Global Singularity-Free Prescribed Performance Control for Faulty Nonlinear Systems via Parameterized Nonmonotonic Constraints

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***Abstract*—In this paper, we investigate potential singularity issues in prescribed performance control induced by actuator faults and propose a global nonmonotonic prescribed performance scheme for strict-feedback nonlinear systems. This scheme allows for parameterized relaxation of constraint boundaries in the presence of actuator faults. Unlike existing prescribed performance control schemes that rely on redesigning nonmonotonic rate functions to modify boundary relaxation properties, the proposed method introduces a novel adjustment module into the prescribed performance function, enabling the parametric design of nonmonotonic boundaries. Moreover, the proposed method simultaneously addresses the removal of the initial feasibility condition and the imposition of asymmetric constraints by introducing a global asymmetric design with an error correction module. This module enables flexible conversion from asymmetric to symmetric boundaries at a predetermined time instant, thereby reducing transient overshoot while maintaining steady-state tracking precision. Simulation results validate the effectiveness and superiority of the proposed scheme.**

***Index Terms*—Actuator fault, error correction, global asymmetric design, nonmonotonic prescribed performance control, strict-feedback nonlinear system.**

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I. Introduction

IN industrial systems, various constraints are commonly encountered. These constraints generally fall into two main categories: firstly, performance-related constraints [1]–[3], which primarily concern the transient characteristics of the system, such as tracking accuracy, convergence speed, and overshoot; secondly, reliability-related constraints, including issues like actuator faults [4], input quantization [5], and input saturation [6]. During the long-term operation of industrial systems, abrupt actuator faults are a common and inevitable phenomenon. These faults not only pose a severe threat to system reliability but also degrade system performance [7]. Therefore, compensating for actuator faults while ensuring prescribed performance metrics has become a critical challenge in the control engineering field.

As a methodology capable of parametrically regulating both transient and steady-state control performance, prescribed performance control [8] has attracted extensive academic attention and continued development, as seen in [9]–[13]. However, existing prescribed performance control methods generally suffer from a critical theoretical limitation: Their design process does not adequately account for the impact of actuator faults on system robustness. In practice, when actuator faults occur, the system's control input capability is degraded, which may cause tracking errors to violate the prescribed performance boundaries. This scenario may induce the singularity issue in the control law and ultimately lead to a complete loss of system stability. Current research on singularity problem avoidance in prescribed performance control remains at a nascent stage. Berger [14] proposed an innovative perspective: When actuator faults occur, strict adherence to monotonically decreasing prescribed performance boundaries becomes unnecessary. By introducing nonmonotonic performance boundaries, contact between the degraded tracking error and the boundaries can be effectively prevented, thereby avoiding the singularity issue. Inspired by this concept, Zhao *et al.* [15] and Xia *et al.* [16] proposed a class of prescribed performance control schemes based on nonmonotonic rate functions, effectively relaxing the prescribed performance constraints to avoid the singularity issue. However, the effectiveness of such methods heavily depends on the specific form of the rate function. If adjusting the nonmonotonic characteristics becomes necessary, the rate function must be redesigned, which reduces the practicality and convenience of the method.

Therefore, it would be of significant value to achieve the flexible adjustment of nonmonotonic constraints through a parameterized method, addressing the potential singularity issue that may arise due to actuator faults, which constitutes one of the key motivations of this study.

The quality of prescribed performance control remains a critical research focus. The desired performance metrics should simultaneously achieve: 1) Small overshoot during transient phases; and 2) High tracking precision in steady-state operation. Asymmetric design of prescribed performance constraints has been demonstrated as an effective technique for reducing system overshoot [17]. However, it is crucial to note that asymmetric constraints should only be applied during the transient phase. Once the system stabilizes, they must immediately switch back to symmetric constraints; otherwise, they may lead to additional errors and degrade steady-state tracking precision, a phenomenon that is particularly evident in some unified [10], [11], [15] and dual [3], [12] prescribed performance designs. In addition, the global applicability of prescribed performance control is inherently limited by its initial feasibility condition—the requirement that the system's initial state must strictly lie within the prescribed performance boundaries. This restriction poses a significant practical challenge: Any changes in initial conditions would mandate a redesign of the prescribed performance function. Although the time-varying scaling method in [18], [19] eliminates the need for the initial feasibility condition, this approach only applies to symmetric constraints. Currently, there is a lack of research on asymmetric prescribed performance control considering the elimination of the initial feasibility condition. Therefore, achieving reduced transient overshoot while ensuring steady-state tracking precision, coupled with removing the initial feasibility condition to enable global applicability of prescribed performance control, holds significant value. This constitutes another key motivation of this study.

Motivated by the above observations, this paper proposes a global nonmonotonic prescribed performance control scheme for strict-feedback nonlinear systems subject to actuator faults, with the following key contributions:

1) This study proposes a novel global asymmetric prescribed performance control method that overcomes the limitations of existing approaches [3], [10]–[12] by simultaneously addressing the initial feasibility condition and asymmetric constraints. The key innovation is a dual-phase mechanism that actively enforces asymmetric constraints during the transient phase of system regulation to suppress overshoot, while automatically reverting to symmetric constraints at steady state. This mechanism eliminates dependence on initial conditions, prevents steady-state bias caused by persistent asymmetry, and achieves superior performance in both transient and steady-state scenarios.

2) This study addresses the singularity issue in existing prescribed performance control schemes [20]–[22] under actuator faults [23], [24] by establishing an intrinsic relationship between prescribed performance control and actuator faults. By incorporating a parameterized nonmonotonic module into the prescribed performance function, the study ensures singularity-free operation during actuator faults, allowing for a customizable configuration of nonmonotonic regions through adjustable parameters. Unlike the nonmonotonic rate function design methods [15], [16], which rely on fixed nonmonotonic structures to relax constraint boundaries, the proposed approach enables fully parameterizable nonmonotonic designs, offering greater flexibility and adaptability to varying fault conditions.

