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ADAPTIVE FAULT-TOLERANT CONTROL FOR AIRCRAFT SYSTEMS BASED ON OFF-POLICY LEARNING

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Abstract. *This paper focuses on the challenges of actuator faults and disturbances during aircraft operation, which can threaten the safety and reliability of the aircraft. Fault-tolerant control techniques have been proposed as a solution to enhance system robustness and ensure stable operation under such conditions. In this paper, a data-driven approach is adopted, which is based on off-policy learning and can effectively address the complexity and uncertainty associated with aircraft modeling. Specifically, a linearized aircraft model is proposed for calm approach air environments, and a fault-tolerant control law is developed to account for time-varying external disturbances and coupled state vectors. Theoretical stability analysis is also conducted to establish the stability of the proposed control law. Finally, a carrier-based aircraft system with actuator fault and disturbance is simulated to confirm the efficacy of the proposed adaptive fault-tolerant control law in the final approach phase.*

Keywords: Adaptive fault-tolerant control, Data-driven, Off-policy learning, Aircraft system

1. **Introduction.** In recent years, extensive research has been conducted on fault-tolerant control for uncertain systems [1]. Many fault-tolerant control policies have been proposed, with most being model-based, which limits their applicability [2]. Establishing a system model is costly and time-consuming [3], making it challenging to implement model-based control policies when controlled objects are difficult to identify or highly complex.

Due to the influence of wind and other factors, aircraft have complex nonlinear dynamics during approach. Fault-tolerant control for aircraft during approach is always a hot topic. In [4], control policies for aircraft systems with uncertainty are studied to achieve better performance at a high angle-of-attack while considering the effects of disturbances. In [5], a data-driven fault-tolerant control is applied to aircraft to investigate unknown cooperative quadrotors subject to nonlinearities and multiple actuator faults in quadrotor dynamics. In [6], off-policy learning is applied to counteracting aircraft disturbances and explores a switching strategy for altitude control in a variable-sweep wing aircraft. In [7], a robust adaptive fault-tolerant controller is designed, but it lacks the consideration for linear external uncertainties.

In this study, we propose a new data-driven adaptive control policy for aircraft systems which have actuator stuck, outage and loss of effectiveness and coupled state vectors of external disturbances based on off-policy learning. This approach avoids the time-consuming

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process of building a system model required for model-based control strategy design while overcoming the effects of external disturbances constrained by internal system states. Off-policy learning approach does not depend on the initial stabilizing controller and enables online learning based on the collected system input and state. Finally, we evaluate the effectiveness of our data-driven fault-tolerant control approach using simulations of flight dynamic systems with actuators failure and coupling system states affected by external disturbances. All the results demonstrate the validity and applicability of this methodology.

The structure of this paper is organized as follows. A review of problem formulation and preliminaries is provided in Section 2. A novel adaptive controller based on off-policy learning is designed in Section 3. A numerical example focusing on a carrier-based aircraft landing system is discussed in Section 4. In the end, the paper is concluded in Section 5.

2. **Problem Statement and Preliminaries.**

2.1. **Linear modeling for aircraft dynamics in final approach.** Aircraft has complex dynamics during the approach phase. In this section, the perturbation linear model of carrier-based aircraft flight dynamics in longitudinal direction is constructed by means of the general algebraic perturbation linearization scheme [8].

The motion equation of longitudinal aircraft is as follows:

$$\begin{cases} M\dot{v}_I = a_2 J - L - a_3 Mg \\ Mv_I\dot{\gamma} = a_1 J + D - a_4 Mg \\ \dot{q} = M_0/I_y \\ \dot{\theta} = q \\ \dot{h} = v_I a_3 \\ \alpha = \theta - \gamma \end{cases} \tag{1}$$

where M means the mass of aircraft, v_I means the scalar aircraft inertial velocity, J means the scalar total engine thrust, L means the drag, D means the lift, M_0 and I_y are the moment and the moment of inertial in pitch respectively, q is pitch rate, θ is pitch attitude, α is angle of attack, γ is flight-path angle, h is altitude, $a_1 = \sin\alpha$, $a_2 = \cos\alpha$, $a_3 = \sin\gamma$, and $a_4 = \cos\gamma$.

