Pages: 1-15 / Vol. 19 / Issue 1 / Winter- Spring 2026

Journal of Aerospace Science and Technology

Journal Homepage: https://jast.ias.ir

Original Research Article

Multi-Objective Design Optimization of an Intelligent Altitude Controller for a Nonlinear Aircraft Using Fuzzy Logic and Genetic Algorithms

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ARTICLE INFO

Received: 13 August 2025
Revised: 20 Octobr 2025
Accepted: 02 November 2025
Available online: 30 November 2025

KEYWORDS:

Altitude controlle
Fuzzy logic
Genetic algorithm
Nonlinear dynamics
Multi-objective optimization

DOI: https://doi.org/10.22034/jast.2026.541185.1232

ABSTRACT

The objective of this paper is to design an altitude controller for an aircraft using fuzzy logic and genetic algorithms. In this study, two methods (specialist experience and scale mapping) are used to develop the fuzzy rules. First, a basic fuzzy controller is designed using both methods. Then the centers of the membership functions of inputs and outputs are determined using a genetic algorithm, aiming to reduce control effort, steady-state error, and rise time. The TOPSIS method is employed to select the final solution. The results show that, on average, the optimized fuzzy controllers achieve performance improvements of 28%, 53%, and 15% in control effort, steady-state error, and rise time, respectively. Finally, robustness analysis is conducted for the optimized fuzzy controllers in the presence of uncertainties: sensor noise, different aerodynamics derivatives, changing flight conditions, and gust. The results indicate that the optimized fuzzy controller based on specialist experience demonstrates robust performance.

1 INTRODUCTION

In various engineering fields, including aerospace engineering, linear control theory, and Proportional-Integral-Derivative (PID) controllers are extensively used. PID controllers are feedback-based mechanisms that employ three components-proportional, integral, and derivative-to modify system performance parameters, such as steady-state and transient responses. This type of controller is considered one of the most effective and efficient control strategies, offering a simple, economical, and reliable solution for managing engineering systems. The transfer function of these controllers is given as follows [1–3]:

$$u(t) = K_P\, e(t) + K_I \int e(t)dt + K_D \frac{d}{dt} e(t) \qquad (1)$$

The block diagram of this controller is shown in the following figure.

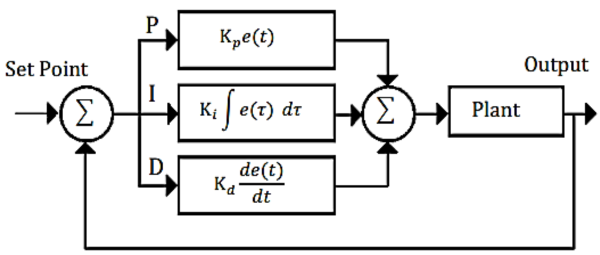

Fig. 1. Block diagram of PID controllers [3]

Each of the three components of the PID controllers affects the system's performance. Therefore,

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Print ISSN:1735-2134 Online ISSN: 2345-3648

understanding and tuning these components are critical and essential for achieving optimal performance. Table 1 shows the effect of each of these components on the system's performance individually. Despite their considerable advantages, these controllers have the following disadvantages that limit their practical applications [1–3]:

- These controllers can only be used for linear, minimum-phase, single-input and single-output (SISO) systems.
- Lack of robustness against uncertainties.
- Dependence on system dynamics.

Table 1. The effect of PID controller parameters [2]

Close loop response	Rise time	Overshoot	Settling time	Steady state error	Stability
$K_P \uparrow$	decrease	increase	slight increase	decrease	decrease
$K_I \uparrow$	slight decrease	increase	increase	significant decrease	decrease
$K_D \uparrow$	slight decrease	decrease	decrease	slight change	increase

To overcome the aforementioned limitations of the PID control method, various techniques such as adaptive control, nonlinear control, and gain scheduling are available for controller design. However, each of these methods also has its limitations. For instance, while adaptive and nonlinear control methods can adjust to system dynamics and environmental conditions, they require greater computational resources and more complex implementation. Similarly, gain scheduling does not provide guaranteed stability during transitions between equilibrium points [4–6].

Recently, significant advances have been made in the application of Artificial Intelligence (AI) techniques to address the existing challenges in flight control. With the emergence of AI, flight control systems have improved safety, efficiency, and performance, demonstrating more robust behavior across varying environmental conditions. Artificial intelligence is defined as the science and engineering of creating intelligent machines, particularly intelligent computer programs. In essence, AI is a field that equips machines with human-like intelligence. AI techniques can be categorized into two groups: symbolic AI techniques and data-driven AI techniques. Symbolic AI methods (such as rule-based systems, expert systems, and knowledge-based systems) generally rely on rules developed by domain experts. In contrast, data-driven AI techniques generate new knowledge by analyzing historical data using powerful algorithms. Fuzzy logic and evolutionary optimization algorithms are two important and widely used branches of AI. Fuzzy logic is a knowledge- and human experience-based method developed to handle complex and uncertain systems. Evolutionary optimization algorithms, on the other hand, are a type of optimization method aimed at finding a global optimum using heuristic principles [7–9].

Nowadays, intelligent control methods have been able to overcome many of the aforementioned limitations (such as robustness against uncertainties, no need for linearization of nonlinear dynamics, and high computational costs) and even offer additional advantages. One of the intelligent control approaches is fuzzy control, which demonstrates robust performance due to its independence from system dynamics and is applicable to many nonlinear systems. Another advantage of this method is its relatively low computational complexity and simple formulation compared to other control techniques. Some of the fuzzy logic-based controllers include: pure fuzzy controllers, self-tuning fuzzy PID controllers (in which the gains are automatically adjusted based on fuzzy logic), and fuzzy logic adaptive controllers based on sliding mode control [5,10-13].

Prayitno et al. [3] described the design and implementation of fuzzy gain-scheduling PID control for the position of the AR. Drone. This control scheme has been used three PID controllers as the main controller of the AR. Drone. A fuzzy-genetic altitude controller was designed for an unmanned aerial vehicle (UAV), and its performance was compared with a classical linear controller in [4]. Elhami et al. [5] presented an autopilot altitude-holding controller using fuzzy control and a combination with a PID controller based on a precise state-space model. Melo et al. [14] proposed a novel method combining gain scheduling and fuzzy logic to enhance the PID controller for position and altitude control of a UAV. The implementation results demonstrated improved performance, reduced error, and increased robustness in the proposed method. Anomer et al.

[15] investigated a fuzzy adaptive sliding mode controller for altitude control of a UAV. Hamidi et al. [16] utilized a hybrid control approach combining PID with two intelligent control methods (neural networks and fuzzy logic) for stabilization, path tracking, and PID parameter tuning. Ansarian et al. [17] designed a PID controller based on sliding surface concepts, model order reduction, and fuzzy systems for a nonlinear UAV, aiming to improve controller performance in the presence of disturbances through fuzzy logic. Fahmizal et al. [18] studied the automatic tuning of PID controller gains for altitude control of a quadrotor using fuzzy logic. Bian et al. presented an improved Nondominated Sorting Genetic Algorithm II (NSGA-II) for control allocation optimization of aircraft landing [19]. Rodriguez et al. [20] described a study that gained the benefits of a PID controller system optimized based on a genetic algorithm and fuzzy system. The aim of the genetic algorithm is to tune the PID gains so that the settling time and overshoot are minimized. Sarhan et al. [21] developed an adaptive PID altitude controller based on fuzzy inference. In this study, the PID parameters have been tuned online by fuzzy inference.