II. Problem Formulation and Preliminaries

Consider the following nonlinear system in strict-feedback form:

$$\begin{cases} \dot{x}_i = f_i(\bar{x}_i,t) + g_i(\bar{x}_i,t)\, x_{i+1}, \ \ i = 1,\dots,n-1 \\ x_n = f_n(x,t) + g_n(x,t)\, u \\ y = x_1 \end{cases} \tag{1}$$

where $x = [x_1,\dots,x_n]^T \in \mathbb{R}^n$ and $\bar{x}_i = [x_1,\dots,x_i]^T \in \mathbb{R}^i$ are the state vectors, $u \in \mathbb{R}$ is the input, $y \in \mathbb{R}$ is the output, $f_i(\bar{x}_i,t)$ denotes a smooth nonlinear function, and $g_i(\bar{x}_i,t)$ represents the control gain.

Accounting for actuator faults, the actual control input u is

$$u = \varrho(t,t_1)\, v + \jmath(t,t_2) \tag{2}$$

where v denotes the designed control input, $\varrho(t,t_1) \in (0,1]$ represents the gain related to the actuation effectiveness fault, $\jmath(t,t_2)$ represents the bias related to the actuation stuck fault, and t_1, t_2, respectively, denote the times of occurrence for the two faults. Then, (1) can be rewritten as

$$\begin{cases} \dot{x}_i = f_j(\bar{x}_i,t) + g_i(\bar{x}_i,t)\, x_{i+1}, \ \ i = 1,\dots,n-1 \\ x_n = f_n(x,t) + g_n(x,t)(\varrho v + \jmath) \\ y = x_1. \end{cases} \tag{3}$$

Define the tracking error $e = y - y_d$ with y_d denoting the reference signal. The control goal is to design a control scheme for the nonlinear system (1) such that 1) Globally ultimately uniformly bounded (GUUB) stability for all signals in the closed-loop system; 2) Tracking error e always evolves within the prescribed boundaries.

To this end, the following assumptions are imposed:

Assumption 1: For $i = 1,\dots,n$, the control gain $g_i(\bar{x}_i)$ is bounded by unknown positive parameters $\underline{g}_i$ and $\overline{g}_i$, i.e., $0 < \underline{g}_i \le g_i(\bar{x}_i) \le \overline{g}_i < \infty$.

Assumption 2: For the gain fault $\varrho(t,t_1)$ and bias fault $\jmath(t,t_2)$, there exist unknown positive parameters $\underline{\varrho}$, $\overline{\varrho}$, $\underline{\jmath}$, $\overline{\jmath}$ such that $0 < \underline{\varrho} \le \varrho(t_1,t) \le \overline{\varrho} \le 1$ and $0 \le \underline{\jmath} \le |\jmath(t_2,t)| \le \overline{\jmath}$.

Assumption 3: For $i = 1,2,\dots,n$, there exists an unknown positive parameter ϕ_i and a known smooth function $\Psi_i(\bar{x}_i)$ such that $|f_i(t,\bar{x}_i)| \le \phi_i \Psi_i(\bar{x}_i)$, $\forall \bar{x}_i \in \mathbb{R}^i$.

Assumption 4: The reference signal y_d and its derivatives up to order $n-1$ are bounded, known, and piecewise continuous.

Remark 1: Assumption 1 ensures the controllability of the system by bounding the control gains, which is physically reasonable since most real-world actuators (e.g., motors, manipulators) exhibit finite and non-zero gain ranges [6], [13]. Assumption 2 ensures actuator faults (both gain reduction and bias effects) remain within known physical limits, preventing complete control failure while allowing for unknown but bounded fault magnitudes [15], [21]. Assumption 3 allows the system's nonlinearities to be captured by known basis functions with unknown scaling, a common approach in adaptive control to handle model uncertainties [10], [11]. Assumption 4 ensures the reference signal's derivatives are bounded because unbounded derivatives would cause control signals to diverge in backstepping control methods [3], [12].

Remark 2: Although Assumption 3 enables global stabilization through the bounding condition $|f_i(t,\bar{x}_i)| \le \phi_i \Psi_i(\bar{x}_i)$, it inherently limits the control scheme's applicability to systems with completely unknown nonlinear structures or non-smooth nonlinearities. The worst-case bounding approach may also induce conservatism in control inputs when actual nonlinearities are smaller than their bounds. While this assumption covers many practical systems with polynomial-type nonlinearities, integrating disturbance observers and local adaptive techniques may help relax these constraints.

III. Main Results

A. Global Prescribed Performance Design With Nonmonotonic Constraints

A traditional rate function with time setting can be defined as follows [25]:

$$r(t) = \begin{cases} e^{lt/(t-T_1)}, & t \in [0, T_1) \\ 0, & t \in [T_1, +\infty) \end{cases} \tag{4}$$

where T_1 and l are positive design parameters associated with the settling time and convergence rate, respectively. The function $r(t)$ satisfies:

$\mathcal{P}_1$) Initial condition: $r(0) = 1$;

$\mathcal{P}_2$) Limit behavior: $\lim_{t\to T_1^-} r(t) = 0$;

$\mathcal{P}_3$) Range constraint: $r(t) \in [0,1]$ for all $t > 0$;

$\mathcal{P}_4$) Functional properties: bounded, known, and piecewise continuous;

$\mathcal{P}_5$) Continuity and differentiability: $r(t)$ maintains both continuity and differentiability across its entire domain. The continuity at the critical point $t = T_1$ is verified by $\lim_{t\to T_1^-} r(t) = 0 = r(T_1)$, with the exponential term dominating the behavior as t approaches T_1^-. The derivative $r'(t) = -\frac{lT_1}{(t-T_1)^2} e^{lt/(t-T_1)}$ exists for all $t \in [0, T_1)$ and exhibits the important property that $\lim_{t\to T_1^-} r'(t) = 0$, which coincides exactly with the right-derivative at T_1 (being zero for $t \ge T_1$). This establishes that $r(t)$ is not only continuous but also differentiable everywhere, including at the transition point $t = T_1$, despite the piecewise definition.