Based on the common coordinate system of flight dynamics, the six-degree-of-freedom motion equation of aircraft landing configuration is established in the reference frame attached to the aircraft's body. The longitudinal 3-DOF motion equation is decoupled as Equation (1).

The changes in altitude and airspeed during carrier approach and landing have a subtle impact on engine thrust, which means J_h and J_v can be discarded.

Longitudinal motion equations of the aircraft are expressed as follows after linearization:

$$\frac{d}{dt}(\Delta v_I) = -a_4^* g\Delta\gamma + \frac{a_2^*\Delta J - a_1^* J^*\Delta\alpha - \Delta L}{M} \tag{2}$$

$$\frac{d}{dt}(\Delta\gamma) = \frac{a_3^* g\Delta\gamma}{v_I^*} + \frac{a_1^*\Delta J - a_2^* J^*\Delta\alpha - \Delta D}{Mv_I^*} \tag{3}$$

$$\frac{d}{dt}(\Delta q) = \frac{\Delta M_0}{I_y} \tag{4}$$

$$\frac{d}{dt}(\Delta\theta) = \Delta q \tag{5}$$

$$\frac{d}{dt}(\Delta h) = a_4^* v_I^*\Delta\gamma + a_3^*\Delta v_I \tag{6}$$

$$\Delta\alpha = \Delta\theta - \Delta\gamma \tag{7}$$

Define the control derivatives and longitudinal stability [9], the deviations of the aircraft's moment and longitudinal forces are shown as Equations (8)-(11).

$$\Delta J = J_{\delta_p}\Delta\delta_p + J_h\Delta h + J_v\Delta v \tag{8}$$

$$\Delta D = D_{\alpha^*}\Delta\alpha + D_{h^*}\Delta h + D_{\delta_e^*}\Delta\delta_e + D_{v^*}\Delta v + D_{\delta_c^*}\Delta\delta_c \tag{9}$$

$$\Delta L = L_{\delta_c^*}\Delta\delta_c + L_{h^*}\Delta h + L_{\alpha^*}\Delta\alpha + L_{\delta_e^*}\Delta\delta_e + L_{v^*}\Delta v \tag{10}$$

$$\Delta M_0 = M_{0_{v^*}}\Delta v + M_{0_{h^*}}\Delta h + M_{0_{\delta_e^*}}\Delta\delta_e + M_{0_{q^*}}\Delta q + M_{0_{\dot\alpha^*}}\Delta\dot\alpha + M_{0_{\delta_c^*}}\Delta\delta_c + M_{0_{\alpha^*}}\Delta\alpha \tag{11}$$

$$a_4^* g\Delta\theta + (K - x^v)\Delta v - x^h\Delta h - (a_4^* g + x^\alpha)\Delta\alpha = x^p\Delta\delta_p + x^c\Delta\delta_c + x^e\Delta\delta_e \tag{12}$$

$$-\left(y^\alpha + K - a_3^*\frac{g}{v^*}\right)\Delta\alpha - y^h\Delta h + \left(-a_3^*\frac{g}{v^*} + K\right)\Delta\theta - y^v\Delta v = y^p\Delta\delta_p + y^c\Delta\delta_c + y^e\Delta\delta_e \tag{13}$$

$$-\left(\mu^\alpha + \mu^{\dot\alpha}K\right)\Delta\alpha - \mu^v\Delta v + \left(K^2 - \mu^\alpha K\right)\Delta\theta = \mu^e\Delta\delta_e + \mu^c\Delta\delta_c \tag{14}$$

