

Article

Actuator Fault-Tolerant Control of Anthropomorphic Manipulator Using Adaptive Backstepping and Neural Estimation of LuGre Friction Torque

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Abstract

This paper presents a fault-tolerant control (FTC) strategy for a six-degree-of-freedom (DoF) anthropomorphic manipulator operating under actuator faults and complex friction dynamics. The proposed framework integrates a backstepping control methodology with LuGre friction modeling and a feedforward neural network (FFNN) for friction estimation. Actuator faults are considered in the form of multiplicative efficiency losses and additive disturbances. An adaptive control law is developed to estimate and compensate for both friction and actuator faults in real time. The stability of the closed-loop system is guaranteed through Lyapunov theory. The simulation results validate the effectiveness and robustness of the proposed approach in ensuring precise trajectory tracking despite faults and friction uncertainties.

Keywords: LuGre friction model; manipulator; backstepping control; fault-tolerant control (FTC); LuGre friction model; feedforward neural network (FFNN)

1. Introduction

Robotic manipulators are widely used in industrial and research applications due to their versatility and precision. However, their performance is significantly affected by model uncertainties, actuator faults, and nonlinear joint friction [1,2]. Over the past decades, numerous control strategies have been proposed to enhance the robustness and accuracy of robotic systems under such conditions.

Nonlinear control techniques, including feedback linearization [3], Backstepping Control [4], Adaptive Nonlinear Control [5], Passivity-Based Control and sliding-mode control (SMC) [6], have been extensively applied to robotic manipulators [7]. These methods offer robustness to some parametric uncertainties. The adaptive capability of robust controllers removes the requirement for a priori knowledge of the upper bounds of system uncertainties, which are generally difficult to determine in practice [8]. To overcome this challenge, adaptive sliding-mode control (ASMC) has been extensively investigated and successfully applied in diverse engineering domains, such as automatic carrier landing of aircraft [9], projective synchronization of flexible manipulators and robotic manipulators [10], which



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often struggle in the presence of unmodeled dynamics or actuator degradation. In contrast, adaptive control methods dynamically adjust control parameters based on real-time system behavior and have proven more effective in handling uncertainties. Among these, adaptive backstepping control has emerged as a powerful tool for controlling nonlinear systems due to its recursive structure and guaranteed stability under specific conditions [11]. The authors of [12] propose an adaptive backstepping control approach for tracked robots, where a backpropagation neural network (BPNN) adjusts control parameters online, and a soft-switching sliding mode observer (SSMO) estimates slip parameters to enhance robustness against slippage. In [13], backstepping control has been applied to nonholonomic mobile robots to address the trajectory tracking problem under disturbances and uncertainties. Both kinematic and dynamic control frameworks have been investigated, with the backstepping controller (BSC) serving as the primary strategy in the kinematic domain for achieving robust tracking performance [13]. Several researchers have investigated backstepping-based controllers for robotic manipulators. For instance, Yu et al. [14] designed an adaptive backstepping controller for a class of nonlinear systems with unknown parameters and disturbances. Similarly, Tong et al. [15] extended this approach to robotic systems by incorporating position- and velocity-tracking errors in the Lyapunov design. However, these strategies typically assume that actuators operate fault-free, which is rarely the case in practice [15–17].

In order to address reliability concerns in practical applications, fault-tolerant control (FTC) strategies have been extensively developed to preserve system stability and performance in the presence of actuator faults [18]. The generalized framework of FTC for robotic manipulators is depicted in Figure 1.

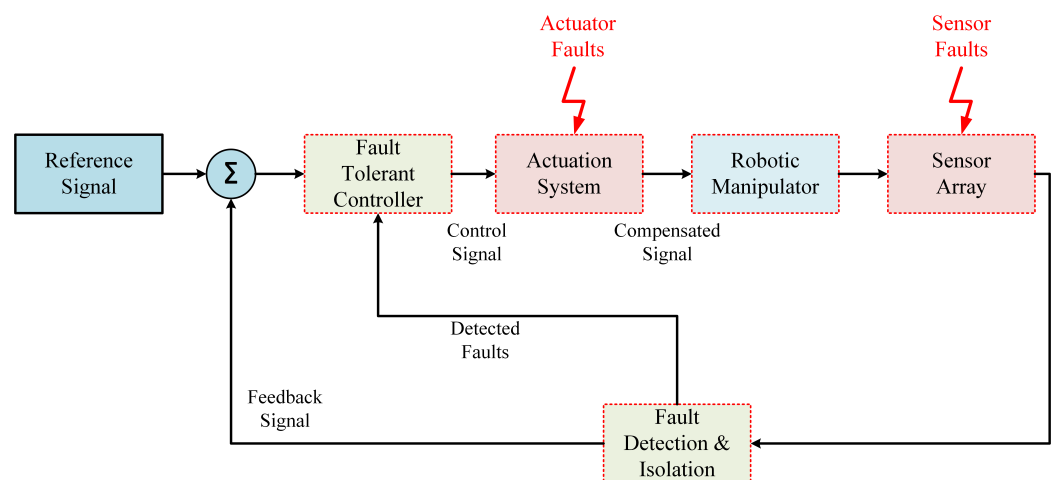


Figure 1. Basic block diagram of FTC of robotic manipulator.

The FTC methodology is generally categorized into two main approaches: passive and active techniques. Passive FTC relies on robust controller design to tolerate a predefined set of faults without the need for online fault detection or reconfiguration, thereby offering simplicity but limited adaptability [19]. Unlike passive fault-tolerant control (FTC), which relies on sturdy designs like H control, LMI methods, gain scheduling, or redundancy to handle known faults without any changes, active FTC actively spots problems in real time [20]. It uses fault detection and diagnosis (FDD) to reconfigure the controller on the fly, offering more flexibility and better fault handling, but at the cost of heavier computation. Active approaches pair FDD with adaptive or reconfigurable techniques such as backstepping, sliding mode, or model predictive control to tackle faults as they happen. Lately, smart tools like neural networks, fuzzy logic, and reinforcement learning have supercharged active FTC for tricky real-world scenarios.

Yu and Jiang's [21] survey dives deep into FTC methods, stressing how crucial it is to model actuator faults properly. This is echoed in adaptive techniques from Zhang and Jiang [22], which estimate actuator performance online and tweak the control law to match fault severity, with no human tweaks needed [20]. In the meantime, joint friction modeling has become much more advanced in order to replicate actual actuators. Compared to simple Coulomb or viscous models, the LuGre model is now much better at capturing complex behaviors like hysteresis, pre-sliding, and stick-slip, especially for precision tasks [23]. Real-time identification is challenging because its parameters are nonlinear and change over time. To estimate and offset friction, people are turning to data-driven techniques, especially neural networks. For example, one study used NNs for dynamic friction in servos, while Zhang et al. [24] deployed radial basis function neural networks (RBFNNs) for robotic arms [25]. Feedforward neural networks (FFNNs) shine here due to their quick approximation power and low computational load in real time. Some recent works have attempted to combine neural friction estimation with advanced control strategies. For example, Wang et al. [26] integrated an FFNN with a sliding-mode controller for friction compensation in robotic actuators. However, few studies have integrated LuGre friction modeling [27], adaptive backstepping, and fault-tolerant control into a unified framework for robotic manipulators, especially those with multiple degrees of freedom. The main contributions of the article are listed below:

- The LuGre friction model is incorporated into the Lagrangian equation of motion dynamics for the ED-7220C robotic manipulator, capturing nonlinear and hysteretic joint friction behavior.
- An adaptive backstepping controller is developed to ensure robust trajectory tracking, especially in relation to the occurrence of the actuator faults.
- The feedforward neural network (FFNN) is employed for real-time estimation and compensation of LuGre friction, enhancing tracking precision.
- An adaptive law is designed for the online estimation of actuator effectiveness, enabling fault-tolerant control under partial actuator failures.
- The proposed method demonstrating effective performance under simultaneous actuator faults and friction disturbances is validated through simulations.