Subsequently, to ensure that the prescribed performance boundaries can adaptively relax—thereby avoiding the singular issue when the tracking error approaches or crosses the boundary—we introduce a parameterized nonmonotonic adjustment module $\mathcal{N}(t)$ into the prescribed performance function $\rho(t)$ as follows:

$$\rho(t) = \begin{cases} \left(r_0 - r_f\right) r(t) + r_f, & t \notin [T_2, T_3] \\ r_f + \mathcal{N}(t), & t \in [T_2, T_3] \end{cases} \tag{5}$$

where the design parameters $0 < r_f << r_0$ characterize the steady-state value (r_f) and initial value (r_0) of the prescribed performance constraints, the parameterized nonmonotonic adjustment module is designed as $\mathcal{N}(t) = \mathcal{A} \sin\left(\frac{\mathcal{D}\pi}{2}(t - T_2)\right)^2$, with $\mathcal{A}$, $\mathcal{D}$ being positive design parameters that regulate the amplitude and quantity of nonmonotonic boundaries, and $T_2 > 0$ and $T_3 > 0$ denote the starting and ending times for the nonmonotonic boundaries, respectively.

The function $\rho(t)$ inherits properties from $r(t)$ as:

$\mathcal{P}_1$) Initial value: $\rho(0) = r_0$;

$\mathcal{P}_2$) Limit behavior: $\lim_{t\to T_1^-} \rho(t) = r_f$;

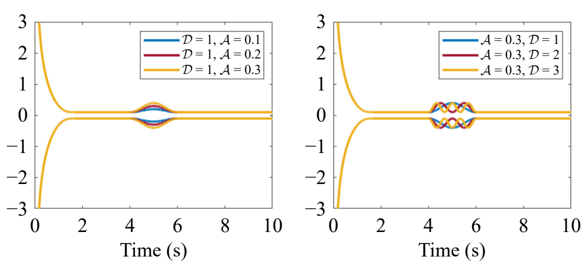
$\mathcal{P}_3$) Range constraints:

- $\rho(t) \in [r_f, r_f + \mathcal{A}]$ for $t \in [T_2, T_3]$
- $\rho(t) \in [r_f, r_0]$ otherwise;

$\mathcal{P}_4$) Functional properties: bounded, known, and piecewise continuous;

$\mathcal{P}_5$) Continuity and differentiability: $\rho(t)$ maintains continuity and differentiability through careful parameter selection. The transition at $t = T_2$ ensures $\lim_{t\to T_2^-} \rho(t) = (r_0 - r_f) r(T_2) + r_f = \rho(T_2^+)$, which simplifies to $\rho(T_2^+) = r_f$ when $T_2 \ge T_1$ (since $r(T_2) = 0$). The nonmonotonic adjustment module $\mathcal{N}(t)$ is designed with $\mathcal{D} = 2/(T_3 - T_2)$ to guarantee $\lim_{t\to T_3^-} \rho(t) = r_f = \rho(T_3^+)$. Differentiability is preserved through the piecewise derivative $\rho'(t) = (r_0 - r_f) r'(t)$ for $t \notin [T_2, T_3]$ and $\rho'(t) = \mathcal{A}\mathcal{D}\pi \sin(\frac{\mathcal{D}\pi}{2}(t - T_2)) \cos(\frac{\mathcal{D}\pi}{2}(t - T_2))$ for $t \in (T_2, T_3)$, with smooth transitions at the boundaries since $\rho'(T_2^-) = \rho'(T_2^+) = 0$ and $\rho'(T_3^-) = \rho'(T_3^+) = 0$ under these parameter constraints. These conditions are automatically satisfied by our default settings $T_2 = T_1$ and $\mathcal{D} = 2/(T_3 - T_2)$.

Remark 3: The nonmonotonic adjustment module $\mathcal{N}(t)$ can coordinate the relaxation of constraint boundaries when actuator faults occur, thus preventing the singularity issue. The shape of $\mathcal{N}(t)$ is primarily determined by $\mathcal{A}$ and $\mathcal{D}$, where $\mathcal{A}$ determines the amplitude of the nonmonotonic boundaries, and $\mathcal{D}$ determines the quantity of the nonmonotonic boundaries. A schematic for parameter adjustment is illustrated in Fig. 1.



(a) The effect of $\mathcal{A}$ (b) The effect of $\mathcal{D}$

Fig. 1. The effect of nonmonotonic adjustment module $\mathcal{N}(t)$.

Remark 4: Although the nonmonotonic rate function design method in [15] and [16] has also achieved constraint boundary relaxation, this approach relies on incorporating nonmonotonicity into the rate functions and thus cannot achieve parameterizable nonmonotonic designs.

Building upon the achieved nonmonotonic prescribed performance constraints, we further propose the following global asymmetric design method to ensure that the prescribed performance constraints are independent of the initial state, reduce the transient overshoot, and maintain the steady-state precision:

For $t \in [T_2, T_3]$,

$$\begin{aligned} \mathcal{F}_u(t) &= \rho(t) \\ \mathcal{F}_l(t) &= -\rho(t). \end{aligned} \tag{6}$$

For $t \notin [T_2, T_3]$,

$$\begin{aligned} \mathcal{F}_u(t) &= \frac{\hbar_u \rho(t)}{[r_0 - \rho(t)]^{\Lambda}} + \Pi_u \\ \mathcal{F}_l(t) &= -\frac{\hbar_l \rho(t)}{[r_0 - \rho(t)]^{\Lambda}} - \Pi_l \end{aligned} \tag{7}$$

where $0 < \Lambda \le 1$ serves as a convergence rate tuning parameter, $\Pi_u = r_f - \hbar_u r_f/(r_0 - r_f)^{\Lambda}$ and $\Pi_l = r_f - \hbar_l r_f/(r_0 - r_f)^{\Lambda}$ denote error correction modules that maintain steady-state precision, and $\hbar_u$ and $\hbar_l$ are asymmetric regulation parameters defined as follows:

$$\begin{cases} \hbar_u \in (1, +\infty), & e_0 > 0, \\ \hbar_u = 1, & e_0 = 0, \\ \hbar_u \in (0, 1), & e_0 < 0, \end{cases} \quad \begin{cases} \hbar_l \in (0, 1), & e_0 > 0 \\ \hbar_l = 1, & e_0 = 0 \\ \hbar_l \in (1, +\infty), & e_0 < 0 \end{cases}$$

where e_0 represents the initial tracking error.

