Research Article

Neuro-Fuzzy-Based Adaptive Control for Autonomous Drone Flight

Makhabane Molapo[1], Bhekisipho Twala[2]

1. Advances in Defence and Security, Council for Scientific and Industrial Research, Pretoria, South Africa; 2. Tshwane University of Technology, South Africa

Adaptive control is the capability of a control system to modify its operation and achieve the best possible operation mode. A quadcopter is a nonlinear, unstable and under-actuated dynamic system, thus providing a challenge to control engineers in controlling and stabilising it during flight. This paper proposes the design, development, and application of an intelligent adaptive hybrid controller to control and stabilise the drone. The training data for adaptive neuro-fuzzy inference systems (ANFIS) are generated by the Linear Quadratic Regulator (LQR) under white-noise disturbance. The trained ANFIS is subsequently used to estimate the parameters of the control distribution matrix for the actual fault condition and the reconfiguration is carried out by computing new feedback gain using the pseudo-inverse technique. For the simple adaptive controller, LQR is also used to generate the desired trajectories of the reference model. In both experiments, the extended Kalman filter is implemented due to its non-linearity benefit. We demonstrate the performance of the proposed approach as a representative case study. The preliminary numerical simulation results further indicate that the proposed method is promising compared to conventional control techniques to control and stabilise a quadcopter drone.

Corresponding authors: Makhabane Molapo, mmolapo1@csir.co.za; Bhekisipho Twala, twalab@tut.ac.za

1. Introduction

Unmanned aerial vehicles (UAVs), especially quadrotors, have developed rapidly and have been widely applied in many ways, for example, in aerial photography, power line patrol, and surveillance. However, these applications mentioned all avoid interacting with the environments. It is a well-known fact that UAVs have many stability problems, such as shaking, being out of control, and even crashing, if endowed with manipulators. Hence, UAV stability will additionally be affected by manipulator movements and environment contacts. One of the possible alternatives for the flight control system is to use intelligent adaptive control techniques that provide online learning capability to cope with varying dynamics and disturbances.

An unmanned aerial vehicle's dynamic stability and operational safety are the most desired attributes required by the defence and civil aviation industries [1]. For instance, UAVs are being deployed for different missions by the military and used diversely by civil operators. The military can deploy them for combat missions, surveillance, search and rescue, etc. Civil operators also have a vast type of operations which may include photography, parcel delivery and blood sample delivery, among many other things. All these types of missions and processes depend on the system's dynamic stability and safety; if these attributes are not achieved, the UAV will not be certified to operate any task or operation.

However, despite the environment, they operate a UAV and will face several uncertainties, failures and threats, most of which will occur during flight phases. These challenges will require a drone flight to have a robust and powerful adaptive, intelligent controller, which can adapt to any disturbances during flight. Adaptive control deals with uncertainties in the design of systems providing Lyapunov stability. In such a situation, the better option would be to follow the non-model or data-driven methodology. One such method is the Adaptive Neuro-Fuzzy Inference System (ANFIS) wherein Fuzzy logic is used to predict or estimate the system states used in control law to achieve the desired system response. The performance of Fuzzy logic is based on how accurately the rules are known and they can be either obtained from experts or fetched from the input/output data of the plant.

This paper presents an intelligent hybrid adaptive controller design that incorporates a Linear Quadratic Regulator-Adaptive Neuro-Fuzzy Inference System (LQR-ANFIS) controller which can be attributed to both adaptive and intelligent. We start by proposing the design of an adaptive hybrid controller for an unmanned aerial vehicle; the intelligent adaptive hybrid controllers combine advantages from more than one control philosophy [2] and they can accommodate uncertainties by adapting and adjusting to the changing system online.

To this end, the major contribution of the paper is the proposal of the design, development and application of an intelligent hybrid controller to stabilise a drone flight. A neural network and fuzzy-based indirect adaptive control strategy are applied for the current work with the implementation of the extended Kalman filter. Numerical experimental results show that the proposed algorithm is more efficient than the traditional control algorithms. So, such an algorithm will ensure that the whole UAV system is safe and reliable.

Moreover, this paper's contribution will lead to several benefits including an enhanced and broadened understanding of the nature and characteristics of adaptive and intelligent control systems, and a better understanding of UAV dynamics, to give the researcher, students and industry the ability to solve adaptive control problems. Another benefit will be the development of an intelligent hybrid adaptive tool that the industry will be able to utilise to control and stabilise a drone flight. What sets this algorithm apart is that it can easily be integrated into any controller and any drone flight [3].

The paper is structured as follows: Section II provides an overview of the related work followed by the presentation of the process of platform development and the discussion of the proposed method in Section III. The velocity term of the drone to the observation equation is added to make it more accurate than previous studies. Then, the robustness of the proposed method is tested in Section IV. We close with remarks and conclusions in Section V.

2. Related Work

This section of the paper discusses the related work. This work lays a foundation for this study by looking into the applications of other researchers' different control techniques. The related work survey comprises the types of UAVs, their applications and different control techniques currently in use.

For example, an application of Model Reference Adaptive Control (MRAC) was presented by Armah and Yi [4][5] for a quadrotor type of UAV they were looking at time delay in the altitude control system. Firstly, they designed a model reference adaptive control based on the MIT rule.

Since the MIT rule could not ensure steadiness [6], they combined the MRAC with a tuned proportional-plus-velocity (PV) controller. Secondly, their design used a black-box approach to determine the model for the drone flight's altitude control. Then, they applied the MATLAB system identification toolbox App to obtain the LTI SISO (Single Input Single Output) ARX transfer function, a stable system, with no time delay [4], [5].

Romero *et al*. [7] investigated the stabilisation of a quadcopter by applying PID controllers to control its basic movements such as roll and pitch. To show effectiveness between a range of ± 10 degrees for roll and pitch angles and complete coverage on yaw angle and altitude. The stabilisation of the system was formed from a model that eased the controllers' implementation on a SISO system.

The PID controller module was developed with commercial quadcopters and then implemented through inertial and ultrasonic sensors. The system also included a wireless boundary to observe the aircraft's performance during the flight [8].

An LQR quadcopter controller was designed by Okyere *et al*. [9] to present an analysis and performance of an algorithm of an LQR control. To start with, a dynamic quadcopter model was developed to get a successful investigation. Then, a controller which was tuned and tested was designed. In adjusting the LQR, the focus was on the feedback gain matrix (K). Nonetheless, the controller's performance was verified for delay time, rise time, overshoot, settling time and tolerance limits. A general analysis of the overall performance of the LQR controller was done [9].

The intelligent autopilot system (IAS) was recommended by Baomar and Bentley [10]. The system is capable of autonomous navigation and landing large jets. They used the imitation concept learning approach and the ANN technique of using human pilots who demonstrate the tasks to be learned in a flight simulator during which training data sets are captured. After that, these datasets were used by artificial neural networks (ANN) to generate control models automatically.

