellite is modeled as a rigid tetrahedral body with diagonal inertia matrices defined according to the controller type:

$$I = \begin{cases} \mathrm{diag}([5, 6, 4]) & \text{for PD Controller} \\ \mathrm{diag}([10, 12, 8]) & \text{for Fuzzy and Adaptive Fuzzy Controller} \end{cases}$$

Different inertia values were assigned to the PD and fuzzy-based controllers to ensure fair and stable performance evaluation. The PD controller used a lower inertia to maintain numerical stability, while the fuzzy and adaptive fuzzy controllers were tested with higher inertia to assess their robustness under more complex and nonlinear satellite dynamics.

No external disturbance torques are applied during the simulations so that controller performance can be evaluated purely based on internal dynamic response and control effectiveness. This configuration isolates the controller's capability to achieve stabilization without interference from unmodeled environmental effects.

4.3 Initial Conditions

The simulation starts from an intentionally perturbed orientation to test the controllers' ability to stabilize the satellite from large initial errors. The state vector x representing attitude angles and angular velocities is initialized as:

$$x = [10, 5, -8, 0, 0, 0]^T$$

where the first three components correspond to roll (ϕ), pitch (θ), and yaw (ψ) angles (in degrees), and the last three represent the corresponding angular velocity components (in degrees per second). This configuration provides a nonlinear and asymmetric starting condition, suitable for evaluating the transient performance of each controller.

4.4 Controller Parameter Settings

Each of the three control schemes uses its own configuration, but all operate under identical sampling and dynamic conditions to enable fair comparison.

(a) PD Controller Parameters

The proportional–derivative controller employs diagonal gain matrices given by:

$$K_p = \mathrm{diag}([0.8, 0.8, 0.8]), \qquad K_d = \mathrm{diag}([1.2, 1.2, 1.2])$$

These gains were selected through manual tuning to achieve stable yet responsive attitude control.

(b) Fuzzy Logic Controller Parameters

The Fuzzy Logic Controller (FLC) uses a Mamdani-type fuzzy inference system with two inputs and one output:

Variable	Type	Range
Input 1	Error (e)	[-20 20]
Input 2	Rate ($\dot{e}$)	[-10 10]
Output	Torque (T)	[-1 1]

Table 1: FLC Parameters

Triangular membership functions are used for simplicity and computational efficiency. The rule base follows a 3 × 3 structure, resulting in nine rules that map combinations of error and rate to corresponding torque commands.

(c) Adaptive Fuzzy Logic Controller

The Adaptive Fuzzy Logic Controller (AFLC) extends the FLC by introducing adaptive gain scaling. The initial and adaptive parameters are:

$(\alpha, K_e, K_{de}, K_u)$ = (0.2, 1, 1, 1)

The adaptation mechanism modifies the scaling gains K_e, K_{de}, and K_u online in proportion to the instantaneous magnitude of attitude error and rate, enabling faster and more stable convergence.

4.5 Simulation Procedure and Data Collection

For each controller, the simulation follows a standardized sequence:

1) Initialize the satellite state with the specified initial conditions.
2) Apply the selected control law (PD, FLC, or AFLC) to generate control torques.
3) Integrate the satellite's rotational dynamics using the ODE45 solver.
4) Record the system response variables over the 100 s simulation time.

Two primary response plots are generated for each controller:

- **Attitude Response:** shows the variation of roll, pitch, and yaw angles over time, indicating the controller's stabilization performance.
- **Control Torque:** presents the actuator torque commands in each axis, used to evaluate smoothness and energy efficiency.

5. Results and Discussion

This section presents and interprets the simulation results obtained for the three-axis attitude control of the tetrahedral satellite. Individual controller behaviors are analyzed first, followed by comparative evaluations in the next subsection. The analysis focuses on transient behavior, settling characteristics, control torque smoothness, and steady-state accuracy.

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5.1 Individual Results of Controllers

5.1.1 Fuzzy Controller - Attitude Response

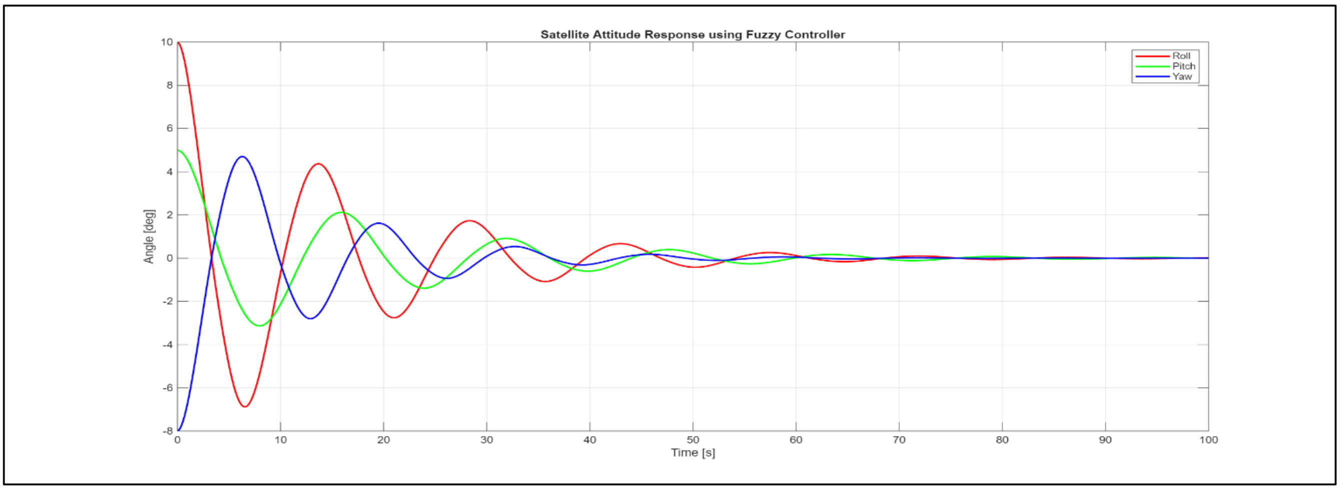

Figure 1: Attitude Response using Fuzzy Controller

The attitude response of the fuzzy-logic controller shows smooth convergence of roll, pitch, and yaw angles from their initial displacements toward the commanded orientation. All three axes exhibit small oscillatory transients that decay gradually without divergence. The roll axis stabilizes first, with pitch requiring a slightly longer damping period and yaw displaying minor oscillations before settling. Steady-state error in all channels is essentially zero. The controller's rule-based nonlinear mapping between error and rate effectively reduces residual error while maintaining continuous, smooth motion. Although the transient oscillations persist for a few seconds longer than those of the PD controller, the fuzzy controller achieves a desirable balance between responsiveness and stability, providing gentle attitude correction suitable for systems sensitive to abrupt control actions.

