Journal of
Advanced Applied Technology and Engineering (JAATE)

https://journals.univ-msila.dz/index.php/JAATE

JAATE
JOURNAL OF ADVANCED APPLIED TECHNOLOGY & ENGINEERING
UNIVERSITY OF M'SILA
Faculty of Technology

كلية التكنولوجيا
FACULTY OF TECHNOLOGY

Enhanced UAV Fault Diagnosis and Compensation via Nonlinear Disturbance Observer and Adaptive Control

1st Abdellah Bekhiti
LAGE laboratory
University of Ouargla
Ouargla , Algeria
bekhiti.abdellah@univ-ouargla.dz

Houari Toubakh
LAGE laboratory
University of Ouargla
Ouargla , Algeria
houaritoubakh@gmail.com

Zakaria Bouzid
LAGE laboratory
University of Ouargla
Ouargla , Algeria
bouzid.zakaria@univ-ouargla.dz

***Abstract*— This study highlights the pivotal role of a nonlinear disturbance observer (NDO) in enhancing fault-tolerant control for fixed-wing unmanned aerial vehicles (UAVs) operating under adverse conditions such as icing. The proposed control framework integrates the NDO with nonlinear dynamic inversion and radial basis function neural networks to address complex nonlinearities introduced by simultaneous actuator and sensor faults, environmental disturbances, and model uncertainties. Central to this approach, the NDO enables accurate detection and estimation of sensor faults, significantly improving overall system robustness and reliability. To further optimize performance, the observer is designed to minimize deviations of the closed-loop eigenvalues from their desired locations and to achieve near-unity steady-state gain.**

***Keywords*—** *fault-tolerant controller; flight control; adaptive control; radial basis functions neural network; nonlinear dynamic inversion control; fixed-wing UAVs ;nonlinear disturbance observer*

I. Introduction

Unmanned aerial vehicles (UAVs) enhance efficiency and safety in various applications. They optimize agriculture by improving crop monitoring [1], aid search and rescue operations in remote areas [2], and ensure safe infrastructure inspections [3]. Additionally, UAVs contribute to environmental monitoring by tracking wildlife and assessing pollution [4]. These benefits highlight the importance of ensuring their safe and reliable operation [5].

However, UAVs are vulnerable to actuator and sensor faults that affect performance [6]. Failures arise from mechanical wear, harsh environments, and electrical malfunctions. To address this, fault-tolerant control (FTC) systems help maintain operation despite faults [7]. Simultaneous actuator and sensor failures, especially in fixed-wing UAVs, pose significant challenges [8]. For example, icing conditions can cause speed sensor faults alongside actuator issues, compromising stability [9]. Extensive research has advanced FTC methodologies, including adaptive control [10,11], model predictive control [12,13], optimal control [14,15], sliding mode control [16,17,18], nonlinear dynamic inversion [19], backstepping control [20], fuzzy logic-based robust control [21,22], and neural network-based control [23].

Fault-tolerant control methods for UAVs include adaptive control [7,10] and robust strategies combining adaptive control with nonlinear dynamic inversion [24]. Sliding mode disturbance observers with adaptive dynamic inversion improve resilience in fixed-wing UAVs [25], while L1 adaptive control enhances robustness in damaged electric aircraft [26]. Adaptive dynamic inverse control with control allocation mitigates icing effects [27], and radial basis function (RBF) neural networks ensure real-time adaptability [28,29]. Nonlinear disturbance observers (NDO) detect and compensate sensor faults [7], consolidating uncertainties and disturbances into a lumped model [25,30]. NDO are also key to fault-tolerant control systems, with recent recovery approaches detailed in [6,31].

This research tackles the underexplored challenge of managing simultaneous actuator and sensor faults in fixed-wing UAVs under adverse weather, such as icing [9]. While most studies address these faults separately [32,33], this work provides an integrated recovery approach. Unlike prior research using simplified models [11], it employs a six Degrees of Freedom (6DoF) nonlinear model for greater accuracy. The proposed method combines an adaptive fault-tolerant controller with radial basis function neural networks to handle nonlinearities [28,29] and a nonlinear disturbance observer to estimate and mitigate sensor errors [25,30]. Additionally, nonlinear dynamic inversion enhances robustness against simultaneous faults [19], significantly improving UAV reliability and safety.