The functions $\mathcal{F}_u(t)$ and $\mathcal{F}_l(t)$ inherit properties from $\rho(t)$ as

$\mathcal{P}_1$) Initial values:
- $\mathcal{F}_u(t) \to +\infty$ as $t \to 0^+$
- $\mathcal{F}_l(t) \to -\infty$ as $t \to 0^+$;

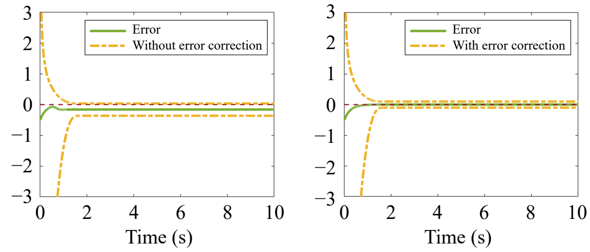
$\mathcal{P}_2$) Limit behaviors:
- $\lim_{t \to T_1^-} \mathcal{F}_u(t) = r_f$ and
- $\lim_{t \to T_1^-} \mathcal{F}_l(t) = -r_f$;

$\mathcal{P}_3$) Range constraints:
- $\mathcal{F}_u(t) \in [r_f, r_f + \mathcal{A}]$ for $t \in [T_2, T_3]$
- $\mathcal{F}_l(t) \in (-r_f - \mathcal{A}, -r_f]$ for $t \in [T_2, T_3]$
- $\mathcal{F}_u(t) \in [r_f, +\infty)$ for $t \notin [T_2, T_3]$
- $\mathcal{F}_l(t) \in (-\infty, -r_f]$ for $t \notin [T_2, T_3]$;

$\mathcal{P}_4$) Functional properties: Both are bounded, known, and piecewise continuous.

Remark 5: The error correction modules Π_u and Π_l play a crucial role in transforming the asymmetric constraint boundaries into symmetric ones once the system becomes stable, thus preventing the generation of additional errors. This issue is commonly encountered in some unified [10], [11], [15] and dual [3], [12] prescribed performance designs. As depicted in Fig. 2, without the error correction modules, the constraint boundaries are always asymmetrically squeezed, resulting in steady-state errors that exhibit significant deviation from zero. However, with the introduction of the error correction modules, this problem can be effectively addressed.

Remark 6: Although numerous studies have investigated prescribed performance control with asymmetric designs to achieve controllable overshoot, approaches that simultaneously ensure both asymmetric constraints and global applicability remain limited. In [18], [19], global prescribed performance was achieved but only with symmetric constraints. In [26], an attempt was made to design global asymmetric constraints; however, only one boundary's initial value could approach infinity while the other remained finite. In contrast, the proposed method in this work achieves global prescribed performance where both boundaries' initial values approach infinity under asymmetric constraints.



(a) Without error correction (b) With error correction

Fig. 2. The effect of error correction modules Π_u and Π_l.

To guarantee that the tracking error satisfies $\mathcal{F}_l(t) < e(t) < \mathcal{F}_u(t)$, for all $t \ge 0$, the following nonlinear mapping function $\mathcal{M}(t)$ is employed [25]:

$$\mathcal{M}(t) = \ln\left(\frac{\varsigma(t)}{1 - \varsigma(t)}\right) \tag{8}$$

where

$$\varsigma(t) = \frac{e(t) - \mathcal{F}_l(t)}{\mathcal{F}_u(t) - \mathcal{F}_l(t)}.$$

The derivative of $\mathcal{M}(t)$ with respect to time is

$$\dot{\mathcal{M}}(t) = \varpi[\dot{x}_1 - \dot{y}_d + \wp] \tag{9}$$

where

$$\begin{aligned} \varpi &= \frac{1}{\varsigma(t)[1 - \varsigma(t)][\mathcal{F}_u(t) - \mathcal{F}_l(t)]} > 0 \\ \wp &= \frac{\mathcal{F}_l(t)\dot{\mathcal{F}}_u(t) - \dot{\mathcal{F}}_l(t)\mathcal{F}_u(t) - e(t)\left[\dot{\mathcal{F}}_u(t) - \dot{\mathcal{F}}_l(t)\right]}{\mathcal{F}_u(t) - \mathcal{F}_l(t)} \\ \dot{\mathcal{F}}_u(t) &= \frac{\hbar_u[r_0 + (\Lambda - 1)\rho(t)]\dot{\rho}(t)}{[r_0 - \rho(t)]^{\Lambda+1}} \\ \dot{\mathcal{F}}_l(t) &= -\frac{\hbar_l[r_0 + (\Lambda - 1)\rho(t)]\dot{\rho}(t)}{[r_0 - \rho(t)]^{\Lambda+1}}. \end{aligned}$$

B. Control Design and Stability Analysis

The error system is defined as

$$\begin{cases} s_1(t) = \mathcal{M}(t) \\ s_j(t) = x_j(t) - \alpha_{j-1}(t) \end{cases} \tag{10}$$

where $\alpha_{j-1}(t)$, $j = 2, 3, \ldots n$, are the virtual controllers to be designed.

