

Article

Novel Predefined Performance Control of Robotic Manipulators with FDI Attacks and Actuator Faults

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Abstract

Based on a fixed-time extended state observer (FESO), this paper proposes a novel predefined performance control (PPC) method for robotic manipulators with false data injection (FDI) attacks and actuator faults. First, a mathematical model of robotic manipulators with parameter uncertainties and external disturbances is constructed. Then, to compensate for the FDI attacks and actuator faults, an extended state is introduced such that the FESO is designed. Moreover, to avoid the transformation from nonlinear constraints to unconstrained variables in PPC, the barrier Lyapunov function (BLF) is introduced. By adopting the novel PPC, tracking errors of the robotic manipulators are driven into a predefined region. Finally, simulations on a two-degree-of-freedom manipulator demonstrate that, compared with FTESO-based sliding mode control, the proposed method has shorter settling times and better tracking accuracy.

Keywords: manipulators; robot control; fault tolerant control; cyberattack; sliding mode control

1. Introduction

With the development of intelligent manufacturing systems, robotic manipulators have been widely used in complex and dangerous industries, spacecraft manipulators, industrial welding robots, shipboard manipulators and medical puncture due to their high accuracy, flexibility and ability [1]. At present, robotic manipulators are often expected to execute tasks with high control performance demands. However, robotic manipulators may be subject to external disturbances, which bring degradation and even lead to instability of the system [2]. To deal with these problems, many control methods such as torque control [3], adaptive control [4] and sliding mode control [5] have been proposed. As the tasks of robots become more and more complex, requirements on flexibility, robustness, and accuracy of robotic manipulators are being proposed, such as in [6]. Therefore, designing new control methods is essential.

Recently, an increasing number of systems are run through networks. However, due to the introduction of open communication networks, robotic manipulators may be subject to cyberattacks, which may destroy the integrity and availability of the data. For robotic manipulators, communication through networks is important to guarantee coordination and reliable control. However, the networks are vulnerable to various cyber-attacks such as replay attacks, FDI attacks, and denial-of-service attacks, which may affect system stability and even lead to faults. Among these, FDI attacks, which may destroy the integrity and availability of the data, have attracted much attention from researchers [7,8]. To



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compensate for FDI attacks, an adaptive sliding mode control of robotic manipulator systems is considered in [9]. In [10], an extended observer is designed to compensate for the cyberattack and terminal integral SMC is employed to realize tracking of the networked control systems. As the dynamics of FDI attacks are often unknown or unpredictable, a novel adaptive fixed-time estimator-based defense method is designed to eliminate the negative effects induced by FDI attacks in [11]. In [12], a novel super-twisting nonsingular terminal sliding mode control (NTSMC) is proposed for cyber-physical systems under false data injection (FDI) attacks. In [13], a collaborative control method integrating the AETM and the observer-based sliding mode control is proposed to utilize the robustness of sliding mode control to enhance the security and reliability of the NDSSs.

In mechanical control systems, for instance, lumped disturbance torques arising from unmodeled dynamics, external wind gusts and parameter variations generally exert direct influences on the system states [14]. Under such mismatched conditions, the sliding motion characteristic inherent in traditional SMC is severely compromised, which consequently reduces its most salient feature [15]. To overcome this issue, recent studies have discussed disturbance observer-based SMC strategies, with the objective of attenuating the effects of mismatched disturbances while preserving nominal control performance [16]. To further improve the control performance of manipulators, some control methods such as neural network control [17], extended state observer-based control [18] and disturbance-observer-based control [19] have been proposed. In [20], to overcome the free-floating dynamics and fuel constraints in space manipulators, a tracking method combining time-delay estimation with adaptive fuzzy integral sliding mode control is proposed. Later, to compensate for the system uncertainties, a second-order non-singular fast terminal sliding mode controller is proposed in [21]. To further improve the robustness of the robotic manipulators, a nonlinear disturbance observer-based sliding mode control method is proposed in [22]. To significantly enhance convergence and response speeds, several scholars have developed fast fixed-time control strategies. These innovative algorithms are capable of achieving faster convergence rates under identical controller parameters, thereby minimizing the system's settling time [23]. In [24], a fixed-time extended state observer is designed to address modeling errors and unknown external disturbances in the robotic arm system. Considering the impact of actuator faults on tracking performance, a fixed-time controller is introduced for manipulators, characterized by faster response to reduce tracking errors, minimize chattering and enhance robustness in [25]. Additionally, an innovative fixed-time adaptive fault-tolerant backstepping control strategy by integrating the barrier Lyapunov function and neural networks is proposed in [26]. It is worth noting that the previous results are focused on stability and steady-state performance, while transient performance, such as a predefined convergence rate, is rarely considered.

Although these methods improve steady-state accuracy, they cannot guarantee transient performance such as a predefined convergence rate and overshoot limits in nonlinear systems. To solve this problem, PPC is introduced. It is noted that, by this method, the tracking error is driven into a predefined region. Moreover, the convergence rate is faster than the predefined value. In PPC, the performance function is the main issue since it defines the constraints of the tracking errors for which the predefined performance is satisfied. In [27], a hyperbolic tangent function is designed as the transformation function, but the design of the controller is complex. To overcome this difficulty, BLF is introduced in the controller design of PPC. In [7], based on logarithmic-type BLF, tracking control of wheeled mobile manipulators is researched. In [8], an integral nonsingular fast terminal sliding mode control approach is introduced for robotic manipulator systems experiencing uncertainties and external disturbances. In [28], an adaptive backstepping PPC with tangent-type BLF is proposed for a 3-DOF PUMA 560 manipulator such that the tracking

errors are driven into a predefined bound in the presence of actuator faults. However, the controller design is complex. In [29], to realize tracking of robotic manipulators under actuator faults within a predefined region, a nonfragile PPC method is proposed. In [30], a novel global fixed-time sliding mode control strategy (FTSMC) is proposed for trajectory tracking control of robotic manipulators subject to internal uncertainties and external disturbances. In [31], for a 3-DOF serial manipulator under external disturbances, a PPC mechanism is further embedded into the controller to constrain the tracking errors. In [32], based on the adaptive neural network, a novel fixed-time non-singular SMC is proposed to guarantee that the tracking errors are driven into a small region of the origin in a fixed time. In [33], a fixed-time tracking control algorithm is proposed for uncertain robotic systems with prescribed performance and input saturation constraints.