The rest of this paper is structured as follows. Section 2 displays the dynamic modeling of the robotic manipulator, incorporating the LuGre friction model. In Section 3, the control problem is formally stated, highlighting the challenges posed by nonlinear friction and actuator faults. Section 4 describes the design of the adaptive backstepping controller with actuator fault tolerance, along with a detailed stability analysis using Lyapunov methods. Section 5 discusses the simulation results and analyzes the performance of the proposed approach. Finally, Section 6 concludes the paper.

2. System Modeling

In order to enable robots to carry out difficult tasks in human-centric environments, anthropomorphic robot models try to approximate the structure, motion capabilities, and functionality of the human arm. A design with DoFs, joint locations, and kinematic chains corresponding to human biomechanics is usually implied by the term anthropomorphic. The human arm is frequently represented by standard serial manipulators with six or more degrees of freedom, from which the forward and inverse kinematics solutions are derived to control the end-effector position and orientation [28]. Research is placing increasing emphasis on biomimetic approaches that replicate not only human arm kinematics but also natural motion patterns through redundancy resolution, workspace similarity, and motion optimization [29]. Regarding the workspace and performance metrics [30], in addition to being structural, the anthropomorphism of robot arms is frequently measured using

indices that contrast the kinematics of robots with the workspaces of human arms. These metrics provide standardised methods to evaluate design quality and human compatibility for manipulation tasks and prosthetic design by measuring how closely a robot's reachability and motion capabilities match those of human limbs. High-speed and accurate motion are key to effective robotic manipulation. Traditional feedback controllers often fall short by neglecting system dynamics. This work employs the ED-7220C anthropomorphic manipulator manufactured by ED Corporation, Seongnam, Republic of Korea, which is the Autonomous Articulated Robotic Educational Platform (AUTAREP), as presented in Figure 2, to explore model-based control for improved performance.

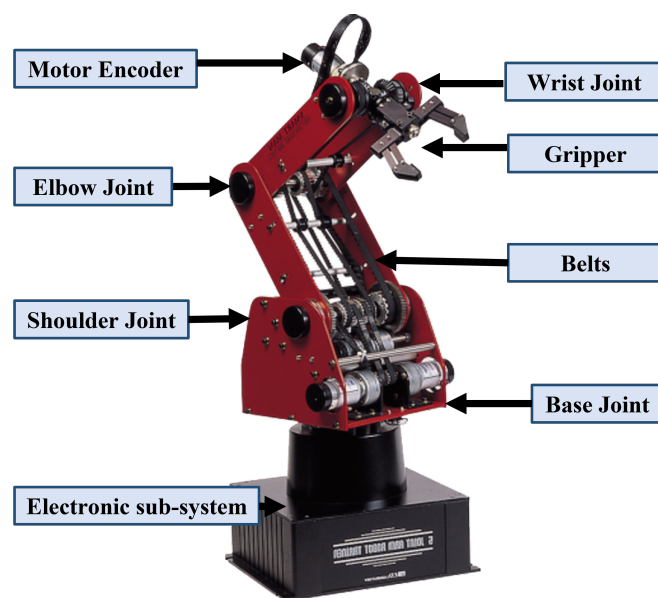


Figure 2. AUTAREP robotic manipulator ED-7220C.

The 6-DoF articulated manipulator consists of a kinematic chain influenced by link coupling, low rigidity, and nonlinearities like friction and dead zones. Each manipulator joint is driven by a servo motor, with the wrist joint of the manipulator using two motors for roll and pitch. Joint positions are measured via optical encoders. The dynamic model of the 6-DoF ED-7220C manipulator is formulated using the Euler–Lagrange approach. This formulation captures the inertial, Coriolis, centrifugal, and gravitational effects of the system. The resulting mathematical representation is expressed in Equation (1)

$$M(b)\ddot{b} + C(b, \dot{b})\dot{b} + G(b) + \tau_{lf} = \tau_{tb} \quad (1)$$

For a manipulator with n joints:

- $M(b) \in \mathbb{R}^{n \times n}$ is the mass matrix,
- $G(b) \in \mathbb{R}^{n \times 1}$ is the gravitational force vector,
- $C(b) \in \mathbb{R}^{n \times n}$ represents Coriolis and centripetal forces,
- $\tau_{lf} \in \mathbb{R}^{n \times 1}$ denotes the friction torque vector,
- τ_{tb} is the total joint torque of the robotic manipulator.

This study's research platform is the ED-7220C manipulator, whose full technical characterisation is crucial to comprehending the analysis and findings that follow. The manipulator's specifications are presented in detail across several dimensions in Tables 1 and 2. The basic mechanical and kinematic parameters that define the system's workspace and dynamic capabilities are described in Table 1. These parameters include the physical dimensions of each link and joint angle ranges.

Table 1. Link Length and range of motions specifications of the robotic manipulator [31].

Parameter	Base	Shoulder	Elbow	Wrist
Link Length (mm)	385	220	220	155
Range of Motion (deg)	310	+130/−35	±130	360 (Rot.), ±130 (Up-Down)

The technical specifications of the ED-7220C manipulator, including its structural dimensions, kinematic limits, performance characteristics, and friction-related parameters, are comprehensively summarized in Table 2. These specifications define the operational framework within which the proposed control algorithms are developed and implemented.

Table 2. Technical specifications of the robotic manipulator [31].

Parameter	Specification
Construction	Vertical Articulated Arm
Maximum Movement Speed	Approx. 100 mm/s
Number of Joints	5 Joints + Gripper
Weight	33.0 kg
Actuator	DC Servo Motor (Optical Encoder)
Load Capacity	1.0 kg
Precision (Position)	±0.005 m

Dyanmic LuGre Friction Model

Another important factor in control system performance is friction. In addition to decreasing positioning and pointing systems' accuracy, friction can lead to system instability. To some extent, friction compensation can lessen the detrimental effects. For usage in the applications of control, it is helpful to have basic models of friction that represent its fundamental characteristics. The T_{lf} which is the dynamic friction will be formulated in this subsection using the LuGre friction model [32], a nonlinear dynamic friction model commonly utilised in mechanical and servo systems. The formulation of the LuGre model as in Equations (2) and (3) and Table 3 demonstrates the LuGre friction model parameters [33].

$$\frac{dz_{lf}}{dt} = \omega - \sigma_0 \frac{|\omega|}{g(\omega)} z_{lf} \quad (2)$$

$$T_{lf} = \sigma_0 z_{lf} + \sigma_1 \dot{z}_{lf} + f(\omega) \quad (3)$$

$$T_{lf} = \sigma_0 z_{lf} + \sigma_1 \dot{z}_F + \sigma_2 \omega \quad (4)$$

where

- T_{lf} denotes the predicted friction torque.
- z_{lf} represents the internal state of the friction model.
- ω is the relative velocity between the two contacting surfaces.
- The velocity-dependent function ω is defined in Equation (5).
- σ_1 and σ_0 are the bristle-related coefficients of the friction model.

$$g_b(\omega) = \tau_{cb} + (\tau_{sb} - \tau_{cb}) e^{-(|\omega/\omega_s|)} \quad (5)$$

- τ_{cb} represents the Coulomb friction torque.
- τ_{sb} denotes the stiction (static) friction torque.

