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Application of Fuzzy Control Allocation Approach for Coordinated Landing of Multi-Aircrafts Considering Ground Obstacles

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ABSTRACT

Achieving agreement among agents is crucial in multi-agent systems to enable coordinated operations and synchronized path alignment. These agreements enhance safety, streamline planning, reduce interference, and improve efficiency. Coordination methods vary based on factors such as prioritization, routes, constraints, and shared information, with agreements established directly, interactively, or via a central agent. This study explores the coordinated control of multiple aircraft for synchronized landings using a fuzzy control allocation approach. A fuzzy controller is implemented and its parameters are optimized through the Non-dominated Sorting Genetic Algorithm (NSGA-II), ensuring the effective distribution of control signals between elevator operators and thrust vector systems. This approach enables synchronized, automated landings from different initial altitudes, maintaining stability with minimal control effort across two scenarios. In the first, agents coordinate landings without ground obstacles, where one agent leads and others follow. The second scenario incorporates a ground obstacle into the coordination process. In both cases, the approach ensures synchronized landings with minimal control effort, high precision, and stable performance. Simulation results demonstrate that the optimized fuzzy controller successfully achieves coordinated automatic landings in both scenarios, handling obstacles effectively. The system ensures synchronized landings with reduced control effort, high accuracy, minimal time, and reliable stability.

1 INTRODUCTION

Coordinated landing and positioning among multiple aircraft is one of the challenging aspects of aerial maneuvers and automated aircraft landings. In this process, several aircraft simultaneously approach landing or designated areas, maintaining synchronization. The primary objective is to prevent accidents, avoid obstacles, consider air friction, and ensure the safety and accuracy of aircraft landings. Various algorithms are employed to control agents during automated landings, including artificial intelligence-based methods such as fuzzy logic, neural networks, etc. Fuzzy systems are a type of intelligent system that, unlike classical systems that work with precise values and Boolean logic, can accommodate

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uncertainty and ambiguity in data. By using fuzzy concepts and probabilities, fuzzy systems can operate with data that are typically ambiguous and unclear in real environments. Therefore, these systems are widely used in process control, intelligent decision-making, and complex information processing systems. Control systems designed based on fuzzy logic have greater adaptability to different environments and conditions, leading to significant improvements in controlling complex systems. The benefits of using fuzzy logic in controlling complex systems like aircraft include increased accuracy, reduced oscillations, greater system stability, and the elimination of the need for a detailed system model. Fuzzy logic can also be utilized for allocating control signals among system operators. Control allocation refers to the division and distribution of control signals among the operators of a system. Various methods exist for control allocation. In the fuzzy logic-based control allocation method, control signals are intelligently distributed among system operators with low computational complexity. This improves overall system efficiency, reduces instability time, decreases computational load, and ultimately enhances aircraft performance during landing. Moreover, this intelligent approach can significantly contribute to increasing safety and fostering coordination among agents during automated landings. Soriano and colleagues, propose an innovative systematic method for preventing collisions in mobile robots, employing multi-agent systems to create solutions that improve the entire system. This proposed method depends on the exchange of information among the participating agents. The implemented procedure involves multiple steps: collision detection, obstacle identification, negotiation, agreement formation, and collision avoidance [1]. Dong et al. propose a method for creating formation protocols using the common Lyapunov functional approach and the algebraic Riccati equation, which defines the collective movement of a UAV group [2]. Wang et al. focus on event-driven consensus in leader-follower frameworks with actuator faults, reducing communication load and introducing a control allocation method to address these faults [3]. Du et al. introduce a distributed fault-tolerant control strategy for over-actuated multi-agent systems, incorporating a distributed observer to estimate the leader's state and system matrix, improving robustness [4]. Pfeifle et al. present an incremental control allocation method that minimizes power consumption, especially for transition aircraft using an INDI controller [5]. Baggi et al. develop a dynamic control allocation strategy for over-actuated aircraft, prioritizing primary effectors and reallocating control signals when faults or limitations occur, eliminating the need for fault detection schemes [6]. Ren et al. introduce a cooperative decision-making framework based on incomplete information dynamic games to develop maneuver strategies for multiple UAVs in air combat situations [7]. Liu et al. analyze air combat missions with multiple UAVs in hostile environments, creating a multi-UAV threat assessment model and using matrix game theory for target allocation. They propose a modified Estimate of Distribution Algorithm (EDA) and employ social behavior-based sliding mode control to coordinate UAV swarm movements [8]. Elgohary et al. apply two adaptive controllers: a Model Predictive Controller (MPC) for formation stability and an Energy-optimal Search Controller (ESC) to optimize position search and minimize energy consumption for follower aircraft [9]. Wang et al. present a cooperative flight and collision avoidance model inspired by the Local Pursuit (LP) strategy in foraging ants. Their model integrates formation control and obstacle avoidance, using velocity alignment with shill agents to maneuver around hazards and enhance UAV safety [10]. Martinez-Ponce et al. investigate how formation flight impacts energy efficiency and stability, evaluating drone performance to improve flapping-wing aerodynamics and autonomous flight for applications like environmental monitoring and search and rescue [11]. Tabassum et al. develop an allocation agent for integration into onboard Detect and Avoid (DAA) systems of UAS, exploring scenarios for managing control authority in mixed-initiative environments with latency-prone communication [12]. Cao et al. address communication delays in networked multi-agent systems by proposing a cloud predictive control protocol that compensates for delays and ensures stability in formation control [13]. Kang et al. introduce a second-order differentiable virtual force-based metric for local trajectory planning, using artificial potential fields and a distributed optimization framework for dynamic formations and obstacle avoidance [14]. Zhang et al. propose the Multi-Agent Cooperative Search Learning (MACSL) algorithm, which uses reinforcement learning for effective search tracking in dynamic environments with intermittent communication, improving distributed coverage and efficiency [15]. The present paper focuses on the coordinated control of multiple aircraft for simultaneous and synchronized automatic landings using a fuzzy control allocation approach. A nonlinear aircraft model with three degrees of freedom is utilized, with a focus on the longitudinal dynamics of the aircraft. The efficacy of a fuzzy controller is enhanced and its performance is optimized through the implementation of the NSGA-II genetic algorithm, which facilitates the optimization of its parameters. This enhancement ensures the effective distribution of control signals between two actuators: the elevator and the Thrust Vector Control (TVC) system. This configuration enables the agents to achieve automatic and coordinated landings with optimal stability, proper timing, high accuracy, and minimal control effort across two distinct scenarios. In the first scenario, each agent executes a coordinated landing with different initial conditions, ensuring the absence of ground obstacles. Here, one agent assumes the role of the leader, while the other two agents function as followers. The second scenario introduces an obstruction on the ground, and the agents must coordinate using a leader-follower approach to navigate around it without colliding. In both scenarios, the position coordination among agents is structured to achieve a synchronized landing with minimal effort and control costs, high accuracy, sufficient stability, and relatively short time frames. The existence of such agreements among agents in multi-agent systems has been shown to lead to improved efficiency, safety, and coordination in various operations, significantly enhancing their overall performance. The contributions of this paper are as follows:

1. A fuzzy controller is employed to allocate control signals between elevator actuators and TVC systems, thereby facilitating coordinated and synchronized landings in two scenarios: one without obstacles and another with ground obstacles.
2. The paper employs a novel integration of aerodynamic actuators and TVC systems, a combination that has not been previously documented in the extant literature. A significant number of extant studies have opted to utilize either aerodynamic actuators or TVC systems in isolation for the purposes of aircraft control or control signal allocation. However, this paper is distinctive in its approach, as it combines both actuator types. The control signals generated by the fuzzy control allocation mechanism are distributed between these two systems.
3. The NSGA-II algorithm is applied to optimize the parameters of the fuzzy controller, enabling coordinated and synchronized landings for the agents in both scenarios with minimal control effort, high accuracy, and reduced time, all while maintaining an appropriate and acceptable level of system stability.

Section 2 focuses on presenting the dynamical model of the aircraft, including the kinetic, kinematic, and aerodynamic models used for the aircraft. Section 3 analyzes the development of the longitudinal flight control system, which includes subsections on fuzzy systems and the optimization of fuzzy controller parameters using the genetic algorithm-based NSGA-II method. Finally, Section 4 presents and analyzes simulation results for a detailed examination. In conclusion, the final section offers concluding observations.

2. MATHEMATICAL MODEL

2.1 Dynamical Model

This section deals with extracting the equations of motion for agents. Our equations of motion consist of a set of nonlinear differential equations with six degrees of freedom for each aircraft. However, aircraft equations of motion are expressed as nonlinear equations with 6 degrees of freedom [15,17], divided into rotational and translational equations. It is assumed that changes in mass (m) and moments of inertia of the aircraft are negligible over the entire process. Rotational dynamics equations are calculated as follows:

$$\begin{aligned}
&\dot{p}I_{xx} - I_{xz}(\dot{r} + pq) + \left(I_{zz} - I_{yy}\right)rq = L_A + L_T \\
&\dot{q}I_{yy} + pr(I_{xx} - I_{zz}) - (p^2 - r^2)I_{xz} = M_A + M_T \\
&\dot{r}I_{zz} - \dot{p}I_{xz} + pq\left(I_{yy} - I_{xx}\right) + rq\, I_{xz} = N_A + N_T
\end{aligned} \tag{1}$$

$I_{xx}, I_{yy}, and\ I_{zz}$ are the moments of inertia about the three axes of the body-fixed coordinate system, and $I_{xy}, I_{yz}, and\ I_{xz}$ are the products of inertia. Additionally, p, q, and r are the angular velocities about the body-fixed coordinate axes, and L, M, and N represent the torque acting on the aircraft along the X-axis, Y-axis, and Z-axis, respectively. Index A refers to aerodynamic torques, and index T represents torques resulting from thrust forces. Translational dynamics equations are calculated as follows:

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{z}\end{bmatrix} = \begin{bmatrix}cos\psi & -sin\psi & 0\\ sin\psi & cos\psi & 0\\ 0 & 0 & 1\end{bmatrix}\begin{bmatrix}cos\theta & 0 & sin\theta\\ 0 & 1 & 0\\ -sin\theta & 0 & cos\theta\end{bmatrix}\begin{bmatrix}1 & 0 & 0\\ 0 & cos\,\phi & -sin\phi\\ 0 & sin\phi & cos\phi\end{bmatrix}\begin{bmatrix}u\\ v\\ w\end{bmatrix} \quad (2)$$

The rates of change of linear velocities can be expressed as follows [17]:

$$\begin{aligned}\dot{u} &= rv - wq - gsin\theta + \frac{T_x}{m} + \frac{QSC_L sin(\alpha) - QSC_D cos(\alpha)}{m}\\ \dot{v} &= -ur + wp + gsin\phi cos\theta + \frac{T_y}{m} + \frac{QSC_D}{m}\\ \dot{w} &= uq - vp + gcos\phi cos\theta + \frac{T_z}{m} - QSC_D sin(\alpha) - QSC_L cos(\alpha)\end{aligned} \quad (3)$$

The components of linear velocities of the aircraft in the direction of x, y, and $z$axes are represented by u, v, and w, respectively. Additionally, the rates of change of Euler's angles can be expressed as follows [17]:

$$\begin{bmatrix}\dot{\phi}\\ \dot{\theta}\\ \dot{\psi}\end{bmatrix} = \begin{bmatrix}1 & sin\phi\ tan\theta & cos\phi\ tan\theta\\ 0 & cos\,\phi & -sin\phi\\ 0 & sin\phi\ sec\theta & cos\phi\ sec\theta\end{bmatrix}\begin{bmatrix}p\\ q\\ r\end{bmatrix} \quad (4)$$

Euler angles, denoted by ϕ (roll), θ (pitch), and ψ (yaw), describe the rotation of an aircraft around its principal axes x, y, and z, respectively. The initial conditions for each agent at the start of the flight are provided in Table1.