5.1.2 Fuzzy Controller - Control Torque

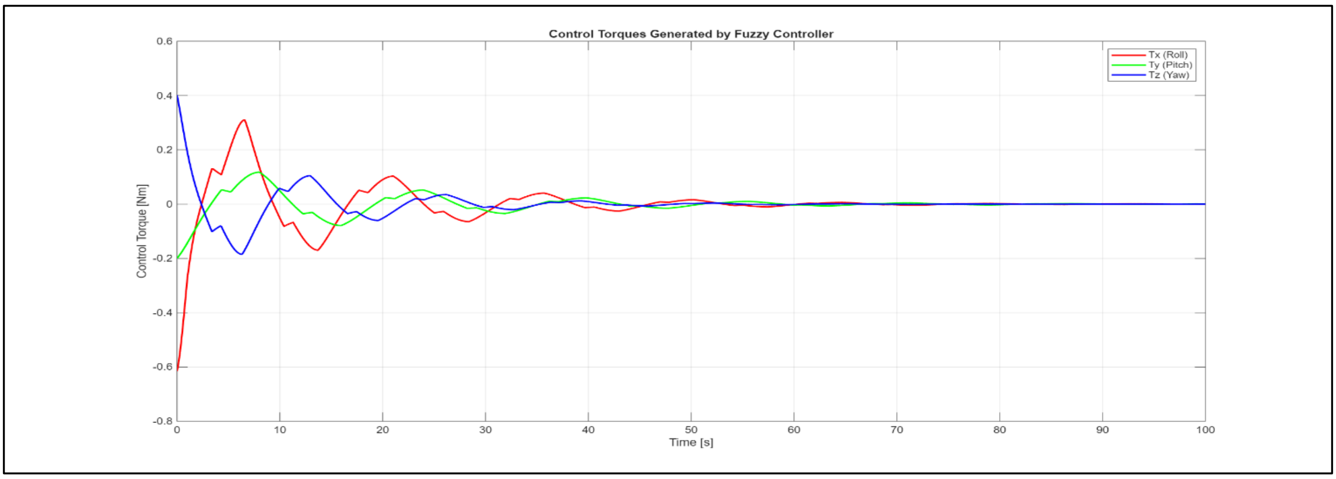

Figure 2: Control Torque using Fuzzy Controller

The control torque signals generated by the fuzzy controller begin with moderate initial peaks that correspond to the early corrective phase of the attitude response. Subsequently, the torque magnitudes decay steadily and settle near zero as the orientation reaches equilibrium. The torque waveforms remain continuous and free from impulsive spikes, confirming the fuzzy inference system's smoothing capability.

Peak torque amplitudes remain within safe actuator limits, and no saturation tendency is observed. Overall, the fuzzy controller delivers a smooth control effort with moderate energy use, providing stable convergence and low actuator stress while maintaining effective disturbance rejection.

5.1.3 PD Controller - Attitude Response

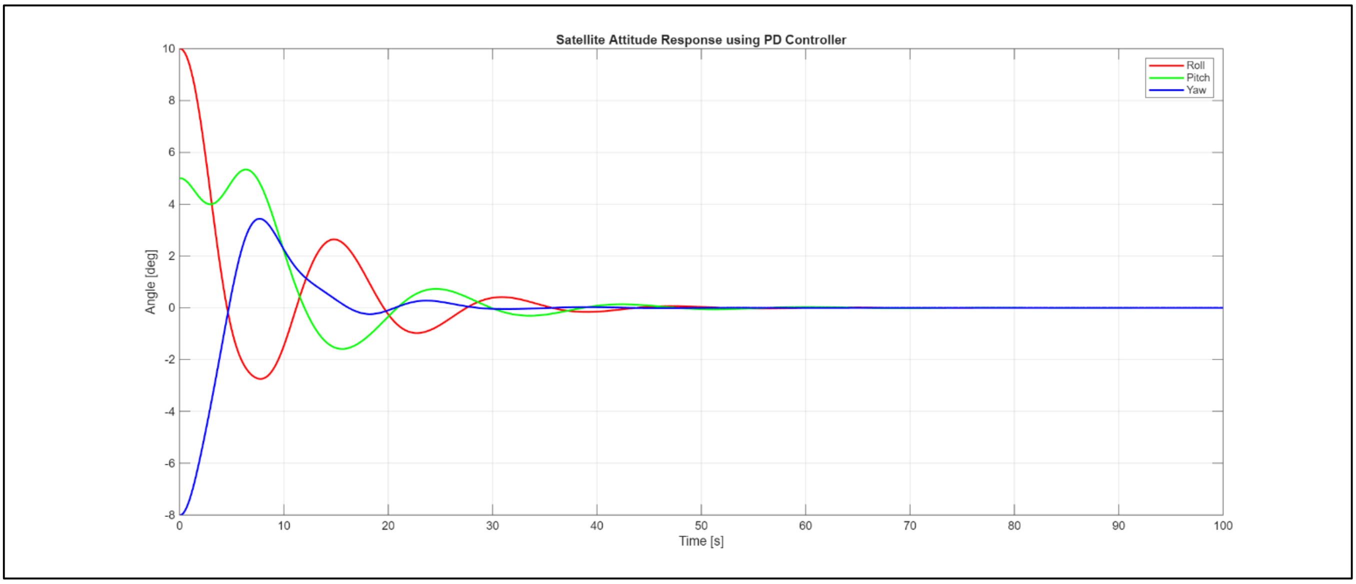

Figure 3: Attitude Response using PD Controller

The proportional–derivative controller produces a noticeably faster initial correction compared with the fuzzy-based controllers. Roll, pitch, and yaw angles exhibit steep initial slopes, reflecting the PD controller's aggressive response to large attitude errors. However, this fast action leads to larger overshoots, particularly along the yaw axis, before damping takes effect. The oscillations decay quickly owing to the derivative term, but the transient period is marked by sharper, more abrupt motion. Steady-state error remains negligible, confirming accurate tracking under ideal conditions. The PD controller therefore offers rapid stabilization but requires careful gain selection to avoid excessive overshoot or potential actuator stress.