- The parameter ω_s governs the rate at which the function $g_b(\omega)$ transitions to the Coulomb friction torque τ_{cb} .
- Specifically, ω_s determines how rapidly $g_b(\omega)$ reaches τ_{cb} as the velocity increases.

Table 3. Parameters of LuGre friction model [33].

Parameter	Description	Value	Unit
σ_0	Stiffness coefficient	2750	Nm/rad
σ_2	Viscous friction coefficients	1.819	Nm·s/rad
τ_{sb}	Static friction torque	8.875	Nm
σ_1	Damping coefficient	45.2	Nm·s/rad
τ_{cb}	Coulomb friction torque	6.975275	Nm
ω_s	Velocity	$6.109 \cdot 10^{-2}$	rad/s

The LuGre model operates based on complex nonlinear functions with six parameters where coupling exists among them, making identification difficult. More critically, the internal state of the model is immeasurable and depends on the unknown friction parameters, creating a circular dependency problem. These are primarily mathematical abstractions rather than directly measurable physical quantities. The lack of physical interpretability means that real-time parameter estimates may provide good model fits without necessarily reflecting the actual physical state of the system, limiting diagnostic and predictive capabilities.

3. Problem Formulation

The performance and stability of robotic manipulators in practical applications are greatly impacted by actuator failures, which are defined as deviations from normal actuator behaviour. These shortcomings frequently have nonlinear friction effects and can be caused by mechanical wear, thermal stress, electrical failures, or long-term degradation. Such uncertainties may result in poor tracking performance or even system instability if they are not adequately addressed. Actuator faults and friction nonlinearities must therefore be explicitly modelled in the control framework. In order to estimate and compensate for unknown friction dynamics, this research proposes an adaptive backstepping-based FTC technique enhanced with a FFNN.

In general, actuator faults are classified into one of the following categories [22,34–36]:

- Loss of Effectiveness (LOE): The actuator produces a reduced output torque compared to the commanded input. Loss-of-effectiveness (LOE) faults are widely regarded as one of the most common actuator faults because they naturally arise from gradual degradation mechanisms such as mechanical wear, aging, thermal stress, and partial electrical failures.
- Stuck Actuator: The actuator remains fixed at a certain torque value regardless of the control command.
- Bias Fault: A constant offset is added to the commanded torque.
- Total Failure: The actuator ceases to produce any torque.

This article focuses on loss-of-effectiveness (LOE) errors, which occur extremely frequently and are particularly important for industrial manipulators. Let $\tau_{lf} \in \mathbb{R}^n$ be the controller's nominal control torque vector for an n-DoF manipulator. The actual torque that reaches the joints when actuator faults occur is modelled as follows:

$$\tau_{lf} = \tau_{nom} \odot \mathcal{F} \quad (6)$$

where:

- $\tau_{lf} \in \mathbb{R}^n$ is the actual torque applied;
- $\mathcal{F} = [\mathcal{E}_1, \mathcal{E}_2, \dots, \mathcal{E}_n]^T \in \mathbb{R}^n$ is the actuator effectiveness vector;
- $\odot$ denotes the element-wise (Hadamard) product;
- $\mathcal{E}_i \in (0, 1]$ denotes the health of actuator i , with $\mathcal{E}_i = 1$ for a fully functional actuator and $\mathcal{E}_i < 1$ indicating partial failure.

This multiplicative fault model, which does not interfere with the underlying system dynamics, accurately depicts how actuator output declines as a result of loss of effectiveness. The standard dynamic equation of a robotic manipulator incorporating the actuator fault model becomes

$$M(b)\ddot{b} + C(b, \dot{b})\dot{b} + G(b) + \tau_{lf} = \tau_{tb} = \mathcal{F} \odot \tau_{nom} \quad (7)$$

The development and application of FTC laws depend heavily on this fault model. In particular, it makes it possible to implement strategies that

- Recognise and adjust to actuator degradation.
- Make up for decreased torque availability.
- Preserve system performance and stability in the event of faults.

In subsequent sections, this model equation will serve as the basis for incorporating fault compensation into the backstepping control framework, providing accurate trajectory tracking and robustness even in the event of actuator failures.

4. Adaptive Backstepping Controller with Actuator Fault Tolerance

The design of a backstepping controller and an adaptive backstepping controller for a robotic manipulator exposed to actuator faults—more precisely, loss-of-effectiveness (LOE) faults—is presented in this section. The fundamental control strategy employed in the proposed design is illustrated in Figure 3. FFNN is used in the control scheme to estimate the LuGre friction model's internal friction state. The proposed control law incorporates an adaptive approach to estimate and accommodate for unknown actuator degradations and is based on the robotic manipulator's nonlinear dynamics. This method improves the system's performance and resilience when friction and actuator uncertainties are present.

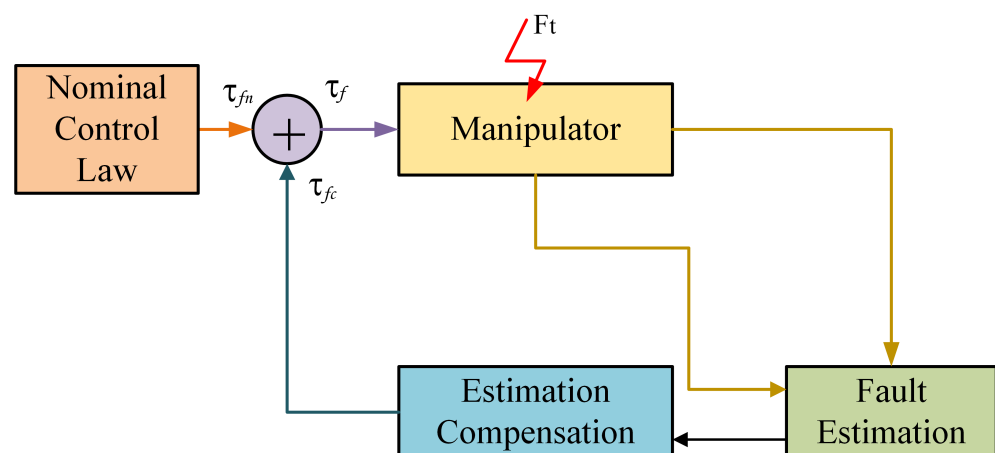


Figure 3. Actuator fault control design method.

