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Altitude Controller Based on Artificial Neural Network - Genetic Algorithm for a Quadcopter MAV

José Ramón Meza Ibarra [a,1], Joaquín Martínez Ulloa [a,2], Luis Alfonso Moreno Pacheco [a,3,*], Hugo Rodríguez Cortés [b,4]

[a] Sección de Estudios de Posgrado, Escuela Superior de Ingeniería Mecánica y Eléctrica, Instituto Politécnico Nacional, Av. Instituto Politécnico Nacional, S/N, Col. Lindavista, Ciudad de México, 07738, México
[b] Departamento de Ingeniería Eléctrica, Centro de Investigación y de Estudios Avanzados del Instituto Politécnico Nacional, Av. Instituto Politécnico Nacional No. 2508, Col. San Pedro Zacatenco, Ciudad de México, 07360, México
[1] jmezai1600@alumno.ipn.mx; [2] jmartinezu1901@alumno.ipn.mx; [3] lamoreno@ipn.mx;
[4] hrodriguez@cinvestav.mx
* Corresponding Author

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ABSTRACT

Mechanical systems with high dynamic complexity often face challenges due to unmodeled uncertainties and external perturbations, making effective control difficult. Therefore, new advanced, robust, intelligent control theories have been developed through the sudden advance of computational power in recent years. In this research work, these new theories of automatic control are used, mainly based on what is currently called Artificial Intelligence (AI) algorithms, to develop a novel altitude controller based on the theory of Genetic Algorithms (GA) and Artificial Neural Networks (ANN). The performance of the designed controller is evaluated by employing the numerical simulation model in MATLAB & SIMULINK, which was created for the commercial MAV Mambo Parrot. The developed intelligent ANN-GA controller uses the Levenberg-Marquardt optimization method and a Genetic Algorithm (GA) to improve Artificial Neural Network performance. The initial PID gains are obtained according to the GA, generating optimal values that initialize the neural network and contribute to optimal performance of the ANN training through evaluation of (Mean Square Error) MSE and (Integral Time Absolute Error) ITAE; the ANN takes then, the adequate output and signals as data from input to calculate the required combination of gains as output for MAV altitude controller. Simulation results demonstrate that the self-tunable controller improves the settling time, decreasing by 31.6% compared to the original PID controller. The certainty of the implemented controller opens new routes for automatic control strategies based on artificial intelligence algorithms for the complex nonlinear dynamics of unmanned aircraft.

1. Introduction

The discipline of control engineering has allowed the realization of various techniques that can be applied to countless applications. Thanks to supervisory control systems, there is currently a set of electronic devices capable of achieving effective and efficient behavior established by the designer; these show that there has been a considerable advance in the control of cyber - physical systems [1].

The control applications of Unmanned Aerial Vehicles (UAVs) generally require robust schemes capable of compensating disturbances, modeling errors, and measurement noise to achieve autonomous navigation [2]. One promising approach to overcome such challenges is based on the use of Artificial Intelligence (AI). Due to significant computational advances, working with UAVs has become an international trend with many scientific developments. However, for the current state of the art of this research article, it is decided to enumerate and identify specific helpful knowledge for the theoretical foundation of the research, listing the most relevant ones.

This research proposes establishing a novel implementation of the classical PID control technique [3] employing artificial intelligence tools [4]. It is widely known in automatic control that a Neural Network (NN) and Genetic Algorithm (GA) are methods for optimizing and learning [5] with their respective weaknesses and strengths. Although both methods have evolved separately, the main task of this research article is to propose a method for combining the two self-learning systems. A cooperative approach has been developed between both techniques to find the optimal algorithm to control the UAV's altitude robustly. Uniting both intelligent techniques has only recently been intended, and this research reports a successful case. The evaluation of the proposed algorithms for the MAV is established in the numerical simulation software MATLAB & SIMULINK, more explicitly using the available libraries: *Simulink Support Package for Parrot Minidrones*, which were developed by the group Sertac Karaman from MIT in 2016 [6]. The simulator includes an atmospheric model and a model of the multiple sensors integrated into the UAV (ultrasonic sensor, pressure sensor, camera, and IMU). The sensor's performance has excellent precision and fidelity. It is worth mentioning that the simulator's mathematical model presents certain advantages and disadvantages. Among the advantages are flight dynamics and onboard sensors' high fidelity. The main disadvantage is the restriction of being able to influence the redesign of its architecture freely, both modeling and physical parameters, which makes the authors highlight the achieved task even more from the point of view of this research article.

Remarkably, UAVs use the PID control technique to provide stabilization and reliable trajectory tracking; nevertheless, it is needed to optimize the closed-loop dynamics response, for instance, by decreasing the settling time. In the research article [7], a new intelligent controller is designed using a neural network based on the Levenberg-Marquardt feedforward training method; the optimal controller gains are generated by the PSO (Particle Swarm Optimization), and it is evaluated by the Mean Square Error (MSE). The evaluation shows that the intelligent controller outperformed the manual tuning PID controller. An essential task in aerial robotics is controlling the altitude. The article [8] reports the design of an adaptive PID controller using Artificial Neural Networks. The proposed controller is improved by a Genetic Algorithm illustrating the advantages of the adaptive neural PID controller. The main advantage of this method is the adaptive capability to new conditions and variations in the system's dynamics. In reference [9], a discrete-time PID controller is implemented over a hexacopter. The PID is programmed for trajectory tracking tasks, an adaptive neural technique is used to develop the controller and closed-loop stability is verified by the Lyapunov discrete theory. A BP (Back-Propagation) network is used to adjust the PID gains. Experimental results demonstrate a good performance of the proposed ANN-PID controller. An effective PID controller is applicable when the center of gravity of the aerial vehicle does not match its geometric center. The use of a PID algorithm and the GA and BP traditional systems is reported in [10].

The proposed algorithm can be optimized to adapt the controller to more complex UAV environments and improve the control's robustness; the algorithm can learn while it is being simulated. In [11], to improve the PID controller of a quadrotor UAV, a neural network algorithm joining a genetic algorithm is used to provide robustness and dynamic performance for a trajectory-tracking controller. The overall convergence speed is improved, the attitude tracking controller is improved, and the desired trajectory is faster achieved, eliminating the overshoot adverse effects; its overall performance improves the classical PID. To solve the optimization problem for path planning of a UAV, the report in [12] uses a Genetic Algorithm (GA) as the optimization tool with an Artificial Neural Network (ANN), which helps to converge faster to a given trajectory, the UAV can avoid obstacles coming in its path. The Genetic Algorithms train the Neural Network. 3D simulations are presented to verify the performance of the proposed approach. In the future, the transfer of information among UAVs will be addressed. A new adaptive neural network control is proposed in [13]; the controller aims to stabilize a quadrotor under the effect of modeling error and wind disturbances. Numerical simulations verify that the new method outreaches the adaptive techniques known as dead zone and e-modification; real-time prototype tests will be conducted soon.

UAV communications generally depend on wireless protocols, which are under substantial security threats; to solve this issue in correlation with the Principal Component Analysis (PCA), a new technique based on an Artificial Neural Network (ANN) and Genetic Algorithm (GA) is proposed in [14]. The algorithm generates the optimal weights for the communication network, and a comparison between the proposed model and the BP network is made. This system detects an intruder in the communications protocol system to prevent and respond to possible threats; training and validating the system in real- time attacks makes the proposed algorithm very effective.

In this research article reported in [15], a self-tuning ANFIS (Adaptive Neural - Fuzzy Inference System) controller working with a GA (Genetic Algorithm) is applied to solve the trajectory tracking problem for UAVs. As the quadrotor dynamics is highly nonlinear, intelligent control is a valuable tool for controlling this type of nonlinear system. The ANFIS is employed to reproduce the desired trajectory. Meanwhile, the GA algorithm facilitates convergence to optimal parameters, reducing learning errors and improving the controller's robustness. The presented controller performs better thanks to parameter updates than other UAV controllers. The instantaneous adjustment of aerial trajectories is highly needed in military unmanned vehicles. The work in [16] proposes a path planning model based on a Genetic Algorithm (GA) that builds a series of segments connected by circular arcs, resulting in suitable paths for the UAV. The model developed is tested in more that eighteen realistic scenarios on 3D terrains, and the proposed algorithm can find almost optimal solutions in flight planning every time. Reference [17] presents the design of a controller based on an evolutionary neural network; the controller's goal is to reach a specific position during flight. With the help of a single multilayer Perceptron neural network, the controller was implemented; the network training was performed using an evolutionary algorithm underlying the cost function definition. The designed neural controller is tested in simulation.

In [18], a hybrid controller based on combining fuzzy and sliding mode techniques to stabilize complex mechanical systems is reported. A Genetic Algorithm (GA) has been added to the controller structure to optimize the control system requirements by exploiting the fuzzy approach. The sliding modes controller assures the stability of the nonlinear system; besides guaranteeing the robustness of the controller, the designed system also deals with the disturbances and uncertainties, thanks to the use of the fuzzy approach.

The research report [19] establishes the design process of the conceptual design phase of an airfoil for unmanned aerial vehicles. The wing parameters are determined through an aerodynamic optimization process using both Genetic Algorithms (GA) and Artificial Neural Networks (ANNs); the designed wing is tested in CFD (Computational Fluid Dynamics) simulations and wind tunnels. Artificial intelligence optimization allows an exhaustive aeronautical comparison to determine the best aerial configuration; since the numerical results are available at any time, it is easy to change possible configurations; both artificial algorithms decrease the require computation time. Intelligent artificial algorithms have proven to be an optimal solution to control unmanned aerial vehicles when the computational power is limited. In [20], a learning control strategy based on a fuzzy neural network is proposed with a conventional proportional controller and a sliding mode estimator to update parameters that feed the learning algorithm. Simulation studies are carried out to validate the performance of the proposed controller; the Gaussian activation function for the Fuzzy Neural Network (FNN), as well as Lyapunov-based stability analysis, supports the effectiveness of the control algorithm.

