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HYBRID NATURE-INSPIRED OPTIMIZATION FOR STABILITY AND DISTURBANCE REJECTION IN TETHERED UNMANNED AERIAL VEHICLES

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Doctor of Philosophy

Supervisor

Assoc. Prof. Dr. Sefer KURNAZ

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The dissertation titled HYBRID NATURE-INSPIRED OPTIMIZATION FOR STABILITY AND DISTURBANCE REJECTION IN TETHERED UNMANNED AERIAL VEHICLES prepared by ALIALHADI KHALEEL ISMAEL ISMAEL and submitted on 09/12/2025 has been **accepted unanimously** for the degree of Ph.D. in Electrical and Computer Engineering Department.

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Signature

DEDICATION

I would like to extend my sincere gratitude to my supervisor, Assoc. Prof. Dr. Sefer Kurnaz. It is with great appreciation that I acknowledge your invaluable guidance, continuous support, and unwavering encouragement throughout this journey. Your knowledge, direction, and generous assistance have significantly shaped my academic progress. I wish you continued success, fulfillment, and outstanding achievements in all aspects of your life.

ABSTRACT

HYBRID NATURE-INSPIRED OPTIMIZATION FOR STABILITY AND DISTURBANCE REJECTION IN TETHERED UNMANNED AERIAL VEHICLES

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The study proposes a new hybrid optimization model that is intended to be used in the design of a high-level attitude control system to be applied in tethered Unmanned Aerial Vehicles (UAVs). The suggested solution is based on a Fractional-Order Proportional-Derivative-Integral (FOPDD-I) controller alongside a hybrid optimum algorithm that will be a fusion of Harris Hawks Optimization, the Eagle Strategy, and Particle Swarm Optimization (HHHO-ES-PSO). A systematic comparison of the optimized FOPDD-I controller performance with a number of benchmark control schemes is made, such as the Conventional PID, Cascade PID, classical Active Disturbance Rejection Control (ADRC), and Advanced ADRC. Extensive simulations with MATLAB indicate that the HHHO-ES-PSO-tuned FOPDD-I controller has a better dynamic behavior, which is characterized by higher stability, quicker transient response, and better disturbance rejection than the traditional ones. The quantitative results of optimization show an increase in the proportional gain (K_p) by 56.5% and in the integral (K_i) gain by 65.2% and a reduction in the derivative gain (K_d) by 98.4% effectively reducing the yaw overshoot and oscillatory behavior. In addition, the parameters of the fractional-order were also adjusted in an adaptive manner, which resulted in adaptability gains of 12.5% and 14.7% in nonlinear dynamic conditions. Conversely, traditional PID and Cascade PID controllers only offered small gains in tuning, whereas classical and improved ADRC methods demonstrated moderate, but relatively small, gains in performance. The results of the study have also demonstrated that a significant portion of the value of applying a fractional-order control in conjunction with

hybrid metaheuristic optimization lies in the fact that the suggested model, FOPDD-I controller, is a powerful and adaptable approach to tethered UAV attitude control in highly complex and uncertain operating conditions.

Keywords: Unmanned Aerial Vehicles, Harris Hawks Optimization, Eagle Strategy FOPDD-I Controller, Active Disturbance Rejection Control, Particle Swarm Optimization.

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ABBREVIATIONS

FLC	:	Fuzzy Logic Controller
FOPDD-I	:	FOPID-Integral
FOPID	:	Fractional-Order PID
GA	:	Genetic Algorithms
GNSS	:	Global Navigation Satellite Systems
GPS	:	Global Positioning System
HHHGO-ES-PSO	:	Hybrid Harris Hawks Optimization-Eagle Strategy-Particle Swarm Optimization
HHO	:	Harris Hawks Optimization
IAE	:	Integral Absolute Error
ITAE	:	Integral of Time-Weighted Absolute Error
LQR	:	Linear Quadratic Regulator
MPC	:	Model Predictive Control
MS-HHO	:	Mixed-Strategy Harris Hawk Optimization
PID	:	Proportional-Integral-Derivative
PSO	:	Particle Swarm Optimization
RMSE	:	Root-Mean-Square Error
RSLQR	:	Robust LQR Servomechanism
UAS	:	Unmanned Aircraft System
UAVs	:	Unmanned Aerial Vehicles
VTOL	:	Vertical Take-Off and Landing

LIST OF SYMBOLS

K_p	:	Proportional Gain of the Controller
K_i	:	Integral Gain of The Controller
K_d	:	Derivative Gain of the Controller
λ	:	Order of The Integral Term of The Controller
μ	:	Order of The Derivative Term of The Controller
ψ	:	Yaw Angle
θ	:	Pitch Angle
ϕ	:	Roll Angle
β	:	Controls of The Degree of Local Refinement
ω	:	Angular Velocity Vector
τ	:	Total Control Torque From The Rotors
l	:	Rotor Arm Length
ε	:	Linear Weight Per Unit Length

1. COMPREHENSIVE BACKGROUND

1.1 INTRODUCTION

Unmanned Aerial Vehicles (UAVs) are an emerging category of aerial platforms that have been developed to work without a human pilot on board. These systems combine aerodynamic designs, propulsion systems, navigation systems, and sophisticated control algorithms in order to execute autonomous or remotely controlled missions. The term UAV is used in engineering and scientific texts to refer to a flying vehicle, whereas Unmanned Aircraft System (UAS) is used to refer to the whole system of operation, including the UAV, ground control station, communication infrastructure, and data-processing units. The UAVs have revolutionized many areas, including defense, reconnaissance and surveillance, precision agriculture, aerial photography, infrastructure inspection, and disaster assessment because of their flexibility, reduced cost of operation, and accessibility to dangerous or otherwise inaccessible areas. The advancement of technology in lightweight materials, micro-electromechanical sensors, satellite navigation, and artificial intelligence has greatly increased the capabilities of UAVs, providing extra stability, increased endurance, and complete autonomous flight [1]. Aerodynamically, UAVs may be categorized into three broad groups, which include fixed-wing, rotary-wing, and hybrid systems, as shown in Figure 1.1. Fixed-wing UAVs are similar to traditional aircraft and utilize forward propulsion and lift provided by fixed wings, which is why they would be most ideal in long-range and high-altitude operations. Rotary-wing UAVs, such as quadcopters, hexacopters, and octocopters, are able to provide lift and maneuverability with the use of rotating blades, which enable them to the mode in the Vertical Take-Off and Landing (VTOL) and hover. The hybrid UAVs are a combination of both the aerodynamic principles with the endurance of the fixed-wing aircraft and the agility of the rotary-wing. All types have their own trade-offs in terms of flight duration, payload capacity, power consumption, and complexity of control, causing different researchers to use UAVs in specific configurations to meet certain mission requirements [2].

Basically, the UAV systems represent an amalgamation of numerous engineering fields, such as mechanical design, aerodynamics, control theory, embedded systems, and communication networks. The way they have evolved over the years proves the possibility of autonomous technology of aerial vehicles to maximize the situation awareness, data collection, and efficiency of operations, both in the military and the civilian environment. Figure 1.1 shows that the awareness of the structural diversity and functional schemes of the UAV types is the basis of the analysis of their performance, restrictions, and the new opportunities in the modern aerospace systems [3], [4].

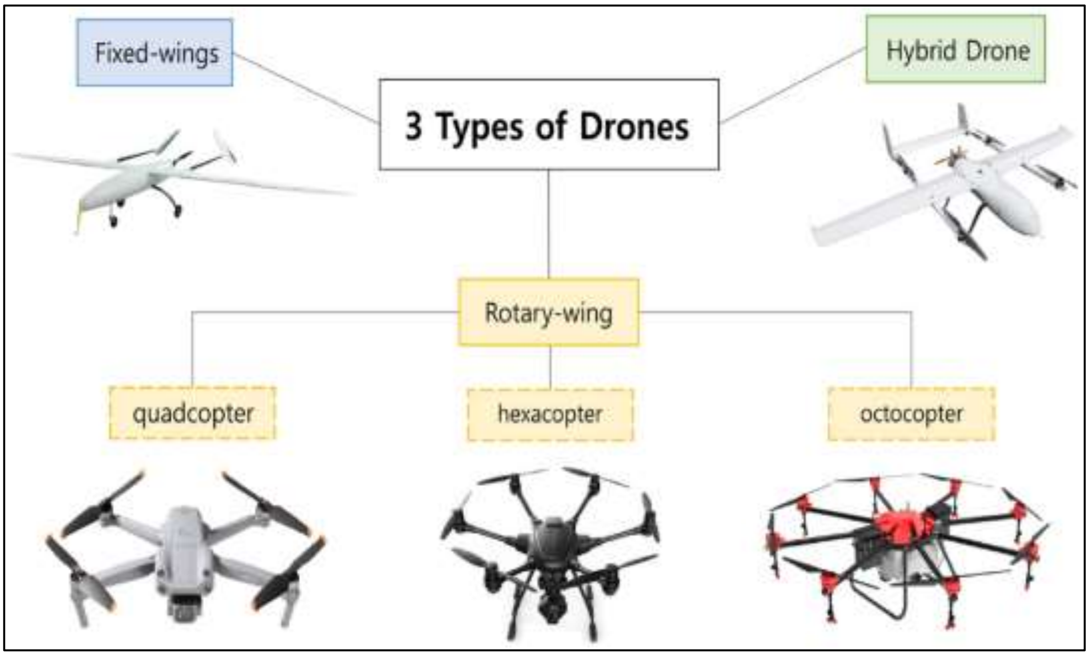

Figure 1.1: Main Types of Uavs [3].

1.2 HISTORICAL EVOLUTION OF UAVS

The history of the development of unmanned aerial vehicles has developed in a sequence of the last one hundred years, as a result of the convergence of technological advancement and the desire of humans to prolong the flight beyond the scope of direct control. In the early twentieth century, inventors explored remotely controlled airframes, which could be controlled without pilots, and this was driven by the fact that safer training equipment and reconnaissance systems were needed. The Ruston Proctor Aerial Target project and the Hewitt-Sperry Automatic Aeroplan of the First World War showed that a craft could be able to fly with the aid of gyroscopes and primitive radio connections. By the mid-1930s, the Queen Bee, or radio-controlled version of Tiger Moth, was the first widely used target drone, and the word drone as such was created [5]. This direction of research became even more rapid during the Second World War and resulted in the creation of the V-1 "Doodlebug" and other pilotless planes to be used both in reconnaissance and in attack. The next few decades of Cold War competition stimulated the development of better control systems, propulsion performance, and real-time data transmission, which have enabled UAVs to undertake longer and complicated missions. Since 2001, unmanned platforms ceased to serve in an experimental support capacity and started taking center stage in defense and intelligence operations, and smaller electric quadcopters started to emerge in the civilian market, including maps, agriculture, and inspection. The recent 20 years have seen developments in satellite navigation, lightweight composite materials, and embedded computers that have led to the emergence of a new generation of autonomous and miniaturized UAVs. Even though this timeline, as indicated in Figure 1.2, indicates a series of mechanical inventions, it is based on a constant increase of purpose where each technological breakthrough redefined the role of unmanned flight in serving scientific, industrial, and humanitarian interests [6].

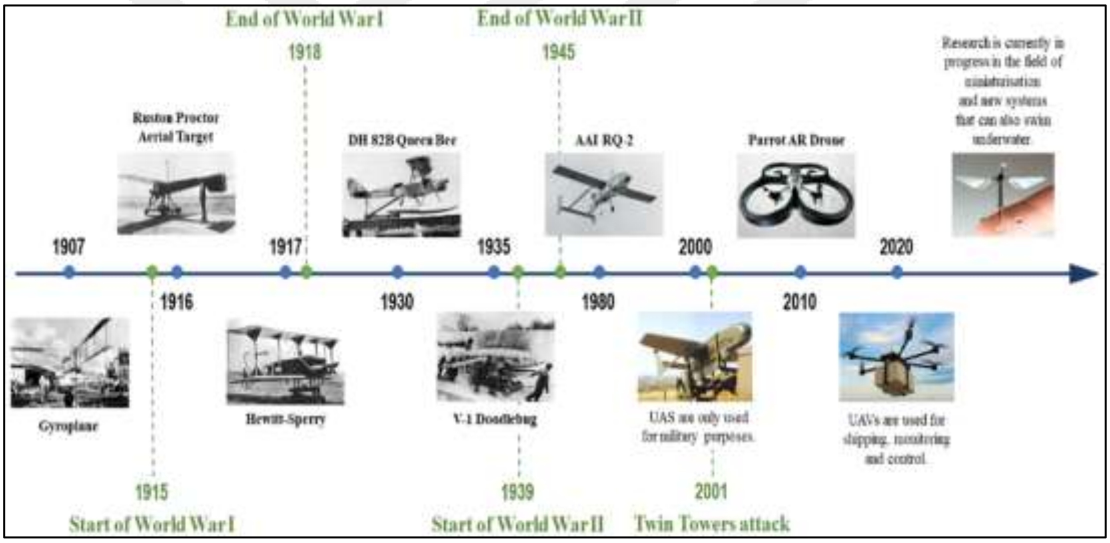

Figure 1.2: Evolution of UAV Development From Early to Modern Systems [6].

1.3 UAVS' ROLE IN INTELLIGENT AND AUTONOMOUS SYSTEMS

UAVs have evolved into manually controlled airframes to become equivalent to intelligent and autonomous systems of the present era. Their operations are based on the combination of advanced sensing, control, and computation that, in turn, allows them to perceive, reason, and make a decision without constant human control. UAVs are also equipped with optical, thermal, and LiDAR sensors, which can be used to gather high-fidelity spatial and environmental data that are processed with onboard microprocessors and embedded artificial-intelligence modules. Such systems use machine-learning algorithms to recognize features, avoid obstacles, and plan paths and control-theoretic models like Proportional-Integral-Derivative (PID) and model-predictive control to keep the plane stable by providing constant feedback of inertial and Global Positioning System (GPS) modules [7].

UAVs, in networked environments, are not only active agents of a distributed cyber-physical system, but they also perform other functions, namely, data acquisition. They can use high-bandwidth connections like 5G or Wi-Fi 6 to communicate in real time with the base stations, satellites, and other autonomous agents integrated through Internet-of-Things (IoT) infrastructures and supported by edge- and cloud-computing technologies. This networked nature enables UAVs to cooperate in Flying Ad-Hoc Networks (FANETs) and exchange information, coordinate their maneuvers, as well as distribute computing resources. The UAVs may serve as a mobile edge-computing agent, as shown in Figure 1.3, as a relay of airborne communication, or a node of a multi-agent robotic swarm- each has the benefit of increasing the intelligence, efficiency, and flexibility of the broader system. UAVs, along with being a link between digital intelligence and the physical world, represent a multidomain integration of sensing, computation, and connectivity that forms a vital component of autonomous infrastructures of the future that will assist in environmental monitoring, industrial automation, and robust communication networks [8].

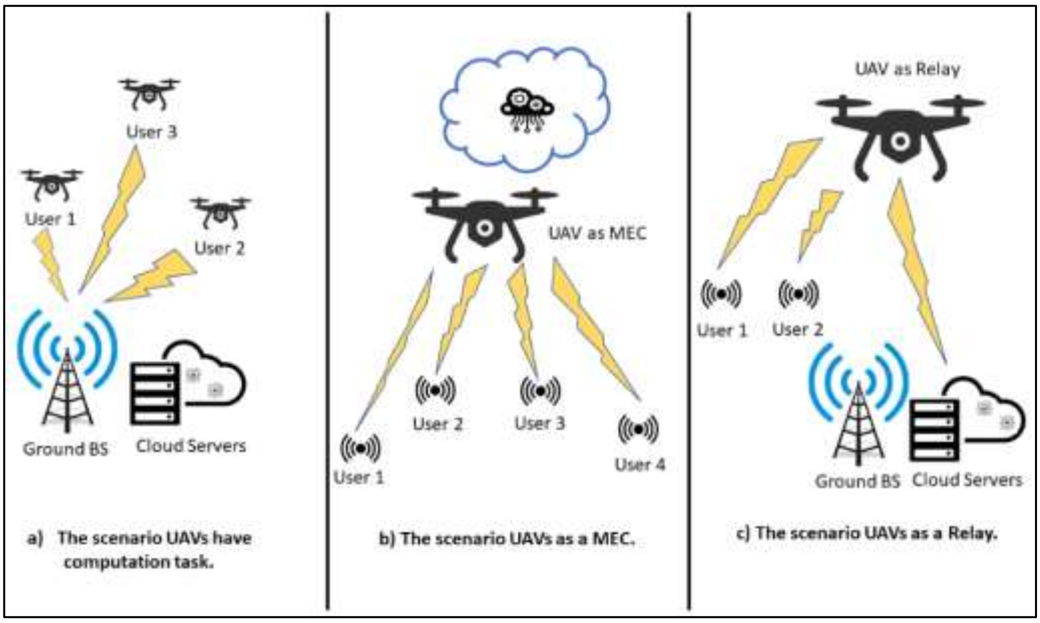

Figure 1.3: Roles of Uavs in Intelligent and Autonomous Systems.

1.4 IMPORTANCE OF UAVS

The importance of UAVs lies in the fact that they are revolutionary in the modern technological, economic, and social contexts. The remotely controlled or autonomous systems have revolutionized the concept of air operations in that accuracy, versatility, and effectiveness are brought together in a way aviation cannot achieve to date. The use of UAVs can be used to collect data at a scale never seen before in terms of spatial and temporal resolution which offers real time information that can be utilized in evidence-based decision-making in civilian and military settings. The capability to operate in hazardous or inaccessible locations, such as a disaster location, forest, or war zone, reduces the risk to human beings and offers continuity of operations. The scientific studies can use the UAVs as a cost-efficient tool in monitoring, sampling the atmosphere, and mapping the geology to boost the expediency of the discoveries that can be applied in the sustainable development and climate resilience requirements [9]. In economic terms, drones cause innovation and provide new industries that are related to air logistics, smart farming, surveillance, and digital mapping. They have further been utilized with artificial intelligence, IoT technologies, and novel sensors to even a higher degree in automation and intelligent systems, which guarantees efficiency in the industrial processes and resource management. Besides this, UAVs complement situational awareness, early warning systems, and border surveillance systems in national security and national defense, which enable the military forces to respond expeditiously to the arising threats without involving their manpower in large numbers. The other benefit of UAVs in the society is humanitarian aid that UAVs search and rescue, provide medical supplies, and make the aerial image of the situation, which is used to coordinate actions of other units. Overall, the importance of UAVs is even more significant than the mechanical properties; it is one of the blaring examples of engineering innovations, digital intelligence, and utility to society. UAVs are an ideal of an autonomous, networked, data-driven business that is the core of security, performance, and strategic superiority in a more sophisticated world need [10].

1.5 ADVANTAGES AND DISADVANTAGES OF USING UAVS

The fact that UAVs are becoming a common tool in the different industries evidences that they can benefit the modern society a lot. UAVs have turned into a powerful technological tool that would make the efficiency, accuracy, and safety meet. The fact that their work can be done either remotely or by themselves has not only minimized the risks of operations but it has also significantly enhanced the level of productivity and quality of data in most fields. UAVs offer practical and affordable alternatives which greatly outweigh what more rigid traditional manned systems can accomplish in terms of mapping, surveillance, agriculture or research. Incorporating real-time sensing, artificial intelligence and comparatively advanced communications systems, UAVs have turned out to be irreplaceable in the realm of such applications, which demand accuracy, rapid response, and extended outcomes. The advantages of UAVs could be listed as follows [11], [12]:

i. Cost Wise: UAVs prevent the need to use costly aircraft, fuel, and manpower; hence, the air operations are less expensive, commercially and in the government.

ii. Operational Safety: They are also able to explore dangerous or inaccessible places such as war zones, disaster area or industries without placing human beings in danger.

iii. High-Resolution Data collection: UAVs are provided with sophisticated sensors and cameras, which allow them to capture precise images and measurements to increase the validity in the field of mapping, inspection, and analysis.

iv. Small and Maneuverable: The size and maneuverability allow them to operate in most types of environments, including the city, forest and the remote scenery.

v. Time Efficiency: UAVs complete monitoring tasks and survey assignments in a fraction of the time that the traditional process requires, and making decisions and responding to emergencies becomes faster than using traditional methods.

vi. Environmental Sustainability: UAVs can operate in an environmental-friendly manner consistent with the environmental impact of the conventional aerial systems due to less energy usage and low emissions.

vii. Independent and Smart Control: The introduction of AI and GPS technologies allows planning the autonomous flight, avoiding the obstacles, and smart data processing.

viii. Enhanced Communication and Connection: UAVs can serve as temporary communication links in remote locations or disaster-affected locations to assist in the process of rescue and relief.

ix. Flexibility of Use: UAVs are customizable to suit any industry with payload versatility and mission structure deployed in defense and law enforcement, and agriculture and filmmaking.

UAVs are also associated with a range of challenges and limitations even despite their many benefits. It is sensitive to weather, and may seriously impact on the stability, flight time, and accuracy of the data, especially in high winds or heavy rain. Short power life is one of the key drawbacks of long or distance operations which may involve frequent recharging or several batteries to cover such a vast distance. Also, the UAVs bring about privacy and security issues because upon uncontrolled operation, they may lead to unauthorized surveillance or breach of data. There is also the danger of accidents, collisions, and signal jamming in congested airspace which may bring threats to the safety of people and property. Moreover, initial prices of premium drones are expensive, and legal regulations in most countries might restrict their mass adoption. Thus, although UAVs have significant technological advantages, it is crucial to mitigate the associated drawbacks to make their implementation to the current systems safe, ethical, and sustainable [13].

1.6 APPLICATIONS OF UAVS

As it has been mentioned above, Drones, or more to the point, UAVs, have quickly become a necessity in both civilian and military fields. They have made them perfect in a wide variety of tasks due to their flexibility, data gathering capability, and comparatively lower cost of operation. Their ability to deliver a wide range of different equipment, including optical cameras, thermal cameras, multispectral cameras, and high-performing communication modules, has seen them now finding application in a wide range of real-world applications. As Figure 1.4 demonstrates, the UAV usage can be divided into two broad categories: civilian and military. Both types have different purposes and require varied technological requirements. Some of the most important applications of UAVs can be briefly described below [14, 15]:

i. Intelligence, Surveillance, and Reconnaissance: The UAVs developed today with electro-optical and infrared cameras are utilized to collect intelligence indefinitely and without exposing people to danger. They permit early-warning and tactical situational awareness.

ii. Fighting and Direct Strike: Armed drones are deployed for precision attacks and tactical operations that reduce collateral damage and maximize the effectiveness of the operation.

iii. Logistical and Support Operations: UAVs are used more and more in the transportation of medical kits, ammunition, and supplies into areas that are remote or contested.

iv. Electronic Warfare and Border Security: Advanced systems are used to intercept signals, jamming, and real-time monitoring to build national defense supporting capabilities.

v. Agriculture and Precision Farming: Drones equipped with multispectral imaging sensors help farmers track crop status, assess soil moisture content, and identify pest infestations the resulting data help in making precision-based decisions that will enhance yield and minimize chemical waste.

vi. Environmental Observation and Disaster Management: UAVs may be deployed to provide real-time information when it comes to measuring natural disasters such as floods, wildfires, and earthquakes. They assist in rapid evaluation of damage, control of rescue, and provision of emergency resources to inaccessible locations.

vii. Urban Planning and Infrastructure Inspection: The drones help to improve the planning of construction, bridge monitoring, and road repair with high-resolution aerial mapping and photogrammetry. They have the capacity to produce three-dimensional terrain models, which makes project management cost-effective and less risky.

viii. Media, Entertainment, and Logistics: UAVs are being used in the business sector to perform aerial cinema, advertisement, journalism, and even the delivery of parcels. Their dynamism, as well as low cost of operation, make them an important tool to every industry that needs flexibility in data capture and transport solutions.

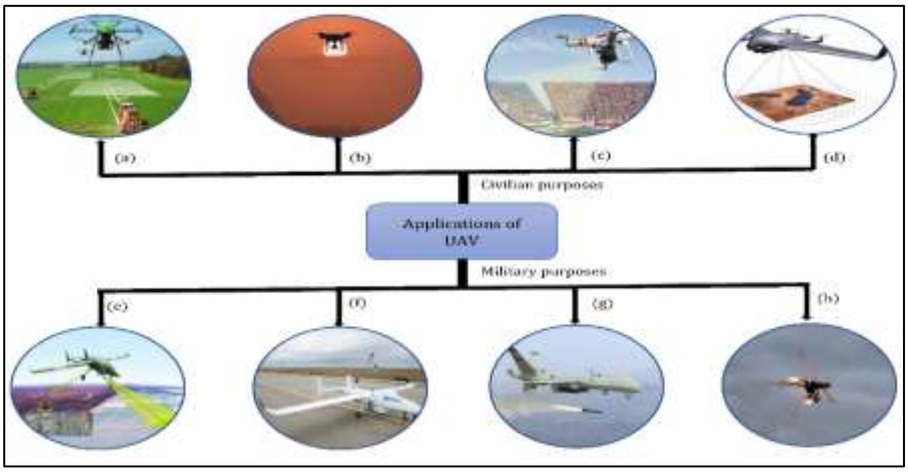

Figure 1.4: Applications of Uavs Across Various Operational Domains [14].

1.7 UAVS CONTROL AND OPTIMIZATION SYSTEMS

The control, guidance, and optimization of the UAVs are the main structure that regulates the stability, navigation, and mission-level intelligence of the aircraft. These systems are interactive so that the UAV is able to achieve reliable flight performance, precise flight following planned trajectories, and dynamically respond to environmental variations or operational constraints. Their functionality depends on the incorporation of high-tech sensors, smart algorithms, and strong communication channels that provide a connection between the vehicle and the ground control station. A UAV system generally entails a closed-loop interaction among the ground control station, the real UAV platform, and an artificial or simulated UAV system, as shown in Figure 1.5, in which computational experiments are crucially involved in the optimization of missions as well as predicting their performance [15].