It is worth noting that many constructive results on PPC have been proposed. However, there is little work on robotic manipulators with FDI attacks and actuator faults. Moreover, the existing results on PPC cannot be directly extended to systems subject to actuator faults, external disturbances and FDI attacks simultaneously. Motivated by the discussion above, this paper proposes a novel PPC method for robotic manipulators. The contribution of this work is specified as follows:

- (i) To estimate the disturbances, FDI attacks and actuator faults, FESO is introduced. Compared with the adaptive observer in [11], the proposed FESO realizes fixed-time control of the system.
- (ii) BLF is adopted such that the tracking errors are driven into the predefined region despite the presence of FDI attacks and actuator faults. Moreover, the proposed method simplifies the controller design.

2. Problem Statements

Considering the external disturbances, FDI attacks and actuator faults, the mathematical model of the n -link robotic manipulators is described as

$$\begin{aligned} M(q(t))\ddot{q}(t) + C(q(t), \dot{q}(t))\dot{q}(t) + G(q(t)) + F(q(t), \dot{q}(t)) \\ = \tau(t) + \tau_d(t) + d(t), \end{aligned} \quad (1)$$

where $q(t)$, $\dot{q}(t)$, $\ddot{q}(t)$ are joint positions, velocities and accelerations, $M(q(t))$ is the inertia matrix, $C(q(t), \dot{q}(t))$ is the Coriolis-centrifugal matrix, $G(q(t))$ is the gravity matrix, $\tau(t)$ is the torque input to be designed, $\tau_d(t)$ is the external disturbances and $d(t)$ denotes the FDI attacks.

Considering the model errors and parameter uncertainties, the uncertainties of the system are described as

$$\begin{aligned} M(q(t)) &= M_0(q(t)) + \Delta M(q(t)), \\ C(q(t), \dot{q}(t)) &= C_0(q(t), \dot{q}(t)) + \Delta C(q(t), \dot{q}(t)), \\ G(q(t)) &= G_0(q(t)) + \Delta G(q(t)), \end{aligned} \quad (2)$$

where $M_0(q(t))$, $C_0(q(t), \dot{q}(t))$, $G_0(q(t))$ are the nominal terms, $\Delta M(q(t))$, $\Delta C(q(t), \dot{q}(t))$ and $\Delta G(q(t))$ are the uncertainties.

Considering the actuator faults, the torque under faults is described as [16]

$$\tau(t) = \tau_u(t) + \theta_a(t - T_f)\phi(q, \dot{q}, \tau) = \tau_u(t) + \tau_a(t), \quad (3)$$

where $\tau_u(t)$ is nominal actuator input signal, $\tau_a(t)$ is actuator faults, $\phi(q(t), \dot{q}(t), \tau(t))$ is a nonlinear function of link displacement, velocity and actuator faults, T_f is the time instant that actuator faults occurs and $\theta_a(t - T_f)$ is the faults function described as

$$\theta_a(t - T_f) = \text{diag}\{\theta_{a1}(t - T_f), \dots, \theta_{ai}(t - T_f), \dots, \theta_{an}(t - T_f)\}, \quad (4)$$

where θ_{ai} satisfies

$$\theta_{ai}(t - T_f) = \begin{cases} 1 - e^{-l_{ti}(t - T_f)}, & t \geq T_f, \\ 0, & t \leq T_f, \end{cases} \quad (5)$$

with $i = 1, 2, \dots, n$ and $l_{ti} > 0$.

In this paper, the FDI attacks are described as

$$d(t) = \begin{cases} \Delta(t)\Theta(q, \dot{q}, t), & t \in [\omega, \bar{\omega}], \\ 0, & t \notin [\omega, \bar{\omega}], \end{cases} \quad (6)$$

where $\Delta(t)\Theta(q(t), \dot{q}(t), t)$ is the position and velocity hijacked by the malicious attacker that occurs in the interval $t \in [\omega, \bar{\omega}]$.

Combining (2)–(6), system (1) is rewritten as

$$M_0(q(t))\ddot{q}(t) + C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t)) = \tau_u(t) + g_d(t), \quad (7)$$

where

$$g_d(t) = \tau_a(t) + \tau_d(t) + d(t) - \Delta M(q(t))\ddot{q}(t) - \Delta C(q(t) - \dot{q}(t))\dot{q}(t) - \Delta G(q(t)) - F(q(t), \dot{q}(t)). \quad (8)$$

Considering system (7), one has

$$\ddot{q}(t) = M_0^{-1}\tau(t) - M_0^{-1}(C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t))) + g(t), \quad (9)$$

where $g(t) = M_0^{-1}g_d(t)$ denotes the parameter uncertainties, external disturbances, FDI attacks and actuator faults. Thus, the robotic manipulators (7) become

$$\begin{aligned} \ddot{\Omega} &= \omega \\ \dot{\omega} &= M_0^{-1}\tau(t) - M_0^{-1}(C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t))) + g(t), \end{aligned} \quad (10)$$

where $\Omega = [q_1, q_2, \dots, q_n]^T$ is the angle and $\omega = [\dot{q}_1, \dot{q}_2, \dots, \dot{q}_n]^T$ is the angular rate.

The control objective of this paper is to design a predefined performance controller such that tracking of the robotic manipulators (10) is realized.

For convenience of later analysis, the following assumptions and lemmas are proposed.

Assumption 1 ([7]). The inertia matrix $M(q) \in \mathbb{R}^{n \times n}$ is symmetric and positive, and the Coriolis and centrifugal matrix $C(q, \dot{q})$ satisfies that $\dot{M}(q) - 2C(q, \dot{q})$ is skew-symmetric.

Assumption 2 ([7]). The desired trajectory $q_d(t)$ and its time derivatives $\dot{q}_d(t)$, $\ddot{q}_d(t)$ are smooth and bounded.

Assumption 3 ([7]). The model nominal terms $M_0(q(t))$, $C_0(q(t), \dot{q}(t))$, $G_0(q(t))$ are bounded and satisfy

$$\begin{aligned}\|M(q(t))\| &\leq M_m, \\ \|C(q(t), \dot{q}(t))\| &\leq C_m \|\dot{q}(t)\|, \\ \|G(q(t))\| &\leq G_m,\end{aligned}\quad (11)$$

where $M_m > 0$, $C_m > 0$ and $G_m > 0$ are positive scalars.

Assumption 4 ([8]). The FDI attacks $d(t)$ are bounded and satisfy

$$\|\Delta(t)\| \leq \lambda_1, \quad \|\Theta(q, \dot{q}, t)\| \leq \psi(q, \dot{q}, t), \quad (12)$$

where λ_1 is a positive constant and $\psi(q, \dot{q}, t)$ is a positive function.

Assumption 5 ([33]). The FDI attacks $d(t)$ satisfy

$$\|\dot{d}(t)\| \leq \lambda_2, \quad (13)$$

where λ_2 is an unknown positive constant.