Since the aerodynamic coefficients of lift and drag for an aerial system are highly dependent on flight altitude, and due to the reduction of pilot workload, it is necessary to have an autopilot altitude-holding controller in aerial systems. Altitude control is one of the most important components of aircraft autopilot systems. This controller allows the pilot to maintain the aircraft at a constant altitude under air traffic control for ease of operation. Therefore, the aim of this research is to design a simple altitude-holding controller for a jet aircraft. Initially, an altitude controller was designed using fuzzy logic with two different methods. This issue is important from two points of view: a) there is no need for any modeling of the system or its linearization or designing any inner loop in this design, and b) a comprehensive comparison has been conducted for the first time between the results of the two methods used for designing the fuzzy altitude controller and assigning the range of usage of each of them. At the next step, to achieve more precise tuning of the fuzzy controller parameters, a genetic algorithm is utilized with the objective of minimizing control effort, steady-state error, and rise time. Simultaneous optimization of the specifications of the system response and the control cost is a valuable idea in this research, because typically only the specifications of the system response are considered when designing controllers. Another strength of this study is a comprehensive robustness analysis in which four practical types of uncertainties have been considered as part of the evaluation. So, the following novelties and differences compared to other studies can be said briefly:

- Designing a pure fuzzy altitude controller by using two methods and determining their response specifications and the range of their applications.
- Optimal tuning of input and output parameters of the designed fuzzy controller by using a genetic algorithm to improve response specifications and reduce control effort simultaneously.
- Comprehensive robustness analysis of the designed fuzzy controller in the presence of four environmental, estimation, and measurement uncertainties.

2. THE NONLINEAR MODEL OF AIRCRAFT

The aim of this section is to develop a nonlinear, six-degree-of-freedom (6-DOF) model of the aircraft in question for simulating its behavior and analyzing the performance of the designed controllers. The six-degree-of-freedom aircraft motion model is expressed as follows [10]:

$$m(\dot{u} - vr + wq) = -mgsin\theta + F_{A_x} + F_{T_x} \quad (2)$$

$$m(\dot{v} + ur - wp) = mgsin\emptyset cos\theta + F_{A_y} + F_{T_y} \quad (3)$$

$$m(\dot{w} - uq + vp) = mgcos\emptyset cos\theta + F_{A_z} + F_{T_z} \quad (4)$$

$$\dot{p}I_{xx} - I_{xz}(\dot{r} + pq) + (I_{zz} - I_{yy})rq = L_A + L_T \quad (5)$$

$$\dot{q}I_{yy} + (I_{xx} - I_{zz})pr - (p^2 - r^2)I_{xz} = M_A + M_T \quad (6)$$

$$\dot{r}I_{zz} - I_{xz}\dot{p} + (I_{yy} - I_{xx})\,pq + rqI_{xz} = N_A + N_T \quad (7)$$

The above equations are the nonlinear equations of motion of the aircraft. Equations (8) to (10) and (11) respectively describe the kinematic relations and the aircraft's position.

$$\dot{\emptyset} = p + qtan\theta sin\emptyset + rcos\emptyset tan\theta \quad (8)$$

$$\dot{\theta} = qcos\emptyset - rsin\emptyset \quad (9)$$

$$\dot{\psi} = \frac{qsin\emptyset + rcos\emptyset}{\cos\theta} \quad (10)$$

$$\begin{bmatrix}\dot{x}\\ \dot{y}\\ \dot{z}\end{bmatrix} = \begin{bmatrix}cos\psi & -sin\psi & 0\\ sin\psi & cos\psi & 0\\ 0 & 0 & 1\end{bmatrix}\begin{bmatrix}cos\theta & 0 & sin\theta\\ 0 & 1 & 0\\ -sin\theta & 0 & cos\theta\end{bmatrix}\begin{bmatrix}1 & 0 & 0\\ 0 & cos\phi & -sin\phi\\ 0 & sin\phi & cos\phi\end{bmatrix}\begin{bmatrix}u\\ v\\ w\end{bmatrix} \quad (11)$$

In the above relations, [u,v,w] are the linear velocities, [p,q,r] are the angular velocities, [Ixx, Iyy, Izz] are the moments of inertia about the three body axes, [x,y,z] denote the position of the aircraft in the inertial frame, mmm is the mass of the aircraft, and [ψ,θ,ϕ] are the euler angles. The next topic is modeling the aerodynamic forces and moments, which are expressed in equations (12) to (17) [22].

$$F_{A_x} = \left[-(C_{D_u} + 2C_{D_1})\frac{u}{U_1} - (C_{D_\alpha} + 2C_{L_1})\alpha - C_{D_{\dot{\alpha}}}\left(\frac{\dot{\alpha}\bar{C}}{2U_1}\right) - C_{D_q}\left(\frac{q\bar{C}}{2U_1}\right) - C_{D_{\delta_E}}\delta_E\right]\bar{q}S \tag{12}$$

$$F_{A_z} = \left[-(C_{L_u} + 2C_{L_1})\frac{u}{U_1} - (C_{L_\alpha} + 2C_{D_1})\,\alpha - C_{L_{\dot{\alpha}}}\left(\frac{\dot{\alpha}\bar{C}}{2U_1}\right) - C_{L_q}\left(\frac{q\bar{C}}{2U_1}\right) - C_{L_{\delta_E}}\delta_E\right]\bar{q}S \tag{13}$$

$$M_A = \left[(C_{m_u} + 2C_{m_1})\frac{u}{U_1} + (C_{m_\alpha})\alpha + C_{m_{\dot{\alpha}}}\left(\frac{\dot{\alpha}\bar{C}}{2U_1}\right) + C_{m_q}\left(\frac{q\bar{C}}{2U_1}\right) + C_{m_{\delta_E}}\delta_E\right]\bar{q}S\bar{C} \tag{14}$$

$$F_{A_y} = \left[C_{y_\beta}\beta + C_{y_{\dot{\beta}}}\left(\frac{\dot{\beta}b}{2U_1}\right) + C_{y_p}\left(\frac{pb}{2U_1}\right) + C_{y_r}\left(\frac{rb}{2U_1}\right) + C_{y_{\delta_A}}\delta_A + C_{y_{\delta_R}}\delta_R\right]\bar{q}S \tag{15}$$

$$L_A = \left[C_{l_\beta}\beta + C_{l_{\dot{\beta}}}\left(\frac{\dot{\beta}b}{2U_1}\right) + C_{l_p}\left(\frac{pb}{2U_1}\right) + C_{l_r}\left(\frac{rb}{2U_1}\right) + C_{l_{\delta_A}}\delta_A + C_{l_{\delta_R}}\delta_R\right]\bar{q}Sb \tag{16}$$

$$N_A = \left[C_{n_\beta}\beta + C_{n_{\dot{\beta}}}\left(\frac{\dot{\beta}b}{2U_1}\right) + C_{n_p}\left(\frac{pb}{2U_1}\right) + C_{n_r}\left(\frac{rb}{2U_1}\right) + C_{n_{\delta_A}}\delta_A + C_{n_{\delta_R}}\delta_R\right]\bar{q}Sb \tag{17}$$

In the above relations, $[S, b, \bar{c}]$ are the wing area, span, and mean aerodynamic chord, respectively; [CL, CD, CY] are the aerodynamic force coefficients; [Cm, Cl, Cn] are the aerodynamic moment coefficients; [δE,δA,δR] are the deflection angles of the elevator, aileron, and rudder control surfaces; $\bar{q}$ is the dynamic pressure, and [α,β] are the angles of attack and sideslip.
The aircraft used in this study is a jet aircraft named the Siai-Marchetti S-211. The geometric characteristics, flight conditions, and aerodynamic coefficients used for the simulation are presented in Tables 2 and 3.

Table 2. Aircraft geometric specifications and the considered flight condition

Parameters	S	C	b	h	U1	W	Ixx	Iyy	Izz	Ixz
Unit	(ft2)	(ft)	(ft)	(ft)	(ft/s)	(lbs)	(slugft2)	(slugft2)	(slugft2)	(slugft2)
Value	136	5.4	26.3	25000	610	4000	800	4800	5200	200

Table 3. Longitudinal aerodynamics derivatives

C_{L_1}	C_{D_1}	C_{m_1}	C_{D_u}	C_{D_α}	C_{L_u}	C_{L_α}	$C_{L_{\dot{\alpha}}}$	C_{L_q}	C_{m_u}	C_{m_α}	$C_{m_{\dot{\alpha}}}$	C_{m_q}	$C_{D_{\delta_E}}$	$C_{L_{\delta_E}}$	$C_{m_{\delta_E}}$
0.1	0.02	0	0.05	0.1	0.08	5.5	4.2	10	0	-0.2	-9	-17	0	0.38	-0.8
$C_{n_{\delta_R}}$	C_{l_β}	C_{l_p}	C_{l_r}	C_{y_β}	C_{y_p}	C_{y_r}	C_{n_β}	C_{n_p}	C_{n_r}	$C_{l_{\delta_A}}$	$C_{l_{\delta_R}}$	$C_{y_{\delta_A}}$	$C_{y_{\delta_R}}$	$C_{n_{\delta_A}}$	$C_{n_{\delta_R}}$
-0.1	-0.1	-0.4	0.3	-1	-0.1	0.6	0.2	0.09	-0.2	0.1	0.05	0	0.03	-0.003	-0.1

3. ALTITUDE FUZZY CONTROLLER DESIGN

In this section, the design of the aircraft altitude controller is discussed using fuzzy logic in two cases. In the first case, a conventional fuzzy controller was designed, while in the second case, an optimized fuzzy controller was developed. In the optimized fuzzy controller, the centers of the membership functions for the inputs and outputs were obtained using a genetic algorithm to reduce control effort, steady-state error, and rise time. It is worth mentioning that in both cases, the fuzzy control rules were determined in two ways, and the results of each were compared with one another. The first method, which is well-known as the scale mapping method, was introduced by King and Mamdani, and the details of this method are described in reference [20]. In the second method, the fuzzy control rules were extracted based on the experience of a specialist familiar with the dynamics under consideration. For the optimized fuzzy controller case, the Pareto front points were obtained by changing the weights of the objective functions.