In [21], a four-rotor UAV sensor fault diagnosis and fault-tolerant control based on genetic algorithm, improved by a BP Neural Network algorithm is presented. The Mean Squared Error (MSE) is proposed as a performance function and is used to quickly and accurately detect programmed faults. Fault-tolerant control on the UAV is achieved by improving the classic GA-BP algorithm. The development of a dual-net model ANN (Artificial Neural Network), i.e., capable of learning on and offline, is the main task of the work reported in [22]. The multilayer Perceptron Network (MLP) identifies the UAV's system dynamics, while the robust model updates through the dual-net model switch. Integrating the network and the Model Predictive Control (MPC) produces sufficient robustness to obtain accuracy in predicting and controlling the system. In [23], two flight control methods are proposed. One is a self-tuning PID controller based on Genetic Algorithms (GAs), and the other is an Adaptive Neuro-fuzzy Inference (ANFIS) controller. In the central navigation system, neural-fuzzy networks are designed to estimate heading angle, altitude, and speed. Durability and high robustness are validated through numberless simulations. The controller can achieve the desired heading angle in nominal conditions and under external wind disturbances.

An online learning adaptive neural network for small unmanned aerial vehicle is proposed in [24] to improve the control performance during flight. The network generates the turn-around trajectory on a radial basis using control methods that samples data and have training time. The neural network's performance relies highly on the type of data; the state error information generates the weight matrix of the adaptive neural network and can be updated online using a Lyapunov function. Combining the traditional feedback control method with the adaptive controller, the designed controller demonstrates its effectiveness. Cooperative coverage for multi-UAV mission planning is the purpose of the research article [25]. The problem is solved by involving a Neural Network and Genetic Algorithm. The weights and thresholds of the network are optimized by using the Genetic Algorithm, which allows to solve the optimal paths of the multi-UAV platoon. The UAV agents learn reconnaissance rules not only independently but also autonomously. A convergence analysis proves the efficiency of the method.

Stabilization of the altitude and the attitude of an unmanned vehicle around its hovering configuration is highly needed in aerial robotics. In reference [26], a method to optimize a regulation controller is presented. Two control architectures, PD (Proportional-Derivative) and PID (Proportional-Integral-Derivative), are tuned through the Linear Quadratic Regulator (LQR). A genetic algorithm was implemented To optimize the inputs to the LQR and minimize the settling time in hovering flights. Tests are conducted in presence of disturbances to validate the efficiency and effectiveness of the proposed algorithm.

All of the cited research articles describe solutions in aerial robotics in all the dynamic systems spectrum, e.g., modeling, identification, model-based controllers, unmodeled uncertainties compensation and observer-based controllers. Nevertheless, only some integrate two artificial intelligence algorithms to achieve a common objective. Hence, the main objective of this investigation is to achieve cooperation between a Genetic Algorithm and an Artificial Neural Network to optimize the performance of a PID-based altitude controller.

The main contributions of the research are:

- The design of a self-tuning intelligent altitude controller based on optimizing a feedforward neural network using a genetic algorithm for the *Mambo Parrot* commercial unmanned aircraft.
- The data set used to train the artificial neural network consists of the best gains obtained from the genetic algorithm implemented to generate a satisfactory performance by the quadcopter

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altitude controller.

- The MAV's altitude is being adequately controlled considering its nonlinear mathematical model, whose performance is very close to the real plant. It should be emphasized that this model presents a great complexity due to its excellent design, which in turn leads to modification restrictions. Despite these disadvantages and constraints, the desired controller was successfully implemented.
- The designed intelligent controller can be applied to multiple rotary-wing UAV configurations.
- The designed altitude controller would impact the UAV industry by incorporating the proposed controller algorithm, which does not require specific knowledge of unmanned aerial vehicle dynamics; it only requires reliable input-output data provided by onboard sensors. Inevitably the arrangement of the data structure is still a major issue for feeding the architecture of the network; hence, it should be noted that for such structure, the optimal design will only be determined through the fly envelope of the required aircraft.

This research article is divided in to four main parts, starting with Section 1, which describes the current state of the art and the main contributions of this investigation. Section 2 establishes in detail the mathematical model of the Mambo Parrot dynamics, where the described model is based on the Newton-Euler equations. Aside from the methodology used, a brief description of the training methods of both intelligent algorithms is also included. The general basis of the PID controllers is analyzed. The design of the Artificial Neural Network is widely depicted. The architecture of the implemented intelligent controller is explained. In Section 3, results, performance and validation are all discussed, and finally, Section 4 concludes this investigation by establishing the link between the objectives and results obtained.

2. Research Methodology

In Fig. 1 illustrates the UAV employed in this work; it also explains the reference systems used in the mathematical model. The body frame will be assigned with the letter b and the inertial reference with the letter i. Fig. 2 presents the configuration of the vehicle's rotor up and establishes the corresponding direction of rotation.

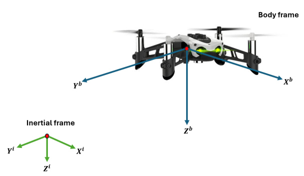

Fig. 1. Reference coordinate systems

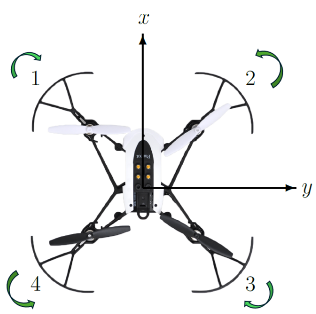

Fig. 2. Direction of rotation of the rotors

2.1. Mathematical Modeling of the Quadcopter

The vectors $\xi = [x\,, y\,, z]^{\top}$ and $\xi = [\dot{x}\,, \dot{y}\,, \dot{z}]^{\top}$ describe the quadcopter translational position and velocity, respectively. In the same manner, the orientation of the UAV will be represented by the rotation matrix $R^i : b \to i$, which is obtained from the rotation around each of the fixed axis as follows:

$$R_i = R_z(\psi)\, R_y(\theta)\, R_x(\phi) \tag{1}$$

Using the commonly sequence of rotation employed in aeronautics. Each rotation matrix is given by

$$R_x(\phi) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos(\phi) & -\sin(\phi) \\ 0 & \sin(\phi) & \cos(\phi) \end{bmatrix}$$

$$R_y(\theta) = \begin{bmatrix} \cos(\theta) & 0 & \sin(\theta) \\ 0 & 1 & 0 \\ -\sin(\theta) & 0 & \cos(\theta) \end{bmatrix} \tag{2}$$

$$R_z(\psi) = \begin{bmatrix} \cos(\psi) & -\sin(\psi) & 0 \\ \sin(\psi) & \cos(\psi) & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

With ϕ, θ and ψ the roll, pitch and yaw angles, respectively.The rotation array employed is depicted in Fig. 3. The figure shows the angles that define the orientation between the inertial and body frames. From equation (1), it follows that

$$R_i = \begin{bmatrix} \cos\psi\cos\theta & \sin\psi\cos\theta & -\sin\theta \\ \cos\psi\sin\theta\sin\phi - \sin\psi\cos\phi & \sin\psi\sin\theta\sin\phi + \cos\psi\cos\phi & \cos\theta\sin\phi \\ \cos\psi\sin\theta\cos\phi + \sin\psi\sin\phi & \sin\psi\sin\theta\cos\phi - \cos\psi\sin\phi & \cos\theta\cos\phi \end{bmatrix} \tag{3}$$

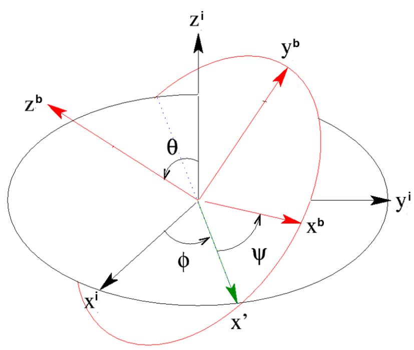

Fig. 3. Rotation matrix diagram

The velocity expressed in body frame coordinates is $V = [u\ v\ w]^{\top}$. The relationship between body frame and inertial frame velocities is given by the expression:

$$\dot{\xi} = R^i V \tag{4}$$

The angular velocities with respect to the inertial frame will be designated as $[\dot{\phi}\ \dot{\theta}\ \dot{\psi}]^{\top}$ and in reference to the body frame, the velocities will be $\omega = [p\ q\ r]^{\top}$. To transform these velocities

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from the inertial frame to the body frame, some considerations are needed, e.g., $\hat{e}_1 = [1\ 0\ 0]^\top$, $\hat{e}_2 = [0\ 1\ 0]^\top$ and $\hat{e}_3 = [0\ 0\ 1]^\top$, hence one can show that:

$$\omega = \hat{e}_1\dot{\phi} + R_x(\phi)\,\hat{e}_2\dot{\theta} + R_x(\phi)\,R_y(\theta)\,\hat{e}_3\dot{\psi} \tag{5}$$

