Swarm optimization of the drone's intelligent control system: comparative analysis of hybrid techniques

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Abstract

Over recent years, bioinspired swarm techniques have gained significant popularity for addressing real-world engineering optimization challenges. One promising application of these methods is developing and optimizing of intelligent systems, specifically fuzzy control systems. This paper examines research issues and performs a comparative analysis of bioinspired swarm methods for parameter optimization in fuzzy control systems. It compares various hybrid modifications of particle swarm optimization and grey wolf optimization techniques, specifically adapted for fuzzy system parameter optimization, against traditional search methods. As a case study, the paper uses the parametric optimization of a Takagi-Sugeno fuzzy control system designed for a quadrotor-type unmanned aerial vehicle (UAV). The simulation results confirm the effectiveness of the presented swarm bioinspired optimization techniques, taking into account both the performance of the UAV's fuzzy control system and the computational costs involved.

Keywords

Bio-inspired optimization, hybrid swarm methods, particle swarm optimization, grey wolf optimization, fuzzy control system, unmanned aerial vehicle

1. Introduction

At designing intricate objects and systems in diverse fields like technology, agriculture, manufacturing, economics, and medicine, there's often a need to locate optimal solutions within a complex, multidimensional search space [1-4]. Standard optimization techniques frequently fail to meet these demands due to the unpredictable nature of the terrain and the existence of multiple local optima in the functions under consideration, which capture the complex relationships between solution effectiveness and unknown parameters [5-8]. Currently, approximate techniques of global optimization are gaining traction due to their capacity to find high-quality solutions efficiently in terms of both computational resources and time [9-12]. Bioinspired swarm and evolutionary algorithms stand out among these methods [13-15]. Unlike traditional methods of local search, bioinspired approaches are effective even with limited information about the nature and characteristics of the systems being optimized. They are proficient at avoiding local minima and are versatile enough to be applied to a wide array of real-world optimization problems. Additionally, these methods utilize straightforward computational procedures that mimic the behaviors of social animals, evolutionary concepts such as natural selection, and certain physical phenomena. In essence, bioinspired intelligent algorithms can be effectively combined with various

ICST-2024: Information Control Systems & Technologies, September, 23 – 25, 2024, Odesa, Ukraine

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local search methods, significantly improving the optimization process by strategically merging global and local search principles [16, 17].

In recent years, several intelligent algorithms have proven particularly effective and widely adopted for tackling diverse optimization challenges. Notable among these are particle swarm optimization (PSO) [18], ant lion optimization (ALO) [19], cuckoo search (CS) algorithm [20], grey wolf optimization (GWO) [21], whale optimization algorithm (WOA) [22], firefly algorithm (FA) [23], and chaotic swarming of particles (CSP) algorithm [24]. Moreover, numerous hybrid techniques have been successfully applied in the development of complex systems [25].

The use of metaheuristic swarm and evolutionary techniques for designing and optimizing intelligent control and decision support systems is a promising field, particularly when applied to systems based on fuzzy logic [14, 26, 27]. Recent research shows that fuzzy systems (FS) optimized with bioinspired methods are highly effective in tackling complex control and decision support issues across various domains [13, 28]. For instance, studies [29-32] have adapted PSO methods for the parametric optimization of linguistic terms (LT) in fuzzy automatic control systems (ACS) for different technical applications. Specifically, [29] discusses the optimization of triangular LT vertices for a fuzzy power control system in an industrial wireless sensor network. Meanwhile, [31] focuses on optimizing 1st type Gaussian LT parameters for a fuzzy ACS in an autonomous mobile robot operating in uncertain environments. Additionally, the GWO method has shown highly competitive results in parametric optimization for various fuzzy system configurations, outperforming other well-known bioinspired techniques [17, 33, 34]. Therefore, ongoing research into developing, refining, and implementing bioinspired swarm methods for synthesizing and optimizing different types of fuzzy systems is essential and highly relevant.