Then, using the TOPSIS method, the final point for each set of fuzzy control rules was selected.

1-3 Conventional fuzzy controller

In the real world, human knowledge and information generally stem from two main sources [4]:

- An expert or specialist who is knowledgeable about the system in question.
- A mathematical model derived from natural laws.

As mentioned earlier, fuzzy systems are those systems that allow the use of the first source (expert knowledge) in engineering processes. These systems transform the experience and knowledge of a specialist into a nonlinear mapping, and through this nonlinear mapping, the expertise of specialists can subsequently be utilized. Fuzzy systems are essentially knowledge-based, with their core component being a set of fuzzy if-then rules (the rule base).

Figure 2 shows the block diagram of a fuzzy system. As can be seen, a fuzzy system consists of four main components [24]:

1. Fuzzifier: In this component, real-valued variables are converted into corresponding fuzzy sets.
2. Fuzzy rule base: All fuzzy rules developed by the expert are stored in this database.
3. Fuzzy inference engine: In this component, based on various fuzzy logic principles, the rules in the rule base are combined, and an appropriate output is generated according to the input.
4. Defuzzifier: In this component, fuzzy sets are converted back into real numbers.

For more information about fuzzy systems, refer to Reference [25].

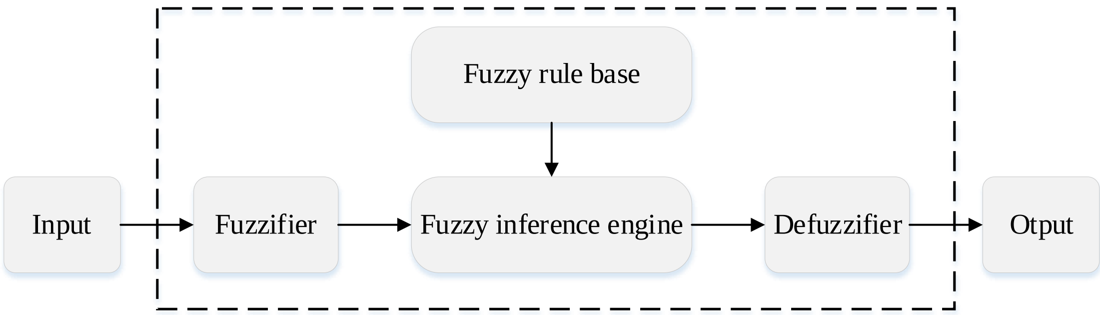

Fig. 2. The structure of a fuzzy system [24]

In this study, the altitude error concerning the desired altitude (e) and the rate of this error ($\dot{e}$) has been considered as the inputs to the fuzzy system. The output of this system is the elevator deflection angle (δ_E). It is worth mentioning that, in this study, the product inference engine, singleton fuzzifier, and center of average defuzzifier have been used to develop the fuzzy controller. Figure 3 also shows the membership functions for the fuzzy input and output sets. It is worth noting that the considered numerical ranges and their linguistic terms are based on expertise, experience, and operational conditions.

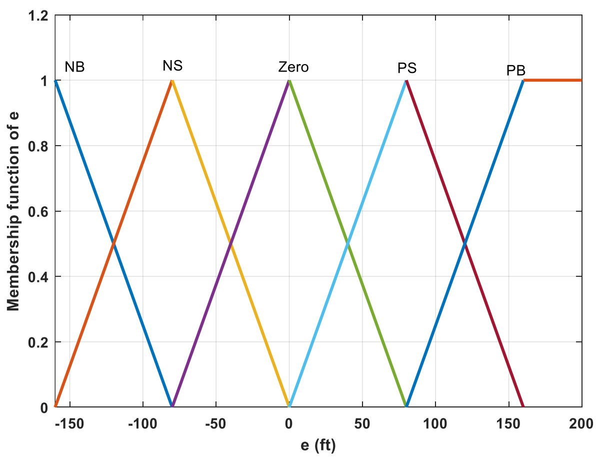

Fig. 3. The membership function of error (the first input)

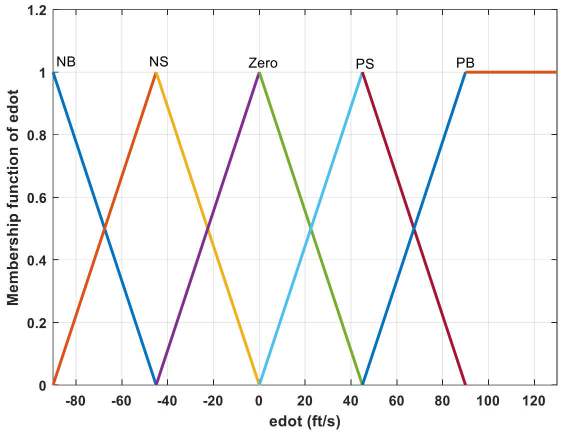

Fig. 4. The membership function of the error rate (the second input)

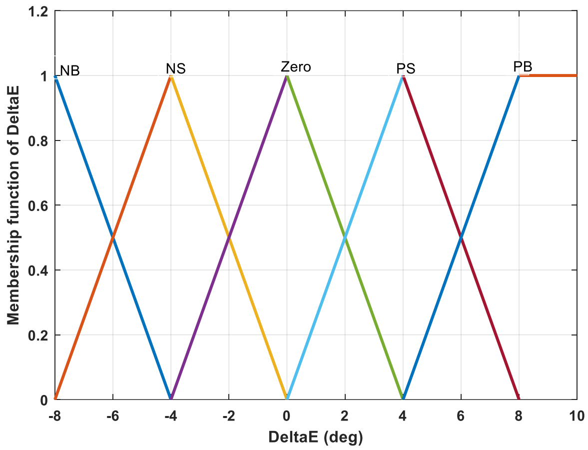

Fig. 5. The membership function of the elevator (output)

In the above figures, NB stands for Negative Big, NS stands for Negative Small, Zero means Zero, PS stands for Positive Small, and PB stands for Positive Big. As mentioned earlier, in this study, the fuzzy control rules were obtained using two different methods. Tables 4 and 5, respectively, present the fuzzy control rules, and Figures 4 and 5 show the fuzzy control rule surfaces derived from the scale mapping method and the experience-based method of the specialist.