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = \begin{bmatrix} \dot{\phi} \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ \dot{\theta}\cos\phi \\ \theta\sin\phi \end{bmatrix} + \begin{bmatrix} \dot{\psi}\sin\theta \\ -\dot{\psi}\sin\phi\cos\theta \\ \dot{\psi}\cos\phi\cos\theta \end{bmatrix} = \begin{bmatrix} \dot{\phi} + \dot{\psi}\sin\theta \\ \dot{\theta}\cos\phi - \dot{\psi}\sin\phi\cos\theta \\ \dot{\theta}\sin\phi + \dot{\psi}\cos\phi\cos\theta \end{bmatrix}$$

Where the matrix form is:

$$\begin{bmatrix} p \\ q \\ r \end{bmatrix} = J_1(\phi\,, \theta) \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & 0 & -\sin\theta \\ 0 & \cos\phi & \sin\phi\cos\theta \\ 0 & -\sin\phi & \cos\phi\cos\theta \end{bmatrix} \begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} \tag{6}$$

Where $J_1(\phi\,,\,\theta)$ is the transformation matrix to change the angular velocities from the inertial reference system to the body fixed system. Which establish the inverse matrix as follows:

$$\begin{bmatrix} \dot{\phi} \\ \dot{\theta} \\ \dot{\psi} \end{bmatrix} = J^{-1}(\phi\,,\,\theta) \begin{bmatrix} 1 & \sin\phi\tan\theta & \cos\phi\tan\theta \\ 0 & \cos\phi & -\sin\phi \\ 0 & \sin\phi\sec\theta & \cos\phi\sec\theta \end{bmatrix} \begin{bmatrix} p \\ q \\ r \end{bmatrix} \tag{7}$$

Where the value of $\theta \neq \pm 90$ has to exist in order to compute the inverse transformation.

The equations that describe the dynamics of any rigid body which mass center is subjected to external forces have to be expressed in the body fixed reference frame, which can be described with the Newton-Euler method as follows,

$$\begin{bmatrix} m\,I_{3\times3} & 0 \\ 0 & J \end{bmatrix} \begin{bmatrix} \dot{V} \\ \dot{\omega} \end{bmatrix} + \begin{bmatrix} \omega\, \times\, mV \\ \omega\, \times\, J_\omega \end{bmatrix} = \begin{bmatrix} F^b \\ \tau^b \end{bmatrix} \tag{8}$$

Where $I_{3\times3} \in \mathbb{R}^{3\times3}$ is the identity matrix, m is the total mass of the vehicle, and

$$J = \begin{bmatrix} I_{xx} & 0 & 0 \\ 0 & I_{yy} & 0 \\ 0 & 0 & I_{zz} \end{bmatrix} \tag{9}$$

Is the inertia tensor. Fig. 4 shows the forces produced by the rotors on the unmanned aerial vehicle, as well as the direction of the rotation axis, respectively with its angles.

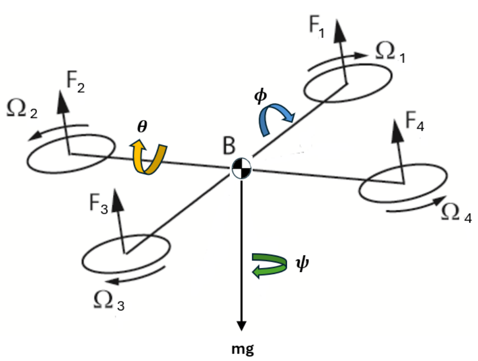

Fig. 4. Aerodynamic angles and produced forces

Designating $\eta = [\phi\ \theta\ \psi]^\top \in \mathbb{R}^3$ as the angular position with respect to the inertial frame system; the equations of movement of a rigid body, then can be written as, [27]:

$$\begin{aligned} \dot{\xi} &= R^i V \\ m\ddot{\xi} &= R^i F^b \\ \dot{\eta} &= J_1^{-1}(\eta)\omega \\ J\dot{\omega} &= -\omega \times J\omega + \tau^b \end{aligned} \tag{10}$$

To express the forces acting on the quadrotor one has:

$$R^i F^b = -mg\hat{e}_3 + \left(\sum_{i=1}^{4} C_T \Omega_i^2\right) R^i \hat{e}_3 + A_T \tag{11}$$

Where C_T represents the coefficient of thrust. The torques will be represented by

$$\tau^b = -\sum_{i=1}^{4} J_R(\omega \times \hat{e}_3)\,\Omega_i + \tau_a + A_R \tag{12}$$

Where g is the gravitational constant, $g = 9.81 m/s^2$, J_R is the rotational inertial moment around the rotor's axis, ω_i is the angular velocity of the $i-nth$ rotor and the vectors $A_T = [\,A_x\, A_y\, A_z\,]^\top$ and $A_R = [\,A_p\, A_q\, A_r\,]^\top$ represent the aerodynamic forces and torques on the vehicle. Taking into account, the last equations the dynamics model can be arranged as, [27]:

$$\begin{aligned} \dot{\xi} &= V \\ \dot{V} &= -g\hat{e}_3 + R^i_{\hat{e}_3} \frac{C_T}{m}\left(\sum_{i=1}^{4} \Omega_i^2\right) + \frac{A_T}{m} \\ \dot{\eta} &= J_1^{-1}(\eta)\omega \\ J\dot{\omega} &= -\omega \times J\omega - \sum_{i=1}^{4} J_R(\omega \times \hat{e}_3)\Omega_i + \tau_a + A_R \end{aligned} \tag{13}$$

The main control input U_1 applied on the aerial vehicle can be represented as,

$$U_1 = \left(\sum_{i=1}^{4} f_i\right) = \left(\sum_{i=1}^{4} C_T \Omega_i^2\right) \tag{14}$$

Where f_i is the thrust force generated by each rotor. Writing the state vector in extended form one has,

$$x = \begin{bmatrix} x & y & z & \dot{x} & \dot{y} & \dot{z} & \phi & \theta & \psi & p & q & r \end{bmatrix}^\top \tag{15}$$

Hence, the equations of movement that describe the dynamics of the quadrotor can be written as:

$$
\begin{aligned}
\dot{x} &= u \\
\dot{y} &= v \\
\dot{z} &= w \\
\ddot{x} &= \frac{1}{m}\big(\cos\psi\sin\theta\cos\phi + \sin\psi\sin\phi\big)U_1 + \frac{A_x}{m} \\
\ddot{y} &= \frac{1}{m}\big(\sin\psi\sin\theta\cos\phi + \cos\psi\sin\phi\big)U_1 + \frac{A_y}{m} \\
\ddot{z} &= -g + \frac{1}{m}\big(\cos\theta\cos\phi\big)U_1 + \frac{A_z}{m} \\
\dot{\phi} &= p + q\sin\phi\tan\theta + r\cos\phi\tan\theta \\
\dot{\theta} &= q\cos\phi - r\sin\phi \\
\dot{\psi} &= q\sin\phi\sec\theta + r\cos\phi\sec\theta \\
\dot{p} &= \frac{I_{yy}-I_{zz}}{I_{xx}}qr - \frac{J_R\Omega}{I_{xx}}q + \frac{l}{I_{xx}}U_2 + \frac{A_p}{I_{xx}} \\
\dot{q} &= \frac{I_{zz}-I_{xx}}{I_{yy}}pr + \frac{J_R\Omega}{I_{yy}}p + \frac{l}{I_{yy}}U_3 + \frac{A_q}{I_{yy}} \\
\dot{r} &= \frac{I_{xx}-I_{yy}}{I_{zz}}pq + \frac{1}{I_{zz}}U_4 + \frac{A_r}{I_{zz}}
\end{aligned}
\tag{16}
$$

Where $U_2 = l\,C_T(-\Omega_2^2 + \Omega_4^2)$, $U_3 = l\,C_T(-\Omega_1^2 + \Omega_3^2)$ and $U_4 = C_D(-\Omega_1^2 + \Omega_2^2 - \Omega_3^2 + \Omega_4^2)$; where the C_D is the drag coefficient of the aircraft.

The next Table 1, describes the physical features of the UAV, all the information cited below is extracted from the research article [28], that also uses the Mambo Parrot quadrotor as a scientific platform:

Table 1. Quadcopter parameters

UAV Characteristics	Units		
Dimensions	13.2 × 13.2 × 4.1 cm		
Weight	0.063 kg		
Motor	Brushless (4)		
Flight time	8 min		
Sensors	IMU	Ultrasonic	Pressure
Camara	Monocular	60 FPS	
Distance	Arms	l	0.0624 m

2.2. Controller's Architecture

This section describes the controller architecture in the unmanned aerial vehicle system. The figure shows in a block diagram the methodology and design of the intended PID controller, using an Artificial Neural Network (ANN) [29]. The block model depicts the overall control architecture of the whole system, including all the designed controllers from the Mambo Parrot; the blocks not only show the altitude controller but also the other subsystems controllers, such as position, yaw and attitude, that configures the complete quadrotor system shown in Fig. 5.