The control models emulate the human pilot skills in controlling the aeroplane. This means that an Intelligent Autopilot System (IAS) is an apprentice that looks at the demonstrations of tasks performed by an experienced teacher who is the pilot in this case, after which it performs similar duties autonomously [11][12].

A Fuzzy Logic-based robust and autonomous safe landing for a UAV quadcopter was used by Muhammad Talha *et al*. [13]. They proposed a secure landing system for their experiment. In this experiment, a safe landing is the most significant component of the whole operation process, and it requires extensive practice and effort. They suggested a look-up table method used to implement Fuzzy Logic inside the Arduino Mega microcontroller. This method took a short implementation time for data to be processed in FL. This was important for high-speed data processing and updating [14][15][16].

Rezazadeh *et al*. [16] designed an Adaptive neuro-fuzzy Inference System (ANFIS) to monitor a UAV quadrotor. For non-dominated sorting genetic algorithm II to be included in quadcopter control was a better ANFIS combination. The controller parameters were first optimised using the Genetic Algorithm II Then, the proposed controller's adaptive capabilities helped stabilise the complicated and yet under-actuated rotorcraft system. Lastly, simulations demonstrated that ANFIS enhanced the response properties that are matched to simple PID control [17][18][19][20].

To the best of our knowledge, and from the highlighted studies above, this is the first study where a combination of the LQR-ANFIS algorithm is ever used to control and stabilise a drone flight. In all the literature reviewed, we could not find the application of this combination. The reviewed literature presented some of the following control algorithm applications.

3. Proposed Method

The problem explored in the paper relies heavily on the frames and equations of motion. The rigid body of drone flight remains the key interest. The drone motion can be described by the following [Etkin, 1972].

$$\dot{u} = rv - qw - g\sin\vartheta + \frac{p_d S C_x}{m} \qquad (1)$$
$$\dot{v} = pw + g\cos\vartheta\sin\emptyset + \frac{p_d S C_y}{m} \qquad (2)$$
$$\dot{w} = qu - pv + g\cos\vartheta\sin\emptyset + \frac{p_d S C_z}{m} \qquad (3)$$
$$\dot{p} = \frac{L + I_{zx}(\dot{r} + pq) + (I_y - I_z)\,qr}{I_x} \qquad (4)$$
$$\dot{q} = \frac{M + I_{zx}\left(r^2 - p^2\right) + (I_z - I_x)\,rp}{I_x} \qquad (5)$$
$$\dot{r} = \frac{N + I_{zx}(\dot{p} + qr) + (I_x - I_y)\,pq}{I_y} \qquad (6)$$
$$\dot{\emptyset} = p + q\sin\emptyset\tan\vartheta + r\cos\emptyset\tan\vartheta \qquad (7)$$
$$\vartheta = q\cos\emptyset - r\sin\emptyset \qquad (8)$$
$$\dot{\varphi} = (q\sin\emptyset + r\cos\emptyset)\sec\vartheta \qquad (9)$$
$$\dot{h} = u\sin\vartheta - v\sin\emptyset\cos\vartheta - w\cos\emptyset\cos\vartheta \qquad (10)$$

where

$$
\begin{aligned}
p_a &= \frac{1}{2}\rho V^2 \\
C_X &= C_L \sin \propto - C_D \cos \propto \cos\beta + C_C \cos\alpha \sin\beta C_T \\
C_Y &= -C_D \sin\beta - C_C \cos\beta \\
C_Z &= -C_L \cos \propto - C_D \sin \propto \cos\beta + C_C \sin\alpha \sin\beta \\
C_L &= C_{L_\propto} \propto + C_{L_q} + \bar{q} + C_{L_{\dot{\propto}}} \bar{\dot{\propto}} + C_{L_e}\delta_e \\
C_D &= 0.001625 C_L^3 + 0.30061 C_L^2 + 0.007446 C_L + C_{D_0} \\
C_Y &= C_Y \beta + C_{Y_p}\bar{p} + C_r \bar{r} + C_{Y_r}\delta_r \\
C_C &= \frac{-C_Y - C_D \sin\beta}{\cos\beta} \\
C_R &= C_{T_v}\bar{V} + C_{T_{th}}\delta_{th} \\
M &= \frac{1}{2}\rho V^2 S C_m c \\
L &= \frac{1}{2}\rho V^2 S C_l b \\
N &= \frac{1}{2}\rho V^2 S C_n b \\
C_m &= C_{m_0} + C_{m_a} \propto + C_{m_q}\bar{q} + C_{m_e}\delta_e + C_m \overline{\dot{\propto}} \\
C_l &= C_l \beta + C_{l_p}\bar{p} + C_{l_r}\bar{r} + C_{l_a}\delta_a + C_{l_r}\delta_r \\
C_n &= C_n \beta + C_{n_p}\bar{p} + C_{n_r}\bar{r} + C_{n_a}\delta_a + C_{n_r}\delta_r
\end{aligned}
$$

where

u, v, w are velocity components in a body reference frame.; p, q, r are roll, pitch and yaw angular speeds; $\varphi, \vartheta$are Euler angles; $m$is the drone mass; $I_X, I_Y, I_Z$are drone movements in inertia; $V$is the airspeed; $C_l, C_d, C_m, C_t$are the lift coefficient, drag coefficient, pitch coefficient, and thrust coefficient; $C_{la}, C_{ma}, C_{lq}, C_{mq}, C_{l\dot{a}}, C_{m\dot{a}}, C_{y\beta}, C_{l\beta}, C_{n\beta}$,

$$C_{lp}, C_{np}$$

C_{yr}, C_{nr} are the stability derivatives; $C_l, C_n, C_y C_y$ are coefficients of roll movement, yaw movement and side force; $C_{l\delta e}, C_{m\delta e}, C_{y\delta r}, C_{l\delta a}, C_{n\delta a}, C_{n\delta r}, C_{T\delta th}$ are control derivatives.

Notice that the overline individual non-dimensional quantities; besides, in Equation 10, altitude variation is considered.

Finally, instead of modelling the drag coefficient utilizing stability derivatives, an analytical expression of the drag polar is employed. Such an equation has been obtained by Computational Fluid Dynamics (CFD) analysis of the whole aircraft.

Based on these assumptions, the state of the system is given by **x** = $[u\ v\ w\ p\ q\ e\ \varphi\ \vartheta\ \psi\ h]^T$, while the set of inputs ***in*** = $[\delta_e, \delta_{th}, \delta_a, \delta_r]^T$ is made up of the control surfaces and throttle deflections, where δ_e is the elevator deflection; δ_a is the aileron deflection; δ_r is the rudder deflection and δ_{th} is the throttle displacement.

