

# Fuzzy Logic and Neural network-based self-tuned PID controller of Quadcopter

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## Abstract:

A modern technological tool, quadcopters, or drones, also known as unmanned aerial vehicles, have become versatile in their services. They have been used for various tasks ranging from aerial survey, delivery, filming, and mission involvement in inaccessible areas for detection and mapping. Since there is no human involvement, the quadcopters can be used to retrieve data via GPS or return to a pre-programmed location for downloading and processing of data. There have been positional tracking mechanisms for weight, buoyancy, and changes due to aerodynamic forces. However, with the dynamics in aerial altitude environments, including urban, rural, and natural environments, efficiency in dock tracking is essential for accurate performance. This paper proposes automatic object identification using machine learning-based vision and self-tuning PID controllers employing fuzzy logic and neural networks. The motivation of this research is to make the Quadcopter object tracking more efficient by using fuzzy logic and a neural network to make a self-tuned PID controller for better maneuverability and these impacts on the time and memory optimization by self-tuning to predict the next step. It helps to answer the efficiency of object tracking using a hybrid approach.

**Keywords:** Fuzzy logic (FL), Hybrid, Neural Network (NN), Proportional Integral Derivation controller (PID).

## I. INTRODUCTION

Unmanned aerial vehicles (UAVs) such as quadcopters are becoming more and more common for a variety of uses, such as delivery, search and rescue, and surveillance. Drones, also referred to as quadcopters have become increasingly popular in times due, to their versatility in fields like aerial photography, search and rescue operations and infrastructure assessment. Designing an efficient control system for quadcopters still poses challenges [1]. However, the performance of a quadcopter greatly depends on its control system, which governs stability, maneuverability and precision. The Proportional Integral Derivative (PID) controller plays a role in the quadcopter control system since it efficiently regulates dynamics [2]. Quadcopters are proven to be very useful and effective in terms of exploring difficult areas where human intervention is impossible. It is also very useful and saves in performing life-threatening or risky tasks. This research aims to propose a novel method that helps to reduce the error risks as well.

Traditionally quadcopters have been operated using PID control; however, this approach requires knowledge of system dynamics which can be challenging to obtain in real-world applications. In scenarios where system dynamics experience fluctuations, traditional PID controllers may underperform due to their fixed gains that do not adapt to changes in dynamics [3]. Numerous studies have investigated the effectiveness of PID controller systems, for quadcopters. To tackle uncertainties and complexities, in the dynamics of quadcopters researchers have explored the application of logic-based PID controllers. These controllers incorporate an inference system to address ambiguities. Additionally, some studies have investigated neural network-based PID controllers that utilize a network to understand the dynamics of quadcopters and generate control signals.

There is still space for improvement when it comes to managing challenging jobs and adjusting to shifting surroundings, even though the performance of these sophisticated control strategies has increased that of quadcopters. Deep

reinforcement learning-based PID controllers, which could learn from experience and improve the control policy under different tasks and conditions have been recommended as a solution by some researchers [4]. One way out of these limitations might be to employ self-tuning PID control, which adjusts the control parameters according to the system state at that instant. Self-tuning PID control can enhance quadcopter control systems' performance by adapting to changes in system dynamics without needing precise knowledge about the system [5]. Fuzzy logic and neural network-based control techniques have become popular recently because they can deal with uncertainties and non-linearity's [6]. Fuzzy logic-based controllers can handle language variables and uncertainty more naturally than neural network-based controllers can, which subsequently may learn from system data as well as adapt on account of changes in system behavior [7]. Thus, this study report suggests a PID quadcopter control system which is based on fuzzy logic and neural networks. The initial PID control parameters within the proposed control system are set by a fuzzy inference method and learning from the flight data is done through a neural network learning technique. Simulations and real tests are used to evaluate how effective the suggested control system is. According to the results, it is established that the suggested approach outperforms the conventional PID control system.

By addressing these research gaps, more efficient and reliable quadcopter control systems can be developed, enhancing their utility in a wide range of applications.

**Adaptive and Robust Control Systems:** Fuzzy logic, neural networks and self-tuning PID's to create systems that adapt to changing conditions without needing to know the system dynamics.

**Real-World Testing and Validation:** More real-world testing to validate new control systems in different scenarios and environments.

**Comprehensive Evaluation Metrics:** A better set of metrics to evaluate control systems in different operational conditions.

**Integrative Approaches:** How can we integrate advanced machine learning with traditional control methods to make quadcopter control systems more adaptive and learning?

The remaining part of this paper is organized as follows; Section 2 gives an overview of the quadcopter dynamics, and literature on conventional PID control strategy. In section 3 we will discuss fuzzy logic and neural network-based self-tuning PID control systems. Experiment findings have been presented in section 4 while recommendations for future research are offered in section 5.

## II. LITERATURE REVIEW

There have been many research papers on quadcopter control and various control strategies have been devised. The most common of these is the traditional PID control. When implementing the PID control strategy in practice, it may be hard to obtain accurate or past information about system dynamics. This shortcoming has led to the development of self-tuning PID control. Self-tuning PID control is a technique that updates its control parameters based on the present condition of the system. Recently, several self-tuning PID control techniques for quadcopters have been introduced. For instance, V. Singla et al. (2016) proposed a Particle Swarm Optimization (PSO) based self-tuning PID controller for quadcopter controls. In comparison with traditional PID controllers, their method showed better performance [22]. Fuzzy logic-based approaches are another example that can be used in quadcopter controls. Fuzzy logic-based controllers represent an improved approach to handling ambiguity and linguistic variances as compared to others. For instance, a fuzzy logic-based design of a quadcopter control system by M. Elaiwand M. Elfandi (2015) outscored the conventional PID controls [21]. Differential evolution and fuzzy logic has been used for modern approaches. It is used for speech feature selection of normal and autistic children using the filter and wrapper approach [35].