4.1. Backstepping Controller for ED-7220C Robotic Manipulator

Backstepping is a systematic, Lyapunov-based control design methodology that is particularly well suited for dealing with nonlinear systems such as robotic manipulators. Unlike classical linear control approaches, backstepping handles nonlinearities directly and

provides a recursive framework for constructing stabilizing control laws. The backstepping control design begins by defining the position tracking errors as

$$e_1 = b - b_d \quad (8)$$

where b_d is the desired trajectory in Equation (8). The time derivative of e_1 results in the velocity-tracking error, which is presented in Equation (9).

$$e_2 = \dot{e}_1 = \dot{b} - \dot{b}_d \quad (9)$$

Similarly for n -joints, the position state for i th joint is b_{2i-1} for $1 \leq i \leq 6$ and the desired trajectory for respective joints is b_i . The dynamics of the tracking error are given below:

$$e_{1i} = b_i - b_{di}, \quad b = 1, 2, \dots, 6 \quad (10)$$

$$e_{2i} = \dot{b}_i - \dot{b}_{di}, \quad i = 1, 2, \dots, 6 \quad (11)$$

In the backstepping control framework, a virtual control input is introduced at each step of the recursive design to stabilise intermediate subsystems. To stabilise the error dynamics, a virtual control input α is introduced as a desired velocity in Equation (12)

$$\alpha = \dot{b}_d - K_1 e_1 \quad (12)$$

where $K_1 \in \mathbb{R}^{n \times n}$ is a symmetric positive definite gain matrix. The virtual input α is not the actual control torque applied to the system but a desired velocity trajectory for the second step of the backstepping procedure. Define the auxiliary error:

$$s = \dot{b} - \alpha = e_2 + K_1 e_1 \quad (13)$$

The virtual control input in backstepping plays a critical role by providing a stabilizing reference signal for the next step in the control law. It enables a recursive Lyapunov-based design approach and simplifies the control of higher-order nonlinear systems such as robotic manipulators by breaking down the complex dynamics into a sequence of lower-order subsystems that can be stabilized step-by-step. To analyse the stability of the closed-loop system under the proposed backstepping control law, we construct a Lyapunov candidate function as presented in Equation (14) that incorporates the position and velocity tracking errors. Choose the following Lyapunov function:

$$V = \frac{1}{2} e_1^T K_1 e_1 + \frac{1}{2} s^T M(b) s \quad (14)$$

This function is positive definite and radially unbounded, satisfying the conditions for a valid Lyapunov function. To prove stability, the time derivative of Equation (14) is computed in Equation (15) along the system trajectories: Its time derivative is:

$$\dot{V} = e_1^T K_1 \dot{e}_1 + s^T M(b) \dot{s} + \frac{1}{2} s^T \dot{M}(b) s \quad (15)$$

$$= e_1^T K_1 (\dot{b} - \dot{b}_d) + s^T [\tau - C(b, \dot{b}) \dot{b} - G(b) - M(b) \ddot{b}] + \frac{1}{2} s^T \dot{M}(b) s \quad (16)$$

Substituting the error dynamics and applying the property of the skew-symmetric $\dot{M} - 2C$, we simplify the expression as presented in Equation (17).

$$\dot{V} \leq -e_1^T K_1^2 e_1 - e_2^T K_2 e_2 \quad (17)$$

To ensure $\dot{V} \leq 0$, we select the control input as: where $K_2 \in \mathbb{R}^{6 \times 6}$ is a positive definite gain matrix. Therefore, $\dot{V}$ is negative definite, and the closed-loop system is globally asymptotically stable. Therefore, the nominal torque can be expressed as in Equation (18).

$$\tau = \tau_{\text{nominal}} = M(b)[\ddot{b}_d - K_1 \dot{e}_1 - K_2 s] + C(b, \dot{b})\dot{b} + G(b) \quad (18)$$

where $K_2 \in \mathbb{R}^{n \times n}$ is another symmetric positive definite gain matrix.

4.2. Adaptive Fault Compensation Control Law

The control law combines a nominal adaptive backstepping controller with a fault compensation term as demonstrated in Equation (19).

$$\tau_{tb} = \tau_{\text{nominal}} + \tau_{\text{aftc}} \quad (19)$$

where τ_{nominal} is nominal controller torque based on backstepping controller and τ_{aftc} is fault compensation term. The nominal part ensures trajectory tracking under ideal conditions, while the adaptive term compensates for actuator faults by adjusting control input based on estimated effectiveness, ensuring robust performance. The nominal controller, derived through the adaptive backstepping approach, is presented in Equation (20), ensures robust trajectory tracking and compensates for the nonlinear dynamics of the manipulator under ideal, fault-free conditions.

$$\tau_{\text{nominal}} = M(b)[\ddot{b}_d - K_1 \dot{e}_1 - K_2 s] + C(b, \dot{b})\dot{b} + G(b) \quad (20)$$

Let the unknown actuator effectiveness vector be defined as

$$\mathcal{F} = [\mathcal{E}_1, \mathcal{E}_2, \dots, \mathcal{E}_6]^T \in (0, 1]^6 \quad (21)$$

where each $\mathcal{E}_i$ represents the torque scaling factor for the i th actuator. The actual torque applied to the joints is

$$\tau_{tb} = \mathcal{F} \odot \tau_{\text{nominal}} \quad (22)$$

Here, $\tau_{\text{nominal}} \in \mathbb{R}^6$ is the nominal torque command, since $\mathcal{F}$ is unknown, an adaptive estimation scheme is introduced to estimate $\hat{\mathcal{F}} = [\hat{\mathcal{E}}_1, \hat{\mathcal{E}}_2, \dots, \hat{\mathcal{E}}_6]^T$ online. Based on Lyapunov stability theory, the adaptation law for estimating actuator effectiveness is defined as

$$\dot{\hat{\mathcal{E}}}_i = \Gamma_i \tau_i s_i, \quad i = 1, \dots, 6 \quad (23)$$

The parameter $\hat{\mathcal{E}}_i$ represents the estimate of the effectiveness of the i th actuator, while $\Gamma_i > 0$ denotes the corresponding adaptation gain. In this context, τ_i refers to the control input applied to the i th joint, and s_i is the filtered tracking error or sliding variable used to drive the adaptation process. The estimated fault vector is incorporated into the control law to compensate for actuator degradation. The compensated torque command becomes

$$\tau_{\text{aftc}} = \hat{\mathcal{F}}^{-1} \odot \tau_{\text{nominal}} \quad (24)$$

where τ_{nominal} is the nominal control law (e.g., from adaptive backstepping), and $\hat{\mathcal{F}}^{-1}$ denotes element-wise inverse of the estimated effectiveness.

4.3. Friction Torque Estimation Using a FFNN

In robotic manipulators, accurate modeling of joint friction is essential for high-performance control, particularly under conditions involving low velocities and direction reversals. The LuGre model provides a physically grounded representation of friction

phenomena such as stiction, Stribeck effect, and Coulomb/viscous components. However, the model parameters are often unknown, nonlinear, and difficult to identify in real time. To address this, a data-driven approach using a FFNN is adopted to approximate the unknown joint friction torque.