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We employ an extended Kalman Filter (EKF) for state-from-measurements estimation [21][22]. An EKF has been designed to estimate both the state and stability and control derivatives for the UAV. Its goals are to estimate the drone's position, velocity and angular orientation based on gyroscope rates, an accelerometer, a global positioning system (GPS), airspeed and barometric pressure measures. The EKF is also used for noise filtering, processing multiple measurements of a single variable, and predicting the state of the system (location of the drone) in the near future. Furthermore, the extended version of KF is necessary due to the nonlinearity nature of the drone's flight dynamics.

To obtain a joint estimation of state and parameters, the state vector has been augmented by defining the unknown parameters as additional state variables, described as:

$$X = \left[\frac{x}{p}\right] \tag{11}$$

where$x = [u\ v\ w\ p\ q\ e\ \varphi\ \vartheta\ \psi\ h]$

and p is the set of unknown stability and control derivatives that, according to Equations 1 to 9 is:

$$\boldsymbol{p} = \begin{bmatrix} C_L C_m C_{L_q} C_{m_q} C_{L_e} C_{m_e} C_m C_Y \cdots \\ C_l C_n C_{Y_p} C_{l_p} C_{n_p} C_{Y_r} C_{l_r} C_{n_r} C_{Y_r} C_{l_a} C_{l_r} C_{n_a} C_{n_r} \end{bmatrix}^2$$

We have since postulated the constant system parameter p and the following equations have been incorporated into the UAV model:

$$\dot{p} = 0 \tag{12}$$

The following augmented dynamic model of the system has been obtained by joining Equations 1–10 and Equation 12, where

$$x = \left[\frac{f(x, in, \dot{p}, t)}{\mathbf{0}_{22\times1}}\right] + \left[\frac{w(t)}{w_p(t)}\right] \tag{13}$$

$w(t)$ and $wp(t)$ are 10 x 1 and 22 x 1 random processes with unknown statistics at time t, respectively. They both represent uncertainties in the system model.

For the augmented model, the output equation is:

$$y(t) = h(x, in, p, t) \tag{14}$$

The discrete measurement equation is:

$$z_k = h(x, in, p, t) + v(t) \tag{15}$$

with

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$h(x, in, p, t) = h(x, in, p, t)$ if $t = kT$

$h(x, in, p, t) = [0_{1x9}]$ if $t \neq kT$

where

$v(t)$ is the measurement noise vector and T is the sampling interval of the instrumentation [23].

Following the above problem formulation, the proposed control algorithm is a hybrid Linear Quadratic Regulator-Adaptive Neuro-Fuzzy Inference System (LQR-ANFIS). To the best of our knowledge, this is the first study where such a combination of control techniques approach is used to control and stabilise a drone flight with the implementation of the EKF in dealing with rapid changes in behaviour at a cost of a less precise measure overall.

This method combines adaptive control and artificial intelligence techniques; resulting in an intelligent and adaptive hybrid controller. Intelligent control algorithms apply several synthetic intelligence approaches, and some biologically inspired controller systems, this controller will control the position and orientation of a drone flight with good response during simulation [7].

On the other hand, an adaptive control system automatically compensates for variations in system dynamics by adjusting the controller characteristics so that the overall system performance remains the same or is maintained at an optimum level. This type of control system considers any degradation in plant performance with time.

The adaptive control system includes elements to measure the process dynamics and other elements and alter the controller characteristics accordingly. The controller adjusts the controller characteristics in a manner that maintains the overall system performance [24].

The whole process is depicted in Figure 1

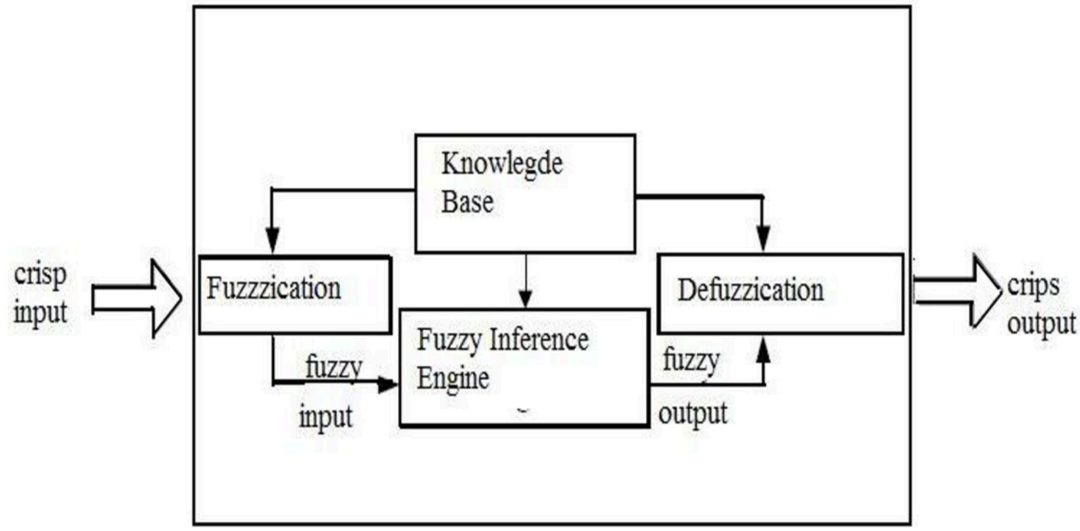

Fig. 1. Fuzzy Inference System

4. Experiments

A. Experimental Set-Up

A method for determining the roll angle and the pitch angle of the drone flight using an adaptive filter is summarised. The object of the invention is to provide a method and a device for determining the roll angle of a drone, which permits a more reliable determination of the roll angle compared to existing realizations, particularly in several and/or most and/or all driving conditions, and/or a higher level of accuracy compared to existing realizations, particularly in several and/or most and/or all driving conditions. Particularly in this context, the cost of implementing the method and of manufacturing the device is to be low.

The proposed control scheme of LQR-ANFIS was designed using Matlab 2016a/Simulink, and the test environment was an ACER laptop with the following specifications: Intel Celeron processor 2955U (1.4 GHz, 2 MB L3 Cache). Intel HD Graphics, 2GB DDR 3 L Memory 500 GB HDD and 32-bit Windows 8 pro Home basic operating system.

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$$x = Ax + Bx + \begin{bmatrix} -g\sin\theta \\ g\cos\theta\sin\phi \\ g\cos\theta\sin\phi \\ 0 \\ 0 \\ 0 \\ q\cos\phi - r\sin\phi \\ (q\sin\phi + r\cos\phi)\cdot\tan\theta \end{bmatrix} \tag{16}$$

The newly proposed LQR-ANFIS hybrid control scheme is summarised in Fig. 2. Using equation (16), the space state representation of the system is as stated below. After the design of the ANFIS, training and checking of data was done, and the ANFIS structure was developed. Finally, data checking and FIS output were depicted and plotted. The ANFIS was then integrated into the LQR controller by importing it with MATLAB software into Simulink.