5.1.4 PD Controller – Control Torque

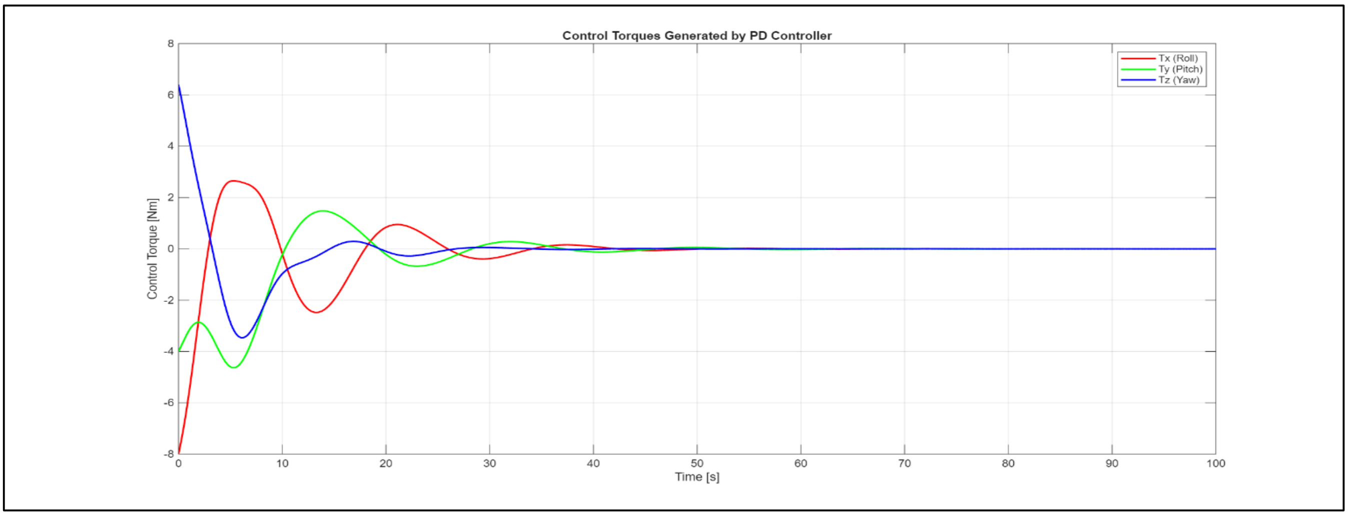

Figure 4: Control Torque using PD Controller

The torque response of the PD controller shows pronounced initial spikes that coincide with the rapid attitude correction phase. These high-amplitude peaks especially on the roll and yaw channels suggest heavy instantaneous control effort and possible actuator saturation if implemented on hardware. After the initial transient, the torques decay rapidly toward zero as damping dominates. The control signals settle earlier than in the fuzzy-logic case but consume significantly more energy at the start. This behavior illustrates the typical trade-off of PD control: fast response achieved at the cost of high torque demand and less smooth control action.

5.1.5 Adaptive Fuzzy Controller - Attitude Response

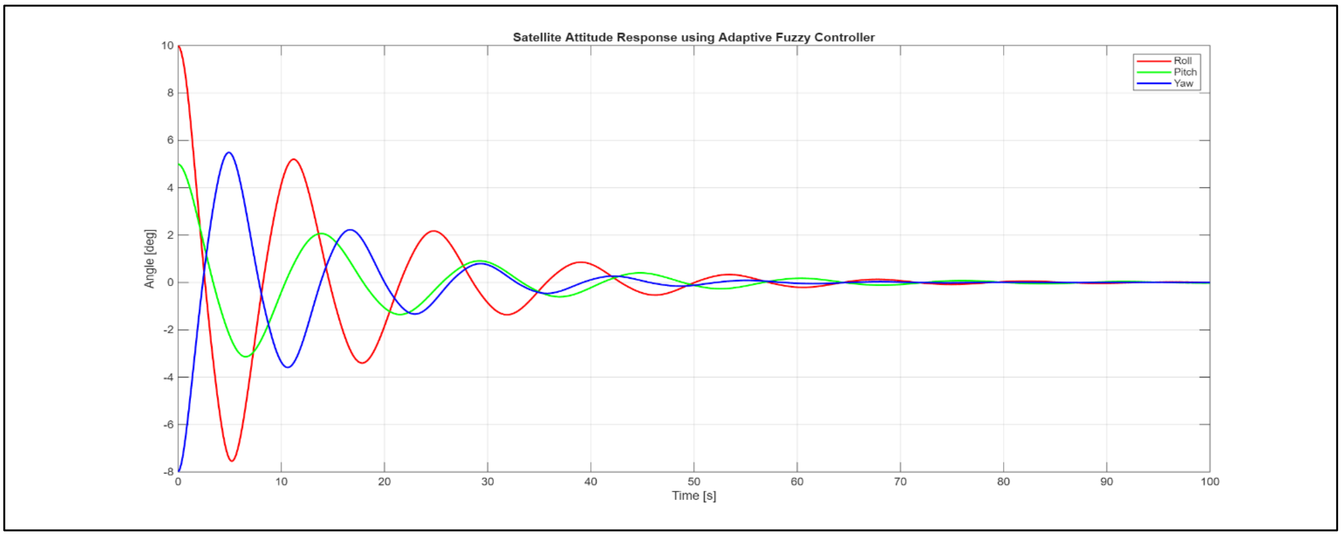

Figure 5: Attitude Response using Adaptive Fuzzy Controller

The adaptive fuzzy controller demonstrates the most balanced performance among the individual schemes. Compared with the static fuzzy controller, overshoot is smaller and damping occurs more rapidly while maintaining smooth transient curves. All attitude channels converge within a shorter time window, with minimal oscillatory behavior. The controller's online adjustment of scaling factors (K_e, K_{de}, K_u) strengthens corrective authority during large-error conditions and softens it as the satellite approaches equilibrium. This adaptive mechanism allows efficient transient suppression and stable steady-state tracking without sacrificing smoothness, confirming the controller's improved robustness and responsiveness.