This paper proposes an adaptive fault-tolerant control strategy integrating radial basis function neural networks with a nonlinear dynamic inversion controller for fixed-wing UAVs. A nonlinear perturbation observer detects and estimates sensor faults, ensuring robustness. this holistic approach improves fault tolerance. Simulations show the AI-enhanced controller maintains safe flight,

II. PROBLEM FORMULATION

In the following, the 6DOF dynamic model and the kinematic model in the body frame for the fixed-wing UAV are described by the following equations [35].

$$\begin{aligned} \dot{\boldsymbol{V}}^b &= \frac{1}{m}\left(\boldsymbol{R}_s^b \boldsymbol{F_a} + \boldsymbol{F_g} + \boldsymbol{F_T}\right) - \boldsymbol{\omega} \times \boldsymbol{V^b} \\ \dot{\boldsymbol{\omega}} &= \boldsymbol{I^{-1}}(\boldsymbol{M_a} - \boldsymbol{\omega} \times \boldsymbol{I\omega}) \\ \dot{\boldsymbol{\Phi}} &= \boldsymbol{C}_n \boldsymbol{\omega} \\ \boldsymbol{V}^E &= \boldsymbol{R}_b^E \boldsymbol{V}^b \end{aligned} \tag{1}$$

where the mass of the aircraft is denoted by m, and $\boldsymbol{V}^b = [u \quad v \quad w]^T$ represents the velocity vector of the aircraft in the body axes. The aerodynamic force vector acting on the aircraft is $\boldsymbol{F}_\mathrm{a} = [D \quad Y \quad L]^T$, while the gravitational force vector in the body axes is $\boldsymbol{F}_\mathrm{g} = \boldsymbol{R}_b^E[0 \quad 0 \quad mg]^T$, and $\boldsymbol{F}_\mathrm{T}$ is the thrust force vector. The transformation between the stability frame and the body frame is described by the rotation matrix $\boldsymbol{R}_s^\mathrm{b}$. The inertia matrix of the aircraft, which governs its rotational dynamics, is represented by $\boldsymbol{I}$. The angular velocity vector is $\boldsymbol{\omega} = [p \quad q \quad r]^T$, and the moment vector, which includes the roll, pitch, and yaw moments, is $\boldsymbol{M}_\mathrm{a} = [l_a \quad m_a \quad n_a]^T$. The Euler angles vector, $\boldsymbol{\Phi} = [\phi \quad \theta \quad \psi]^T$, represents the roll, pitch, and yaw angles. The navigation matrix is denoted by $\boldsymbol{C}_n$, and $\boldsymbol{V}^E = [x_e \quad y_e \quad z_e]^T$ is the velocity vector in the Earth axes. The transformation from the body frame to the Earth frame is given by the rotation matrix $\boldsymbol{R}_\mathrm{b}^\mathrm{E}$, while the control surface vector is given by $\boldsymbol{\delta} = [\delta_a \quad \delta_e \quad \delta_r]^T$ and δ_t is the throttle control surface.

The UAV dynamic model can be represented as a nonlinear affine system described by the following equation.

$$\begin{aligned} \dot{\mathbf{x}}(\mathrm{t}) &= \mathbf{f}(\mathbf{x}(t)) + \mathbf{g}(\mathbf{x}(t))\mathbf{u}(t) \\ \mathbf{y}(t) &= \mathbf{h}(\mathbf{x}(t)) \end{aligned} \tag{2}$$

where $\mathbf{x}(t) \in R^{\boldsymbol{n}}$ is the state vector, $\mathbf{f}(\mathbf{x}(t)): R^{\boldsymbol{n}} \to R^{\boldsymbol{n}}$, $\mathbf{g}(\mathbf{x}(t)): R^{\boldsymbol{n}} \to R^{\boldsymbol{n\times m}}$ and $\mathbf{h}(\mathbf{x}(t)): R^{\boldsymbol{n}} \to R^{\boldsymbol{m}}$ are non linear smooth functions,$\mathbf{u}(t) \in R^{\boldsymbol{m}}$ is the control vector and $\mathbf{y}(t) \in R^{\boldsymbol{m}}$ is the output vector. In fact, the model described in the previous section does not describe the system accurately because of the uncertainty in the model, and also the system is subject to faults in the actuators and/or sensors. There are various types of actuator faults hard-over, locked-in-place, loss of effectiveness, time-varying and bias faults [7]. This work deals with faults in actuators of loss of effectiveness and time-varying types where they are integrated together. After the system faults appear, the model becomes

$$\begin{aligned} \dot{\mathbf{x}}(t) &= \mathbf{f}(\mathbf{x}(t)) + \mathbf{g}(\mathbf{x}(t))\{\mathbf{u}(t) + \mathbf{u}_{\mathbf{f_a}}(t)\} \\ \mathbf{y}(t) &= \mathbf{h}(\mathbf{x}(t)) + \mathbf{f_s}(t) \end{aligned} \tag{3}$$

where $\boldsymbol{u}_{\boldsymbol{f_a}}(t) \in R^m$ is the actuator fault and $\mathbf{f_s}(t) \in R^m$ is the sensor fault. $\mathbf{u}_{\mathbf{f_a}}(t) \in R^m$ is take the form $\mathbf{u}_{\mathbf{f_a}}(t) = -\boldsymbol{\gamma}\mathbf{u}(t) + \mathbf{b}_{\mathbf{f_a}}(t)$, $\boldsymbol{\gamma} \in R^{m\times m}$ is a diagonal matrix where all elements are positive and smaller than one and $\mathbf{b}_{\mathbf{f_a}}(t) \in R^m$ is vector time function represent the bias fault.