The FFNN is trained to estimate the nonlinear friction torque $\hat{\tau}_{lf}(t)$ for each joint i based on observable signals. The input feature vector includes the joint velocity and its recent history to capture dynamic behaviors associated with the LuGre friction effects:

$$z_i(t) = [\dot{b}_i(t), \dot{b}_i(t - \Delta t), \dot{b}_i(t - 2\Delta t), \text{sgn}(\dot{b}_i(t)), |\dot{b}_i(t)|] \quad (25)$$

The neural network is constructed with a three-layer fully connected architecture, composed of an input layer, two hidden layers with ReLU activation functions, and a linear output neuron. The architecture can be summarized as follows:

- Input layer: 5 neurons (velocity-based features).
- Hidden layer 1: 32 neurons.
- Hidden layer 2: 16 neurons.
- Output layer: 1 neuron (estimated friction torque).

The network is trained offline using supervised learning with measured friction torques obtained from either experimental data or a simulated LuGre model. The training objective is to minimize the mean squared error (MSE) between the true and estimated friction torque:

$$\mathcal{L}(\theta) = \frac{1}{N} \sum_{i=1}^N \left(\tau_{lf_i}(t_i) - \hat{\tau}_{lf_i}(t_i) \right)^2 \quad (26)$$

where θ denotes the network parameters. Optionally, a regularisation term can be added to improve generalization and prevent overfitting. During control execution, the trained FFNN is used online to provide real-time friction compensation within the backstepping control law.

This approach enables accurate friction estimation without requiring explicit identification of the LuGre parameters, and enhances robustness in the presence of unmodeled or varying friction dynamics.

4.4. Stability Analysis

The friction torque τ_{lf} is approximated by a FFNN as $\hat{\tau}_{lf}$. Define the friction estimation error

$$\tilde{\tau}_{lf} = \tau_{lf} - \hat{\tau}_{lf}, \quad (27)$$

and assume the error is bounded:

$$\|\tilde{\tau}_{lf}\| \leq \delta_f, \quad (28)$$

for some known constant $\delta_f > 0$. Let $\hat{\mathcal{E}}$ be the estimate of actuator effectiveness and define the estimation error

$$\tilde{\mathcal{E}} = \mathcal{E} - \hat{\mathcal{E}}. \quad (29)$$

The adaptive backstepping control law with fault compensation and friction estimation is given by

$$\tau = \hat{\mathcal{E}}^{-1} \left[M(b)(\ddot{b}_d - \Lambda \dot{e}) + C(b, \dot{b})\dot{b} + G(b) + \hat{\tau}_{lf} + K_s s \right], \quad (30)$$

where $K_s = \text{diag}(k_1, \dots, k_n) > 0$ is a positive definite gain matrix.

Consider the Lyapunov candidate function

$$V = \frac{1}{2} s^T M(q) s + \sum_{i=1}^n \frac{1}{2\Gamma_i} \tilde{\mathcal{E}}_i^2, \quad (31)$$

where $\Gamma_i > 0$ are adaptation gains. Using the property that $\dot{M}(b) - 2C(b, \dot{b})$ is skew-symmetric, the time derivative of V along the system trajectories is

$$\dot{V} = s^T \left[-K_s s + \tilde{\tau}_{lf} + \tilde{\mathcal{E}} \tau \right] + \sum_{i=1}^n \frac{1}{\Gamma_i} \tilde{\mathcal{E}}_i \dot{\mathcal{E}}_i. \quad (32)$$

Choose the adaptive law for actuator faults as

$$\dot{\mathcal{E}}_i = \Gamma_i s_i \tau_{tbi}, \quad (33)$$

which implies

$$\dot{\tilde{\mathcal{E}}}_i = -\Gamma_i s_i \tau_{tbi}. \quad (34)$$

Substituting this into $\dot{V}$ yields

$$\dot{V} = -s^T K_s s + s^T \tilde{\tau}_{tbi}. \quad (35)$$

Using the Cauchy–Schwarz inequality and the friction estimation error bound, we have

$$\dot{V} \leq -\lambda_{\min}(K_s) \|s\|^2 + \|s\| \delta_f = -\|s\| \left(\lambda_{\min}(K_s) \|s\| - \delta_f \right). \quad (36)$$

Therefore, $\dot{V} < 0$ when

$$\|s\| > \frac{\delta_f}{\lambda_{\min}(K_s)}. \quad (37)$$

This implies that the filtered tracking error s and hence the tracking error e are uniformly ultimately bounded within a neighborhood depending on the friction estimation accuracy.

Remark 1. The closed-loop system is Lyapunov stable with uniformly ultimately bounded tracking errors. The size of the ultimate bound depends on the friction approximation error and can be reduced by improving the FFNN estimation accuracy.

5. Discussion

By numerical simulations on a 6-DoF robotic manipulator, the proposed methodology approach is verified with a traditional backstepping controller that lacks fault tolerance and friction compensation. The same dynamic model, reference trajectories, and simulation parameters are used in the evaluation of both controllers. LuGre-modeled joint friction and different actuator fault scenarios are included for validation, and tracking accuracy and robustness are used to evaluate performance. In order to test the controller's robustness, the manipulator's dynamic model integrated the LuGre friction model, which captures nonlinear friction phenomena like Coulomb friction, viscous friction, and the Stribeck effect, as well as joint-level actuator faults with varying severity. For every joint, smooth reference trajectories were created, and the controller's objective was to track these trajectories while frictional nonlinearities and actuator degradations were present. The simulation results show that the suggested methodology effectively compensates for actuator faults and nonlinear friction while guaranteeing precise trajectory tracking. Specifically, even at high actuator degradation levels, the controller minimizes tracking errors and maintains stability. The suggested approach significantly improves steady-state accuracy, overshoot reduction, and transient performance when compared to a traditional backstepping controller without friction compensation. These findings demonstrate the benefit of adding adaptive friction estimation to the control system.

Figure 4 illustrates the backstepping controller for the waist joint of the robotic manipulator in nominal operation, including the LuGre friction model and excluding actuator

faults, showing the control architecture and trajectory-tracking process. The position, velocity and control effort torque of waist joint are presented in Figure 4. Actuator faults in robotic manipulators can take many different forms, each of which has a distinct impact on the system and necessitates particular considerations in fault-tolerant control design. Three typical categories of actuator faults are outlined below to show the kinds of problems taken into account in this study and are also depicted in Figure 5:

- **Abrupt Faults:** An unexpected actuator failure that results in an instantaneous loss of output torque due to a power supply drop or mechanical breakage.
- **Intermittent Faults:** frequent deviations from desired torque due to actuator sticking or signal dropout triggered on by loose wiring or transient electrical contact problems.
- **Incipient Faults:** Actuator performance gradually declines over time due to wear, increased friction, or long-term component degradation.