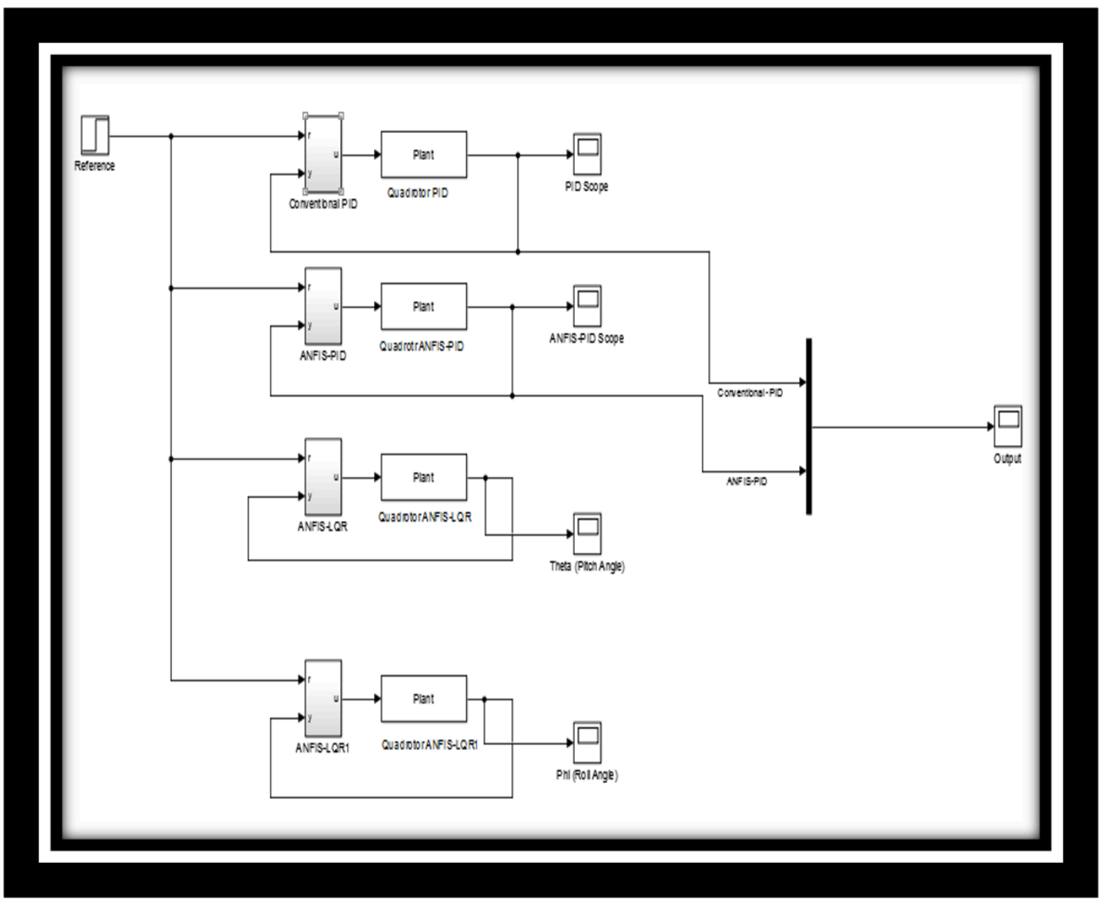

Fig. 2. LQR-ANFIS

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B. Experimental Results

A comparative and empirical analysis was done during the experiments to demonstrate the effectiveness of hybrid controllers vs traditional controllers. This proved that the hybrid controllers have superior performance to their traditional counterparts. The results of an LQR-ANFIS controller are depicted in Figures 3-8. Furthermore, the PID vs ANFIS-PID was also observed, and the performance results are demonstrated in Fig. 13. The hybrid controller of ANFIS-PID outperformed its competitor PID by not having any overshoot, better disturbance rejection, and less settling time.

Fig. 3 shows the LQR-ANFIS controller having an excellent steady-state error with no pitching overshoot challenges as would be expected when using a conventional control technique.