This paper proposes a fault-tolerant control strategy for fixed-wing UAVs to maintain stability under faults and uncertainties. The solution includes a nonlinear observer for sensor fault detection, an adaptive controller based on nonlinear dynamic inversion for actuator faults, and sensor data integration for full fault compensation. This design ensures robust and stable UAV performance. As shown in Figure 01.

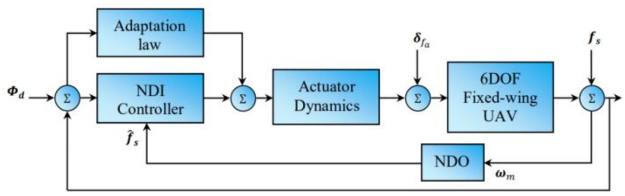

Fig. 1. Adaptive FTC strategy for a fixed-wing UAV

III. ADAPTIVE FTC DESIGN

A. Nonlinear disturbance observer design

This subsection presents a methodology to reformulate the original system into a structure that isolates the disturbance dynamics, thus facilitating accurate disturbance estimation. In systems influenced by unknown disturbances, the disturbance observer design plays a crucial role in estimating both the system states and the disturbance dynamics [36] For nonlinear affine systems of the form

$$\dot{\mathbf{x}} = \mathbf{f}(\mathbf{x}) + \mathbf{g}(\mathbf{x})\mathbf{u} + \mathbf{d}$$

Where $\mathbf{d}$ represents the disturbance vector. This system can be transformed into the following structured form [36]

$$\begin{aligned} \dot{\mathbf{x}}_1 &= \mathbf{f}(\mathbf{x}_1) + \mathbf{g}(\mathbf{x}_1)\mathbf{u} + \mathbf{x}_2 \\ \dot{\mathbf{x}}_2 &= \dot{\mathbf{d}} \end{aligned}$$

To design an observer for this system, The following observer dynamics introduced

$$\begin{aligned} \dot{\mathbf{z}}_1 &= \mathbf{f}(\mathbf{x}_1) + \mathbf{g}(\mathbf{x}_1)\mathbf{u} + \mathbf{z}_2 - \mathbf{L_1 e} \\ \dot{\mathbf{z}}_2 &= \mathbf{L_2 e} \end{aligned}$$

where the observer error is defined as $\mathbf{e} = (\mathbf{x} - \mathbf{z_1})$. The time derivative of the error $\dot{\mathbf{e}}$, is given by $\dot{\mathbf{e}} = \mathbf{x}_2 - \mathbf{z}_2 + \mathbf{L_1 e}$ Analyzing the dynamics of $\dot{\boldsymbol{e}}$ and $\dot{\boldsymbol{z}}_2$, the following augmented dynamic model is obtained

$$\begin{cases} \begin{bmatrix} \dot{\mathbf{e}} \\ \dot{\mathbf{z}}_2 \end{bmatrix} = \begin{bmatrix} \mathbf{L}_1 & -\mathbf{I}_{n\times n} \\ \mathbf{L}_2 & \mathbf{0}_{n\times n} \end{bmatrix} \begin{bmatrix} \mathbf{e} \\ \mathbf{z}_2 \end{bmatrix} + \begin{bmatrix} \mathbf{I}_{n\times n} \\ \mathbf{0}_{n\times n} \end{bmatrix} \mathbf{x}_2 \\ \mathbf{y} = [\mathbf{0}_{n\times n} \quad \mathbf{I}_{n\times n}] \begin{bmatrix} \mathbf{e} \\ \mathbf{z}_2 \end{bmatrix} \end{cases} \tag{4}$$

Equation (4) describes a linear system where $\mathbf{x}_2$ serves as the input and $\mathbf{z}_2$ as the output. The objective of the observer is to accurately estimate the disturbance signal $\mathbf{x}_2$. For this, it is essential that the observer gains $\mathbf{L_1}$ and $\mathbf{L_2}$ are chosen to ensure stability and proper estimation performance of the augmented system. This objective can be achieved by solving the following optimization problem

$$\min_{L_1, L_2} \left(\left\| \mathrm{eig}\left\{ \begin{bmatrix} L_1 & -I_{n\times n} \\ L_2 & 0_{n\times n} \end{bmatrix} \right\} - \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_{2n} \end{bmatrix} \right\|_2^2 + \left\| \mathrm{dcgain}\left(\begin{bmatrix} L_1 & -I_{n\times n} \\ L_2 & 0_{n\times n} \end{bmatrix}, \begin{bmatrix} I_{n\times n} \\ 0_{n\times n} \end{bmatrix}, [0_{n\times n} \quad I_{n\times n}] \right) - I_{n\times n} \right\|_2^2 \right) \tag{5}$$

This formulation seeks to minimize the deviation of the Eigen values of the observer dynamics matrix from a desired set $(\lambda_1, \lambda_2, \cdots, \lambda_{2n})$ and to ensure that the DC gain of the system is close to unity, thereby achieving robust disturbance estimation.