Step 1: The derivative of $\frac{1}{2}s_1^2$ with respect to time can be obtained from (1), (9), and (10).

$$s_1\dot{s}_1 = \varpi(g_1 s_1 s_2 + g_1 s_1 \alpha_1 + s_1 f_1 - s_1 \dot{y}_d + s_1 \wp). \tag{11}$$

According to Assumption 1 and Young's inequality, one has

$$\varpi g_1 s_1 s_2 \le \underline{g}_2 \varpi^2 s_1^2 s_2^2 + \frac{\overline{g}_1^2}{4\underline{g}_2^2}, \; \varpi s_1 f_1 \le \underline{g}_1 \phi_1^2 \varpi^2 s_1^2 \Psi_1^2 + \frac{1}{4\underline{g}_1^2}$$

$$-\varpi s_1 \dot{y}_d \le \underline{g}_1 \varpi^2 s_1^2 \dot{y}_d^2 + \frac{1}{4\underline{g}_1^2}, \; \varpi s_1 \wp \le \underline{g}_1 \varpi^2 s_1^2 \wp^2 + \frac{1}{4\underline{g}_1^2}.$$

Following this, we get

$$s_1\dot{s}_1 = g_1\varpi s_1\alpha_1 + \underline{g}_2\varpi^2 s_1^2 s_2^2 + \underline{g}_1\varpi^2\theta_1 s_1^2 + \underline{g}_1\varpi^2\psi_1\varphi_1 s_1^2 + \Theta_1 \tag{12}$$

where $\theta_1 = \wp^2 + \dot{y}_d^2$, $\varphi_1 = \Psi_1^2$, $\psi_1 = \phi_1^2$, and $\Theta_1 = \frac{\bar{g}_1^2}{4\underline{g}_2^2} + \frac{3}{4\underline{g}_1^2}$.

The virtual controller α_1 is designed as

$$\alpha_1 = -\frac{k_1}{\varpi}s_1 - \varpi\hat{\psi}_1\varphi_1 s_1 - \varpi\theta_1 s_1$$
$$\dot{\hat{\psi}}_1 = -\varepsilon_1\hat{\psi}_1 + \lambda_1\varphi_1\varpi^2 s_1^2 \tag{13}$$

where $\hat{\psi}_1$ denotes the estimate of ψ_1, and k_1, ε_1, λ_1 represent positive design constants. From (13), one has

$$g_1\varpi s_1\alpha_1 \le -\underline{g}_1 k_1 s_1^2 - \underline{g}_1\varpi^2\hat{\psi}_1\varphi_1 s_1^2 - \underline{g}_1\varpi^2\theta_1 s_1^2. \tag{14}$$

Choose the Lyapunov function candidate as

$$V_1 = \frac{1}{2}s_1^2 + \frac{\underline{g}_1}{2\lambda_1}\tilde{\psi}_1^2 \tag{15}$$

where the estimation error $\tilde{\psi}_1 = \hat{\psi}_1 - \psi_1$.

Differentiating (15) and incorporating (12)−(14) yields

$$\dot{V}_1 \le -\underline{g}_1 k_1 s_1^2 - \frac{\underline{g}_1\varepsilon_1}{\lambda_1}\tilde{\psi}_1\hat{\psi}_1 + \underline{g}_2\varpi^2 s_1^2 s_2^2 + \Theta_1. \tag{16}$$

According to Young's inequality, one has

$$-\tilde{\psi}_1\hat{\psi}_1 = -\tilde{\psi}_1(\tilde{\psi}_1 + \psi_1) \le -\tilde{\psi}_1^2 + \frac{\tilde{\psi}_1^2}{2} + \frac{\psi_1^2}{2} \le -\frac{\tilde{\psi}_1^2}{2} + \frac{\psi_1^2}{2}.$$

It follows that:

$$\dot{V}_1 \le -\underline{g}_1 k_1 s_1^2 - \frac{\underline{g}_1\varepsilon_1}{2\lambda_1}\tilde{\psi}_1 + \underline{g}_2\varpi^2 s_1^2 s_2^2 + \bar{\Theta}_1 \tag{17}$$

where $\bar{\Theta}_1 = \Theta_1 + \frac{\underline{g}_1\varepsilon_1}{2\lambda_1}\psi_1^2$.

Step 2: Differentiating $s_2 = x_2 - \alpha_1$ yields

$$\dot{s}_2 = f_2 + g_2 s_3 + g_2\alpha_2 - \dot{\alpha}_1 \tag{18}$$

where

$$\dot{\alpha}_1 = \frac{\partial\alpha_1}{\partial x_1}f_1 + \frac{\partial\alpha_1}{\partial x_1}g_1 x_1 + \frac{\partial\alpha_1}{\partial y_d}\dot{y}_d + \frac{\partial\alpha_1}{\partial\dot{y}_d}y_d^{(2)} + \frac{\partial\alpha_1}{\partial\rho}\dot{\rho} + \frac{\partial\alpha_1}{\partial\dot{\rho}}\rho^{(2)} + \frac{\partial\alpha_1}{\partial\hat{\psi}_1}\dot{\hat{\psi}}_1.$$

The virtual controller α_2 is designed as

$$\alpha_2 = -k_2 s_2 - \hat{\psi}_2\varphi_2 s_2 - \theta_2 s_2 - \varpi^2 s_1^2 s_2$$
$$\dot{\hat{\psi}}_2 = -\varepsilon_2\hat{\psi}_2 + \lambda_2\varphi_2 s_2^2 \tag{19}$$

where $\hat{\psi}_2$ denotes the estimate of $\psi_2 = \max\{\phi_1^2, \phi_2^2\}$, k_2, ε_2, λ_2 represent positive design constants, $\varphi_2 = \Psi_2^2 + \left(\frac{\partial\alpha_1}{\partial x_1}\Psi_1\right)^2$, and

$$\theta_2 = \left(\frac{\partial\alpha_1}{\partial x_1}x_2\right)^2 + \left(\frac{\partial\alpha_1}{\partial x_1}\right)^2 + \sum_{j=0}^{1}\left(\frac{\partial\alpha_1}{\partial y_d^{(j)}}y_d^{(j+1)}\right)^2 + \sum_{j=0}^{1}\left(\frac{\partial\alpha_1}{\partial\rho^{(j)}}\rho^{(j+1)}\right)^2 + \left(\frac{\partial\alpha_1}{\partial\hat{\psi}_1}\dot{\hat{\psi}}_1\right)^2 + 1.$$