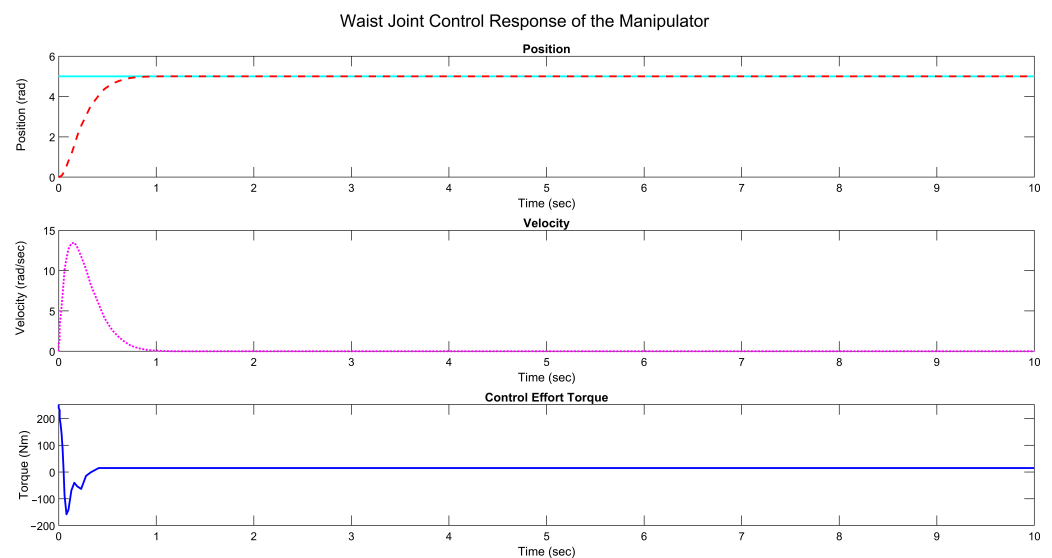


Figure 4. Backstepping controller response of the manipulator.

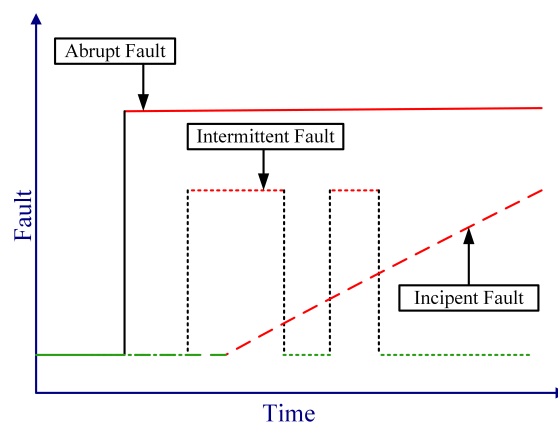


Figure 5. Types of fault profiles.

Abrupt faults represent sudden loss of actuator effectiveness, intermittent faults occur sporadically due to temporary disruptions, and incipient faults evolve gradually over time due to wear or degradation. These fault scenarios were considered to comprehensively evaluate the robustness and adaptability of the proposed control scheme. Figure 6 illustrates the actuator fault control of the elbow joint of the manipulator under backstepping control with an abrupt fault. The fault is introduced at 6 s, causing a sudden loss of actuator effectiveness. At this instant, the proposed controller rapidly accommodates the fault, ensuring system stability and driving the steady-state error to zero.

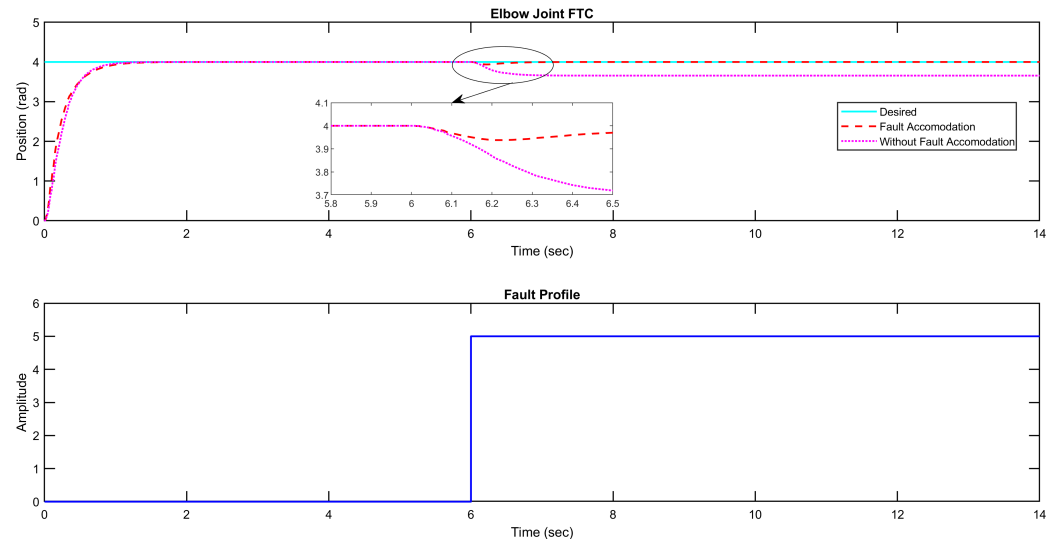


Figure 6. Step response of elbow joint of a robot manipulator with abrupt fault profile.

In addition to the abrupt fault case, two more fault scenarios were simulated to examine the performance of the proposed controller under varying fault conditions. Figure 5 shows the system response under an intermittent fault introduced for shoulder joint of the manipulator, where the actuator experienced alternating degradations at 3–5 s, 6–8 s and 9–11 s with varying amplitudes. Despite these sporadic disturbances, the adaptive backstepping fault-tolerant controller quickly adjusted to the fault reappearances, maintaining stability and preserving the desired trajectory tracking as demonstrated in Figure 7.

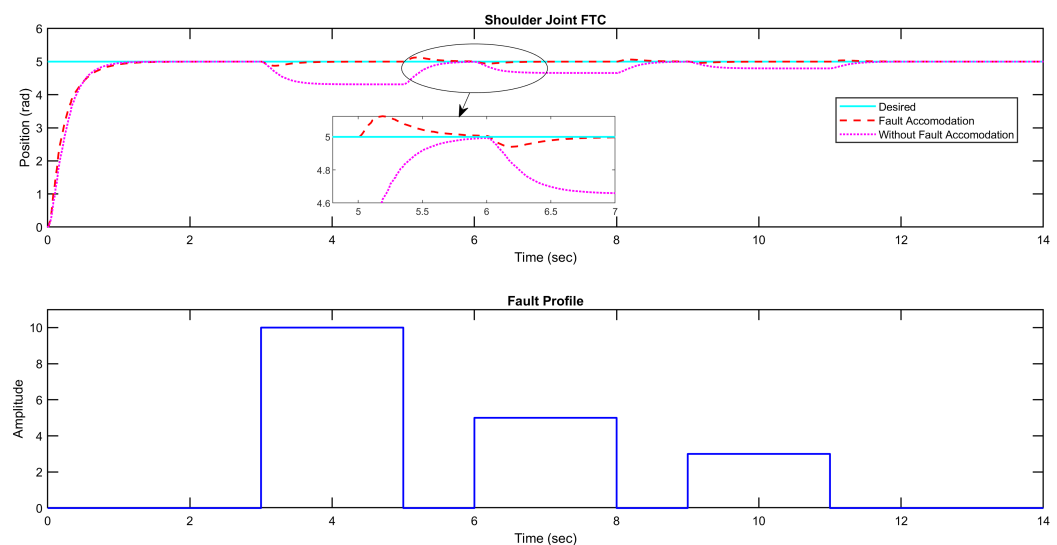


Figure 7. Step response of shoulder joint of a robot manipulator with incipient fault profile.