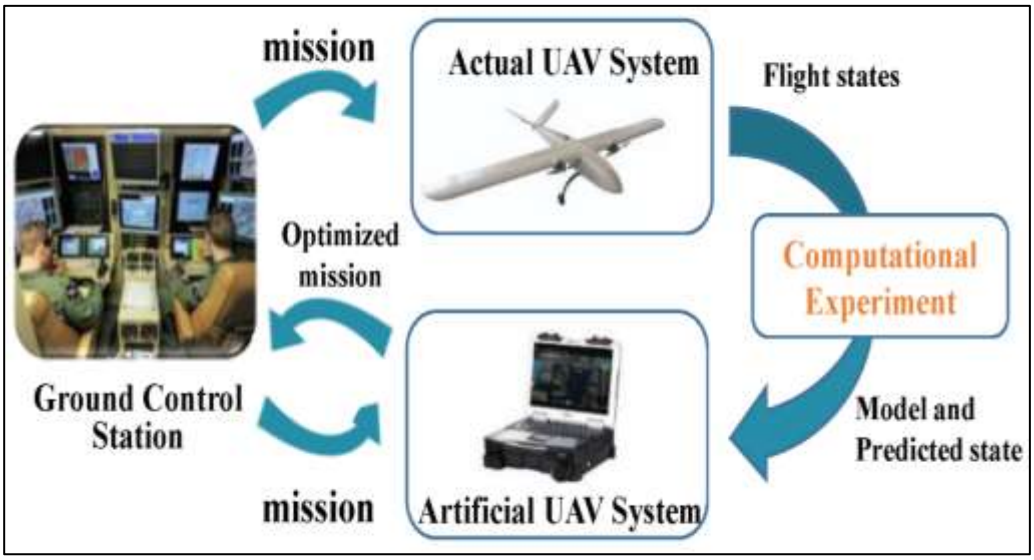

Figure 1.5: Framework of UAV Control, Guidance, and Optimization Systems.

The control system takes care of the stabilization of the UAV and flight parameters like altitude, velocity, and orientation at the desired level. It uses onboard sensors, such as Inertial Measurement Units (IMUs), gyroscopes, accelerometers, and magnetometers, to make continuous feedback signals. The flight control computer processes these signals, and based on algorithms like PID, Linear Quadratic Regulator (LQR), or Model Predictive Control (MPC), the flight control system keeps the aircraft stable. But outside disturbances, nonlinear systems, and modelling errors have made optimization processes essential in the fine-tuning of controller parameters [16]. The most frequently used algorithms to determine the optimal control gains are the Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and the Gray Wolf Optimizer (GWO) that will minimize tracking error, enhance transient response and reduce energy usage. Through this, under the assistance of adaptive optimization, UAV controllers can offer more regular and constant functionality even in cases where the flight environment is not foreseeable. At the same time, the guidance system will choose the route and the plan of navigation of the UAV based on the mission objectives and the environmental data [17]. It combines Global Navigation Satellite Systems (GNSS), inertial sensors, and vision-based navigation to come up with precise location and velocity determinations. Optimization algorithms are also decisive here, specifically in path planning, where the system is required to recognize an optimal path that reduces flight time, energy use, or the risk level. Methods like (A*), the algorithm of Dijkstra, Simulated Annealing, and Multi-

Objective Evolutionary Optimization are used to get efficient collision-free paths and respond to changes in the environment in real time. Moreover, the hybrid models based on MPC and heuristic optimization improve the predictive capabilities of the UAVs, which enables them to predict disturbances and dynamically replan paths. UAV systems point optimization goes beyond tuning the trajectory planning and decision-making on the mission level. Computational experiments are done with the artificial or simulated UAV systems depicted in Figure 1.7, where the parameters of the missions are modeled, tested, and refined before actual deployment. The process helps in minimizing operational risk, minimizing cost, and also allows for designing autonomous strategies that will maximize safety and performance. Lastly, the technology supporting UAV autonomy is control, guidance, and optimization systems. They can be precisely controlled and regulated to fly, regulate their path, and execute missions intelligently, owing to their integration. With the use of advanced optimization methods to achieve controller adjustment and improvement of navigation, UAVs gain high stability, efficiency, and reliability features necessary in contemporary applications in defense, surveillance, logistics, and scientific research [18].

1.8 PROBLEM FORMULATION

The increasing use of tethered UAVs in surveillance, communication, and environmental monitoring can be explained by their capability to remain in prolonged flight (long periods of time) with a constant power supply. Nonetheless, tethered UAVs' attitude control is a complicated problem, mainly because of nonlinear dynamics, external forces, and cable forces, as well as parameter uncertainties that are involved in the system. More conventional approaches like PID, Cascade PID, and even more sophisticated methods like Active Disturbance Rejection Control (ADRC) tend to have low flexibility and resilience in such dynamic and uncertain operating conditions. These traditional controllers have a tendency to have difficulty in stabilizing the system in case the system is exposed to different tether forces, aerodynamic disturbances, or changes in payload. Moreover, they are limited to specific parameters and thus, their performance is not optimal in various flight conditions, causing them to overshoot, their reaction is delayed, and their disturbance rejection performance is worse.

1.9 PROPOSED CONTRIBUTION

This paper has proposed a new control and optimization system that can enhance the disturbance rejection and the attitude stability of tethered UAVs. The essence of this work is the Fractional-Order Proportional-Derivative -Derivative -Integral (FOPDD-I) controller that is optimized by using a Hybrid Harris Hawks Optimization-Eagle Strategy-Particle Swarm Optimization (HHHO-ES-PSO) algorithm. The hybrid method proposed overcomes the merits of several metaheuristics, namely global exploration, adaptive refinement, and rapid convergence, in order to come up with optimal controller tuning. The FOPDD-I structure has an extra degree of freedom that improves accuracy in addressing nonlinearities and uncertainties of the UAV system by incorporating the concept of fractional-order dynamics. Simulation experiments prove that the HHHO-ES-PSO-tuned FOPDD-I controller is much better than the conventional PID, cascade PID, and classical and advanced ADRC in terms of stability, transient response, and the ability to reject disturbances. The results prove this hybrid fractional-order control scheme as a strong and adaptive control scheme for tethered UAV attitude control in complex and uncertain dynamic conditions.

1.10 DISSERTATION ORGANIZATION

Generally, this dissertation consists of six fundamental chapters that together complete the proposed work. The contributions of the chapters are presented as follows:

ix. Chapter Two: This chapter of the dissertation presents the related works that have been made in the literature.

x. Chapter Three: This chapter of the dissertation presents the architecture of the UAVs, such as the available controllers and their structure, and the role of some of the available optimization algorithms in the tuning of the controllers' parameters, which contributes to the performance enhancement for the UAVs.

xi. Chapter Four: This chapter of the dissertation presents the proposed framework to carry out this work, which presents the completed study stages, the proposed controller, and the utilized optimization algorithms.

xii. Chapter Five: This chapter of the dissertation presents the obtained results after completing the proposed framework.

xiii. Chapter Six: This chapter of the dissertation presents the conclusion from this study and the recommended additions for future work.

2. LITERATURE REVIEW

2.1 INTRODUCTION

Over the past few years, UAVs have developed into complex autonomous vehicles that can be used in many civilian and military functions since they have evolved into complex remotely controlled aircraft. This has been a result of developments in sensor technologies, embedded processors, communication systems, and intelligent control methods. The growing need for UAV tasks of surveillance, mapping, precision agriculture, disaster response, and others requires control mechanisms that could be stable, accurate, and survive in uncertain and dynamic conditions. Traditional control techniques that were useful in the relatively straightforward situations tend to find it difficult to sustain performance in the face of nonlinearities, variation in parameters or external disturbances. This constraint has encouraged the inclusion of optimization algorithms in control systems of the UAV, with the controllers being capable of evolving, training, and optimizing their behavior in the real-time [19].

The development of optimization algorithms has become the mainstay of modern UAV controller design and optimization. These algorithms have been based on biological, physical or social processes; they provide a flexible and efficient solution to a problem that is hard to approach analytically. The GA, PSO, Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) are metaheuristic algorithms that have been actively utilized to optimize the parameters of controllers to improve the results of trajectory optimization, energy efficiency and stability. These algorithms are attractive because they can search large and complicated solution spaces without the gradient information needed, and this is appropriate in the nonlinear and coupled dynamics of UAV systems [20].

Within the context of UAV control, optimization algorithms have primarily been applied to the optimization of classical controllers, such as Proportional-Integral-Derivative (PID), Linear Quadratic Regulator (LQR) and Sliding Mode Controllers (SMC). It is possible to optimize the control parameters so that UAVs can display a smaller response time, less overshoot and disturbance rejection. Further, the renewed interest in hybrid control structures, resulting in the combination of optimization algorithms with intelligent controllers (Fuzzy Logic or Neural Networks), has led to additional opportunities in the direction of adaptive and self-learning UAVs. These smart systems allow UAVs to adjust their control strategies autonomously according to the demands of the mission and the environmental feedback and, therefore, increase operational reliability and autonomy [21].

A current pattern of advancing the understanding of incorporating optimization techniques into the control parameter tuning, as well as into the higher-level decision-making systems like path planning, formation control and resource management, is evident in the literature. Swarm-based tools have been successfully applied as an example to improve the path of UAV and optimize the controller performance. On a similar note, evolutionary algorithm is effective in the optimization of the control law of dynamic obstacle avoidance, and fault-tolerant operation. As the range of UAV applications to more complicated environments start expanding, this type of optimization-based control is already becoming the key to the maintenance of not only efficiency but also safety [22].

Therefore, the chapter shows a critical review of the implementation of the optimization algorithms into the UAV control systems. It examines the theory of optimization methods, their application to various structures of control, and their performance that has been observed in the recent literature. The importance of metaheuristic and nature-inspired algorithms in enhancing the robustness of controllers, accuracy of the trajectory, and the efficiency of the computation is given special focus. This chapter will combine the techniques and results obtained by previous studies to present the existing challenges, tendencies and research gaps that may be used to enhance the future evolution of intelligent and optimized UAV control systems.

2.2 RELATED WORKS

The last several years have presented an impressive growth of UAV control due to the application of improved intelligent algorithms, strong control design, and real-time computation possibilities. Scholars have been working on flight stability, trajectory control, and energy-efficient optimization solutions by numerous optimization-based and adaptive control methods. PID and classical controllers have also been refined into other, more sophisticated controllers like fuzzy-PID, fractional-order, and MPC, whereas metaheuristic controllers have been used more commonly to perform automatic tuning and performance improvement. This evolution points to an obvious transition to self-optimizing and intelligent UAV systems that can perform well in uncertainties and nonlinear systems. The literature has given several studies; some of these studies have been listed in the next section.

A study by the authors Sa, Araujo, Varela, and Barreto (2013) was one of the first systematic studies of quadrotor UAVs in terms of their construction, modeling, and control with classical PID control. The authors modeled a small-scale quadrotor and constructed it, as well as constructed a dynamic model of the quadrotor based on the Newton-Euler formulation. To control vertical movement and attitude, a PID controller was introduced, and simulations were conducted in MATLAB/Simulink, and the experimental results were verified on a microcontroller-based prototype. The model and controller design have proven to be accurate, as indicated by the results of effective stabilization of the altitude and the stability of the hover behavior. The authors of the study concluded that the classical PID controller can be used to stabilize a quadrotor with nominal conditions of operation, but its non-adaptive and fixed-parameter character restricts the ability to handle external disturbances, so adaptive or optimization-based controllers should be further developed [23].

Shamseldin (2022) has suggested an adaptive control scheme that consists of a model reference adaptive control (MRAC) scheme coupled with three PID compensators, including classical PID, Fractional-Order PID (FOPID), and nonlinear PID (NPID), through a novel Covid-19 algorithm optimization. The study led to the creation of smart adaptive controllers that are capable of managing nonlinearities and disturbances in electric and wind-driven vehicle systems that are conceptually applicable to UAV dynamics. The proposed hybrid MRAC-PID architecture was experimented with by carrying out comparative simulations, which revealed better tracking results of the MRAC-NPID setup up which had the lowest overshoot and a settling time of 35 seconds. The author concluded that the incorporation of adaptive schemes with optimization algorithms can go a long way in enhancing the stability, fidelity, and reaction velocity of nonlinear dynamic systems, in contrast to conventional PID-based designs [24].

Cajo, Mac, Plaza, Copot, De Keyser, and Ionescu (2019) provided a review of the literature on the use of Fractional-Order Control (FOC) processes in unmanned aerial and ground vehicles and provided a decade-long outlook on the benefits of using fractional calculus to improve the control process. The research systematically examined the use of FOPID in different UAV control issues that included tracking, formation control, path planning, and fault-tolerant operation. It also indicated that the fractional-order controllers have an advantage over the more traditional integer-order controllers in the provision of adjustable gain and phase margins, better isodamping characteristics, and reduced sensitivity to parameters and load changes and wind clutter. The analyzed studies were discovered as evidence that the application of fractional-order control tools represents more versatile and effective control of UAVs and makes possible to reach the desired precision of control and stability in the workplace in a broad spectrum [25].

Nguyen Xuan-Mung and Sung-Kyung Hong (2019) proposed an improved altitude control algorithm of the quadcopter UAVs, using the combination of nonlinear and linear control mechanisms to overcome the weaknesses of the traditional PID controllers. The authors developed a hybrid controller that ensured a well-posed transition between linear and nonlinear operating regions using gain-scheduling functions that were mathematically computed to establish its existence and proved it through the Lyapunov theory. The suggested controller was confirmed both in numerical simulation and real-flight experiment on a DJI-F450 platform and could achieve shorter settling times and reduced overshoot than conventional PID control. The results found that the method was helpful in the trade-off between the simplicity and strength of the implementation, and the authors concluded that such hybrid control plans were helpful in offering a practical answer to the altitude regulation in a real-time UAV system where the non-linearity is widespread [26].

Next, the authors Zuniga-Pena et al. (2022) researched optimization-driven tuning of the proportional-derivative (PD) and PID controllers of 3D path tracked UAVs. They developed a nonlinear dynamic model that is formulated using the Newton-Euler approach and used eight metaheuristic-based optimization algorithms: PSO, GWO, Hybrid Gradient Search (HGS), LSHADE, LSPACMA, MPA, SMA, and WOA to optimize controller parameters to minimize the Root-Mean-Square Error (RMSE). The relative analysis has demonstrated that the HGS algorithm has done the most favorable thing, and it has achieved the RMSE values of 0.0326 in PID and 0.0372 in PD control. These findings demonstrated the advantages of algorithmic tuning compared to the manual trial-and-error techniques. The authors found that metaheuristic optimization has the potential to enhance the accuracy of the trajectories, their stability, and the flight performance in general, which underlie the intelligent parameterization of the UAV control process [27].

Amertet, Gebresenbet, and Alwan (2024) concentrated on the use of hybrid fuzzy-PID control of UAVs that are working in smart agricultural systems. In their research, they sought to enhance stability and precision when the environment and operating conditions varied, as in the case of agricultural fields. The authors simulated the roll, altitude, and airspeed dynamics of the UAV using MATLAB/Simulink and incorporated fuzzy logic into the PID to allow them to adjust the gains in real time. Compared to the classical PID control, comparative analysis showed that major performance improvements were achieved- roll improvement of 41.5, altitude improvement of 11% and airspeed regulation improvement of 44. The authors concluded that fuzzy-PID hybrid controllers are stronger and are more adaptable to environmental uncertainties, which is why it especially fit precision-farming UAVs when the autonomous steady flight and prompt reaction to the environment are essential [28].

You, Hu, Lian, and Yang (2024) proposed a Mixed-Strategy Harris Hawk Optimization (MS-HHO) algorithm and implemented it on the UAV path planning and various engineering problems with complex settings. They primarily improved the standard HHO algorithm with four new mechanisms: positive-charge repulsion of various initializations, a non-linear decreasing parameter to enhance the exploration-exploitation ratio, a Gaussian random walk to refine the local optimization, and mutual-benefit position updates to improve the convergence. Benchmark tests applied as experimental validation of the proposed model on benchmark functions and optimization tasks of UAV trajectories revealed that MS-HHO can converge much faster and reach better quality solutions than ten other popular optimization algorithms. The authors found that the mixed-strategy option offers an effective and efficient global search, which is very appropriate in solving complex UAV optimization problems that include multi-objective path planning and energy-efficient routing [29].

Israr et al. (2022) have undertaken an extensive review, which is titled Optimization Methods Applied to Motion Planning of Unmanned Aerial Vehicles. The authors summarized the key issues of UAV motion planning and reviewed optimization algorithms and especially bio-inspired ones, to promote robustness and convergence in the determination of flight paths. They are useful in categorizing the contemporary motion-planning strategies and assessing their efficiency and inefficiency in convergence rate, flexibility, and affordability. The paper emphasized the fact that hybrid bio-inspired methods seem to be better than classical deterministic methods because of the improved exploration-exploitation ratio. The authors came to the conclusion that optimization combined with cooperative UAV networks may reduce the mission time to a significant extent, increase its fault tolerance, and react dynamically in uncertain conditions [30].

Erkol (2018) examined the article Attitude Controller Optimization of Four-Rotor Unmanned Air Vehicle, which follows the tuning of PID controller parameters as a result of nature-inspired optimization algorithms. The paper simulated a quadrotor and compared ABC, PSO, and GA algorithms to obtain the optimal PID parameters. The suggested methodology proved that metaheuristic algorithms allow a significant decrease in tuning time and enhance flight stability in relation to hand-based or Ziegler-Nichol's tuning. The outcomes of the simulation showed that the fastest convergence was obtained by the ABC, whereas PSO had smoother control signals and less overshoot. The author concluded that the use of algorithmic optimization would increase the stability, decrease the error, and enhance the efficiency of UAV control missions in terms of energy [31].

The study by Zhao et al. (2018) is entitled Integrating Communications and Control for UAV Systems: Opportunities and Challenges, which highlights the interdependence between the UAV flight control and communication systems. Their work provided a novel model of a 3D channel and the study of the co-design of communication and control algorithms with the view of enhancing the transmission of data and the stability of the trajectory. They suggested control-aware communication protocols under which flight dynamics feedback is directly used to make channel selection and beamforming decisions. They found that control with communication is better in increasing system reliability and decreasing latency in multi-UAV networks. The authors concluded that these areas need to be co-optimized to enable future autonomous UAV swarms with minimum human oversight [32].

Andrade et al. (2022) came up with a fuzzy tuning of cascaded-PID Gains to UAV Motion Control image, which brings in a layer of fuzzy logic to tune the parameters of the PID online. They help to remove the necessity of manual tuning, which is tiresome, and enable flexibility to UAV nonlinearities. The proposed fuzzy-PID was implemented in the Robot Operating System (ROS) and, based on Unreal Engine simulations, had better control than the conventional Ziegler-Nichols and ArduPilot controllers, and achieved a faster stabilization and reduced steady-state error. The findings affirmed the hypothesis that fuzzy-based adaptive control can enhance the accuracy of the trajectory under dynamic states, and the authors concluded that the approach is relatively applicable to different UAV models without having to use explicit mathematical equations [33].

Elkhatem et al. (2025) created a New FOPID Control Design of Flight Dynamics with Special Phenomena, which overcomes the shortcomings of classical PID control in Non-Minimum Phase (NMP) aircraft. They came up with a FOPID controller with a fractional derivative filter and optimized it through PSO. They used a method that reduced the integral performance indices like IAE and ITAE in the event of actuator faults and parametric uncertainties. The results of the simulation showed many improvements in sustaining reduced overshoot (reduction by more than 50 to less than 3), as well as robustness with actuator loss of less than 50-80%. The analysis found the PSO-tuned FOPID controller to be more stable with better margins and has more versatility in flight systems with bandwidth limitations and reverse response nature [34].

D'Antuono et al. (2023) proposed an Optimization of UAV Robust Control with the help of GA. The authors developed a hybrid form of control system that involved a Robust LQR Servomechanism (RSLQR) that is integrated with a GA-based optimization to optimally tune weight matrices to achieve improved dynamic response. Their analytical and software-in-the-loop simulation results showed that the GA-optimized RSLQR was more robust and tracked the trajectory than the classical PID and MRAC controllers using turbulence and model uncertainties to test the results. It was concluded that the GA-powered optimization structure minimizes manual adjustments, decreases the time spent on its development, and provides consistent stability when operating in different flight scenarios [35].

Altan (2020) discussed the article on the performance of metaheuristic optimization algorithms based on swarm intelligence in UAV attitude and altitude control. The experiment was carried out based on comparing PSO and Harris Hawks Optimization (HHO) in the process of PID parameter tuning on a quadrotor path-following. The authors compared the results of tractory tracking on a variety of routes, which consisted of rectangular, circular, and lemniscate routes, and discovered that HHO was faster at converging and more resistant to route disturbances in comparison to PSO. The contribution of this piece is that it demonstrates HHO as an effective solution in real-time path-following. These authors developed the conclusion that swarm-based intelligence techniques are better to control UAVs optimization since they are less energy-consuming and are more adaptable [36].

The article by Admas et al. (2024) delved into the issue of control of a fixed-wing UAV through a higher-order SMC-based nonlinear PID controller. They were aimed at comparing the NPID with Higher-Order SMC (HOSMC) in representation of strong flight stability to external disturbances. The simulations with MATLAB/Simulink proved that NPID was more effective on the airspeed control and HOSMC is skillful in the attitude strength. The performance of the two controllers was compared in terms of the error indices, such as ITAE and MSE, and it was revealed that the combination of the two controllers could offer the best control of the fixed-wing UAVs. These authors made the conclusion that nonlinear control schemes are superior to the conventional PID design because of the complicated nature of UAV flight dynamics [37].

The authors (Metekia et al., 2025) talked about managing a fixed-wing UAV with the help of a Robust foc (RFOC). The authors have provided an augmented with PSO-parameter-tuning RFOC-SMC in the control of the trajectory tracking under the condition of uncertainties. RFOSMC was shown to have an error performance that was 76 points superiors to that of LQR, FOPID, and traditional SMC and a shorter settling time (0.835 Seconds). Their results were that nonlinearities and disturbances of fixed-wing UAVs are controlled effectively through fractional-order sliding techniques. They concluded that PSO-optimized fractional control strategies can achieve high-precision tracking and the strategies are highly robust to changes in parameters [38].

Finally, the survey, given by Poudel et al. (2023), made a systematized taxonomy and comparative analysis of nature-inspired algorithms, including GA, PSO, the Grey Wolf, Ant Colony, and Harris Hawks, utilized in the optimization of UAV paths. The authors presented the comparison of these algorithms through convergence, adaptability, and cost of computation, which are the capabilities of bio-inspired techniques to evade local minima and adjust to changing environments. The review has concluded that the most promising way of future path-planning and collaborative control of UAVs is hybrid bio-inspired algorithms that combine swarm intelligence with evolutionary algorithm s [39].

3. UAV STRUCTURE AND CONTROL OPTIMIZATION

3.1 INTRODUCTION

As explained and mentioned above, the UAVs have become advanced flying platforms that are essential in various civil and military activities such as environmental survey, aerial survey, relay communication devices, and search-and-rescue operations. The innovations in UAV technology development have been mostly achieved due to the refinement of the structural design, control methods, and optimization algorithms that have combined to define the stability, agility, and reliability of the vehicle. Since UAV operations are growing more complicated, robust stability and effective disturbance rejection have taken on a key role, particularly in situations where operations occur under uncertainty or dynamic environmental conditions.

The design of UAV control systems requires the extensive experience with the UAV structure and dynamics, as well as the ability to overcome nonlinearities, coupling effects, and environmental interactions such as wind gusts or load variations. Traditional controllers such as PID controllers or LQR controllers, are typically capable of providing reasonable performance in nominal conditions, but do not provide robustness to time-varying behavior or uncertain behavior. Trying to beat such limitations, the more recent research on control has adopted intelligent and hybrid approaches to optimization in tuning and optimization of the controller performance.

Hybrid metaheuristic optimization algorithms have been the keenest of these new methods since they are more useful in providing a trade-off between global exploration and local exploitation. In UAV control problems, the algorithms can be applied in the optimization of better parameters, precision of the movement of the path, and rejecting perturbations. These optimization-based control plans are particularly effective in instances of tethered UAV systems where aerodynamic and mechanical interaction may be very powerful on stability.

Lastly, the development of the state-of-the-art control measures with smart optimization methods provides a viable system that can improve the stability, diversity, and overall status of UAV systems. The chapter describes the structural characteristics of UAVs, various control measures that have been used to ensure stability of the flight and how optimization algorithms have been used to enhance precision and robustness of control.

3.2 UAVS ARCHITECTURE

UAV architecture is an extremely complicated apparatus of mechanical engineering, sensory frameworks, an embedded computer, and advanced control calculation to deliver and sustain autonomous and steady flight. On the whole, it is possible to divide the UAV architecture into three fundamental layers, such as the physical platform, the embedded processing system and control and decision layer. The layers interact in the sense of interacting in real time to ensure that the flight is stabilized and that the trajectory is followed and that there is an adaptive response to changes in the environment. Physical level The UAV is made up of the airframe, propulsion system, and actuation system which transform the control commands into tangible movement. These include motors, servos and control surfaces which create the thrust both directly and alter the aerodynamic forces. In order to monitor the behavior of the UAV, a number of sensors are equipped, such as accelerometers, gyroscopes, magnetometers, GPS position, and a barometric altimeter, which are constantly in operation to measure position, orientation, speed, and height of the UAV. These sensory inputs are the foundation of feedback control, and these inputs provide the necessary information to the navigation and stabilization. The embedded processor performs the role of the core computational unit, which links sensing and actuation. It gets live information from onboard sensors, calculates it using estimation algorithms (e.g., Kalman filtering), and implements control laws to decide how the actuators should respond. This closed-loop design creates the ability of the UAV to be autonomous to respond to the changes in the flight conditions. The control algorithms are normally written in low-level programming languages such as C to ensure that timing is deterministic and there is efficient utilization of resources, which is critical in ensuring that flights are safe [40].