Substituting Equations (8)-(11) into Equations (2)-(4) and then replacing $\Delta\gamma$ and Δq with Equations (7) and (5) yield Equations (12)-(14), where K is the differential operator sign, and the definition of the control and longitudinal stability derivatives are mentioned above. Without considering wind interference, the linear state-space equation of the aircraft system in final approach can be expressed as

$$\dot x = Ax + Bu \tag{15}$$

where $x = [\Delta v \quad \Delta\alpha \quad \Delta q \quad \Delta\theta \quad \Delta h]^T$, $u = [\Delta\delta_e \quad \Delta\delta_c \quad \Delta\delta_p]^T$,

$$A = \begin{pmatrix} x^v & x^\alpha + a_4^* g & 0 & -a_4^* g & x^h \\ -y^v & -y^\alpha + a_3^*\dfrac{g}{v^*} & 1 & -a_3^*\dfrac{g}{v^*} & -y^h \\ \mu^v - \mu^{\dot\alpha}y^v & \mu^\alpha - \mu^{\dot\alpha}y^\alpha + a_1\mu^{\dot\alpha}\dfrac{g}{v^*} & \mu^q + \mu^{\dot\alpha} & -a_3^*\mu^{\dot\alpha}\dfrac{g}{v^*} & 0 \\ 0 & 0 & 1 & 0 & 0 \\ a_1 & -a_4^* v^* & 0 & a_4^* v^* & 0 \end{pmatrix},$$

$$B = \begin{pmatrix} B_1 \\ B_2 \\ B_3 \\ O_{2\times 3} \end{pmatrix}, \quad B_1 = \begin{pmatrix} x^e \\ x^c \\ x^p \end{pmatrix}^T, \quad B_2 = \begin{pmatrix} -y^e \\ -y^c \\ -y^p \end{pmatrix}^T, \quad B_3 = \begin{pmatrix} \mu^e - \mu^{\dot\alpha}y^e \\ \mu^c - \mu^{\dot\alpha}y^c \\ -\mu^{\dot\alpha}y^p \end{pmatrix}^T.$$

2.2. **Analysis of system uncertainty and actuator failure.** Linearization modeling is an approximate method, which brings some uncertainties to the model. In order to approximate the real system, we should consider the possible actuator failures, uncertainties and perturbations of the system (15). In this subsection, we will delve into the analysis of linear aircraft systems featuring coupled state vectors affected by external disturbances and actuator faults.

Consider a linear continuous system with external disturbance of coupled state vector and actuator fault

$$\dot x = Ax(t) + Bu_c(t) + B_\omega\omega(t) + BG(x) \tag{16}$$

where $\omega(t) \in \mathbb{R}^p$ is the bounded external disturbance, such as wind. $G(x)$ is the external uncertainty of the coupled state vector, introduced by the uncertainty of the system model. The norm of $G(x)$ is bounded by unknown but estimable constant h, i.e., $\|G(x)\| \le h\|x\|$. And $B_\omega = BF$ is also assumed the matching condition [10], where F is unknown, and the norm of F is bounded by unknown constant d_f, i.e., $\|F\| \le d_f$.

Considering the possibility of actuator failure, offset, and jamming, we define the actual control input

$$u_c(t) = \begin{bmatrix} \rho & 0 \\ 0 & \sigma \end{bmatrix} \begin{bmatrix} u(t) \\ u_d(t) \end{bmatrix} \tag{17}$$

$$\rho = diag(\rho_1, \rho_2, \rho_3), \quad \sigma = diag(\sigma_1, \sigma_2, \sigma_3), \quad \sigma_j = \begin{cases} 0 \text{ or } 1 & \rho_j = 0 \\ 0 & 0 < \rho_j \leq 1 \end{cases} (j = 1, 2, 3)$$

where ρ is the efficiency factor and σ determines whether the actuator is stuck.