Lemma 1 ([34]). For any $X \in \mathbb{R}^3$, $y > 0$, if $|x| < y$, then holds

$$\ln \left[\frac{y^2}{(y^2 - x^2)} \right] \leq \frac{x^2}{y^2 - x^2}. \quad (14)$$

Lemma 2 ([35]). For robotic manipulators (1), if there is a positive Lyapunov function $V(x)$ satisfying

$$\dot{V}(x) + d(V(x))^\theta \leq 0, \quad (15)$$

where $d > 0$ and $\theta \in (0, 1)$, then the predefined time T satisfies

$$T \leq \frac{1}{d(1-\theta)} (V(x))^{(1-\theta)}. \quad (16)$$

3. Controller Design Based on FESO and PPC

In this section, tracking of the manipulator system is achieved by the novel PPC. To compensate for the system uncertainties, the FESO is introduced. Based on the FESO, the stability of the error systems is analyzed. Moreover, by employing the BLE, tracking of the system (1) is realized with the predefined performance controller.

3.1. FESO Design

In practice, the bounds of the FDI attacks are usually unknown. To compensate FDI attacks, an extended state $[x_1(t) \ x_2(t)]^T$ is introduced. Considering the extended state

$$\begin{aligned}x_1(t) &= \dot{q}(t), \\ x_2(t) &= g(t) - M_0^{-1}(C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t))) = F_\omega,\end{aligned}\quad (17)$$

the robotic manipulator is written as

$$\begin{aligned}\dot{x}_1(t) &= M_0^{-1}\tau(t) + x_2(t), \\ \dot{x}_2(t) &= \dot{F}_\omega,\end{aligned}\quad (18)$$

where $\|\dot{F}_\omega\| < H$ with H being a positive constant.

To estimate the velocity x_1 and the lumped disturbance x_2 , the observer variables z_1 and z_2 are introduced. We defined the observation error as $e_1 = z_1 - x_1$. Thus, the FESO is designed as

$$\begin{aligned}\dot{z}_1 &= z_2 - \lambda_1 \text{sig}^a(e_1) - k_1 \text{sig}^b(e_1) + M_0^{-1} \tau(t), \\ \dot{z}_2 &= -\lambda_2 \text{sig}^{2a-1}(e_1) - k_2 \text{sig}^{2b-1}(e_1) + K \text{sgn}(e_1),\end{aligned}\quad (19)$$

where $\text{sig}^a(e_1) = \text{sgn}(e_1) \cdot |e_1|^a$, a and b are positive scalars that satisfying $0.5 < a < 1$ and $b > 1$.

Remark 1. It is shown from (19) that the convergence of the error system relies on the control parameters λ_1 , λ_2 , k_1 , k_2 , K and the nonlinear exponent parameters a_1 , a_2 , b_1 , b_2 . Therefore, by selecting the parameters appropriately, the chattering phenomenon is compensated for.

Define $e_2 = z_2 - x_2$. Combining (17)–(19), the error system is obtained as follows:

$$\begin{aligned}\dot{e}_1 &= e_2 - \lambda_1 \text{sig}^a(e_1) - k_1 \text{sig}^b(e_1), \\ \dot{e}_2 &= -\lambda_2 \text{sig}^{2a-1}(e_1) - k_2 \text{sig}^{2b-1}(e_1) + K \text{sgn}(e_1) - \dot{F}_w.\end{aligned}\quad (20)$$

Next, the fixed-time convergence of the observation error system (20) is analyzed. The main result is presented in the following theorem.

Theorem 1. Considering the system (1) with FESO (19), if there exists positive matrix $Q_1 > 0$, $Q_2 > 0$, $P_1 > 0$ and $P_2 > 0$ satisfying the following Linear Matrix Inequalities (LMIs)

$$\begin{aligned}P_1 A_1 + A_1^T P_1 &= -Q_1, \\ P_2 A_2 + A_2^T P_2 &= -Q_2,\end{aligned}\quad (21)$$

where

$$A_1 = \begin{bmatrix} -\lambda_1 & 1 \\ -\lambda_2 & 0 \end{bmatrix}, \quad A_2 = \begin{bmatrix} -k_1 & 1 \\ -k_2 & 0 \end{bmatrix}.\quad (22)$$

Then, the error system (20) converges to the region within a fixed time $T = T_1 + T_2$.

Proof. Considering (20), the first error system is

$$\begin{aligned}\dot{e}_1 &= e_2 - \lambda_1 \text{sig}^{a_1}(e_1) - k_1 \text{sig}^{b_1}(e_1), \\ \dot{e}_2 &= -\lambda_2 \text{sig}^{a_2}(e_1) - k_2 \text{sig}^{b_2}(e_1).\end{aligned}\quad (23)$$

Define $e = [e_1, e_2]^T$. There are positive matrix Q_1 , Q_2 , P_1 and P_2 such that

$$\begin{aligned}P_1 A_1 + A_1^T P_1 &= -Q_1, \\ P_2 A_2 + A_2^T P_2 &= -Q_2.\end{aligned}\quad (24)$$

Choose the Lyapunov function as

$$V_i(e(t)) = e^T P_i e, \quad (25)$$

In view of (21) and (22), one has

$$\begin{aligned}\dot{V}_1(t) &= \dot{e}^T P_1 e + e^T P_1 \dot{e} \\ &= (A_1 \text{sig}^a(e_1))^T P_1 e + e^T P_1 (A_1 \text{sig}^a(e_1)) \\ &= \text{sig}^a(e_1) e^T (A_1^T P_1 + P_1 A_1) e \\ &= -\text{sig}^a(e_1) e^T Q_1 e.\end{aligned}\quad (26)$$

Similarly, it is obtained that

$$\begin{aligned}
 \dot{V}_2(t) &= \dot{e}^T P_2 e + e^T P_2 \dot{e} \\
 &= \left(A_2 \operatorname{sig}^b(e_2) \right)^T P_2 e + e^T P_2 \left(A_2 \operatorname{sig}^b(e_2) \right) \\
 &= \operatorname{sig}^b(e_2) e^T \left(A_2^T P_2 + P_2 A_2 \right) e \\
 &= -\operatorname{sig}^b(e_2) e^T Q_2 e,
 \end{aligned} \tag{27}$$

where $\lambda_{\min}(Q_i) > 0$ and $\lambda_{\max}(A_i) > 0$ are the minimum eigenvalue and maximum eigenvalue of the matrices Q_i and A_i .

According to Lemma 2, the tracking errors are driven into the region within a fixed time

$$T_1 \leq \frac{(\lambda_{\max}(A_1))^{\vartheta}}{(\gamma_1)^{\vartheta}} + \frac{1}{(\gamma_2)^{\vartheta}(\Delta)^{\vartheta}}, \tag{28}$$

where $\gamma_1 = \frac{\lambda_{\min}(Q_1)}{\lambda_{\max}(A_1)}$, $\gamma_2 = \frac{\lambda_{\min}(Q_2)}{\lambda_{\max}(A_2)}$, $\vartheta = 1 - a$, $\sigma = b - 1$ and $\Delta \leq \lambda_{\min}(A_2)$ are positive constant.