2.2 Aerodynamic Model

The aerodynamic model comprises equations and parameters that represent the effects of airflow on the structure and forces acting on the aircraft. In the aerodynamic model, aerodynamic coefficients for various components of the aircraft, such as wings, tail, and fuselage, are determined. This model assists in calculating aerodynamic forces and moments used in flight analysis, control design, and flight simulations. The aerodynamic model is outlined as follows [16]:

$$\begin{aligned}C_D &= C_{D_0} + C_{D_{\alpha^2}}\alpha^2 + C_{D_\alpha}\alpha + C_{D_q}q\\ C_L &= C_{L_0} + C_{L_\alpha}\alpha + C_{L_q}q + C_{L_{\delta_{ele}}}\delta_{ele}\\ C_Y &= C_{Y_0} + C_{Y_\beta}\beta + C_{Y_p}p + C_{Y_r}r + \left(C_{Y_{\delta_{ail_\alpha}}}\alpha + C_{Y_{\delta_{ail}}}\right)\delta_{ail} + \left(C_{Y_{\delta_{ail_\alpha}}}\alpha + C_{Y_{\delta_{rud}}}\right)\delta_{rud}\end{aligned} \quad (5)$$

$$\begin{aligned}C_m &= C_{m_0} + C_{m_\alpha}\alpha + C_{m_q}q + C_{m_{\delta_{ele}}}\delta_{ele}\\ C_l &= C_{l_\alpha}\alpha + C_{l_\beta}\beta + C_{l_p}p + C_{l_r}r + \left(C_{l_{\delta_{ail_\alpha}}}\alpha + C_{l_{\delta_{ail}}}\right)\delta_{ail} + \left(C_{l_{\delta_{rud_\alpha}}}\alpha + C_{l_{\delta_{rud}}}\right)\delta_{rud}\\ C_n &= C_{n_\alpha}\alpha + C_{n_\beta}\beta + C_{n_p}p + C_{n_r}r + \left(C_{n_{\delta_{ail_\alpha}}}\alpha + C_{n_{\delta_{ail}}}\right)\delta_{ail} + \left(C_{n_{\delta_{rud_\alpha}}}\alpha + C_{n_{\delta_{rud}}}\right)\delta_{rud}\end{aligned} \quad (6)$$

Here, C_D, C_L, and C_Y represent the aerodynamic force coefficients, while C_m, C_l, and C_n denote the aerodynamic moment coefficients. The angles $\delta_{rud}, \delta_{ele}$, and δ_{ail} correspond to the rudder, elevator, and aileron angles, respectively. The angle of attack is denoted by α, and the aircraft's sideslip angle is represented by β.

3 LONGITUDINAL FLIGHT CONTROL SYSTEM DEVELOPMENT

The longitudinal control system for flight is a crucial part of an aircraft's control system, tasked with managing movements along the longitudinal axis. It regulates forces and moments associated with longitudinal motions, including pitch, altitude, and speed, thereby contributing to the aircraft's stability and overall flight control. Effective operation of this system is essential for maintaining stable flight and appropriately adjusting altitude and speed. This system, based on information from sensors and continuous monitoring of the flight status, takes corrective actions to maintain the aircraft's desired state.

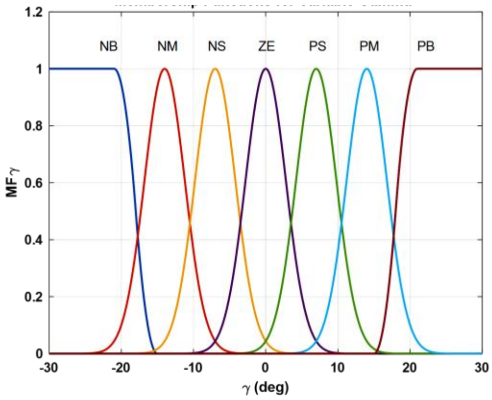


Figure 1. Membership function for variable ($\boldsymbol{\gamma}$).

Table 1. Fuzzy rules-base

Rul. no	$\dot{h}$	γ	U_{TVC}
1	NB	NS	NXL
2	NB	NM	N2XL
3	NB	NB	NB
4	PM	PS	PL
5	PM	PM	PXL
6	PM	PB	P2XL
7	PM	NS	PS
8	PM	NM	ZE
9	PM	NB	NS
10	NM	PS	NS
11	NM	PM	ZE
12	NM	PB	PS
13	NM	NS	NL
14	NM	NM	NXL
15	NM	NB	N2XL
16	PS	NS	ZE
17	PS	NM	NS
18	PS	PS	PM
19	PS	PM	PL
20	PS	PB	PXL

1.3 Fuzzy Logic Controller

A fuzzy controller is a type of artificial intelligence controller that operates based on fuzzy logic. In comparison to many other controllers, fuzzy controllers have very low computational complexity and can tolerate uncertainties to some extent. Additionally, fuzzy controllers are model-free and are highly practical in complex systems or systems with unknown models. In this controller, both inputs and outputs are represented as fuzzy values rather than exact values. However, the actual controlled systems operate with precise values for their inputs and outputs. Consequently, a fuzzification method is necessary to convert these exact values into fuzzy values. This transformation process can be divided into two steps: determining the fuzzy domain and fuzzification. The controller operates using a set of fuzzy rules determined by humans or automatically. Using fuzzy logic, this controller can adapt to dynamic and nonlinear input environments and perform better against uncertainty and noise. Fuzzy controllers are generally employed when an accurate system model is unavailable or when the system is complex and nonlinear. In this paper, to design a fuzzy flight control system, it is necessary to define the input variables of the controlled system (the aircraft) as well as the control variables. Considering that the fuzzy controller controls the longitudinal aircraft control during the landing process with two control operators, namely elevator and TVC, appropriate variables need to be specified as inputs to the fuzzy controller. For this purpose, variables α, γ, and $\dot{h}$, representing the angle of attack, gamma angle, and rate of altitude change at each moment, respectively, are chosen as the inputs to the controller, while δ_T and δ_{ele} will be the outputs of the fuzzy controller, where δ_{ele} represents elevator angle changes and δ_T represents thrust vector angle changes. Seven membership functions are utilized to describe each of the inputs α, γ, and $\dot{h}$, These are classified as large negative (NB), medium negative (NM), small negative (NS), zero (ZE), small positive (PS), medium positive (PM), and large positive (PB). Thirteen membership functions are also defined to describe the outputs of the fuzzy system, including ZE, PS, PM, PL, PXL, P2XL, PB, NS, NM, NL, NXL, N2XL, NB (P for positive and N for negative). Membership functions (μ) for input and output variables are selected to represent fuzzy sets of Gaussian type. These functions are defined by their centers and standard deviations. Gaussian functions are widely used due to their computational simplicity and resistance to noise. The Gaussian membership function is expressed as follows:

$$\mu = exp\,(-\frac{(x-c)^2}{2\sigma^2}) \qquad (7)$$

where x is the input variable, c is the center of the Gaussian function, and σ is the standard deviation that determines the width of the function. The Gaussian membership functions are commonly used in fuzzy logic systems due to their smoothness and ability to capture gradual transitions between membership levels. Due to the similarity between the membership functions of inputs and outputs, only one example of each will suffice. In Figure 1, the membership function corresponding to the variable gamma (γ) is depicted. The rule base of the fuzzy controller is expressed according to Table 1. Accordingly, forty-nine rules have been defined for the TVC operator, twenty of which are stated in Table 1. The rule base for the elevator operator is also similar to the rules in Table 1, therefore, its statement is withheld. Figure 2 illustrates the general schematic of a fuzzy flight control system for the autonomous coordinated landing of agents, considering position consensus. Additionally, the optimization of the fuzzy controller parameters using the NSGA-II method is depicted to enhance its performance in the longitudinal control of each agent.

U_{TVC} represents the amount of deviation of the thrust vector angle. According to Table 1, the second law is expressed as follows:

If $\dot{\boldsymbol{h}}$ is NB and $\boldsymbol{\gamma}$ is NM Then $\boldsymbol{U_{TVC}}$ is N2XL

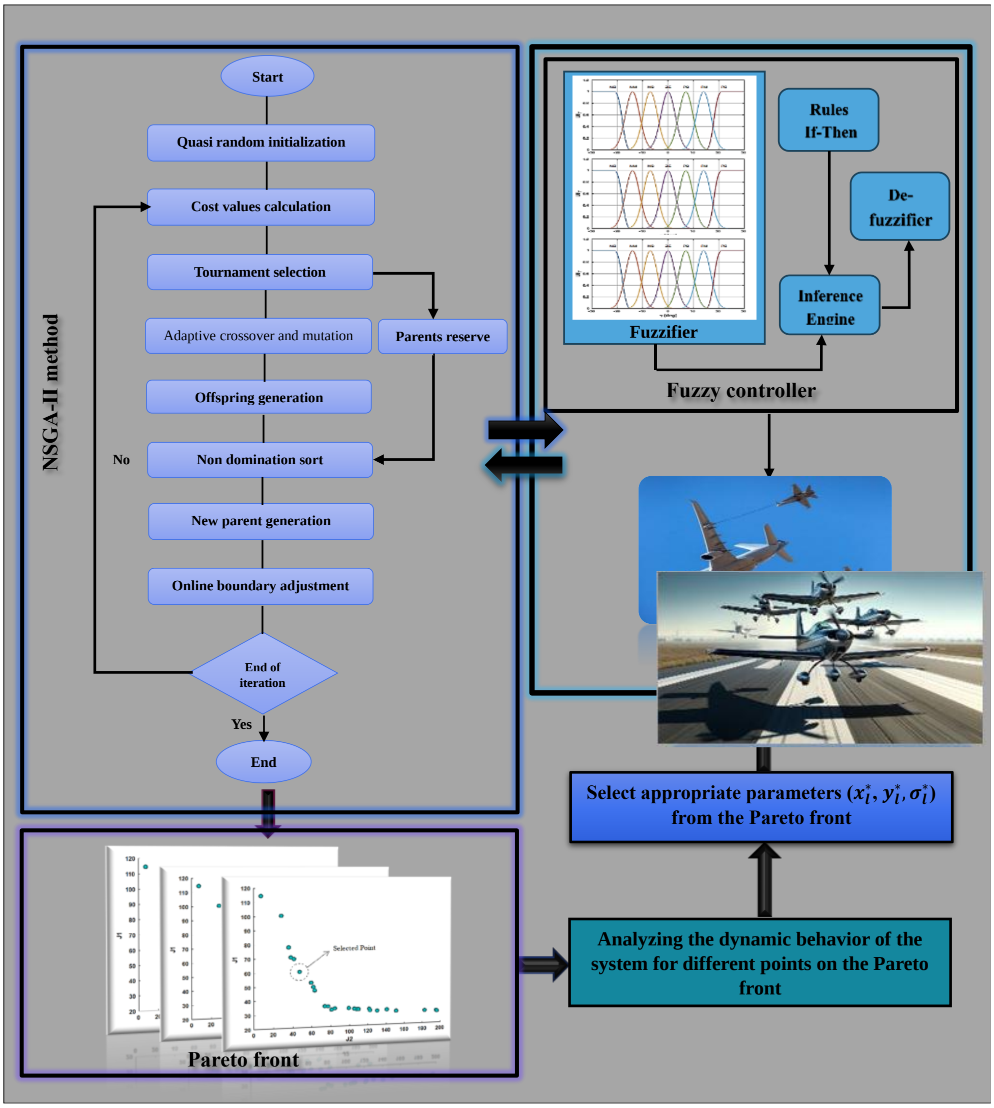


Fig. 2. The overall schematic of the fuzzy flight control system.

