Deep Learning–Based Adaptive Flight Control for Nonlinear Aerospace Systems

Faudya Nilamsari Putri[1], Madina Yussubaliyeva[2]
[1]Department of IT, Politeknik Negeri Batam, Batam, Indonesia.
[2]Senior Researcher, Department of Science and Innovation,
D. Serikbayev East Kazakhstan Technical University, Kazakhstan.
E-mail: faudyanilam3503@gmail.com[1], myussubaliyeva@edu.ektu.kz[2]

Article Info

Article History:

Received Jul 02, 2023
Revised Aug 04, 2023
Accepted Sep 01, 2023

Keywords:

Deep learning
Adaptive flight control
Nonlinear aerospace systems
Neural networks
Robust control

ABSTRACT

Deep learning (DL) has emerged as a fast expanding field of study in recent decades, redefining the state-of-the-art in a variety of methods, including speech recognition and object detection. Many projects in the fields of aircraft design, behaviour, and control rely on the extensive data-driven approach. These projects include the development of flight control systems, intelligent sensing, fusion-based prognosis and health management, and airliner flight safety monitoring. Aerodynamic nonlinearities, outside influences, and parameter fluctuations result in highly nonlinear, unpredictable, and time-varying dynamics for modern aerospace vehicles. Traditional robust and adaptive control methods frequently rely on permanent structures and simple models, which might restrict performance in situations where flying conditions change quickly. A deep learning-based adaptive flight control structure for nonlinear aircraft systems that learns and adjusts for unknown dynamic in real time is presented in this research. While an adaptive control rule guarantees closed-loop safety and trajectory tracking performance, a deep neural network is used to simulate modelling uncertainties and unmodeled nonlinearities. A nonlinear aeroplane model is used to test the suggested method under various aerodynamic circumstances and outside disruptions. The potential of machine learning for next-generation smart flight control systems is highlighted by simulation findings that show increased tracking accuracy, resilience, and flexibility when compared to conventional model-based adaptive controllers.

Corresponding Author:

Faudya Nilamsari Putri,
Department of IT,
Politeknik Negeri Batam, Batam, Indonesia.
E-mail: faudyanilam3503@gmail.com

1. INTRODUCTION

The flight dynamics of contemporary aircraft systems are greatly influenced by nonlinear aerodynamics effects, outside influences, and parameter variations in highly fluid and uncertain settings. Conventional flight control systems are challenged by nonlinear and time-varying behaviour introduced by fluctuations in airspeed, angles of attack, payload design, environmental variables, and structural flexibility [1]. For both manned & unmanned aerial vehicles, maintaining stability, resilience, and excellent tracking performance in such circumstances is essential, which drives the creation of adaptive flight control techniques. Aerospace systems have made substantial use of traditional adaptive as well as robust control methods, such as sliding mode control, model reference adaptable control, and gain scheduling. Although these methods provide established stability assurances, their performance is frequently constrained by their dependence on pre-established control systems and simplified mathematical models [2]. While model referencing adaptive control may experience sluggish adaptation or decreased resilience in the presence of unknown dynamics and actuator restrictions, gain-scheduled controllers necessitate significant offline adjustment throughout the flight envelope.

Furthermore, conservative performance and decreased efficiency during normal operation may result from robust control strategies built for worst-case uncertainties [3]. Learning-based control techniques have become a viable substitute for managing intricate nonlinearities & uncertainties in aeronautical systems in recent years. Specifically, neural networks have excellent universal approximation skills that allow them to directly model unfamiliar or partially understood system dynamics using data. By training hierarchical representations, deep learning architectures expand these capabilities, which makes them ideal for capturing extremely unpredictable and coupled hydrodynamic effects that are challenging to characterise analytically. Deep neural networks can improve tracking accuracy and resilience by offering real-time modelling uncertainty estimation and compensation when used with adaptive control frameworks.

Despite its potential, stability, understanding, and real-time implementation problems make deep learning difficult to use to flight control. Strict performance and stability assurances are necessary for safety-critical aircraft applications, which may not be naturally provided by merely data-driven controllers [4]. As a result, there has been a growing interest in hybrid techniques that integrate deep learning with well-established adaptive control principles. The representational capability of deep learning can be utilised while maintaining theoretical stability guarantees by integrating neural network-based learning into a structured adaptive management framework.