This study centers on the research and comparison of bio-inspired swarm techniques for the parametric optimization of a Takagi-Sugeno fuzzy automatic control system, specifically designed for a quadcopter UAV. The quadcopter drone possesses the ability to navigate through various terrains and environments, serving as a versatile tool for conducting intricate inspection and monitoring tasks in various environments and conditions. To fully harness the potential of this UAV, an intelligent control system optimized using advanced methods is essential [35]. Selecting the most suitable method to achieve high efficiency while maintaining low computational costs is a challenging task. Hence, the main goal of this study is to carry out efficiency research and perform a comparative analysis of various adaptations (basic and hybrid) of PSO and GWO swarm techniques for the parametric optimization of fuzzy ACSs.

2. Hybrid fuzzy automatic control system for the unmanned aerial vehicle

Quadcopter-type UAVs are among the most advanced and popular types of micro-class drones, which have recently been widely used for monitoring and inspection tasks in various civil and military sectors [36-38]. Also, such drones can be effectively used in critical infrastructure facilities along with other mobile robotic means to perform complex tasks of increased importance and danger [39]. These devices have several advantages over other types of unmanned aerial vehicles, including high maneuverability, the ability to take off and land vertically, hovering capability, high energy efficiency, and ease of maintenance. However, quadcopters are also quite complex to control, making it appropriate to use intelligent ACS, particularly fuzzy control systems, for their automation [35, 40]. One of the most important tasks in automating the spatial movement of such drones is the stabilization and automatic regulation of their flight altitude.

In this work, the fuzzy control system for quadcopter flight altitude is considered for researching and comparing different swarm optimization methods. To improve the quality of the UAV's flight altitude control and, accordingly, the overall efficiency of the processes of automating its vertical movement, it is advisable to use a hybrid fuzzy ACS based on a classical PID controller and a sliding mode controller, the structure of which is shown in Figure 1.

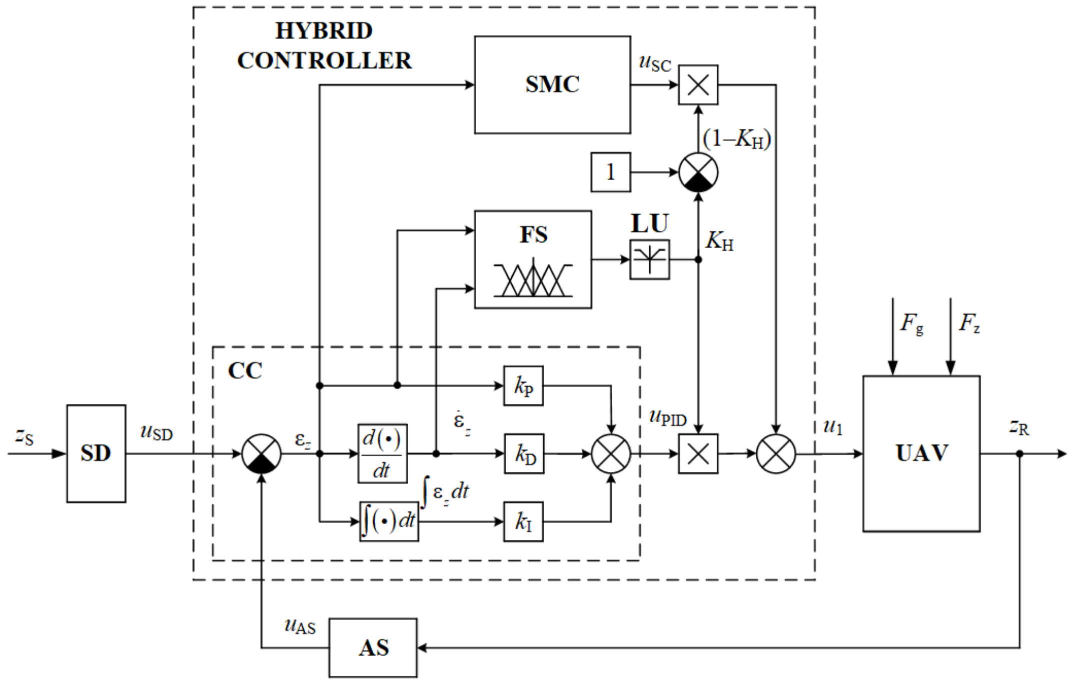

Figure 1: Basic structure of the hybrid fuzzy ACS for the UAV.