Table 4. Fuzzy control rules (based on scale mapping method)

e \ $\dot{e}$	NB	NS	ZE	PS	PB
NB	-	-	NB	NB	-
NS	-	-	NS	-	PS
ZE	NB	NS	ZE	PS	PB
PS	NS	-	PS	-	-
PB	-	PS	PB	-	-

Table 5. Fuzzy control rules (based on specialist experience)

e \ $\dot{e}$	NB	NS	ZE	PS	PB
NB	NB	NB	NB	NB	NS
NS	NB	NS	NS	NS	ZE
ZE	NB	NS	ZE	PS	PB
PS	NS	NS	PS	PS	PB
PB	NS	PS	PS	PB	PB

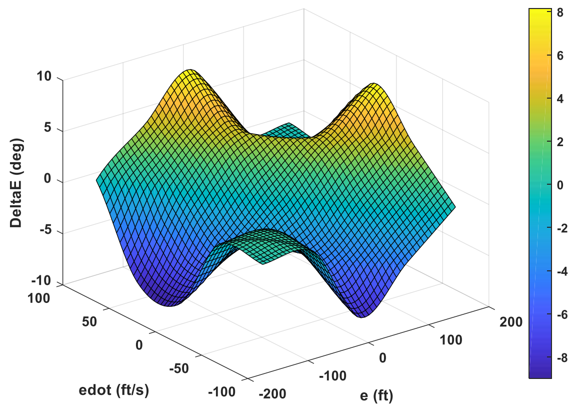

Fig. 4. Fuzzy control rules surface (based on scale mapping)

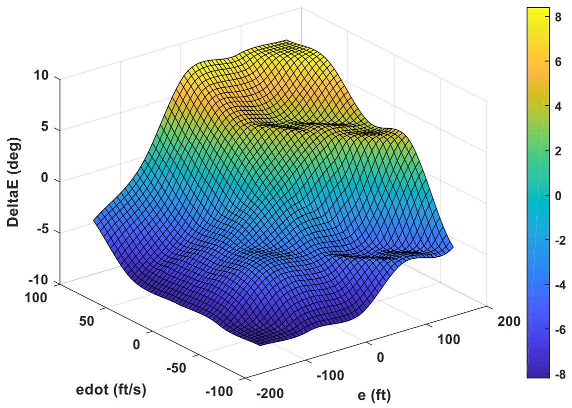

Fig. 5. Fuzzy control rules surface (based on specialist experience)

The simulation of the aircraft response has been done after the altitude fuzzy controller design. Figure 6 shows this response for both fuzzy controllers. This figure shows that the fuzzy controller based on scale mapping performs better in terms of response speed (rise time), although there is no significant difference in the steady-state error between the two controllers' responses. From the control effort point of view, the fuzzy controller based on expert experience has a control effort of 0.061 rad^2.s while the fuzzy controller based on scale mapping has a control effort of 0.0165 rad^2. s. This issue is evident because the scale mapping method proposes rules only for a specific condition, while the expert experiences method proposes a comprehensive fuzzy rule. From these results, it is clear that in a deterministic environment (without any uncertainties), the fuzzy controller based on the scale mapping method has a better performance.

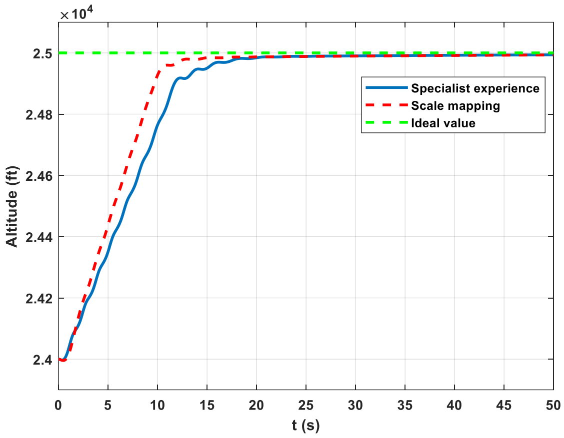

Fig. 6. Altitude variation of two fuzzy controllers

3.2. Optimized Fuzzy Controller

This section aims to determine the centers of the input and output membership functions (altitude error, error rate, and elevator deflection) of the fuzzy system, which had previously been set by an expert, using an optimization algorithm. This process aims to improve the performance of the fuzzy altitude-hold controller. It is noteworthy that in this section, the procedure explained earlier will also be implemented for both sets of fuzzy control rules mentioned in the previous section.

In this research, given the capabilities of evolutionary optimization algorithms (as a branch of artificial intelligence), one of the subcategories of these algorithms, the genetic algorithm, has been used as an optimizer. The genetic algorithm is a computational algorithm inspired by natural evolution. It is used for searching large and unknown spaces. The operation of this algorithm includes cost functions, selection, crossover, and mutation [3].

To design an appropriate controller, suitable cost functions must be chosen. A cost function can be defined based on characteristics such as overshoot, rise time, settling time, and steady-state error. However, other criteria also exist for evaluating controller performance, such as the Integral of Squared Error (ISE).

3.2.1. Problem Formulation

The objective functions considered in this study are a combination of control response characteristics and control effort. In other words, the objective functions aim to reduce rise time, minimize steady-state error, and reduce the control effort of the elevator. These objective functions will cause the system response to have a proper characteristic, while this response will be obtained using a minimum control effort, which is ideal. Therefore, the optimization problem is a multi-objective one. The weighted-sum method is one of the simplest and most widely used scalarization techniques for solving multi-objective optimization problems. Although more advanced methods, such as the Non-dominated Sorting Genetic Algorithm II (NSGA-II) or other Multi-Objective Evolutionary Algorithms (MOEAs), are available, they often involve higher computational complexity and implementation costs, especially when the number of objectives increases. In this study, since the optimization problem involves three objective functions, the weighted-sum method was adopted to efficiently generate the Pareto frontier while keeping the optimization framework simple and computationally tractable. To adequately explore the objective space, 29 different weight combinations were assigned to W_1, W_2, and W_3, ensuring that the sum of the weights equals one. This systematic variation of weights allowed for a well-distributed set of Pareto-optimal solutions to be obtained, thereby providing a comprehensive view of the trade-offs between the objectives. With attention to the above explanations, the considered cost function is:

$$Cost\ function = \min(W_1 S_1 + W_2 S_2 + W_3 S_3) \quad (18)$$

$$S_1 = \int_0^{t_1} |h - h_c| dt \ \ (desribes\ rise\ time) \quad (19)$$

$$S_2 = \int_{t_1}^{T} |h - h_c| dt \ \ (desribes\ steady\ state\ error) \quad (20)$$

In the above equation, S_1, S_2, S_3 are obtained from the following equations (see Figure 7):

$$S_3 = \int_0^{\mathrm{T}} (\delta_E)^2 dt \quad (21)$$

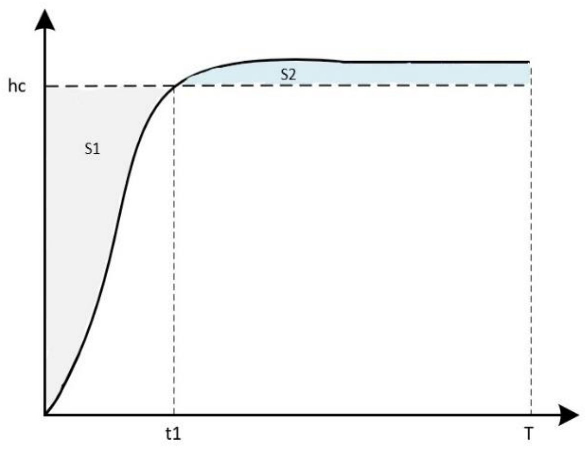

Fig. 7. Definition of S1 and S2

The objective is to minimize the above function by optimally adjusting the centers of the input and output membership functions. These centers are exemplified in Figure 8 (a, b, c, d, e). With attention to two inputs and one output of the fuzzy system, fifteen variables must be considered for optimization, representing the centers of the membership functions for the error, error rate, and elevator deflection. The permissible ranges of these variables are provided in Table 6.

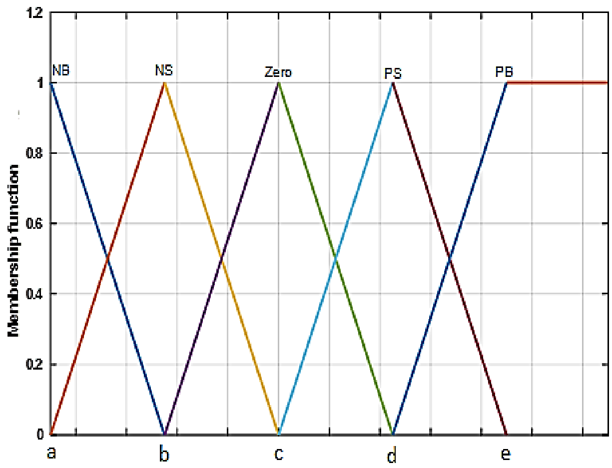

Fig. 8. The centers of fuzzy membership functions as variables of the optimization problem

Table 6. Range of variation for the membership function centers of error, error rate, and elevator deflection

Variables	a_e	b_e	c_e	d_e	e_e	$a_{\dot{e}}$	$b_{\dot{e}}$	$c_{\dot{e}}$	$d_{\dot{e}}$	$e_{\dot{e}}$	a_{δ_E}	b_{δ_E}	c_{δ_E}	d_{δ_E}	d_{δ_E}
Lower limit	-170	-90	-10	60	140	-110	-60	-10	40	90	-9	-5	-1	3	7
Upper limit	-140	-60	10	90	170	-90	-40	10	60	110	-7	-3	1	5	9

3.2.2. Optimization

After determining the objective function, the optimization variables, and their permissible ranges, the next step is to optimize the given problem. In this study, considering the capabilities of the genetic algorithm, it has been employed as the optimizer. The specifications of the genetic algorithm used are provided in Table 7.