2.3. PID Controller

The importance of the PID controllers remains principally for three main reasons: record of success, simplicity in use and wide availability. These justifications reinforce each other, by ensuring that the general framework of digital automatic control with higher order controllers has not really

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been capable to substitute PID control [3]. Even in the case where the complexity process of control requires multiple - loop or multi - variable solution a network based on PID control blocks is used. In the manned aviation only PID controllers are implemented. The next equations describe the continuous and discrete time mathematical PID formula, [3]:

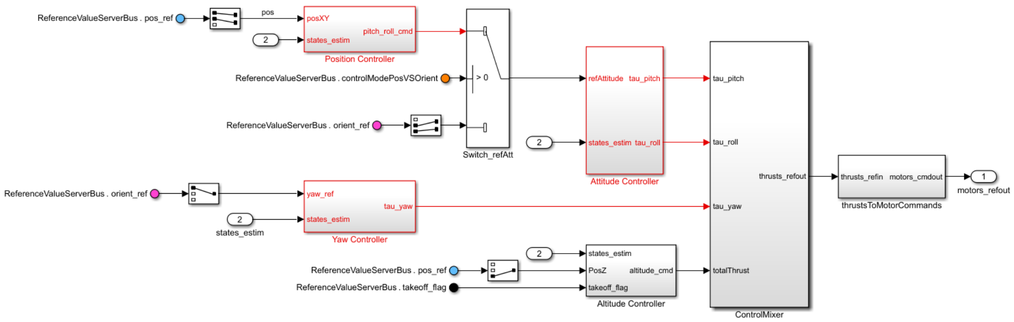

Fig. 5. Mambo parrot's control system

$$U_1(t) = k_P\, e(t) + K_I \int^t e(\tau)\, d\tau + k_D \frac{de}{dt} \quad ; \quad U(n) = K_p\, e(n) + k_i \sum_{k=0}^{n} e(k) + k_d \left(e(n) - e(n-1)\right) \tag{17}$$

where: $k_i = \frac{k_p T}{T_i}$ and $k_d = \frac{k_p T_d}{T}$

Particularly, in the context of unmanned aerial vehicles quadrotors, a comparison can be established between PID controllers and SMC (Sliding Mode Control), associating this distinct advantages and challenges with each control strategy. This comparison is intended to strength the research methodology applied in this investigation. The next Table 2 establishes the above described comparison, where in conclusion the choice between PID and SMC for UAVs largely depends on the specific application requirements including desired performance characteristics and environmental conditions, [30].

Table 2. Comparison between PID & SMC

Features	PID	SMC
Complexity	Low	High
Robustness	Moderate	High
Ideal Application	Linear Systems	Non Linear Systems
Parameters Adjustment	Manual Setting	Automatic
Sensitivity	High	Low

Inside the recent developments in controllers for unmanned aerial vehicles, specifically in quadrotors, advances have been made using different control strategies, which comprises the use of ANN and MPC (Model Predictive Control), both techniques are frequently employed in robotics, power systems and automation. The ANN is commonly used in applications where system dynamics are highly nonlinear or difficult to model accurately, such as robotic control systems, rehabilitation devices, and adaptive systems, [31], [32]. Meanwhile, MPC is widely applied in industrial processes, power systems, and situations where constraints must be explicitly handled, such as chemical process control and energy manage systems. While both controllers offer advance solutions for control problems, they cater to different need based on system characteristics, complexity, and operational requirements, [33], [34]. ANNs excel in an adaptability and quick execution after training, while MPC provides robust performance with optimal control strategies but may require more computational resources. Due to the understanding of these differences, the appropriate control strategy has been selected, as the next Table 3 shows, [35]

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Table 3. Comparison between ANN & MPC

Features	ANN	MPC
Learning Method	Data - Driven Learning	Model - Based Optimization
System Representation	No Explicit Model Required	Requires a Predictive Model
Constraint Handling	Limited Explicit Constraint Handling	Explicity incorporates Constraints
Adaptability	Highly Adaptable	Less Adaptable; relies on Model Updates
Computational Requirements	Fast Inference Post - Training	High Computational Cost per Step

2.4. Altitude Controller

The difference between the desired altitude z_{ref} and the actual measured altitude $\hat{z}_{KF} \approx z$, estimated using a *Kalman Filter*, is designated as the regulation error, this is, thus, the controller U_1 will output a correction signal to keep the aerial vehicle flying at a desire altitude [36].

$$e(k) = z_{ref} - \hat{z}_{KF} \tag{18}$$

The next figure indicates the general architecture for the altitude controller of the system, where $\hat{\dot{z}}_{KF} \approx \dot{z}$ shown in Fig. 6.

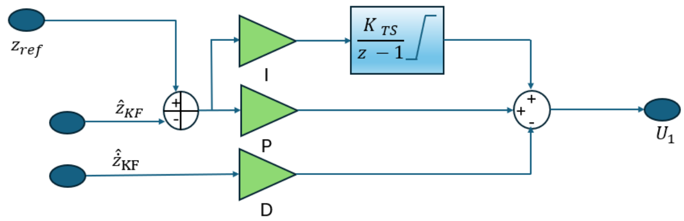

Fig. 6. Altitude controller

2.5. Artificial Neural Networks (ANNs)

An Artificial Neural Network (ANN) is a mathematical model that simulates the structure and functionalities of biological neural networks. The basic building block of every network is an artificial neuron, i.e. a simple mathematical model [29].

$$\bar{y}_i = f_i\left(\sum_{j=0}^{n} w_{ij}\, x_j - \bar{\theta}_i\right); \quad w_{i0} = \bar{\theta}_i \quad x_0 = -1 \tag{19}$$

Such calculation unit has three simple sets of rules: multiplication, addition and activation. The objective of the neuron is that the inputs x_j are weighted w_{ij}, this means that every input value is multiplied with individual weight; in the middle section the neuron sums all weighted inputs $w_{ij}x_j$ and bias θ_i; the neuron output y_i is the addition of all previously weighted inputs and bias crossed through an activation function $f_i(\cdot)$ [37].

Since the current use of the artificial intelligence, different training methods have been designated to help the networks to learn simple and fast, one of the current used methods is the BP - Backpropagation which finds the minimum error function from a determined learning problem through the descent in the direction of the gradient shown in Fig. 7. The combination of weights which minimizes the error function is a solution of the learning problem. It is needed the computation requirement of the gradient error's function, at each iteration; continuity and differentiability of the error function must be guaranteed, [29].

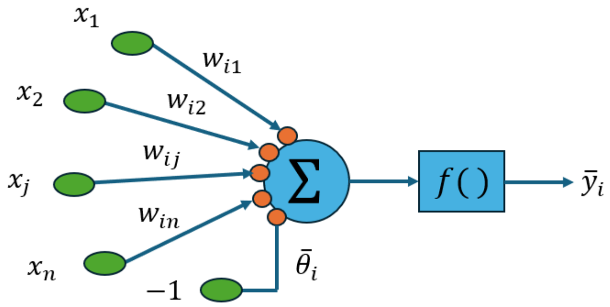

Fig. 7. Artificial neuron

2.6. Genetic Algorithms (GA)

Genetic Algorithms (GA) are optimization methods, an optimization problem generally is given in the form, find an $x_0 \in \mathcal{X}$ such that f is maximal x_0 where $f : \mathcal{X} \longrightarrow \mathbb{R}$ is an aleatory real valued function, this is $f(x_0) = \underset{x \in \mathcal{X}}{max}\, f(x)$ [38].

The general concept of the use of a GA basically relies in four main components:

- **Selection**: Process for selecting individuals for reproduction according to their objective function value (fitness).
- **Crossover**: Method of bringing together the genetic information of two individuals, if the right coding is properly chosen, two good parents would produce a good children.
- **Mutation**: The genetic material can be changed randomly by erroneous reproduction. In GA mutation is a random deformation of the individuals with certain probability; the preservation of the genetic diversity is an effect of the local maximal being avoided.
- **Sampling**: Process which computes a new generation from the previous one and it is decedents.

Other optimization methods, such as Newton or Gradient Descent don't have the same advantages as the GA algorithm, e.g. the algorithm manipulates encoded versions of problem parameters instead of parameters themselves. Contrary to the traditional methods the GA algorithm searches to a whole population of points instead of one, reducing the risk of getting trapped in a local stationary point. GAs do not use auxiliary information about the objective function value such as derivatives, i.e. it can be applied for continuous or discrete optimization problems. Finally, a GA uses probabilistic transition operators, specifically to create new generations, [29]. Hence, the basic structure of Genetic Algorithm can be written as follows:

GA - Algorithm:

t: = 0;
Compute initial population $\mathcal{B}_0$;
while *stopping condition not fuldilled* **do**
  begin;
  select individuals for reproduction;
  create offsprings by crossing individuals;
  eventually mutate some individuals;
end

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2.7. GA - ANN Self Tuning PID Controller

In this subsection the developed controller will be explained, and its overall architecture will be depicted. A Genetic Algorithm (GA) is an adaptive heuristic search algorithm that imitates biological evolutionary mechanism of the survival of the fittest, this algorithm is widely used to solve optimization problems in combination with Artificial Neural Networks (ANNs) [39]; GA is efficient, practical and robust, by selecting the best individuals it optimizes the weights and thresholds of the neural network, avoiding to fall into local optima an improve the training speed effectively. Although a BP Neural Network is highly accurate, there is improvement space.

The idea of the improved neural network with GA, firstly by Genetic Algorithm structure of neural network, the initial connection weights, optimize the architecture of the initial threshold and learning rate and momentum factor, locate the better search space and the solution space, then the ANN algorithm is used in the small solution space of the network connection weights and thresholds re-optimization, search the optimal solution, the optimized ANN can predict better the output function, [26]. The developed controller is based on the synergy composed of a feed forward multi-layer artificial neural network fused with a genetic algorithm. From this combination the prediction capabilities of the neural network are improved, which estimates with high precision the proportional, integral and derivatives gains that make up the altitude controller of the unmanned aircraft.

The methodology implemented to build this novel control strategy, consists primarily of executing a genetic algorithm, employing an ITAE (Integral Time Absolute Error) as a main cost function, which aims to minimize it. The choice of implementing the ITAE consists in the broad use in control systems to optimize the performance of controllers. It emphasizes minimizing error over time, which is critical for systems requiring fast response to disturbances. The ITAE drives the system toward faster convergence and stability; it also minimizes the overshoot in the response, [40]. The cost (fitness) function to be minimize is the ITAE performance criterion; the integral of the absolute magnitude of error criterion is defined as: $ITAE = \int_0^T t \mid e(t) \mid dt$. The function's index has the advantages of producing smaller overshoots and oscillations than the Integral of the Absolute Error IAE or the Integral Square Error ISE indices. Therefore, it is the most sensitive of the three, i.e. has the best performance, [41].