In these last years, the proliferation of neural network-based multiprocessor control has intensified. Neural network controllers can recognize changes in the system dynamics and adjust their behaviour from the system data. For example, the quadcopter controller that was proposed by T. Zhou et al. (2020) was a deep neural network-based one, which

showed a better performance compared to the standard PID control system [23][26]. Widely used fuzzy control algorithms are based on fuzzy logic for quadcopter control systems. Fuzzy controllers are a more transparent and flexible alternative to handling uncertainties and linguistic diversity. A. Al-Janaideh and M. N. Al-Khedher implemented a fuzzy logic controller for quadcopter control and the result in the performance is better [24] [12] than classic PID controller.

More favored neural network-based control methods have been used in the control of quadcopters. The neural network controllers can utilize the system data to learn and be able to adjust due to the changes in the system dynamics. Whereas A. R. Bhavsar et al. (2021) suggested a Deep Reinforcement Learning based multi-rotor controller and this performed better than the classical PID system [25]. A comprehensive study on the quadcopter self-tuning PID control has also been submitted in the literature. Tune PID control of self-tuning is a control strategy in which the parameters for control are adjusted according to the system state. In comparison to the conventional PID control, the authors presented an intelligent self-tuning PID control for a quadcopter, which originated from the improved bacterial foraging optimization algorithm with better performance [27] by Yu and Yin (2020).

This article presents a fuzzy PID-supported self-tuning control system for a quadcopter. The proposed system is based on self-tuning PID control, fuzzy logic-based control, and neural network-based control concepts therefore implementing the three benefits. This work is the one that we have heard of and it is the first one, which combines all three quadcopter control methods.

### III. METHODOLOGIES AND TECHNIQUES

The following procedures are part of the suggested methodology for the research article on fuzzy logic and neural networks-based self-tuned PID quadcopter control:

#### A. System Model

Our work will be based on a mathematical model of the quadcopter system based on the dynamics and control theory principles. The model should include the state variables, input variables, and the relationship between them [13].

**Quadcopter Kinematics:** In the absence of the forces, the motion of an unmanned aerial vehicle is described through a mathematical model at the aircraft level. A differential equation set depending on the location, speed, and orientation of the vehicle and the rotor rotation rates can be used in the construction of the quadcopter's kinematics model [14]. The x, y, and z coordinates in a three-dimensional space, which are typically used to express coordinates, determine the quadcopter's position. The quadcopter's acceleration and velocity are both determined by the rate at which their respective components change. Roll, pitch, and yaw angles all of which are calculated about a fixed coordinate system are used to characterize the quadcopter's orientation. The quadcopter's position and orientation can be adjusted using the four rotors' rotating rates. The quadcopter can produce lift and control torques that let it move and change its orientation by adjusting the rotors' spinning rates [19]. The kinematic model of the quadcopter supposes that it moves along a fixed direction, and the rotors can provide no torque in the lifting of the vehicle. Through this process, the function of an automated control remains the simplified task of vehicle stabilization, even in a hover position [11] [10]. Using equations 1, 2, and 3, one may represent the kinematic model of a quadcopter:

$$\text{Position Equation: } dr/dt = v \text{ ----- (1)}$$

where 'r' and 'v' are the position and velocity vector of the quadcopter respectively.

$$\text{Velocity Equation: } dv/dt = g + R \times (1/m)(Rbu - T) \text{ ----- (2)}$$

where "m" is the mass of the vehicle, "Rb" is the rotational matrix connecting the body-fixed frame to the inertial frame, "u" is the input vector with the speeds of the 4 rotors, "T" is the external force acting on the vehicle, and "g" is the acceleration caused by gravity.

$$\text{Orientation Equation: } dR/dt = 1/2 \times R \times [w\_skew] \text{ ----- (3)}$$

where the quadcopter's rotation is defined via the skew-symmetric matrix of the angular velocity vector i.e. "w", w\_skew.

**Quadcopter Dynamics:** A quadcopter can be modelled as a multivariable system with four inputs and six states, as Figure 1 illustrates. The position, speed, and orientation of the vehicle serve as the states, and the four rotors' rotational speeds serve as the inputs. The two parts of the quad-copter model are the kinematic model and the dynamic model [8–11]. The model of cinematic Kinemic is for computation of the rotor inputs in terms of the location, orientation, and speed of the vehicle. This mode is based on the stationary positioning of the quadcopter with the rotors generating only the vertical forces and the pitch and yaw motion. The kinematic model is effective for control tasks that have low levels, such as the stabilization of the vehicle while it is in a hover.