Considering the error system (20), the second error system is

$$\dot{e}_2 = K \operatorname{sgn}(e_1) - \dot{F}_\omega = 0, \quad t \geq T_1, \tag{29}$$

where $\operatorname{sgn}(e_1) = -\operatorname{sgn}(e_2)$.

By choosing the Lyapunov function

$$V(t) = \frac{1}{2} e_2^T e_2, \tag{30}$$

one has

$$\begin{aligned}
 \dot{V}(t) &= e_2^T \dot{e}_2 \\
 &= -K e_2^T \operatorname{sgn}(e_2) - e_2^T \dot{F}_\omega \\
 &\leq -(K - H) \|e_2\| \\
 &= -\sqrt{2}(K - H)(V(t))^{\frac{1}{2}}.
 \end{aligned} \tag{31}$$

Thus, it is obtained from (31) that

$$T_2 \leq \frac{\varepsilon}{K - H}, \tag{32}$$

where ε is a positive parameter. Moreover, the convergence time of the FESO satisfies

$$T = T_1 + T_2, \tag{33}$$

which completes the proof. $\square$

Remark 2. It is noted that the first error system (23) converges within the fixed time T_1 , while the second error system (29) converges within the fixed time T_2 . According to the superposition principle, the convergence time of the fixed-time extended state observer (FESO) is obtained as $T = T_1 + T_2$.

3.2. FESO-Based Predefined Performance Controller Design

To realize tracking of the error system (20) within a predefined bound, a BLF is introduced in PPC. Compared with the conventional PPC, the proposed method not only avoids the singularity phenomenon but also simplifies the controller.

Theorem 2. *Considering the system (1) with the predefined performance (34), the controller (44) guarantees the tracking of the system (1) within a predefined region.*

Proof. The predefined performance function is defined as

$$\rho_i = (\rho_{i0} - \rho_{i\infty})e^{-l_{it}} + \rho_{i\infty}, \quad (34)$$

where ρ_{i0} , $\rho_{i\infty}$ and l_{it} are the initial bound, ultimate bound and boundary decay rate, respectively.

Define $\Omega_e = \Omega - \Omega_d$, where Ω_d is a desired angle. To realize the predefined tracking performance $\|\Omega_e\| < \rho_1$, the following BLF is introduced

$$V_1 = \frac{1}{2} \ln \frac{\rho_1^2}{\rho_1^2 - \Omega_e^T \Omega_e}. \quad (35)$$

Considering (35), one has

$$\begin{aligned} \dot{V}_1 &= \frac{1}{2} \frac{\rho_1^2 - \Omega_e^T \Omega_e}{\rho_1^2} \frac{2\rho_1\dot{\rho}_1(\rho_1^2 - \Omega_e^T \Omega_e) - \rho_1^2(2\rho_1\dot{\rho}_1 - 2\Omega_e^T \dot{\Omega}_e)}{(\rho_1^2 - \Omega_e^T \Omega_e)^2} \\ &= \frac{-\dot{\rho}_1\Omega_e^T \Omega_e + \rho_1\Omega_e^T \dot{\Omega}_e}{\rho_1(\rho_1^2 - \Omega_e^T \Omega_e)}. \end{aligned} \quad (36)$$

Considering (10) and (36), one further has

$$\begin{aligned} \dot{V}_1 &= \frac{1}{\rho_1^2 - \Omega_e^T \Omega_e} \left(-\frac{\dot{\rho}_1}{\rho_1} \Omega_e^T \Omega_e + \Omega_e^T (\dot{\Omega} - \dot{\Omega}_d) \right) \\ &= \frac{1}{\rho_1^2 - \Omega_e^T \Omega_e} \left(-\frac{\dot{\rho}_1}{\rho_1} \Omega_e^T \Omega_e + \Omega_e^T (\omega - \dot{\Omega}_d) \right). \end{aligned} \quad (37)$$

The virtual control ω_d is designed as

$$\omega_d = \dot{\Omega}_d + \frac{\dot{\rho}_1}{\rho_1} \Omega_e - K_1 \Omega_e. \quad (38)$$

The tracking error ω_e is

$$\omega_e = \omega - \omega_d, \quad (39)$$

where ω_d is the desired angular rate.

To guarantee $\|\omega_e\| < \rho_2$, the BLF is designed as

$$V_2 = V_1 + \frac{1}{2} \ln \frac{\rho_2^2}{\rho_2^2 - \omega_e^T \omega_e}. \quad (40)$$

Considering (40), one has

$$\begin{aligned} \dot{V}_2 &= \dot{V}_1 + \frac{1}{2} \frac{\rho_2^2 - \omega_e^T \omega_e}{\rho_2^2} \frac{2\rho_2\dot{\rho}_2(\rho_2^2 - \omega_e^T \omega_e) - \rho_2^2(2\rho_2\dot{\rho}_2 - 2\omega_e^T \dot{\omega}_e)}{(\rho_2^2 - \omega_e^T \omega_e)^2} \\ &= \dot{V}_1 + \frac{-\dot{\rho}_2\omega_e^T \omega_e + \rho_2\omega_e^T \dot{\omega}_e}{\rho_2(\rho_2^2 - \omega_e^T \omega_e)}. \end{aligned} \quad (41)$$

In view of (10), one further has

$$\begin{aligned}\dot{\omega}_e &= \dot{\omega} - \dot{\omega}_d \\ &= M_0^{-1}\tau(t) - M_0^{-1}(C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t))) + g(t) - \dot{\omega}_d.\end{aligned}\quad (42)$$

Combining (41) and (42), there holds

$$\begin{aligned}\dot{V}_2 &= \dot{V}_1 + \frac{1}{\rho_2^2 - \omega_e^T \omega_e} \left(-\frac{\dot{\rho}_2}{\rho_2} \omega_e^T \omega_e \right) + \frac{1}{\rho_2^2 - \omega_e^T \omega_e} \left(\omega_e^T \dot{\omega}_e \right) \\ &= -\frac{K_1 \Omega_e^T \Omega_e}{\rho_1^2 - \Omega_e^T \Omega_e} + \frac{1}{\rho_2^2 - \omega_e^T \omega_e} \left(-\frac{\dot{\rho}_2}{\rho_2} \omega_e^T \omega_e \right) + \frac{1}{\rho_2^2 - \omega_e^T \omega_e} \left(\omega_e^T M_0^{-1} \tau(t) \right) \\ &\quad + \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e} \left(-M_0^{-1} (C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t))) \right) + \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e} (g(t) - \dot{\omega}_d) \\ &= -\frac{K_1 \Omega_e^T \Omega_e}{\rho_1^2 - \Omega_e^T \Omega_e} + \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e} \left(-\frac{\dot{\rho}_2}{\rho_2} \omega_e + M_0^{-1} \tau(t) \right) \\ &\quad + \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e} \left(-M_0^{-1} (C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t))) \right) \\ &\quad + \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e} \left(g(t) - \dot{\omega}_d + \frac{1}{2} \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e} \right) - \frac{1}{2} \frac{1}{\rho_2^2 - \omega_e^T \omega_e} \omega_e^T \omega_e.\end{aligned}\quad (43)$$