5.1.6 Adaptive Fuzzy Controller - Control Torque

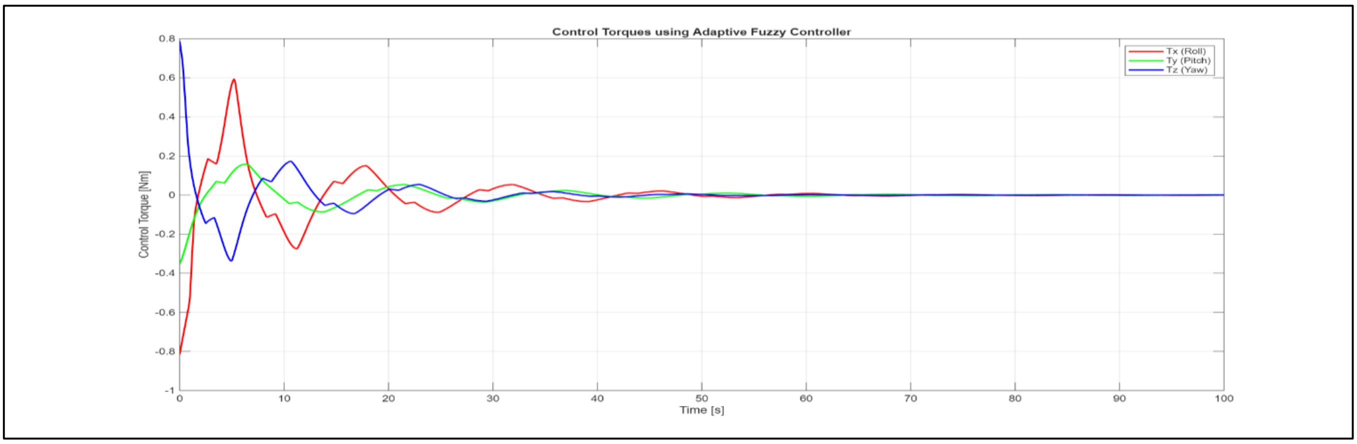

Figure 6: Control Torque using Adaptive Fuzzy Controller

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The corresponding torque responses of the adaptive fuzzy controller feature small initial peaks—larger than those of the static fuzzy controller but far below the PD levels—followed by quick attenuation to near-zero steady values. Torque waveforms are smooth, continuous, and bounded, indicating effective modulation by the adaptive gains. The adaptive mechanism momentarily increases torque when large corrections are needed and then reduces it as the error diminishes, resulting in efficient use of actuator energy. Compared with both PD and static fuzzy control, the adaptive fuzzy approach achieves superior damping with moderate torque magnitudes and no indication of instability. Overall, it provides the best compromise between rapid correction and low control effort among the individual controllers.

5.2 Comparison Between Controllers

5.2.1 Fuzzy vs PD - Attitude Response

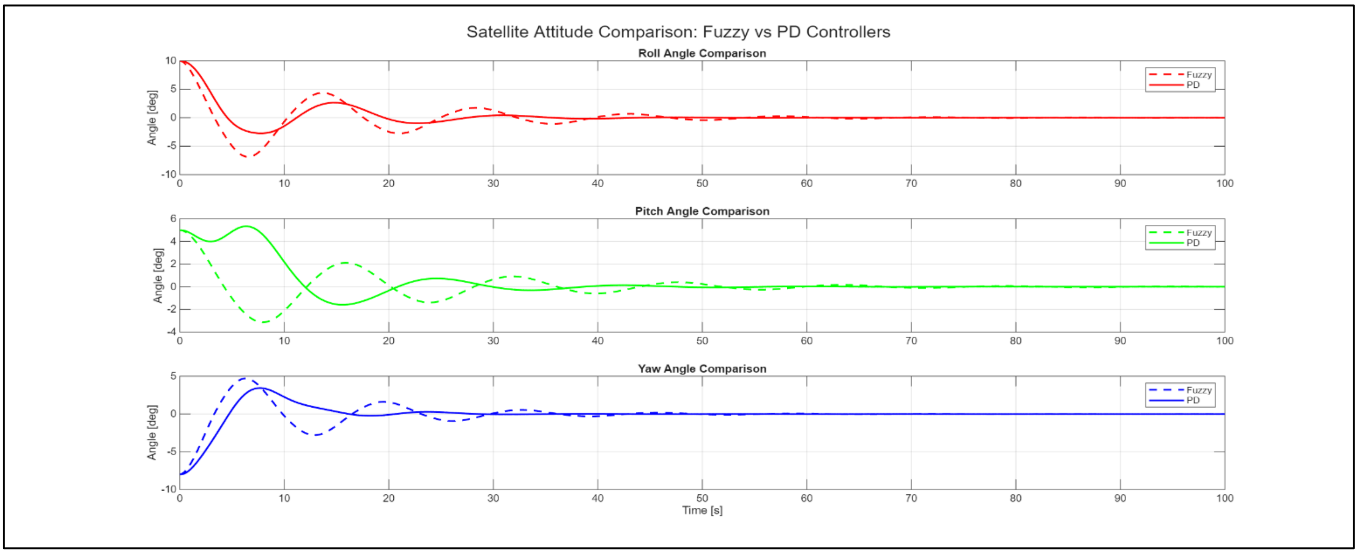

Figure 7: Comparison of Attitude Response - Fuzzy vs PD Controller

The comparative attitude response between the fuzzy and PD controllers highlights the classical trade-off between **response speed** and **smoothness**. The PD controller exhibits a noticeably faster initial correction, bringing the attitude angles toward the reference more quickly. However, this rapid response introduces significant overshoot, particularly in the yaw channel, and causes sharper oscillations during the transient phase. In contrast, the fuzzy controller responds more gradually but achieves smoother convergence with smaller oscillation amplitudes. The roll and pitch axes show visibly lower transient energy under fuzzy control, while the steady-state accuracy of both controllers remains nearly identical. These results confirm that fuzzy logic control offers a softer, more stable transition, whereas PD control achieves quicker correction at the cost of higher transient excitation. Hence, for missions prioritizing actuator safety and payload stability, the fuzzy controller provides a more desirable response.