Table 7. Genetic algorithm specification

Parameter	Generation	Population	Mutation	Selection Rate
value	50	50	0.1	0.5

3.2.3. Optimized Fuzzy Controller (Expert Experience Method)

The fuzzy control rules in this case are the same as those given in Table 4, except that the centers of the input and output membership functions are considered optimization variables and are determined by the optimization algorithm to minimize equation (18). By varying the values of W1 to W3 such that their sum equals one and solving the optimization problem for each combination of W1 to W3, a total of 29 optimal solutions were obtained for this case, forming the Pareto front. Table 8 shows the objective functions of these Pareto frontiers with the corresponding weights for the expert experience method. Figure 9 illustrates these solutions, too.

Table 8. The objective functions of the Pareto frontier set (expert experience method)

Pareto frontier	W_1	W_2	W_3	Rise time (s)	Steady state error (ft.s)	Control effort ($rad^2.s$)
1	0.1	0.1	0.8	11.98	247.88	0.038
2	0.1	0.8	0.1	13.84	920.77	0.037
3	0.8	0.1	0.1	14.02	649.6	0.037
4	0.2	0.3	0.5	14.1	330.8	0.037

Pareto frontier	W_1	W_2	W_3	Rise time (s)	Steady state error (ft.s)	Control effort (rad^2.s)
5	0.3	0.5	0.2	13.56	718.45	0.035
6	0.5	0.2	0.3	13.92	813.9	0.037
7	0.05	0.05	0.9	10.68	642.8	0.033
8	0.05	0.9	0.05	12	756.2	0.042
9	0.9	0.05	0.05	13.34	412.2	0.04
10	0.1	0.2	0.7	13.88	650.38	0.037
11	0.2	0.7	0.1	15.3	842.04	0.051
12	0.7	0.1	0.2	13.84	278.99	0.036
13	0.2	0.2	0.6	14.08	772.5	0.037
14	0.2	0.6	0.2	13.92	627.2	0.039
15	0.6	0.2	0.2	12.22	671.2	0.038
16	0.3	0.3	0.4	14.08	760.99	0.035
17	0.3	0.4	0.3	13.78	449.8	0.04
18	0.3	0.1	0.6	11.98	572.46	0.044
19	0.3	0.6	0.1	12.48	1155.4	0.042
20	0.6	0.1	0.3	14	872.1	0.037
21	0.1	0.3	0.6	12.06	466.8	0.039
22	0.4	0.1	0.5	13.92	999.1	0.036
23	0.5	0.4	0.1	13.56	252.8	0.0395
24	0.1	0.5	0.4	13.1	231.7	0.046
25	0.2	0.4	0.4	13.64	146.5	0.036
26	0.4	0.2	0.4	12.5	981.65	0.037
27	0.4	0.4	0.2	13.7	931.3	0.036
28	0.5	0.1	0.4	13.66	380.6	0.037
29	0.1	0.4	0.5	13.54	412.9	0.038

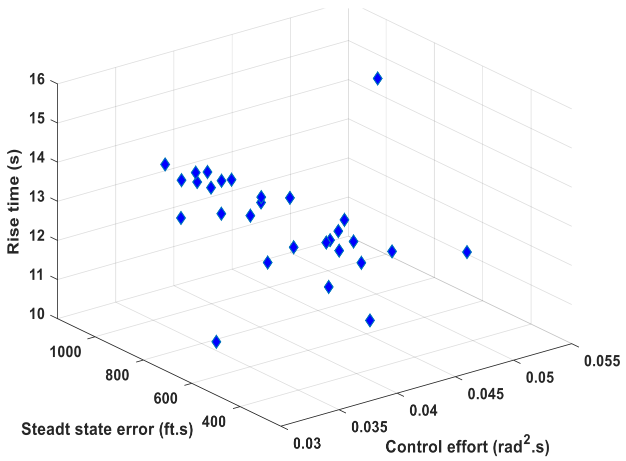

Fig. 9. Pareto front of expert experience method

To select the final optimal solution from the Pareto front, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method was used. This method is a Multi-Criteria Decision-Making (MCDM) approach that helps to choose the best option from among several alternatives based on proximity to the ideal solution. The additional details on the implementation of the TOPSIS method are provided in the following:

- Normalization: All objective functions were normalized using vector normalization to ensure comparability across criteria with different units.
- Weighting: Equal weights were assigned to all objectives ($W_j = \frac{1}{m}$) since no prior preference among criteria was assumed.
- Ideal and anti-ideal solutions: Because all objectives were considered as minimization problems, the ideal solution was taken as the minimum of each normalized criterion, and the anti-ideal as the maximum.
- Ranking metric: The closeness coefficient $C_i = \frac{S_i^-}{S_i^+ + S_i^-}$ was used, and the alternative with the highest value was selected as the best solution.

For more details about the TOPSIS method, refer to [26]. It is worth noting that in this study, all considered objective functions have the same importance, so using the TOPSIS method, the first point on the Pareto front was identified as the final optimal solution. The details of the final solution are provided in Tables 9 and 10.

Table 9. Optimal variables of fuzzy controller (expert experience)

Variables	a_e	b_e	c_e	d_e	e_e	$a_{\dot{e}}$	$b_{\dot{e}}$	$c_{\dot{e}}$	$d_{\dot{e}}$	$e_{\dot{e}}$	a_{δ_E}	b_{δ_E}	c_{δ_E}	d_{δ_E}	d_{δ_E}
Value	-157.2	-61.2	-4.3	60.7	140.8	-94.5	-50	1.97	43.2	93.8	-7	-3.2	0.5	3.1	8

Table 10. Cost functions of optimized fuzzy controller (expert experience) and fuzzy controller (expert experience

	Control effort (rad^2s)	**Steady state error (ft.s)**	**Rise time (s)**
Optimized fuzzy controller (expert experience)	**0.038**	**247.8**	**11.98**
Fuzzy controller (expert experience)	0.061	402.96	15
Improvement percentage (%)	38	39	20

As the results in Table 10 show, the optimized fuzzy controller performed significantly better than the basic fuzzy controller in terms of control effort, steady-state error, and rise time. These results clearly demonstrate the important impact of appropriately choosing the parameters of the input and output membership functions on the performance of fuzzy controllers. Figure 10 shows the optimized fuzzy control rules surface derived from the scale mapping method.

3.2.4. Optimized fuzzy controller (scale mapping method)

In this case, the fuzzy control rules are the same as those given in Table 5, except that the centers of the input and output membership functions are considered optimization variables. By varying the values of W_1 to W_3 , a total of 29 optimal solutions were obtained for this case, too. Table 11 shows the objective functions of these Pareto frontiers with the corresponding weights for the scale mapping method. Figure 11 illustrates these solutions.