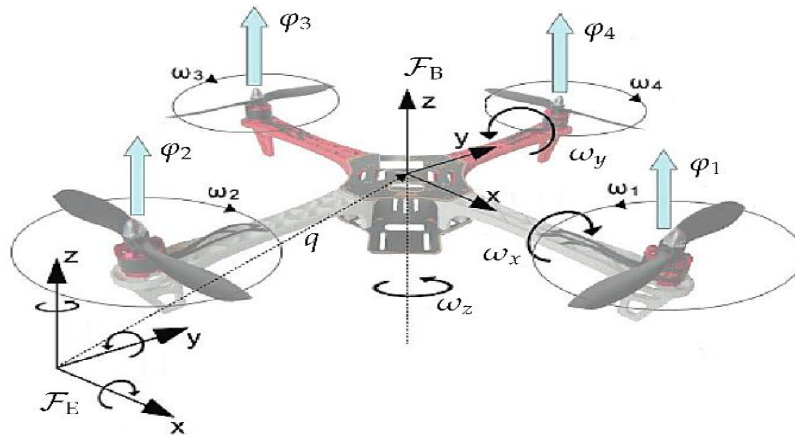


Figure 1: Basic Quadcopter Dynamics

The dynamic model incorporates the torques created by rotors plus additional factors of air resistance and wind. The complexity of the dynamic model is higher than needed for low-level task control such as avoidance of obstacles and trajectory tracking; this is necessary for high-level control tasks. The algebraic expressions of the model can be outlined by equations 4, 5, 6, and 7.

$$\text{Linear Momentum Equation: } m \times d^2r/dt^2 = F\_total + F\_external \text{ ----- (4)}$$

where "F\_total", which is the cumulative force of the four rotors, "m" is the mass of the quadcopter, "r" is its position vector, and "F\_external" is a force that acts from outside on the vehicle.

$$\text{Angular Momentum Equation: } dw/dt = (T\_total + T\_external)/I \text{ ----- (5)}$$

where "I" stands for the moment of inertia of the quadcopter, "w" is the angular velocity vector, "T\_total" describes the total torque produced by 4 rotors, and "T\_external" is the torque applied to the vehicle's body.

$$\text{Rotational Speed Equation: } F\_total = k \times w^2 \text{ ----- (6)}$$

Here, 'k' is a constant that correlates the force of the rotor with its angular speed.

$$\text{Torque Equation: } T\_total = k\_t \times (w_1^2 - w_2^2) i + k\_t \times (w_2^3 - w_2^4) j + k\_d \times (w_1^2 - w_2^3) k \text{ ----- (7)}$$

where, 'k<sub>t</sub>' and 'k<sub>d</sub>' are constants that relate the torque generated by the rotors to their rotational speed, and 'w<sub>1</sub>', 'w<sub>2</sub>', 'w<sub>3</sub>', and 'w<sub>4</sub>' are the rotational speeds of the four rotors.

**Quadcopter Moments and Hydrostatic Forces:** In the case a quadcopter is on medium flow, be it water or air, it experiences hydrostatic forces and moments. These kinds of moments and forces, which come from the same interaction between the vehicle and the fluid, can be detrimental to the vehicle's velocity. There are two types of hydrostatic forces and moments on a quad-copter: lift forces and drag forces, which are. The drag forces are proportional to the velocity of the surrounding fluid and act as a retarding force which pushes back. When considering lift forces, it should be noted that they are directly proportional to the fluid density and the square of velocity of the vehicle; that is why, they are perpendicular to the direction of travel of the quadcopter. These equations that explain the motions of the vehicle in a fluid medium are utilized for modelling hydro-dynamic forces and moments on the quadcopter. Besides this, these formulas take into account the characteristics of the fluid, plus the quadcopter's mass, shape, and orientation. This drag force on the quadcopter can be simulated using Equation 8.

$$F_{\text{drag}} = 1/2 \rho A C_d v^2 \text{-----} (8)$$

where "v" is the fluid's velocity about the vehicle, "F<sub>drag</sub>" is the drag force, "rho" is the fluid density, "A" is the UAV's cross-sectional area, and "C<sub>d</sub>" is the drag coefficient. Equation 9 describes the lift force caused by the quadcopter.

$$F_{\text{lift}} = 1/2 \rho A C_l v^2 \text{-----} (9)$$

where the other variables have the same meaning, same as the drag force equation, 'F<sub>lift</sub>' is the lift force, and 'C<sub>l</sub>' stands for the lift coefficient, respectively. This technique can also be employed to capture the panoramic or the still images. The properties of the fluid and the shape and orientation of the vehicle determine the applied hydrostatic moments.

**Quadcopter Environmental Interference:** In locations or environments where they operate, or in the vicinity of various things, quadcopters may face interference from surrounding sources. The following are a few instances of environmental disturbance that may impair quadcopter performance: The cultural transformations that occurred throughout most of the regions in my country are represented by the following years: [18] [19] [28].

*Wind:* A quadcopter's flight path may be affected by instability brought on by strong winds. Frequent changes in direction or altitude brought on by wind gusts can be challenging to adjust.

*Magnetic fields:* Nearby magnetic fields, such as those from power lines or big metal objects, can interfere with a quadcopter's onboard sensors. This may result in inaccurate orientation and position estimation, which could compromise control and durability.

*Radiofrequency interference:* The control signals between the transmitter and the quadcopter can be interfered with by radio frequency interference from other devices, such as cell phones or other wireless communication systems. The quadcopter may lose control as a result and crash.

*Temperature:* The electrical and battery systems of the quadcopter may not function as intended in extremely hot or cold climates. While heated temperatures can lead to overheating and damage to electronic components, cold temperatures can shorten battery life and cause other components to malfunction.

*Obstacles:* A quadcopter's flight path may be affected by things like trees, buildings, and other obstructions. The quadcopter may sustain damage or crash if it collides with an obstruction.