In turn, the following notations are used in Figure 1: SD is the setting device; CC is the classical PID controller; SMC is the sliding mode controller; FS is the fuzzy system for determining value of the aggregating weight coefficient K_H; AS is the sensor for altitude measuring; LU is the limiting unit that passes only positive signals and limits them to a level of no more than one; z_S and z_R are the set and real values of the flight altitude of the UAV; u_{SD}, u_{AS}, u_{PID}, u_{SC}, and u_1 are the corresponding output signals of the SD, AS, classical PID controller, sliding mode controller, and the entire hybrid controller; ε_z is the control error formed at the output of the adder in the main feedback channel; $\dot{\varepsilon}_z$ and $\int \varepsilon_z dt$ are the control error derivative and integral, respectively; k_P, k_D, and k_I are the PID controller gains; F_g and F_z are the gravity force and various disturbances acting on the UAV.

In this hybrid ACS, the classical PID controller is combined with the sliding mode controller using a specific fuzzy system that calculates the weighting factor K_H. At the same time, the aggregation of the output control signals of the classical u_{PID} and sliding mode u_{SC} controllers is carried out using the K_H coefficient, as a result of which the control signal of the hybrid controller u_1 is calculated according to the expression:

$$u_1 = K_H u_{PID} + (1 - K_H) u_{SC}. \quad (1)$$

At sufficiently small values of the control error ε_z (in the vicinity of the set value of the controlled coordinate z_S), the coefficient K_H approaches unity, and the resulting control signal u_1 for the UAV is largely determined by the output signal of the classical PID controller u_{PID}. In turn, at significant values of the error ε_z, the coefficient K_H approaches zero, and the greatest contribution to the signal u_1 is made by the control signal of the sliding mode controller u_{SC}. Moreover, due to the additional use of the derivative of the flight altitude control error $\dot{\varepsilon}_z$, when calculating the K_H coefficient, the dynamics of transitions from one control mode to another are better taken into account, which in general significantly increases the efficiency of the presented UAV's ACS. In turn, the limiting unit LU calculates the modulus of the output signal of the FS and limits it to a level of no more than one.

The output control signal of the sliding mode controller u_{SC} is calculated based on the current values of the sliding surface S_K according to relationship (2), and the sliding surface S_K itself is calculated based on equation (3).

$$u_{SC} = \begin{cases} +u_{C\max}, \text{ at } S_K > 0; \\ 0, \quad \text{ at } S_K = 0; \\ -u_{C\max}, \text{ at } S_K < 0; \end{cases} \tag{2}$$

$$S_K = a_1 \varepsilon + a_2 \dot{\varepsilon} + \ldots + a_{n-1} \varepsilon^{(n-2)} + \varepsilon^{(n-1)}, \tag{3}$$

where $u_{C\max}$ is the maximum possible value of the SMC control signal; a_1, a_2, ..., a_{n-1} are coefficients of the Hurwitz polynomial (a polynomial with real coefficients, all zeros of which are located in the left complex half-plane); n is the differential equation's order of the control plant.

In this case, a sliding surface of the first order is used, its only coefficient according to the Hurwitz polynomial a_1 is equal to 2.4 ($a_1 = 2.4$). The parameters of the traditional PID controller are as follows: $k_P = 2.54$; $k_D = 1.43$; $k_I = 0.513$. In turn, these coefficients are calculated on the basis of a mathematical model of a quadcopter UAV [17, 37] for the conditions of constancy of all its coefficients.