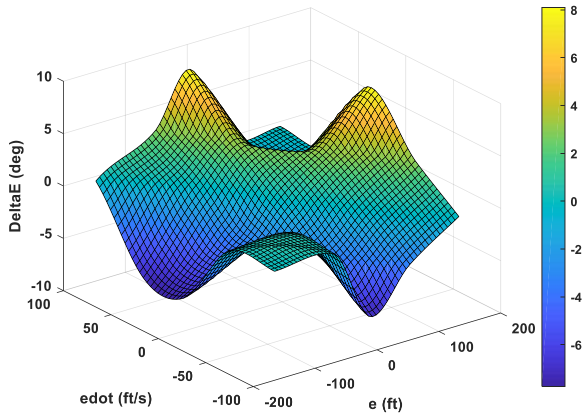

Fig. 10. Optimized fuzzy control rules surface (expert experience)

Table 11. The objective functions of the Pareto frontier set (scale mapping method)

Pareto Frontier	**W_1**	**W_2**	**W_3**	**Rise Time (S)**	**Steady State Error (Ft.S)**	**Control Effort (Rad^2.S)**
1	0.1	0.1	0.8	9.86	688.8	0.0136
2	0.1	0.8	0.1	9.8	466.75	0.017
3	0.8	0.1	0.1	8.56	150.43	0.017
4	0.2	0.3	0.5	10.74	166.3	0.0129
5	0.3	0.5	0.2	10.4	373.5	0.014
6	0.5	0.2	0.3	8.82	191.1	0.0166
7	0.05	0.05	0.9	9.72	388.6	0.0138
8	0.05	0.9	0.05	9.74	952.2	0.0161
9	0.9	0.05	0.05	8.58	157.6	0.0178
10	0.1	0.2	0.7	10	231.33	0.0136
11	0.2	0.7	0.1	9.9	160.4	0.0135
12	0.7	0.1	0.2	8.88	209.9	0.0158
13	0.2	0.2	0.6	9.44	156.9	0.0136
14	0.2	0.6	0.2	10.02	364.8	0.014
15	0.6	0.2	0.2	9.08	245.1	0.0154
16	0.3	0.3	0.4	10.16	776.1	0.014
17	0.3	0.4	0.3	10.26	838.79	0.0156
18	0.3	0.1	0.6	9.58	331.1	0.014

Pareto Frontier	W_1	W_2	W_3	Rise Time (S)	Steady State Error (Ft.S)	Control Effort (Rad^2.S)
19	0.3	0.6	0.1	8.94	436.8	0.0149
20	0.6	0.1	0.3	8.96	202.8	0.0149
21	0.1	0.3	0.6	10.76	909.7	0.0136
22	0.4	0.1	0.5	9.54	540.76	0.0147
23	0.5	0.4	0.1	8.8	173.5	0.0176
24	0.1	0.5	0.4	10.94	782.8	0.0155
25	0.2	0.4	0.4	10.34	622.3	0.0132
26	0.4	0.2	0.4	9.62	730.6	0.0166
27	0.4	0.4	0.2	9	182.88	0.0146
28	0.5	0.1	0.4	9.48	795.2	0.015
29	0.1	0.4	0.5	10.66	146.5	0.0138

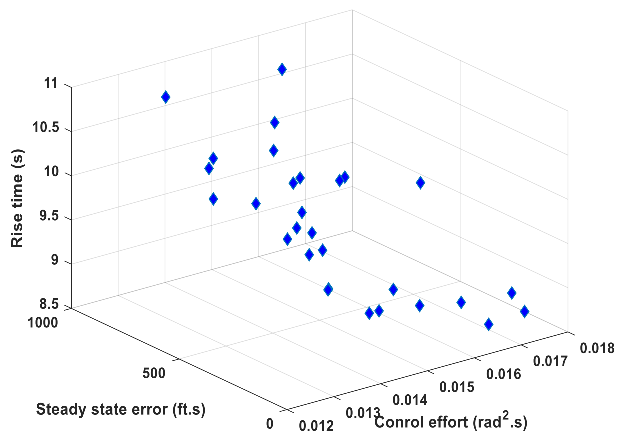

Fig. 11. Pareto front of the scale mapping method

Table 12. Optimal variables of fuzzy controller (scale mapping)

variables	a_e	b_e	c_e	d_e	e_e	$a_{\dot{e}}$	$b_{\dot{e}}$	$c_{\dot{e}}$	$d_{\dot{e}}$	$e_{\dot{e}}$	a_{δ_E}	b_{δ_E}	c_{δ_E}	d_{δ_E}	d_{δ_E}
value	-153	-60.5	1.8	60.1	156.9	-109.2	-59.4	1.1	42.5	106.3	-7.7	-3.1	0.88	3.1	8.4

Table 13. Cost functions of optimized fuzzy controller (scale mapping) and fuzzy controller (scale mapping)

	Control effort (rad^2s)	Steady state error (ft.s)	Rise time (s)
Optimized fuzzy controller (scale mapping)	0.0136	156.9	9.44
Fuzzy controller (scale mapping)	0.0165	485.7	10.4
Improvement percentage (%)	18	67	10

In this case, too, the TOPSIS method was used for final solution selection, similar to the previous case. The details of the final solution are provided in Tables 12 and 13.

As the results in Table 11 show, the optimized fuzzy controller performed significantly better than the basic fuzzy controller in all aspects. Figure 12 shows the optimized fuzzy control rules surface derived from the expert experience method.

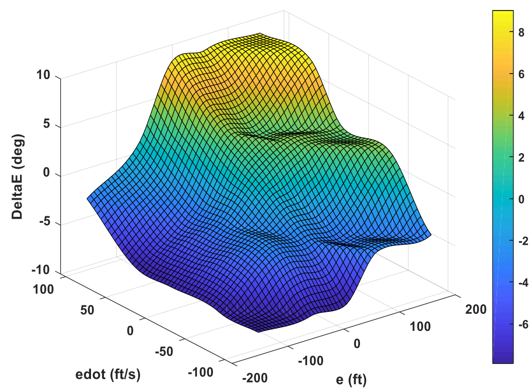

Fig. 12. Optimized fuzzy control rules surface (scale mapping method)

4. RESULTS AND ANALYSIS

In the previous part, two optimized fuzzy altitude-hold controllers have been designed using two different methods and compared to a basic fuzzy controller. The results decisively showed that both optimized fuzzy controllers significantly outperformed the basic one. Now, the focus shifts to directly comparing the performance of these two optimized controllers. Figure 13 shows linear velocities in the x and z axes of the body coordinate system and angular velocity about the y-axis for both fuzzy controllers. It is worth noting that the climb and cruise of the aircraft occur in the x-z plane, so other linear and angular velocities are zero. Figure 13 shows that both fuzzy controllers reached near-zero linear velocity (w) and angular velocity (q) to hold the aircraft altitude (keeping attitude in the z-axis). Also, linear velocity (u) has decreased because the aircraft needs to climb (to reach the target altitude of 25,000 ft), and after reaching the target altitude, this velocity has been maintained. The variations of pitch angle, angle of attack, and elevator deflection angle are shown in Figure 14. The pitch angle and angle of attack must reach zero using fuzzy controllers to keep the aircraft's altitude, as shown in Figure 14. Figure 15 shows the variations of aircraft position in the X and Z (altitude) axes of the inertia coordinate system. As Figure 15 shows, the optimized fuzzy controller based on the scale mapping method has better performance compared to the optimized fuzzy controller based on the specialist experience method in terms of rise time. The results of Tables 9 and 11 express that the optimized fuzzy controller based on the scale mapping method has a better specification relative to the optimized fuzzy controller based on specialist experience. These results are consistent with the results of the base fuzzy controller.