Figure 8 illustrates the case of an incipient fault, where a random increasing-amplitude fault profile was applied at different time intervals. Specifically, actuator degradation

was introduced gradually within the different time intervals to evaluate the controller's response. The proposed controller effectively compensated for the slow loss of effectiveness, keeping the tracking error bounded and driving it close to zero, which demonstrates its capability to adapt to progressive actuator faults.

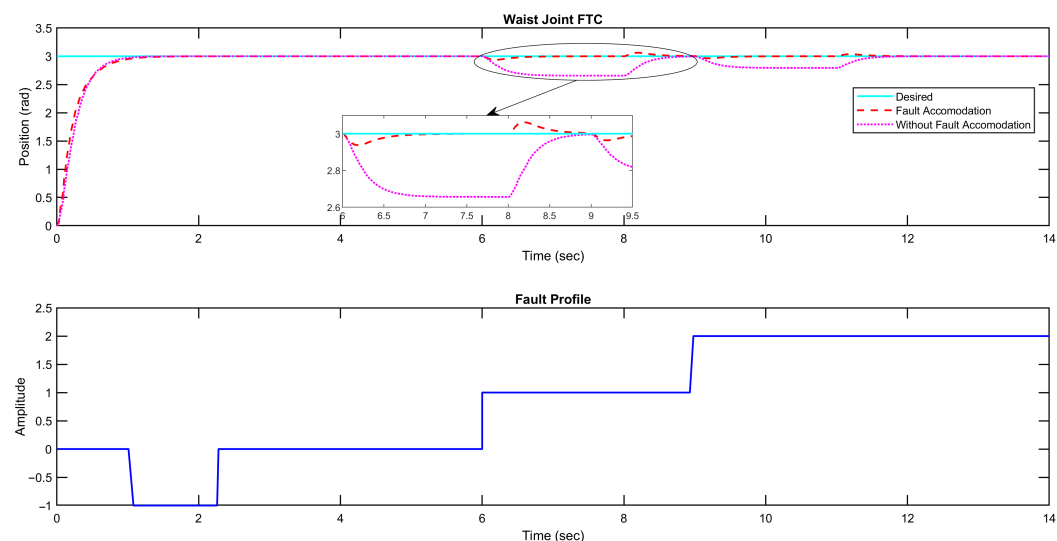


Figure 8. Step response of elbow joint of a robot manipulator with an incipient fault profile.

By simulating these fault types, the robustness of the proposed controller was evaluated under diverse and realistic fault scenarios. The results demonstrate that the adaptive backstepping FTC scheme can handle abrupt and intermittent faults by rapid adjustment, while incipient faults are effectively mitigated through continuous adaptation of actuator effectiveness estimates. The adaptive law successfully estimated the actuator effectiveness parameters in real time, and the controller maintained stable tracking performance. The tracking error remained bounded and converged close to zero despite to loss of actuator effectiveness.

The FFNN effectively estimated the LuGre friction torque, providing compensation that enhanced system smoothness and reduced oscillations, particularly in the low-velocity regime where stick-slip effects are dominant. Figure 9 depicts the estimated joint friction torque obtained using the FFNN. Since the friction state in the manipulator's dynamic model is not directly measurable, the FFNN was employed to approximate and learn the nonlinear friction dynamics. The results confirm that the network successfully captures the LuGre friction behavior, enabling real-time compensation and improving overall trajectory tracking accuracy.

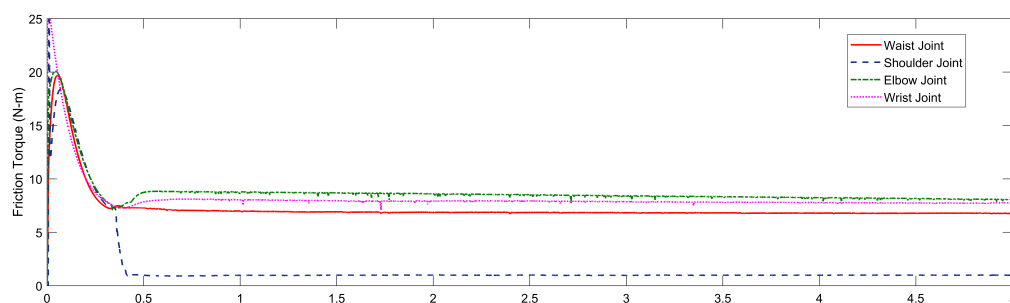


Figure 9. Estimated friction torque (LuGre) of the joints of the manipulator.

Remark 2. The Lyapunov-based stability analysis was confirmed by the simulation results, showing that both tracking errors and parameter estimation errors converge asymptotically. The overall control torque remained within feasible bounds, ensuring physical realisability.

6. Conclusions

In this work, a six-degree-of-freedom robotic manipulator was remodelled by incorporating the LuGre friction model to capture nonlinear friction dynamics. An adaptive backstepping controller was designed to ensure stable trajectory tracking under nonlinearities, while actuator fault-tolerant control was implemented to handle three common types of faults: abrupt, incipient, and intermittent. To further enhance performance, a FFNN was employed for real-time friction compensation, enabling accurate estimation of the LuGre friction torque. The simulation results demonstrated that the proposed control strategy effectively maintained stability, reduced steady-state error, and improved tracking accuracy despite the presence of actuator faults and complex frictional effects. This framework provides a robust foundation for reliable robotic manipulation in fault-prone and uncertain environments.