B. Nonlinear Dynamic Inversion Control Design

Now the NID control strategy will be applied to the fixed-wing UAV model ,According equations (1) the UAV attitude take

$$\dot{\boldsymbol{\omega}} = \boldsymbol{I}^{-1}\left(\left(\boldsymbol{M}_{a_0} + \boldsymbol{M}_{a_\delta}\boldsymbol{\delta}\right) - \boldsymbol{\omega} \times \boldsymbol{I}\boldsymbol{\omega}\right)$$
$$\dot{\boldsymbol{\Phi}} = \boldsymbol{C}_n \boldsymbol{\omega}$$

The first equation is called the slower angular loop and the second is called the faster angular loop [38]. The commanded angular velocity $\boldsymbol{\omega}_c$ as the input of the slower loop, can be obtained by NDI method $\boldsymbol{\omega}_c = \boldsymbol{C}_n^{-1}\boldsymbol{v}_{\boldsymbol{\Phi}}$ where $\boldsymbol{v}_{\boldsymbol{\Phi}} = \dot{\boldsymbol{\Phi}}_{\boldsymbol{d}} + \boldsymbol{\Lambda}_{\boldsymbol{\Phi}}(\boldsymbol{\Phi}_{\boldsymbol{d}} - \boldsymbol{\Phi})$ and $\boldsymbol{\Phi}_{\boldsymbol{d}}$ is the desired attitude. To control the faster angular loop, the input $\boldsymbol{\delta}$ is given by

$$\boldsymbol{\delta} = \boldsymbol{M}_{a_\delta}^{-1}\left(\boldsymbol{I}\boldsymbol{v}_{\boldsymbol{\omega}} + \boldsymbol{\omega} \times \boldsymbol{I}\boldsymbol{\omega} - \boldsymbol{M}_{a_0}\right) \tag{6}$$

Where $\boldsymbol{v}_{\boldsymbol{\omega}} = \boldsymbol{\Lambda}_{\boldsymbol{\omega}}(\boldsymbol{\omega}_c - \boldsymbol{\omega})$ and $\boldsymbol{\Lambda}_{\boldsymbol{\Phi}}$, $\boldsymbol{\Lambda}_{\boldsymbol{\omega}}$ are positive definite matrices respectively

C. Adaptive FTC control design

This subsection deals with attitude control of the fixed-wing UAV in the presence of an actuator fault, with the goal of designing a control law that compensates for the faults and maintains the desired performance. To achieve this, an adaptive control approach is adopted, which allows real-time adjustments to counteract the effects of faults. As shown in equation (3), the dynamic model of the UAV is susceptible to faults that may affect stability and control. From the above, the faulty UAV attitude model is given by

$$\dot{\boldsymbol{\omega}} = \boldsymbol{I}^{-1}\left(\left(\boldsymbol{M}_{a_0} + \boldsymbol{M}_{a_\delta}(\boldsymbol{\delta} + \boldsymbol{\delta}_{fa})\right) - \boldsymbol{\omega} \times \boldsymbol{I}\boldsymbol{\omega}\right)$$
$$\dot{\boldsymbol{\Phi}} = \boldsymbol{C}_n \boldsymbol{\omega}$$
$$\boldsymbol{\omega}_m = \boldsymbol{\omega} + \boldsymbol{f}_s$$

where $\boldsymbol{\delta}_{fa}$, $\boldsymbol{f}_s$, $\boldsymbol{\omega}_m$ are the actuator fault, sensor fault and the measured angular velocity. As mentioned earlier, the fault in the actuators takes the form $\boldsymbol{\delta}_{fa} = -\boldsymbol{\gamma}\boldsymbol{\delta} + \boldsymbol{b}_{fa}$, Based on the universal approximation theorem [39], a neural network of sufficient complexity (e.g., an RBF neural network) can approximate any continuous function, including fault dynamics, allowing the controller to account for model uncertainties and disturbances. Thus, in general, the fault function can be represented as follows.

$$\boldsymbol{\delta}_{fa} = \boldsymbol{W}^{\boldsymbol{T}}\boldsymbol{\varphi}(t)$$

Where $\boldsymbol{\varphi}(t)$ is the kernel function $\boldsymbol{\varphi}(t) = [\varphi_1(t) \quad \varphi_2(t) \quad \ldots \quad \varphi_m(t)]^T$. with each $\varphi_i(t)$ potentially taking a Gaussian form, To compensate for the actuator fault, the NDI control law given in Equation (6) is modified as follows, See Figure 02.