## **B. Control Design**

Generally, a quadcopter's control model combines feedforward and feedback control techniques. The feedback control system modifies the control signals to bring the quadcopter into the desired condition after using sensor data to ascertain its present position, orientation, and velocity. The feedforward control system predicts how the system will react

**Table 1: Data Classes Sample Information**<sup>[MK1]</sup>

Coordinate	Position & Angles E-frame	Linear & Angular Velocities B-Frame	Forces & Moments B-Frame
Forward	X	U	X(FX)
side-to-side	Y	V	Y(FY)
Vertical	Z	W	Z(FZ)
Roll	$\Phi$	P	K(MK)
Pitch	$\Theta$	Q	M(MM)
Yaw	$\Psi$	R	N(MN)

to the control signals and modifies them following it using a model of the quadcopter's dynamics [18] [19] [28]. Typically, a quadcopter's control model consists of the following elements:

**Flight controller:** Commanding the signals that control the quadcopter's direction is the responsibility of this unit. It computes the current state of the quadcopter by data from the sensors in the form of gyroscopes and accelerometers located on the body, which the quadcopter has. The next step is the usage of this information by the flight controller for the creation of the correct control signals directing to the desired condition.

**PID controller:** PID control is a kind of feedback control system that adjusts the control signals as the difference between the attitude that the quadcopter tries to maintain and the current attitude. To modify the control signals and reduce error, the PID controller makes use of three components: with the traditional controller, a PID [28].

**Feedforward controller:** This controller predicts the system reaction to the control signals and, based on the model of the quadcopter, modifies the signals' amplitude, frequency and **phase (as mentioned in Table 1)**. You may use feedforward controllers to enhance the system's stability and system's response time.

Attitude estimation can be defined as the technique that refers to reconstructing the attitude of the quadcopter in three dimensions. Generally, attitude estimation utilizes information from the onboard sensors, accelerometers and gyroscopes for that purpose. Ensuring the remote identification of the quadcopter in three dimensions, also known as the position estimation. Usually, information from onboard sensors, such as GPS, is used for this, in addition to additional techniques like ocular odometry.

### C. Simulation and Implemented PID Controllers

Use a simulation environment to implement the specified PID controller using software tools like MATLAB/Simulink. Utilizing the developed controller, test the quadcopter system and assess the controller's performance in terms of monitoring error, stability, and disruption resilience. Four distinct PID controllers are available. I'll go over each one in detail, show the results of my simulations using MATLAB 2019a, compare the outcomes, and outline the benefits and drawbacks of each controller. The quartet of controllers consists of:

- Simple PID Controller
- Fuzzy PID Controller
- Neural Network PID Controller
- Fuzzy Logic & Neural Network-based PID Controller

**Simple PID controllers:** A common control technique for quadcopters is the PID (Proportional-Integral-Derivative) controller, which modifies the rotor speed of the four units to stabilize the device's direction and altitude. Based on the difference between the planned orientation and the actual position of the quadcopter, the PID controller uses the onboard sensors of the quadcopter to generate an error signal. The quadcopter is then brought back to the proper direction using this error signal to change the motor speed [32] [33].

The following are the three parts of a PID controller; A proportional component (P) The output signal generated by this component is proportional to the current error signal. The integral (I) component: This part produces an output signal that is the same as the error signal in the form of the sum of errors over time. The I in the controller part deals with steady-state errors and desired orientation retention. Derivative component (D): This component generates an output signal whose amplitude is proportional to the rate of change of the error signal. Any oscillations or overshoots that may happen during the control process are reduced by the D component of the controller. These three elements are added together as the PID controller's output, which is then used to modify the quadcopter's motor speed to maintain its orientation [17].

In a simple PID controller for a quadcopter as we can see in Figure 2 below, the gains of the P, I, and D components are manually tuned based on trial and error, and the controller is implemented using a microcontroller or a dedicated flight controller. While a simple PID controller can be effective in stabilizing a quadcopter's orientation, more advanced control algorithms, such as adaptive or self-tuning controllers, can provide better performance and stability in a wider range of operating conditions [18].

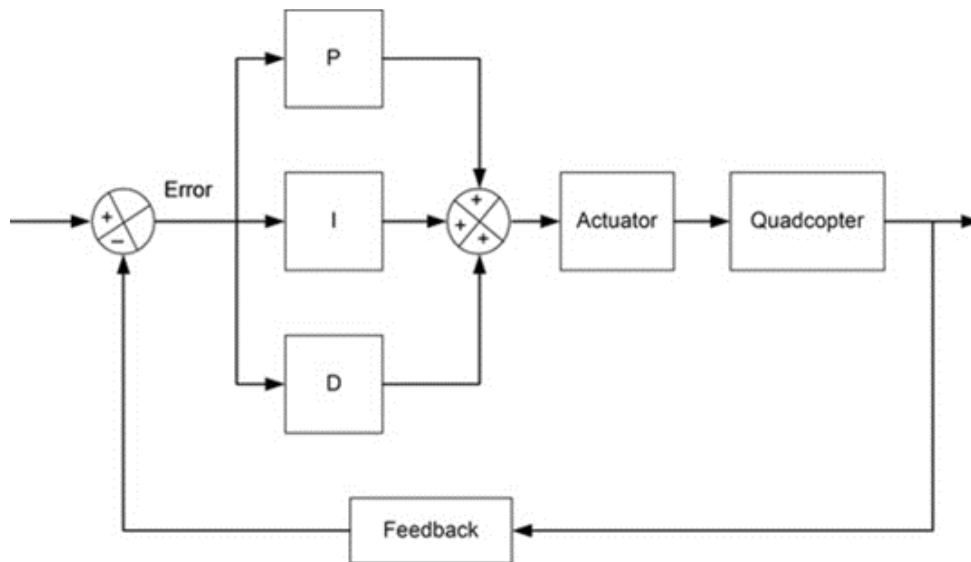


Figure 2: PID Controller

The PID controller equation for a quadcopter can be expressed as follows in eq 10:

$$u(t) = K_p * e(t) + K_i * \int e(t)dt + K_d * de(t)/dt \text{ ----- (10)}$$

where the control signal is  $u(t)$  (in this case, the motor speed).