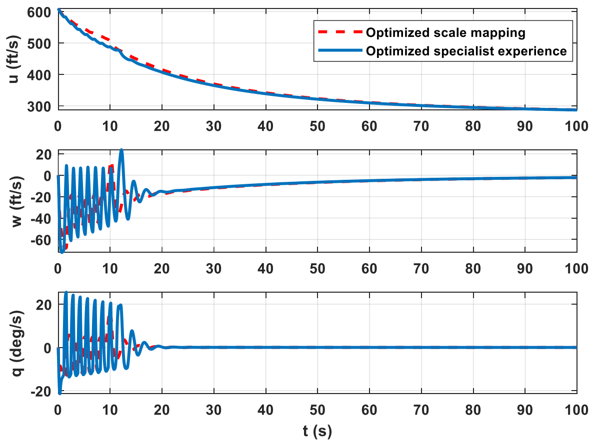

Fig. 13. Linear and angular velocities of aircraft in the X-Z plane

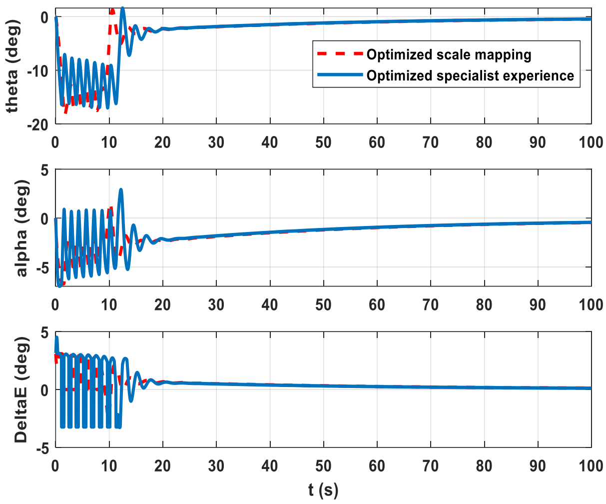

Fig. 14. Variations of theta angle, alpha angle, and elevator angle

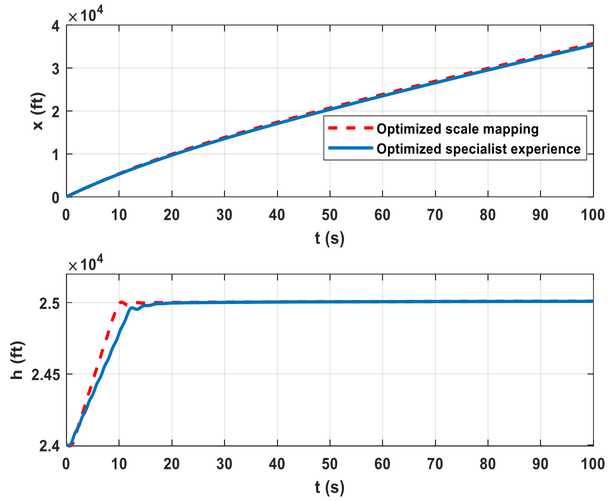

Fig. 15. Variations of aircraft position

Another issue is the ability of combined commands tracking and robustness analysis of optimized fuzzy controllers in the presence of available uncertainties. Therefore, two analyses have been done as follows. In the first analysis, an altitude combined command has been applied as ideal altitude values. As Figure 16 shows, the optimized fuzzy controller based on specialist experience could follow this command, while the optimized fuzzy controller based on the scale mapping method is unstable and unable to track this command. This issue is the first drawback of the optimized fuzzy controller based on the scale mapping method.

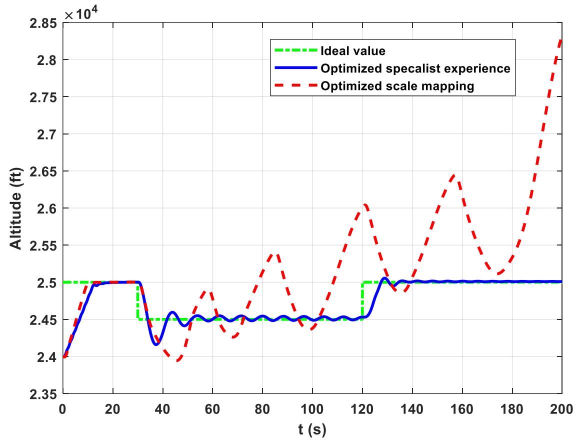

Fig. 16. Analysis of the ability of combined commend tracking

Four uncertainties have been applied in the robustness analysis of the optimized fuzzy controllers in the second analysis, which are as follows:

1) Noise in the aircraft altimeter sensor
   To model this uncertainty, a Band-limited white noise block with power 0.2 has been used.
2) Different aerodynamic conditions
   It is assumed that aircraft aerodynamics and control derivatives have a 10% error from the nominal values in the simulation.
3) Different flight initial conditions
   The initial altitude has been considered 20000 ft in this analysis instead of 25000 ft.
4) Presence of gust
   It is assumed that in the second second of flight, a relatively strong gust has been applied for 10 seconds. Because gusts are not durable and are momentary in the flight, only 10 seconds have been considered for gust application. Figure 17 shows the components of gust speed in the x and z axes of the body coordinate system.

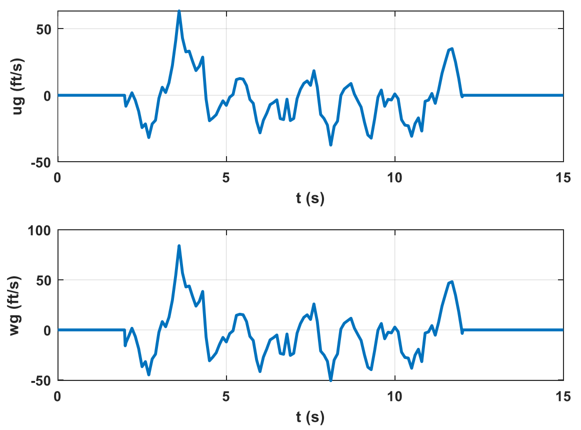

Fig. 17. Components of gust speed in the x and z axes of the body coordinate system

Figure 18 shows the flight simulation of the aircraft in the presence of the mentioned uncertainties. As shown, the optimized fuzzy controller based on the scale mapping method is unstable, while the optimized fuzzy controller based on specialist experience has good robustness. Lack of comprehensive fuzzy rules (for various conditions) is the main reason for the instability of the scale mapping method in the tracking of combined comments and in the presence of uncertainties. With attention to table 4 and table 5, it is clear that the fuzzy control rules in the scale mapping method did not consider conditions such as NB-NB, PB-PS, etc., while in the specialist experience method, this condition has been considered. So it can be concluded that in a nondeterministic environment, the optimized fuzzy controller based on specialist experience must be used, while in a deterministic environment, it is efficient to use the optimized fuzzy controller based on the scale mapping method because it has a lower control effort and rise time.

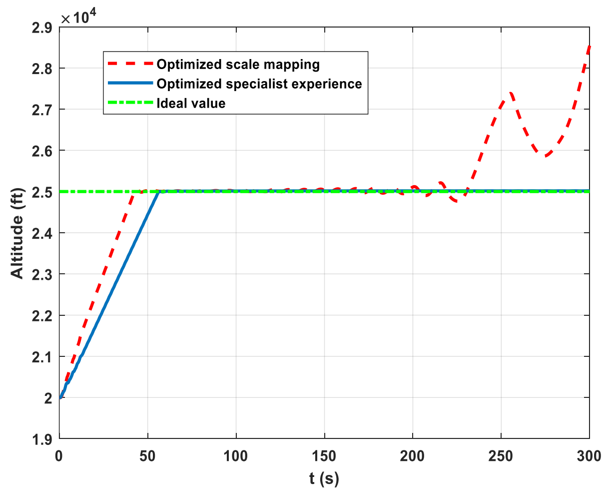

Fig. 18. Response of the two optimized fuzzy controllers in the presence of uncertainties

5. CONCLUSION

In this study, an intelligent aircraft altitude controller was designed by using two artificial intelligence techniques (fuzzy logic and genetic algorithm) so that aircraft control performance is improved and control effort is reduced. Two methods (specialist experience and scale mapping) have been used to design the fuzzy controller, and a comprehensive comparison between these methods has been done from the performance point of view. At first, a basic fuzzy controller for altitude holding was designed based on the two mentioned methods.

The results show that both basic fuzzy controllers can bring the aircraft to the target altitude, but the fuzzy controller based on the scale mapping method has a higher speed and less control effort. In the following, the centers of fuzzy membership functions for both methods were obtained using a genetic algorithm to achieve optimal performance. The optimization aims to reduce control effort, steady state error, and rise time. The optimization results show that both optimized fuzzy controllers have a significant improvement relative to basic fuzzy controllers. The difference between the two optimized fuzzy controllers is that the optimized fuzzy controller based on the scale mapping method has less rise time, less control effort, and less steady state error relative to the optimized fuzzy controller based on the specialist experience method. In the following analysis, the robustness of optimized fuzzy controllers and combined command tracking was investigated. The results of this analysis show that the optimized fuzzy controller based on the specialist method has good robustness against the considered uncertainties (sensor noise, different aerodynamics and flight conditions, and presence of gust), while the optimized fuzzy controller based on the scale mapping method becomes unstable. So, it can be concluded that if there are no uncertainties, the performance of the optimized fuzzy controller based on the scale mapping method is better, and vice versa. Future work will focus on extending the proposed framework by integrating advanced multi-objective optimization algorithms, such as NSGA-II/III, to enhance the efficiency of parameter tuning. Moreover, employing adaptive and type-2 fuzzy control structures is expected to improve the robustness and adaptability of the controller under modeling uncertainties and varying flight conditions.