2.3 NSGA-II Optimization Method

To enhance the performance of the fuzzy controller, its parameters are optimized using the NSGA-II genetic algorithm. The objectives are to achieve optimal responses by optimizing the parameters $\bar{x}_0^l$ ، σ_0^l ،$\bar{y}_0^l$ which minimizes the control effort and cost while reducing undesirable aircraft deviations. Ultimately, all three aircraft factors with appropriate stability and sufficient accuracy accomplish coordinated landing. For this purpose, the centers of the membership functions ($\bar{x}_0^l$ ،$\bar{y}_0^l$) and deviation from the standard deviation σ of the fuzzy system inputs and outputs are optimized. The cost functions of the optimization problem, representing the control effort of both system operators, are expressed as follows:

$$J_1 = \int (\delta_{ele})^2 \, dt \qquad J_2 = \int (\delta_T)^2 \, dt \tag{8}$$

The multi-objective optimization problem, taking constraints into account, is defined as follows:

$$S = Min\,\{J_1, J_2\} \tag{9}$$

$$S.t. \begin{cases} |x_i| < X_i \\ |\delta_{ele}| < \delta_{ELE} \\ |\delta_T| < \delta_{TB} \\ |sse_i| < SSE_i \\ po_i < PO_i \\ tr_i < TR_i \end{cases} \tag{10}$$

In which S represents a set of optimal solutions. x_i is the deviation of state variables i around the equilibrium point, And X_i is its maximum allowable value. δ_{ELE} and δ_T also indicates the maximum deviation of the angles of the elevator and thrust vector, respectively. tr_i and TR_i represent the rise time and its maximum value, po_i and PO_i express the percentage of maximum overshoot from the desired value and its upper limit, and sse_i and SSE_i denote the steady-state error and its maximum allowable value for each state variable i. The optimization problem constraints are presented according to Table 2. The NSGA-II algorithm settings for optimizing the parameters of the fuzzy controller are provided in Table 3. In coordinated flights, after agents reach suitable stability, a control signal is generated to create agreement among them. Upon entering each agent, this control signal fosters agreement and coordination between them. For this purpose, a control signal is proposed in this section, generated by a fuzzy controller, enabling agents to achieve the desired agreement and coordination for automatic landing. As previously stated, for coordinated landing, agents are examined in two scenarios. In the first scenario, agents perform coordinated and agreed-upon landing without considering obstacles. The proposed control signal is derived from the following equation:

$$\begin{gathered} \dot{q}_i = f(q_i, t) + g(q_i, t)U_i \\ U_i = k_i \sum aij \left\{\alpha_i\left(q_j - q_i\right)\right\} \quad i, j = 1,2,3 \\ \lim_{t\to\infty}\left(q_j - q_i\right) = 0 \end{gathered} \tag{11}$$

In the second scenario, agents perform coordinated and agreed-upon landing while considering obstacles on the ground. By generating a proposed control signal through a fuzzy controller, agents adjust their altitude before reaching the obstacle in a way that allows them to pass the obstacle without collision. The proposed control signal is derived from the following equation:

$$\begin{gathered} \ddot{q}_i = U_i \\ U_i = \lambda_1(q_1 - q_i - d_i) + \lambda_2(\dot{q}_1 - \dot{q}_i) \quad i = 2,3 \\ U_1 = \ddot{q}_d + (\dot{q}_d - \dot{q}_1) + (q_d - q_1) + u_{oi} \\ u_{oi} = \frac{k(q_1 - q_o)}{r_1^2}\left(\frac{1}{r_1} - \frac{1}{r_a^m}\right) \quad r_1 \le r_a^m \\ r_1 = \|q_1 - q_o\| \end{gathered} \tag{12}$$

Where q_i, $q_1$and q_d respectively represent the positions of the follower agents, the position of the leader agent, the desired value along the z-axis, and their desired values. q_o is the position of the obstacle. r_a is the distance between the obstacle and the nearest agent to it. U_i and U_1 are respectively the proposed control signals applied to each of the follower agents and the leader agent. The index i represents the agent number. Before the agents reach the obstacle, collision avoidance with obstacles is achieved by entering these control signals. The position and height of the obstacle are expressed according to Table 4.

Table 2. Optimization problem constraints

Parameter	Value	Parameter	Value
X_θ	[-0.5, 0.5]	δ_{ele}	[-20,20] deg
X_γ	[-0.5, 0.5]	δ_T	[-20,20] deg
X_{n_z}	[-1, 1]	X_q	[-0.5, 0.5]
PO	10%	$X_{\dot{h}}$	[-0.5, 0.5] m
SSE	≤ 0.02	X_h	[-0.5, 0.5] m
TR	≤ 30 s	X_α	[-5, 5] deg

Table 3. NSGA-II Algorithm parameter settings

Parameter	Value
N_{pop}	60
I_{max}	1000
V_{dim}	10
M_p	0.06
P_m	0.10
η_c	15
η_m	15

Table 4. Initial Conditions for Each Agent

Parameters	Agent 1	Agent 2	Agent 3
V_0	46 m/s	46 m/s	46 m/s
α_0	8.2 deg	8.2 deg	8.2 deg
β_0	0 deg	0 deg	0 deg
x_0	0 m	0 m	0 m
y_0	0 m	0 m	0 m
z_0	560 m	460 m	510 m
ϕ_0	0 deg	0 deg	0 deg
θ_0	5.2 deg	5.2 deg	5.2 deg
ψ_0	0 deg	0 deg	0 deg
p_0	0 deg/s	0 deg/s	0 deg/s
q_0	0 deg/s	0 deg/s	0 deg/s
r_0	0 deg/s	0 deg/s	0 deg/s

Table 5. The position of an obstacle

Position	Value
x	10333 m
z	50 m

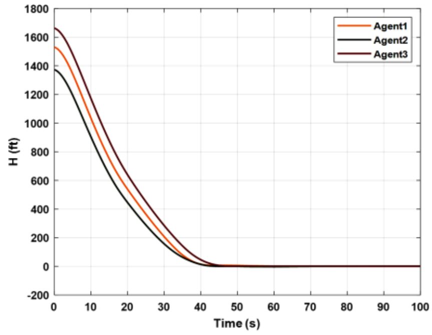
Figure 2 displays the Pareto front. To select the optimal point, it is essential not only to minimize the cost functions but also to ensure that the agents exhibit suitable dynamic behavior. While several other points in the figure show lower cost functions compared to the selected point, using their parameters in the fuzzy controller could lead to slight oscillations of the agents around zero altitudes as they approach the ground. Such oscillations are undesirable because the agents should perform coordinated landings without any oscillations, even minor ones, to maintain stability. Therefore, the point shown in (Figure 2) is the most appropriate choice for this problem, as it enables the agents to achieve coordinated landings with minimal cost while maintaining proper dynamic behavior.