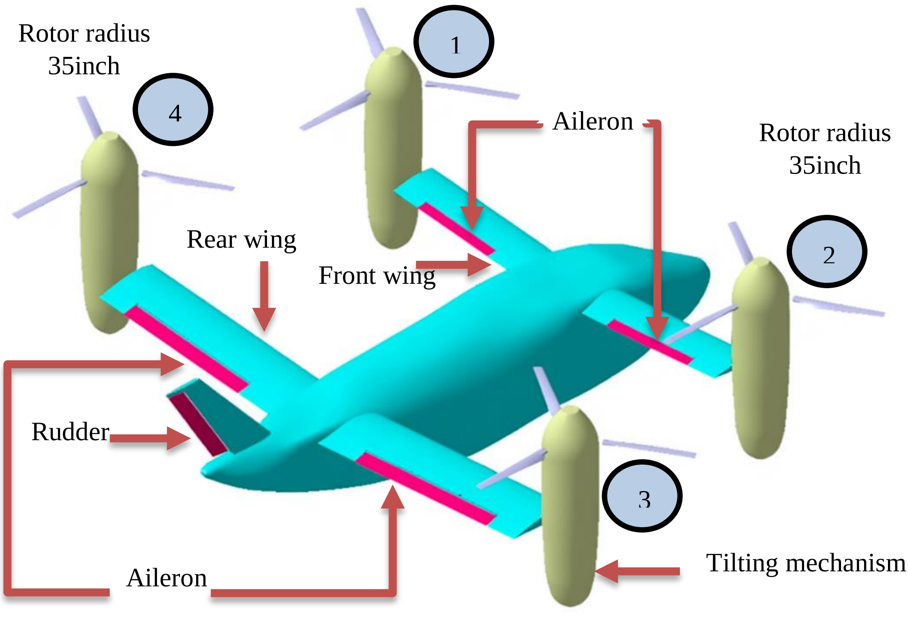

Figure 1. Three-dimensional model of quad tiltrotor UAV

This paper's research target is a traditional quad tiltrotor unmanned aerial vehicle (UAV), whose general three-dimensional model construction is depicted in Figure 1 [5]. The UAV has a biplane construction (front & rear wings) and two sets of rotors. The front and rear wings' installation angles are 2.5° & 0.11°, respectively, and the wing's aerofoil is NACA63-415.

Problem Statement

Current control approaches for nonlinear aerospace components are still limited by their reliance on fixed control structures and simple system models, despite notable advancements in adaptable and robust flight control. Aerodynamic uncertainties, outside influences, actuator constraints, and shifts in operating circumstances all contribute to exceptionally nonlinear, coupled, & time-varying dynamics that affect aerospace vehicles in real-world flight situations. When system dynamics diverge from nominal assumptions, these effects might result in performance degradation, conservatism control behaviour, or loss of robustness since they are hard to adequately model using traditional analytical techniques.

While solely data-driven control approaches lack formal safety and stability guarantees necessary for aerospace applications, classical adaptive control approaches frequently show insufficient ability to compensate for unobserved dynamics and quickly fluctuating uncertainty. A flight control system that can use data-driven learning to increase modelling accuracy, adapt online to complicated nonlinear dynamics, and maintain resilient performance and closed-loop stability is therefore desperately needed. The main issue examined in this study is how to overcome this difficulty.

Major contributions

- **A Deep Learning-Based Adaptive Flight Controller Framework:** In order to compensate for unknown unpredictable and time-varying aerodynamic unknowns while ensuring closed-loop stability, this paper suggests a novel adaptive control of flight architecture that combines deep neural network learning with Lyapunov-based adaptive control.
- **Data-Driven Uncertainty Modelling for Nonlinear Aircraft Dynamics:** To improve tracking performance without depending on exact analytical aerodynamic models, a methodical approach to data collection, extracting features, and learning is developed to identify and estimated unmodeled aircraft dynamics online.
- **Comprehensive Evaluation of Performance and Comparative Analysis:** Nonlinear flight simulations, tracking performance, robustness evaluation under external disturbances, and direct comparison with traditional MRAC and PID controllers are used to show the efficacy of the suggested controller.