$$\boldsymbol{\delta} = \boldsymbol{M}_{a_\delta}^{-1}\left(\boldsymbol{I}\left(\boldsymbol{\Lambda}_{\boldsymbol{\omega}}(\boldsymbol{\omega}_c - \boldsymbol{\omega})\right) + \boldsymbol{\omega} \times \boldsymbol{I}\boldsymbol{\omega} - \boldsymbol{M}_{a_0}\right) - \widehat{\boldsymbol{\delta}}_{fa}$$

Where $\widehat{\boldsymbol{\delta}}_{fa}$ is the estimated actuator fault given by $\widehat{\boldsymbol{\delta}}_{fa} = \widehat{\boldsymbol{W}}^T\boldsymbol{\varphi}(t)$, By applying the control law to the system, the following equation is obtained $\dot{\boldsymbol{e}}_{\boldsymbol{\omega}} = -\boldsymbol{\Lambda}_{\boldsymbol{\omega}}\boldsymbol{e}_{\boldsymbol{\omega}} + \boldsymbol{M}_{a_\delta}\widetilde{\boldsymbol{\delta}}_{fa}$, where $\boldsymbol{e}_{\boldsymbol{\omega}} = (\boldsymbol{\omega}_c - \boldsymbol{\omega})$ and $\widetilde{\boldsymbol{\delta}}_{fa}$ represents the error of the fault signal, defined as $\widetilde{\boldsymbol{\delta}}_{fa} = \boldsymbol{\delta}_{fa} - \widehat{\boldsymbol{\delta}}_{fa}$. Alternatively, it can be expressed as $\widetilde{\boldsymbol{\delta}}_{fa} = \widetilde{\boldsymbol{W}}^T\boldsymbol{\varphi}(t)$ where $\widetilde{\boldsymbol{W}}^T = \boldsymbol{W}^T - \widehat{\boldsymbol{W}}^T$. The adaptation law is given as follows:

$$\dot{\boldsymbol{W}} = \boldsymbol{\Gamma}\boldsymbol{\varphi}(t)\boldsymbol{e}_{\boldsymbol{\omega}}^T\boldsymbol{M}_{a_\delta} \tag{7}$$

Where $\boldsymbol{\Gamma}$ is a positive definite matrix satisfy the dimensions.

The control law in equation (6) depends on the angular velocity $\boldsymbol{\omega}$, which is measured by on-board sensors. However, these sensors are also prone to faults that may affect the accuracy of the $\boldsymbol{\omega}$ readings and, consequently, the effectiveness of the control law. To address this issue, the observer developed in section II is designed to detect and compensate for sensor faults, ensuring reliable measurements for stable control performance. Therefore, the partial model is considered.

$$\dot{\boldsymbol{\Phi}} = \boldsymbol{C}_n \boldsymbol{\omega}$$
$$\boldsymbol{\omega}_m = \boldsymbol{\omega} + \boldsymbol{f}_s$$

The dynamic will be as follow $\dot{\boldsymbol{\Phi}} = \boldsymbol{C}_n\boldsymbol{\omega}_m - \boldsymbol{C}_n\boldsymbol{f}_s$, If the following putting is carried out $\boldsymbol{d} = \boldsymbol{C}_n\boldsymbol{f}_s$, then will be $\dot{\boldsymbol{\Phi}} = \boldsymbol{C}_n\boldsymbol{\omega} + \boldsymbol{d}$, in order to estimate the disturbance signal the

NDO designed in II is used, than the observer dynamic given by

$$\dot{\hat{\boldsymbol{\Phi}}} = \boldsymbol{C}_n \boldsymbol{\omega}_m + \hat{\boldsymbol{d}} - \boldsymbol{L}_1 \boldsymbol{e}_{\boldsymbol{\Phi}}$$
$$\dot{\hat{\boldsymbol{d}}} = \boldsymbol{L}_2 \boldsymbol{e}_{\boldsymbol{\Phi}}$$
$$\hat{\boldsymbol{f}}_s = \boldsymbol{C}_n^{-1} \hat{\boldsymbol{d}}$$

Where $\boldsymbol{L}_1$ and $\boldsymbol{L}_2$ are satisfy equation (5)

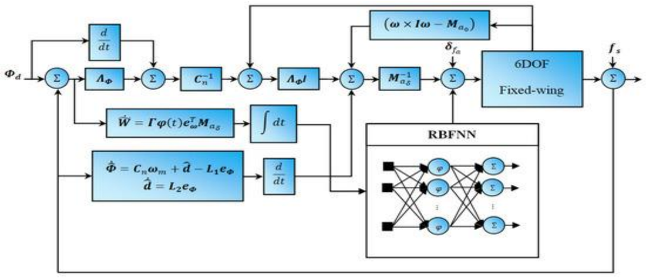

Fig. 2. Adaptive FTC control for fixed-wing UAV.