Finally, the system (16) can be restructured as the following form

$$\dot{x} = Ax + B\rho u + B\sigma u_d + BF\omega + BG \tag{18}$$

In order to effectively design the control law of fault-tolerant control model, it is necessary to assume that ω and u_d are limited by positive real parameters (i.e., $\|\omega\| \leq \eta_1$ and $\|u_d\| \leq \eta_2$), and $\text{Rank}(B\rho) = \text{Rank}(B) = l$ $(l = 1, 2)$.

3. Adaptive Control Policy Based on Off-Policy Learning.

According to the classical theory of optimal control [11],

$$A^T P_t + P_t A + Q - P_t B R^{-1} B^T P_t = 0 \tag{19}$$

where P_t is the unique positive definite solution to Riccati equation.

Denote

$$K_t = R^{-1} B^T P_t \tag{20}$$

Equation (19) can be expressed as

$$A^T P_t + P_t A + Q - K_t^T R K_t = 0 \tag{21}$$

Here, we give an important lemma.

Lemma 3.1. *Let ρ and K_t be given in Equations (17) and (20). And then there exists the following inequality relationship such that*

$$x^T K_t^T R \rho R K_t x \geq \|R K_t x\|^2 \tag{22}$$

The proof is similar to [7].

In order to attain the desired performance in Equation (18), we design the adaptive fault-tolerant control law as follows:

$$u(t) = K_1(x) + K_2(t) + K_3(t) \tag{23}$$

Substitute Equation (23) into Equation (18) to obtain the closed-loop system as follows:

$$\dot{x} = Ax(t) + B\rho(K_1(x) + K_2(t) + K_3(t)) + B\sigma u_s(t) + BF\omega(t) + BG(x) \tag{24}$$

An unknown positive constant k_4 exists and satisfies the following inequation

$$\|\sigma u_s(t) + F\omega(t)\| \leq \|\sigma\| \overline{u_{so}} + \|F\| \overline{\omega_{se}} \leq \overline{u_{so}} + d_f \overline{\omega_{se}} \leq k_4 \tag{25}$$

Now the actuator structure control law is designed as follows:

$$K_1(x) = -\varepsilon K_t x = -\varepsilon R^{-1} B^T P_t x \tag{26}$$

$$K_2(t) = -\frac{\widehat{k}_4^{\,2}}{\|R K_t x\| \widehat{k}_4 + \gamma(t)} R K_t x \tag{27}$$

$$K_3(t) = -\frac{1}{2} \widehat{k}_5 R K_t x \tag{28}$$

where ε is any positive constant, and $\gamma(t) \in \mathbb{R}^+$ is a uniformly bounded positive function that satisfies

$$\lim_{t \to \infty} \int_{t_0}^{t} \gamma(\tau) d\tau \leq \overline{\gamma} \leq \infty \tag{29}$$

where $\overline{\gamma}$ is arbitrary positive constant. Besides, $\widehat{k_4}$ and $\widehat{k_5}$ are set as the estimates of k_4 and k_5. And they are also set to satisfy the following law:

$$\frac{\mathrm{d}\widehat{k_4}}{\mathrm{d}t} = -r_4\gamma(t)\widehat{k_4} + 2r_4\|RK_tx\| \tag{30}$$

$$\frac{\mathrm{d}\widehat{k_5}}{\mathrm{d}t} = -r_5\gamma(t)\widehat{k_5} + r_5\|RK_tx\|^2 \tag{31}$$

where r_4 and r_5 are any positive constants. Without loss of generality, let $k_5 = \frac{2}{\lambda_{\min}(R)} - 2\varepsilon$, denote $\widehat{k_4} = k_4 + \widetilde{k_4}$ and $\widehat{k_5} = k_5 + \widetilde{k_5}$, then the error system can be obtained as follows:

$$\frac{\mathrm{d}\widetilde{k_4}}{\mathrm{d}t} = -r_4\gamma(t)\widetilde{k_4} - r_4\gamma(t)k_4 + 2r_4\|RK_tx\| \tag{32}$$

$$\frac{\mathrm{d}\widetilde{k_5}}{\mathrm{d}t} = -r_5\gamma(t)\widetilde{k_5} - r_5\gamma(t)k_5 + 2r_5\|RK_tx\| \tag{33}$$

Then consider the group of x, $\widetilde{k_4}$, $\widetilde{k_5}$. By $\left(x, \widetilde{k_4}, \widetilde{k_5}\right)$, the solutions in Equation (23) can be obtained. Now the final result can be presented as Theorem 3.1.