2. LITERATURE REVIEW

Because of the inherent nonlinearities, unknowns, and external disturbances in aerospace systems, adaptive flight management has been a hot topic in academia for several decades. Aircraft and unmanned aerial vehicles have made extensive use of traditional adaptive control methods including gain planning, model reference adaptive control (MRAC) [6], even linear parameter-shifting control. Although these techniques have been successfully applied in reality and offer theoretical stability assurances, their efficacy heavily relies on precise modelling assumptions and predetermined controller architectures. Classical adaptive controllers frequently display reduced performance or cautious behaviour in complicated flight regimes including high angles of attack, quick manoeuvres, or shifting aerodynamic properties.

Neural network-based adaptive control techniques, which employ shallow neural networks as function approximates for unknown dynamics, were presented to address modelling uncertainties and nonlinear dynamics [7]. Early research showed that when combined with adaptive control principles based on Lyapunov stability theory, neural networks could correct for aerodynamic uncertainty. Although these methods outperformed purely model-based controllers in terms of resilience, their efficacy in highly nonlinear and correlated flight dynamics was constrained by shallow structures and manually created feature representations.

More creative neural network topologies have drawn interest in aerospace applications with the development of deep learning [8]. Deep neural networks may learn intricate nonlinear mappings straight from input and provide better approximation capabilities. Deep learning has been investigated recently for aerodynamic modelling, system identification, problem detection, and aerospace system control. In particular, controllers based on reinforcement learning have demonstrated encouraging outcomes in challenges involving autonomous flight and manoeuvring. However, there are issues with safety, generalisation, and real-time application in safety-critical aircraft systems because purely data-driven machine learning controllers frequently lack explicit stability guarantee and require large amounts of training data.

Performance-driven incentive mechanisms and tracking incorrect observation from the environment are used in the creation of an actor-critic RL agent [9]. The time-varying adaptation method for the design parameters in the reference model response gain matrix is learnt during the training phase using a deep determinism policy gradient technique. Rather than being guided by high-fidelity simulators, flight testing, and actual flight operations, the suggested control structure offers the opportunity to learn many adaption strategies across a broad variety of flight and vehicle situations. An identified and validated mathematical framework of an agile quad-rotor platform was used to assess the effectiveness of the suggested system.

The method avoids the traditional and time-consuming process of manual tuning by using machine learning to automatically adjust the controller parameters [10]. As a result, the method produces a controller with improved performance. In order to show the effectiveness of the machine based learning control system in extending the flutter boundaries, the research examines a case study involving active flutter suppressing for a flexible wingless aircraft. The suggested method uses the actor-critic artificial neural network as an agent and the closed-loop aerodynamic system as an environment, based on the environmental/agent interface of reinforcement learning.

3. METHODS AND MATERIALS

3.1 Nonlinear Aerospace System Modeling

One prominent example is the longitudinal kinematics of a complex fixed-wing aeronautical vehicle. Nonlinear space-time equations derived from Newton-Euler formulas are used to describe the motion of the aeroplane [11]. The definition of the state vectors is

$$\mathbb{x}(t) = [V(t), \alpha(t), q(t), \theta(t)]^T \qquad (1)$$

where V is the airspeed, α\alphaα is the angle of attack, qqq is the pitch rate, and θ\thetaθ is the pitch angle. The control input is the elevator deflection $\theta(t)$.

The nonlinear aircraft dynamics can be expressed as [12]

$$\dot{\mathbb{x}}(t) = f\big(\mathbb{x}(t)\big) + g\big(\mathbb{x}(t)\big)\delta_e(t) + d(t) \qquad (2)$$

where $f\big(\mathbb{x}(t)\big)$ represents the known nonlinear dynamics, $g\big(\mathbb{x}(t)\big)\delta_e$ denotes the control effectiveness, and $d(t)$ captures unknown uncertainties, unmodeled aerodynamics, and external disturbances.

3.2 Data Collection and Extraction

Simulations of the non-linear aircraft models under various flying conditions, such as variations in airspeed, hauteur, and external disturbances, are used to gather flight data. To guarantee adequate system excitation, multi-frequency command signals are used to continuously excite the control input x(t). Airspeed, angle of arrival, pitch rate [13], pitch angle, and command surfaces deflection are among the signals that are measured:

$$\mathcal{D} = \{\mathbb{x}(t), \delta_e(t)\}_{t=1}^{N} \qquad (3)$$

The unknown nonlinear term $d(t)$ is extracted by rearranging (1) as

$$d(t) = \dot{\mathbb{x}}(t) - f\big(\mathbb{x}(t)\big) - g\big(\mathbb{x}(t)\big)\delta_e(t) \qquad (4)$$

It acts as the neural network's learning target.