In turn, the FS calculates the value of the K_H weighting factor according to the dependence:

$$K_H = f_{FS}\left(K_P \varepsilon_z, K_D \dot{\varepsilon}_z\right), \tag{4}$$

where K_P and K_D are the normalizing factors of the FS.

The desired flight altitude of the UAV z_S can be specified by the upper-level control system, which is recommended to be implemented using IoT (Internet of Things) technology [41-43].

In this study, to conduct a comparative analysis of the considered swarm techniques, a parametric optimization of the Takagi-Sugeno type FS was performed for the hybrid ACS of the UAV's flight altitude. In this case, the parameter vector X to be optimized is defined by the expression (5)

$$\mathbf{X} = \left\{\mathbf{K}_i, \mathbf{P}_{LT}, \mathbf{P}_C\right\}, \tag{5}$$

where K_i is the vector of normalizing factors (K_P and K_D); P_{LT} is the vector of adjustable parameters of the FS's linguistic terms; P_C is the vector of weighting gains for the consequences of the rule base's rules.

For the input signals of the fuzzy system the following linguistic terms of the triangular type are chosen: ε_z – 5 LTs (BN – big negative; SN – small negative; Z – zero; SP – small positive; BP – big positive); $\dot{\varepsilon}_z$ – 3 LTs (N – negative; Z – zero; P – positive). Therefore, the P_{LT} vector contains 24 tunable parameters, each of which must be optimized. In turn, the rule base of this fuzzy system consists of 15 rules, each defined by expression (6)

$$\text{IF “}K_P \varepsilon_z = LT_1\text{” AND “}K_D \dot{\varepsilon}_z = LT_2\text{” THEN “}K_H = k_{1r}\left(K_P \varepsilon_z\right) + k_{2r}\left(K_D \dot{\varepsilon}_z\right) + k_{3r}, \tag{6}$$

where LT_1 and LT_2 are certain linguistic terms; k_{1r}, k_{2r}, and k_{3r} are the weighting gains of the r-th rule.

Thus, the P_C vector of consequent weighting coefficients consists of 45 coefficients. Overall, the parameter vector X to be optimized in this case comprises 71 parameters.

Next, we move directly to optimizing the parameters of the proposed hybrid fuzzy control system. This step involves conducting efficiency research and a comparative analysis of various modifications (both basic and hybrid) of PSO and GWO swarm techniques.

3. Swarm-based parameter optimization of the hybrid fuzzy control system for a quadcopter UAV

The authors propose the parametric synthesis and optimization of the UAV's hybrid fuzzy control system using effective and well-established swarm methods like PSO and GWO [17, 18, 21, 44]. These methods, along with their various hybrid modifications integrated with local search techniques, aim to expedite convergence. Specifically, hybrid PSO modifications based on the elite strategy with gradient descent (GD) and extended Kalman filter (EKF) algorithms, as proposed in [44], will be applied. Furthermore, an enhanced GWO technique [45], along with its hybridization with GD and EKF techniques as suggested in [17], will be considered. Finally, for thorough comparison, it is recommended to optimize the parameters of the UAV's fuzzy control system using individual local search techniques as GD and EKF.

The fundamental principles of the PSO algorithm and its application for the synthesis and parametric optimization of FSs are thoroughly covered in [16, 18]. Additionally, the authors in [44] proposed enhancing the FS optimization processes by hybridizing PSO with GD and EKF, utilizing an elite strategy. The key idea behind these modifications is to enable an independent parallel search by the best particle in the swarm using GD or EKF, which can potentially speed up convergence and reduce the computational and time costs associated with these methods.