Theorem 3.1. *Take the adaptive state-feedback system (24) and the actuator structure (23) that contains the error system change law (26)-(28) and (32)-(33) into consideration. Then the relation (34) is satisfied*

$$\lim_{t\to\infty} \|x(t)\| = 0 \tag{34}$$

Proof: Considering the adaptive control system (24), we define a scalar function as

$$V\left(x, \widetilde{k_4}, \widetilde{k_5}\right) = x^TP_tx + \frac{1}{2}r_4^{-1}\widetilde{k_4}^2 + \frac{1}{2}r_5^{-1}\widetilde{k_5}^2 \tag{35}$$

According to Equations (24), (26)-(28) and (32)-(33), the derivative of V for $t > 0$ is

$$\begin{aligned}
&\frac{\mathrm{d}V\left(x, \widetilde{k_4}, \widetilde{k_5}\right)}{\mathrm{d}t} \\
&= 2x^TP_t((Ax + B\rho(K_2 + K_3)) + B(\sigma u_s + F\omega)) + 2x^TP_tB\rho K_1(x) \\
&\quad + r_4^{-1}\widetilde{k_4}\dot{\widetilde{k_4}} + r_5^{-1}\widetilde{k_5}\dot{\widetilde{k_5}} + x^TP_tBG(x) + G^T(x)B^TP_tx \\
&= x^T\left(A^TP_t + P_tA\right)x + 2x^TP_tB\rho(K_2 + K_3) + 2x^TP_tB(\sigma u_s + F\omega) \\
&\quad + 2x^TP_tB\rho K_1(x) + 2x^TP_tBG(x) + r_4^{-1}\widetilde{k_4}\dot{\widetilde{k_4}} + r_5^{-1}\widetilde{k_5}\dot{\widetilde{k_5}}
\end{aligned} \tag{36}$$

Substitute ARE equation into Equation (36)

$$\begin{aligned}
&\frac{\mathrm{d}V\left(x, \widetilde{k_4}, \widetilde{k_5}\right)}{\mathrm{d}t} \\
&= -x^TQx + x^TK_t^TRK_tx + 2x^TP_tB\rho(K_2 + K_3) + 2x^TP_tB(\sigma u_s + F\omega) \\
&\quad + 2x^TP_tB\rho K_1(x) + 2x^TP_tBG(x) + r_4^{-1}k_4\dot{\widetilde{k_4}} + r_5^{-1}k_5\dot{\widetilde{k_5}} \\
&\leq -x^TQx + 2x^TK_t^TRK_tx + 2x^TP_tB\rho(K_2 + K_3) + 2x^TP_tB(\sigma u_s + F\omega) \\
&\quad + 2x^TP_tB\rho K_1(x) + G^T(x)RG(x) + r_4^{-1}\widetilde{k_4}\dot{\widetilde{k_4}} + r_5^{-1}\widetilde{k_5}\dot{\widetilde{k_5}}
\end{aligned} \tag{37}$$

Notice that

$$\begin{aligned}
&-x^TQx + 2x^TK_tRK_tx + 2x^TP_tB\rho K_1(x) \\
&= -x^TQx + 2x^TK_tRK_tx - 2\varepsilon x^TK_t^TR\rho K_tx \\
&\leq -x^TQx + \frac{2}{\lambda_{\min}(R)}\|RK_tx\|^2 - 2\varepsilon\|RK_tx\|^2
\end{aligned}$$

$$\leq -x^T Qx + \left(\frac{2}{\lambda_{\min}(R)} - 2\varepsilon\right) \|RK_t x\|^2$$
$$\leq -x^T Qx + k_5 \|RK_t x\|^2 \tag{38}$$