5.2.2 Fuzzy vs PD - Control Torque

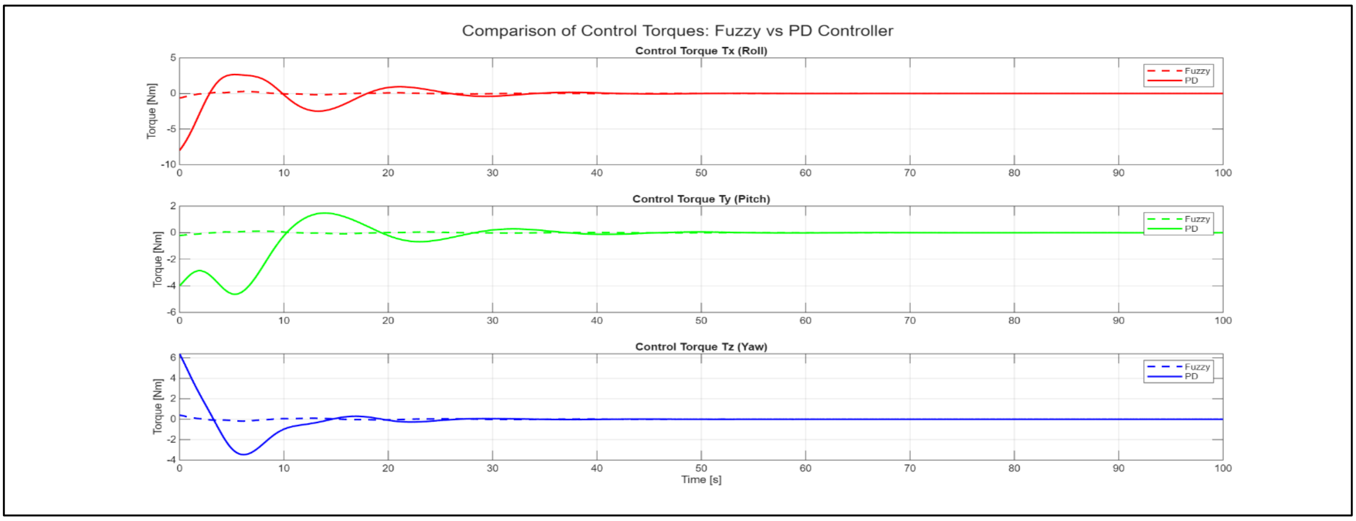

Figure 8: Comparison of Control Torque - Fuzzy vs PD Controller

The torque comparison between fuzzy and PD controllers further reinforces their performance contrast. The PD controller generates large, sharp torque spikes at the onset of correction, particularly in the roll and yaw axes, indicating heavy actuator demand. Peak torques are several times higher than those produced by the fuzzy controller. In contrast, the fuzzy controller produces smoother and smaller torque profiles, showing gradual variation and quick attenuation after the transient phase. These results suggest that the fuzzy controller achieves effective attitude stabilization with substantially lower control effort, reducing actuator stress and energy consumption. Therefore, although the PD controller offers faster settling, its high torque requirement makes the fuzzy controller more suitable where energy efficiency and actuator longevity are critical.

5.2.3 Fuzzy vs Adaptive Fuzzy - Attitude Response

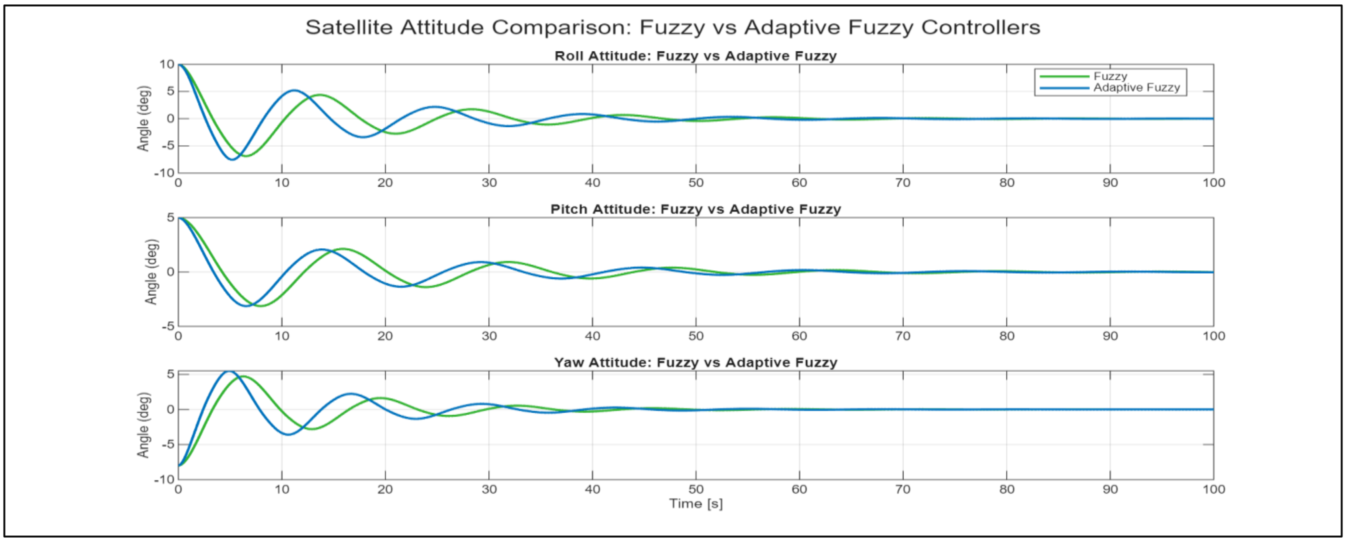

Figure 9: Comparison of Attitude Response - Fuzzy vs Adaptive Fuzzy Controller

The comparative attitude plot between the static and adaptive fuzzy controllers demonstrates the advantage of introducing online parameter adaptation. The adaptive fuzzy controller consistently achieves smaller overshoot and faster damping than the static fuzzy system across all attitude axes. The improvement is especially clear during the first 20 s of simulation, where oscillations under the static fuzzy controller persist longer before settling. The adaptive mechanism dynamically increases corrective gains when large attitude errors occur and automatically reduces them as the system approaches equilibrium. This real-time tuning accelerates convergence while preserving the inherent smoothness of fuzzy inference, resulting in improved transient and steady-state performance across roll, pitch, and yaw channels.