RESULT

This section presents the simulation results to evaluate the effectiveness and capability of the fuzzy controller in coordinating the landing process. Figures 3 and 4 show the diagrams for the first scenario, where no ground obstacle is considered, while Figures 5 and 6 display the diagrams for the second scenario, which includes a ground obstacle.

In Figure 3, the coordinated landing of agents is analyzed in the absence of obstacles. Panel (a) illustrates the initial altitudes of the agents as they initiate the automatic landing process. The flight control system stabilizes the agents, while the optimized controller sends control signals to achieve position consensus with minimal error and without oscillations. Consequently, the agents attain their designated positions with high stability and in a relatively brief timeframe. Panel (b) presents the pitch rate of the agents.

The target pitch rate is approximately zero, and the applied control signal ensures that the pitch rate for each agent converges to zero and remains stable. Panels (c) and (d) illustrate the x-y plane positions and flight path angle of the agents, respectively. The flight path angle is a critical factor for the success of a coordinated landing, and the controller manages it to avoid disruption. The target value for the flight path angle is approximately zero. Panel (e) illustrates the load factor, which has a maximum value of less than 1g, indicating relatively low vertical acceleration. Finally, the angle of attack for each agent is shown in panel (f). In Figure 4, the angles of the thrust vector control and elevator actuators during the coordinated landing process are depicted. Panel (a) illustrates the thrust vector control actuator angle for each agent during the mission, within the allowable range of -15 to 15 degrees. Panel (b) illustrates the elevator actuator angle for the agents, which remains within the defined range. Panels (c) and (d) illustrate the control efforts of each actuator, demonstrating the efficacy of the fuzzy controller in guiding the agents to a stable landing. Figure 5 illustrates the coordinated landing of agents while considering a ground obstacle. Panel (a) illustrates the agents' trajectories, with a red obstacle delineating the impediment. The agents detect the obstacle and navigate around it, maintaining a safe distance. Panel (b) illustrates the pitch rate of the agents during the mission, which is adjusted to avoid collision with the obstacle. Panel (c) presents the two-dimensional positions of the agents, and panel (d) shows the flight path angle for each agent. The application of an optimized fuzzy controller successfully adjusts the flight path angle to the desired zero value. In Panel (e), the load factor exhibits a maximum near the obstacle, while Panel (f) demonstrates the angle of attack for each agent. In Figure 6, the actuator angles and control efforts of the operators during the flight with an obstacle are presented. Panels (a) and (b) demonstrate the thrust vector control and elevator angles for each agent during the mission. Panels (c) and (d) illustrate the control efforts when encountering the obstacle. These panels demonstrate the efficacy of the fuzzy controller in guiding the agents to a stable, accurate, and timely landing, even in the presence of obstacles on the ground. In the research process of this paper, several challenges were identified and examined, considering the complexities involved in the autonomous landing of agents. Addressing these challenges necessitated meticulous precision and focused attention. The most significant challenge encountered pertains to the complete elimination of oscillations in the agents at ground level. These oscillations, even the slightest, have the potential to induce disruptions in the agents' landings. Consequently, this issue has exerted a substantial influence on the extraction of fuzzy rules and the optimization of problem parameters, thereby constituting the most critical and time-consuming facet of this research.



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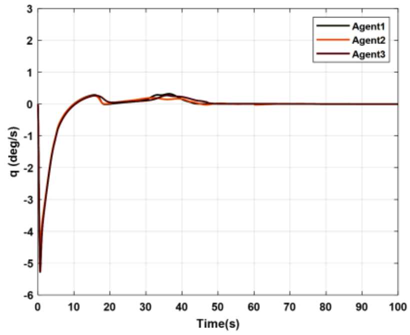
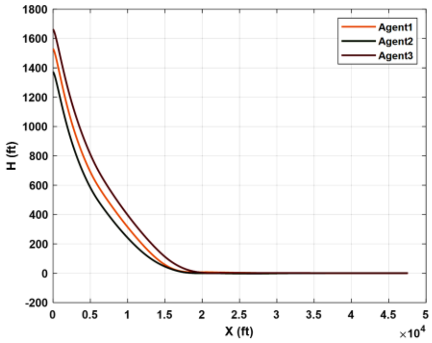


(b)



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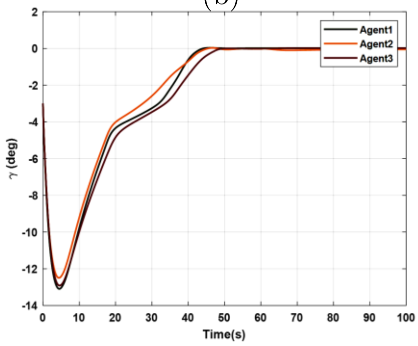