Once the GA has found the optimal gains values, the obtained output is used as a database to feed, establish and train the artificial neural network. Through the input data, it adjusts an optimizes its weights and thresholds. As well as the ITAE criterion, the Mean Square Error is a widely use metric for measuring the average squared difference between predicted and actual values, it assesses model accuracy; its lower value indicates better model performance, [42]. Subsequently, the Mean Square Error (MSE) belonging to the network is evaluated over time for each iteration, which decreases by updating new weights and thresholds. The method used to train the network is called BP, by means the Levenberg - Marquardt optimization method, based on gradient descend. The next block diagram, Fig. 8, illustrates the described process.

It is worth mentioning, that the integration of GA with ANN has demonstrated performance in automatic control systems by reducing the time required to train the network and increasing the precision in the predictions and decisions made by the system. In studies were both GA and ANN are applied, it has been found that the model generated by GA can outperform ANN in terms of robustness and predictive capacity, especially in contexts with high variability or noise in the data [43]. As the block diagram, Fig. 8, explains in its information flow.

To conceptualize the process of the network creation starting from the use of the datasets, the network structure denotes the input into the network and shows the three calculated outputs; the hidden layers are made up of three layers, the first one has ten neurons, the second and third one has eight neurons respectively shown in the Fig. 9.

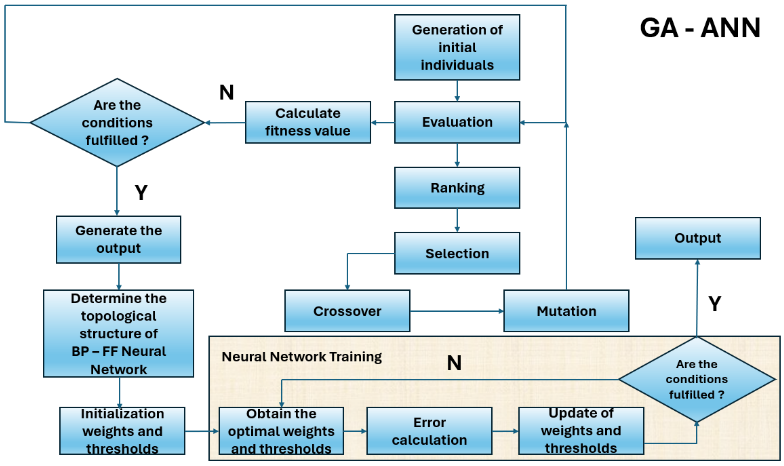

Fig. 8. Evaluation and optimization algorithm

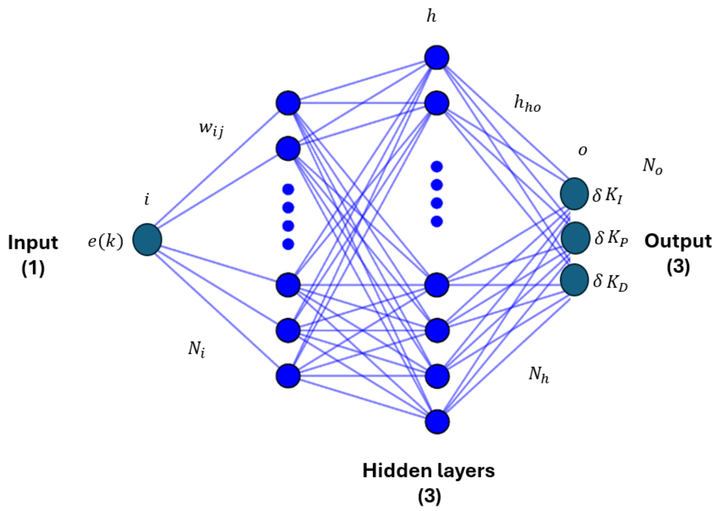

Fig. 9. SIMO ANN structure

In Table 4 illustrates, the mathematical link between the ANN structure and its mathematical counterpart. The table describes each of the layer's inputs and outputs and its corresponding equations; in the same manner it shows the employed activation function, as well as it correspondingly designation.

Table 4. ANN architecture

ANN's Equations	ANN's Features
$N_i = \sum_{i=1}^{n} w_{ij}\, e_k$	Hidden layer input
$N_h = \frac{2}{(1+e^{-2N_i})-1}$	Hidden layer output
$r = \sum_{j=1}^{n} N_h h_{ho}$	Output layer input
$\delta K_{PID} = \frac{2}{(1+e^{-2r})-1}$	Output layer output
$e = \delta K_{PID} - T$	Training error
$MSE = \frac{\sum_{i=1}^{n} e^2}{i}$	Mean Square Error

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3. Results and Discussion

In this section, the results obtained from this research project are presented, the results show the performance of the implemented controller, based on the synergy from an Artificial Neural Network (ANN) with a Genetic Algorithm (GA). The next graph shows the activation function used in the ANN Fig. 10. The block diagram in Fig. 11 illustrates the setting configuration of the designed controller, which highlights the cooperation between the ANN and GA algorithms to stabilize the MAV, it is worth mentioning that in aerial terms the stabilization of the aircraft is of great importance to validate the parameter [44]. The design of the GA is programmed in order, that none of the three gains of the vehicle's PID controller exceed the constant value 10 [45] - [46]. For its structure the main consideration was the ITAE, as previously explained; 25 generations were considered to train the Genetic Algorithm and the designed population consists of the best 50 individuals.

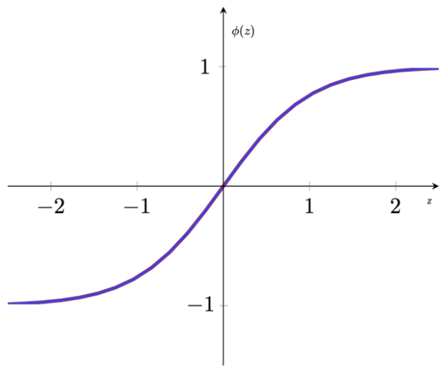

Fig. 10. Activation function of the ANN (tan - sigmoid transfer function)

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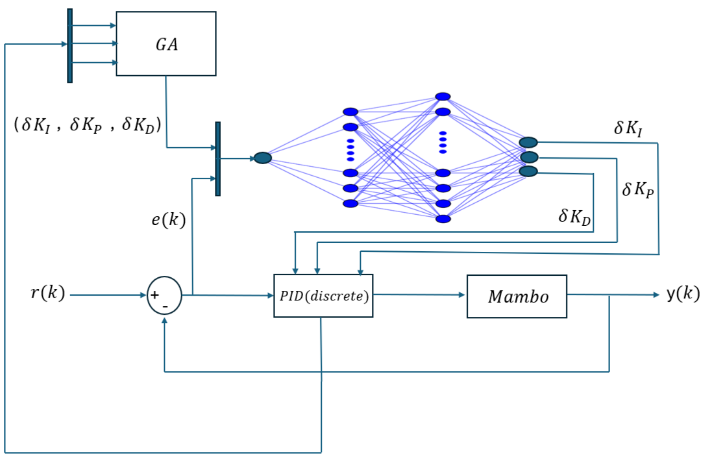

Fig. 11. Controller structure

The designed network is SIMO (Single Input Multiple Outputs) type, which includes an input layer, three hidden layers and three output layers, as shown in Fig. 12. The first hidden layer is made up of 10 neurons, while the second and third one is made up of 8, respectively. The network used is a Feed-forward type, the BP method used for its training is the Levenberg - Marquardt, due to its excellent convergence speed. The activation function employed for the three hidden layers is the sigmoid tangential function, 500 iterations or epochs were used for optimal training and an objective error of the gradient with the value of 0.0001 was considered.

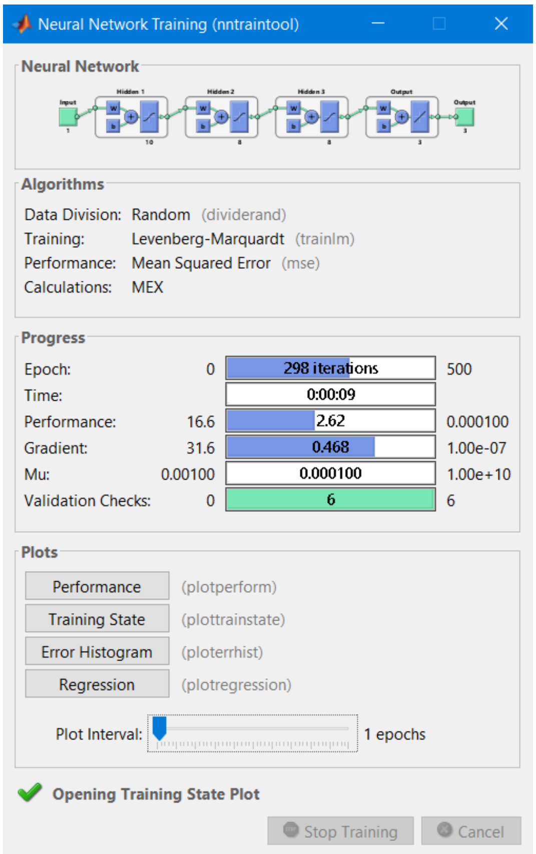

Fig. 12. ANN architecture

The following Fig. 13 shows, the behavior of the gradient used for the network optimization. Additionally, as can be seen, despite of the a priori establishment of 500 epochs for the optimal training, the network finds its own optimal point of convergence in iteration 298. The objective of the illustrations is to establish the numerical methodology implemented of the design of an ANN, which in the corresponding literature is established as an art and not as a recipe, i.e. this is the real meaning of the use of Artificial Intelligence (AI).