5.2.4 Fuzzy vs Adaptive Fuzzy - Control Torque

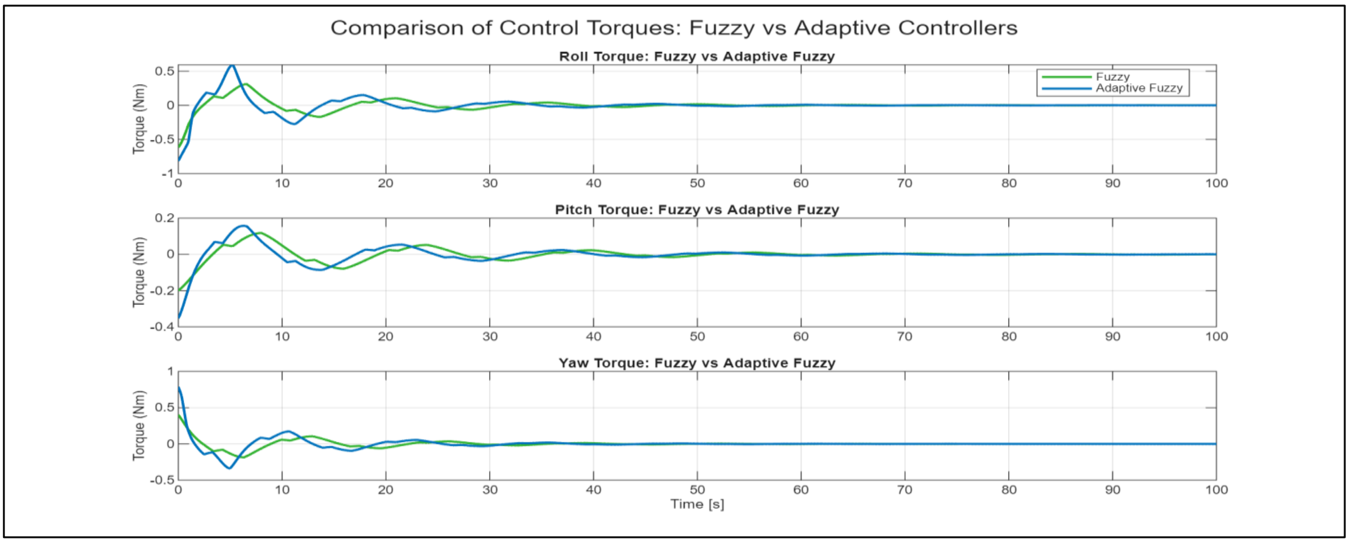

Figure 10: Comparison of Control Torque - Fuzzy vs Adaptive Fuzzy Controller

The torque comparison between fuzzy and adaptive fuzzy controllers reveals a targeted and intelligent control effort by the adaptive scheme. During the initial correction phase, the adaptive controller produces slightly higher torque pulses to accelerate response, but these peaks remain moderate and decay much faster than in the static fuzzy case. After the transient period, the adaptive fuzzy torque settles near zero with minimal oscillations, while the static fuzzy controller retains small residual fluctuations. Overall, the adaptive fuzzy approach demonstrates better torque shaping—delivering temporary increases when needed for large corrections and conserving energy during fine adjustments. This confirms the adaptive mechanism's ability to enhance response speed and damping without compromising smoothness or stability.

5.2.5 PD vs Fuzzy vs Adaptive Fuzzy – Attitude Response

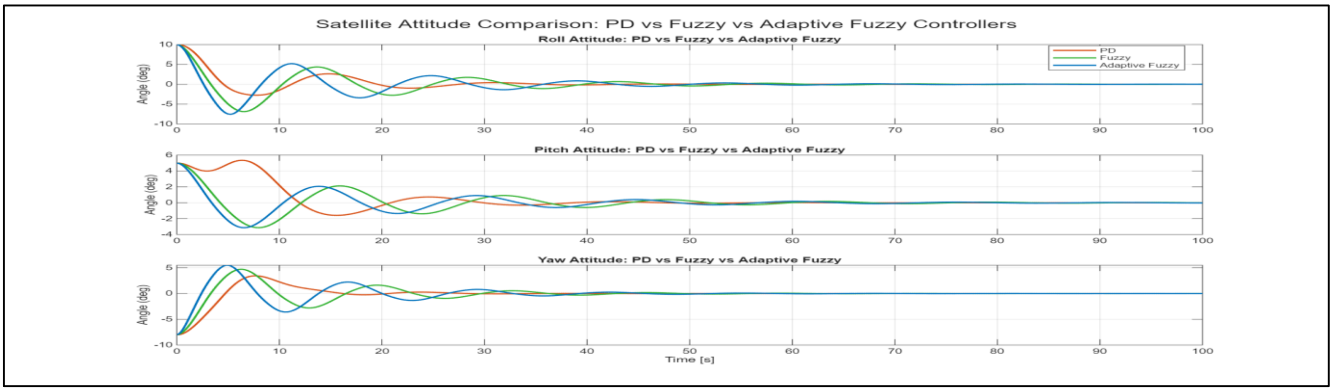

Figure 11: Comparison of Attitude Response - PD vs Fuzzy vs Adaptive Fuzzy Controller

The combined attitude comparison among all three controllers PD, fuzzy, and adaptive fuzzy illustrates their relative control characteristics clearly. The PD controller achieves the fastest initial correction but produces the highest overshoot and most aggressive transients. The fuzzy controller, by contrast, maintains very smooth behavior but with slower convergence and extended oscillations before complete stabilization. The adaptive fuzzy controller achieves an optimal balance: it converges nearly as fast as PD while avoiding its excessive overshoot and maintaining the smooth trajectory typical of fuzzy control. Across all attitude axes, the adaptive fuzzy controller provides the shortest settling time with minimal oscillation, demonstrating superior dynamic performance and stability.