The control layer is, in fact, hierarchical in structure. The inner loop, the attitude controller, controls the angular movement and provides a quick stabilization process through changing the roll, pitch, and yaw angle. The outer loop controls translational motion and that of position, altitude, and tracking. Since classical PID controllers are simple and robust, they are nevertheless popular with modern UAVs that are becoming more adaptive, nonlinear, or MPC as they attempt to address the uncertainties and nonlinear dynamics, as well as external disturbances, with more accuracy. Such algorithms also increase maneuverability as well as energy efficiency without compromising on safety margins. In order to have a smooth communication between the subsystems, the UAV architecture incorporates estimation, control, and communication within a real-time feedback environment. Sensor fusion involves the use of multiple sources of measurements to come up with accurate state estimates, and fault detection and redundancy mechanisms are established to protect against sensor or actuator failures. The communication between onboard modules and the ground control station provides the situational awareness and flexibility of command, where both manual supervision and fully autonomous operation are possible. In general, the design reflects a feedback-closed-loop of interaction between the control algorithm, embedded processor, and UAV components, which allows continuous feedback and adaptive correction. As Figure 3.1 illustrates, this interaction is what controls sensor data processing, state estimation, and actuator control, which is the general pathway of the sensor data, state estimation, and actuator control in the UAVs to attain precise and stable flight [41].

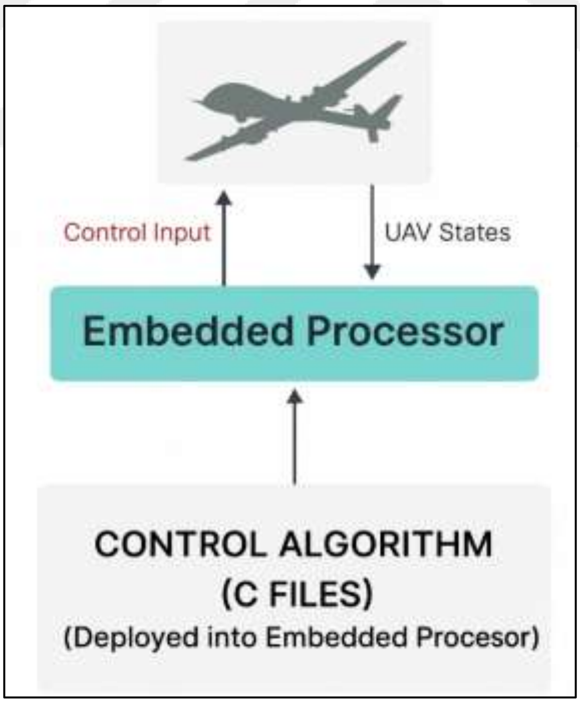

Figure 3.1: UAV Control System Architecture.

3.3 TYPES OF CONTROLLERS IN UAV SYSTEMS

The controller is crucial in the definition of the dynamic performance, stability, and accuracy of UAVs. It is the calculation system that continually manages the movement of the UAV as a result of closed-loop feedback to keep the vehicle in the desired attitude, position, and trajectory in spite of the internal uncertainties and external disturbances like wind or payload variations. In the last several years, a broad selection of control strategies has been created to improve UAV performance, with each having a particular benefit in the aspect of robustness, adaptation, and computing efficiency. Modern controller UAVs use a board of different controllers, including conventional PID schemes to MPC, SMC, as well as Adaptive or Intelligent Controllers by means of fuzzy logic and neural networks. The choice of a controller relies on the configuration of the UAVs, mission demands, the complexity of dynamic models, and the limitations of the environment. The controllers actually used in the UAV systems will be introduced and explained in the following subsections in terms of their principles of operation, their merits, and applicability on various UAV platforms.

3.3.1 PID Controller

The PID controller is considered to be one of the simplest yet common control strategies in the UAV systems due to its simplicity, robustness and capacity to control levels of stable flight conditions in changing conditions. It is specifically useful in attitude control, altitude control as well as in path tracking in fixed-wing as well as rotary wing unmanned aircraft. The controller works on the principle of minimizing the error between the desired reference signal ($r(t)$) (such as the target altitude or attitude) and the measured output ($y(t)$), producing a control signal ($u(t)$) that drives the UAV toward the desired state. In mathematical terms, the PID control law can be expressed as [42]:

$$u(t) = K_{\mathrm{p}}e(t) + K_{\mathrm{i}}\int_0^t e(\tau)d\tau + K_d\left(\frac{de(t)}{dt}\right) \tag{3.1}$$

where:

$e(t) = r(t) - y(t)$, which refers to the instantaneous error between the reference and actual output,

K_p: is referring to the proportional gain,

K_i: is referring to the integral gain, and

K_d: is referring to the derivative gain.

All the terms in the PID equation make a different contribution to the control performance. The proportional term ($K_p e(t)$) gives an immediate correction according to the existing error, which has a direct effect on the responsiveness of the UAV. The integral term ($K_i \int e(\tau)d\tau$) is used to remove steady-state error by averaging the past errors with time, such that the UAV motor follows the desired position/altitude accurately. In the meantime, the derivative term ($K_d \frac{de(t)}{dt}$) is used to predict the future trends of error and brings about a damping influence that minimizes the overshoot and the oscillations and makes the system more stable [42].

PID controllers are also usually used in UAVs; in this case, the inner loop is an angular rate (or attitude) control loop (pitch, roll, yaw), and the outer loop is a translational control loop (altitude, trajectory, etc.). The hierarchical structure enables rapid stabilization of attitude dynamics, and slower position adjustments are then carried out. The gains (K_p, K_i, and K_d) are adjusted to achieve a balance between the responsiveness of the system, its robustness, and its energy efficiency. Poor tuning will cause instability, oscillation, or over actuation [43].

The integration of the PID controller on a UAV takes real-time calculations inside the embedded processor. Gyroscopes, accelerometers, and GPS modules' sensor data are used to give continuous feedback to compute ($e(t)$). In order to make the implementation numerically stable, discrete-time implementations are frequently adopted, and are represented by [43]:

$$u(k) = K_{\mathrm{p}} \cdot e(k) + K_{\mathrm{i}} \cdot \sum_{i=0}^{k} e(i) \cdot \Delta t + K_d \cdot \frac{\left(e(k) - e(k-1)\right)}{\Delta t} \tag{3.2}$$

Where:

$u(k)$: is referring to the control signal applied to the system;

k: is referring to the discrete time step;

Δt: is referring to the fixed sampling interval between each control update.

Despite its simplicity, the PID controller shows remarkable effectiveness when properly tuned. However, it assumes linearity and invariance over time, which may not fully represent the dynamics of UAVs in high-speed maneuvers or variable aerodynamic conditions. Therefore, programmed gain or adaptive PID versions are often employed, where controller parameters are dynamically adjusted depending on flight mode, altitude, or payload conditions. In general, the PID controller is one of the foundations in the UAV control design with its intuitive design, simplicity in implementation, and durability in a broad platform of aerial systems. The operation structure and signal flow are depicted in Figure 3.2, which demonstrates the three control actions (proportional, integral, and derivative) in collaboration to produce a corrective control signal to stabilize the UAV flight system [44].

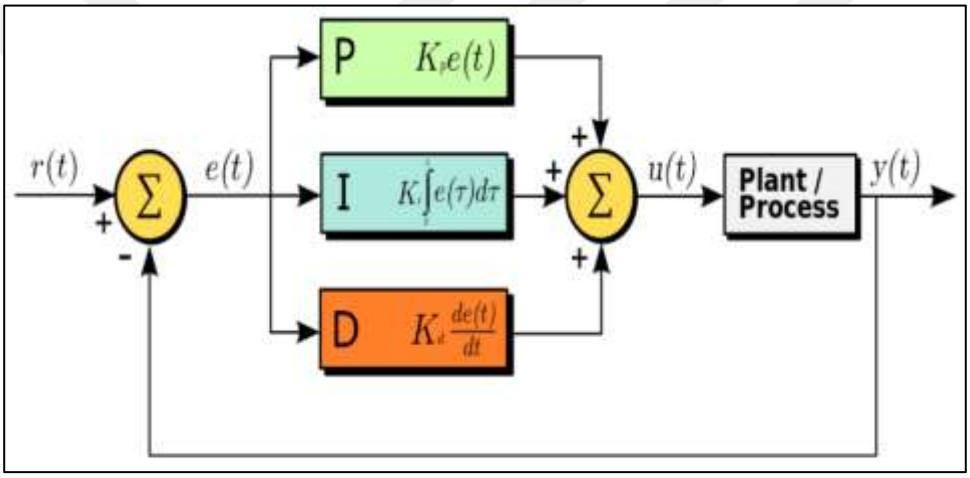

Figure 3.2: Block Diagram of A PID Controller Used in UAV Systems [44].

3.3.2 LQR Controller

This LQR controller is one of the most effective and mathematically sound control strategies utilized within the UAV systems. It is founded on optimal control theory and seeks to stabilize the system and drive the system performance to a minimum of some preset cost function that balances the control effort and the system state deviations. LQR controller is especially applicable to unmanned aerial vehicles in that it can manage multivariable systems, can resist small perturbations and has a systematic methodology of tuning, as opposed to heuristically tuned systems. Generally, UAVs dynamics may be represented in the state space form as in the following Equations [45]:

$$\dot{x}(t) = A \cdot x(t) + B \cdot u(t) \tag{3.3}$$

$$y(t) = C \cdot x(t) + D \cdot u(t) \tag{3.4}$$

Where:

$x(t)$: is referring to the state vector representing the UAV's dynamic variables,

$u(t)$: is referring to the control input vector, and

(A), (B), (C), and (D): are referring to the system matrices defining the dynamic behavior of UAVs.

Generally, the main objective of utilizing the LQR controller is to design a control law of the following form [45]:

$$u(t) = -Kx(t) \tag{3.5}$$

Where:

K: is referring to the feedback gain matrix that determines how each state variable influences the control input. This profit matrix is obtained by minimizing a quadratic cost function (i.e., the performance index), which defined by means of the following Equation [45]:

$$J = \int_0^\infty (x^T Q x + u^T R u) dt \tag{3.6}$$

where:

Q and R: are symmetric, positive-definite weighting matrices. The matrix Q penalizes deviations from the desired values for the state variables, while R penalizes excessive control effort. The optimal balance between system performance and energy consumption is achieved by appropriately selecting these weighting metrics.

The optimal gain matrix (K) is obtained by solving the "Riccati algebraic" equation in continuous time, to be represented as follows [45, 46]:

$$A^T P + PA - PBR^{-1}B^T P + Q = 0 \tag{3.7}$$

Where, (P) is referring to the unique positive-definite solution of the equation. Once (P) is determined, the optimal feedback gain matrix is computed by means of the following Equation [46]:

$$K = R^{-1}4B^{T}P \tag{3.8}$$

This gain feedback device provides that the closed-loop system $\dot{x}(t) = (A - BK)x(t)$ is asymptotically stable, assuming that the pair (A, B) is controllable.

The LQR controller finds use in the UAV case, where it is applied in attitude control, trajectory control, and disturbance rejection. Its state-feedback allows it to take into consideration multiple UAV dynamics simultaneously: roll, pitch, yaw, and altitude, which improve the overall flight performance. The LQR provides the most effective control law grounded on mathematical optimization over manual control tuning of classical controllers like PID. It will also have the capacity to manage the association among control axes as well as comfortable use of actuators, which is significant in energy consumption and decreased wearage of UAV motors and servos [46].

In practice, the control of the LQR controller involves proper state estimation. Not every state can be measured directly in UAV systems, so state observers or Kalman filters are typically combined to estimate the unknown variables in real-time. The combination enhances control accuracy and stability, particularly when performing complex maneuvers or in environments with sensor noise and external distractions. Generally, the LQR controller offers a good theoretical foundation and performance benefits in terms of UAV control, especially when stability and energy saving are paramount. Its schematic form is provided in Figure 3.3, which presents the feedback mechanism in which the control input is created in accordance with full-state feedback to bring the plant dynamics of the UAV to the desired equilibrium state [47].

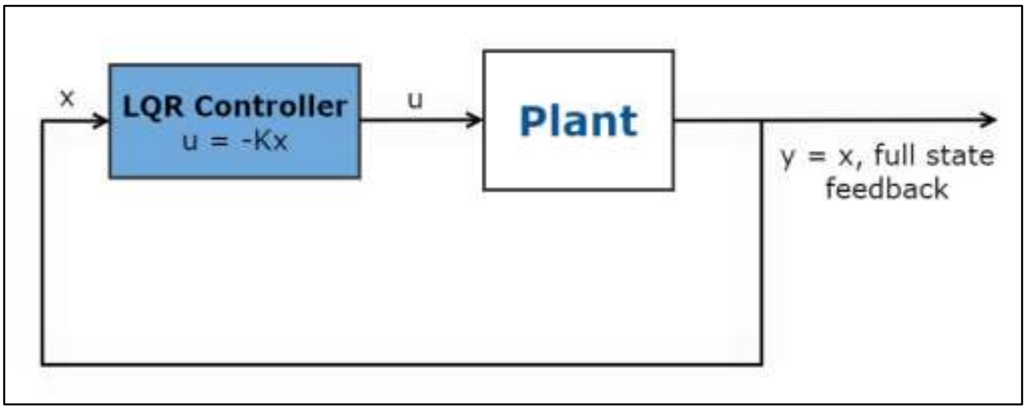

Figure 3.3: Block Diagram of LQR Controller with Full-State Feedback.

3.3.3 Sliding Mode Controller (SMC)

The SMC is a nonlinear control strategy that has gained significant attention to be employed in the field of unmanned aerial vehicles, the UAV control due to its robustness, simplicity, and insensitivity to system uncertainties and external perturbations. Unlike classical linear controllers such as PID or LQR, SMC operates on the variable structure control principle, where the control law switches between different structures (or modes) depending on the state of the system. This switching action drives the system states toward a predefined slip surface, over which the system dynamics become insensitive to modeling errors and external perturbations. The general mathematical representation of a nonlinear UAV system can be represented as [48]:

$$\dot{x}(t) = f(x,t) + B(x,t)u(t) + d(t) \tag{3.9}$$

Where:

$x(t)$: is referring to the state vector;

$u(t)$: is referring to the control input;

$f(x,t)$: is referring to the UAV's nonlinear dynamics;

$B(x,t)$: is referring to the input matrix; and

$d(t)$: is referring to the external disturbances or model uncertainties.

It is necessary to mention that the goal of the SMC is to design a control input ($u(t)$) such that the system trajectory ($x(t)$) reaches and remains on the sliding surface defined by a scalar function, which is presented as follows [48]:

$$s(x, t) = 0 \tag{3.10}$$

The sliding surface ($s(x, t)$) is usually chosen as a linear combination of the tracking error and its derivatives. For a single-input system, this can be expressed as the following mathematical expression [48]:

$$s(x, t) = \frac{d^{(n-1)e(t)}}{dt^{(n-1)}} + C_{n-1}\frac{d^{(n-2)e(t)}}{dt^{(n-2)}} + \cdots + c_1 e(t) \tag{3.11}$$

Where:

$e(t)$: is referring to the tracking error; and

c_i: is referring to the positive constants selected to ensure the desired dynamic response.

The control law in a SMC is designed in two fundamental stages. In the first stage, known as the reach phase, the system state is driven toward the slip surface by a discontinuous control law that ensures that the state trajectory converges to the predefined manifold in a finite time. Once the trajectory reaches the surface ($s(x, t) = 0$), the second stage begins, called the sliding phase. In this phase, the motion of the system is restricted to the slip surface, making the closed-loop dynamics independent of model uncertainties and external perturbations. The general control input in SMC usually takes the form [48]:

$$u(t) = u_{eq(t)} - K \tag{3.12}$$

Where:

$u_{eq(t)}$: is referring to the equivalent control maintaining motion on the sliding surface,

K: is referring to the positive gain of ensuring the convergence, and

$sgn\big(s(x, t)\big)$: is referring to the signum function.

The equivalent control is derived from the nominal model assuming perfect slip, while the discontinuous term compensates for uncertainties and perturbations.

In the case of UAVs, SMC can be particularly useful in stabilizing the aircraft in the air and maintaining its altitude, as well as following any given path, in which case the system is prone to aerodynamic disturbances, gusts of wind, and changes in any parameter. Its high stability enables the UAV to be stable even in cases where precise model parameters are not known. But another predominant issue of the practical application is the chattering, a high-rate oscillation that occurs due to the switching control act. To reduce this, smoothing of the boundary layer or the use of higher order SMC is used to ensure that the actuator response is smooth without compromising on the robustness. The application of the SMC in the UAV control system is seen in the embedded processor, whereby the sliding variable is computed and the control inputs updated as the process runs in real time. The controller ensures that the UAV state is close to the sliding surface, which ensures fast response, high disturbance rejection, and large margins of stability-essential properties of aerial vehicles operating in unsafe conditions. Figure 3.4 provides the schematic diagram of the working principle of the SMC, where the control law corrects the disturbances and stabilizes the system by means of feedback and switching control [49].

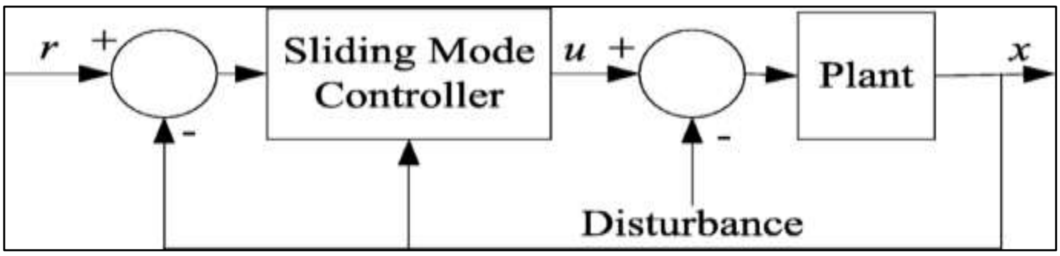

Figure 3.4: Block Diagram of The SMC For UAV Systems.

3.3.4 Adaptive Controller

The Adaptive Controller is a very versatile control approach that aims to adapt to time-varying dynamics, model uncertainties, and external disturbances that often feature in UAV systems. The adaptive control method is also able to vary its parameters in real time, unlike traditional fixed-parameter controllers, to achieve the desired performance and stability even in cases where the system properties vary due to operation. This self-tuning is particularly helpful in the applications relying on UAVs, in which a shift in the payload or aerodynamic coefficients, or environmental factors can substantially impact the flight behavior. The fundamental structure of adaptive control system consists of three major components, that is, a reference model, an adaptive mechanism, and a controller. The reference model describes what the UAV desires to accomplish in the closed loop (i.e. stay at a specific attitude response or altitude profile). This signal is used to generate an adaptation signal which adjusts the controller parameters dynamically in order to remove the difference between the model output and the actual plant output. The controller subsequently calculates the control input ($u(t)$) according to the adjusted parameters with the object of reducing the tracking error ($e(t) = y_m(t) - y_p(t)$) in which ($y_m(t)$) and ($y_p(t)$) represent the model and plant output, respectively. An adaptive control law will typically be formulated mathematically, such as [50]:

$$u(t) = \theta^T(t)x(t) \tag{3.13}$$

Where:

$\theta(t)$: is referring to the time-varying parameter vector; and

$x(t)$: is referring to the system state or regressor vector.

The adaptation law governing parameter updating is often defined using a gradient descent or Lyapunov-based approach, ensuring both parameter convergence and system stability. A typical adaptation rule can be expressed as [50]:

$$\dot{\theta}(t) = -\gamma x(t)e(t) \tag{3.14}$$

Where:

γ: refers to the positive adaptation gain that determines the parameter adjustment rate.

This formulation ensures that the tracking error asymptotically approaches zero under suitable conditions, even when the UAV system experiences perturbations or unknown parameter variations.

There are two major broad categories of adaptive controllers: Model Reference Adaptive Control (MRAC) and Self-Tuning Regulators (STR). The controller parameters in MRAC are set with an adjustment so that the system output follows the response of a specified reference model. On the contrary, STR trains system parameters on the Internet and adjusts controller coefficients. Adaptive controllers have found widespread use in UAVs in the attitude stabilization of the UAV, altitude control, and tracker maintenance. Their application is especially efficient in missions that involve changes in mass distribution or aerodynamic loading of the UAV that are substantial (e.g., when carrying the payload or in high-wind conditions). Adaptive control ensures robustness because the controller gains are automatically adjusted, and returning or recalibration of models is not required. Figure 3.5 shows the general schematic of the adaptive control system, with the reference model defining the desired dynamic behavior that should be followed. The adaptive mechanism continually updates the controller parameters as the tracking error, and the controller implements the required control actions to ensure the UAV system is steered into the target performance path [50].

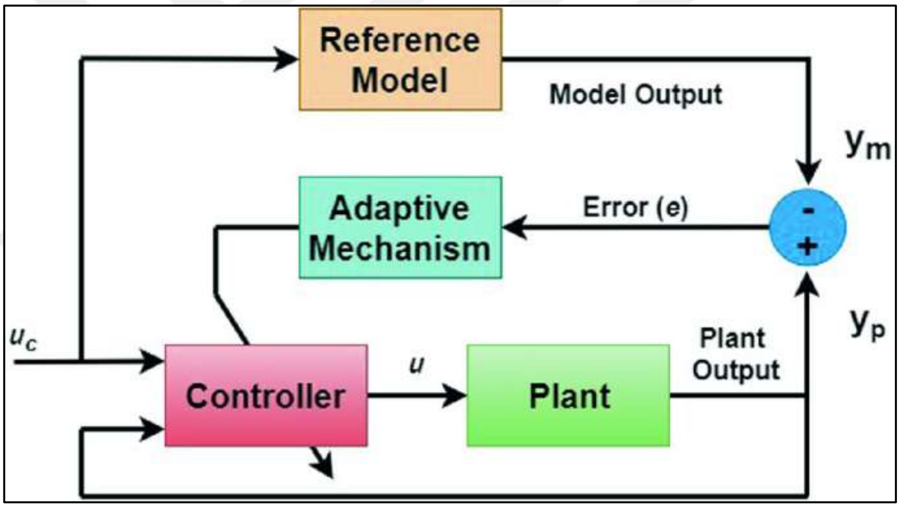

Figure 3.5: Block Diagram of The Adaptive Controller for UAV Systems [50].

3.3.5 Fuzzy Logic Controller (FLC)

The FLC represents an intelligent control approach that is extensively applied to Unmanned Aerial Vehicle (UAV) systems to manage nonlinearities, model uncertainties, and external disturbances. The FLC is especially appropriate to be applied to complex and uncertain environments, unlike traditional controllers that are based on accurate mathematical modeling and use linguistic rules and reasoning more similar to human reasoning. This has enabled it to be a potent instrument in the UAV attitude stabilization, altitude control, and path tracking applications due to its capacity to predict nonlinear functions and cope with variable flight conditions. The main principle of fuzzy logic control is to convert the idea of human expert knowledge into some rules of logic, which define the way of reaction to this or that situation. The FLC has four major segments, which comprise fuzzification, rule base, inference engine, and defuzzification. During the fuzzification, crisp input variables (e.g., the tracking error ($e(k)$) and its derivatives are brought into fuzzy linguistic terms (e.g., positive large, negative small, zero) through membership functions. The rule base, which is an expert knowledge, is a set of if-then rules that stipulate the relationship between the input and output fuzzy variables. These rules are then run through the inference engine to come up with the fuzzy sets of outputs based on logical thinking. The second step is defuzzification, which transforms the sets of fuzzy outputs back into crisp control signals ($u(k)$) which may then be fed into the UAV actuators. This transformation is usually done in terms of the centroid method or the mean of maximum so that smooth and continuous actions of control are achieved. The last control signal is used to minimize the difference between the desired command ($r(k)$) and the measured system output ($y(k)$) allowing the UAV to perform stable flight in the presence of uncertainty or non-linear dynamics. Mathematically, the FLC can be modelled as a transfer between the input ($E \times \dot{E}$) and the output (U), and it can be expressed as follows [51]:

$$u(k) = f_{FLC}(e(k), \dot{e}(k) \qquad (3.15)$$

Where:

$e(k)$& $\dot{e}(k)$: are referring to the input error and its rate,

f_{FLC}: is referring to the nonlinear mapping defined by the fuzzy inference system.

This design enables the FLC to be a nonlinear adaptive controller that can smoothly change control actions and does not need an absolute UAV model. FLCs are especially useful in the flight control uses of UAVs that involve highly nonlinear motion behavior (e.g., hovering, take-off, landing, gust rejection) in addition to the simpler (e.g., stepper motor-controlled) behaviors of line/point missions (i.e., controlling point movements). These offer high robustness and flexibility and are sure to offer a high level of reliability in varied conditions of operation. Moreover, it is possible to combine FLCs with other control means, including PID or adaptive control, to create hybrid intelligent controllers, which combine the analytical precision of analytical control with the rule-based reasoning. The fuzzy logic controller can be drawn as Figure 3.6, in which fuzzification, inference, and defuzzification cooperate in order to provide a proper control signal that stabilizes the UAV plant and produces the desired system response [52].

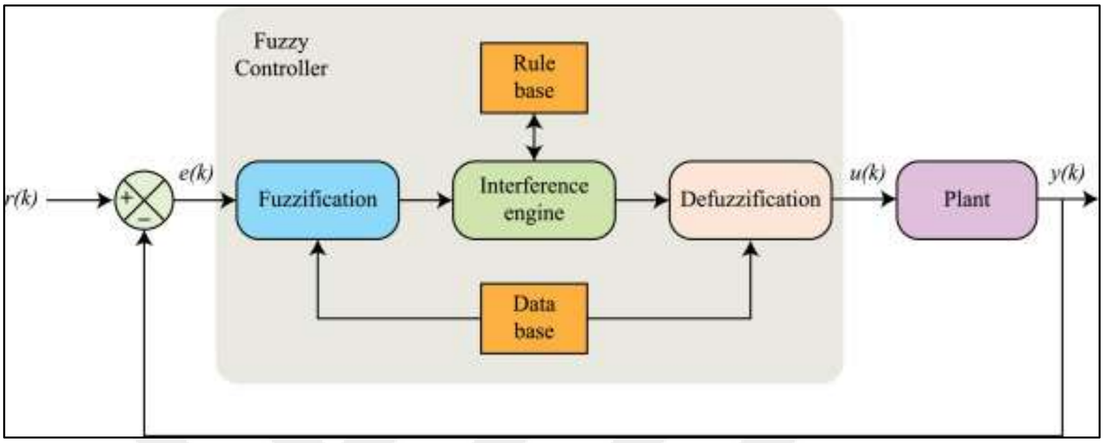

Figure 3.6: Block Diagram of The FLC For UAV Systems [52].