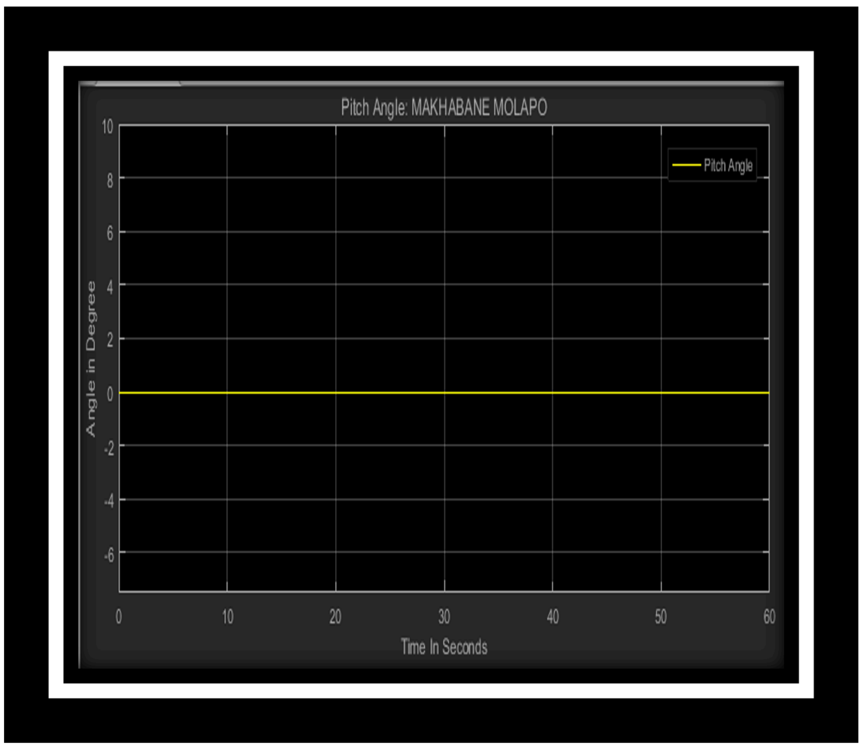

Fig. 3. 0° Degree Pitch Angle

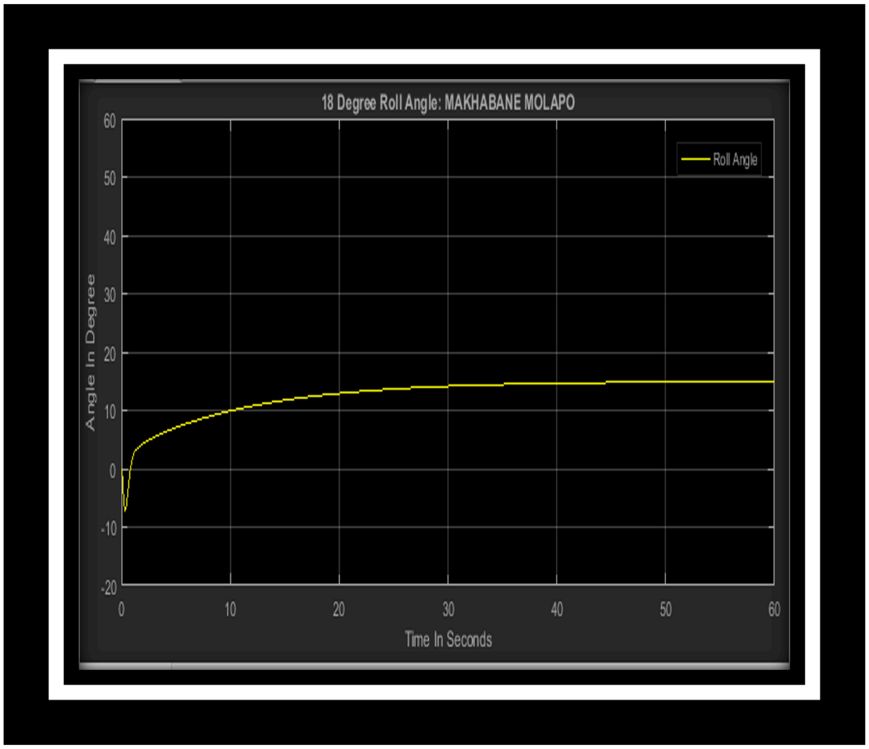

Fig. 4. 18° Degree Roll Angle

Figures 5 to 9 show a variation and relatively high accuracy of roll angles in degrees from 18°, 20°, 30°, 40°, 50° and 60°; the experiment aimed to perform a steady coordinated turn by going through a roll of all these angles.

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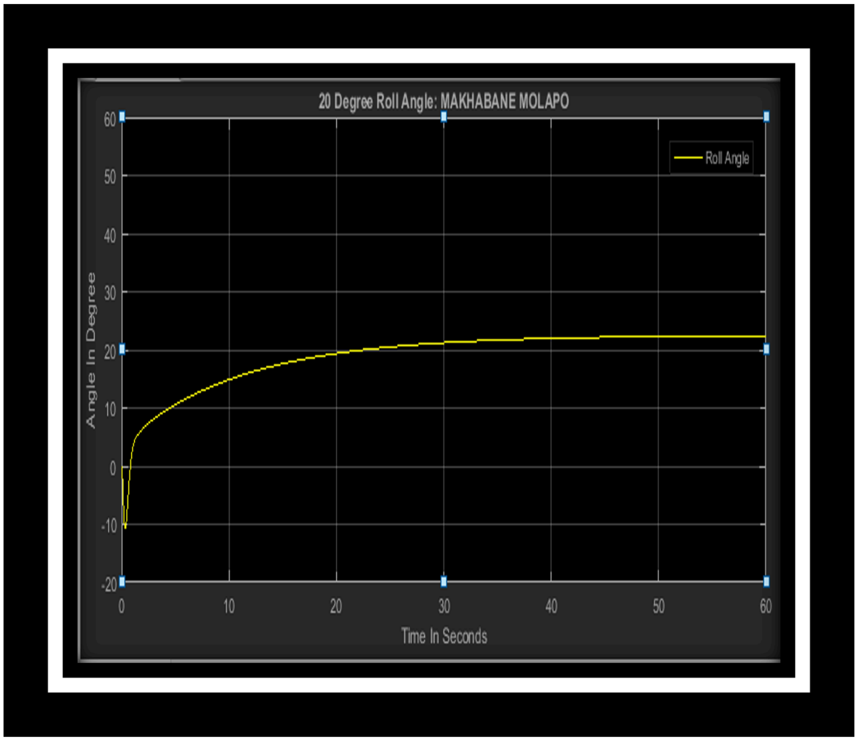

Fig. 5. 20° Degree Roll Angle

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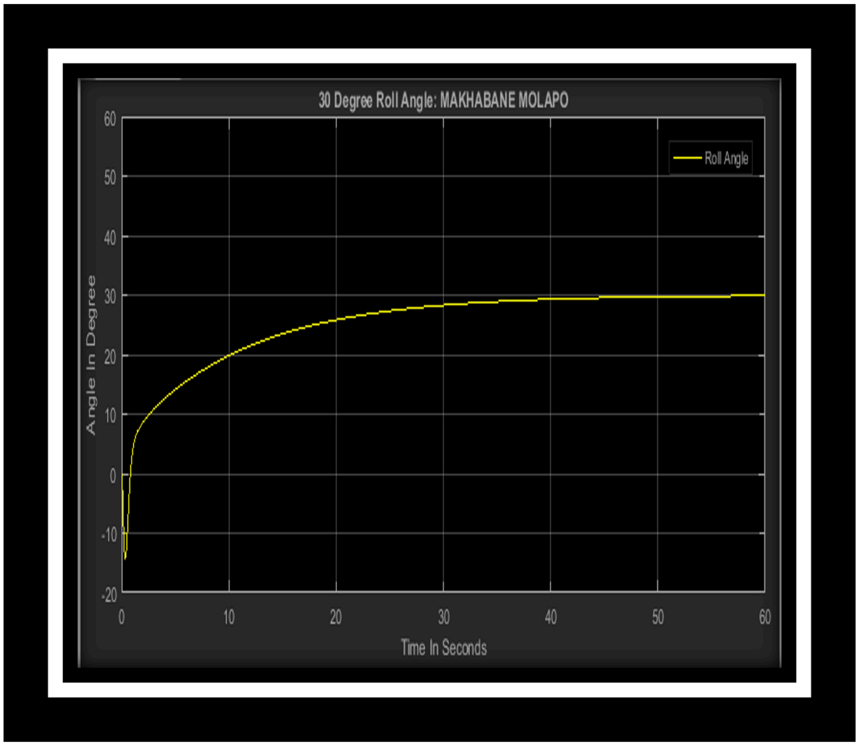