5.2.6 PD vs Fuzzy vs Adaptive Fuzzy - Control Torque

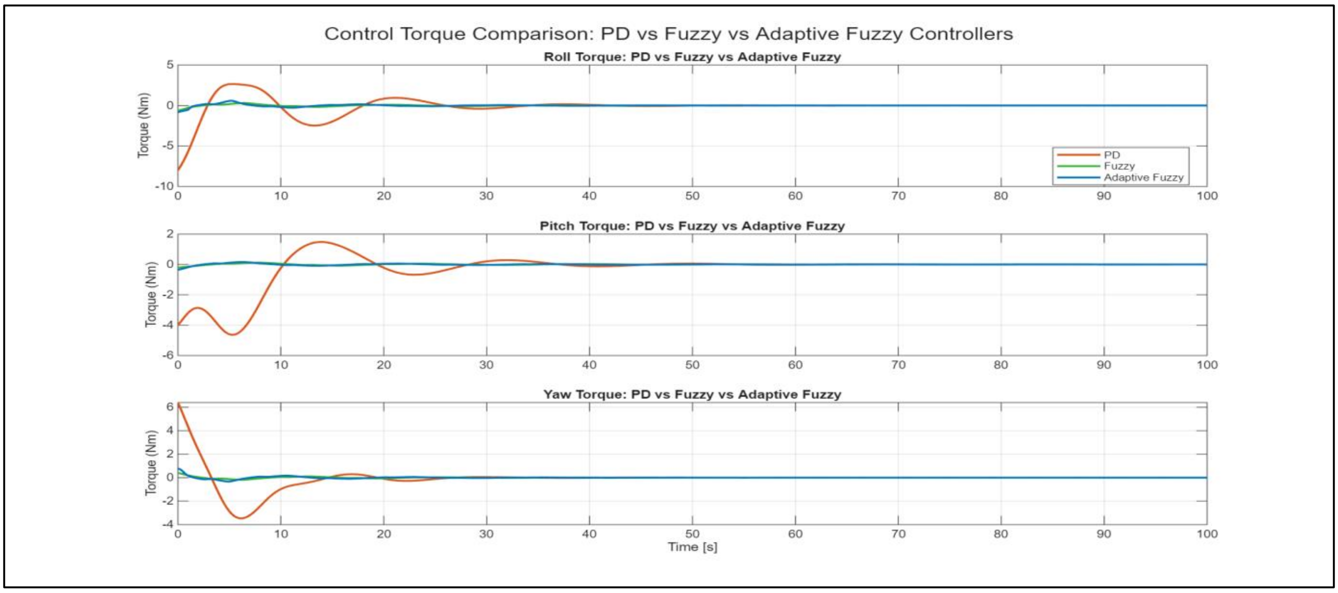

Figure 12: Comparison of Control Torque - PD vs Fuzzy vs Adaptive Fuzzy Controller

The torque comparison among all three controllers mirrors their attitude response behavior. The PD controller shows the highest torque magnitudes and steepest initial spikes, reflecting its aggressive corrective action. The fuzzy controller exhibits the lowest torque amplitudes and smoothest transitions but requires slightly more time to settle. The adaptive fuzzy controller lies between the two extremes producing short, moderate torque pulses that efficiently drive the system to stability without excessive energy expenditure. After the transient phase, all controllers converge to near-zero torque, but the adaptive fuzzy traces are notably smoother and decay faster. This indicates that adaptive fuzzy control achieves improved transient performance while maintaining torque levels well within safe limits, making it the most balanced option among the three.

5.3 Performance Metrics Evaluation

		Settling Time (s)	**Over Shoot (%)**	**IAE**	**ISE**	**RMS Control Torque (N.m)**
PD	**1**	4.5	10	61.3395002	269.001848	1.135835159

	2	11.9	5.33722392	62.3565125	218.268731	1.131780754
	3	4.7	3.438707717	44.0744922	182.779746	0.953734676
Fuzzy	**1**	3.3	10	101.723255	412.001523	0.07980259
	2	4.2	5	58.4101575	116.145794	0.03572016
	3	3.3	4.705193197	61.4709397	198.918228	0.049522276
Adaptive Fuzzy	**1**	2.6	10	101.455484	411.127815	0.115492954
	2	3.4	5	52.4745992	97.9990661	0.045179148
	3	2.4	5.487542005	63.5977565	201.161902	0.078539727

Table 2: Performance Metrics

Table 5.1 summarizes the quantitative performance of the three controllers in terms of settling time (T_s), percent overshoot (M_p), integral absolute error (IAE), integral squared error (ISE), and root-mean-square (RMS) torque (τ_{rms}) for each attitude axis. These indices collectively describe the transient speed, steady-state accuracy, and control-effort efficiency of the PD, Fuzzy, and Adaptive Fuzzy controllers. Across all three axes, the PD controller achieves rapid stabilization, with settling times between 4.5 s and 11.9 s. However, this fast action comes at the expense of higher overshoot up to 10 % and relatively large control energy, reflected in RMS torques exceeding 1 N·m on all axes. The PD scheme also exhibits higher IAE and ISE values (up to 61.34 and 269.00 for Axis 1, respectively), indicating greater cumulative error and less smooth transient behavior. The Fuzzy Logic controller demonstrates improved smoothness and reduced control effort. Its settling times lie between 3.3 s and 4.2 s, comparable to or better than the PD controller on individual axes, while maintaining lower RMS torques (below 0.1 N·m). Overshoot remains modest (≈ 5 – 10 %), but IAE and ISE values vary depending on the axis larger on Axis 1 yet significantly smaller on Axes 2 and 3 suggesting that fuzzy inference handles moderate nonlinearities effectively but may yield higher integrated error when the attitude dynamics are highly coupled. Overall, the fuzzy controller provides smoother responses with considerably reduced torque demand, confirming its energy-efficient nature. The Adaptive Fuzzy Logic controller outperforms both other schemes in combined performance. Settling times are the shortest overall between 2.4 s and 3.4 s showing accelerated convergence across all axes. Overshoot levels are contained within 5 – 10 %, comparable to the fuzzy controller, but IAE and ISE values are consistently lower (e.g., IAE = 52.47 and ISE = 98.00 on Axis 2). RMS torques remain extremely low, not exceeding 0.12 N·m, reflecting efficient actuator usage. The adaptive gain mechanism enables temporary torque amplification during large deviations and automatic attenuation as the system approaches equilibrium, thereby minimizing overall control energy while maintaining precision. In summary, the PD controller delivers fast but energy-intensive stabilization, the Fuzzy controller provides smooth and efficient control with slightly slower convergence, and the Adaptive Fuzzy controller achieves the best trade-off—fast convergence, low integrated error, and minimal torque demand. These quantitative findings validate the adaptive fuzzy strategy as the most effective and robust approach for three-axis satellite attitude regulation.