3.3.6 Fractional-Order Controllers

Fractional-order controllers are an important development in contemporary control science, as an extension of classical integer-order control theory to the situation of non-integer (fractional) differentiation and integration, the latter being characterized by non-integer order. The idea enables the controller to describe system dynamics with more flexibility and accuracy, especially when it shows memory, hereditary behavior, or highly nonlinear dynamics, as is often the case in the dynamics of the UAV. Fractional-order approach offers a controllable and more natural transition between the proportional, integral, and derivative effects, which has a better stability margin, disturbance rejection, and control accuracy than traditional controllers. An example of a well-known fractional-order controller is the FOPID controller, which is also called ($PI^{\lambda}D^{\mu}$ controller. It is an extension of the traditional PID controller in that it adds two new parameters (λ and μ), which are the order of integration and differentiation, respectively. This extra control degree will make the flexibility of the control system more flexible and enable one to fine-tune the frequency response and transient behavior of the system, which is especially important in the case of UAVs that are used in different aerodynamic and environmental conditions. The FOPID controller control law may be written as [53]:

$$u(t) = K_p e(t) + K_i D^{(-\lambda)} e(t) + K_d D^{(\mu)} e(t) \tag{3.16}$$

where:

K_p, K_i, and K_d: are referring to the proportional, integral, and derivative gains,

$e(t)$: is referring to the tracking error between the reference input and measured output,

$D^{(-\lambda)}$: is referring to a fractional integral of order (λ), and

$D^{(\mu)}$: is referring to the fractional derivative of order (μ).

In the Laplace domain, the transfer function of the FOPID controller can be expressed as follows [53]:

$$C(s) = K_p + K_i s^{(-\lambda)} + K_d s^{(\mu)} \tag{3.17}$$

This model shows that ($\mu = 1$) and ($\lambda = 1$) make the FOPID controller transition into the classical PID model. But in case (λ) and (μ) are admitted to have a fractional value, the controller offers greater dynamic shaping, which allows higher robustness to parameter disturbances and greater noise reduction. The FOPID controller presents some benefits of UAV control systems. It is capable of improved transient response, decreased overshoot, and enhanced steady-state accuracy without adding more control effort. Further on, the phase of the system could be controlled by designers independently by changing the fractional orders (λ) and (μ), which provides greater adaptability in complex UAV missions like hovering stabilization, path tracking, and altitude control. This is to say that they are in full control of the gains. Figure 3.7 represents the inside of the FOPID controller, and it illustrates the three control components, namely, proportional, integral, and derivative control components with extensions by fractional operators ($s^{(-\lambda)}$) and ($s^{(\mu)}$). Such a setup indicates the ability of the fractional calculus components to increase the flexibility of the control response beyond the constraints of the traditional integer-order controllers [54].

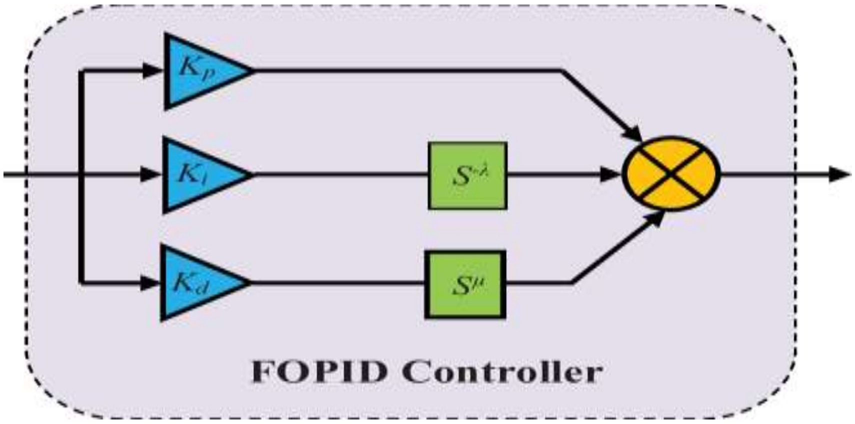

Figure 3.7: Block Diagram of The FOPID Controller [54].

In addition to the FOPID controller, a number of other fractional-order control design strategies have been designed to address the needs of nonlinear and uncertain UAV dynamics. These include [54, 55]:

i. Fractional-Order PI (FOPI): This is a simplification of FOPID in which the derivative term is ignored, but the fractional integration is retained, where derivative noise may be a problem in the system.

ii. Fractional-Order PD (FOPD): It uses fractional differentiation to improve the responsiveness in high-speed UAV maneuvering without causing drift due to integrators.

iii. Fractional-Order Sliding Mode Controller (FOSMC): This method represents a combination of the principles behind fractional calculus and sliding mode control to achieve good robustness and minimize chattering effects.

iv. Fractional-Order Adaptive Controllers (FOAC): Combine fractional operators with adaptive laws in order to enhance the learning and adjustment rate when dealing with time-varying UAV dynamics.

v. Fractional Model Predictive Control (FMPC): It employs a fractional-order system model in trajectory optimization and path planning to increase the accuracy of long-term predictions.

3.3.7 Comparison of UAV Controller Types

The choice of a suitable controller of a UAV is considerably dependent on the dynamic nature of the system, the purpose of the missions, the external interferences, and the computing power of the onboard processor. All the types of controllers mentioned, PID, LQR, SMC, Adaptive, FLC, and FOPID, possess their own strengths and weaknesses, which make them applicable in particular applications of UAVs. The most popular of them is the PID controller because of its simplicity, dependability, and simplicity of tuning. It is remarkably effective with low to moderately nonlinear UAV systems, and those missions that demand crude stability and or altitude control. Nevertheless, it is not very robust in the middle of strong disturbances or very nonlinear flight dynamics. Contrarily, the LQR controller is mathematically optimum and guarantees smooth control performance since it reduces a quadratic cost functional, which would be best suited in multivariant UAVs with clearly defined linear models. However, under conditions of a significant change of system parameters or the prevalence of nonlinearities, its effectiveness weakens. The SMC also offers a very solid ability to resist disturbances and model uncertainties, hence it’s very useful in aggressive or turbulent air behavior. Nevertheless, the high frequency switching nature (chattering) may result in mechanical damage to actuators unless it is alleviated appropriately. The Adaptive Controller, however, is best in time-varying and uncertain conditions, and the method automatically varies its parameters online to ensure stability and tracking LM. Particularly, it applies for the UAVs of variable payloads or tasks depending on dynamic environmental conditions such the wind bursts or temperature changes. The FLC is the one that provides human reasoning, which means it could effectively control nonlinear UAVs without an exact mathematical model. Its functionality is largely determined by the quality of the fuzzy rules and membership functions, and even though it offers a great deal of adaptability, it might prove computationally intensive with real-time embedded systems. Lastly is the FOPID controller; the controller is a more sophisticated controller, which offers an additional degree of tuning flexibility, with its fractional parameters. It has more tolerant responses, greater hardiness, and greater disturbance rejection, especially when the UAV requires great accuracy and smooth movements, like an autonomous surveillance or inspection drone [55].

The optimal decision when buying a controller will be determined by the mission and conditions of work of the UAV. In the case of basic and low-cost UAVs, a PID controller will be needed. The LQR is better in missions that have known dynamics and need optimal performance. Where there is uncertainty or variation in conditions, then Adaptive or Fuzzy Logic controllers are more resilient. In the case of high-performance UAVs, which require accuracy and stability, the FOPI is the most balanced as it provides flexibility and control refinement features. One should add that significant innovations in the construction of the current UAV controllers have occurred as a result of the introduction of hybrid controllers, that combine the features of multiple approaches to control in order to escape the limitations of single strategies. By integrating the classical, optimal and intelligent principles of control, these hybrid systems are more precise, robust and adaptable. The fundamental idea behind hybridization is to have the flexibility and modular capability of advanced methods and the ease and reliability of conventional controllers. This combination allows the control system to cope with nonlinearities, adapt to real-time variations in the system dynamics and will work efficiently under diverse operating conditions. Therefore, the hybrid controllers enhance the final performance and reliability of the UAV systems through providing better balanced, stable, and effective control solution [55, 56].

A comparative analysis is based on the peculiarities of each type of controller deployed in UAV systems, which are enumerated in Table 3.1. The table provides an overview of their basic concepts, strengths, as well as weaknesses, showing how specific mission needs, environmental conditions, as well as the complexity of the UAV platform influence the decision of the controller.

Table 3.1: Comparison Summary for Common UAV Controller Types.

Controller Type	Main Principle	Strengths	Limitations	Best Application in UAVs
PID Controller	Proportional, integral, and derivative control of error	Simple, easy to implement, stable for basic systems	Limited robustness and adaptability to nonlinearity	Basic stabilization and altitude control
PID Controller	Proportional, integral, and derivative control of error	Simple, easy to implement, stable for basic systems	Limited robustness and adaptability to nonlinearity	Basic stabilization and altitude control
LQR Controller	Optimal state feedback minimizing a quadratic cost	Smooth performance, optimal control effort	Requires an accurate linear model	Multivariable UAVs with defined dynamics
SMC	Variable structure and switching control	Strong robustness to uncertainties and disturbances	Causes chattering; may stress actuators	Robust attitude and trajectory control
Adaptive Controller	Real-time parameter adjustment	Handles time-varying dynamics and uncertainties	Complex design, high computation demand	UAVs with variable payloads or environments
FLC	Rule-based decision and inference system	Handles nonlinearities without an exact model	Requires expert tuning, computationally heavy	Nonlinear flight control and disturbance handling
FOPID	Fractional calculus-based PID extension	High precision, improved robustness, tunable frequency response	Complex tuning and implementation	High-performance, precision UAV missions

3.4 CONTROLLER OPTIMIZATION FOR UAV SYSTEMS

Because stability of the flight, response time, energy efficiency, and overall system robustness are directly dependent on parameters of the controller, their appropriate tuning is important to the effectiveness of any UAV control system. Traditional or manual tuning methods, including rule-based or trial-and-error methods, are often not the best at providing the best results, especially when the dynamics of a nonlinear and time-varying UAV are involved. To address these limitations modern studies are increasingly using optimization algorithms to systematically find the best controller parameters to attain excellent control performance subject to a variety of operating conditions. In the section, we will dwell on controller optimization techniques that enhance the work of the UAV control system by minimizing error measures such as Root Mean Square Error (RMSE), Integral Absolute Error (IAE) and Integral of Time-Weighted Absolute Error (ITAE). We will explain in details the role played by advanced metaheuristic optimization algorithms which include PSO, JAYA algorithm, Black Hole Optimization (BHO), Harris Hawks Optimization (HHO) and Eagle Strategy (ES). These algorithms allow the optimal tuning of the controllers of the PID, LQR, fuzzy, and fractional-order type by intelligently searching global optima in complex, multidimensional space by emulating natural and social behaviors. These optimization methods will be discussed in the following subsections and how optimization can be applied to adjust UAV controllers to enhance accuracy, stability and energy efficiency when flying [57].

3.4.1 Metaheuristic Algorithms

Due to the effective search space exploration capability of large and complex search spaces, the use of metaheuristic algorithms has become an important tool in the optimization of UAV controller parameters when traditional gradient-based or analytical optimization tools are often ineffective. These algorithms are based on a natural, biological, or social process and are aimed at achieving a compromise between exploration (searching the whole world to find possible solutions) and exploitation (optimizing the best-found solutions). They are flexible and can therefore deal with nonlinearity, noise, and uncertainty- features that are inherent in the UAV dynamics. Most algorithms in meta-hypermetrics can be further broken down into four broad categories: evolutionary algorithms (including Genetic Algorithms and Differential Evolution), swarm-based algorithms (including PSO and Artificial Bee Colony), algorithms based on physics (including Simulated Annealing and Black Hole Optimization), and algorithms based on human or animal behavior (including Jaya, HHO, and Grey Wolf Optimizer). All types utilize varied mechanisms to generate and adapt solutions, but all are aimed at converging to the global optimum efficiently and reliably. These algorithms have been invaluable in the design of UAV controllers in the fine-tuning of PID, FOPID, LQR, and other higher-order controllers to enhance flight stability, tracking performance, and energy efficiency in the presence of unpredictable operating conditions. Fundamental types will be explained and discussed in the ensuing subsections [58].

3.4.1.1 Particle swarm optimization

The PSO algorithm is among the most common and efficient metaheuristics optimization algorithms that can be used to optimize UAV controllers. PSO was first proposed by Kennedy and Eberhart in 1995, and so it is based on the collective behavior seen in fish schools and flocks of birds. When used with UAVs, PSO is effectively used to tune parameters of control, including proportional, integral, and derivative gains (in the case of PID/FOPID controllers) or weighting matrices (in the case of LQR) to achieve the desired high dynamic stability, reduced tracking error, and energy-efficient controller. In PSO, every solution potential is a representation of a particle in a search space of dimension n. A possible answer is that the position of each particle and its velocity determine the motion of each particle within the search domain. The swarm in general explores the global optimum by adjusting the positions and velocities of the particles based on their personal experience as well as the performance of the group as a whole. The general equations that govern the process are the following [58]:

$$v_i{}^{k+1} = wv_k^i + c_1 r_1 (p_i - x_k^i) + c_2 r_2 (g - x_k^i) \tag{3.18}$$

$$x_i{}^{k+1} = x_k^i + v_i{}^{k+1} \tag{3.19}$$

where:

v_i^k: is referring to the velocity of the i^{th}particle at k-iteration,

x_i^k: is referring to the current position of the particles,

p_i: is referring to the personal best position found by the particle,

g: is referring to the global best position found by the swarm,

w: is referring to the inertia weight controlling the influence of the previous velocity,

$c_1$and $c_{2:}$ are referring to the cognitive and social acceleration coefficients, respectively,

$r_1$and r_2: are referring to random numbers uniformly distributed in the range 0 and 1.

The former ((wv_i^k)) is the inertia which keeps the particle in its current momentum, the latter ($(c_1 r_1 (p_i - x_i^k)$) is the memory component which incentivizes the particle to move to a position of its own optimum, and the third component ($c_2 r_2 (g - x_i^k)$) is the cooperation or social influence which draws the particle towards the optimum position of the whole swarm. The two effects together have the effect that the particles search the search space all over the world during the initial iterations and utilize the local optima during the subsequent iterations to enable PSO to converge effectively to the optimal solution. In the UAV context, PSO has been found extremely useful in maximizing the controller gains to achieve a smaller response time, less overshoot, and reduced steady-state error. The exploration (global search) and exploitation (local refinement) balance allows the UAV to be stable in diverse flight conditions, disturbances, and non-linearities. In addition, the algorithm is simple, and its computational efficiency has led to its adoption in real-time applications in embedded UAV systems. Figure 3.7 demonstrates the conceptual operation of the PSO mechanism, as well as inertia, memory, and cooperation forces acting on every particle [58].

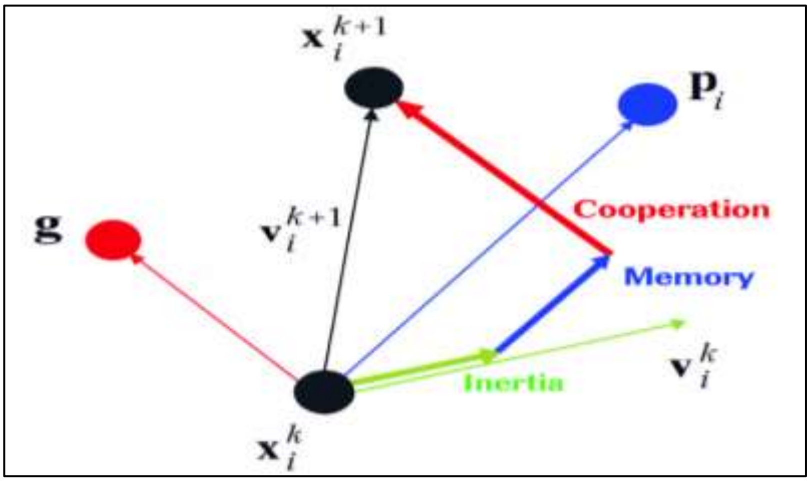

Figure 3.8: PSO Particle Motion [59].

Whereas Figure 3.8 shows the overall PSO algorithm flow (i.e., how it interacts with the starting state and what forces lead to its convergence). Collectively, these numbers reveal an explicit description of the way PSO is used to gradually optimize the parameters of controllers and improve the performance of UAVs [59].

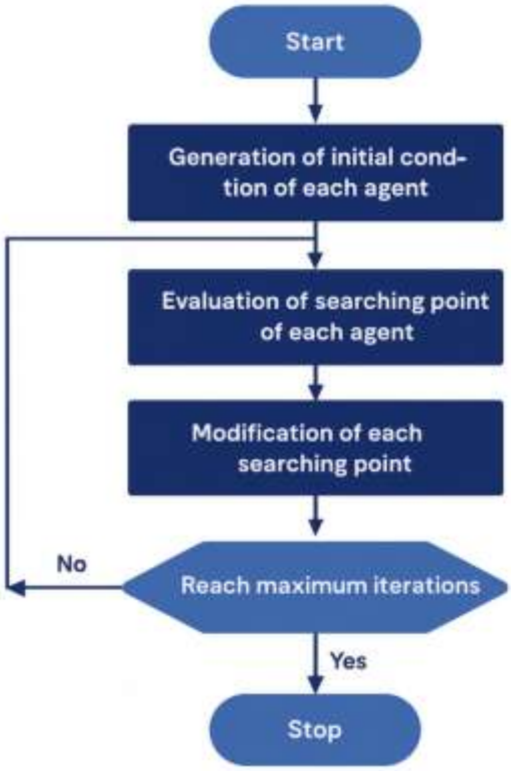

Figure 3.9: PSO Algorithm Flowchart for UAV Controller Tuning.

3.4.1.2 Jaya algorithm

JAYA algorithm is a comparatively new optimization algorithm proposed by Rao in 2016, and it continues to gain momentum regarding the use in UAV controller tuning because of its simplicity, efficiency, and parameter-free nature. The name of the algorithm, which the Sanskrit word Jayaya means victory, shows the philosophy of the algorithm: to get closer to the solution with the highest performance and farther distant from the worst-performing solution. This simple but effective mechanism avoids tuning parameters of algorithms, including inertia weights or acceleration constants, used in other algorithms, like PSO, and JAYA is comparatively very easy to apply when optimizing UAVs. The JAYA algorithm optimization has been applied to optimize PID, LQR, or FOPID gains, where the objective function can be an error in tracking, overshoot, or settling time. The standard update rule of the JAYA algorithm is as follows [60]:

$$x_{i,j}^{(t+1)} = x_{i,j}{}^{(t)} + r_1\left(x_{best,j}^{(t)} - \left|x_{i,j}^{(t)}\right|\right) - r_2\left(x_{worst,j}^{(t)} - \left|x_{i,j}^{(t)}\right|\right) \tag{3.20}$$

where:

$x_{i,j}^{(t)}$: is referring to the current position of the i^{th}candidate in the j^{th}dimension at iteration,

$x_{best,j}^{(t)}$and $x_{worst,j}^{(t)}$: are referring to the best and worst candidates in the population, respectively,

$r_1$and r_2: are referring to the random numbers uniformly distributed between 0 and 1.

The first term in the equation pulls the solution towards the candidate that has performed best, and the second one pushes the solution towards the worst candidate, effectively choosing a balance between exploration and exploitation without extra control parameters. This adaptive behavior allows the global optimum of JAYA to be reached with high speed without the high rate of convergence to a local optimal which is a significant issue with other algorithms. The JAYA algorithm proves to be very advantageous in the instance of UAV systems: it converges to faster; it is cheaper to compute and can be utilized in both noisy and uncertain environs. It is also parameter-free, which makes it easier to integrate with embedded systems, which are constrained in computational resources. Through the JAYA method, the UAV controllers are able to attain the optimal gains, which would provide greater flight stability, responsiveness, and energy efficiency in a range of flight modes. The general flow of the JAYA optimization procedure, including the initiation, evaluation, and updating of solutions by an iterative process till convergence, is represented by Figure 3.10 and the overall procedure of the algorithm as applied to the UAV controller tuning [61, 62].

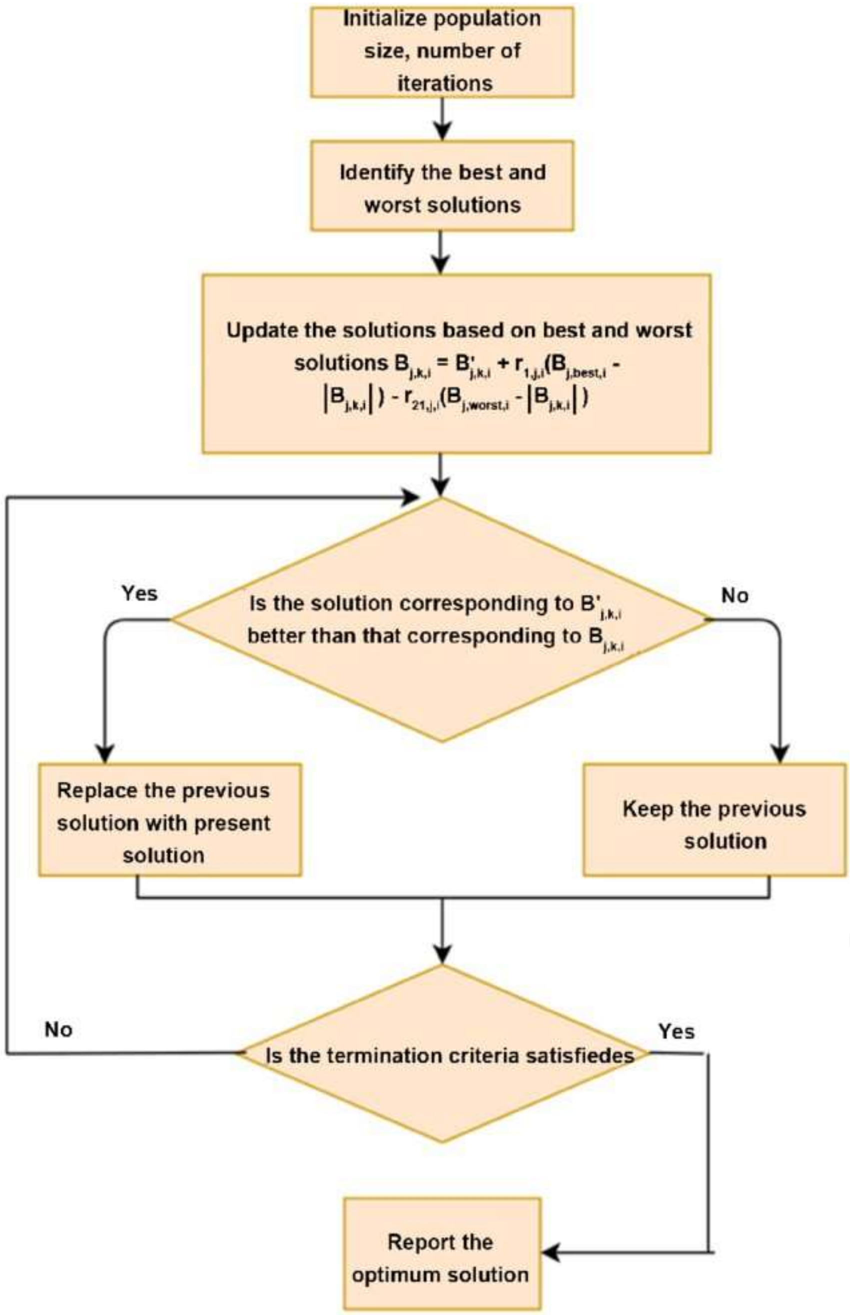

Figure 3.10: Flowchart of The JAYA Algorithm for UAV Controller Optimization [62].

3.4.1.3 Black hole optimization algorithm

BHO algorithm is a physics-inspired metaheuristic algorithm that simulates the gravitational characteristics of black holes in space. This algorithm was introduced by Hatamlou (2013) and has since been popular in UAV control optimization as it is simple and has a good convergence property and global search ability. The algorithm works by modeling a set of candidate solutions, also known as stars, that wander in the search space under the presence of a dominant star, known as a black hole, which represents the best available solution. In consecutive replication, the stars will approach the black hole, and the fitness of the population will generally increase, ultimately converging on the optimal controller parameters. The BHO algorithm is also used in the UAV control system to optimize such parameters as proportional, integral, and derivative gains, nonlinear or fractional-order controller coefficients. It aims to reduce performance metrics such as Integral of ITAE, ISE, or RMSE and consequently attain quicker reaction, turbulent control signals, and enhanced disturbance rejection. Mathematically, the motion of any star toward the black hole is [63]:

$$X_{new}^{i} = X_i + rand \times (X_{BH} - X_i) \tag{3.21}$$

where:

X_i: is referring to the position of the i^{th}star,

X_{BH}: is referring to the position of the black hole (best solution), and

$rand$: is referring to a random number uniformly distributed between 0 and 1.

The event horizon radius, which determines whether a star is absorbed by the black hole, can be represented by the following mathematical equation [63]:

$$R = \frac{f_{BH}}{\sum_{i=1}^{N} f_i} \tag{3.22}$$

Where:

f_{BH}: is referring to the fitness value of the black hole, and

f_i: is referring to the fitness of the i^{th}star in a population of size N.

The moment a star goes past this event horizon, it is thought to be swallowed by the black hole, and thus, a new star randomly generated in the search space replaces it. This way, the method facilitates diversity among the population and prevents premature convergence. In the case of UAV applications, the BHO algorithm is shown to be an efficient tool for exploring (searching new areas) and exploiting (refining good solutions) at the same time. Hence, it turns out to be an excellent choice for very complex UAV systems where the aerodynamic parameters differ depending on the conditions of speed, altitude, and load. The

BHO algorithm, with its deterministic nature and minimal control parameters, is still very fast and suitable for real-time UAV optimization integration. The whole stepwise algorithm of the BHO method from initialization to convergence has been depicted in Figure 3.11. The process of stars being evaluated one by one, drawn to the black hole, and being substituted when absorbed is shown, and thus, the whole process leads to the optimal solution search [63, 64].