IV. SIMULATION RESULTS

This section investigates the effectiveness of the proposed fault-tolerant control law for attitude control in a fixed-wing UAV. The Aerosonde fixed-wing UAV model is used to implement the control laws and perform numerical simulations in MATLAB. The aerodynamic coefficients and parameters for the Aerosonde UAV are given in Table 01 and .

TABLE 02: PARAMETERS FOR THE AEROSONDE UAV

Parameter	Value	Parameter	Value
m	31.5 (kg)	b	2.8956 (m)
I_x	0.8244 (kg/m²)	$\bar{c}$	0.18994 (m)
I_y	1.135 (kg/m²)	S_p	0.2027 (m²)
I_z	1.759 (kg/m²)	ρ	1.2682 (kg/m³)
I_{xz}	0.1204 (kg/m²)	K_m	80 (-)
S	0.55 (m²)		

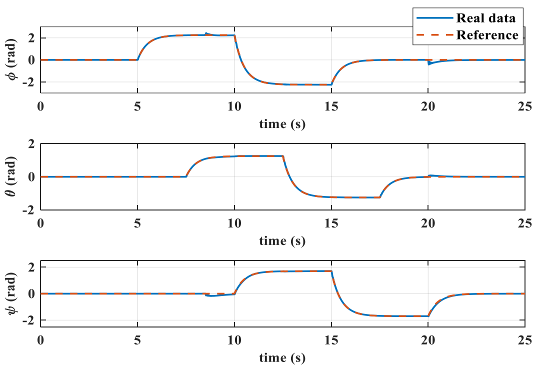

Fig. 3. Time evolution of attitude of the UAV

Figure 3 shows the evolution of the UAVs attitude, specifically the roll, pitch and yaw angles, under fault conditions. The attitude remains stable and closely follows the reference values even when the system experiences actuator faults. Although small disturbances occur at critical moments of actuator faults, these small deviations remain within a narrow range, ensuring that they do not significantly affect the overall performance. In addition, the control system quickly adapts to changing dynamics with minimal delay, enabling reliable tracking and rapid return to steady-state behavior.

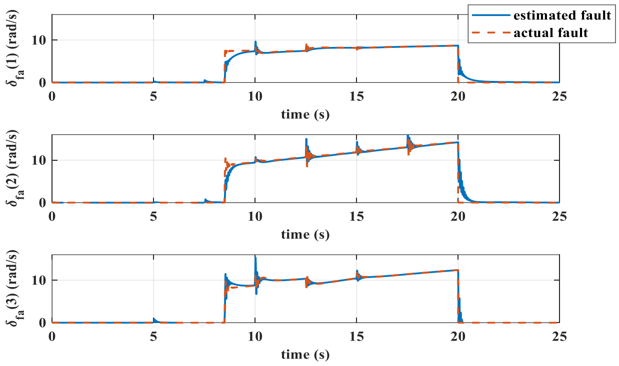

Fig. 4. Time evolution of actuator faults

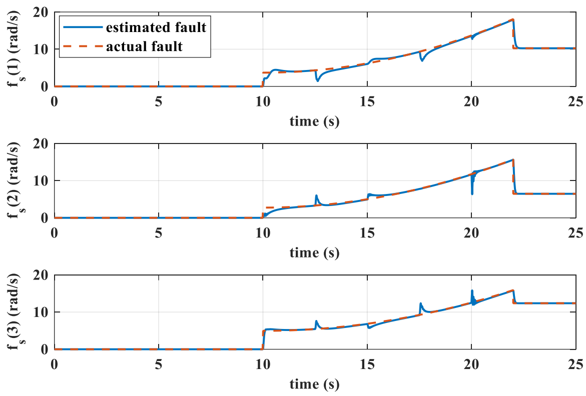

Fig. 5. Time evolution of sensor faults

Figures 4 and 5 show the time evolution of actuator and sensor faults, demonstrating the system's ability to handle these faults effectively. The adaptive controller uses a radial basis function neural network to estimate and compensate for actuator faults with high accuracy. As shown in Figure 4, the estimated values closely match the actual values, confirming the system's quick and precise fault identification and correction, which helps maintain aircraft performance.

The system also adapts rapidly to fault-induced changes, preserving stability in attitude and speed. Figure 5 highlights the performance of the nonlinear disturbance detector, where estimated sensor fault values align well with actual ones. This accurate detection supports the controller in making timely adjustments, minimizing performance loss and ensuring reliable operation in faulty or disturbed conditions.

V. CONCLUSION

This paper proposes an adaptive fault-tolerant control (FTC) strategy for fixed-wing aircraft to ensure reliable operation under icing conditions, addressing the combined challenges of actuator faults, sensor faults, model uncertainties, and external disturbances. The control framework integrates radial basis function neural networks with nonlinear dynamic inversion and a nonlinear disturbance observer, forming a comprehensive solution for real-time fault detection and compensation. By leveraging the strengths of these advanced control techniques, the system maintains robust performance, stability, and precise control, even under severe fault and disturbance conditions.