5.4 Gain Adaptation Visualization

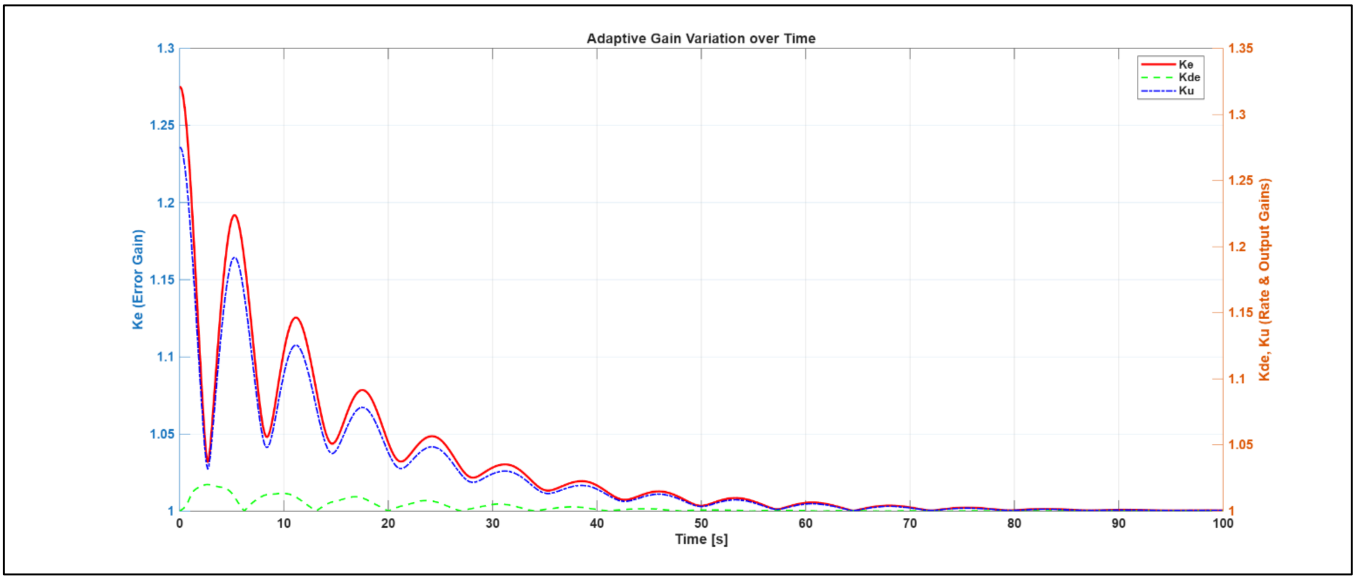

Figure 13: Visual Presentation of Adaptive Gains

The adaptive gain visualization illustrates how the three scaling gains K_e, K_{de} and K evolve in real time within the Adaptive Fuzzy Logic Controller during the satellite's stabilization process. At the start of the simulation, all gains rise sharply as the controller detects large initial attitude and rate errors. K_e increases first to strengthen the proportional influence, enabling a more assertive correction, while K_{de} and K_u adjust slightly later to fine-tune the derivative and output scaling responses. As the attitude errors decrease, all three gains gradually return toward their nominal values, stabilizing smoothly without abrupt changes. This behavior confirms the controller's self-tuning capability it automatically amplifies control effort during significant deviations and attenuates it as the system approaches equilibrium. The gain trajectories remain continuous and well bounded, demonstrating numerical stability of the adaptive law. This adaptive adjustment mechanism enables the controller to maintain responsiveness during strong transients while avoiding excessive torque once near the target orientation. Overall, the plot effectively validates the adaptive fuzzy controller's intelligence in dynamically optimizing its internal parameters to balance speed, accuracy, and smoothness.

6. Conclusion and Future Work

This research demonstrated the successful design and implementation of an adaptive fuzzy logic controller for the attitude stabilization of a tetrahedral satellite. The controller effectively handled system nonlinearities through dynamic gain tuning and fuzzy inference mechanisms, ensuring accurate and stable orientation control. Comparative simulations with conventional PD and static fuzzy controllers showed that the adaptive fuzzy approach achieved faster convergence, lower overshoot, and smoother torque responses, confirming its superior dynamic performance and control efficiency. These outcomes highlight the adaptive fuzzy controller's strong potential for autonomous satellite attitude regulation, offering an effective balance between responsiveness, robustness, and energy economy.

Future investigations can further enhance this framework by integrating machine learning or neural network–based optimization for real-time rule adaptation and gain adjustment. Hardware implementation through hardware-in-the-loop (HIL) testing or onboard processor validation would help assess computational feasibility and real-time reliability. Additionally, incorporating external environmental effects such as gravity-gradient torque, magnetic disturbances, and solar radiation pressure would yield a more realistic simulation of in-orbit dynamics. Expanding the controller design toward fault-tolerant and cooperative multi-satellite attitude coordination could also broaden its application in advanced, distributed space mission architectures.

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