The basic and improved GWO methods are thoroughly detailed in [21] and [45]. The enhanced GWO method incorporates an additional dimension learning-based hunting (DLH) strategy to boost population diversity and prevent premature convergence to suboptimal solutions [45]. In [17], the authors suggested hybridizing the improved GWO with local search methods such as GD and EKF. To implement this, similar to hybrid PSO techniques, alpha, beta, and delta agents are assigned to perform local searches in their nearby areas using GD or EKF, alongside utilizing group hunting and DLH strategies.

In this research to conduct a comparative analysis during the optimization processes, the generalized integral deviation of the system's actual transient response from the desired response was selected as the objective function J [17]. In turn, the desired response was calculated based on the reference model, which had the transfer function of the second-order dynamic object [17]. The objective function's optimal value was set to J_{opt} = 3100, which needed to be reached during the optimization process. To ensure comprehensive research, the maximum number of iterations was capped at N_{max} = 200, serving as the termination criterion for the optimization. For the PSO algorithm and its hybrid modifications, the following adjustable parameters were used: the swarm size Z_{max} = 30, the maximum particle velocity V_{max} = 10, and acceleration coefficients $C_1 = C_2 = 0.1$. For the GWO method's modifications, the pack size was also set to Z_{max} = 30. The same constraints as in [44] and [17] were applied in this case.

The procedures for optimizing the parameter vector X were conducted sequentially using each of the investigated swarm methods, repeating the process five times and selecting the best outcomes. During each iteration, the objective function values were computed by simulating the transients for the hybrid fuzzy control system controlling the UAV's flight altitude across various operating modes, specifically addressing both large and small deviations from the specified values. In addition, all simulation calculations were performed using the mathematical model of the UAV flight detailed in papers [17, 37].

To evaluate the efficacy of the swarm optimization methods used in this study, it is suggested to compare the achieved minimum values of the objective function J_{min} alongside the associated computational costs. Moreover, the computational resources required to reach the predefined optimal value J_{opt} of the objective function are considered for evaluation. In this regard, the computational costs of the analyzed techniques are largely determined by the total number of objective function evaluations υ_J needed to achieve specific values, such as υ_{Jopt} for the optimal value J_{opt} and υ_{Jmin} for the best value J_{min}. This is explained by the fact that the calculation of the current value of the objective function using a complex simulation model of a fuzzy control system requires significantly greater computational and time costs compared to simpler computational operations of the considered optimization algorithms [17]. Also, based on a certain value of the total number of objective function evaluations, the total time of the calculations performed can be determined quite simply, depending on the power of the computing resources used.

The Figure 2 illustrates the progression of the best values of the objective function during the optimization of the vector X using the methods under study: 1 – basic PSO; 2 – hybrid PSO with GD; 3 – hybrid PSO with EKF; 4 – basic GWO; 5 – IGWO (improved GWO); 6 – hybrid IGWO with GD; 7 – hybrid IGWO with EKF; 8 – GD; 9 – EKF.