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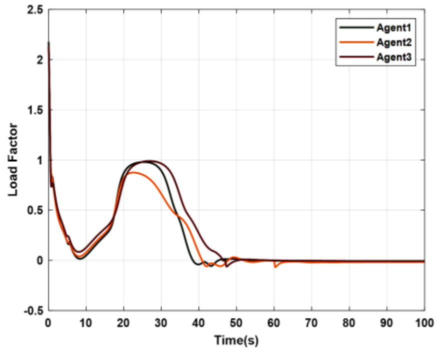
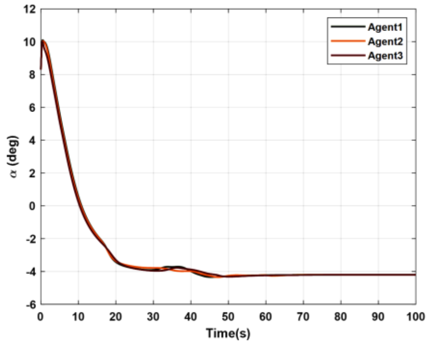
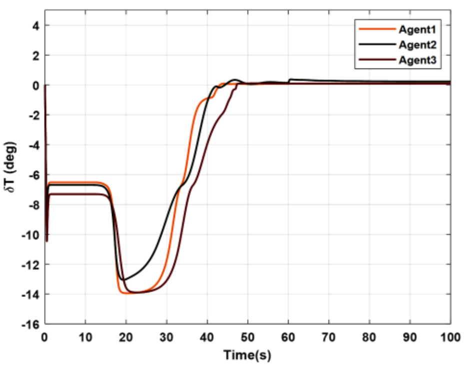


(e)

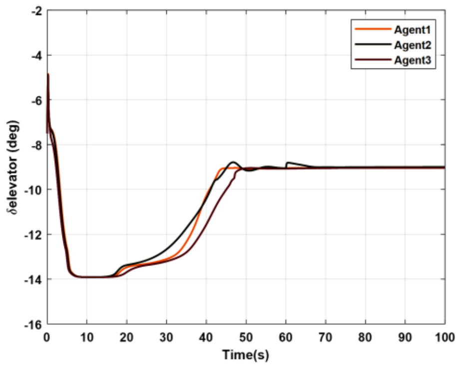


f)(

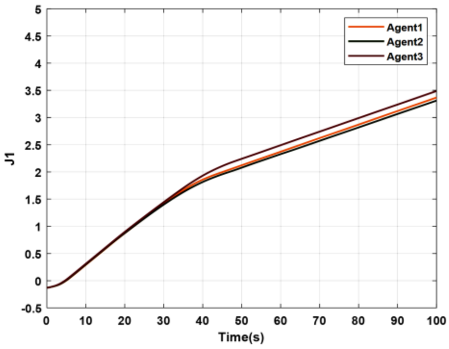
Fig. 3- State Variables for Each Agent (first scenario): (a)Altitude of Agents(H), (b)Pitch Rate($\boldsymbol{q}$), (c)Two-dimensional Position of Agents (x-y), (d)Flight Path Angle($\boldsymbol{\gamma}$) (e)Load Factor(n), (f)Angle of Attack($\boldsymbol{\alpha}$).



(a)



(b)



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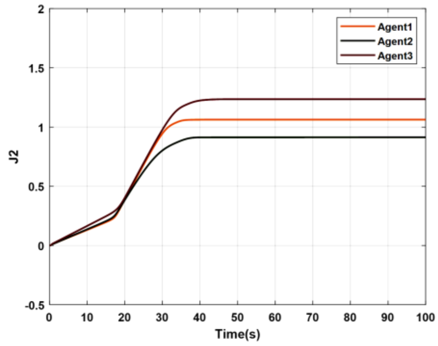
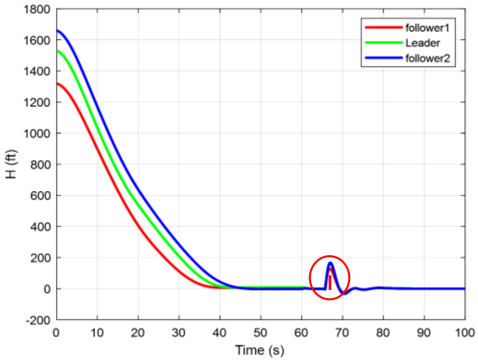
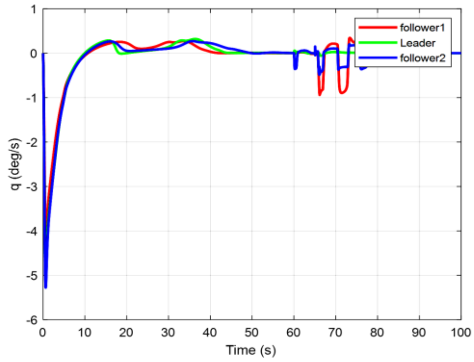


(d)

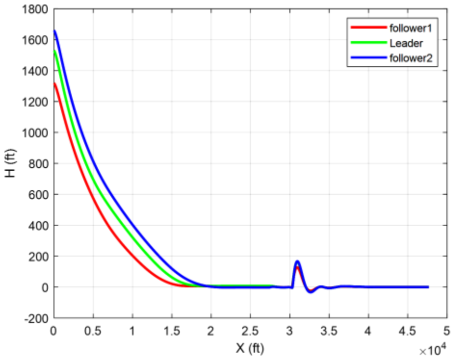
Fig. 4. Angles and Control Efforts of Operators (first scenario): (a)Elevator Angle($\boldsymbol{\delta_{ele}}$) (b)Thrust Vector Angle($\boldsymbol{\delta_T}$), (c)Elevator Control Effort(J_1), (d)Thrust Vector Control Effort (J_2).