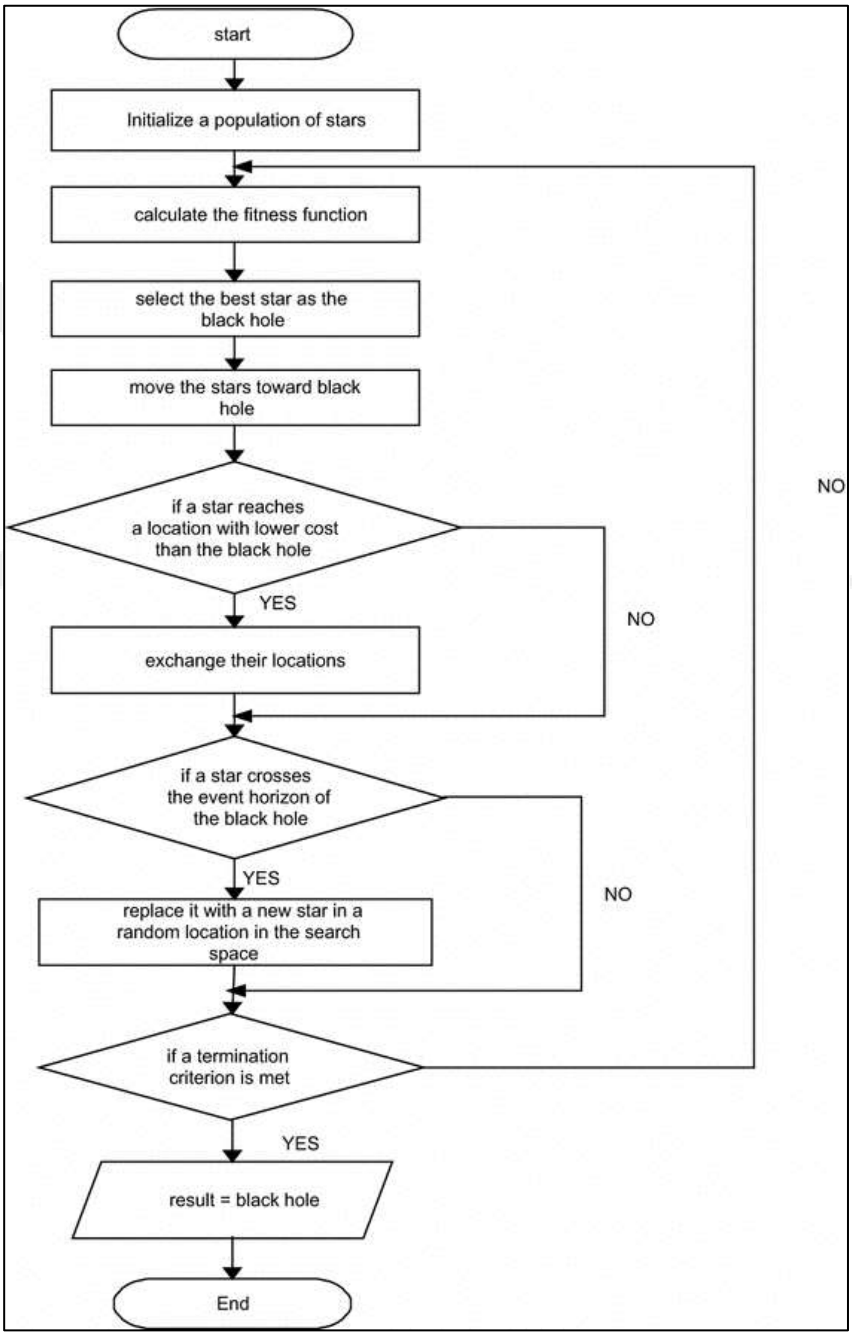

Figure 3.11: Flowchart of The BHO Algorithm for UAV Controller Tuning [64].

3.4.1.4 Harris Hawks Optimization (HHO)

The HHO algorithm is a metaheuristic method, which is nature-inspired, and was created by Heidari et al. in 2019, based on the cooperative hunting of hawks, which involves Harris hawks. Groups of these birds of prey work together to attack fast-moving prey like rabbits with dynamic and energy-saving saving and coordinated attacks. The algorithm is a mathematical model of this intelligent hunting process, which is used to solve complicated optimization problems. HHO has been highly successful in the optimization of UAV controllers to refine the parameters of nonlinear, multi-objective, and time-varying systems, offering better accuracy, stability, and adaptability. The HHO algorithm has three primary phases, which are exploration, transition, and exploitation. Throughout the exploration stage, the hawks (candidate solutions) randomly perch or around other hawks depending on the location of the prey (best solution), which allows them to search globally and achieve diversity in the population. The transition stage varies between exploration and exploitation depending on the escaping energy of the prey, which is given as follows [65]:

$$E = 2E_0\left(1 - \frac{T}{t}\right) \tag{3.23}$$

Where:

E_0: is referring to the initial energy,

t: is referring to the current iteration, and

T: is referring to the maximum number of iterations.

The value of $E\ is\ generally$ determines whether the prey has sufficient energy to escape ($|E| \geq 1$) or is weakened and ready to be attacked ($|E| < 1$).

In the course of the exploitation stage, the hawks use coordinated attacks that are called soft besiege and hard besiege strategies depending on the energy of the prey and the possibility of escaping. The positions of the hawks are updated using different mathematical models that simulate encircling, rapid dives, and adaptive movements around the prey. For example, in the soft besiege case, the hawk's position is updated as [65]:

$$X(t+1) = \Delta X(t) - E\ |\ JX_{prey}(t) - X(t)\ | \tag{3.24}$$

Where:

$X(t)$: is referring to the current position of the hawk,

$X_{prey}(t)$:is referring to the prey's position,

E: is referring to the escaping energy,

J: is referring to the random jump strength, and

$\Delta X(t)$: is referring to the position difference between the prey and the hawk.

These dynamically updated position messages guarantee a trade-off between exploration (global search) and exploitation (refinement), enabling HHO to focus on the best solution effectively. HHO has been applied in the design of UAVs to minimize gains of controller designs, like PID, FOPID, or adaptive controllers, by minimizing performance indices such as ITAE or Rise Time. Its ability to switch flexibly between local and global search allows it to be able to focus precisely under uncertain aerodynamic and environmental conditions. HHO is faster converging and enhances the global optimality, and therefore, it is well adapted to UAVs, which need precision and adaptability [65, 66]. The general working design of the HHO algorithm, including the initialization, energy update, and attack plans, is shown in Figure 3.12.

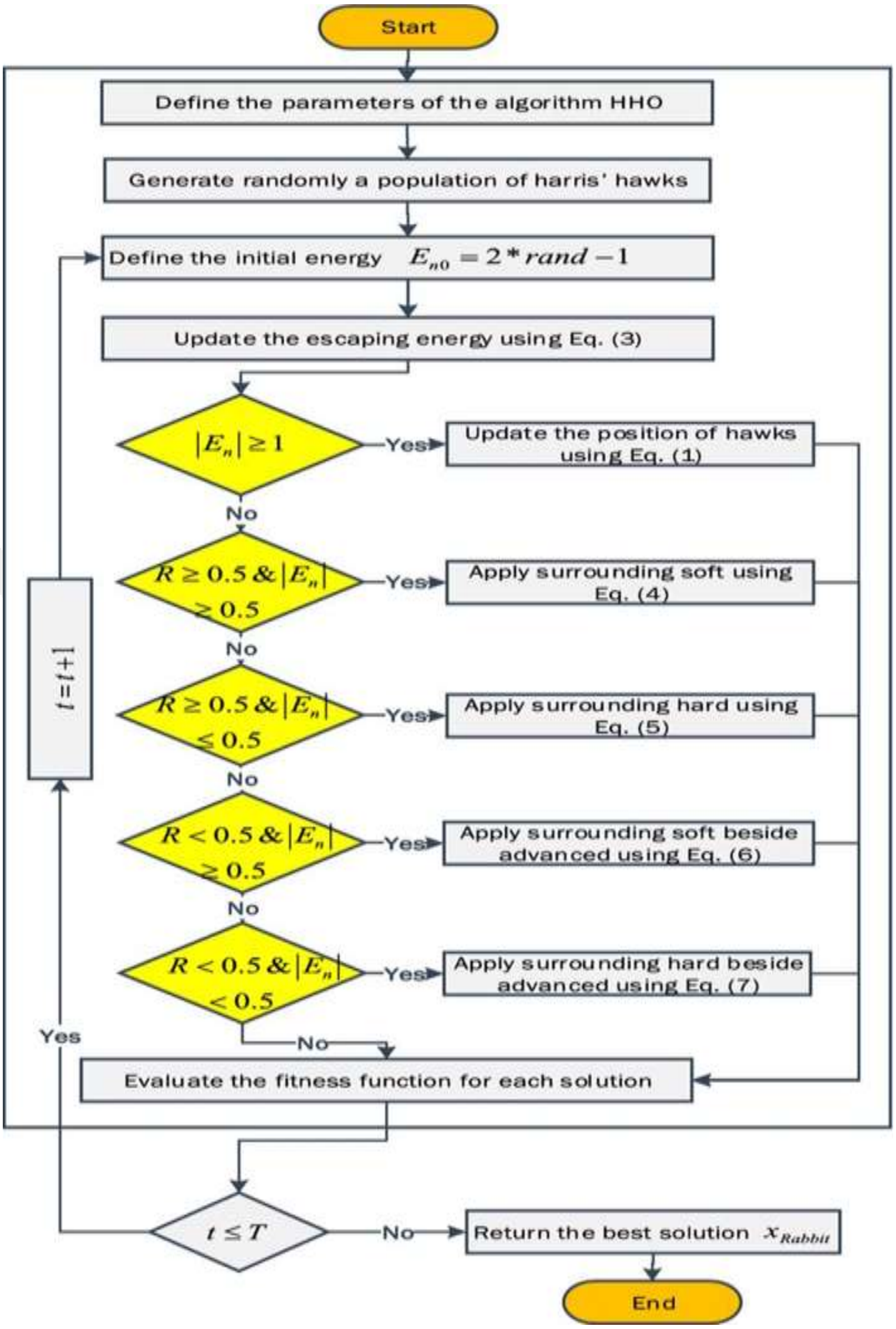

Figure 3.12: Flowchart of The HHO Algorithm for UAV Controller Tuning [65].

In contrast, the exploration-exploitation system of hawks, as well as the adaptations of these birds to various hunting tactics, is depicted in Figure 3.13. This value shows that the algorithm adapts to dynamic trade-offs between global exploration, in which the hawks search potential prey on a large scale, and local exploitation, in which the hawks concentrate their attacks on the best solution discovered thus far. The algorithm is capable of refining solutions by adapting to the soft and hard besiege strategies based on the energy and escape probability of the prey in the adaptive switching of these strategies, with no premature convergence. It is this combination of these mechanisms that underscores how the cooperative intelligence and the coordinated nature of hunting of Harris hawks can be mathematically mapped into an efficient and powerful optimization framework to design UAV controllers to be able to tune their parameters appropriately and perform well over a range of flight modes [66].

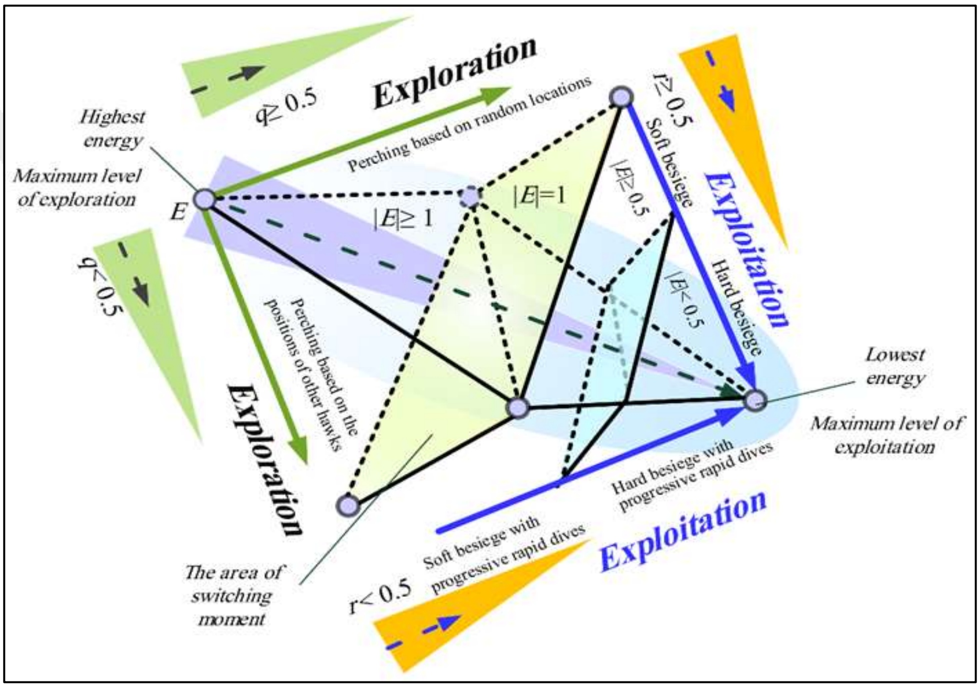

Figure 3.13: Exploration and Exploitation Behavior in The HHO Algorithm [66].

3.4.1.5 Eagle Strategy (ES)

The Eagle Strategy (ES) is a metaheuristic hybrid optimization algorithm that is based on the intelligent hunting behavior of eagles in a two-stage process consisting of global exploration and local exploitation. The strategy introduced by Yang and Deb (2010) aims to strike a balance between the scope of search required and refined search in near-optimal solutions. The balance of the Eagle Strategy makes it especially useful in the optimization of the UAV controllers, where the global adaptability alongside the possibility to reliably modify the control parameters are essential to achieve stability, accuracy, and strength in the dynamic flight conditions. The global search stage in the ES framework emulates the movement of the eagle across wide fields of search in search of areas of creatures of interest (potential solutions). This stage tends to be modelled by a stochastic process, which allows long-range steps and random search of the search space, like a Levy flight. After identifying promising regions, the local search phase is triggered, during which the eagle concentrates itself in a particular region and does the detailed searches with local optimization schemes Differential Evolution (DE), PSO, or another advanced refined process, in order to explore the best solutions even more accurately. The global search has the eagles in globally varying positions, which can be mathematically expressed as [67]:

$$X_i^{t+1} = X_i^t + \alpha \times Le\acute{}vy(\lambda) \tag{3.25}$$

Where:

X_i^t: is referring to the current position of the i^{th}eagle,

α: is referring to the scaling factor controlling the step size, and

Lévy(λ):is referring to the Lévy flight distribution that introduces randomness and large exploration jumps. Once the promising region is discovered, the local search is performed by utilizing an exploitation equation, which is expressed as follows [67]:

$$X_i^{t+1} = X_{best}^t + \beta \times \left(X_{r_1}^t - X_{r_2}^t\right) \tag{3.26}$$

Where:

X_{best}^t: is referring to the current best solution, X_{r1}^t, and $X_{r2}^t which$ are two randomly selected solutions from the population, and

β: is referring to the controls of the degree of local refinement.

The ES algorithm has a number of benefits in UAV controller tuning. The global stage excludes the possibility of premature convergence by searching in different parts of the parameter space, whereas the local stage guarantees the correct control parameters adjustment, including PID, FOPID, or LQR gains. This two-layer structure also improves the performance of the UAV, reducing the overshoot, increasing the transient response, and ensuring that the UAV is robust to the changing aerodynamic and environmental conditions. Additionally, ES is modular and can therefore be effortlessly used in conjunction with other optimization algorithms to create additional efficient hybrid tuning schemes. The general algorithm of the Eagle Strategy, including the population start, assessment, and two-step search process to convergence, is illustrated in Figure 3.14, which shows the flow of the algorithm step by step [68].

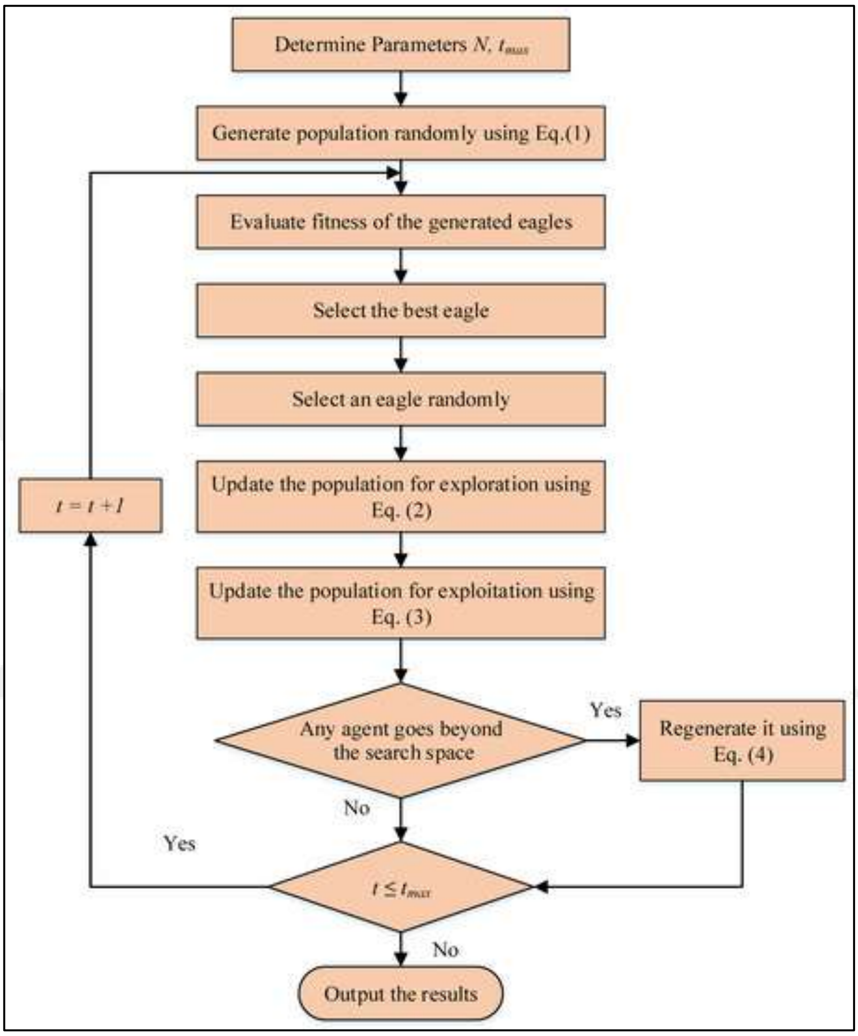

Figure 3.14: Flowchart of The ES Algorithm for UAV Controller Optimization [68].

The extensive and narrow searching movement of the eagle, which helps it to find the world optimum in a simple manner, is conceptually represented in Figure 3.15. The figure illustrates that the eagle switches intelligently between global exploration (wide) and local exploitation (focus), where it explores broad areas of the search space to locate several good areas and narrows in on those areas (best) to increase precision. Such adaptive switching between exploratory and exploitative modes is what is needed to ensure that the algorithm does not converge too soon, and also, its chances of converging to the actual global optimum are very high. An intelligent imitation of this dual-phase hunting approach enables the Eagle Strategy to effectively balance search variety and convergence accuracy, and it is especially effective when applied to complex optimization tasks involving a UAV controller that needs both flexibility and precision [69].

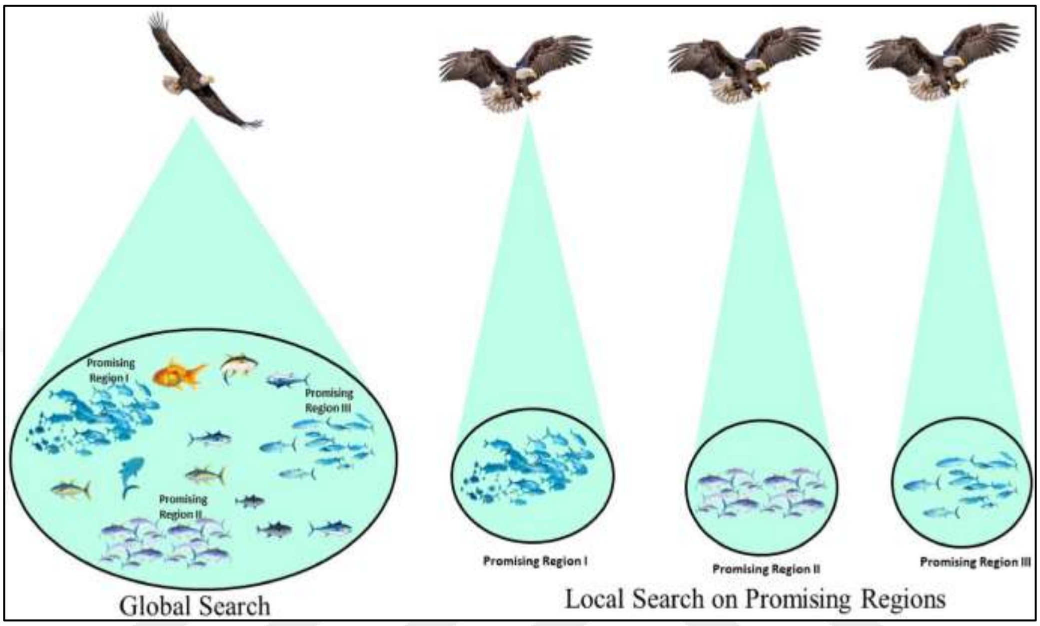

Figure 3.15: Global Exploration and Local Exploitation Behavior in The ES [69].

3.4.1.6 Hybrid algorithms

Hybrid optimization algorithms are presented in the research of modern UAV control as the most effective method of attaining better control performance through the synergistic deployment of two or more complementary optimization methods. The primary rationale of hybridization is to overcome the weaknesses of single algorithms in that they fail to do something as either premature convergence, or lack of robustness, or slow response, by developing a system that balances global exploration (searches widely in the solution space) and local exploitation (optimizes the promising regions). This combination would lead to algorithms that are able to adapt to the highly nonlinear and time-varying, uncertain dynamics of UAVs to achieve quicker convergence, more accurate, and improved stability in the controlled conditions in flight [70].

Hybrid algorithms have been applied successfully in optimizing a diverse variety of controllers, such as PID, FOPID, LQR, and adaptive fuzzy systems, in UAV controller tuning. The process of hybridization may be of various forms [70]:

i. Sequential Hybridization: in which one algorithm is used to initialize the solution, and another algorithm to refine it.

ii. Parallel Hybridization, in which multiple algorithms are simultaneously run, and they communicate with each other as the optimization is done.

iii. Adaptive Hybridization: operates on the concept that the behavior of one algorithm is dynamically changed by the performance feedback of another algorithm.

The combination of these strategies forms a synergistic structure that uses the advantages of each of the methods, which include the exploration effectiveness of PSO, the flexibility of JAYA, the precision of convergence of HHO, or the ES local search ability, for the purpose of obtaining the best tuning results, for example. Additionally, there are several hybrid configurations applied in UAV optimization, some of notable configurations include [70]:

i. PSO -GA (Particle Swarm Optimization + Genetic Algorithm): This is a blend of the global search capability of GA and fast convergence of PSO, that is, improved exploration and local fine-tuning of the UAV controllers.

ii. HHO-BHO (Harris Hawks+ Black Hole Optimization): The two methods are used to combine HHO adaptive hunting techniques with gravitational movement in BHO as a way of improving global stability and precision in convergence.

iii. Fuzzy-PSO/ Fuzzy-JAYA: Applies the fuzzy logic to control adaptive parameters during the optimization process and enhances the ability to react to the changing UAV dynamics.

iv. Eagle Strategy -PSO: It is a combination of ES and PSO with a global-local search balance offering a high-accuracy tuning of FOPID and LQR controllers using the velocity-driven PSO learning mechanism.

v. Hybrid Fractional Optimization (e.g., FOPID–PSO–GA): such configuration is proposed for the fractional-order controllers where offers multiple algorithms collaborate employed to tune fractional order parameters (λ, μ) and the other gains simultaneously for maximum control precision.

The main benefits of the utilization of the hybrid algorithms in the architecture of the UAV controller optimization are summarized in Table 3.2, which emphasizes how hybridization enhances search efficiency, accuracy, and adaptability compared to single-algorithm approaches [70].

Table 3.2: Generic Advantages for Hybrid Algorithms for UAV Controllers.

Feature	**Effect on UAV Controller Performance**
Enhanced global search	Prevents premature convergence and expands exploration capability.
Faster convergence	Accelerates parameter tuning and reduces computational time.
Balanced exploration–exploitation	Improves solution accuracy and consistency.
Robustness under uncertainty	Maintains performance under disturbances and model variations.
Multi-objective optimization	Enables simultaneous improvement in stability, speed, and energy efficiency.
Flexibility and scalability	Adaptable to different UAV types and controller architectures.

4. PROPOSED SYSTEM DESIGN AND MODELLING

4.1 OVERVIEW

The tethered UAV system is an enhanced design in the unmanned aerial technology that has solved a number of constraints associated with the traditional battery-powered UAVs. Although conventional UAVs have been widely used in surveillance, environmental measurement, communication relay, and disaster rescue, their operating range is inherently limited by the limited energy storage on board and communication range. A tethered UAV, in contrast, is literally attached physically to a ground station using a flexible power and data cable, called a tether, that supplies a continuous electrical power supply and a reliable communication link. This design allows it to do away with the reliance on onboard batteries and thus allows it to stay in the sky longer and operate continuously- an invaluable capability when it has to be on continuous observation or where it has to operate in risky conditions, and the manual replacement of the batteries is not practical. A structural plan of a tethered UAV system is usually depicted in Figure 4.1 as consisting of two main parts: an UAV and a ground control unit connected by the tether cable. The UAV is controlled in three-dimensional space in terms of its position coordinates (x_d, y_d, z_d) and the ground anchor point of the tether is positioned on coordinates (x_t, y_t, z_t). This mechanical bond adds more vibrating interactions, which are mainly based on tether tension, which has a greater effect on the translation and rotation of the UAV. The behavior of the system is therefore controlled by a mixture of aerodynamic forces (thrust and drag) and mechanical effects that are caused by the tether, which complicates the process of modeling and control of such systems as compared to conventional UAVs. To guarantee proper performance, a mathematical model of the tethered UAV has to be elaborated, hence taking these interdependent dynamics to represent the real-time behavior in different conditions of operations. In addition to the mechanical framework, the tethered UAV system has a number of strategic benefits. The sustained power supply increases the mission's endurance, and the safe data link reduces latency and signal interference, which is vital to communication-heavy applications. In addition, the physical tether provides an extra level of safety in the operation of the UAV since the tether does not allow it to be completely lost should there be a failure in communication or other disturbances in the environment. The system can be combined with modern control and optimization algorithms, including PSO, JAYA, or HHO, to benefit from better stability and response and adaptive control in the face of uncertain flight conditions. Generally, a tethered UAV system offers a powerful and efficient system to be used on aerial missions over a long period of time. The combination of the freedom of UAVs and the efficiency of a ground-based source of power and communication facilitates a stable and constant work with the ability to operate without failure in civil and industrial practice [71].