Then Equation (37) becomes such that

$$\frac{\mathrm{d}V\left(x, \widetilde{k}_4, \widetilde{k}_5\right)}{\mathrm{d}t}$$
$$\leq -x^T Qx + k_5\|RK_t x\|^2 + 2k_4\|RK_t x\| + 2x^T K_t^T R\rho(K_2 + K_3)$$
$$+ r_4^{-1}\widetilde{k}_4\dot{\widetilde{k}}_4 + r_5^{-1}\widetilde{k}_5\dot{\widetilde{k}}_5 + G^T(x)RG(x)$$
$$\leq -x^T Qx + 2h^2\|x\|^2 + k_5\|RK_t x\|^2 + 2k_4\|RK_t x\| - \widehat{k}_4^{\,2}\frac{2\|RK_t x\|^2}{\|RK_t x\|\widehat{k}_4 + \gamma} - \widehat{k}_5\|RK_t x\|^2$$
$$+ 2\widetilde{k}_4\|RK_t x\| + \widetilde{k}_5\|RK_t x\|^2 - \gamma\left(\widetilde{k}_4^{\,2} + \widetilde{k}_4 k_4\right) - \gamma\left(\widetilde{k}_5^{\,2} + \widetilde{k}_5 k_5\right) \tag{39}$$

And notice that

$$2k_4\|RK_t x\| - \widehat{k}_4^{\,2}\frac{2\|RK_t x\|^2}{\|RK_t x\|\widehat{k}_4 + \gamma} + 2\widetilde{k}_4\|RK_t x\| = \widehat{k}_4\frac{2\|RK_t x\|\gamma}{\|RK_t x\|\widehat{k}_4 + \gamma} \leq 2\gamma \tag{40}$$
$$k_5\|RK_t x\|^2 - \widehat{k}_5\|RK_t x\|^2 + \widetilde{k}_5\|RK_t x\|^2 = 0 \tag{41}$$

Then

$$\frac{\mathrm{d}V\left(x, \widetilde{k}_4, \widetilde{k}_5\right)}{\mathrm{d}t} \leq -x^T Qx + 2h^2\|x\|^2 + 2\gamma - \gamma\left(\widetilde{k}_4^{\,2} + \widetilde{k}_4 k_4\right) - \gamma\left(\widetilde{k}_5^{\,2} + \widetilde{k}_5 k_5\right)$$
$$\leq -x^T\left(Q - 2h^2 I\right)x + \iota\gamma \tag{42}$$

where $\iota = \left(8 + k_4^2 + k_5^2\right)/4$. Since $Q - 2h^2 I > 0$ and $\|Q\| > 2h^2$, Equation (42) becomes

$$\frac{\mathrm{d}V\left(x, \widetilde{k}_4, \widetilde{k}_5\right)}{\mathrm{d}t} \leq -\lambda_{\min}\left(Q - 2h^2 I\right)\|x\|^2 + \iota\gamma \tag{43}$$

Integrate Inequality (43) over $[t_0, t]$, we obtain that

$$0 \leq \int_{t_0}^{t} \lambda_{\min}\left(Q - 2h^2 I\right)\|x(\tau)\|^2 d\tau$$
$$\leq V\left(x(t_0), \widetilde{k}_4(t_0), \widetilde{k}_5(t_0)\right) - V\left(x(t), \widetilde{k}_4(t), \widetilde{k}_5(t)\right) + \iota\int_{t_0}^{t}\gamma(\tau)d\tau$$
$$\leq V\left(x(t_0), \widetilde{k}_4(t_0), \widetilde{k}_5(t_0)\right) + \iota\int_{t_0}^{t}\gamma(\tau)d\tau \tag{44}$$

The rest of proof is similar to [7].