REFERENCES

[1] Kim, J.; Kim, S.; Ju, C.; Son, H.I. Unmanned aerial vehicles in agriculture: A review of perspective of platform, control, and applications. IEEE Access 2019, 7, 105100–105115.

[2] Lyu, M.; Zhao, Y.; Huang, C.; Huang, H. Unmanned aerial vehicles for search and rescue: A survey. Remote Sens. 2023, 15, 3266.

[3] Greenwood, W.W.; Lynch, J.P.; Zekkos, D. Applications of UAVs in civil infrastructure. J. Infrastruct. Syst. 2019, 25, 04019002.

[4] Vasiloni, A.; Guyvenchy, F.; Pașcalău, R.; Șmuleac, A. Use of UAV technology for environmental conservation. Res. J. Agric. Sci. 2023, 55, 4.

[5] Telli, K.; Kraa, O.; Himeur, Y.; Ouamane, A.; Boumehraz, M.; Atalla, S.; Mansoor, W. A comprehensive review of recent research trends on unmanned aerial vehicles (UAVs). Systems 2023, 11, 400.

[6] Fourlas, G.K.; Karras, G.C. A survey on fault diagnosis and fault-tolerant control methods for unmanned aerial vehicles. Machines 2021, 9, 197.

[7] Henna, H.; Toubakh, H.; Kafi, M.R.; Sayed-Mouchaweh, M. Towards fault-tolerant strategy in satellite attitude control systems: A review. Annu. Conf. PHM Soc. 2020, 12, 14.

[8] Zogopoulos-Papaliakos, G.; Karras, G.C.; Kyriakopoulos, K.J. A fault-tolerant control scheme for fixed-wing with flight envelope awareness. J. Intell. Robot. Syst. 2021, 102, 46.

[9] Hann, R.; UNTNU. 2nd international UAV Icing Workshop: Book of abstracts. UAV Icing Workshop, Trondheim, Norway. 3 December 2024.Available online: https://zenodo.org/records/14274740 (accessed on 1 March 2025).

[10] Souanef, T. Adaptive Guidance and Control of Small Unmanned Aerial Vehicles. Ph.D. Thesis, Universität Stuttgart, Stuttgart, Germany, 2019.

[11] Souanef, T. L1 Adaptive Output Feedback Control of Small Unmanned Aerial Vehicles. Unmanned Syst. 2023, 11, 249–260.

[12] Emami, S.; Banazadeh, A. Fault-tolerant predictive trajectory tracking of an air vehicle based on acceleration control. IET Control Theory Appl. 2020, 14, 750–762.

[13] Hu, X.; Zong, G.; Deng, X.; Wang, W. Model predictive control-based non-linear fault-tolerant control for air-breathing hypersonic vehicles. IET Control Theory Appl. 2014, 8, 1147–1153.

[14] Zhang, C.; Zhang, G.; Dong, Q. Fixed-time disturbance observer-based nearly optimal control for reusable launch vehicle with input constraints. ISA Trans. 2022, 122, 182–197.

[15] Almutairi, S.H.; Aouf, N. Fault-tolerant flight control design against actuator impairments using optimal control and fault compensation. In Proceedings of the 11th IEEE International Conference on Control & Automation (ICCA), Taichung, Taiwan, 18–20 June 2014.

[16] Zhang, Y.; Tang, S.; Guo, J. Adaptive-gain fast super-twisting sliding mode fault-tolerant control for a reusable launch vehicle in reentry phase. ISA Trans. 2017, 71, 380–390.

[17] Liang, X.; Zhang, Y.; Zhang, B.; Peng, Y. Fixed-time observer-based fault-tolerant attitude control for reusable launch vehicle with actuator faults. Aerosp. Sci. Technol. 2020, 107, 106314.

[18] Mahboub, M.A.; Rouabah, B.; Kafi, M.R.; Toubakh, H. Health management using fault detection and fault-tolerant control of multicellular converter applied in more electric aircraft system. Diagnostyka 2022, 23, 2.

[19] Ma, X.; Liu, S.; Cheng, H. Civil aircraft fault-tolerant attitude tracking based on extended state observers and nonlinear dynamic inversion. J. Syst. Eng. Electron. 2022, 33, 180–187.

[20] Meng, Y.; Jiang, B.; Qi, R. Adaptive fault-tolerant attitude tracking control of hypersonic vehicle subject to unexpected centroid-shift and state constraints. Aerosp. Sci. Technol. 2019, 95, 105515.

[21] Saied, M.; Belkacem, A.; Khenfouch, M. BFA fuzzy logic-based control allocation for fault-tolerant control of multirotor UAVs. Aeronaut. J. 2019, 123, 1356–1373.