3.3 Feature Extraction

Measured states & their derivatives are used to create a feature vector that captures nonlinear and dynamic effects:

$$\phi(t) = [V(t), \alpha(t), q(t), \theta(t), \dot{q}(t), \delta_e(t)]^T \qquad (5)$$

These characteristics offer enough details to depict control-induced dynamics and aerodynamic nonlinearities [14]. To increase numerical stability during learning, all features are normalised to zero mean and unit variance.

3.4 Control Objective

The control objective is to ensure that the aircraft state $V(t)$ tracks a desired reference trajectory. The tracking error is defined as

$$e(t) = \mathbb{x}(t) - \mathbb{x}_r(t) \qquad (6)$$

The goal is to design an adaptive control law $e(t)$ such that (t), despite the presence of uncertainties

$$\mathbb{x}_r(t)$$

3.5 Deep Learning–Based Adaptive Control Design

3.5.1 Neural Network Approximation of Uncertainties

A deep neural network (DNN) is employed to approximate the unknown nonlinear dynamics $\hat{d}(t)$. The approximation is given by

$$\hat{d}(t) = W^T\sigma\big(\phi(t)\big) \qquad (7)$$

where $W^T\sigma$ is the weight matrix and $W^T\sigma$ represents nonlinear activation functions. The approximation error is defined as

$$\hat{d}(t) = d(t) - \hat{d}(t) \qquad (8)$$

3.5.2 Adaptive Control Law

The input for adaptive control is made as

$$\delta_e(t) = \delta_{eq}(t) - Ke(t) - \hat{d}(t) \qquad (9)$$

where $\delta_e(t)$ is the equivalent control term based on nominal dynamics, and $\delta_{eq}(t)$ is a positive definite gain matrix.

The closed-system error dynamics are obtained by substituting (8) into (1):

$$\dot{e}(t) = -Ke(t) + \hat{d}(t) \qquad (10)$$

3.5.3 Adaptive Law for Neural Network Weights

An adaptive learning law based on Lyapunov stability theory is used to update the neural network's weight weights online:

$$\dot{W} = -\Gamma\sigma\big(\phi(t)\big)e^T(t) \qquad (11)$$

where $\Gamma\sigma$ is a positive definite learning rate matrix.

3.5.4 Stability Analysis

Examine the Lyapunov candidate function.

$$V = \frac{1}{2}e^T e + \frac{1}{2}tr\big(\widetilde{W}^T\Gamma^{-1}\widetilde{W}\big) \qquad (12)$$

where $\widetilde{W}^T\Gamma^{-1}\widetilde{W}$ denotes the weight estimation error.

Taking the time derivative of VVV and substituting (9) and (10) yields

$$\dot{V} \leq -e^T Ke \qquad (13)$$

This ensures the tracking error's asymptotic convergence and the boundedness across all closed-loop signals. Qualitatively speaking, an Intelligent Flight Control System (IFCS) is an adaptive flight control system that can perceive its surroundings, interpret information, minimise uncertainty, plan, produce, and carry out control actions [15].