Fig. 6.30° Degree Roll Angle

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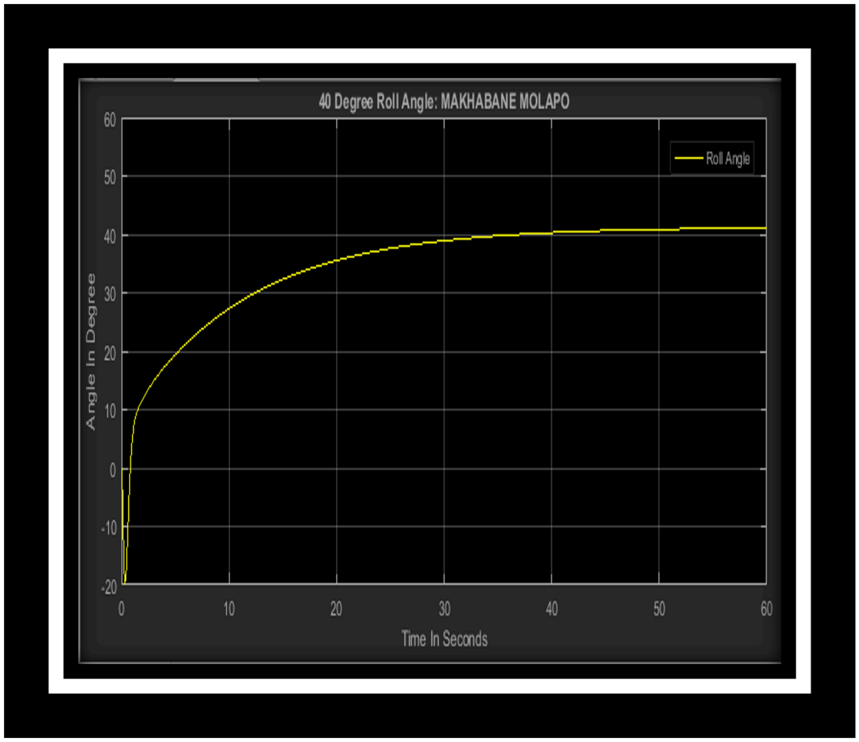

Fig. 7. 40° Degree Roll Angle

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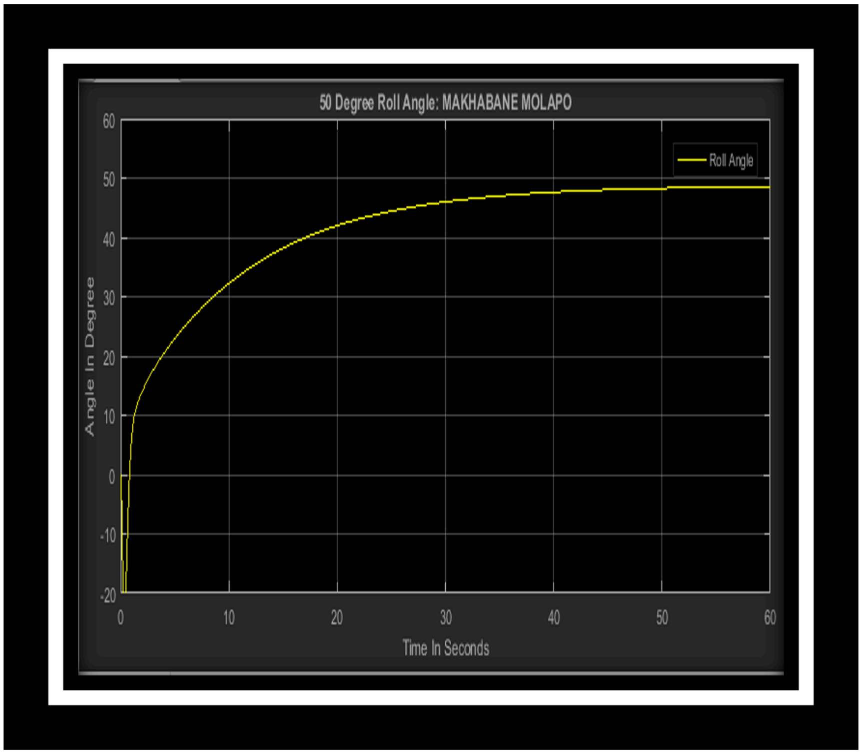

Fig. 8. 50° Degree Roll Angle

In our previous experiments [3], the LQR controller managed to do only a 60° roll turn when a traditional LQR controller was used. In comparison, a hybrid controller LQR-ANFIS performed much better than a single LQR controller.

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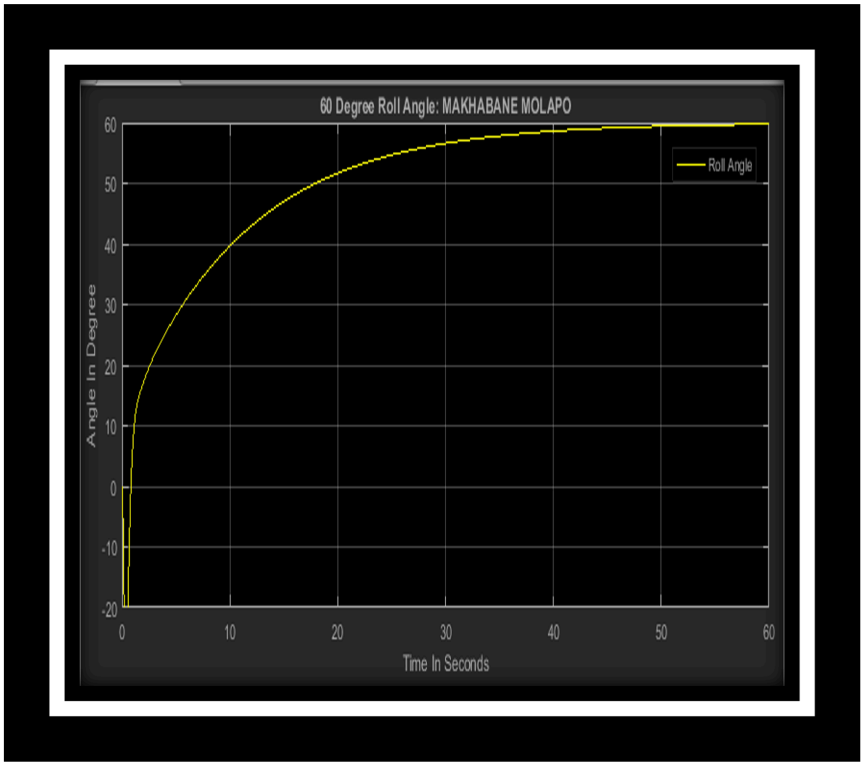