Choose the Lyapunov function candidate as

$$V_2 = \frac{1}{2}s_2^2 + \frac{\underline{g}_2}{2\lambda_2}\tilde{\psi}_2^2 \tag{20}$$

where the estimation error $\tilde{\psi}_2 = \hat{\psi}_2 - \psi_2$.

It follows that:

$$\dot{V}_2 \le s_2 f_2 + g_2 s_2 s_3 + g_2 s_2\alpha_2 - s_2\dot{\alpha}_1 + \frac{\underline{g}_2}{\lambda_2}\tilde{\psi}_2\dot{\hat{\psi}}_2. \tag{21}$$

According to Assumption 1 and Young's inequality, one has

$$s_2 f_2 + g_2 s_2 s_3 - s_2\dot{\alpha}_1 \le \underline{g}_2\psi_2\varphi_2 s_2^2 + \underline{g}_2\theta_2 s_2^2 + \underline{g}_3 s_2^2 s_3^2 + \Theta_2$$

where $\Theta_2 = \frac{7}{4\underline{g}_2^2} + \frac{\bar{g}_1^2}{4\underline{g}_2^2} + \frac{\bar{g}_2^2}{4\underline{g}_3^2}$. Given that $s_2\alpha_2 \le 0$, thus

$$\dot{V}_2 \le -\underline{g}_2 k_2 s_2^2 - \frac{\underline{g}_2\varepsilon_2}{2\lambda_2}\tilde{\psi}_2 - \underline{g}_2\varpi^2 s_1^2 s_2^2 + \underline{g}_3 s_2^2 s_3^2 + \bar{\Theta}_2 \tag{22}$$

where $\bar{\Theta}_2 = \Theta_2 + \frac{\underline{g}_2\varepsilon_2}{2\lambda_2}\psi_2^2$.

Step i (i = 3,4,...,n): Combining Steps 1–2 and selecting the Lyapunov function candidate $V_i = \frac{1}{2}s_i^2 + \frac{\underline{g}_i}{2\lambda_i}\tilde{\psi}_i^2$, where $\tilde{\psi}_i = \hat{\psi}_i - \psi_i$, the actual controller follows via standard back-stepping.

$$\alpha_i = -k_i s_i - \hat{\psi}_i\varphi_i s_i - \theta_i s_i - s_{i-1}^2 s_i$$
$$v = \alpha_n,\ \ \dot{\hat{\psi}}_i = -\varepsilon_i\hat{\psi}_i + \lambda_i\varphi_i s_i^2 \tag{23}$$

where $\hat{\psi}_i$ denotes the estimate of $\psi_i = \max_{1\le j\le i}\{\phi_j^2\}$, k_i, ε_i, λ_i represent positive design parameters,

$$\varphi_i = \Psi_i^2 + \sum_{j=1}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial x_j}\Psi_j\right)^2$$
$$\theta_i = \sum_{j=1}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial x_j}x_{j+1}\right)^2 + \sum_{j=1}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial x_j}\right)^2 + \sum_{j=0}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial y_d^{(j)}}y_d^{(j+1)}\right)^2 + \sum_{j=0}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial\rho^{(j)}}\rho^{(j+1)}\right)^2 + \sum_{j=1}^{i-1}\left(\frac{\partial\alpha_{i-1}}{\partial\hat{\psi}_j}\dot{\hat{\psi}}_j\right)^2 + 1.$$

It follows that:

$$\dot{V}_m \le -\underline{g}_m k_m s_m^2 - \frac{\underline{g}_m\varepsilon_m}{2\lambda_m}\tilde{\psi}_m - \underline{g}_m s_{m-1}^2 s_m^2 + \underline{g}_{m+1}s_m^2 s_{m+1}^2 + \bar{\Theta}_m,\ \ m = 3,4,\ldots,n-1 \tag{24}$$

$$\dot{V}_n \le -\underline{g}_n\underline{\varrho}k_n s_n^2 - \frac{\underline{g}_n\varepsilon_n}{2\lambda_n}\tilde{\psi}_n + \underline{g}_n s_{n-1}^2 s_n^2 + \bar{\Theta}_n \tag{25}$$

where

$$\bar{\Theta}_m = \Theta_m + \frac{\underline{g}_m\varepsilon_m}{2\lambda_m}\psi_m^2$$
$$\bar{\Theta}_n = \Theta_n + \frac{\underline{g}_n\varepsilon_n}{2\lambda_n}\psi_n^2$$
$$\Theta_m = \frac{(4m-1)}{4\underline{g}_m^2} + \frac{1}{4\underline{g}_m^2}\sum_{j=1}^{m-1}\bar{g}_j^2 + \frac{\bar{g}_m^2}{4\underline{g}_{m+1}^2}$$
$$\Theta_n = \frac{(4n-1)}{4\underline{g}_n^2} + \frac{1}{4\underline{g}_n^2}\sum_{j=1}^{n-1}\bar{g}_j^2 + \frac{1}{2\bar{g}_n^2\bar{J}^2}.$$

Theorem 1: Under Assumptions 1–4, the closed-loop system (1) with controllers (13), (19), and (23) ensures: 1) GUUB stability for all signals; 2) Tracking error confinement within prescribed constraints.