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References

1. Elghoul, A.; Tellili, A.; Abdelkrim, M.N. Reconfigurable control of flexible joint robot with actuator fault and uncertainty. *J. Electr. Eng.* **2019**, *70*, 130–137. [\[CrossRef\]](#)
2. Jung, J.; Penning, R.S.; Ferrier, N.J.; Zinn, M.R. A modeling approach for continuum robotic manipulators: Effects of nonlinear internal device friction. In Proceedings of the 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, San Francisco, CA, USA, 25–30 September 2011; pp. 5139–5146.
3. Bagheri, M.; Naseradinmousavi, P.; Krstić, M. Feedback linearization based predictor for time delay control of a high-DOF robot manipulator. *Automatica* **2019**, *108*, 108485. [\[CrossRef\]](#)
4. Soltanpour, M.; Shafiei, S. Robust backstepping control of robot manipulator in task space with uncertainties in kinematics and dynamics. *Elektron. Ir Elektrotech.* **2009**, *96*, 47–50.
5. Wai, R.J.; Tu, C.Y.; Hsieh, K.Y. Adaptive tracking control for robot manipulator. *Int. J. Syst. Sci.* **2004**, *35*, 615–627. [\[CrossRef\]](#)
6. Fujimoto, K.; Baba, T.; Sakata, N.; Maruta, I. A passivity-based sliding mode controller for a class of electro-mechanical systems. *IEEE Control Syst. Lett.* **2021**, *6*, 1208–1213. [\[CrossRef\]](#)
7. Billard, A.; Kragic, D. Trends and challenges in robot manipulation. *Science* **2019**, *364*, eaat8414. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Jokar, H.; Naghipour, A.; Jeloudari, I. A New Adaptive Robust Control Scheme for Trajectory Tracking of Robot Manipulators With Uncertain Dynamics Model. *IET Control Theory Appl.* **2025**, *19*, e70039. [\[CrossRef\]](#)
9. Shtessel, Y.; Plestan, F.; Edwards, C.; Levant, A. Adaptive sliding mode and higher order sliding-mode control techniques with applications: A survey. In *Sliding-Mode Control and Variable-Structure Systems: The State of the Art*; Springer: Cham, Switzerland, 2023; pp. 267–305.
10. Zhang, L.; Feng, J.; Qiu, W.; Zhang, L. Experiment and simulation research on synchronization control of shaking tables system based on adaptive sliding mode controller. *J. Vib. Eng. Technol.* **2023**, *11*, 1623–1645. [\[CrossRef\]](#)
11. Gao, M.M.; Jin, X.Z.; Ding, L.J. Robust adaptive backstepping INTSM control for robotic manipulators based on ELM. *Neural Comput. Appl.* **2022**, *34*, 5029–5039. [\[CrossRef\]](#)
12. Lu, E.; Ma, Z.; Li, Y.; Xu, L.; Tang, Z. Adaptive backstepping control of tracked robot running trajectory based on real-time slip parameter estimation. *Int. J. Agric. Biol. Eng.* **2020**, *13*, 178–187. [\[CrossRef\]](#)
13. Castaño, M.L.; Tan, X. Backstepping-based tracking control of underactuated aquatic robots. *IEEE Trans. Control Syst. Technol.* **2022**, *31*, 1179–1195. [\[CrossRef\]](#)

14. Yu, Y.; Guo, X.; Mi, Z. Adaptive robust backstepping control of permanent magnet synchronous motor chaotic system with fully unknown parameters and external disturbances. *Math. Probl. Eng.* **2016**, 2016, 3690240. [\[CrossRef\]](#)
15. Tong, Y.; Liu, J.; Zhou, H.; Ju, Z.; Zhang, X. Adaptive tracking control of robotic manipulators with unknown kinematics and uncertain dynamics. *IEEE Trans. Autom. Sci. Eng.* **2023**, 21, 5252–5269. [\[CrossRef\]](#)
16. Noura, H.; Sauter, D.; Hamelin, F.; Theilliol, D. Fault-tolerant control in dynamic systems: Application to a winding machine. *IEEE Control Syst. Mag.* **2002**, 20, 33–49.
17. Gao, B.; Liu, Y.J.; Liu, L. Adaptive neural fault-tolerant control of a quadrotor UAV via fast terminal sliding mode. *Aerosp. Sci. Technol.* **2022**, 129, 107818. [\[CrossRef\]](#)
18. Abbaspour, A.; Mokhtari, S.; Sargolzaei, A.; Yen, K.K. A survey on active fault-tolerant control systems. *Electronics* **2020**, 9, 1513. [\[CrossRef\]](#)
19. Urrea, C. Hybrid Fault-Tolerant Control in Cooperative Robotics: Advances in Resilience and Scalability. *Actuators* **2025**, 14, 177. [\[CrossRef\]](#)
20. Yeom, J. Active Fault-Tolerant Control of Quadrotors for Resilient and Safe Operations. Ph.D. Thesis, New York University Tandon School of Engineering, Brooklyn, NY, USA, 2025.
21. Yu, X.; Jiang, J. A survey of fault-tolerant controllers based on safety-related issues. *Annu. Rev. Control* **2015**, 39, 46–57. [\[CrossRef\]](#)
22. Zhang, Y.; Jiang, J. Bibliographical review on reconfigurable fault-tolerant control systems. *Annu. Rev. Control* **2008**, 32, 229–252. [\[CrossRef\]](#)
23. Johansson, K.; Canudas-De-Wit, C. Revisiting the LuGre friction model. *IEEE Control Syst. Mag.* **2008**, 28, 101–114. [\[CrossRef\]](#)
24. Zhang, S.; Yang, P.; Kong, L.; Li, G.; He, W. A single parameter-based adaptive approach to robotic manipulators with finite time convergence and actuator fault. *IEEE Access* **2020**, 8, 15123–15131. [\[CrossRef\]](#)
25. Zhu, Y.; Li, X.; Kong, L.; Zhang, T.; Zheng, G. Online identification and feed-forward compensation of nonlinear friction in servo system based on RBF neural network model. *Trans. Can. Soc. Mech. Eng.* **2024**, 48, 355–368. [\[CrossRef\]](#)
26. Wang, Y.; Yu, Y.; Wang, Z.; Ji, L.; Yang, J.; Wang, S. Tracking control of humanoid manipulator using sliding mode with neural network and disturbance observer. *Sci. Rep.* **2025**, 15, 38980. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Hu, H.; Zhu, X.; Batou, A.; Ouyang, H. Explicit frictional stick-slip dynamics of elastic contact problem incorporating the LuGre model. *Nonlinear Dyn.* **2024**, 112, 16061–16080. [\[CrossRef\]](#)
28. Katsiaris, P.T.; Artemiadis, P.K.; Kyriakopoulos, K.J. Modeling anthropomorphism in dynamic human arm movements. In Proceedings of the 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems, Taipei, Taiwan, 18–22 October 2010; pp. 3507–3512.
29. Trivedi, U.; Menychtas, D.; Alqasemi, R.; Dubey, R. Biomimetic approaches for human arm motion generation: Literature review and future directions. *Sensors* **2023**, 23, 3912. [\[CrossRef\]](#)
30. Mavrogiannis, C.I.; Liarokapis, M.V.; Kyriakopoulos, K.J. Quantifying anthropomorphism of robot arms. In Proceedings of the 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Hamburg, Germany, 28 September–2 October 2015; pp. 4084–4089.
31. Ali, K.; Ullah, S.; Mehmood, A.; Mostafa, H.; Marey, M.; Iqbal, J. Adaptive FIT-SMC Approach for an Anthropomorphic Manipulator With Robust Exact Differentiator and Neural Network-Based Friction Compensation. *IEEE Access* **2022**, 10, 3378–3389. [\[CrossRef\]](#)
32. Analytical describing function of LuGre friction model. *Int. J. Intell. Robot. Appl.* **2022**, 6, 437–448. [\[CrossRef\]](#)
33. Wang, X.; Wang, S. Output torque tracking control of direct-drive rotary torque motor with dynamic friction compensation. *J. Frankl. Inst.* **2015**, 352, 5361–5379. [\[CrossRef\]](#)
34. Blanke, M.; Kinnaert, M.; Lunze, J.; Staroswiecki, M. Introduction to diagnosis and fault-tolerant control. In *Diagnosis and Fault-Tolerant Control*; Springer: Berlin/Heidelberg, Germany, 2015; pp. 1–35.
35. Piltan, F.; Kim, C.H.; Kim, J.M. Advanced adaptive fault diagnosis and tolerant control for robot manipulators. *Energies* **2019**, 12, 1281. [\[CrossRef\]](#)
36. Tao, G. *Adaptive Control of Systems with Actuator Failures*; Springer Science & Business Media: London, UK, 2004.

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