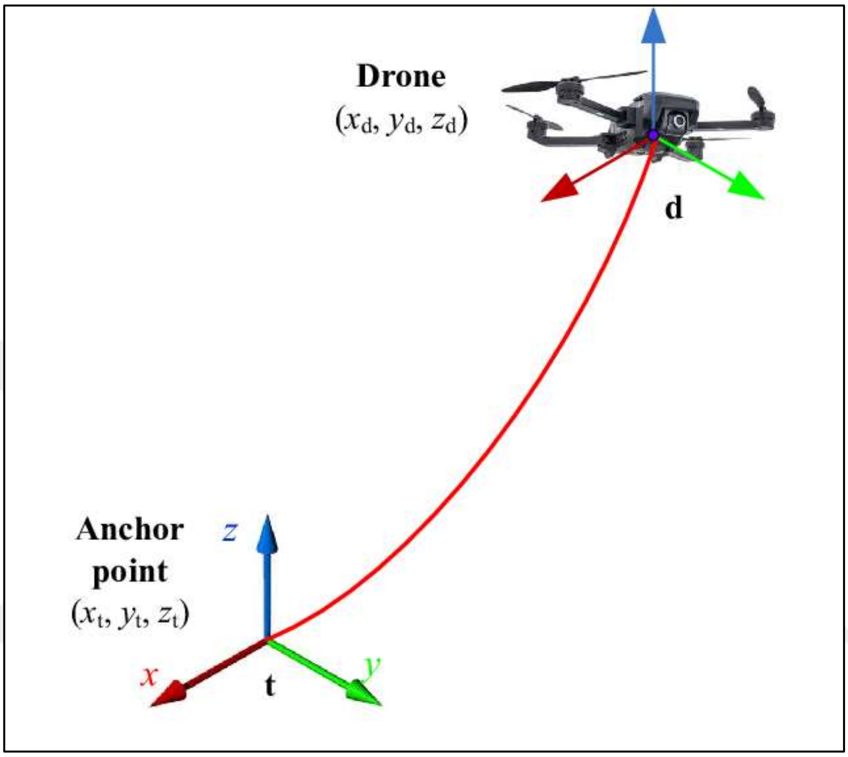

Figure 4.1: Structural Representation of The Tethered UAV System [71].

4.2 DEFORMATION MECHANISM OF THE TETHERED UAV

The adaptive deformation mechanism of the tethered UAV system is one of the most innovative features of such a system, as operational requirements may make the aerial platform change the geometry of the aircraft. The tethered UAV, as opposed to the conventional rigid-structure UAVs, features servo-actuated arms that are capable of extension or folding up during flight, and improve maneuverability, stability, and task flexibility, particularly in physically sensitive environments (e.g., tree canopies or narrow corridors). This deformation capability allows the UAV to dynamically alter its configuration, which is the most efficient and responsive to the chosen mission needs according to aerodynamic efficiency and control response. The UAV experiences two major modes of deformation, namely extension and folding, as shown in Figure 4.2. In the extension mode, servo actuators lengthen out of the wings of the UAV, and the wings lengthen, making the wings more stable both in hovering and heavy-lift load operations. On the other hand, during the folding mode, the arms fold up or close around the central axis of the body to create a small bowl-shaped shape which is small. This arrangement reduces the air resistance and enables the UAV to operate in constrained spaces, such as in overgrown vegetation or buildings, hence highly applicable in inspection, search-and-rescue, and crop harvesting tasks [72].

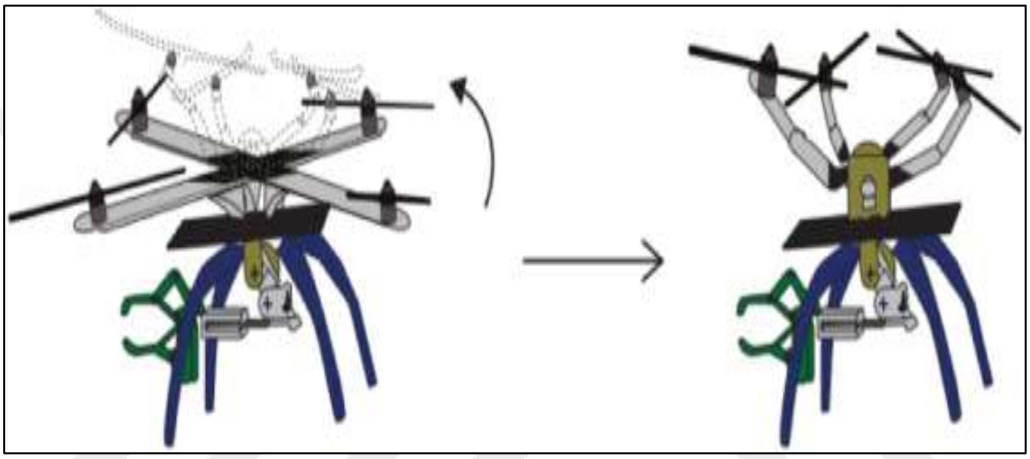

Figure 4.2: Deformation Process of The Tethered UAV Configurations [72].

The Center of Gravity (CG) and inertia matrix of the UAV are also deformed by the deformation of the UAV, which are important factors in ensuring flight stability. The mass redistribution during arm extension or folding changes the moment of inertia of the UAV, and the parameters of control have to be recalibrated and balanced in real time. Continuously, the onboard controller makes rotor thrust and torque outputs changes to counter such geometric variations, so that the UAV is left dynamically stable. Additionally, the ability to alter the geometry of the arm enables the possibility to obtain higher energy efficiency, as UAV is able to modify its aerodynamic profile to restrict or maximize drag or lift accordingly. It is a modular design which can enhance the physical agility of the UAV, resiliency and versatility to missions. In one instance, the folded configuration is more precise in control with precision tasks such as fruit picking or inspection close to the ground whereas the extended configuration has a higher level of control with hovering or transportation. The lightweight materials and high-torque servos are included in the mechanical design so as to maintain the structural strength and minimize the additional weight. Overall, the deformation mechanism is what allows the tethered UAV to not be an inert aerial vehicle but rather an adaptable intelligent platform capable of performing different sort of missions and being highly efficient and versatile. It embodies the ideas of bio-inspired engineering, the mechanical versatility, and advanced control algorithms to achieve the high-performance aerial work in the complicated environmental conditions [73].

4.3 DYNAMIC MODELING OF THE TETHERED UAV SYSTEM

The dynamic modelling of a tethered UAV can be used to give a comprehensive idea of the interaction between aerodynamic forces, the force of gravity, rotor thrust, and tether tension to establish the overall behavior of the system. The addition of a tether compared to free-flying UAVs adds new constraints and nonlinear couplings to simplify the dynamics but stabilize them and increase their reliability in long-duration operations. To obtain an accurate model, the Newton-Euler model of motion, considering both the translational and rotational dynamics, is used to establish the model. Figure 4.3 indicates the distribution of forces and moments acting on the tethered UAV, and Figure 4.4 indicates the coordinate systems relative to the ground anchor and the vehicle [74].

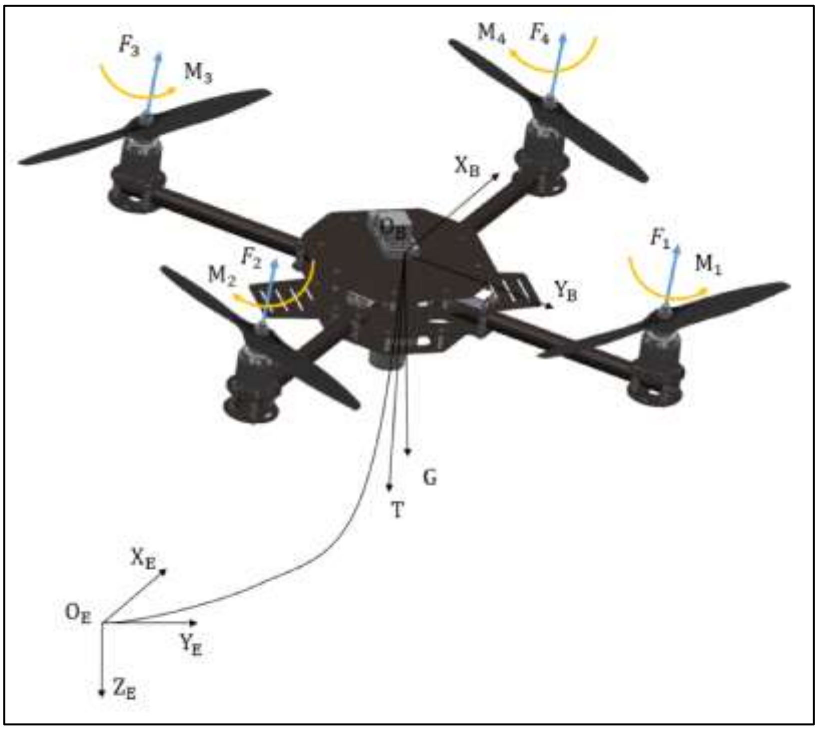

Figure 4.3: Forces and Moments Acting on The Tethered UAV System [74].

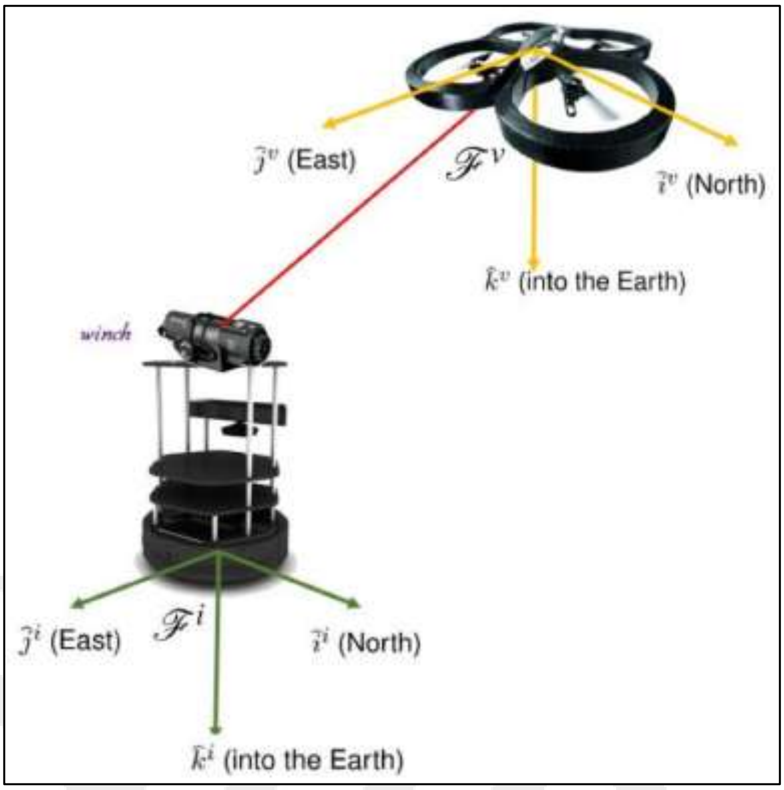

Figure 4.4: Reference Coordinate Frames of The Tethered UAV System [75].

The translational motion for the UAV is derived based on the second law of Newton's, representing the balance between the generated thrust, drag, gravitational, and tether forces acting on the vehicle's center of mass. The equations governing motion in the Earth-fixed axes (X_E,Y_E, Z_E) can be expressed mathematically as follows [74, 75]:

$$m \cdot \frac{dV_x}{dt} = F_t - F_d - T_x, m \cdot \frac{dV_y}{dt} = T_y, m \cdot \frac{dV_z}{dt} = T_z - F_g \tag{4.1}$$

Where:

m: is referring to the UAV mass,

V_x, V_y, V_z: are referring to the linear velocity components,

F_t: is referring to the total thrust,

F_d: is referring to the aerodynamic drag,

T_x, T_y, T_z: are the components of the tether tension, and

$F_g = mg$: is referring to the gravitational force.

In short form, the translational dynamics can be represented mathematically by means of the following Equations [74]:

$$m \cdot \frac{d^2p}{dt^2} = F - m \cdot g \tag{4.2}$$

$$p = [x, y, z]^T \tag{4.3}$$

Where:

p: is referring to the position vector of the UAV in the Earth frame, and

F: is referring to the resultant aerodynamic and thrust force acting on the vehicle.

Following that, the complete translational–rotational coupling in body coordinates can be expressed by means of the following Equation [75]:

$$mv_f = R_b \cdot F_T + F_f + mg + T \tag{4.4}$$

Where:

R_b: is referring to the rotation matrix that maps body-fixed forces into the Earth frame,

F_T: is referring to the total lift produced by the rotors,

F_f: is referring to represents aerodynamic drag, and $T$is the tether tension vector.

For the tether force modeling, the rotational dynamics of the tethered UAV are governed by means of the Euler's rigid-body motion equations, which capture the rotational accelerations that are produced by the combined effects of rotor torque, gyroscopic moments, and tether-induced torques. Mathematically, the rotational equation can be expressed by means of the following Equation [75]:

$$I \cdot \frac{d\omega}{dt} = \tau - \omega \times (I \cdot \omega) \tag{4.5}$$

$$\omega = [p, q, r]^T \tag{4.6}$$

Where:

I: is referring to the UAV's inertia tensor,

ω: is referring to the angular velocity vector, and

τ: is referring to the total control torque from the rotors.

Additionally, the generalized moment balance can also be written as the following Equation [75]:

$$M_0 = I\omega_b + \omega_b \times I\omega_b \tag{4.7}$$

Where:

M_0: is referring to the resultant torque acting on the UAV body.

Following that, the total lift and torque generated by the four rotors can be mathematically expressed as follows [75]:

$$\begin{aligned} U_1 &= C_t(\omega_1^2 + \omega_2^2 + \omega_3^2 + \omega_4^2), \\ U_2 &= 2C_t l(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2), \\ U_3 &= 2C_t l(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2), \\ U_4 &= C_m(\omega_1^2 - \omega_2^2 + \omega_3^2 - \omega_4^2), \end{aligned} \tag{4.8}$$

Where:

C_t and C_m: are referring to the thrust and moment coefficients,

l: is referring to the rotor arm length, and

ω_i: are referring to the angular speeds of the individual rotors. These parameters have a direct influence the vehicle's ability to maintain balance and perform dynamic maneuvers while tethered.

In order to model the tether force of the UAV, the cable exerts an opposing force that has effects on both of the translational and the rotational motion. The tether tension varies with length and elasticity, and its magnitude can be approximated by an exponential decay relation, which is represented by the means of the following Equation [75]:

$$T = T_{\max} \cdot e^{-k \cdot d} \tag{4.9}$$

Where:

$T_{\max}$: is referring to the maximum allowable tension,

k: is referring to the damping coefficient, and

d: is referring to the deployed tether length.

In order to capture the distributed nature of the tether, a segment-based (lumped mass–light rod) model can be utilized. Whereas the equilibrium of the i^{th} segment is governed by the following Equation [75]:

$$T_i \sin \alpha_i - T_{i-1} \sin \alpha_{i-1} = \varepsilon\, ds, T_i \cos \alpha_i = T_{i-1} \cos \alpha_{i-1} \tag{4.10}$$

Where:

α_i: is referring to the inclination angle of the segment,

ε: is referring to the linear weight per unit length, and

ds: is referring to the infinitesimal tether segment.

Under the assumption of symmetry and neglecting lateral deviations, the geometric relation for the tether can be mathematically described by the following Equation [75]:

$$x = \frac{T_n \cos \alpha_n}{\varepsilon} \ln(1 + \tan \alpha_n) + \frac{S}{\varepsilon} T_n \cos \alpha_n \sec \alpha_n + \tan \alpha_n \tag{4.11}$$

$$z = \frac{T_n \cos \alpha_n}{\varepsilon} (1 + \tan \alpha_n) + \frac{S}{\varepsilon} T_n \cos \alpha_n - \frac{T_n}{\varepsilon} \tag{4.12}$$

This formulation allows the determination of the horizontal and vertical coordinates of the UAV relative to the anchor point, based on tether length $S$and end-tension T_n. The three-dimensional tension components are represented as [75]:

$$T = \begin{bmatrix} T_x \\ T_y \\ T_z \end{bmatrix} = T_n \begin{bmatrix} \cos \lambda_1 \cos \lambda_2 \\ \cos \lambda_1 \sin \lambda_2 \\ \sin \lambda_1 \end{bmatrix} \tag{4.13}$$

Where:

λ_1 and λ_2: are referring to the elevation and azimuthal angles of the tether, respectively. In order to express the UAV motion consistently between the Earth and body frames, the rotation matrix T_{R_b} is applied as [75]:

$$T_{R_b} = \begin{bmatrix} \cos(\theta)\cos(\psi) & \cos(\psi)\sin(\theta)\sin(\phi) - \sin(\psi)\cos(\phi) & \cos(\psi)\sin(\theta)\cos(\phi) + \sin(\psi)\sin(\phi) \\ \cos(\theta)\sin(\psi) & \sin(\psi)\sin(\theta)\sin(\phi) + \cos(\psi)\cos(\phi) & \sin(\psi)\sin(\theta)\cos(\phi) - \cos(\psi)\sin(\phi) \\ -\sin(\theta) & \cos(\theta)\sin(\phi) & \cos(\theta)\cos(\phi) \end{bmatrix} \quad (4.14)$$

Where:

ψ, θ, and ϕ: are referring to yaw, pitch, and roll angles, respectively.

Such matrix facilitates the transformation of thrust and inertial vectors between coordinate systems. The total lift generated by the UAV's rotors, mapped into the Earth frame, which expressed by means of the following Equation [75]:

$$\mathrm{F}_T = \mathrm{R}_b \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \sum_{i=1}^{4} C_t \omega_i^2 \quad (4.15)$$

It is necessary to mention that this formulation apprehends how the UAV's collective thrust direction changes with its rapid orientation.

For the Inertia and nonlinear coupled dynamics, due to payload variations or arm deformation, the inertia matrix of the UAV changes dynamically and is expressed mathematically as follows [75]:

$$I = \begin{bmatrix} I_{x0} + \gamma_x & 0 & 0 \\ 0 & I_{y0} + \gamma_y & 0 \\ 0 & 0 & I_{z0} + \gamma_z \end{bmatrix} \quad (4.16)$$

Where:

I_{x0}, I_{y0}, I_{z0}: are referring to the baseline inertias, and

$\gamma_x, \gamma_y, \gamma_z$: are referring to the incremental terms that account for deformation and mass redistribution.

By Combining the translational and rotational equations obtaining the complete nonlinear model of the tethered UAV, which expressed as follows [74, 75]:

$$
\begin{gathered}
\ddot{x} = \frac{1}{m}\left[U_1\left(-C_\psi C_\phi S_\theta + S_\psi S_\theta\right) - TC_{\lambda_1}C_{\lambda_2} - k_f\dot{x}\right] \\
\ddot{y} = \frac{1}{m}\left[U_1\left(-S_\psi C_\phi S_\theta - C_\psi S_\phi\right) - TC_{\lambda_1}C_{\lambda_2} - k_f\dot{y}\right] \\
\ddot{z} = \frac{1}{m}\left[U_1\left(-C_\theta C_\phi\right) - TS_{\lambda_1} - k_f\dot{z} - mg\right] \\
\ddot{\psi} = \frac{I_y - I_z}{I_x}\dot{\theta}\dot{\phi} + \frac{I_r\dot{\theta}\Omega}{I_x} + \frac{lU_2}{I_x} \\
\ddot{\theta} = \frac{I_z - I_x}{I_y}\dot{\psi}\dot{\phi} + \frac{I_r\dot{\psi}\Omega}{I_y} + \frac{lU_3}{I_y} \\
\ddot{\phi} = \frac{I_x - I_y}{I_z}\dot{\psi}\dot{\theta} + \frac{U_4}{I_z}
\end{gathered} \tag{4.17}
$$

$$
\Omega = \omega_1 + \omega_2 + \omega_3 + \omega_4 \tag{4.18}
$$

Where:

I_r: is referring to the rotor inertia,

Ω: is referring to the combined angular velocity of the propellers, and

k_f: is referring to the aerodynamic drag coefficients.

Lastly, one must state that the dynamic equations that have been obtained before give a complete nonlinear description of the tethered UAV system, representing both the rigid-body motion and tether interaction. The tether elasticity, aerodynamic damping and coordinate transformations allow the system to predict the accurate behavior at which the system behavior is predicted in different conditions of operation. This kind of a comprehensive model is used to formulate sophisticated control schemes, including adaptive, robust and optimization-based controllers that aim to enhance trajectory tracking and stability behavior of tethered UAV systems.

4.4 PROPOSED METHODOLOGY

The proposed research framework on the tethered UAV system has three major steps with a separate focus to an important element of modeling, control design, and optimization. This incremental process will ensure that the UAV performs in a stable, precision and flexible way under various environmental and dynamic conditions. Figure 4.5 is the general working arrangement of the offered approach, where the creation of the dynamic model, formulation of the controllers, and the hybrid optimization strategy are interconnected.

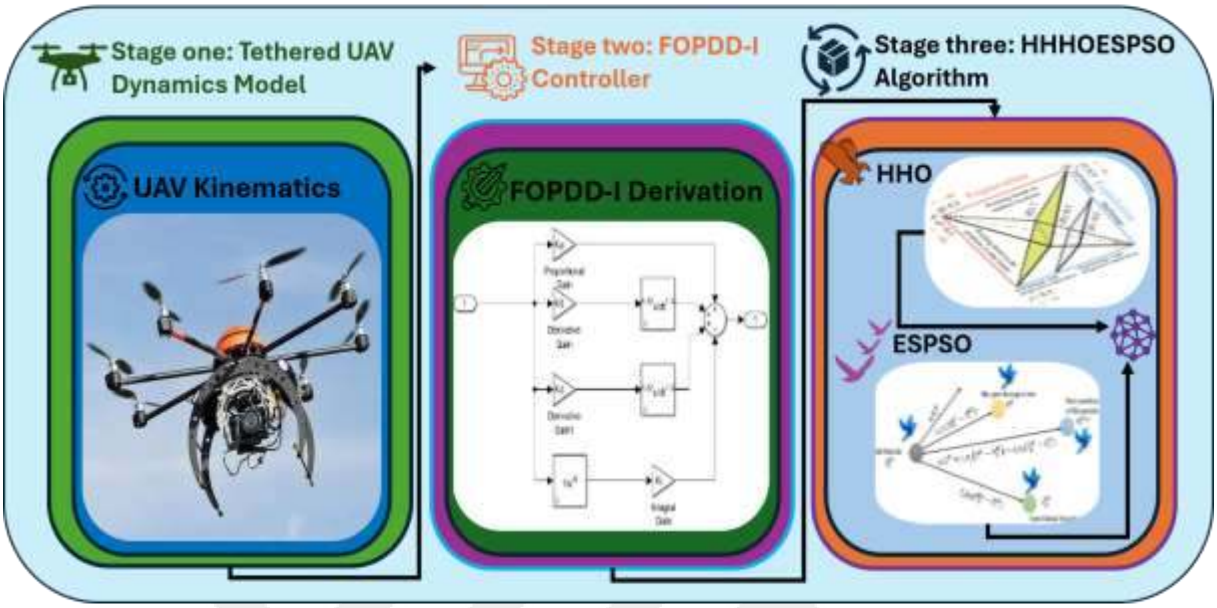

Figure 4.5: Graphical İllustration for The Proposed Methodology.

4.4.1 Stage One: Tethered UAV Dynamics Model

The first step of the proposed methodology is a mathematical representation of the tethered UAV dynamics to provide an accurate description of both translational and rotational motion due to the interplay of the forces associated with aerodynamic, gravitational, and tether forces. This modeling ideal incorporates a nonlinear interaction presented by the tether and aerodynamic forces caused by lift and drag forces produced by the rotors on the UAV. This type of integration enables the model to model the real-life complex behaviors that affect the stability and maneuverability of the UAV. This dynamic model is the basis of the further controller design, so that the control algorithm is going to work on a representation that is closely related to the real system dynamics. The model is based on counting nonlinearities of systems, disturbances in the environment, and translational-rotational coupling that gives a stable platform to controller validation and parameter tuning. The governing dynamics are determined by using the Newton-Euler formalism, and the UAV is assumed to be a rigid body acted upon by external forces and moments. The translational and rotational dynamics may be written respectively as follows [76]:

$$m\ddot{r} = F_{\text{thrust}} + F_{\text{drag}} + F_{\text{tether}} - mg\hat{z} \tag{4.19}$$

Where:

m: is referring to the mass of the UAV,

$\ddot{r}$: is referring to the acceleration vector,

F_{thrust}: is referring to the resultant thrust that generated by the rotors,

F_{drag}: is referring to the aerodynamic drag,

F_{tether}: is referring to the tether force of the tension, and

$mg\hat{z}$: is referring to the gravitational force acting downward along the vertical axis.

Furthermore, the corresponding rotational motion can be mathematically expressed by the following Equation [76]:

$$I\ddot{\theta} = \tau_{\text{prop}} + \tau_{\text{disturbance}} - R_{\text{gyro}} \tag{4.20}$$

Where:

I: is referring to the UAV's tensor of the inertia,

$\ddot{\theta}$: is referring to the angular acceleration vector,

τ_{prop}: is referring to the control torque generated by the propellers,

$\tau_{\text{disturbance}}$: is referring to the external disturbance torques, and

R_{gyro}: is referring to the gyroscopic reaction moment.