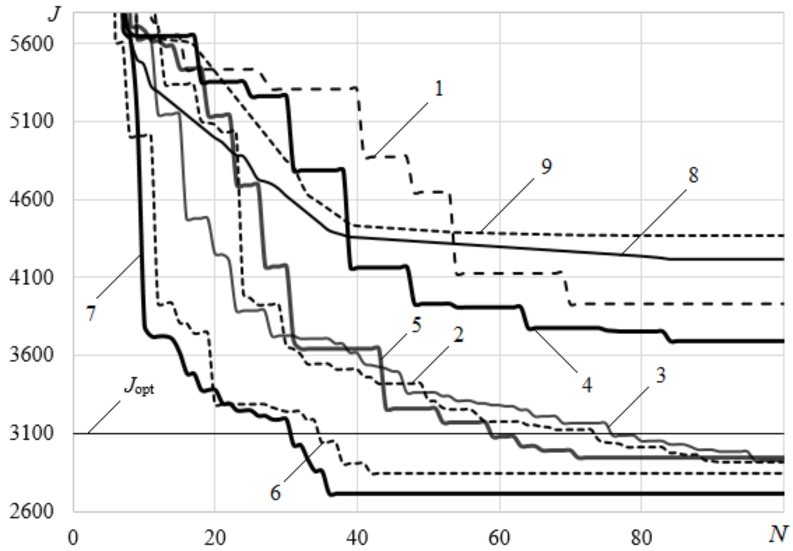

Figure 2: Graphs depicting the variation in the best values of the objective function J throughout the optimization of the hybrid fuzzy ACS for UAV's flight altitude (across iterations N = 0...100).

Table 1 provides a summary of the best results from the computational experiments conducted for optimizing vector X with each of the investigated methods.

Table 1
The best outcomes of the simulation experiments obtained in the optimization of the hybrid fuzzy ACS for UAV's flight altitude

Optimization technique	N_{Jopt}	υ_{Jopt}	J_{min}	N_{Jmin}	υ_{Jmin}
Basic PSO	136	3974	3016	162	4728
Hybrid PSO with GD	74	2250	2918	91	2760
Hybrid PSO with EKF	76	2310	2927	96	2910
Basic GWO	122	3324	3031	149	4053
IGWO	59	3216	2942	71	3864
Hybrid IGWO with GD	35	2025	2847	42	2424
Hybrid IGWO with EKF	31	1797	2712	36	2082
GD	-	-	4366	84	84
EKF	-	-	4218	77	77

In turn, when it comes to swarm methods and their diverse adaptations (including hybrid and improved versions), the parameters υ_{Jopt} and υ_{Jmin} typically exceed the corresponding iteration counts N_{Jopt} and N_{Jmin}. This is because the objective function must be computed at each iteration for every agent within the swarm. In contrast, for standalone methods like the gradient method and the extended Kalman filter, the number of objective function calculations υ_{Jmin} required to reach its minimum value J_{min} equals the iteration count N_{Jmin}.

The presented outcomes in Figure 2 and Table 1 confirm that hybrid IGWO methods demonstrate higher effectiveness compared to hybrid PSO algorithms in the parametric optimization of the fuzzy system for computing the coefficient K_H of the hybrid ACS for the UAV. Thus, to find the optimal value of the objective function J using hybrid IGWO methods with EKF and GD, in the best case scenario, it required 513 and 225 fewer evaluations of the objective function respectively compared to using hybrid PSO algorithms based on the elite strategy with EKF and GD. Furthermore, the implementation of hybrid IGWO methods on average ensured the achievement of a smaller minimum value of the objective function J_{min} compared to hybrid PSO techniques.

For addressing this specific problem (optimization of the hybrid fuzzy ACS for the UAV), the most effective approach is the hybrid IGWO method with EKF. Implementing this method enabled the attainment of the optimal value of the objective function for the hybrid fuzzy ACS ($J \leq 3100$) with the fewest number of evaluations of the objective function ($\upsilon_{Jopt} = 1797$). Furthermore, when implementing this method on the 36th iteration (Figure 2, curve 7), the lowest value of the objective function was achieved ($J_{min} = 2712$).

The separate application of the gradient method and the extended Kalman filter algorithm in this case did not allow achieving the optimal value of the objective function ($J \leq 3100$). A notable feature of this specific problem (parametric optimization of the hybrid fuzzy ACS for the UAV) is that the application of the hybrid PSO method with GD enabled faster attainment of the optimal objective function's value and found its lower minimum compared to using the hybrid PSO technique with EKF. Additionally, the standalone gradient method showed better results than the standalone EKF algorithm.

Furthermore, the optimized parameters of the resulting vector X_{best} exhibit the following specific values. Regarding the vector of normalization factors K_i, the components were determined to be $K_P = 0.0587$; $K_D = 0.072$. The representation of linguistic terms for the input variables of the FS with their optimized parameters is illustrated in Figure 3.