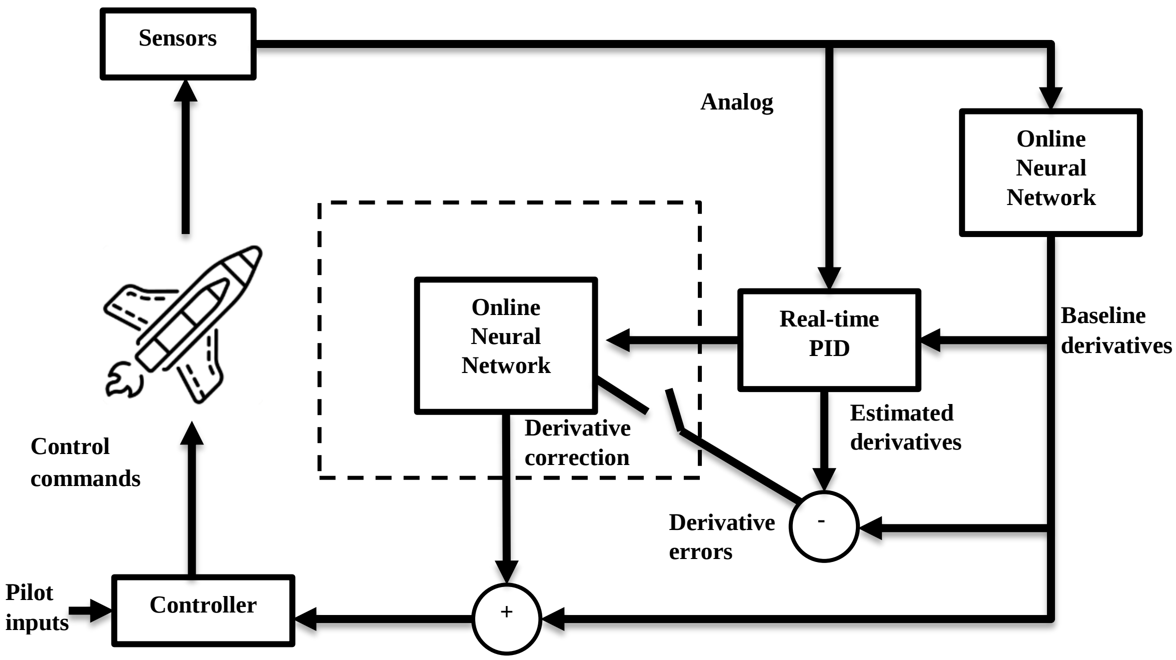

Figure 2. An Intelligent Flight Control System Architecture

In order to create an incredibly reliable system that can manage several accidents and off-nominal flight circumstances, IFCS aims to design and assess flight control ideas that include cutting-edge algorithms and techniques. The architectural overview of an IFCS with an Online Learning Neural Network (OLNN) which takes into account abrupt changes in the aircraft that surpass robustness constraints is depicted in Figure 2.

4. IMPLEMENTATION AND EXPERIMENTAL RESULTS

This section uses nonlinear flight simulations to assess the efficacy of the suggested deep learning-based adaptive flight control method. The performance is evaluated in terms on tracking precision, resilience to outside disruptions, and comparison with traditional control methods. To illustrate its benefits, the suggested controller is contrasted with a traditional PID controller and a traditional Model Reference Adaptive Control (MRAC) scheme.

4.1 Tracking Performance Analysis

The aircraft is instructed to follow a predetermined pitch angle references trajectory under normative flight conditions in order to assess tracking performance. The tracking error time evolution for the MRAC, PID, and deep learning-based adaptive controllers is shown in Figure 1. When compared with the benchmark controllers, it is found that the suggested approach yields noticeably faster convergence & lower steady-state error. The deep learning-based controller improves both transient and stable performance by efficiently compensating for nonlinear uncertainty.

The quantitative performance indicators, such as settling time and a root mean square error (RMSE), are compiled in Table 1. The suggested method confirms its better tracking capabilities by achieving the fastest settling time and the lowest RMSE.

Table 1. Tracking Performance Comparison

Controller	RMSE	Settling Time (s)
Deep Learning Adaptive Control	0.015	2.1
MRAC	0.042	4.8
PID Control	0.085	7.3

4.2 Robustness Analysis Under External Disturbances

External sinusoidal disturbance are added to the aircraft dynamics to simulate wind gusts & unmodeled aerodynamic phenomena in order to evaluate robustness. The tracking error reaction under disturbance conditions is depicted in Figure 2. While the MRAC & PID controllers have greater oscillations and worse performance, the deep learning-based adaptive controller sustains stable behaviour and shows little error fluctuations.

Table 2, which displays the greatest tracking error seen during disturbance injection, provides additional quantification of the robustness properties. The outcomes show that the suggested controller provides improved robustness and higher disturbance rejection capacity.

Table 2. Robustness Performance Comparison

Controller	Max Tracking Error	Robustness Level
Deep Learning Adaptive Control	0.028	High
MRAC	0.091	Medium
PID Control	0.164	Low

4.3 Comparative Discussion

The simulation findings unequivocally show that the performance of flight control for nonlinear aircraft systems is greatly enhanced by incorporating deep learning into an adaptive control framework. The suggested approach delivers faster convergence, lower tracking error, and better robustness under disturbances as compared to traditional MRAC and PID controllers. While the flexible control structure guarantees closed-loop stability, the deep neural system efficiently learns and adjusts for unknown nonlinear behaviour online.