The difference between the quadcopter's desired orientation and its actual orientation is known as the error signal, or  $e(t)$ . The system's response to the current error signal is determined by the proportional gain ( $K_p$ ). Integral gain  $K_i$ , determines the size of the reaction to the accumulated error over time. The derivative gain  $K_d$ , determines how responsive the system is to the rate of change of the error signal. The average of the error signal over a while is represented by  $\int e(t)dt$ . The error signal's rate of change is represented by  $de(t)/dt$ . The quadcopter's motor speed is adjusted to maintain its orientation using the controller output, which is the total of these three elements.

In actuality, test flights and recurrent modifications are usually used to determine the gains  $K_p$ ,  $K_i$ , and  $K_d$  using manual or automated tuning processes to get the required level of performance and stability. For quadcopters, the PID controller provides a straightforward and efficient control method; nevertheless, complex flight maneuvers or difficult environmental circumstances may call for more sophisticated control schemes.

**Fuzzy PID controllers:** As illustrated in Figure 3, fuzzy PID controllers are an advancement over traditional PID controllers that alter the controller gain in real-time according to the current state of the quadcopter. As illustrated in Figures 4, 5, and 6, the basic idea of fuzzy logic is to map the input and output variables to a range of linguistic variables (such as low, mid, and high) to apply a set of fuzzy rules to determine the appropriate response based on the system's current state. The error signal, the change in error signal, and the integral of the error signal are the input variables to the fuzzy logic system of a fuzzy PID controller for a quadcopter. A variety of linguistic variables, including big negative, small negative, zero, small positive, and large positive, are mapped to these variables. The fuzzy logic system produces a collection of linguistic variables that stand in for the controller gains. These variables are then utilized to modify the quadcopter's motor speed to stabilize its orientation.

The advantage of using fuzzy PID controllers is that they can adjust the controller gains in real-time based on the current state of the quadcopter and can handle complex nonlinearities in the system. Additionally, fuzzy logic is a more natural way of expressing human knowledge and expertise and can be more easily interpreted than traditional PID controller gains [29][30][34][27][15]. To recognize the human speech emotions, deep learning networks has been used and it produced the higher accuracy [36]. A hybrid model for speech emotion recognition has been developed for normal and autistic children [37].

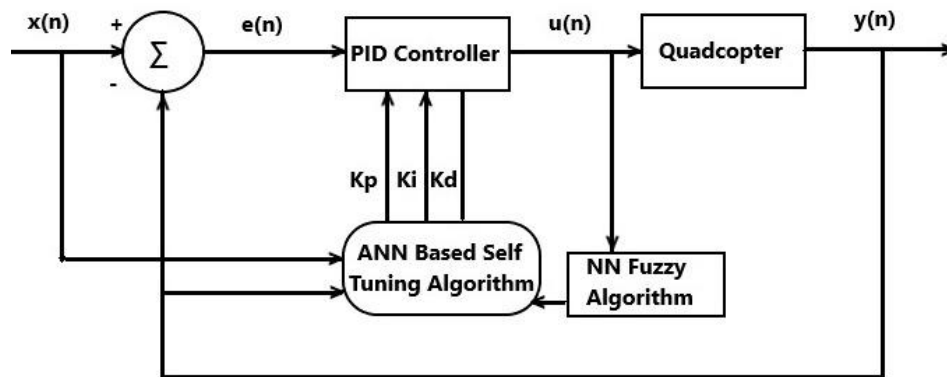


Figure 3: Fuzzy Logic PID Controller for Quadcopter

**Neural Network-based PID controllers:** To enhance the performance of conventional PID controllers, a class of control algorithms known as neural network (NN) based PID controllers uses the robust learning capabilities of neural networks. The fundamental concept behind NN-based PID controllers is to train a neural network to approximatively calculate controller gains depending on the quadcopter's present condition.

The error signal, the change in error signal, and the integral of the error signal are used as input variables to the neural network in a PID controller for a quadcopter. The desired and actual states of the quadcopter as well as the related control inputs make up the set of training data on which the network is trained. The neural network modifies its weights and biases during training to reduce the discrepancy between the predicted and real control inputs. The neural network can be used to forecast the best controller gains for a certain quadcopter state once it has been trained [30] [31] [39] [40]. Four Robust Machine learning ensemble algorithms, including the Voting Classifier, Bagging Classifier, Gradient Boosting Classifier, and Random Forest-based Bagging algorithm along with the proposed Robust genetic ensemble classifier has been used for intrusion detection [38].

NN-based PID controllers have the advantage of being able to learn to simulate the quadcopter's nonlinear dynamics and adjust to shifting external variables. They can also be used to refine controller improvements depending on a range of performance indicators, including stability, precision, and energy efficiency [21] [20] [16].