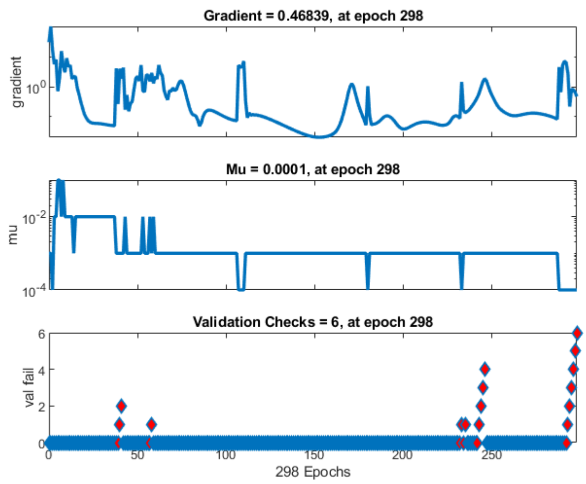

Fig. 13. Training parameters

During the training process it is important to consider the optimization of the error as explained, this parameter has to be minimized, in order that the network finds the optimal solution; Fig. 14 shows this process graphically, in which one can observe the steps required from the network to reach its goal. As expected, even though an Artificial Intelligence (AI) is processing, every dynamical process in the nature relies in the developed Gauss Region.

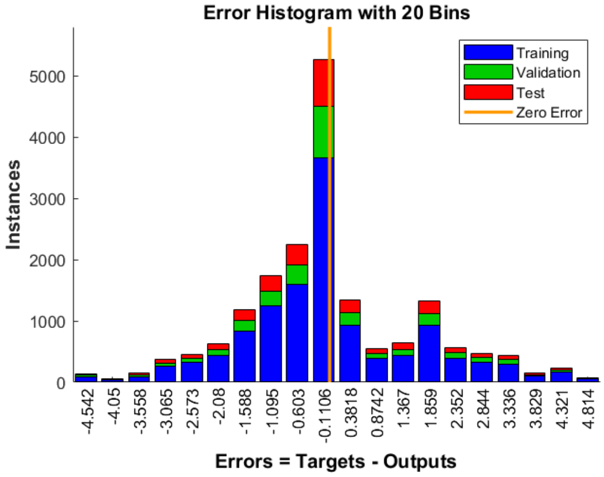

Fig. 14. Error optimization

It is important to remember that to evaluate the performance of the neural network, *Linear Regression Analysis* is considered, which is used to predict the dependence of two variables, i.e. the value of a variable based on the value of the independent variable. When the unity is reached the data fit is perfect. As can be seen in the Fig. 15, the graph depicts a data adjustment equivalent to 80 %, which is a satisfactory result to evaluate the performance of the designed network; the achieved percentage in the output data fulfills the establish goal, taking into account the complexity of the unmanned aerial vehicle dynamics.

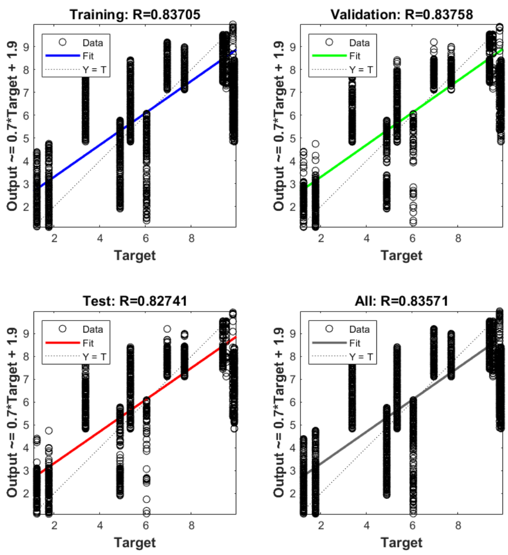

Fig. 15. Linear regression analysis

The statement of the achieved 80 % being satisfactory, may be interpreted particularly in relation to the specific application and data set used; i.e. the complexity and size of the data set is challenging and unbalanced, which again, 80 % may indicate a robust model. Where the performance level from an ANN is convincing under certain conditions, it is essential to evaluate this context with data set characteristics, and overall model robustness. Nevertheless, as mentioned, understanding the UAV's operational environment is crucial.

3.1. Controller Analysis

To test the proposed control algorithm, the simulation environment from the Mambo Parrot in MATLAB & SIMULINK is considered, the Fig. 16 shows the hover mode of the aircraft that is being controlled from the proposed control algorithm.

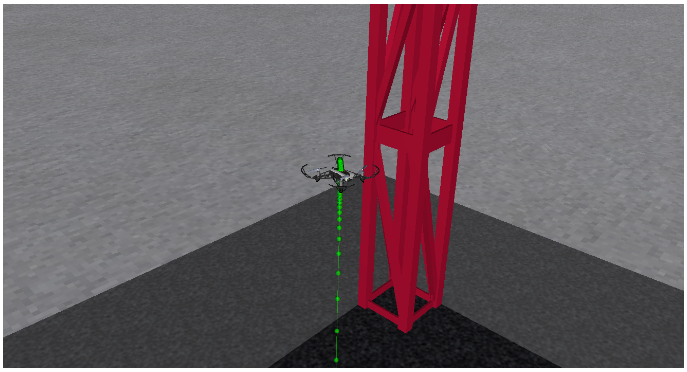

Fig. 16. UAV stationary control

The height at which the controller comes into action is $1.1\,m$, taking this parameter as the reference signal to follow [47]. The reference signal is been reached by the MAV, managing to maintain it in hover flight over the time. To demonstrate the effectiveness of the mathematical model and the altitude controller, a comparison Table 5 between the PID and the ANN - GA is included [48]. The Table shows some signal characteristics belonging to the altitude controller performance, as observed, it varies between attributes of the control signals.

Table 5. Comparison between PID & ANN - GA

Signal Statistics	PID Baseline	ANN - GA
Rise Time	$661.244\ ms$	$766.566\ ms$
Preshoot	$0.521\ \%$	$0.549\ \%$
Overshoot	$3.646\ \%$	$9.341\ \%$
Undershoot	$1.973\ \%$	$1.867\ \%$
ITAE	2.459	1.682
ISE	0.4765	0.4898
IAE	0.8222	0.852

The following Fig. 17 illustrates the performance of the controller implemented based on an ANN optimized from a GA. In the same way, it can be seen in the graph, that the designed controller manages to maintain and establish the aircraft satisfactorily at the selected reference signal of $1.1\,m$ throughout the simulation time.

Looking at Fig. 18, it can be observed that the implemented controller has a similar behavior with the original Mambo's PID controller, nevertheless in the comparison one can see the improvement with the synergy of both artificial intelligence algorithms, in terms of reducing the settling and rise time, the implemented controller demonstrates the efficiency of the stabilization in less time of the quadrotor [49], [50].

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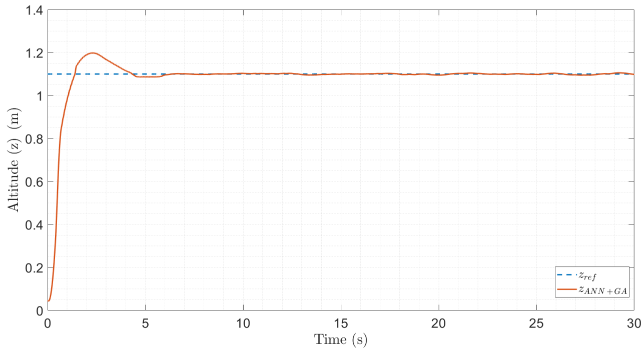

Fig. 17. $ANN + GA$ control performance

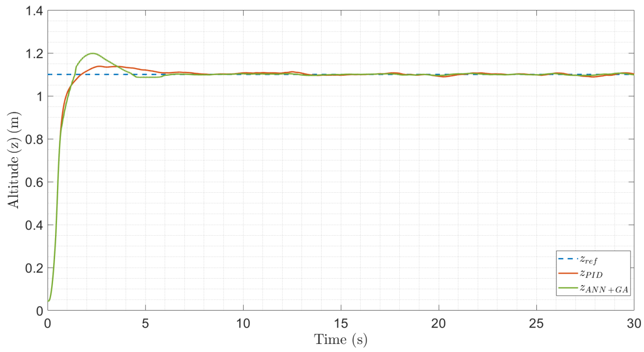

Fig. 18. PID vs $ANN + GA$ control comparison

As can be seen in the Fig. 19, the robustness of the designed controller against external disturbances on the altitude parameter of the aerial vehicle is observed, considering that the quadrotor employed is designed to fly mainly indoors under ideal conditions, without considering disturbances of any kind, the performance of the implemented controller is acceptable eventhough the UAV is disturbed; the controller based on the artificial intelligence algorithms shows efficient behavior. To analyze the trajectory tracking error of the variable altitude, the error known as Integral Time Absolute Error - ITAE is considered.