Whereas, the tether plays a significant role within the UAV's dynamic behavior, furthers it provides both a restoring and stabilizing effect. Mathematically, the tension force can be expressed by means of the following Equation [76]:

$$F_{\text{tether}} = k(r_{\text{tether}} - r_{\text{uav}}) \tag{4.21}$$

Where:

k: is referring to the stiffness coefficient of the tether,

r_{tether}: is referring to the ground-anchored point, and

r_{uav}: is referring to the UAV's instantaneous position vector.

The tether is designed as an elastic constraint in this formulation, which can affect the stability and position control of the UAV. As shown in Table 4.1, following the same signal-tracking procedure utilized for signal (v_1), a compensation mechanism is added to ensure that the model maintains its response to dynamic variations and the fluctuations of the signal.

Table 4.1: The UAV Tethered Characteristics.

Variable Description	Variable	Value
Mass of UAV (kg)	m	3.8
Distance between the propeller and the centroid of UAV (m)	l	0.25
Thrust coefficient ($N/(rad/s)^2$)	C_t	0.1188
Variable Description	**Variable**	**Value**
Moment coefficient ($N/(rad/s)^2$)	C_m	0.0036
Yaw axis moment of inertia ($kg \cdot m^2$)	I_x	0.1104
Pitch axis moment of inertia ($kg \cdot m^2$)	I_y	0.0552
Roll axis moment of inertia ($kg \cdot m^2$)	I_z	0.0552
Tether linear density (kg/m^3)	ρ	1.293
Drag coefficient	k_f	$1.98 \times 10^{-}6$
Lift coefficient	c_L	$1.171 \times 10^{-}5$
Propeller moment of inertia ($kg \cdot m^2$)	I_r	$1.45 \times 10^{-}3$
Tether length (m)	S	12
The mass of the four arms (kg)	ma	1.5
Weight of tether per unit length	$\in$	6.08

The presented mathematical model, which outline the error-based adaptive correction and the energy-like Lyapunov formulation for stability enhancement, provide a mathematical definition of the compensation process by means of the following Equations [77]:

$$H(e) = \begin{bmatrix} \beta_1 & -1 & 0 \\ \beta_2 \frac{mfal(e_1, A, M)}{e_1} & 0 & 1 \\ \beta_3 \frac{mfal(e_2, A, M)}{e_2} & 0 & 0 \end{bmatrix} \tag{4.22}$$

$$D = \begin{bmatrix} 1 & \frac{\beta_2 F_1}{B+\epsilon_1} - \eta \\ -\frac{\beta_2 F_1}{B-\epsilon_1}\eta & \frac{1}{B+\epsilon_2}\eta - \frac{1}{B-\epsilon_2}\eta \end{bmatrix} \tag{4.23}$$

$$V(t) = \int_0^t (DH(e)e, \dot{e})\, dt + C_0 \tag{4.24}$$

$$V(t) = \int_0^t (DH(e)e, -H(e)e)\, dt + C_0 \tag{4.25}$$

$$V(t) = \int_0^t (H(e)e)' \cdot DH(e)e\, dt + C_0 \tag{4.26}$$

All these expressions make up a compensation system that makes systems more responsive by dynamically adjusting control parameters based on tracked error. These adaptive components are used to make the tethered UAV model stable and precise in case of uncertain aerodynamic parameters and external disturbances.

4.4.2 Stage Two: Design of the FOPDD-I Controller

The second step of the suggested methodology is dedicated to the formation of a FOPID-Integral (FOPDD-I) Controller that the classical PID framework will expand with the use of a fractional calculus. The method offers further adaptability and accuracy in defining the dynamic reaction of a complicated framework like tethered UAVs, in which nonlinear dynamics, external disturbances, and parameter uncertainties play a vital role. FOPDD-I controller integrates the commonly used proportional, derivative, and integral actions with the use of the fractional-order differentiation and integration, which provides a broader tuning range and a greater robustness than the integer-order controllers used traditionally. This increased freedom of adjusting both transient and steady-state response, and therefore improves the tracking of the trajectory, decreases overshoot, and increases the rate of convergence. As shown in Figure 4.5, the derivation of the FOPDD-I controller uses fractional operators of differentiation in order to have high flexibility in different dynamic environments.

Fractional calculus typically extends the idea of differentiation and integration of integer order to non-integer (fractional) order to enable dynamical systems to be modeled more accurately. Fractional order derivative of a function $f(t)$ mathematically can be represented by the following Equation [77]:

$$D^{\alpha} f(t) = \frac{1}{\Gamma(n-\alpha)} \frac{d^n}{dt^n} \int_0^t (t-\tau)^{n-\alpha-1} f(\tau)\, d\tau\, , n-1 < \alpha < n \tag{4.27}$$

Where:

$\Gamma(\cdot)$: is referring to the Gamma function, and

α: is referring to the fractional order of the operator.

FOPDD-I controller augmented the conventional PID control law with fractional differentiation (μ) and fractional integration (λ) and a second-order derivative term to obtain a more dynamic response of the system. The time domain control law can be represented as follows [77]:

$$u(t) = K_p e(t) + K_d D^{\mu} e(t) + K_{dd} D^2 e(t) - K_i D^{-\lambda} e(t) \tag{4.28}$$

Where:

$e(t)$: is referring to the tracking error, and

K_p, K_d, K_{dd}, K_i: are referring to the proportional, derivative, second-derivative, and integral gains, respectively.

In the Laplace domain, the controller output can be expressed mathematically, by means of the following Equation [77]:

$$C(s) = K_p + K_d s^{\mu} + K_{dd} s^2 - \frac{K_i}{s^{\lambda}}, \tag{4.29}$$

Where:

s: is referring to the Laplace variable. Whereas, the inclusion of fractional-order terms $s^{\mu}$and $s^{-\lambda}$allows the controller to smoothly adjust between pure differentiation and integration, resulting in improved control precision and stability.

The second derivative term makes the response to steep variations in the reference trajectory more responsive, whereas the fractional integral component is useful to damp the oscillations and decrease the steady-state error. The combination of the above features allows the FOPDD-I controller to achieve strong performance with model nonlinearities, parameter variations, and external disturbances. Besides, the suggested controller architecture is a versatile parameter optimization platform. At Stage Three, the optimization of its coefficients and fractional orders is optimized with the Hybrid Harris Hawks Optimization-Eagle Strategy-Particle Swarm Optimization (HHHGO-ES-PSO) optimization algorithm, which allows the tethered UAV to get accurate, stable, and energy-saving control under different operational conditions.

4.4.3 Stage Three: Optimization Using The HHHGO-ES-PSO Algorithm

The third step of the suggested methodology presents a hybrid optimization model, which is also known as the HHHGO-ES-PSO algorithm. This hybrid metaheuristic integrates the strength of exploration of the HHO, adaptive local search of the EPSO, and dynamic transition control of the Eagle Strategy (ES). The main aim of such an algorithm is to optimize the parameters of the FOPDD-I controller by providing a better stability margin, smaller steady-state values, shorter response times, and better disturbance rejection performances. The optimization scheme is iterative in nature, and it determines the performance of the controller by a fitness function that represents the major key performance indices of the dynamic stability, rise time, settling time, overshoot, and energy efficiency. The balancing search mechanism achieved by the HHHO-ES-PSO algorithm in the adaptive guidance of ES combines the exploration capability of HHO and the exploitation capability of PSO to reach the global optimum solution.

Harris hawks also use cooperative hunting during hunting, and this technique is the basis of this algorithm, the HHO algorithm. The birds use a sort of surprise pounce technique to grab their prey, and the strategies of attack vary dynamically depending on the energy of the prey and how they escape. E is the escape energy, which will dictate whether the hawks will be soft besiegers or hard besiegers, and this is mathematically expressed as [78]:

$$E = 2E_0 \left(1 - \frac{iteration}{maxiterations}\right) \tag{4.30}$$

Where:

E_0: is referring to a random number within the interval $[-1,1]$. Based on the magnitude of E, two primary strategies are employed:

i. Soft Besiege ($E \geq 0.5$): The hawks encircle the prey loosely, with their position updated as in the following Equation [78]:

$$X(t+1) = X^*(t) - E \cdot J \cdot R \tag{4.31}$$

$$R = X^*(t) - X(t) \tag{4.32}$$

Where:

$X^*(t)$: is referring to the best (prey) position,

J: is referring to the jump strength coefficient, and

R: is referring to the distance between the hawk and its prey.

ii. Hard Besiege ($E < 0.5$): The hawks perform a direct attack, modeled by means of the following Equation [78]:

$$X(t+1) = X^*(t) - E \cdot \left(X(t) - X^*(t)\right) \tag{4.33}$$

This adaptive approach actually ensures both local refinement and global exploration in its iteration and naturally places HHO as a very strong foundation for hybrid integration.

In this regard, to enhance the exploitation capability, the PSO is embedded into the hybrid framework structure. PSO performs local refinement of solutions by emulating the social behavior of particles, while each particle updates its velocity and position with regard to the best personal experience and swarm collective intelligence. The velocity and position update Equations can be defined as Follows:

$$V_i(t+1) = \omega V_i(t) + c_1 r_1 \left(P_{best,i} - X_i(t)\right) + c_2 r_2 \big(G_{best} - X_i(t)\big) \tag{4.34}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{4.35}$$

Where:

ω: is referring to the inertia weight that balances exploration and exploitation,

c_1 and c_2: are referring to the acceleration coefficients,

$r_1$and r_2: are referring to the random numbers uniformly distributed in $[0,1]$,

$P_{best,i}$: is referring to the best position of the individual particle, and

G_{best}: represents the best position found by the entire swarm.

This mechanism allows particles to dynamically adjust their trajectories, converging efficiently toward the global optimum once promising regions are identified by the HHO phase.

For the ES serves as a supervisory mechanism that dynamically balances exploration (via HHO) and exploitation (via PSO). This transition is governed by a control coefficient α, which increases proportionally with the iteration number, is expressed by the following Equation [78]:

$$\alpha = \frac{iteration}{maxiterations} \tag{4.36}$$

A lower alpha value is preferable at the start of the search to provide the exploration of wide potential solution spaces on a global basis. With each iteration, the value of alpha is increased, and it tends to shift the algorithm towards local exploitation and optimization of solutions. This adaptive movement guarantees the effective convergence, while preventing the early stagnation in the local minima. For the hybrid HHHGO-ES-PSO algorithm, this algorithm involves the exploration of the search space by the HHO mechanism that identifies the promising candidate regions. PSO then optimizes these solutions by local search using the velocity, which is steered by the adaptive Eagle Strategy, which was used to bring a smooth transition between these two phases. The synergy allows the hybrid algorithm to utilize both the global exploration of HHO and the local optimization accuracy of PSO, all at the same time. The general hybridization improves the strength and convergence speed of the optimization process, that are more effective as compared to traditional single-method algorithms in non-linear and dynamic control systems. These properties render HHHO-ES-PSO extremely useful in the process of tuning the FOPDD-I controller parameters of tethered UAV systems, where adaptive response, dynamic stability, and real-time optimization are critical. The pseudocode for the proposed algorithm is presented as follows:

Algorithm 1: HHHO-ES-PSO

---

1. Initialize the population of hawks and particles: Randomly initialize positions ($\boldsymbol{X_i}$) and velocities ($\boldsymbol{V_i}$) within bounds

2. Define fitness function and parameters **($\boldsymbol{\omega, c_1, c_2, r_1, r_2}$, etc.)**

3. **While** termination criteria not met:

4. **For** each hawk/particle:

5. Perform HHO-based global search:

$\boldsymbol{X(t+1) = X^*(t) - E.J.R}$ **(soft besiege)**

$\boldsymbol{X(t+1) = X^*(t) - E.\left(X(t) - X^*(t)\right)}$ **(hard besiege)**

6. Update the positions based on the equations of the HHO

7. Perform PSO-based local search:

$$\boldsymbol{V_i(t+1) = \omega V_i(t) + c_1 r_1 \left(P_{best,i} - Xi(t)\right) + c_2 r_2 \left(G_{best} - Xi(t)\right)}$$

$$\boldsymbol{Xi(t+1) = Xi(t) + V_i(t+1)}$$

8. Update velocities and positions by using the equations of the PSO

9. Evaluate fitness of all agents

10. Update $\boldsymbol{p_{best}}$ and $\boldsymbol{g_{best}}$

11. Apply Eagle Strategy to switch between global and local search

12. end **while**

13. Return best solution ($\boldsymbol{K_p, K_i, K_d, K_{dd}, \lambda, \mu}$)

4.5 BENCHMARK FUNCTIONS

In order to stringently test the performance of the proposed HHHO-ES-PSO algorithm, nine benchmark test functions were used. These benchmark functions are standardized means to evaluate optimization algorithms on a wide spectrum of mathematical landscapes, each having its own challenges that can simulate various UAV control situations. All of them give information about the efficiency, robustness, and versatility of the algorithm to solve nonlinear and dynamic optimization problems that are of interest in tethered UAV systems.

The Sphere function is a simple, unimodal, and convex function that measures the ability of the algorithm to smoothly converge on the global optimum. Its design enables the consideration of linear response features of the algorithm and its capacity to secure the stability of UAVs when performing simple flight operations. However, the Rosenbrock function, sometimes also called the Banana function, adds a small curved valley, putting a challenge on the algorithm to the trajectory-planning ability and fine-tuning ability in constrained spaces, like the UAV path optimization in cluttered or limited spaces.

The Rastrigin topography is a highly multifaceted topography that is dominated by a large proportion of local minima, and is an enemy to the effectiveness of exploration and resistance of the algorithm to premature convergence. The test is particularly relevant to the case of UAVs that carry out their activities unpredictably or depending on obstacles as in this scenario, it is crucial to ensure that the movement is not affected by the disturbances. Similarly, the Ackley functional with a relatively flat outer surface and a sharp core determines the trade-off between exploration and exploitation as one of the key traits of adaptive UAV control in dynamic environmental conditions.

The Schwefel problem provides an even more challenging optimization surface and the false optima mislead the algorithm to evaluate its capability to come out of false convergence and this is a large consideration in how UAVs can use the algorithms in the most dynamic and unpredictable settings. To verify the correctness of the convergence and the long-term stability which is sensitive to the UAV trajectory tracking and constant hovering control, the accuracy of convergence and long-term stability is examined by means of the smooth but unnecessary optimization surface of the Zakharov function. The rate of convergence and accuracy of the algorithm is measured by the Dixon-Price functional that is a parabolic curve, which indicates the performance of the UAVs when performing accurate point-to-point operations.

Lastly, the Levy shape, characterized by sharp ridges and flat plateaus presents a harsh challenge to the precision and versatility, particularly in the working environment that is sensitive and involves sensitive operation circumstances where the piloting of UAVs is a crucial factor.

Collectively, the benchmark functions offer an overall evaluation system, which studies the HHHO-ES-PSO algorithm efficiency in global search, its stability on nonlinear optimization, and the accuracy of the algorithm in multi-dimensional spaces. As the summarized findings indicate, given in Table 4.2, the algorithm has exceptional potential to generate consistent convergence and stable performance, which proves its applicability in the advanced optimization and control of tethered UAV systems.

Table 4.2: Proposed Algorithm Benchmark Functions.

Benchmark Function	**Dimensionality**	**Search Agents**	**Search Range**
$f_1(x,y) = x^2 + y^2$	2	20	[-5, 5]
$f_2(x,y) = 100(y - x^2)2 + (1 - x)^2$	2	20	[-5, 5]
$f_3(x,y) = 10 \cdot 2 + \left(\mathrm{x2} - 10 \cdot \cos(2\pi\mathrm{x})\right) + \left(\mathrm{y2} - 10 \cdot \cos(2\pi\mathrm{y})\right)$	2	20	[-5, 5]
$f_4(x,y) = 1 + \frac{x^2 + y^2}{4000} - \cos(x) \cdot \cos\left(\frac{y}{\sqrt{2}}\right) + 20 + e$	2	20	[-5, 5]
$f_5(x,y) = \sin(3\pi x)^2 + (x-1)^2(1 + \sin(3\pi y)^2) + (y - 1)^2(1 + \sin(2\pi y)^2)$	2	20	[-10, 10]
$f_6(x,y) = (1.5 - x + xy)^2 + (2.25 - x + xy^2)^2 + (2.625 - x + xy^3)^2$	2	20	[-5, 5]
$f_7(x,y) = (x + 2y - 7)^2 + (2x + y - 5)^2$	2	20	[-5, 5]
$f_8(x,y) = (x^2 + y - 11)^2 + (x + y^2 - 7)^2$	2	20	[-5, 5]
$f_9(x,y) = 2x^2 - 1.05x^4 + \frac{x^6}{6} + xy + y^2$	2	20	[-5, 5]

5. OBTAINED RESULTS AND DISCUSSION

5.1 INTRODUCTION

In this chapter, the results of the modeling, controller design, and optimization processes of the proposed tethered UAV system are introduced and discussed. The main goal is to assess the work of the constructed FOPDD-I controller that is optimized by the HHHO-ES-PSO algorithm. In results analysis, it is measured on the areas of stability of the system, accuracy of response, robustness, and adaptability to changes depending on the dynamic conditions.

The analysis starts with the analysis of the given HHHO-ES-PSO algorithm test on a collection of standard test functions that can be viewed as a benchmark to estimate the global search power of the algorithm, its speed of convergence, and the accuracy of the algorithm in multifaceted optimization areas. The step confirms the efficiency of the algorithm, and then the algorithm is implemented for the UAV control problem. The optimized controller is then tried on the tethered UAV dynamic model, and enhancement of transition response, steady response, and disturbance rejection is studied. The advantages of the proposed approach versus the traditional control mechanisms and one-on-one optimization techniques are shown to show that it is superior. Graphical results, numerical results, and performance indices are presented to indicate the responsiveness, overshoot reduction, and better accuracy of tracking that were realized using the hybrid optimization framework. On the whole, in the chapter, the results of the simulation and the experiment validations have been given in a thorough way, and it gives a clear understanding of how the proposed methodology is going to help in the development of robust and adaptive control of tethered UAV systems.

5.2 HHHO-ES-PSO ALGORITHM FOR UAV TETHERED MODEL

In this section, a tethered UAV model will be used to test the system's performance under external disturbances and dynamic conditions. The comparison analysis encompasses several control methods, including the standard PID, Cascade PID, Traditional ADRC, Advanced ADRC, and the proposed FOPDD-I controller optimized using the HHHO-ES-PSO algorithm. The aim is to demonstrate that the hybrid controller is more effective in enhancing stability, responsiveness, and robustness to disturbances. The performance outcomes are provided in Figures 5.1-5.3 in comparison. The variations of the yaw, pitch, and roll angles with time of various controllers, as in Figure 5.1, show transient and steady-state responses.

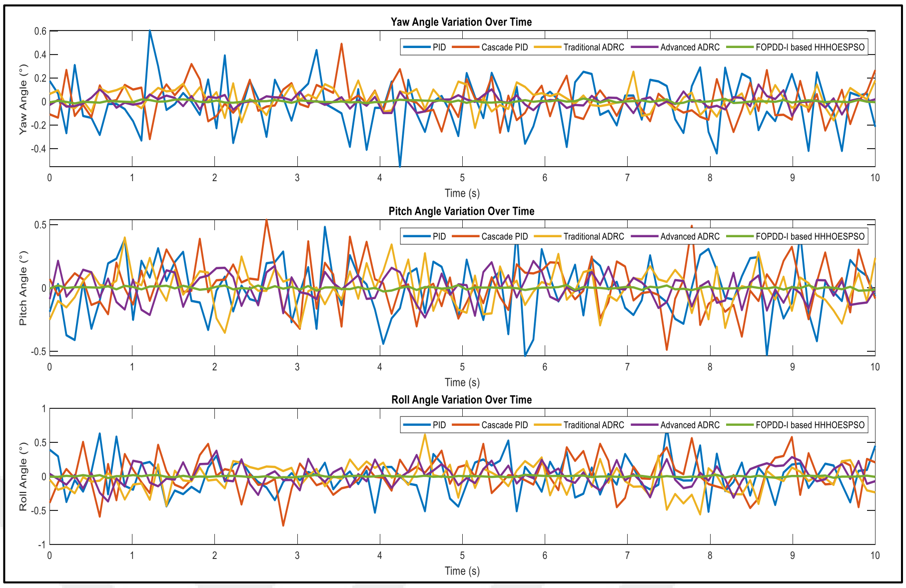

Figure 5.1: Yaw, Pitch, and Roll Responses Comparison in The Different Controllers.

Figures 5.2 represent violin plots of the distribution of angular errors on the three control axes, which help to understand the accuracy and the consistency of errors.

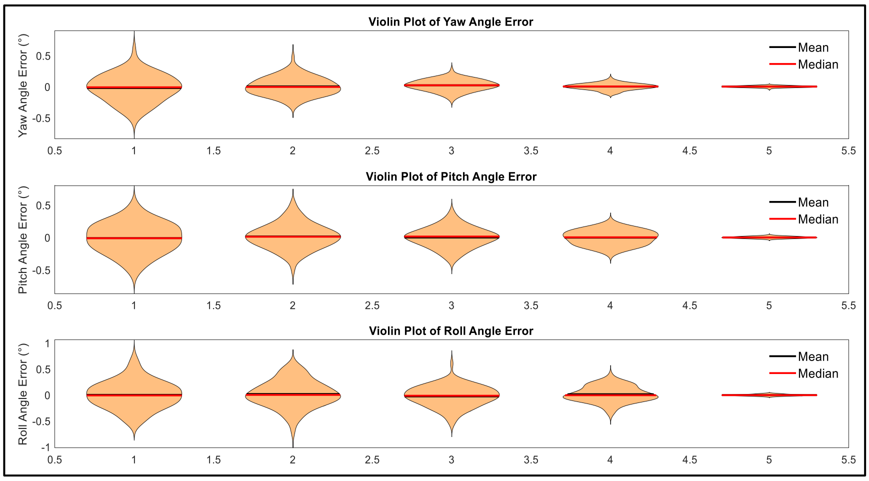

Figure 5.2: Violin Plots of Yaw, Pitch, and Roll Angle Errors for Different Controllers.

Lastly, Figure 5.3 shows a histogram of the MSE of yaw, pitch, and roll, a quantitative analysis of the control accuracy of all methods tested.

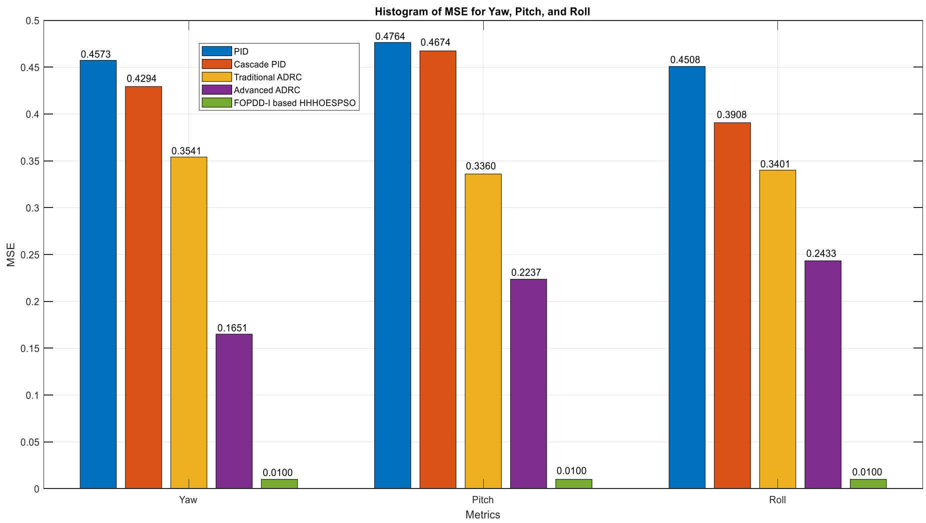

Figure 5.3: Histogram of MSE for Yaw, Pitch, and Roll Across Different Controllers.

The HHHO-ES-PSO algorithm is effective in exploring the multidimensional parameter space to achieve the best FOPDD-I parameters. Its natural balance between exploration and exploitation helps it to escape local minima and approach the global optimum. In this assessment, the size of the population was defined as 30, and the maximum number of iterations was defined as 500, which is sufficient to search thoroughly and at the same time be computationally efficient. As it is presented in the previous Figure 5.1, the HHHO-ES-PSO optimized FOPDD-I controller demonstrates a significant decrease in the oscillations and a quicker stabilization than other controllers. The oscillations about the yaw angle are damped after about three seconds, and this indicates better damping functionality compared to both PID and Cascade PID controllers, which have broader initial movements. Although the Advanced ADRC shows an average performance with respect to the traditional ADRC, the provided HHHO-ES-PSO-based controller has better robustness and increased performance stability. In both pitch and roll responses, the trend is the same- the proposed controller has the lowest oscillation frequency and amplitude, resulting in smoother and more stable dynamics under all test conditions.

Additionally, Figure 5.2 is another indication of these findings. According to the violin plot of angular error distribution of the yaw, pitch and roll, it is clear that the HHGO-ES-PSO-based FOPDD-I controller has the least mean error and a narrow range distribution, which signify high control accuracy and stability. On the other hand, PID and Traditional ADRC controllers are more spread in error distribution and more variability; thus, less predictability, and imprecision. Even though the Advanced ADRC shows better results compared with the traditional one, it is still not as accurate and consistent as the HHHO-ESPSO method. This finding proves the enhanced performance of the proposed algorithm that can provide high-precision control with low tracking error, which is reliable.

Figure 5.3 is a quantitative comparison of control accuracy, plotting the MSE values of each control axis. The FOPDD-I controller optimized with HHHO-ES-PSO has the lowest MSE on the yaw, in pitch, and roll, and exceeds all the other methods that have been benchmarked. This dramatic decrease in MSE shows the optimizing effects of the algorithm on control parameters in order to provide better dynamic response and stability. Finally, the outcomes demonstrate that the HHHO-ES-PSO algorithm is a good means of controlling the nonlinearities and improving the performance of the control of tethered UAVs. It is highly optimising, thus resulting in better stability, responsiveness, and precision, which makes it a potent and reliable method of controlling a UAV in real-time, under complicated and uncertain conditions.