With the fixed time T , the output z_2 is stable. Therefore, the controller is designed as

$$\begin{aligned}\tau(t) &= M_0 \left(-K_2 \omega_e + \frac{\dot{\rho}_2}{\rho_2} \omega_e - z_2 + \dot{\omega}_d \right) \\ &\quad + C_0(q(t), \dot{q}(t))\dot{q}(t) + G_0(q(t)) - \frac{1}{2} M_0 \frac{\omega_e^T}{\rho_2^2 - \omega_e^T \omega_e},\end{aligned}\quad (44)$$

where $K_2 = \text{diag}(k_{21}, k_{22}, \dots, k_{2n})$.

Combining (43) with (44), it is obtained that

$$\dot{V}_2 = -\frac{K_1 \Omega_e^T \Omega_e}{\rho_1^2 - \Omega_e^T \Omega_e} - \frac{K_2 \omega_e^T \omega_e}{\rho_2^2 - \omega_e^T \omega_e} + \frac{\omega_e^T e_2}{\rho_2^2 - \omega_e^T \omega_e} - \frac{1}{2} \frac{\omega_e^T}{(\rho_2^2 - \omega_e^T \omega_e)^2}.\quad (45)$$

Considering

$$\frac{\omega_e^T e_2}{\rho_2^2 - \omega_e^T \omega_e} \leq \frac{1}{2} \frac{\omega_e^T \omega_e}{(\rho_2^2 - \omega_e^T \omega_e)^2} + \frac{1}{2} e_2^T e_2,\quad (46)$$

one has

$$\dot{V}_2 \leq -\frac{k_1 \Omega_e^T \Omega_e}{\rho_1^2 - \Omega_e^T \Omega_e} - \frac{k_2 \omega_e^T \omega_e}{\rho_2^2 - \omega_e^T \omega_e} + \frac{1}{2} e_2^T e_2,\quad (47)$$

where $k_i = \min\{k_{ij}, j = 1, 2, 3, i = 1, 2\}$.

Considering $e_2^T e_2 \geq \|e_2\|^2$ and (47), one has

$$\dot{V}_2 \leq -\frac{k_1 \Omega_e^T \Omega_e}{\rho_1^2 - \Omega_e^T \Omega_e} - \frac{k_2 \omega_e^T \omega_e}{\rho_2^2 - \omega_e^T \omega_e} + \frac{1}{2} \|e_2\|^2.\quad (48)$$

In view of Theorem 1, the error system converges to the region ε , so $\frac{1}{2} \|e_2\|^2 \leq \xi$, with $\xi > 0$ being a positive constant. Thus, it is obtained from (48) that

$$\dot{V}_2 \leq -\frac{k_1 \Omega_e^T \Omega_e}{\rho_1^2 - \Omega_e^T \Omega_e} - \frac{k_2 \omega_e^T \omega_e}{\rho_2^2 - \omega_e^T \omega_e} + \xi.\quad (49)$$

In view of Lemma 1, it follows that

$$\begin{aligned}\dot{V}_2 &\leq -k_1 \ln \frac{\rho_1^2}{\rho_1^2 - \Omega_e^T \Omega_e} - k_2 \ln \frac{\rho_2^2}{\rho_2^2 - \omega_e^T \omega_e} + \xi \\ &\leq -kV_2 + \xi,\end{aligned}\quad (50)$$

where $k = \min\{2k_i, i = 1, 2\}$.

Considering (50), one has

$$V_2(t) \leq e^{-kt} V_2(0) + \frac{\xi}{k} (1 - e^{-kt}). \quad (51)$$

Thus, it's obtained from (51) that

$$\limsup_{t \rightarrow \infty} V_2(t) \leq \frac{\xi}{k}. \quad (52)$$

From the above analysis, it is obtained that

$$\begin{aligned}\limsup_{t \rightarrow \infty} \|\Omega_e\| &\leq \rho_{1\infty} \sqrt{1 - e^{-\frac{2\xi}{k}}}, \\ \limsup_{t \rightarrow \infty} \|\omega_e\| &\leq \rho_{2\infty} \sqrt{1 - e^{-\frac{2\xi}{k}}}.\end{aligned}\quad (53)$$

which completes the proof. $\square$

Remark 3. It is shown from (50) and (53) that the controller (44) guarantees tracking, satisfying the predefined performance. The tracking errors are determined by the parameters ρ_1 and ρ_2 . Moreover, with the proposed PPC, the chattering and singularity phenomena are avoided.

4. Simulations

In the following part, the 2-DoF robotic manipulator is considered in simulation. The referenced trajectory is $q_d(t) = [\sin(3t) \ \sin(3t)]^T$. The initial state is assumed to be $q_0 = [0.50 \ 0.7]^T$. The parameters of the robot manipulator are shown in Table 1.

Table 1. Parameters of the 2-link manipulators.

Symbol	Definition 2	Value
m_1^0	nominal mass of link 1	0.4 kg
m_2^0	nominal mass of link 2	1.2 kg
m_1	mass of link 1	0.5 kg
m_2	mass of link 2	1.5 kg
l_1	length of link 1	1 m
l_2	length of link 2	0.85 m
I_1	moment of inertia of link 1	5 kg·m ²
I_2	moment of inertia of link 2	5 kg·m ²
g	gravitational constant	9.81 m/s ²

The FDI attacks are supposed to be

$$\Delta(t)\Theta(q, \dot{q}(t), t(t)) = \begin{bmatrix} 2 \sin(t) + 0.5 \sin(100\pi t) \\ \cos(2t) + 0.5 \sin(100\pi t) \end{bmatrix}. \quad (54)$$

The parameters of the actuator faults are supposed to be $l_{t1} = l_{t2} = 50$, and the actuator faults satisfy

$$\Phi = \begin{cases} -0.4\tau_1, t \geq 4, \\ -0.5\tau_2, t \geq 5. \end{cases} \quad (55)$$

The predefined performance function is

$$\rho_i = (0.5 - 0.01)^{e^{-3}} + 0.01. \quad (56)$$

The control parameters of EESQ are $\lambda = 1.4$, $a = 18$, $b = 12$, and control gains are solved as $K_1 = \text{diag}(1, 1)$, $K_2 = \text{diag}(5, 5)$. To demonstrate the effectiveness of the proposed FESO, a comparison between the finite-time extended state observer (FTESO) and the FESO is given. The simulation results are shown in Figures 1–3. It is shown from Figures 1 and 2 that the angle and velocity of the robotic manipulator achieve tracking of the system. It is shown in Figure 3 that the angle and velocity tracking errors converge to the predefined region. Moreover, FESO with PPC has a better convergence rate.