Fig. 9. 60° Degree Roll Angle

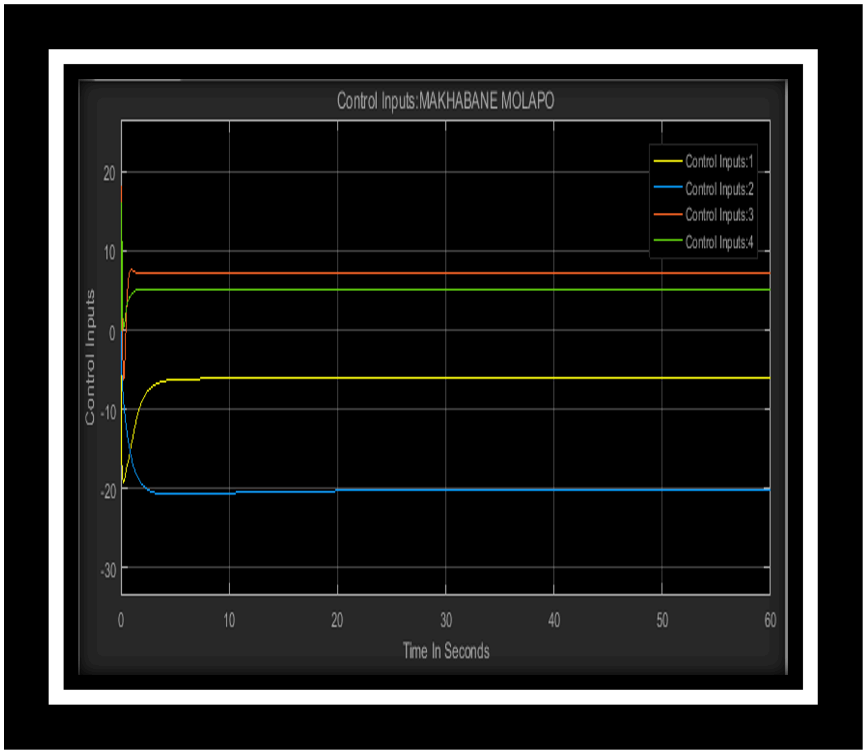

Fig. 10. Adjusted Control Inputs

Fig. 10 shows the response of inputs as adjusted through the matrices of Q and R in Matlab during the simulation. The designed controller's response time was greatly improved by the matrices' adjustment as indicated by the graph in Fig. 9.

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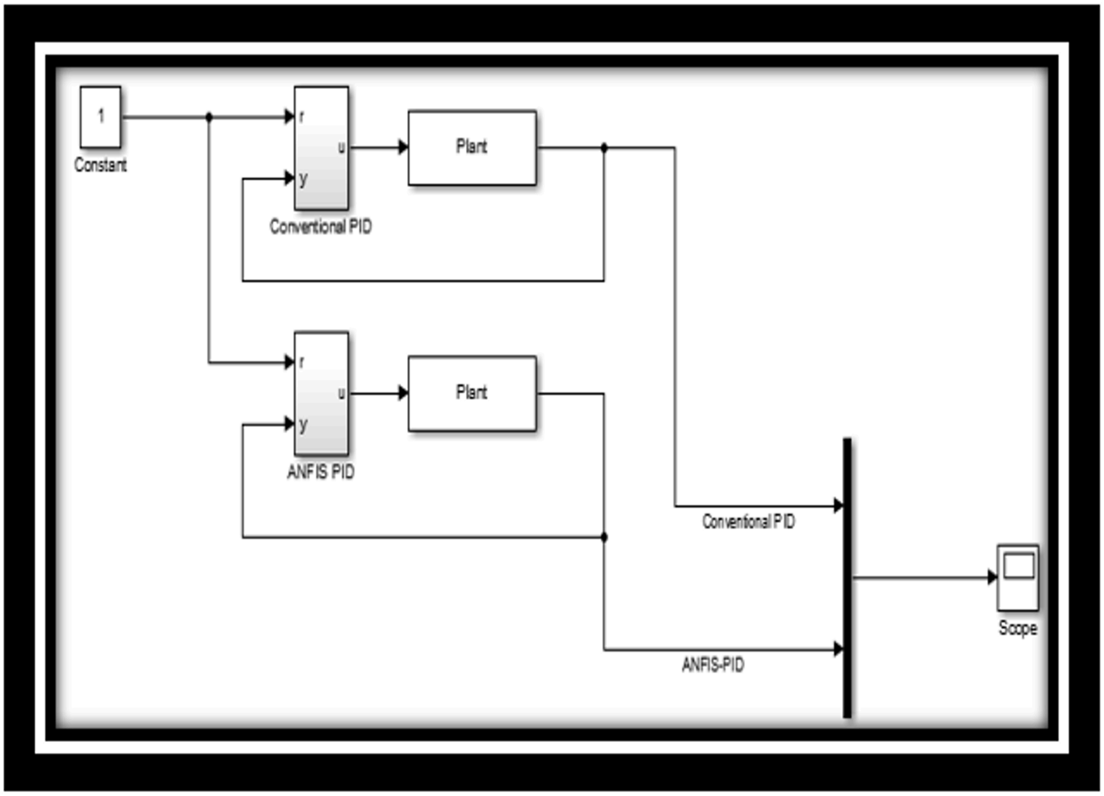

Fig. 11. Block Diagram of ANFIS-PID vs PID

Fig 11 shows a block diagram of a hybrid ANFIS-PID versus a traditional PID controller; the results are shown in Fig. 11 to 13 below.

Fig. 12 shows how the conventional PID performed during the simulations, within 1.3 seconds, the quadcopter had reached an altitude of 1.13 meters with an overshoot of about 50% as referenced from the set altitude of 1 meter and reached a settling time in 5.5 seconds during the flight which lasted for 10 seconds. During climbing, the quadcopter experienced a lot of atmospheric disturbance. As can be seen from the graph, it finally stabilised after 5 seconds during the flight, which lasted for 10 seconds.

Fig. 13 shows the performance of ANFIS-PID in 1.3 seconds, the quadcopter had reached an altitude of 1.01 meters with an overshoot of about 5% and reached a set time in 3 seconds of the flight. During climbing, the quadcopter experienced high atmospheric disturbance. As compared to its competitor conventional PID, the ANFIS-PID performed significantly better in all aspects, and the flight lasted for 10 seconds.