Proof: Define $V=\sum_{i=1}^{n}V_n$. Combining (17), (22), (24), and (25) yields

$$\begin{aligned}\dot{V}&\le-\sum_{i=1}^{n-1}\underline{g}_i k_i s_i^2-\underline{g}_n\underline{\varrho}k_n s_n^2-\sum_{i=1}^{n}\frac{\underline{g}_i\varepsilon_i}{2\lambda_i}\tilde{\psi}_i+\sum_{i=1}^{n}\bar{\Theta}_n\\&\le-cV+\beta\end{aligned}\tag{26}$$

where $c=\min_{1\le i\le n}\left\{k_i,k_n\underline{\varrho},\varepsilon_i,2\underline{g}_i\right\}$ and $\beta=\sum_{i=1}^{n}\bar{\Theta}_n$.

Integration of (26) yields

$$V(t)\le e^{-ct}V(0)+\frac{\beta}{c}\left(1-e^{-ct}\right)\le V(0)+\frac{\beta}{c}.$$

Thus, given the finite initial condition, $V\in L_\infty$ guarantees the boundedness of s_i and $\tilde{\psi}_i$.

Based on (10), the boundedness of s_1 ensures that $\mathcal{M}$ is bounded. From (8), we know that $\mathcal{F}_l<e<\mathcal{F}_u$. Furthermore, analysis of (4) reveals that e converges to the predefined boundaries within T_1. Given the boundedness of both e and s_1, x_1 is also bounded. Under Assumption 3, this further implies the boundedness of Ψ_1. Since $\mathcal{F}_l$, $\mathcal{F}_u$, and their derivatives are bounded, ϖ is bounded as well. The boundedness of α_1 follows directly from the definitions of φ_1 and θ_1. Repeating this analysis for the remaining terms ($\alpha_2,\alpha_3,\ldots,\alpha_{n-1}$) and the control input u confirms their boundedness, thereby completing the proof. ■

For improved visualization, Fig. 3 provides a block diagram representation of the proposed control scheme.

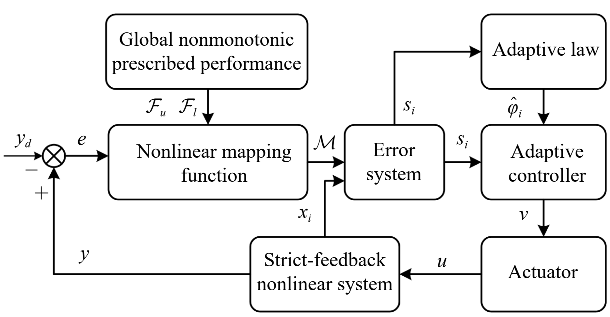


Fig. 3. Block diagram of proposed controller.

Remark 7: The effect of the design parameters is described below.

1) Increasing the values of k_i, λ_i, and ε_i can improve the tracking precision, where k_i determines the control gain, λ_i influences the adaptive capability, and ε_i governs the suppression effect on drift terms. However, excessively large values of k_i, λ_i, and ε_i may induce oscillations in the control input, necessitating a trade-off in parameter tuning.

2) Increasing the values of l and Λ can speed up error convergence. However, excessively large values of l and Λ may induce additional overshoot, necessitating application-oriented parameter tuning. Moreover, with the elimination of the initial feasibility condition, the selection of r_0 is no longer constrained by the initial state $x_1(0)$. The choice of r_f requires practical consideration —while reducing its value improves steady-state accuracy, it simultaneously increases actuation effort.

3) Nonmonotonic behaviors of prescribed performance constraints can be adjusted by tuning $\mathcal{A}$, $\mathcal{D}$, T_2, and T_3 (see Remark 3). For asymmetric behaviors, tuning $\hbar_u$ and $\hbar_l$ (defined in (7)) can effectively reduce the overshoot.

IV. Simulation Results

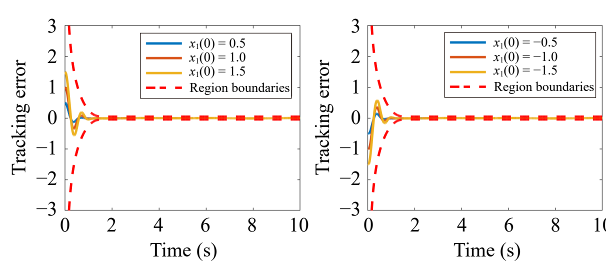
Consider a single-link manipulator that is powered by a brush direct current (DC) motor [26]

$$\begin{cases}D\ddot{q}+B\dot{q}+N\sin(q)=I\\M\dot{I}=-HI-K_m\dot{q}+V\end{cases}$$

where q, $\dot{q}$, and $\ddot{q}$ denote the joint position, velocity, and acceleration, respectively, V denotes the voltage, and I denotes the current. The system parameters are $D=1$, $M=0.04$, $B=1$, $H=0.5$, $N=10$, and $K_m=10$. The states were assumed as $x_1=q$, $x_2=\dot{q}$, $x_3=I$, and $u=V$.

The control parameters were chosen as $k_1=k_2=10$, $k_3=20$, $\varepsilon_1=\varepsilon_2=0.1$, $\varepsilon_3=0.5$, $\lambda_1=\lambda_2=0.2$, $\lambda_3=0.8$. The prescribed performance function was designed as $r_0=2$, $r_f=0.1$, $l=1$, $T_1=2$, $\hbar_u=\hbar_l=1$, and $\Lambda=0.5$. The initial conditions were set as $\psi_1(0)=\psi_2(0)=0.1$ and $\psi_3(0)=0$. The reference signal was set as $y_d=0.5\sin t$.