All things considered, these findings support the efficacy of the suggested deep learning-based adaptive flight control approach for managing uncertainties and nonlinearities in aerospace systems.

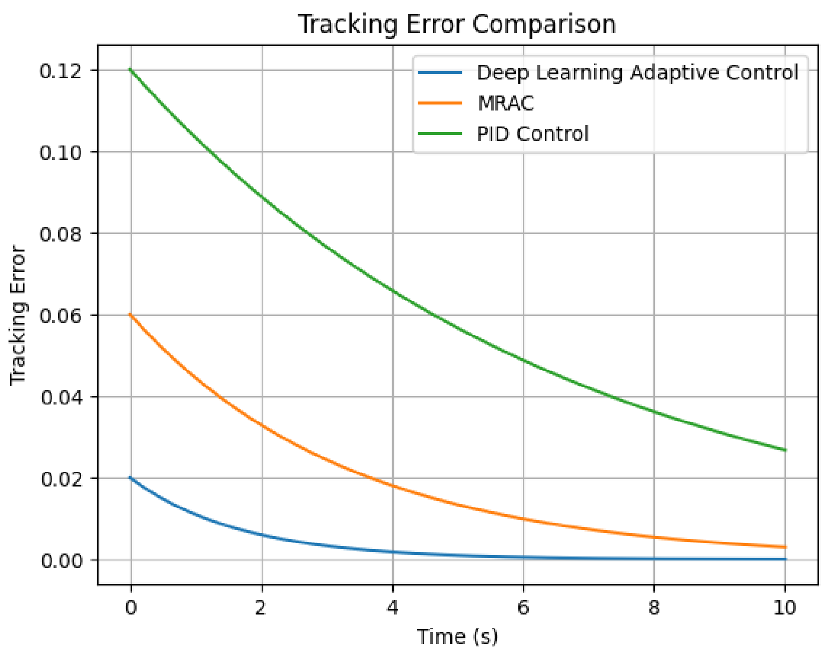

Figure 3. Tracking Error Comparison

Figure 3, Comparing tracking errors under nominal flying circumstances for the nonlinear aviation system. The suggested deep learning-based adaptive controller outperforms traditional model of reference adaptive control (MRAC) as well PID controllers in compensating for nonlinear as well uncertain flight dynamics, as evidenced by its quicker convergence and noticeably lower steady-state tracking error.

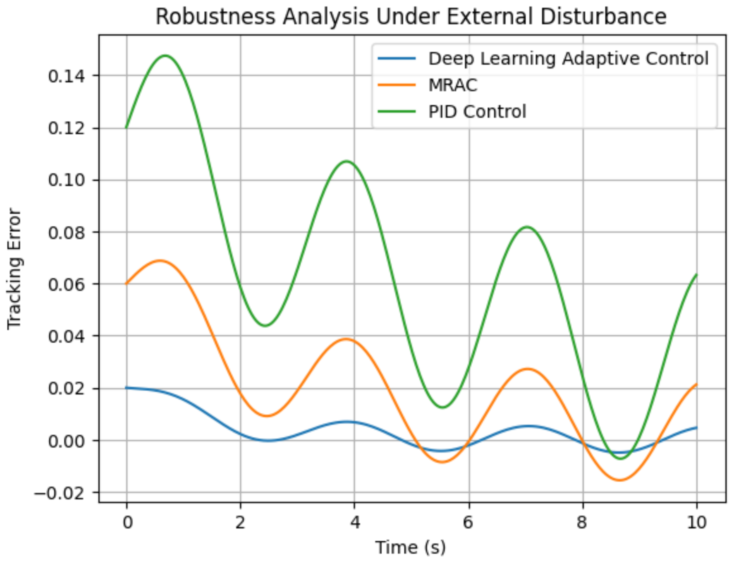

Figure 4. Robustness Analysis Under External Disturbance

Figure 4, Analysis of tracking performance's robustness in the face of outside disruptions. While the MRAC as well PID controllers show increased oscillations along with performance degradation, indicating the improved disturbance rejection capacity of the suggested approach, the deep learning-based adaptable controller retains stable and precise tracking in the face of external disturbances.