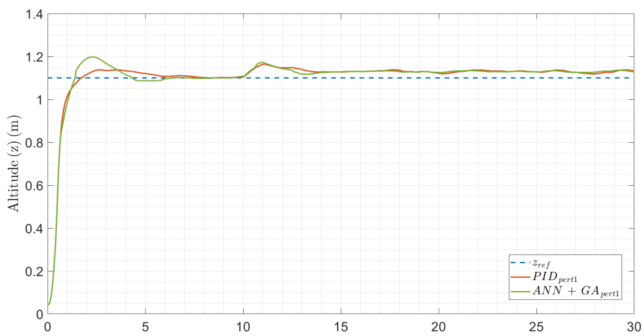

Fig. 19. Perturbated controllers performance

In the following Fig. 20, it can be seen that the performance of the developed controller is much better than the original Parrot Mambo controller; taking into consideration, the simulation time used, the magnitude of the ITAE from the controller based on artificial intelligence is much lower than the original controller of the unmanned aerial vehicle, which as observed has an increasing trend over time.

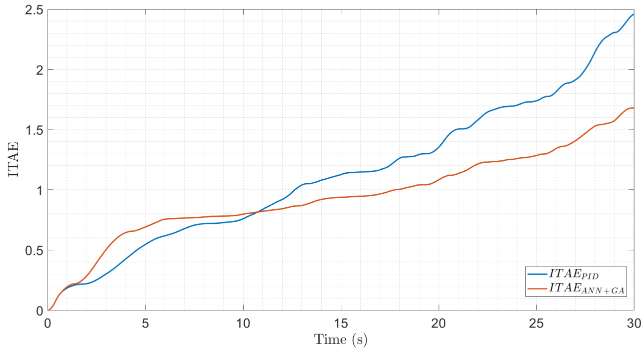

Fig. 20. Controller ITAE's comparison

The appropriate simulations that consider the total behavior of the errors employed is a determining characteristic of the real numerical analysis. Which is the principal intention of these graphs Fig. 20 and Fig. 21, i.e., to test the real numerical and absolute behavior of the artificial intelligence algorithm implemented.

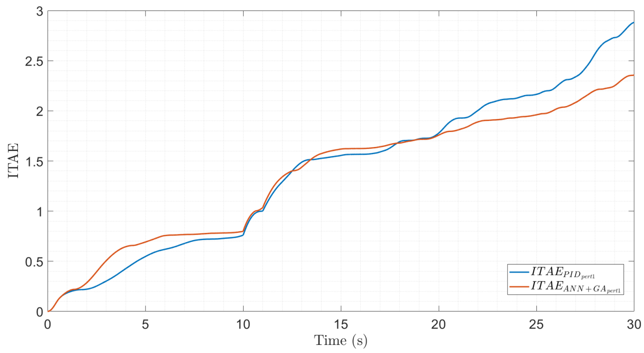

Fig. 21. Perturbated controller ITAE's comparison

It should be emphasized that even though the MAV is subjected to external disturbances on the controlled variable, both controllers show robustness to them, even so the controller designed with the arrangement in the ANN - GA shows better performance over all in the time compared to its counterpart.

4. Conclusions

The results of this research demonstrate the effective performance of an intelligent controller, structured around an Artificial Neural Network (ANN) optimized by a Genetic Algorithm (GA). This controller successfully adapts and enhances the MAV's PID gains over time, achieving optimal self-tuning behavior.

The PID gains optimization process leverages a Genetic Algorithm, which iteratively calculates the optimal gains. This process, initialized with a robust data set of 6000 input-output values, drives the training of the ANN using the Levenberg - Marquardt optimization method, leading to significant improvements in controller performance.

The findings confirm that the self-tuning controller effectively generates improved gain values, which are dynamically optimized through the intelligent algorithm. Notably, the self-tuning controller achieved a lower ITAE difference value of 0.776, i.e., a 31.6% lower ITAE than the original PID controller, demonstrating superior performance in maintaining stability, even when subjected to external disturbances. Moreover, the controller exhibits robust performance in the presence of external disturbances, effectively absorbing these perturbations and maintaining high level stability, which is critical for reliable MAV operations.

As possible future works, the results of this article could be applied in many different scientific fields of the automatic control theory, for instance, the architecture of the actual altitude controller could be easily implemented to intend control other state variables of the aerial vehicle. Finally, this type of designed controller can be implemented in rotary and fixed-wing UAVs to execute flight missions with higher complexity.

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References

[1] A. Isidori, *Lectures in feedback design for multivariable systems*, Springer Cham, 2017, https://doi.org/10.1007/978-3-319-42031-8.

[2] A. H. Khalil, *Nonlinear Control: Adaptation and Learning*, World Scientific, pp. 95–119, 2015, https://doi.org/10.1142/9789812819451_0002.

[3] D. E. Rivera, "PID Control: New Identification and Design Methods - [Book Review]," in *IEEE Control Systems Magazine*, vol. 26, no. 1, pp. 95-97, 2006, https://doi.org/10.1109/MCS.2006.1580159

[4] S. Seshagiri and H. K. Khalil, "Output feedback control of nonlinear systems using RBF neural networks," *Proceedings of the 1999 American Control Conference*, pp. 2808-2812 vol.4, 1999, https://doi.org/10.1109/ACC.1999.786584.

[5] D. A. Coley, *An introduction to genetic algorithms for scientists and engineers*, World Scientific Publishing Company, pp. 1–244, 1999, https://doi.org/10.1142/3904.

[6] J. E. Cross and W. McFarland, *Getting Started With The MATLAB Image Processing Toolbox*, ASEE Conferences, 2022, https://doi.org/10.18260/1-2-620-38769.

[7] N. H. Sahrir and M. A. M. Basri, "Intelligent PID Controller Based on Neural Network for AI-Driven Control Quadcopter UAV," *International Journal of Robotics and Control Systems*, vol. 4. no. 2, pp. 691-708, 2024, https://doi.org/10.31763/ijrcs.v4i2.1374.

[8] M. Fatan, B. L. Sefidgari and A. V. Barenji, "An adaptive neuro PID for controlling the altitude of quadcopter robot," *2013 18th International Conference on Methods & Models in Automation & Robotics*, pp. 662-665, 2013, https://doi.org/10.1109/MMAR.2013.6669989.

[9] C. Rosales, C. M, Soria and F. G. Rossomando, "Identification and adaptive PID Control of a hexacopter UAV based on neural networks," *International journal of Adaptive control and signal processing*, vol. 33, no. 1, pp. 74-91, 2019, https://doi.org/10.1002/acs.2955.

[10] L. Zhou, A. Pljonkin and P. K. Singh, "Modeling and PID control of quadrotor UAV based on machine learning," *Journal of Intelligent Systems*, vol. 31, no. 1, pp. 1112-1122, 2022, https://doi.org/10.1515/jisys-2021-0213.

[11] Y. Chen, S. Liu, C. Xiong, Y. Zhu and J. Wang, "Research on UAV Flight Tracking Control Based on Genetic Algorithm optimization and Improved bp Neural Network pid Control," *2019 Chinese Automation Congress*, pp. 726-731, 2019, https://doi.org/10.1109/CAC48633.2019.8996179.

[12] S. A. Gautam and N. Verma, "Path planning for unmanned aerial vehicle based on genetic algorithm & artificial neural network in 3D," *2014 International Conference on Data Mining and Intelligent Computing*, pp. 1-5, 2014, https://doi.org/10.1109/ICDMIC.2014.6954257.

[13] C. Nicol, C. J. B. Macnab and A. Ramirez-Serrano, "Robust neural network control of a quadrotor helicopter," *2008 Canadian Conference on Electrical and Computer Engineering*, pp. 001233-001238, 2008, https://doi.org/10.1109/CCECE.2008.4564736.

[14] K. Cengiz, S. Lipsa, R. K. Dash, N. Ivković and M. Konecki, "A Novel Intrusion Detection System Based on Artificial Neural Network and Genetic Algorithm With a New Dimensionality Reduction Technique for UAV Communication," in *IEEE Access*, vol. 12, pp. 4925-4937, 2024, https://doi.org/10.1109/ACCESS.2024.3349469.

[15] B. Selma, S. Chouraqui and B. Selma, "A genetic algorithm-based neuro-fuzzy controller for unmanned aerial vehicle control," *International Journal of Applied Metaheuristic Computing*, vol. 13, no. 1, pp. 1-23, 2022, https://doi.org/10.4018/ijamc.292505.

[16] V. Roberge, M. Tarbouchi and G. Labonté, "Fast Genetic Algorithm Path Planner for Fixed-Wing Military UAV Using GPU," in *IEEE Transactions on Aerospace and Electronic Systems*, vol. 54, no. 5, pp. 2105-2117, 2018, https://doi.org/10.1109/TAES.2018.2807558.

[17] M. Mariani and S. Fiori, "Design and Simulation of a Neuroevolutionary Controller for a Quadcopter Drone," *Aerospace*, vol. 10, no. 5, p. 418, 2023, https://doi.org/10.3390/aerospace10050418.

[18] M. Pazooki and A. H. Mazinan, "Hybrid fuzzy-based sliding-mode control approach, optimized by genetic algorithm for quadrotor unmanned aerial vehicles," *Complex & Intelligent Systems*, vol. 4, pp. 79-93, 2018, https://doi.org/10.1007/s40747-017-0051-y.

[19] A. Boutemedjet, M. Samardzic, L. Rebhi, Z. Rajic and T. Mouada, "UAV aerodynamic design involving genetic algorithm and artificial neural network for wing preliminary computation," *Aerospace Science and Technology*, vol. 84, pp. 464-483, 2019, https://doi.org/10.1016/j.ast.2018.09.043.