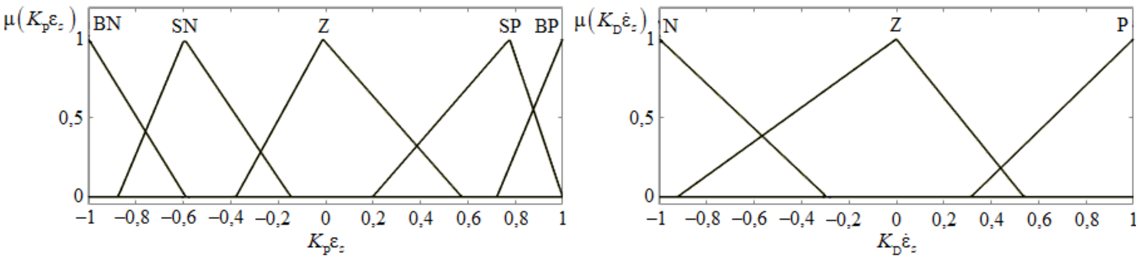

Figure 3: Optimized linguistic terms for the input signals of the hybrid fuzzy system for the UAV control.

The fragment of the rule base within the optimized UAV's fuzzy system, achieved using the hybrid IGWO method incorporating EKF for minimizing the objective function, is detailed in Table 2.

Table 2
Fragment of the rule base for the FS of the hybrid fuzzy system for the UAV control

Rule number	LTs of the input variables		Weighting gains of the rules' consequents		
	$K_P\varepsilon_z$	$K_D\dot{\varepsilon}_z$	k_{1r}	k_{2r}	k_{3r}
1	BN	N	0.004	0.006	0.013
3	BN	P	0	0.024	0.02
5	SN	Z	0.413	0.5616	0.908
10	SP	N	0.825	0.142	0.82
15	BP	P	0	0.016	0.0023

Furthermore, the entire vector comprising optimized weighting coefficients P_C is expressed as follows:

P_C = {0.004; 0.006; 0.013; 0.002; 0.017; 0.016; 0; 0.024; 0.02; 0.307; 0.103; 0.703; 0.413; 0.5616; 0.908; 0.545; 0.653; 0.426; 10.176; 0.134; 1.24; 11.8; 5.386; 1.58; 10.44; 1.851; 1.633; 0.825; 0.142; 0.82; 0.547; 10.24; 0.479; 0.352; 0.139; 0.736; 0.002; 0.006; 0.0075; 0.0054; 0.085; 0; 0; 0.016; 0.0023}.

Let's now move on to examine the results from simulation experiments conducted on the developed UAV's hybrid fuzzy control system to verify the effectiveness of the swarm optimization methods being investigated.

4. Simulation tests of the hybrid fuzzy control system for the UAV

To validate the effectiveness of the developed hybrid fuzzy ACS with optimized FS parameters based on the proposed hybrid IGWO method with EKF, transient flight processes of the UAV are depicted in Figure 4. Curves 1, 2, and 3 represent the system outputs (actual flight altitude values of the quadcopter at constant horizontal coordinates) with the hybrid controller (based on the optimized FS using hybrid GWO method with EKF), fuzzy PID controller, and optimally tuned traditional PID controller (developed in [17]). Line 4 represents the set altitude value of the UAV flight, while line 5 depicts the disturbance influence of wind F_z. Additionally, Table 3 provides a comparative analysis of the altitude control system performance metrics for the aforementioned transient processes.

In turn, the numerical data in Table 3 correspond to the change in time of the actual UAV flight altitude z_R when varying the set altitude value z_S from 0 to 40 m (Figure 4).