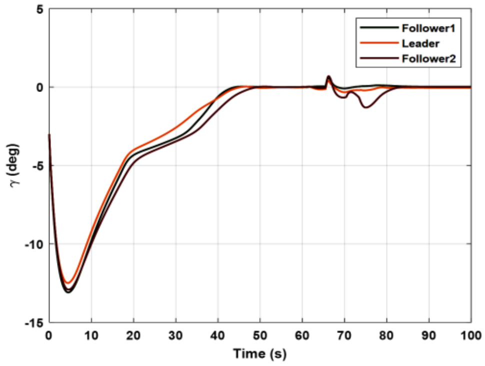
(a)



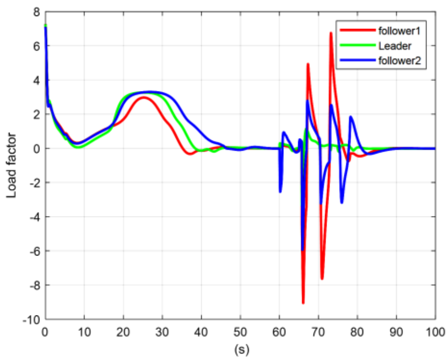
(b)



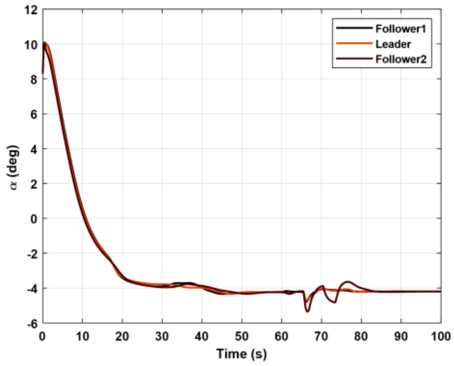
(c)



(d)



(e)



(d)

Fig. 5. State Variables for Each Agent(Second scenario): (a)Altitude of Agents (H) (b)Pitch Rate(q), (c)Two-dimensional Position of Agents(x-y), (d)Flight Path Angle($\boldsymbol{\gamma}$) (e)Load Factor(n), (f)Angle of Attack($\boldsymbol{\alpha}$).

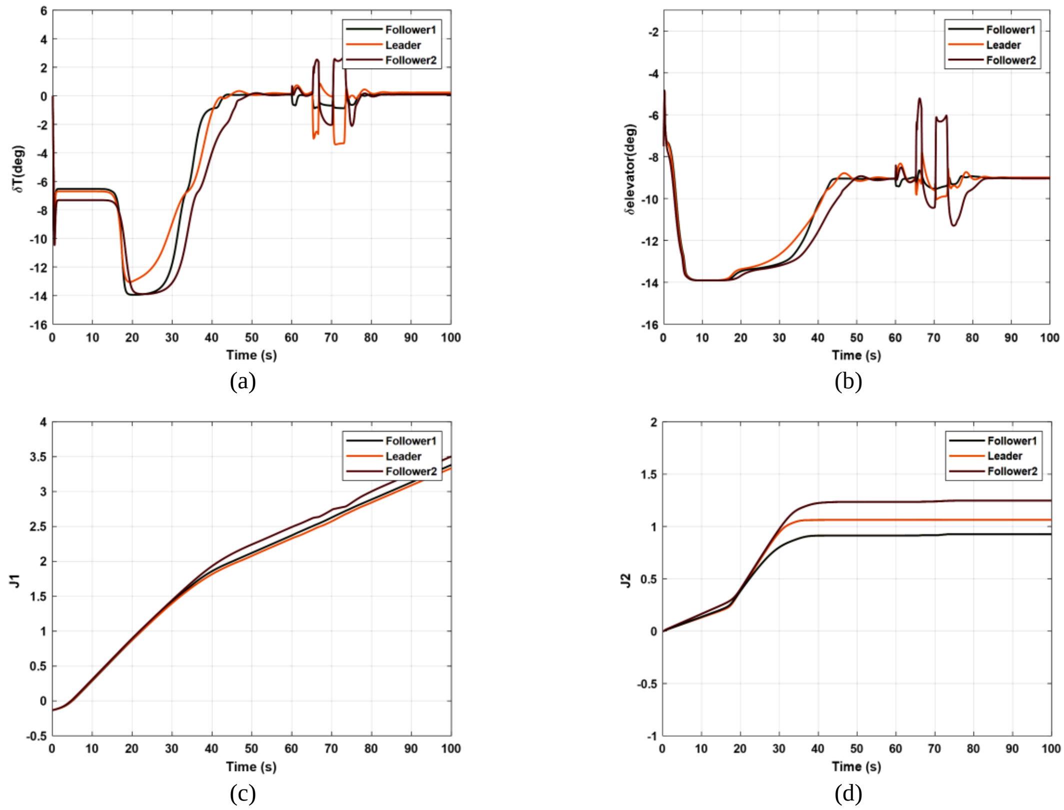


Fig. 6- Angles and Control Efforts of Operators (Second scenario): (a)Elevator Angle($\boldsymbol{\delta_{elevator}}$), (b)Thrust Vector Angle($\boldsymbol{\delta_T}$), (c)Elevator Control Effort(J_1) (d)Thrust Vector Control Effort(J_2).

Conclusion

The present paper focuses on the coordinated control of multiple aircraft for simultaneous landings using the fuzzy control allocation method. A robust NSGA-II algorithm was employed to enhance the performance and accuracy of the fuzzy controller. The parameters of the longitudinal flight control system were optimized and fine-tuned. In the control allocation section, the control signals generated by the optimized fuzzy controller were distributed between the elevator operators and the thrust vector control system. This approach enabled both leader and follower agents to execute coordinated landings from diverse initial altitudes while preserving stability, minimizing time, attaining high accuracy, and reducing control exertion. Two distinct scenarios were examined to assess the capabilities and effectiveness of the optimized controller. In the first scenario, each agent performs a coordinated landing from distinct initial conditions without encountering any ground obstacles. The second scenario involves a leader-follower configuration, where the agents achieve consensus while navigating around a ground obstacle, successfully avoiding collisions. In both scenarios, the agents reach a position consensus that allows for coordinated landings with minimal effort and control cost, high accuracy, sufficient stability, and relatively short timeframes. The ability to achieve consensus among agents in multi-agent systems has been demonstrated to enhance efficiency, safety, and coordination in various operations, thereby improving their overall performance.

CONFLICTS OF INTEREST

No potential conflict of interest was reported by the authors.

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