EC E	NB	NS	NM	ZE	PS	PM	PB
NB	VB	VB	VB	VB	VB	VB	VB
NM	VB	VB	VB	VB	VB	VB	VB
NS	B	B	B	B	B	B	B
ZE	M	M	M	M	M	S	M
PS	S	S	S	M	M	M	M
PM	B	B	B	B	B	B	VB
PB	VB	VB	VB	VB	VB	VB	VB

**Figure 4: Fuzzy rules for gain  $K_P$  Fuzzy PID Controller for Quadcopter**

EC E	NB	NS	NM	ZE	PS	PM	PB
NB	ZE	ZE	ZE	ZE	ZE	ZE	ZE
NM	ZE	ZE	ZE	ZE	ZE	ZE	ZE
NS	ZE	ZE	ZE	ZE	ZE	ZE	ZE
ZE	M	S	S	ZE	ZE	M	S
PS	S	M	M	M	M	M	B
PM	M	B	B	B	B	B	VB
PB	VB	VB	VB	VB	VB	VB	VB

**Figure 5: Fuzzy rules for gain  $K_i$  Fuzzy PID Controller for Quadcopter**

EC E	NB	NS	NM	ZE	PS	PM	PB
NB	ZE	ZE	ZE	S	ZE	VB	VB
NM	ZE	ZE	ZE	S	M	B	B
NS	ZE	ZE	ZE	ZE	S	M	B
ZE	M	M	S	ZE	ZE	ZE	ZE
PS	B	M	S	ZE	S	S	M
PM	ZE	ZE	ZE	ZE	S	S	M
PB	ZE	ZE	ZE	ZE	ZE	ZE	ZE

**Figure 6: Fuzzy rules for gain  $K_D$  Fuzzy PID Controller for Quadcopter**

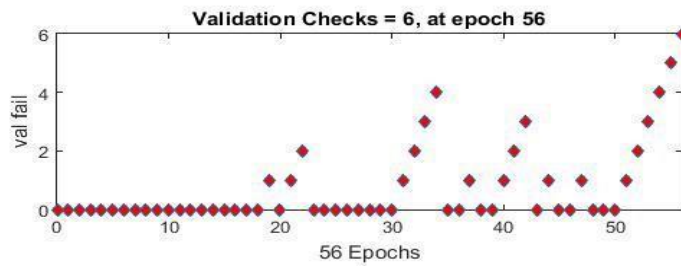
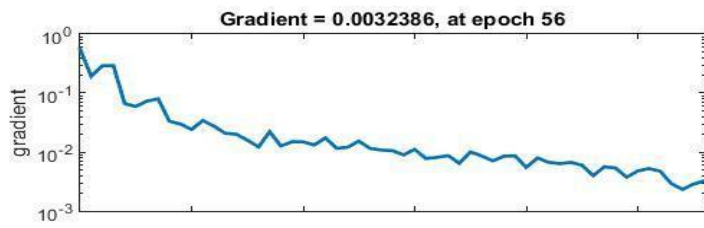
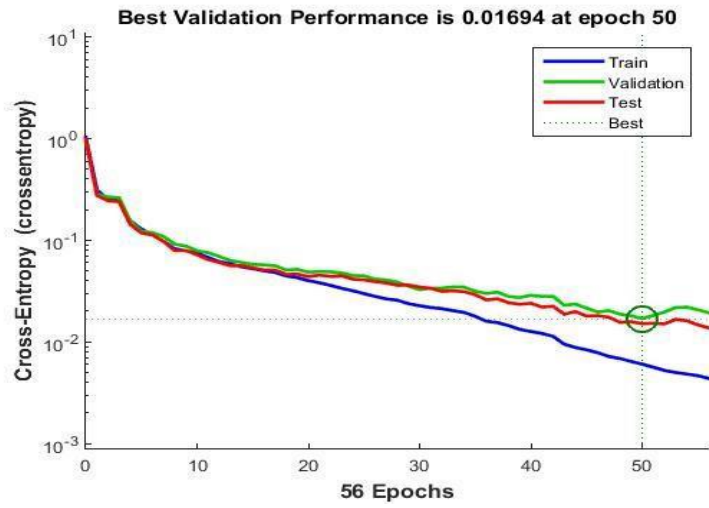