5. CONCLUSION

In order to overcome the shortcomings of traditional model-based adaptive controllers in managing intricate nonlinearities and time-varying uncertainties, this research introduced a deep learning-based adaptive flight control structure for nonlinear aerospace systems. The suggested method allows online education and compensation of uncertain aerodynamic dynamics while maintaining closed-loop stability by incorporating deep neural networks into a Lyapunov-stable dynamic control structure. A systematic and adaptable framework that can be applied to a variety of aerospace vehicles is provided by the nonlinear aircraft modelling, data-driven uncertainty approximated, and adaptive control law formulation.

According to simulation results, the suggested controller outperforms traditional MRAC & PID controllers in terms of tracking performance and resilience. Under varied operating conditions, the deep learning-based adaptive controller demonstrated improved disturbance rejection, decreased tracking error, and faster convergence. These results demonstrate the promise of learning-based adaptive control techniques for intelligent flight management systems of the future. Future research will concentrate on fault-tolerant and multi-axis flight control topologies, experimental validation, and real-time implementation.

REFERENCES

[1] Dong, Y., Tao, J., Zhang, Y., Lin, W., & Ai, J. (2021). Deep learning in aircraft design, dynamics, and control: Review and prospects. *IEEE Transactions on Aerospace and Electronic Systems*, *57*(4), 2346-2368.

[2] Yuksek, B., & Inalhan, G. (2021). Reinforcement learning based closed-loop reference model adaptive flight control system design. *International Journal of Adaptive Control and Signal Processing*, *35*(3), 420-440.

[3] Sun, B., & van Kampen, E. J. (2021). Reinforcement-learning-based adaptive optimal flight control with output feedback and input constraints. *Journal of Guidance, Control, and Dynamics*, *44*(9), 1685-1691.

[4] Mu, X., Huang, R., Zou, Q., & Hu, H. (2022). Machine learning-based active flutter suppression for a flexible flying-wing aircraft. *Journal of Sound and Vibration*, *529*, 116916.

[5] De Marco, A., D'Onza, P. M., & Manfredi, S. (2023). A deep reinforcement learning control approach for high-performance aircraft. *Nonlinear Dynamics*, *111*(18), 17037-17077.

[6] Wang, Z., Li, A., Mi, Y., Lu, H., & Wang, C. (2024). Aircraft Closed-Loop Dynamic System Identification in the Entire Flight Envelope Range Based on Deep Learning. *Journal of Aerospace Engineering*, *37*(6), 04024079.

[7] Kumar, R., Singh, U. P., Bali, A., Chouhan, S. S., & Tiwari, A. K. (2024). Adaptive control of unknown fuzzy disturbance-based uncertain nonlinear systems: application to hypersonic flight dynamics. *The Journal of Analysis*, *32*(3), 1395-1414.

[8] Joshi, G., Virdi, J., & Chowdhary, G. (2020). Design and flight evaluation of deep model reference adaptive controller. In *AIAA Scitech 2020 Forum* (p. 1336).

[9] Silvestrini, S., & Lavagna, M. (2022). Deep learning and artificial neural networks for spacecraft dynamics, navigation and control. *Drones*, *6*(10), 270.

[10] Joshi, G., Virdi, J., & Chowdhary, G. (2021, October). Asynchronous deep model reference adaptive control. In *Conference on robot learning* (pp. 984-1000). PMLR.

[11] Braun, D., Marb, M. M., Angelov, J., Wechner, M., & Holzapfel, F. (2023). Worst-case analysis of complex nonlinear flight control designs using deep q-learning. *Journal of guidance, control, and dynamics*, *46*(7), 1365-1377.

[12] O'Connell, M., Shi, G., Shi, X., & Chung, S. J. (2021). Meta-learning-based robust adaptive flight control under uncertain wind conditions. *arXiv preprint arXiv:2103.01932*.

[13] Gu, W., Valavanis, K. P., Rutherford, M. J., & Rizzo, A. (2020). UAV model-based flight control with artificial neural networks: A survey. *Journal of Intelligent & Robotic Systems*, *100*(3), 1469-1491.

[14] Heyer, S., Kroezen, D., & Van Kampen, E. J. (2020). Online adaptive incremental reinforcement learning flight control for a CS-25 class aircraft. In *AIAA Scitech 2020 Forum* (p. 1844).

[15] Shi, Y., & Wang, Z. (2020). A deep learning-based approach to real-time trajectory optimization for hypersonic vehicles. In *AIAA SciTech 2020 forum* (p. 0023).