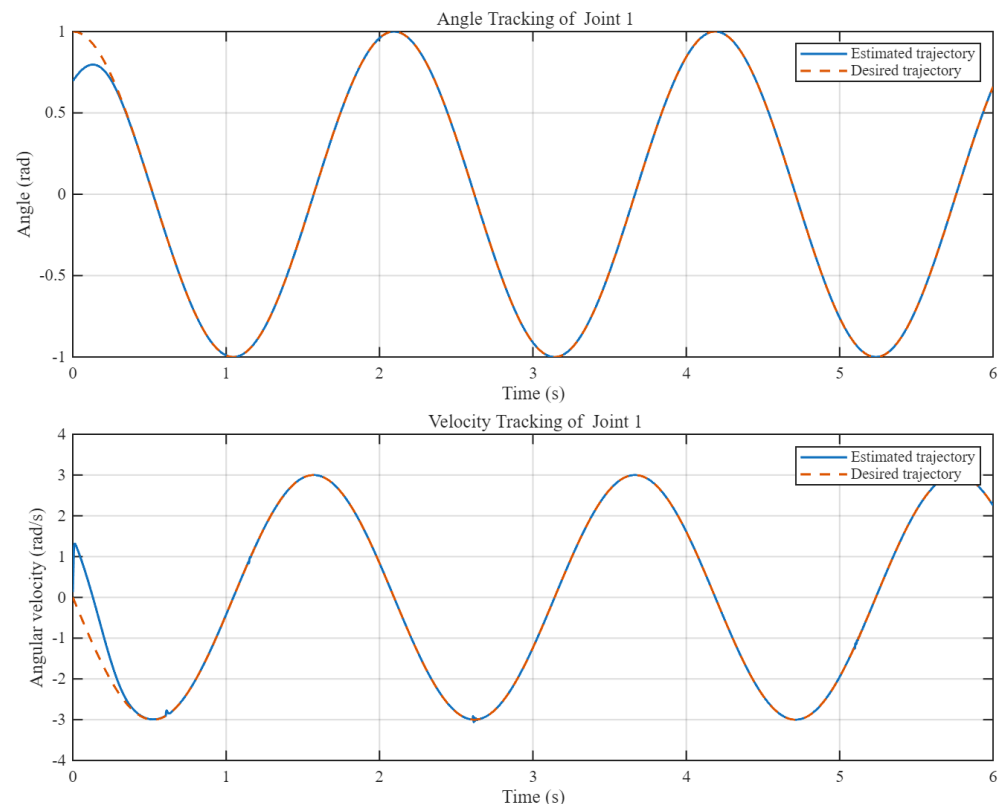


Figure 1. The angle and velocity tracking of joint 1.

As shown in Figures 4 and 5, the angle and velocity tracking errors of the joint with FTESO and FESO are compared. It is shown from Figures 4 and 5 that, with the proposed control method, the angle and velocity tracking errors are driven into the predefined region. Moreover, the convergence time of the angle is shorter than that of FTESO.

To further demonstrate the effectiveness of the proposed method, a comparison with the traditional PPC is given. It is shown in Figure 6 that the proposed PPC with a BLF has a better convergence rate and tracking accuracy within the prescribed boundary. It is shown from Table 2 that the proposed FESO exhibits lower overshoot, shorter settling time and smaller steady-state RMS error. Moreover, it guarantees fixed-time convergence such that the tracking errors converge within a predetermined bound.