Fig. 4 illustrates the tracking errors under symmetric constraints with various initial values ($x_1(0)=\pm0.5,\pm1.0,\pm1.5$). Fig. 5 presents the tracking error under asymmetric constraints (when $e_0<0$, reset $\hbar_u=0.5$, $\hbar_l=20$; when $e_0>0$, $\hbar_u=20$, $\hbar_l=0.5$) with the same initial values. It is noteworthy that the overshoot observed in Fig. 4 is mitigated in Fig. 5 due to the asymmetric constraints. Additionally, the asymmetric constraints do not lead to additional errors typically induced by unified [10], [11] and dual [3], [12] asymmetric designs. Both Figs. 4 and 5 demonstrate that the proposed scheme effectively removes the need for the initial feasibility condition, thus ensuring global realization of the prescribed performance, irrespective of whether the constraints are symmetric or asymmetric. Therefore, the proposed method simultaneously addresses both the elimination of the initial feasibility condition and the enforcement of asymmetric constraints - achieving what prior works [3], [10]–[12] could only accomplish individually.



(a) $x_1(0)>0$ (b) $x_1(0)<0$

Fig. 4. Tracking errors under symmetric constraints.

Fig. 6 confirms that the controller can address the singularity issue by relaxing constraint boundaries when actuator faults occur. The specific configurations for the nonmono-

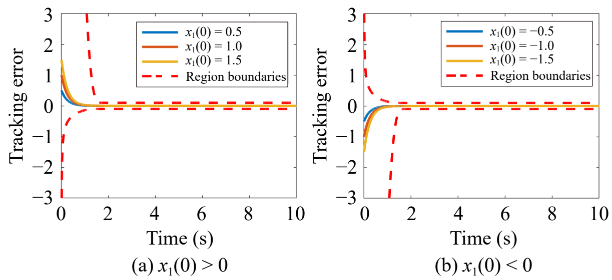


Fig. 5. Tracking errors under asymmetric constraints.

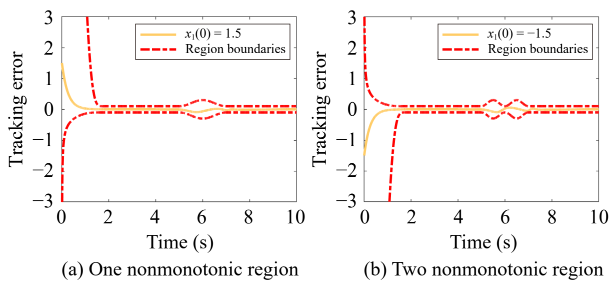


Fig. 6. Tracking errors under nonmonotonic constraints.

tonic adjustment module and actuator faults are detailed as $T_2 = 5,\ T_3 = 7,\ \mathcal{A} = 0.2,\ \mathcal{D} = 1$ (one nonmonotonic region), $\mathcal{D} = 2$ (two nonmonotonic regions),

$$\varrho = \begin{cases} 1, & t \notin [T_2, T_3] \\ 0.2 + 0.1\sin(t - T_2), & t \in [T_2, T_3] \end{cases}$$

$$\jmath = \begin{cases} 0, & t \notin [T_2, T_3] \\ 0.2\cos(t), & t \in [T_2, T_3]. \end{cases}$$

It is evident that the occurrence of actuator faults degrades tracking precision, while the proposed boundary relaxation method prevents constraint violations by avoiding direct contact between tracking error and performance boundaries.

To verify the superiority of the proposed method, we introduce the nonmonotonic rate function adjustment approach adopted in [15], [16] for comparison, where the nonmonotonic rate functions are set with $r(t) = e^{-lt}\cos^2(t)$ and $r(t) = e^{-lt}\cos^4(t)$ respectively, whose nonmonotonic behaviors are shown in Fig. 7. This method requires the adjustment of nonmonotonic rate function construction. For example, here the exponent term of the cos(t) function must be changed from 2 to 4 to modify its nonmonotonic behavior. However, this tuning process is highly cumbersome and yields limited improvement. For instance, we may want to relax the constraints only after 5 seconds and perform periodic or intermittent relaxation. In contrast, the proposed nonmonotonic regulation method eliminates the need for a complete redesign of nonmonotonic rate functions as required in [15], [16], achieved through parametric tuning of $\mathcal{A}$, $\mathcal{D}$, T_2, and T_3, thereby demonstrating better practicality.

V. Conclusion

This paper proposes a global nonmonotonic prescribed performance control scheme for strict-feedback nonlinear systems with actuator faults. The scheme effectively addresses the limitation imposed by the initial feasibility condition,

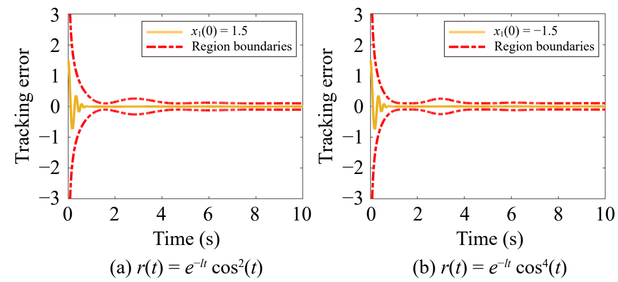


Fig. 7. Nonmonotonic behavior in [15], [16].

offering global asymmetric prescribed performance. Additionally, the incorporation of the error correction module ensures that asymmetric boundaries, while mitigating overshoot issues, do not introduce additional errors. Furthermore, the scheme allows for parameterized relaxation of constraint boundaries when actuator faults occur, thereby avoiding the singularity issue. Simulation results verify the effectiveness and superiority of the scheme.

In future research, enhancing the dynamic adaptability of boundary relaxation will be meaningful. A prospect would implement real-time distance evaluation between the tracking error and constraint boundaries, with adaptive boundary relaxation activated solely when the tracking error is about to contact the boundaries.

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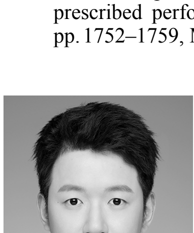

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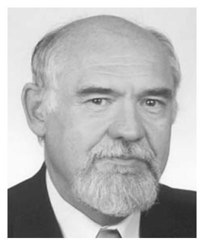

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