[22] Long, H.; Wang, Z.; Guo, L.; Li, J. Fixed-time adaptive fuzzy fault-tolerant control of flapping wing MAVs with wing damage. IEEE Trans. Aerosp. Electron. Syst. 2024, 60, 6594–6607.

[23] Zhang, C.; Luo, H.; Li, J.; Wang, Z. Neural-networks and event-based fault-tolerant control for spacecraft attitude stabilization. Aerosp. Sci. Technol. 2021, 114, 106746.

[24] Lombaerts, T.; Ankersen, F.; Mulder, T.; Voskuijl, M. Dynamic inversion based full envelope flight control for an eVTOL vehicle using a unified framework. In Proceedings of the AIAA Scitech 2020 Forum, Orlando, FL, USA, 6–10 January 2020.

[25] Dong, Z.; Liu, K.; Wang, S. Sliding mode disturbance observer-based adaptive dynamic inversion fault-tolerant control for fixed-wing UAV. Drones 2022, 6, 295.

[26] Zhang, L.; Mu, J.; Ma, H.; Dai, G.; Tong, S. Research on fault-tolerant control of combined airframe damage of electric aircraft. Aerospace 2023, 10, 611.

[27] Jiang, F.; Liu, X.; Chen, T.; Li, K. Research on an Ice Tolerance Control Method for Large Aircraft Based on Adaptive Dynamic Inversion. Actuators 2024, 227.

[28] Wang, H.; Zhou, X.; Tian, Y. Robust adaptive fault-tolerant control using RBF-based neural network for a rigid-flexible robotic system with unknown control direction. Int. J. Robust Nonlinear Control 2022, 32, 1272–1302.

[29] Hou, Z.; Lan, X. Adaptive sliding mode and RBF neural network-based fault-tolerant attitude control for spacecraft with unknown uncertainties and disturbances. Adv. Space Res. 2024, 74, 1680–1692.

[30] Ding, S.; Zhai, Q.; Liu, J.; Ma, J.; Qiu, Y. Disturbance observer design for nonlinear systems represented by input–output models. IEEE Trans. Ind. Electron. 2019, 67, 1222–1232.

[31] He, Q.; Zhao, J.; Hu, X.; Wang, G.; Yan, J. Reconfigurable nonlinear dynamic inversion for attitude control of a structurally damaged aircraft. IEEE Access 2020, 8, 199931–199943.

[32] Xue, Y.X.; Yan, L.; Sun, X.; Ma, D. Adaptive fault-tolerant control for carrier-based UAV with actuator failures. Aerosp. Sci. Technol. 2020, 107, 106227.

[33] Zhou, Y.; Liu, H.; Guo, H. $\mathscr{L}$1 adaptive output-feedback fault-tolerant control for uncertain nonlinear systems subject to unmodeled actuator dynamics and faults. Trans. Inst. Meas. Control 2022, 44, 2177–2192.

[34] Iglesis, E.; Horri, N.; Brusey, J.; Dahia, K.; Piet-Lahanier, H. Simultaneous actuator and sensor faults estimation for aircraft using a jump-Markov regularized particle filter. In Proceedings of the 2021 IEEE International Conference on Prognostics and Health Management (ICPHM), Detroit (Romulus), MI, USA, 7–9 June 2021.

[35] Beard, R.W.; McLain, T.W. Small Unmanned Aircraft: Theory and Practice; Princeton University Press: Princeton, NJ, USA, 2012.

[36] Cecilia, A. Advances in Nonlinear Observer Design for State and Parameter Estimation in Energy Systems; Springer Nature: Berlin/Heidelberg, Germany, 2023.

[37] Snell, S.A. Nonlinear Dynamic-Inversion Flight Control of Supermaneuverable Aircraft; University of Minnesota: Minneapolis, MN, USA, 1991.

[38] Safwat, E.; Farag, M.; El-Bardini, M.; Bayoumi, A. Robustness analysis of modified incremental nonlinear dynamic inversion for small UAVs. Autom. Control. Comput. Sci. 2020, 54, 128–138.

[39] Lavretsky, E.; Wise, K.A. Robust and Adaptive Control with Aerospace Applications; Springer: London, UK, 2013.

[40] Slotine, J.J.E.; Li, W. Applied Nonlinear Control; Prentice Hall: Englewood Cliffs, NJ, USA, 1991.

[41] Stevens, B.L.; Lewis, F.L.; Johnson, E.N. Aircraft Control and Simulation: Dynamics, Controls Design, and Autonomous Systems; John Wiley & Sons: Hoboken, NJ, USA, 2015.

[42] Souanef, T. Multiple model l 1 adaptive fault-tolerant control of small unmanned aerial vehicles. J. Aerosp. Eng. 2024, 37, 04023103.