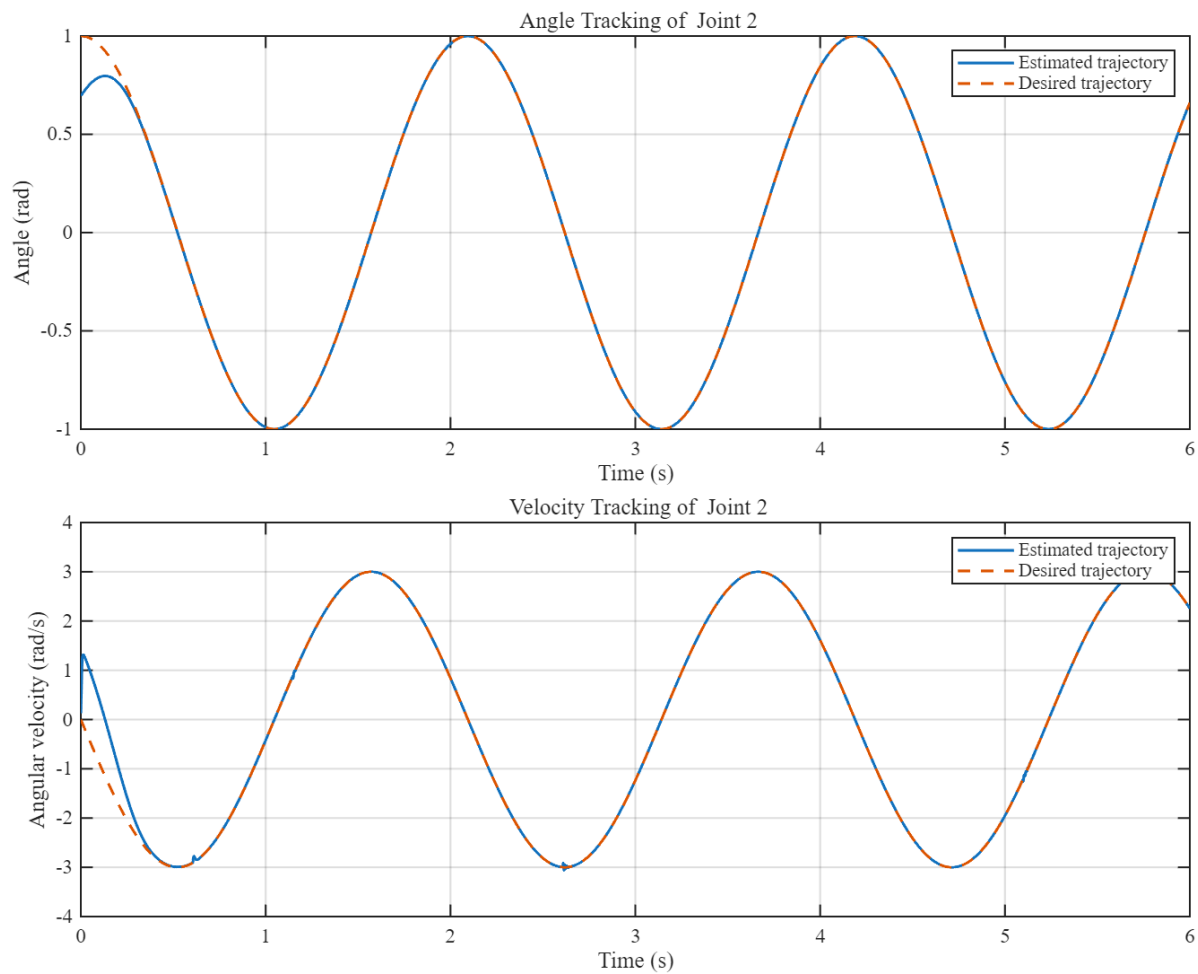


Figure 2. The angle and velocity tracking of joint 2.

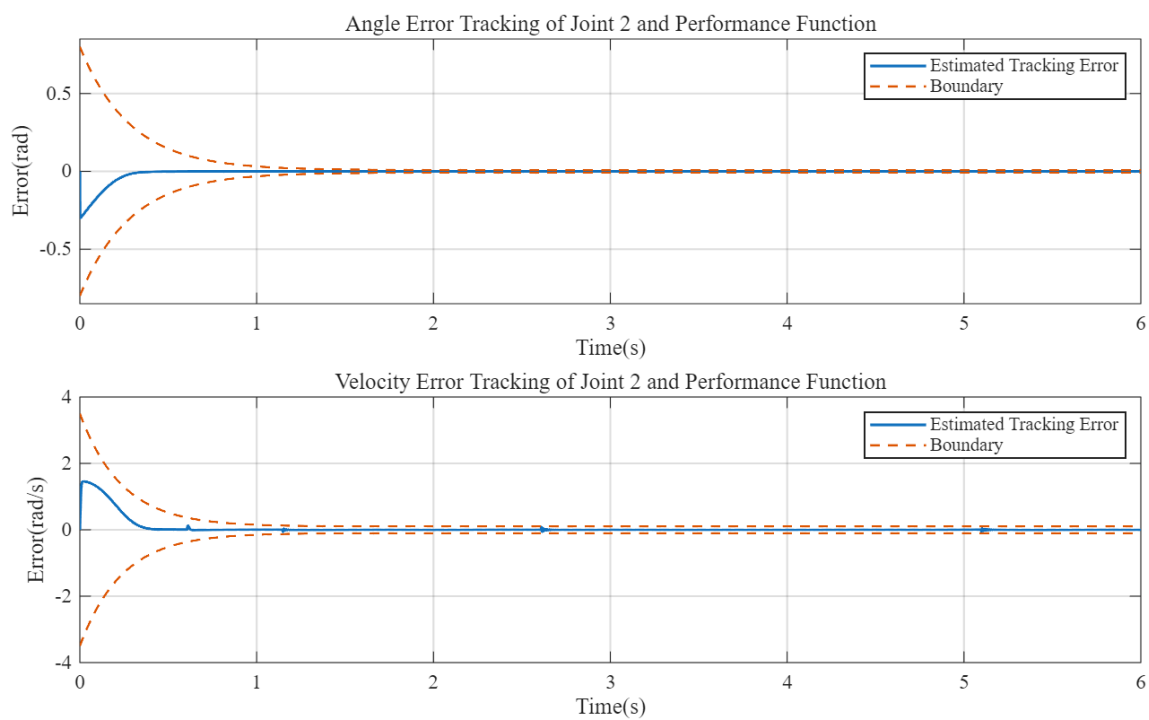


Figure 3. The angle and velocity tracking error of joint 2.

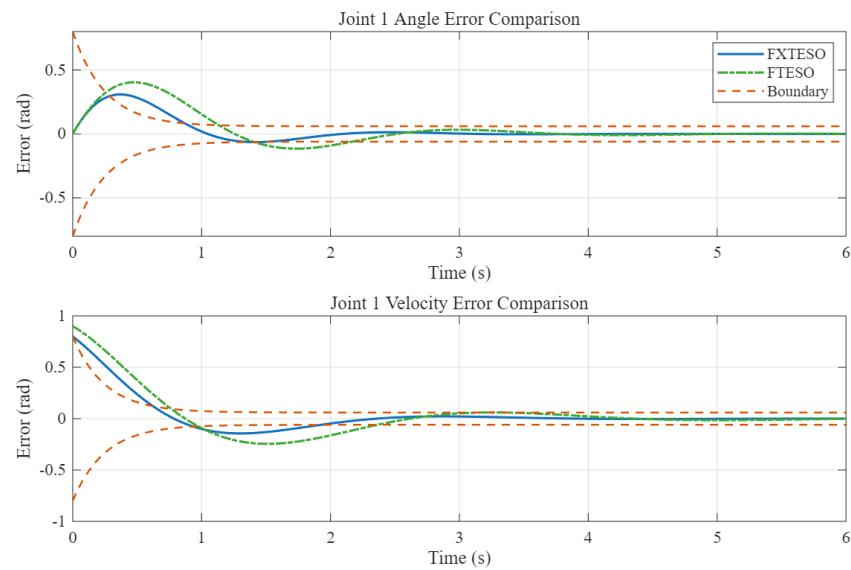


Figure 4. The angle and velocity tracking error of joint 1.

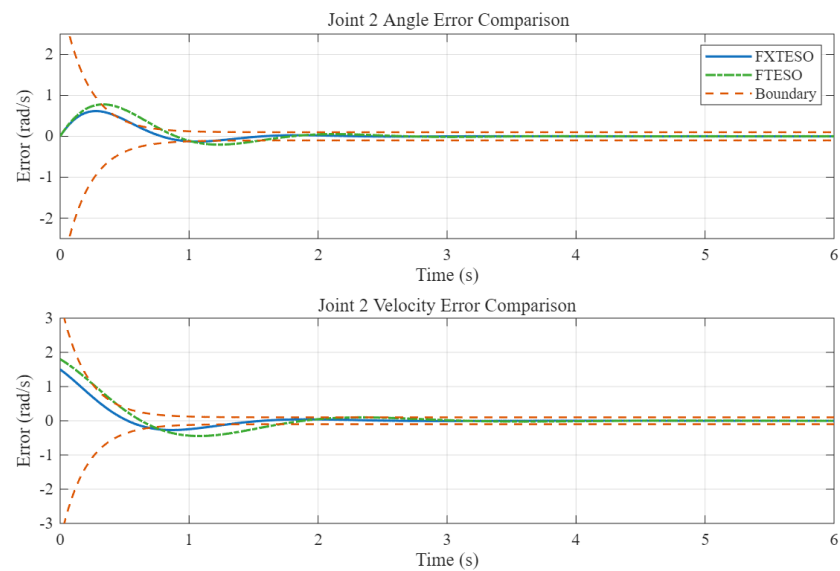


Figure 5. Comparison of the angle and velocity tracking error of joint 2.