The hybrid optimization strategy using the HHHO-ES-PSO algorithm (Table 5.1) has a great impact on the performance of the FOPDD-I controller, which is better than other methods of tuning. The given enhancement can be largely explained by the ability of the algorithm to reach the best control gains, adjust the terms of the fractional derivative (λ and μ), and adjust the derivative elements so that the level of stability, accuracy, and disturbance rejection can be higher. The proposed hybrid is obviously superior to the conventional control methods, including PID and Cascade PID, that do not possess enough flexibility to deal with the nonlinear and time-varying dynamics of tethered UAV systems. Despite the fact that Traditional ADRC and Advanced ADRC controllers exhibit superior performance as compared to PID-based controllers in terms of gain adjustment, they still cannot be compared to the performance provided by the factorial-order structure of the FOPDD-I controller in terms of accuracy and robustness. The proposed controller is intelligent in that it is able to explore and optimize its parameters by using the HHHO-ES-PSO algorithm in the tuning process by taking an intelligent balance of global exploration and local exploitation. This optimistic hybrid control allows the controller to have a smooth tracking of the trajectory, quick stabilization, and resilience to external disturbance. The findings affirm that the HHHO-ES-PSO-optimized FOPDD-I controller is a superior control solution to the tethered UAV cases, which not only offers high performance but also has reliable stability under the complex and uncertain flight conditions.

Table 5.1: Comparison of Controller Parameters for Tethered UAV Systems.

Controller Method	$\boldsymbol{Kp}$ **(Pitch)**	$\boldsymbol{Ki}$ **(Roll)**	$\boldsymbol{Kd}$ **(Yaw)**	$\boldsymbol{\lambda}$ **(Pitch)**	μ **(Yaw)**
Traditional PID Controller	3.1025	0.2898	11.430	-	-
Cascade PID Controller	2.8341	0.3104	10.526	-	-
Traditional ADRC Controller	2.5914	0.2759	9.9045	-	-
Advanced ADRC Controller	2.3507	0.2461	9.5026	-	-
Proposed FOPDD-I based HHHO-ES-PSO	1.3500	0.4800	0.1800	0.3200	0.3500

The proposed HHHO-ES-PSO-optimized FOPDD-I controller showed an order-optimal system parameter configuration of the tethered UAV system, which is vastly superior compared to the traditional types of controllers, including PID, Cascade PID, Traditional ADRC, and Advanced ADRC. The radar chart in Figure 5.4 indicates that the proposed controller has significantly lower values of control gains (K_p), (K_i), and (K_d) and optimally tuned values of fractional-order parameters ((λ) and (μ)) than the other methods. This even-mode tuning has a direct effect of enhancing the disturbance rejection, a higher stability, and a more linear response to control in all the UAV motion axes.

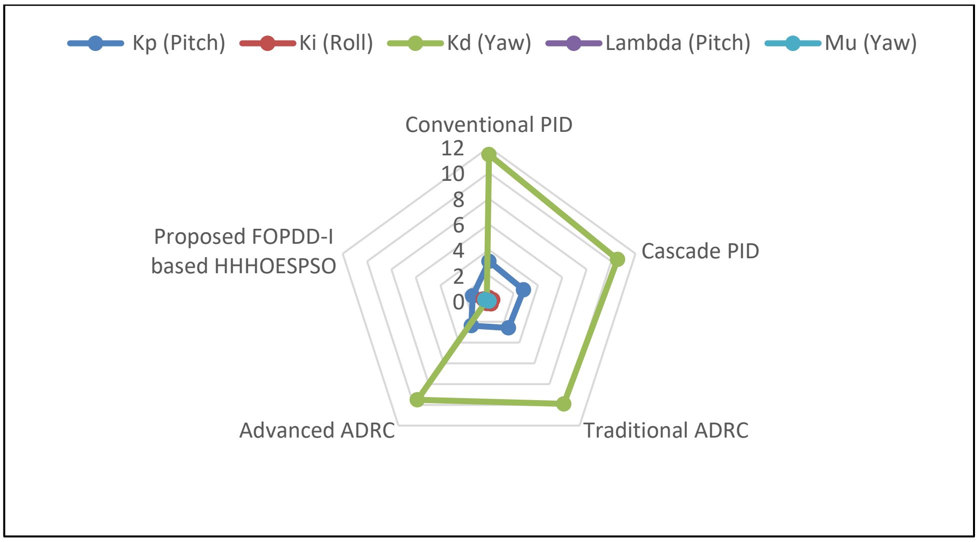

Figure 5.4: Comparison of Controller Parameters for UAV Tethered Systems.

In the conventional types of controllers such as the Conventional PID and the Cascade PID, the derivative gain (K_d) especially in the yaw axis is highly affecting the system dynamics. Nevertheless, the (K_d) values in these controllers are relatively high, which is likely to cause aggressive control and escalate oscillations that reduce stabilization. Conversely, the suggested HHHO-ES-PSO-based FOPDD-I controller is as well positioned to deliver a significantly smaller derivative gain ($K_d = 0.1800$) that, in turn, reduces the oscillations and ensures both the fast and responsive dynamics. This is reinforced by the use of fractional adaptability, or optimized parameters ($\lambda = 0.3200$) of the controller, which is strongly able to manage nonlinear behavior and external disturbances, which contributes to more sophisticated and trustworthy performance.

The radar chart demonstrates clearly how tightly compact and well-balanced the optimized parameters brought out by the HHHO-ES-PSO algorithm are. The proposed controller has the most cohesive distribution of the parameters and shows the high level of precision, robustness, and consistency in all the axes. This justifies the excellent tuning capability of the hybrid optimization framework which proves the method to be effective in producing high-accuracy control when tethered UAVs are used with stability and reliability being paramount.

Additional performance analysis between the HHHO-ES-PSO, Standard PID, and ADRC controllers as presented in Figures 5.5-5.7, shows some specific benefits of the suggested solution. In Figure 5.5, the analysis of error-based metrics of performance, such as the MSE, IAE, Integral Squared Error (ISE), ITAE and Integral Time Squared Error (ITSE) shows that the HHHO-ES-PSO based controller always obtains the lowest values of error metrics in all aspects. This implies there are quicker settling periods, lesser cumulative error, and high-quality tracking error.

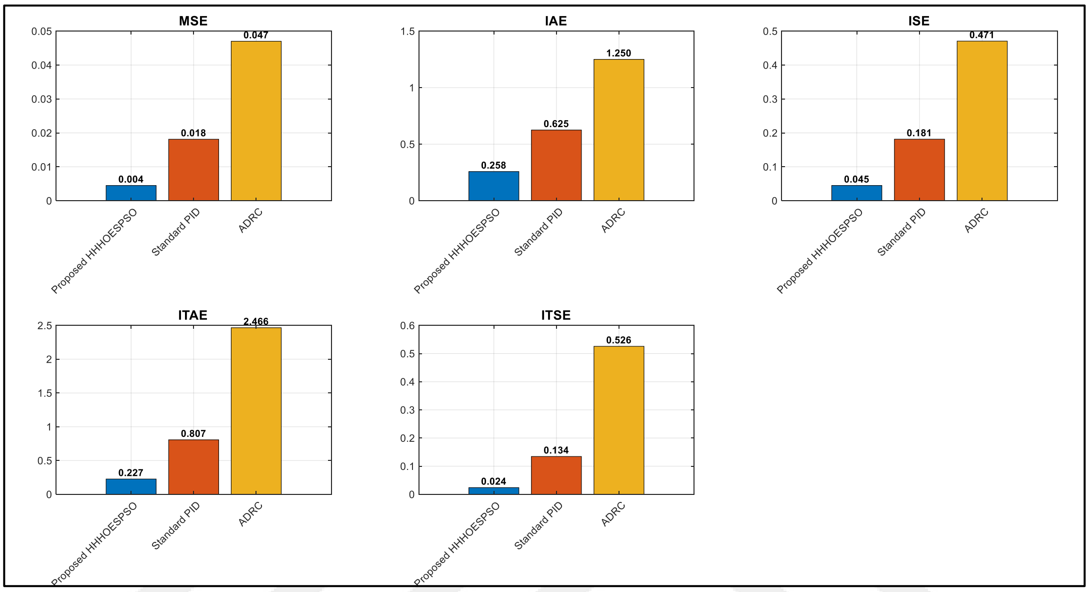

Figure 5.5: Comparison of Error-Based Performance Metrics.

Also, as Figure 5.6 illustrates, the HHHO-ES-PSO controller is the easiest to control, which is proven by its small Total Variation (TV), control energy (ISCO), and largest control amplitude. This efficiency is converted to control signals which are easier to operate as well as better energy use that is also essential in UAV and robotic uses where power efficiency and endurance is an important design factor. Lastly,

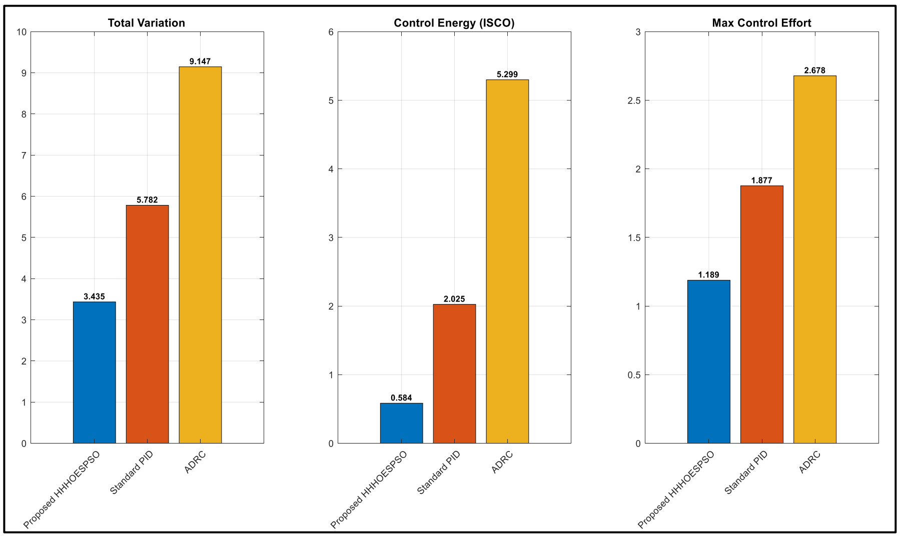

Figure 5.6: Comparison of Control Effort Metrics.

Figure 5.7 also supports these results by plotting the smooth and fast-decaying control signals of the HHGO-ES-PSO controller in a raw and absolute space. These oscillations are reduced, and the converging speed of the controller is higher than that of its analogs, which proves its high adaptability and stability.

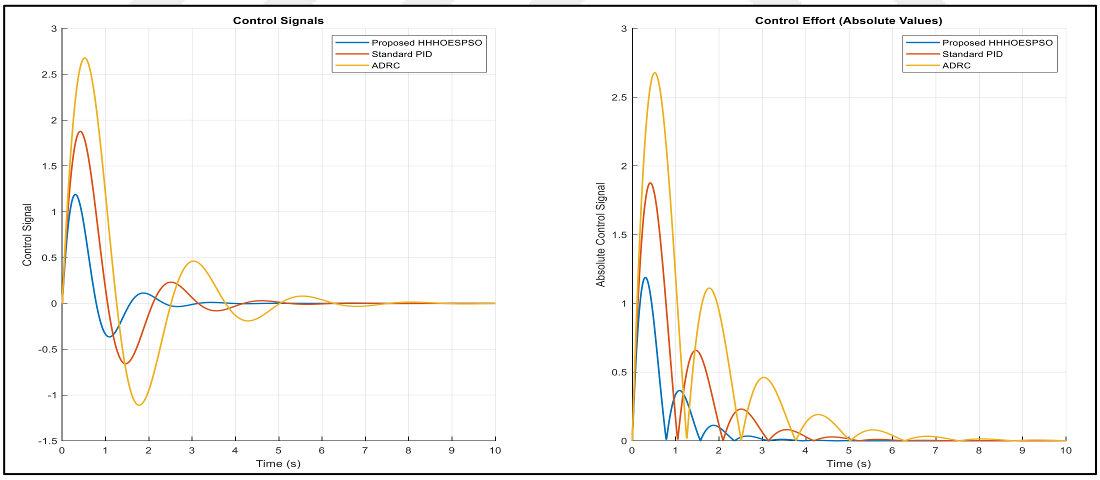

Figure 5.7: Control Signal and Control Effort Responses Over Time.

The overall outcome of these results justifies the strength and efficiency of the HHHO-ES-PSO-optimized FOPDD-I controller. Not only does it perform better than the conventional PID and ADRC controllers both in precision and low energy usage and stability, but it also proves itself to be a highly suitable solution to complex nonlinear systems, especially in

UAV and robotic applications where accuracy and low energy usage are the most important factors.

5.3 RESULTS ON BENCHMARK FUNCTIONS

The effectiveness and stability of the suggested HHHO-ES-PSO algorithm were tested by means of a detailed benchmarking experiment based on nine standard test functions. All the algorithms HHHO-ES-PSO, HHO, and ES-PSO were run under the same conditions with a population size of 20 and 20 trials (independent) and 1000 steps (maximum number of iterations), to be sure that the results were statistically valid. Table 5.2 summarizes the performance measures, such as the highest, lowest, mean, median, and Standard Deviation (STD) of each benchmark function.

Table 5.2: Results Of HHHO-ES-PSO Compared to HHO and ESPSO on Benchmark Functions.

Function	Algorithm	Best value	Worst value	Avg. value	Median value	STD
$f_1(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$1.23E-08$	3.45E-06	7.89E-07	4.23E-07	2.45E-07
	ESPSO	$3.12E-07$	5.67E-05	1.45E-06	9.34E-07	4.12E-07
$f_2(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$5.67E-09$	2.12E-06	6.78E-08	4.89E-08	2.34E-08
	ESPSO	$2.45E-08$	4.56E-05	8.23E-07	5.67E-07	3.12E-07
$f_3(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$3.45E-06$	1.23E-03	4.78E-05	3.56E-05	1.23E-05
	ESPSO	$6.78E-06$	2.34E-02	2.45E-04	1.78E-04	7.12E-05

Table 5.2: Results Of HHHO-ES-PSO Compared to HHO and ESPSO on Benchmark Functions (Table Continued).

Function	Algorithm	Best value	Worst value	Avg. value	Median value	STD
$f_4(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$1.12E-05$	6.78E-03	2.34E-04	1.89E-04	7.45E-05
	ESPSO	2.34E-05	1.23E-01	9.45E-04	6.12E-04	3.45E-04
$f_5(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$8.90E-06$	2.45E-02	3.45E-04	2.34E-04	1.12E-04
	ESPSO	$1.45E-04$	8.90E-02	6.78E-03	4.56E-03	2.34E-03
$f_6(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$4.34E-08$	7.12E-05	2.78E-06	1.89E-06	9.45E-07
	ESPSO	$9.45E-07$	4.56E-02	1.23E-04	9.12E-05	4.12E-05
$f_7(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$1.12E-05$	3.56E-03	7.45E-04	5.12E-04	2.34E-04
	ESPSO	$2.45E-04$	6.78E-02	1.12E-02	8.90E-03	4.34E-03
$f_8(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$3.45E-05$	2.34E-02	1.45E-03	1.12E-03	4.56E-04
	ESPSO	$1.23E-03$	7.45E-02	5.67E-03	4.12E-03	2.12E-03
$f_9(x)$	HHHO-ES-PSO	**0**	**0**	**0**	**0**	**0**
	HHO	$2.34E-06$	3.12E-03	8.90E-05	6.78E-05	2.78E-05
	ESPSO	$3.45E-05$	9.12E-02	1.23E-03	9.45E-04	4.12E-04

Those findings clearly indicate that the HHHO-ES-PSO algorithm has better optimization capacity compared to all the benchmark functions. It repeatedly gave almost zero or very close to zero best values and was able to detect the global minimum in unimodal and multimodal landscapes. However, the traditional HHO and ES-PSO algorithms had non-zero minima, which means that they were not able to leave the local optima or the actual global solution in some cases.

As an example, in the Sphere function (f_1), the HHHO-ES-PSO algorithm has reached a best fitness of 0 and reached the global optimum precisely. At the same time, HHO and ES-PSO got the best values of (1.23×10^{-8} and 3.12×10^{-7}), respectively- showing the accuracy of the suggested hybrid approach. On the same note, in the Rosenbrock (f_2) function, HHHO-ES-PSO once more gave a perfect zero, but HHO and ESPSO gave optimum values of (5.67×10^{-9}) and (2.45×10^{-8}), respectively. The results indicate that the hybrid algorithm is highly convergent with high search efficacy.

This was also true of other multimodal processes like Ackley (f_5) and Griewank (f_6), with the HHHO-ES-PSO algorithm returning the best results, although the other algorithms had larger residual errors, which is indicative of an early stopping on local minima. Furthermore, HHHO-ES-PSO recorded the best values of average, median, and standard deviation on almost all the test functions, which highlights its stability and flexibility to different optimization landscapes.

The benchmark set ensures a balanced test of algorithmic performance due to the diversity of the set. Smooth, convex functionality of the functions like Sphere and Zakharov with single global minima are used in the evaluation of convergence speed and accuracy in unimodal contexts. Conversely, Rastrigin, Ackley, and Griewank functions, which have many local minima, challenge the capability of the algorithm to be able to explore but not be trapped in an unsatisfactory solution. In the meantime, the Rosenbrock and the Dixon-Price functions test the capability of the algorithm to traverse small curvilinear valleys, and the Schwefel and the Levy functions, with their steep ridges and misleading optima, test its ability to survive in a complicated, rugged search space.

It is necessary to mention that the Table 5.2 presents some of the statistical results that are visualized in the following Figure 5.8, which gives an intuitive view of the performance of optimization using all benchmark functions.

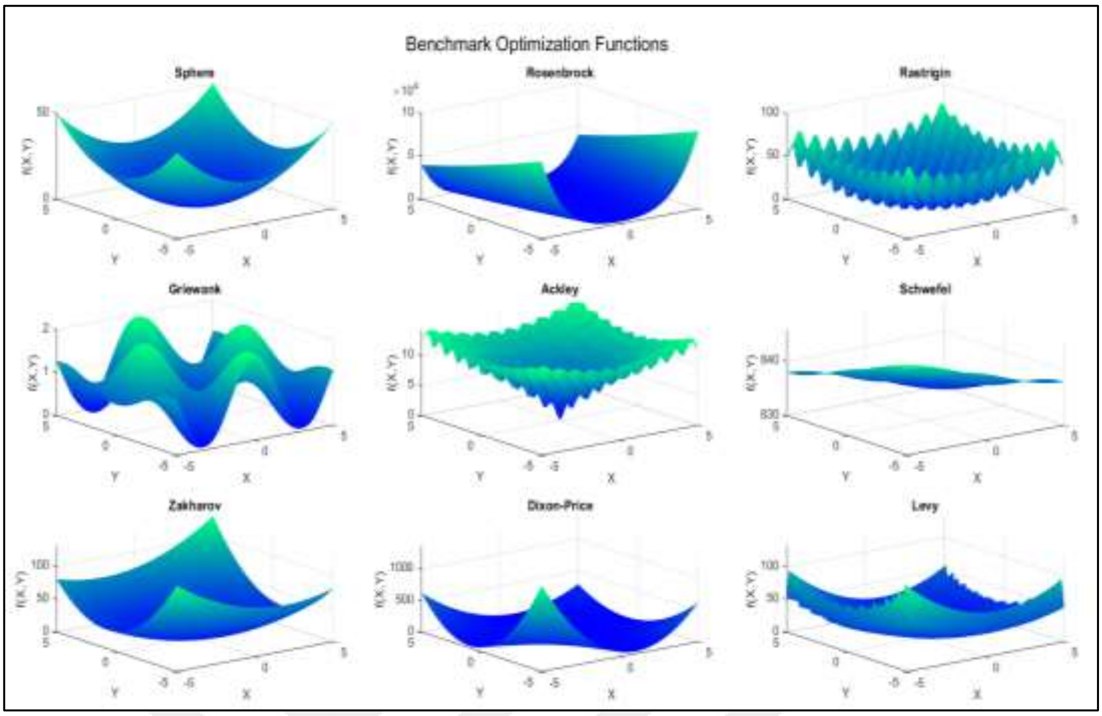

Figure 5.8: Benchmark Optimization Functions of HHHO-ES-PSO Approach.

In addition, Figure 5.9 shows the average history of convergence of the HHHO-ES-PSO, HHHO, and ES-PSO algorithms versus the Number of Function Evaluations (NFE). Convergence rate and precision are different in the logarithmic scale of the Y-axis. The HHHO-ES-PSO algorithm has a steep and swift reduction of the fitness values approaching exponentially to the global optimum. It has almost no error in a fraction of the computation cost of the other two methods.

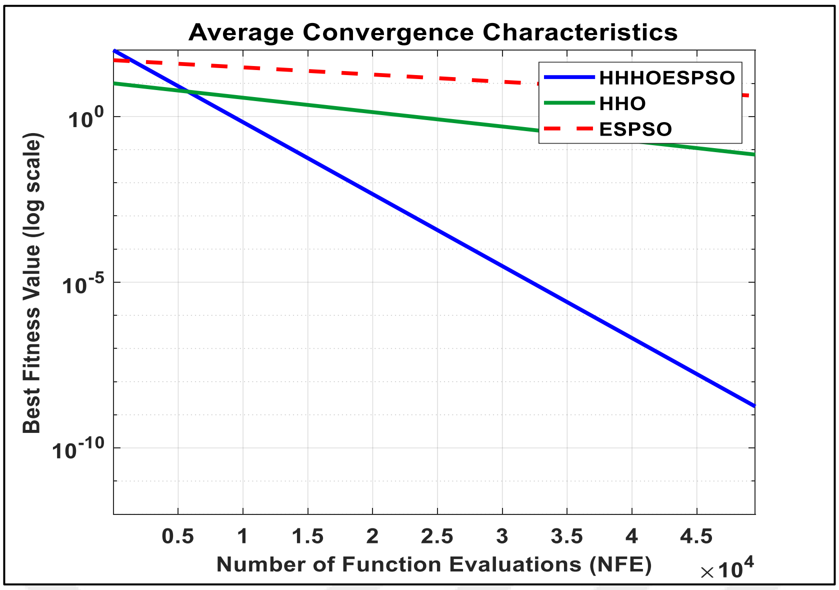

Figure 5.9: Convergence Performance Vs Nfe.

Conversely, both HHO and ES-PSO converge more slowly and hit a stalemate at elevated fitness levels and become commonly stuck in local optima. The steep reduction in value at the beginning and the low values of the HHHO-ES-PSO curve prove that the latter has a better exploitation capacity and that it has a good ability to remain precise during the optimization process. In addition, the fact that it does not experience stagnation plateaus, which can be witnessed in HHO and ES-PSO, once again proves the fact that the algorithm has a solid balance between exploration and exploitation.

To conclude, the statistical and graphical analysis provides a clear result that the HHHO-ES-PSO algorithm is an effective and strong optimization model. Not only does it achieve more correct and consistent results than the corresponding HHO and ES-PSO algorithms, but it also has a faster, steadier, and advantageous convergence, making it especially valuable to nonlinear optimization problems involving parameter optimization of sophisticated UAV control systems.

6. CONCLUSION AND FUTURE WORK

6.1 CONCLUSION

The study proposes a novel control plan of the FOPID controller optimized with the use of the HHHO-ES-PSO algorithm. The proposed hybrid optimization algorithm can dynamically manipulate the parameters of the controllers, and this significantly enhances the robustness, accuracy, and stability of tethered UAVs. The algorithm strikes the conflicting control objectives, such as responsiveness, disturbance rejection, and steady-state accuracy, by satisfying systematic parameter adaptation and thus is more useful in enhancing control performance in the various conditions in flight.

The simulations and the comparison of the analysis prove that the HHHO-ES-PSO-optimal controller is superior to the classic control schemes, such as PID, Cascade PID, and ADRC, as it results in the achievement of the smoother transient response, quicker stabilization, and greater disturbance resistance. In addition, the controller has better torque production in roll, pitch, and yaw directions, and this is translated into better maneuverability and precision in tracking the trajectory. A combination of these results justifies the usefulness of the suggested hybridization approach to solving the complicated nonlinear problems associated with the operation of tethered UAVs.

However, two major limitations must be admitted. To begin with, even though the experiments were done in a complete hardware-in-the-loop simulation model, the controlled testing environment is not a complete representation of the uncertainties of the real world complete aerodynamic effects, wind turbulence, and imperfect actuators. These aspects can have an impact on the performance of the controller during a real-life flight situation. Second, this study was restricted to a certain hybrid optimization and controller structure, and did not perform a comparison with other sophisticated control paradigm models, including adaptive feedback, model predictive, or reinforcement learning-based control strategies, which can also be used to achieve better system adaptability and resiliency.

6.2 FUTURE WORK

The next phase in the development of the results of this study will be to translate the suggested HHHO-ES-PSO-optimized FOPDD-I control system to the actual experimental validation. Even though the present model showed potential implications in terms of simulations as well as hardware-in-the-loop experiments, future research ought to include full-scale flight experiments in real environmental conditions, with wind turbulence, communication pipes, and sensor noise. Testing of this kind will help to gather important information regarding the robustness and flexibility of the controller when subjected to unmodeled system dynamics.

An additional study might also focus on combining the proposed hybrid optimization framework with the more advanced control models, (i.e., the adaptive feedback, Model Predictive Control (MPC), and Reinforcement Learning (RL)), to augment the system's autonomy and decision-making skills. Also, the control performance of tethered UAV systems in dynamic or resource-limited environments can be further optimized by adding multi-objective optimization criteria (trade-off among energy efficiency, stability, and the computational cost).

Lastly, the idea to use the HHHO-ES-PSO algorithm in other aerial and robotic systems, such as multi-UAV cooperative formations or hybrid aerial ground systems, is also a promising avenue. These extensions would prove the scalability and generality of the algorithm to a larger set of complex nonlinear control systems, and lead to more intelligent, adaptive, and energy-efficient autonomous operations.

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