CONFLICTS OF INTEREST

No potential conflict of interest was reported by the authors.

REFERENCES

[1] Y. Hu, Y. Yang, S. Li, Y. Zhou, "Fuzzy controller design of micro-unmanned helicopter relying on improved genetic optimization algorithm," *Aerospace Science and Technology*, vol. 98, Art. 105685 No. pp. 1-12, 2020, https://doi.org/10.1016/j.ast.2020.105685.

[2] M. Azer, A. Ismail, "Attitude control of quadrotor using enhanced intelligent fuzzy PID controller," *International Research Journal of Engineering and Technology*, vol. 7, No. 5, pp. 2593-2602, 2020,

[3] A. Prayitno, V. Indrawati, I. Trusulaw, "Fuzzy gain scheduling PID control for the position of the AR.Drone," *International Journal of Electrical and Computer Engineering*, vol. 8, no. 4, pp. 1939-1946, 2018, http://doi.org/10.11591/ijece.v8i4.pp1939-1946.

[4] A.R. Babaei, M. Mortazavi, M.H. Moradi, "Classical and fuzzy-genetic autopilot design for unmanned aerial vehicles," *Applied Soft Computing*, vol. 11, pp. 365-372, 2011, https://doi.org/10.1016/j.asoc.2009.11.027.

[5] M.R. Elhami, A. Gholami, "Design an altitude holder for a flying boat based on a fuzzy controller," *Aerospace Mechanics*, vol. 12, No. 4, pp. 11-23, 2018.

[6] I. Shafieenejad, "Design optimal robust guidance and model predictive controller for mono-wing aerial robot by the maple seed tree inspired," *Journal of Aeronautical Engineering*, vol. 27, no. 1, pp. 56-74, 2025, https://doi.org/10.22034/joae.2025.481623.1251

[7] W. Li, "The application of artificial intelligence in aerospace engineering," *Proceedings of the International Conference on Machine Learning and Automation*, pp. 17-25, 2023. https://doi.org/10.54254/2755-2721/35/20230353.

[8] A. Zaoui, D. Tchuente, S.F. Wamba, B. Kamsu-foguem, "Impact of artificial intelligence on aeronautics: an industry-wide review," *Journal of Engineering and Technology Management*, vol. 71, pp. 1-19, 2024, https://doi.org/10.1016/j.jengtecman.2024.101800.

[9] M.R. Setayandeh, A.R. Babaei, "A novel method for multi-objective design optimization based on fuzzy systems," *Iranian Journal of Fuzzy Systems*, vol. 18, no. 5, pp. 181-198, 2021, https://doi.org/10.22111/IJFS.2021.6264.

[10] H. Taei, S. Nikseresht, A.R. Babaei, "Control Allocation Based on Fuzzy Approach for Landing Phase of Specific Aircraft," *Aerospace mechanics*, vol. 19, no. 2, pp. 1-10, 2023, https://dor.isc.ac/dor/20.1001.1.26455323.1402.19.2.1.8

[11] I. Shafieenejad, E.D. Rouzi, J. Sardari, "Fuzzy logic, neural-fuzzy network, and honey bees algorithm to develop the swarm motion of aerial robots," *Evolving Systems*, vol. 13, pp. 319-330, 2022, https://doi.org/10.1007/s12530-021-09391-4.

[12] I. Shafieenejad, M.R. Banitalebi Dehkordi, M.A. Nourian Pour, "A review of the application of optimization algorithms nature nature-inspired in the design of flight paths," *Journal of Technology in Aerospace Engineering*, vol. 8, no. 3, pp. 75-98, 2024, https://doi.org/10.22034/jtae.2024.8.3.6.

[13] J. Wang, W. Zhang, "Neural-fuzzy scheduling of H robust controllers for a high-performance fighter aircraft under a Herbst-like maneuver," *International Journal of Control*, Vol.

72, No. 8, pp. 740–754, 2010, https://doi.org/10.1080/002071799220902.

[14] A.G. Melo, F.A.A. Andrade, I.P. Guedes, G.F. Carvalho, A.R.L. Zachi, M.F. Pinto, "Fuzzy gain scheduling PID for UAV position and altitude controllers," *Sensors*, vol. 22, no. 2173, Art. No. 2173, pp. 1-21, 2022, https://doi.org/10.3390/s22062173.

[15] N.B. Ammar, S. Bouallegue, J. Haggege, "Fuzzy gains-scheduling of an integral sliding mode controller for a quadrotor unmanned air vehicle, International," *Journal of Advanced Computer Science and Applications*, vol. 9, no. 3, pp. 132-141, 2018, https://doi.org/10.14569/IJACSA.2018.090320.

[16] K.E. Hamidi, M. Majed, A.E. Kari, H. Ayad, "Neural network and fuzzy-logic-based self-tuning PID control for quadcopter path tracking," *Studies in Informatics and Control*, vol. 28, no. 4, pp. 401-412, 2019, https://doi.org/10.24846/v28i4y201904.

[17] A. Ansarian, M.J. Mahmoodabadi, "Multi-objective optimal design of a fuzzy adaptive robust fractional-order PID controller for a nonlinear unmanned flying system," *Aerospace Science and Technology*, vol. 141, no. 2, pp. 1-20, 2023, https://doi.org/10.1016/j.ast.2023.108541.

[18] F. Fahmizal, A. Surriani, M. Budiyanto, M. Arrofiq, "Altitude control of quadrotor using fuzzy self-tuning PID controller," *5th International Conference on Instrumentation, Control, and /Automation (ICA), Yogyakarta,* Indonesia, pp. 67-72, 2017. https://doi.org/10.1109/ICA.2017.8068415.

[19] Q. Bian, B. Nener, X. Wang, "An improved NSGA-II based control allocation optimization for aircraft longitudinal automatic landing system," *International Journal of Control*, vol. 92, no. 4, pp. 705-716, 2018, https://doi.org/10.1080/00207179.2018.1473643.

[20] O. Rodriguez-Abroe, J. Rodriguez-Resendiz, A. Garicia-Cerezo, J.R. Garcia-Martinez, "Fuzzy logic controller for UAV with gains optimized via genetic algorithm," *Heliyon*, vol. 10, pp. 1-14, 2024, https://doi.org/10.1016/j.heliyon.2024.e26363.

[21] A. Sarhan, S. Qin, "Adaptive PID control of UAV altitude dynamics based on parameter optimization with fuzzy inference," *International Journal of Modeling and Optimization*, vol. 6, no. 4, pp. 246-251, 2016, https://doi.org/10.7763/IJMO.2016.V6.534.

[22] J. Roskam, *Airplane flight dynamics and automatic flight control, Roskam aviation and engineering corporation*, DARcorporation, 1979.

[23] C.C. Lee, "Fuzzy logic in control systems: fuzzy logic controller-part I," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 20, no. 2, pp.404-418, 1990, https://doi.org/10.1109/21.52551.

[24] M.R. Setayandeh, A.R. Babaei, "Multidisciplinary design optimization of an aircraft by using knowledge-based systems," *Soft Computing*, vol. 24, pp. 12429-12448, 2020, https://doi.org/10.1007/s00500-020-04684-3.

[25] L. Wang, *A course in fuzzy systems and control*, Pearson College Div., 1996.

[26] M. Behzadian, S.K. Otaghsara, M. Yazdani, J. Ignatius, A state-of-the-art survey of TOPSIS applications, Expert Systems with Applications, Vol. 39, No. 17, pp. 13051-13069, 2012, https://doi.org/10.1016/j.eswa.2012.05.056.

HOW TO CITE THIS ATRICLE

H. Ansarian and M. Hadidoolaabi, "Multi-Objective Design Optimization of an Intelligent Altitude Controller for a Nonlinear Aircraft Using Fuzzy Logic and Genetic," *Journal of Aerospace Science and Technology,* Vol. 19, Issue 1, 2026, pp. 1-15.

DOI: https://doi.org/10.22034/jast.2026.541185.1232

URL: https://jast.ias.ir/article_235170.html