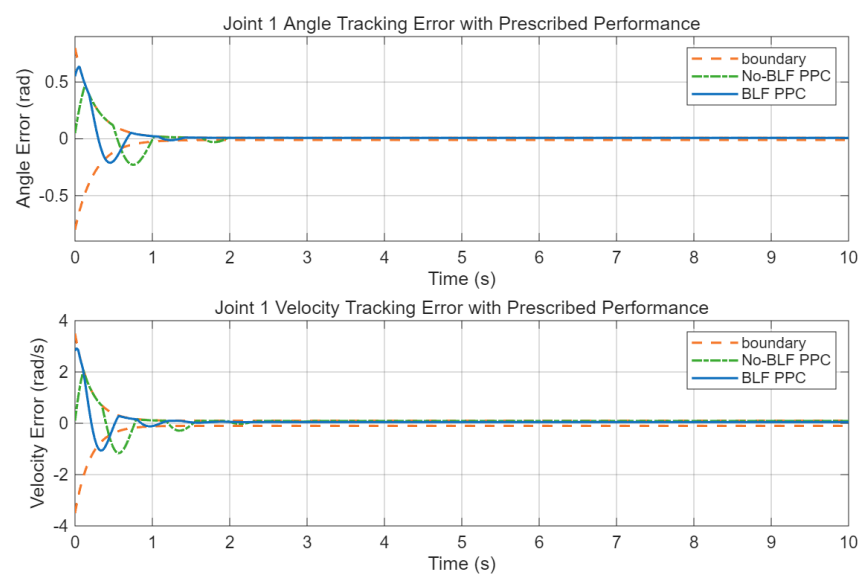


Figure 6. Comparison of the angle and velocity tracking error of joint 1.

Table 2. System performance analysis of the joints under FDI attacks and actuator faults.

Controller	Joint	Metric	Overshoot	Settling Time (s)	Steady-State RMS Error
FTESO	1	Angle (rad)	0.404	8.17	9.6×10^{-5}
	1	Angular vel (rad/s)	0.781	3.41	1.0×10^{-6}
	2	Angle (rad)	0.411	8.01	9.3×10^{-5}
	2	Angular vel (rad/s)	0.793	3.22	1.0×10^{-6}
FESO	1	Angle (rad)	0.309	5.02	1.0×10^{-6}
	1	Angular vel (rad/s)	0.617	2.75	1.0×10^{-6}
	2	Angle (rad)	0.312	5.13	1.0×10^{-6}
	2	Angular vel (rad/s)	0.593	2.64	1.0×10^{-6}

5. Discussion

This study develops an FESO-based predefined performance control framework for robotic manipulators subject to parameter uncertainties, external disturbances, FDI attacks, and actuator faults. These adverse effects are represented as a lumped disturbance and estimated by the proposed FESO. Different from finite-time observers whose convergence time generally depends on the initial estimation errors, the FESO provides a fixed upper bound on the estimation time independent of the initial conditions. The estimated disturbance is subsequently incorporated into the BLF-based controller, enabling the tracking errors to remain within the predefined performance boundaries.

The simulation results demonstrate that the proposed method maintains stable trajectory tracking under simultaneous FDI attacks and actuator faults. Compared with the FTESO-based controller, the proposed method has shorter settling times and better tracking accuracy. These improvements indicate that fixed-time disturbance estimation enhances both transient response and steady-state tracking accuracy. Moreover, the BLF incorporates the prescribed error boundaries into the controller design. Consequently, the nonlinear error transformation and inverse transformation required by conventional PPC methods are avoided, thereby simplifying the controller structure while preventing the tracking errors from violating the prescribed constraints.

Nevertheless, the proposed method has several limitations. Because attacks, faults, uncertainties, and disturbances are combined into a lumped term, the controller compensates for their overall influence but cannot distinguish their individual sources. The theoretical results also rely on bounded disturbances and bounded disturbance derivatives. In addition, the current validation is limited to numerical simulations of a two-degree-of-freedom manipulator and does not explicitly consider measurement noise, communication delays, packet loss, or actuator saturation. Future research will, therefore, focus on attack-fault isolation, noise-robust observer design, constrained control inputs, network-induced effects, and experimental validation on a physical robotic manipulator.

6. Conclusions

This paper investigates predefined performance trajectory tracking for robotic manipulators subject to parameter uncertainties, external disturbances, FDI attacks, and actuator faults. An integrated control framework is developed by combining an FESO with a BLF-based predefined performance controller. The adverse effects acting on the manipulator are first represented as a lumped disturbance. The FESO is then employed to estimate the velocity-related state and the lumped disturbance, with its estimation errors guaranteed to enter a bounded region within a fixed-time interval. Using the observer outputs, the BLF-based control law directly constrains the tracking errors within the predefined performance boundaries without requiring the nonlinear error transformation and inverse transformation commonly used in conventional PPC methods.

Theoretical analysis establishes the boundedness and predefined performance properties of the resulting closed-loop system. Simulations on a two-degree-of-freedom robotic manipulator further verify the effectiveness of the proposed framework under simultaneous FDI attacks and actuator faults. Compared with the FTESO-based method, the proposed FESO-based controller reduces the angular-position settling times. Comparison with conventional PPC further demonstrates that the BLF-based design provides faster convergence and improved tracking accuracy while maintaining the errors within the prescribed boundaries.

Overall, the proposed method provides a unified solution for disturbance estimation, attack and fault compensation, and transient tracking-performance regulation. However, the present study treats different uncertainties and abnormal inputs as a lumped disturbance and is validated only through numerical simulations. Future work will focus on separating FDI attacks from actuator faults, improving robustness against measurement noise and network-induced effects, incorporating actuator saturation and control-input constraints, and experimentally validating the proposed method on a physical robotic manipulator.

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Abbreviations

The following abbreviations are used in this manuscript:

BLF	Barrier Lyapunov function
DOF	Degree of freedom
FDI	False data injection
FESO	Fixed-time extended state observer
FTESO	Finite-time extended state observer
LMI	Linear matrix inequality
PPC	Predefined performance control
RMS	Root mean square
SMC	Sliding mode control

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