The state-feedback gain matrix K_t can be computed using data streams, following the off-policy data-driven approach presented in [10] for linear periodic continuous systems. This approach does not depend on the initial stabilizing controller and enables online learning based on the collected system input and state. Therefore, the control law gain matrix for the linear steady continuous system considered in this paper can be obtained.

4. **Simulation Results.** Consider a carrier-based aircraft landing system without external disturbance

$$\dot{x} = Ax(t) + B\rho u(t) + B\sigma u_s(t) + BG(x) \tag{45}$$

where the values of A and B are shown in [8], $\rho = diag(0.5, 0, 1)$, $\sigma = diag(0, 0, 0)$, and $G(x) = (\sin x_2 - \cos x_4, 0, 0)^T$.

Define $Q = diag(10, 10, 10, 10, 10)$, $R = \begin{cases} I, & t < 15 \\ 0.01 * I, & t \geq 15 \end{cases}$ and $\varepsilon = 1$. Based on the proposed data-driven off-policy method in [10], the matrix K_t can be obtained

$$K_t = \begin{pmatrix} -0.4274 & 231.2449 & -158.8484 & -465.2154 & -2.7451 \\ 0.1779 & -107.0320 & 50.3676 & 188.6997 & 1.3534 \\ 3.0470 & -63.9467 & 7.7677 & 78.4589 & 0.7735 \end{pmatrix} \tag{46}$$

And then the proposed controller (23) can be computed.

Define the fault model as follows. The system is normal before 15 seconds, but it has coupled state vectors at the beginning. After 15 seconds, the 1st actuator shows the loss of efficiency (e.g., 50% reduction in thrust, and 50% decrease in torque), the 2nd actuator is outage, and the 3rd actuator is stuck with time-varying uncertainty.

In order to demonstrate the obvious fault-tolerant and anti-jamming capabilities without loss of generality, the simulation employs the following initial parameters

$$\begin{aligned} &x(0) = [0.7, -1, 0.8, 1.2, 1.3]^T, \quad \widehat{k}_4(0) = 1.45, \quad \widehat{k}_5(0) = 0.90, \\ &\gamma(t) = 0.02, \quad r_4 = r_5 = 20 \end{aligned} \tag{47}$$

The controller parameters $\widehat{k}_4$, $\widehat{k}_5$ are shown in Figure 1 and the state trajectories of system (45) can be observed in Figure 2.

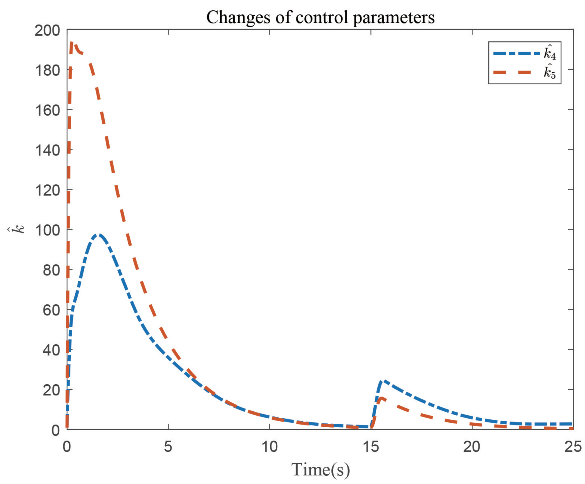

FIGURE 1. Changes of the controller parameters $\widehat{k}_4$ and $\widehat{k}_5$