[20] E. Kayacan, M. A. Khanesar, J. Rubio-Hervas and M. Reyhanoglu, "Learning Control of Fixed-Wing Unmanned Aerial Vehicles Using Fuzzy Neural Networks," *International Journal of Aerospace Engineering*, vol. 2017, no. 1, 2017, https://doi.org/10.1155/2017/5402809.

[21] L. Hua, J. Zhang, D. Li, X. Xi and M. A. Shah, "Sensor fault diagnosis and fault tolerant control of quadrotor UAV based on genetic algorithm," *Journal of Sensors*, vol. 2022, no. 1, p. 8626722, 2022, https://doi.org/10.1155/2022/8626722.

[22] S. H. Hong, J. Cornelius, Y. Wang and K. Pant, "Fault compensation by online updating of genetic algorithm-selected neural network model for model predictive control," *SN Applied Sciences*, vol. 1, no. 1488, pp. 1-16, 2019, https://doi.org/10.1007/s42452-019-1526-9.

[23] A. Elbatal, M. M. Elkhatib and A. M. Youssef, "Intelligent Autopilot Design Based on Adaptive Neuro - Fuzzy Technique and Genetic Algorithm," *2020 12th International Conference on Electrical Engineering*, pp. 377-382, 2020, https://doi.org/10.1109/ICEENG45378.2020.9171702.

[24] X. Lei, S. S. Ge and J. Fang, "Adaptive neural network control of small unmanned aerial rotorcraft," *Journal of Intelligent & Robotic Systems*, vol. 75, pp. 331-341, 2014, https://doi.org/10.1007/s10846-013-0017-2.

[25] C. Liu, W. Xie, P. Zhang, Q. Guo and D. Ding, "Multi-uavs cooperative coverage reconnaissance with neural network and genetic algorithm," *Proceedings of the 2019 3rd High Performance Computing and Cluster Technologies Conference*, pp. 81–86, 2019, https://doi.org/10.1145/3341069.3342968.

[26] V. Artale, C. L. R. Milazzo, C. Orlando and A. Ricciardello, "Genetic algorithm applied to the stabilization control of a hexarotor," *AIP Conference Proceedings*, vol. 1648, no. 1, 2015, https://doi.org/10.1063/1.4912983.

[27] T. Bresciani, "Modelling, identification and control of a quadrotor helicopter," *MSc theses*, 2008, https://lup.lub.lu.se/luur/download?func=downloadFile&recordOId=8847641&fileOId=8859343.

[28] J. R. M. Ibarra, J. M. Ulloa, L. A. M. Pachecho and H. R. Cortés, "A Sensor Fusion Approach to Observe Quadrotor Velocity," *Sensors*, vol. 24, no. 11, p. 3605, 2024, https://doi.org/10.3390/s24113605.

[29] R. Rojas, *Theorie der neuronalen Netze: eine systematische Einführung*, Springer Berlin, Heidelberg, 2013, https://doi.org/10.1007/978-3-642-61231-2.

[30] C. Cömert and C. Kasnakoğlu, "Comparing and developing PID and sliding mode controllers for quadrotor," *International Journal of Mechanical Engineering and Robotics Research*, vol. 6, no. 3, pp. 194-199, 2017, https://doi.org/10.18178/ijmerr.6.3.194-199.

[31] C. J. Lin and T. Y. Sie, "Design and experimental characterization of artificial neural network controller for a lower limb robotic exoskeleton," *Actuators*, vol. 12. no. 2. p. 55, 2023, https://doi.org/10.3390/act12020055.

[32] S. Saadatmand, P. Shamsi and M. Ferdowsi, "Power and Frequency Regulation of Synchronverters Using a Model Free Neural Network-Based Predictive Controller," in *IEEE Transactions on Industrial Electronics*, vol. 68, no. 5, pp. 3662-3671, 2021, https://doi.org/10.1109/TIE.2020.2984419.

[33] S. Buffa, A. Soppelsa, M. Pipiciello, G. Henze and R. Fedrizzi, "Fifth-generation district heating and cooling substations: Demand response with artificial neural network-based model predictive control," *Energies*, vol. 13, no. 17, p. 4339, 2020, https://doi.org/10.3390/en13174339.

[34] K. Yeom, "Design of deep neural network based model predictive controller for a car-like mobile robot," *International Journal of Mechanical Engineering and Robotics Research*, vol. 11, no. 8, pp. 606-613, 2022, https://doi.org/10.18178/ijmerr.11.8.606-613.

[35] G. A. García and S. Keshmiri, "Online artificial neural network model-based nonlinear model predictive controller for the meridian UAS," *International Journal of Robust and Nonlinear Control*, vol. 23, no. 15, pp. 1657-1681, 2013, https://doi.org/10.1002/rnc.3037.

[36] A. A. Najm and I. K. Ibraheem, "Nonlinear PID controller design for a 6-DOF UAV quadrotor system," *Engineering Science and Technology, an International Journal*, vol. 22, no. 4, pp. 1087-1097, 2019, https://doi.org/10.1016/j.jestch.2019.02.005.

[37] S. Bari, S. S. Zehra Hamdani, H. U. Khan, M. u. Rehman and H. Khan, "Artificial Neural Network Based Self-Tuned PID Controller for Flight Control of Quadcopter," *2019 International Conference on Engineering and Emerging Technologies*, pp. 1-5, 2019, https://doi.org/10.1109/CEET1.2019.8711864.

[38] S. Imane, M. Mostafa, A. Hassan and E. K. Abdeljalil, "Control of a quadcopter using reference model and genetic algorithm methods," *2015 Third World Conference on Complex Systems*, pp. 1-6, 2015, https://doi.org/10.1109/ICoCS.2015.7483296.

[39] M. F. Q. Say, E. Sybingco, A. A. Bandala, R. R. P. Vicerra and A. Y. Chua, "A Genetic Algorithm Approach to PID Tuning of a Quadcopter UAV Model," *2021 IEEE/SICE International Symposium on System Integration*, pp. 675-678, 2021, https://doi.org/10.1109/IEEECONF49454.2021.9382697.

[40] A. J. Sultan, "Optimal load frequency control in a single area power system based Genetic Algorithm," *International Journal of Scientific & Engineering Research*, vol. 5, no. 1, pp. 2196-2200, 2014, https://www.researchgate.net/profile/Ahmed-Jasim-12/publication/262105512_Optimal_Load_Frequency_Control_in_a_Single_Area_Power_System_Based_Genetic_Algorithm/links/0a85e536a9139ea254000000/Optimal-Load-Frequency-Control-in-a-Single-Area-Power-System-Based-Genetic-Algorithm.pdf.

[41] D. Maiti, A. Acharya, M. Chakraborty, A. Konar and R. Janarthanan, "Tuning PID and PID controllers using the integral time absolute error criteria," *4th International Conference on Information and Automation for Sustainability ICIAFS*, 2008, https://doi.org/10.1109/iciafs.2008.4783932.

[42] T. R. Fraz, "Modeling and Forecasting of Rainfall Time Series. A Case Study for Pakistan Tayyab Raza Fraz," *International Journal of Economic and Environmental Geology*, vol. 13, no. 1, pp. 37-41, 2022, https://doi.org/10.46660/ijeeg.v13i1.20.

[43] A. Parisi, F. Parisi, and D. Díaz, "Modelos de algoritmos genéticos y redes neuronales en la predicción de índices bursátiles asiáticos," *Cuadernos de economía*, vol. 43, no. 128, pp. 251-284, 2006, https://www.scielo.cl/pdf/cecon/v43n128/art02.pdf.

[44] H. R. Cortés , G. R. Martínez, J. G. Romero and A. M. Luciano, "Asymptotic stabilization of a transformed quadrotor model using energy-shaping method: Theory and experiments," *ISA transactions*, vol. 139, pp. 739-749, 2023, https://doi.org/10.1016/j.isatra.2023.04.034.

[45] M. Sun, L. Yang, Y. Chang, L. Ma, Y. Xe and J. Song, "A Mass Adaptive PID Controller for Quadcopter with Different Burdens," *Proceedings of 2021 International Conference on Autonomous Unmanned Systems*, pp. 2910–2918, 2021, https://doi.org/10.1007/978-981-16-9492-9_285.

[46] N. Bao, X. Ran, Z. Wu, Y. Xue and K. Wang, "Research on attitude controller of quadcopter based on cascade PID control algorithm," *2017 IEEE 2nd Information Technology, Networking, Electronic and Automation Control Conference*, pp. 1493-1497, 2017, https://doi.org/10.1109/ITNEC.2017.8285044.

[47] A. Qi, "Research on prediction model of improved BP neural network optimized by genetic algorithm," *Atlantis Press*, pp. 764-767, 2018, https://doi.org/10.2991/macmc-17.2018.145.

[48] A. Iyer and H. O. Bansal, "Modelling, Simulation, and Implementation of PID Controller on Quadrotors," *2021 International Conference on Computer Communication and Informatics*, pp. 1-7, 2021, https://doi.org/10.1109/ICCCI50826.2021.9402301.

[49] S. Bari, S. S. Zehra Hamdani, H. U. Khan, M. u. Rehman and H. Khan, "Artificial Neural Network Based Self-Tuned PID Controller for Flight Control of Quadcopter," *2019 International Conference on Engineering and Emerging Technologies*, pp. 1-5, 2019, https://doi.org/10.1109/CEET1.2019.8711864.

[50] J. Gómez-Avila, C. López-Franco, A. Y. Alanis and N. Arana-Daniel, "Control of Quadrotor using a Neural Network based PID," *2018 IEEE Latin American Conference on Computational Intelligence*, pp. 1-6, 2018, https://doi.org/10.1109/LA-CCI.2018.8625222.