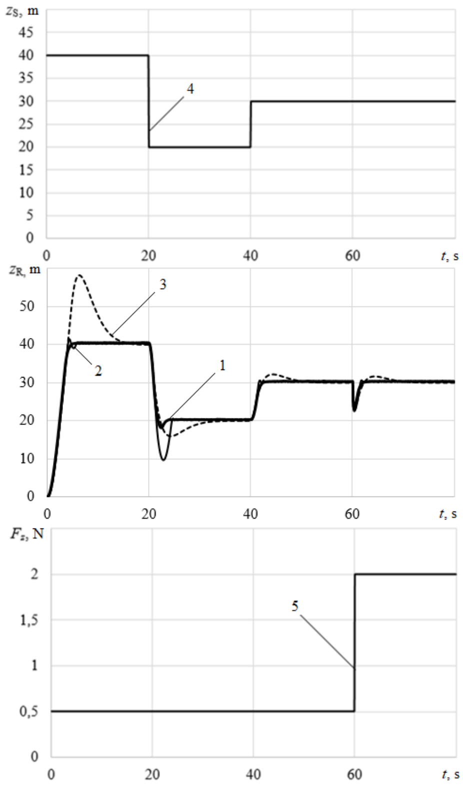

Figure 4: Transients of the UAV's altitude control system.

From the data presented in Figure 4 and Table 3, it is clear that the hybrid fuzzy control system implemented for the quadcopter UAV, utilizing optimized FS via the hybrid IGWO method with EKF, demonstrates significantly higher control quality metrics compared to configurations employing optimized fuzzy and conventional PID controllers. Specifically, this system exhibits faster response times and reduced overshoot, which are key indicators of dynamic control performance.

Table 3
Analysis of quality indicators of the UAV's flight altitude ACS

Quality indicators of the UAV's altitude control system	Quality indicators' values		
	Traditional PID controller	Fuzzy PID controller	Hybrid fuzzy controller
Rise time, s	3.96	4.02	4.26
Regulating time, s	14.21	4.47	4.31
Overshoot, %	45.55	3.75	1.21

5. Conclusions

This research focuses on evaluating and comparing swarm bio-inspired techniques for parameter optimization in fuzzy control systems. In particular, it examines various hybrid adaptations of particle swarm optimization and grey wolf optimization methods, tailored for FS parameter optimization, comparing them both with each other and with traditional search methods.

The study involves research and comparative analysis using a specific case: the parametric optimization of a Takagi-Sugeno hybrid fuzzy automatic control system for an unmanned aerial vehicle of a quadcopter type. The simulation results indicate that hybrid IGWO methods generally outperform hybrid PSO methods in optimizing parameters of a particular fuzzy system that aggregates a classical PID controller with a sliding mode controller within the UAV's ACS. Among the evaluated methods, the hybrid IGWO method with EKF proves to be the most effective for this challenge. Its application achieves the optimal objective function value for the hybrid fuzzy ACS ($J \leq 3100$) with the fewest evaluations of the objective function (υ_{Jopt} = 1797).

Additionally, the hybrid fuzzy ACS, by integrating the benefits of both a classical PID controller and a sliding mode controller via the FS, along with employing a highly efficient parameter optimization method, shows improved responsiveness and reduced overshoot compared to the ACS that utilizes a fuzzy PID controller. As a result, identifying the optimal vector for the FS of the hybrid ACS for the UAV using the hybrid IGWO technique with EKF did not demand substantial computational or time resources (υ_{Jmin} = 2082). This overall confirms the high effectiveness of the proposed fuzzy hybrid ACS model and developed in [17] hybrid swarm parameter optimization approach.

The optimization techniques discussed in this study can also demonstrate their effectiveness in enhancing fuzzy control systems for various complex systems, as evidenced by both this research and other related studies. Future work will focus on a more thorough theoretical analysis of these algorithms, particularly examining their sensitivity to adjustments in parameters such as the swarm size, acceleration coefficients, speed restrictions, etc. Additionally, further research will explore optimizing different fuzzy control systems for several various technical plants and include a comparison of their performance with more state-of-the-art multi-agent and evolutionary algorithms.

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