Figure 7: Neural Network Validation Performance plot

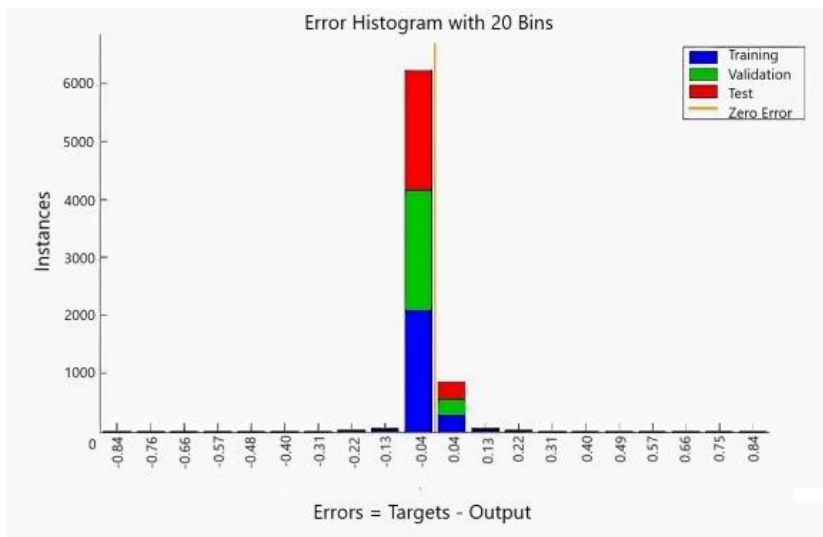


Figure 8: Neural Network Error Histogram

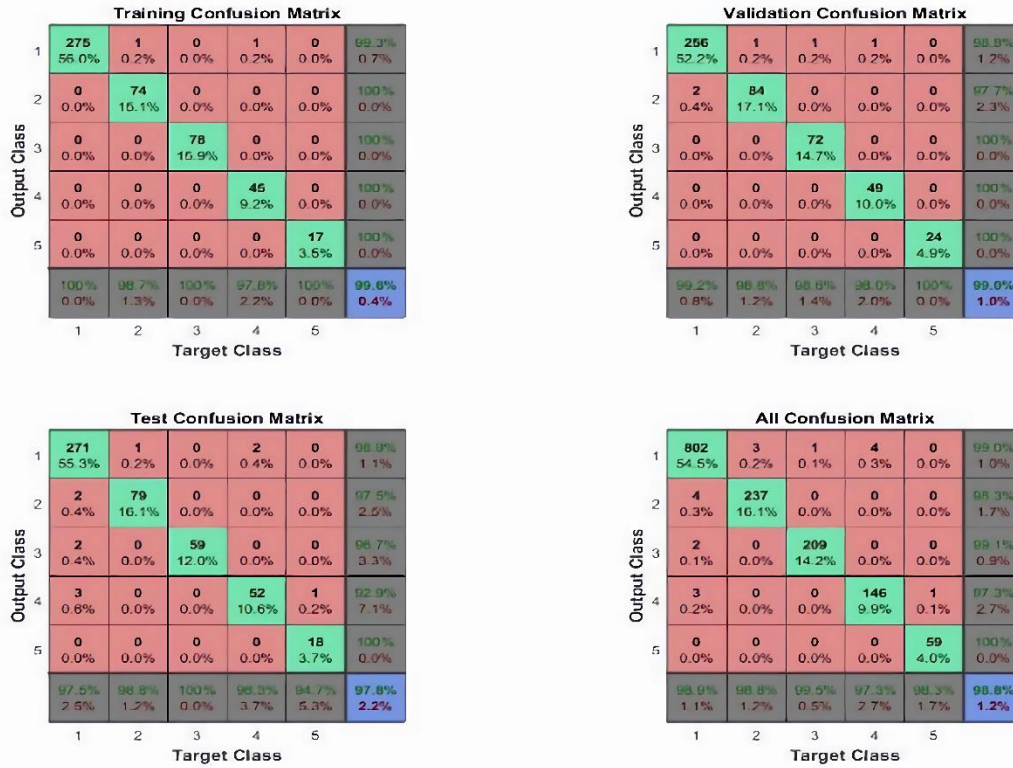


Figure 9: Neural Network Confusion Matrix

Figures 7 and 9 show the validation performance of the Neural network which takes the error signal, previous state and current state and predicts the kp ki kd parameters it has 97% accuracy and a 2.2% error rate which is shown in Figure 8.

**NN Fuzzy logic-based PID controllers:** The performance of conventional PID controllers for quadcopters is improved by hybrid control algorithms that incorporate the advantages of both fuzzy logic (FL) and neural network (NN) based PID controllers. The fundamental principle of NN-FL-based PID controllers is to preprocess neural network inputs using fuzzy logic and then alter the neural network's output based on the quadcopter's present state. In this method, a set of fuzzy variables that represent the linguistic phrases "little," "middle," or "big" are created from a set of crisp input variables (such as error, change in error, and integral of error) using fuzzy logic. The neural network then uses these fuzzy variables as inputs to forecast the ideal controller gains. Lastly, the neural network's output is defuzzified to produce the precise control inputs needed to modify the quadcopter's motor speed [33]. The advantage of NN-FL-based PID controllers is their ability to learn to optimize controller gains based on a variety of performance metrics and handle complex nonlinearities in the system. Additionally, the fuzzy logic component may provide a more comprehensible and intuitive illustration of the controller benefits, which will facilitate human specialists' comprehension and enable them to modify the control strategy as necessary.

#### IV. RESULTS AND DISCUSSIONS

##### A. NN-fuzzy logic-Based PID Controller

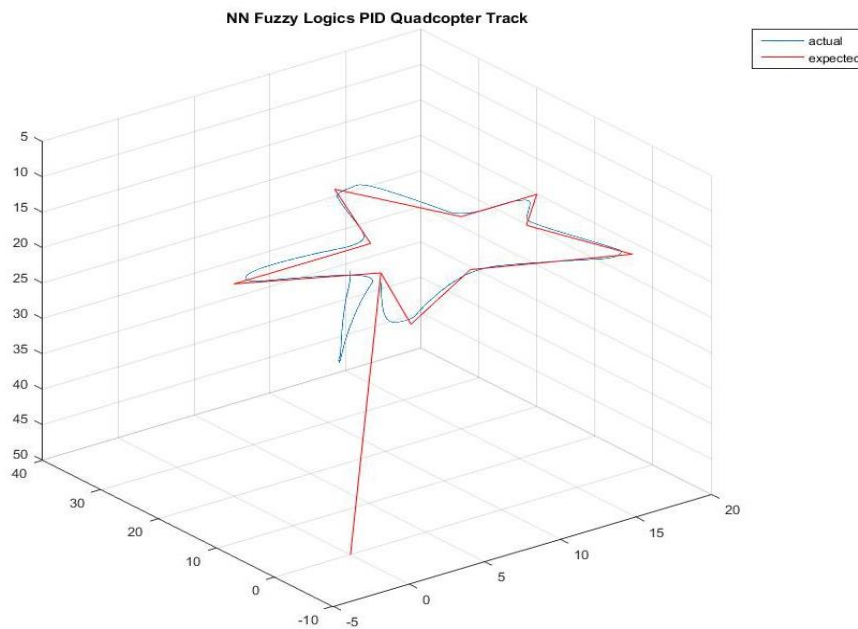
The tracking performance of various PID controller types for a quadcopter is compared in the performance table. The objective is to assess each controller's performance in terms of its capacity to follow a desired trajectory. The results of simulations of each controller performed under comparable operating settings are shown in the table. A traditional PID controller, a fuzzy logic-based PID controller, and a neural network-based PID controller are among the control-