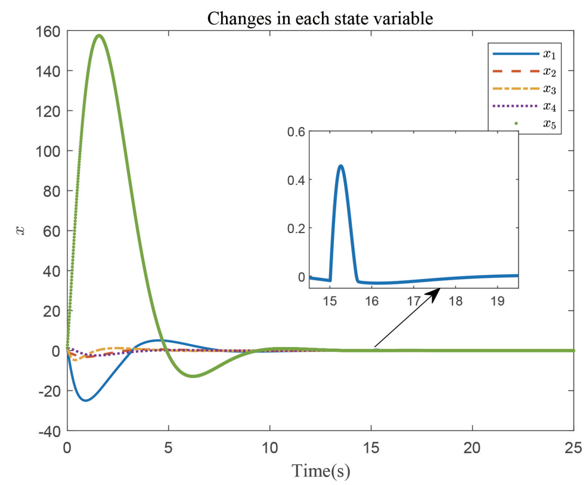

FIGURE 2. State responses under the actuator failures and disturbances

Figure 1 and Figure 2 illustrate that $\widehat{k_4}$ and $\widehat{k_5}$ remain uniformly bounded, and the adaptive control strategy can suppress the unknown disturbance before 15 seconds. After the actuator failure occurs at 15 seconds, the fault-tolerant controller can be activated and the states converge to zero quickly despite under the actuator faults and uncertain disturbances. The effectiveness of the proposed policy is demonstrated in the example.

5. **Conclusions.** This paper proposes an adaptive fault-tolerant control scheme for aircraft systems with coupled state variables, time-varying disturbances, and actuator faults based on off-policy learning. The scheme is designed to be robust and fault-tolerant for general actuator fault models. We derive the system's state equation and prove that the uncertain system is uniformly bounded with states that converge asymptotically to zero. The proposed strategy can effectively control a carrier-based aircraft in final approach under actuator failures and disturbances. It is expected to be extended and applied to nonlinear systems in order to achieve a broader range of applications.

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REFERENCES

[1] S. Chen and D. W. Ho, Sampled-data approach to state estimation performance for heterogeneous distributed system with fault, *Asian Journal of Control*, vol.17, no.5, pp.1498-1508, 2015.
[2] Q. Y. Fan, Y. Sun and B. Xu, Improved data-driven control design based on LMI and its applications in Lithium-Ion batteries, *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol.70, no.12, pp.4504-4508, 2023.
[3] Y. Sun, Q. Y. Fan, H. Li and H. Ren, Data-driven fault-tolerant control for discrete-time systems based on LMI, *IFAC-PapersOnLine*, vol.55, no.3, pp.160-165, 2022.
[4] S. Ijaz, C. Fuyang, M. T. Hamayun and H. Anwaar, Adaptive integral-sliding-mode control strategy for maneuvering control of F16 aircraft subject to aerodynamic uncertainty, *Applied Mathematics and Computation*, vol.402, 126053, 2021.
[5] W. Zhao, H. Liu and F. L. Lewis, Data-driven fault-tolerant control for attitude synchronization of nonlinear quadrotors, *IEEE Transactions on Automatic Control*, vol.66, no.11, pp.5584-5591, 2021.
[6] L. Gong, Q. Wang, C. Hu and C. Liu, Switching control of morphing aircraft based on Q-learning, *Chinese Journal of Aeronautics*, vol.33, no.2, pp.672-687, 2020.
[7] X. J. Li and G. H. Yang, Robust adaptive fault-tolerant control for uncertain linear systems with actuator failures, *IET Control Theory & Applications*, vol.6, no.10, pp.1544-1551, 2012.
[8] G. Xia, R. Dong, J. Xu and Q. Zhu, Linearized model of carrier-based aircraft dynamics in final-approach air condition, *Journal of Aircraft*, vol.53, no.1, pp.33-47, 2016.
[9] Y. X. Li and G. H. Yang, Robust fuzzy adaptive fault-tolerant control for a class of nonlinear systems with mismatched uncertainties and actuator faults, *Nonlinear Dynamics*, vol.81, nos.1-2, pp.395-409, 2015.
[10] B. Pang and Z. P. Jiang, Adaptive optimal control of linear periodic systems: An off-policy value iteration approach, *IEEE Transactions on Automatic Control*, vol.66, no.2, pp.888-894, 2020.
[11] J. K. K. Asamoah, E. Okyere, A. Abidemi et al., Optimal control and comprehensive cost-effectiveness analysis for COVID-19, *Results in Physics*, vol.33, 105177, 2022.