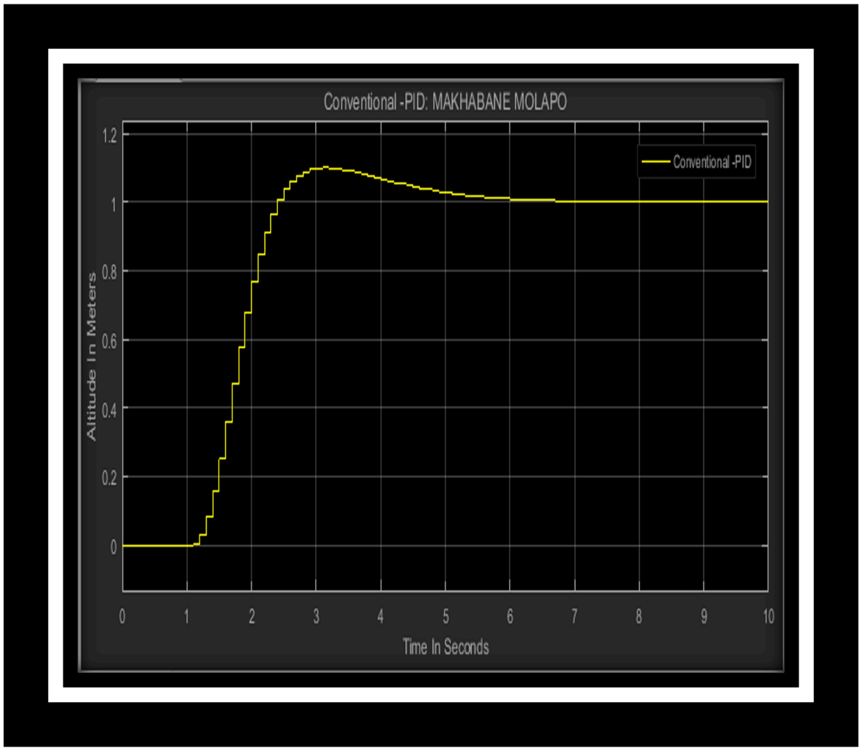

Fig. 12. Conventional PID

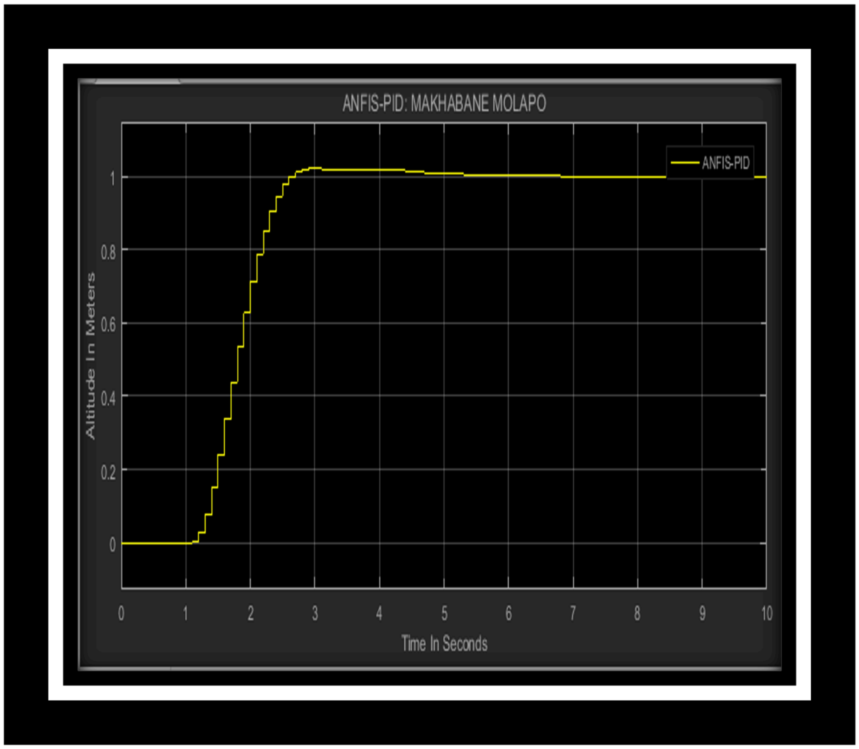

Fig. 13. ANFIS-PID

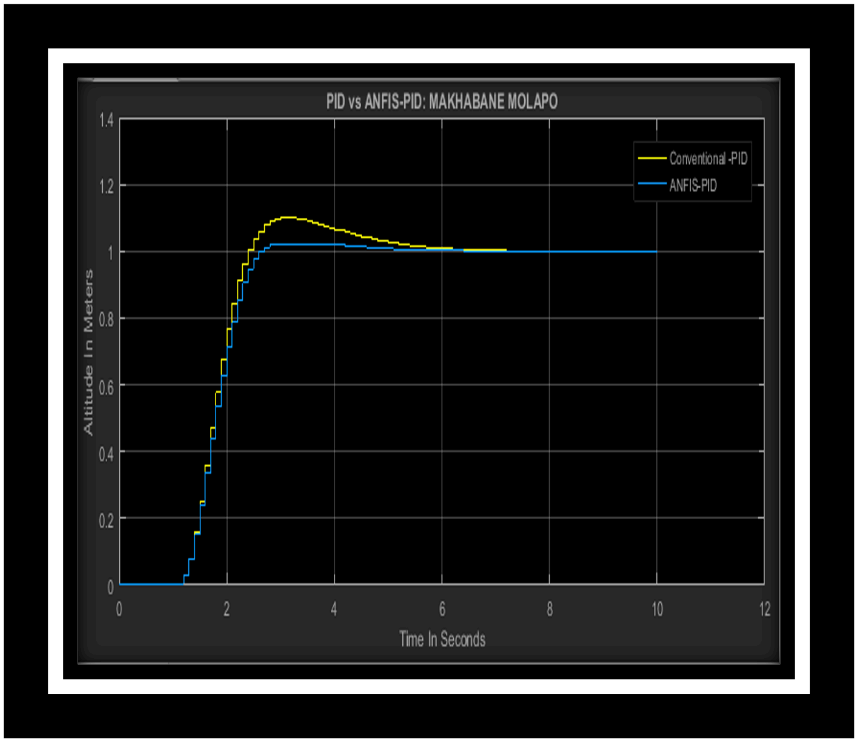

Fig. 14. PID vs ANFIS-PID

Fig. 14 shows the combined analysis of both the conventional PID vs ANFIS-PID, the graph shows how the ANFIS-PID (blue) significantly improved the performance and stability of the drone flight during flight as compared to a PID (Yellow), which experienced some overshoot and delayed settling times.

5. Remarks and Conclusion

The paper's objectives were to study and comprehend adaptive control, intelligent control, hybrid control, and aeronautical characteristics of a UAV-drone flight. To achieve the study's objectives, a review of relevant literature was done, and a comparative and empirical analysis of different UAV control algorithms was reviewed. A comparative analysis of conventional controller vs intelligent hybrid controller was also presented.

To the best of our knowledge, the design and development of an intelligent adaptive hybrid control algorithm have neither been recorded nor designed and developed in the literature. Also, numerical simulations were conducted to see how the algorithm performs. Thus, whether to accept or reject the

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hypothesis, the hypothesis was that the adaptive controller will have the best overall performance in the control and stabilisation of a UAV drone flight compared to traditional control algorithms.

The key observations and findings based on the analysed results show that hybrid controllers perform much better than their traditional counterparts in controlling and stabilising the drone flight while operating precisely in the same atmospheric environment by; not having any overshoot faster settling time and better disturbance rejections. Thus, the observation believes that hybrid controllers are more effective and efficient than conventional controllers while operating in the same atmospheric environment. It is proposed that for future work the quadcopter drone flight will be manufactured to see how the algorithm will perform in the actual operational rather than simulated environment.

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