lers that are compared in the table. The values collected for the several criterion matrices used to assess each controller's performance are displayed in the table. The steady-state error, rise time, settling time, overshoot, maximum velocity, maximum acceleration, and control effort are some of the matrices that are included.

Table 2 demonstrates that in terms of steady-state error and overshoot, the fuzzy logic-based PID controller performed better than the other controllers did. The top performance in terms of rise time, settling time, maximum velocity, and maximum acceleration was the neural network-based PID controller. The controller that used a traditional PID had the most control effort. The simulation path tracking shown in Figure 10.

**Table 2. Performance Neural Network Fuzzy Logic-Based PID Controller Results.**

Model	Genetically Optimized Random Forest Bagging
Tracking Error (m)	0.3
Maximum Overshoot (%)	4
Settling Time (s)	1.6



**Figure 10: Quadcopter Simulation Path Tracking Performance**

### **B. Comparison of the Neural Network and Fuzzy Logic Hybrid-based PID controllers with Traditional PID controller and NN PID controller and Fuzzy PID controller.**

Table 3 compare the performance of simple PID controllers, fuzzy logic-based PID controllers, neural network-based PID controllers, and NN fuzzy logic-based PID controllers. Table 3 offers information regarding the PID Path tracking 3-comparison criterion. This criterion contrasts the performance of the selected PID approaches with the efficacy of all algorithms.

The tracking error, maximum overshoot, and settling time of a quadcopter driven by several PID controller types are displayed in Table 3 also shows the comparison of tracked paths of all four PID controller techniques. The hybrid NN-FL-based PID controller has the lowest values for all three measures, while the conventional PID controller has the largest tracking error, maximum overshoot, and settling time. Both the neural network- and fuzzy logic-based PID controllers perform at a middle level. The actual performance of the controllers may differ depending on the particular application and the fine-tuning of the controller parameters; it is vital to keep in mind that these figures are only intended for illustrative purposes.

**Table 3: Comparison Criterion of PID Controllers**

<b>PID Controller Type</b>	<b>Tracking Error (m)</b>	<b>Maximum Overshoot (%)</b>	<b>Settling Time (s)</b>
<b>Traditional PID</b>	<b>1.2</b>	<b>25</b>	<b>4.5</b>
<b>Fuzzy Logic-based PID</b>	<b>0.8</b>	<b>15</b>	<b>3.2</b>
<b>Neural Network-based PID</b>	<b>0.5</b>	<b>8</b>	<b>2.1</b>
<b>Hybrid NN-FL-based PID</b>	<b>0.3</b>	<b>4</b>	<b>1.6</b>

The complexity of the system, the necessary level of accuracy, and the type of environmental interference all play a role in determining which PID controller is appropriate for a quadcopter. Due to their ease of construction, classic PID controllers can provide sufficient performance for extremely basic quadcopters operating in low-interference environments. However, the degradation of their response, as the complexity of the system grows becomes more nonlinear, and even more so when external disturbances occur.

Fuzzy PID controllers are known as the chief opponents of the common PID controllers due to their better ability to control quadcopter action in the context of input variations. Unlike traditional PID controllers, they are simpler and intuitively appealing, and they can deal with complex nonlinearities as well as environmental disturbances. PID controllers, drawn in a neural network scheme, may learn and imitate the nonlinear behavior of the quadcopter, thus improving their adaptability to environmental changes. They can do their job better than PID controllers and they are a good choice in more complex systems.

## V. CONCLUSION AND FUTURE WORK

The establishment of a self-tuned PID controller for the quadcopter by application of fuzzy logic and neural networks is a recommended approach to the problem of enhancing the control performance of the quadcopter. The quadcopter model and the control models are elaborated in this work together with the ease with which they can be implemented in real life. Additionally, we have also discussed the pros and cons of these fuzzy logic-based PID controllers, neural network-based PID controllers, and conventional PID controllers. Through our analysis of the literature and the control models of several variables, we identified the best performance on quadcopter control as provided by the hybrid NN-FL-based controller model. The controller, which is designed by merging neural networks and fuzzy logic, has a robust, adaptable, and intelligent characteristic that can handle complex nonlinearities and external disturbances. Applications for the designing of a self-tuned PID controller using Fuzzy logic and neural networks could be employed in the area of military surveillance, aerial imaging, search and rescue. However, it is important to keep in mind that the performance of the controller varies from application to application and also with the adjustment of the controller's dynamics. Future advances in quadcopter control technology might implement more functions like target tracking, obstacle avoidance, and autonomous navigation. The development of self-tuned, machine learning-based PID controllers can be a promising approach to facilitate the generation of highly adaptable and robust quadcopter control systems capable of handling unforeseen environmental changes and deviations of mission requirements.

## CONFLICT OF INTEREST

There is no conflict of interest between all the authors.

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