IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 4 November 2023, accepted 28 November 2023, date of publication 30 November 2023, date of current version 13 December 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3338376

RESEARCH ARTICLE

Neural-Networks-Based Adaptive Fault-Tolerant Control of Nonlinear Systems With Actuator Faults and Input Quantization

MOHAMED KHARRAT [1], MOEZ KRICHEN [2], (Member, IEEE), LOAY ALKHALIFA [3], AND KARIM GASMI [4]

[1]Department of Mathematics, College of Science, Jouf University, Sakaka 42421, Saudi Arabia
[2]Faculty of Computer Science and Information Technology (CSIT), Al-Baha University, Alaqiq 65779-7738, Saudi Arabia
[3]Department of Mathematics, College of Sciences and Arts, Qassim University, Ar Rass 51921, Saudi Arabia
[4]Department of Computer Science, College of Arts and Sciences at Tabarjal, Jouf University, Sakakah, Al Jowf 72388, Saudi Arabia

Corresponding author: Mohamed Kharrat (mkharrat@ju.edu.sa)

This work was supported by the Deanship of Scientific Research at Jouf University through the Fast-Track Research Funding Program.

ABSTRACT In this work, the neural networks-based adaptive fault-tolerant control problem for nonlinear systems with actuator faults and input quantization is investigated. To approximate the nonlinear functions in the control system, radial basis function neural networks (RBFNN) are introduced. Additionally, an adaptive fault-tolerant controller is presented for nonlinear systems to compensate for the effects of input quantization and actuator fault using the backstepping approach and Lyapunov stability theory. It is demonstrated that with the proposed control strategy, all signals in the closed-loop system are semi-globally uniformly ultimately bounded and the tracking error converges to an arbitrarily small area of origin. The simulation results of an electromechanical system are shown to verify the validity of the control approach.

INDEX TERMS Adaptive control, nonlinear systems, Lyapunov function, actuator faults, quantization, electromechanical system.

I. INTRODUCTION

The adaptive backstepping control method has developed into an effective way to deal with system uncertainties during the past few decades, and many different adaptive backstepping control techniques have been reported [1], [2], [3]. The backstepping control methodology offers an organized method for addressing nonlinear systems without satisfying the matching conditions. The complicated nonlinear system can be divided into various subsystems, and the virtual controllers for each subsystem can then be designed until the real control law is attained [4]. Adaptive backstepping, on the other hand, can only cope with systems with unknown parameters that appear linearly connected to specific known nonlinear functions, greatly restricting their application scope [5], [6], [7].

Due to their high approximation capabilities, fuzzy logic systems and neural networks have been employed to address the control difficulties of nonlinear systems [8]. In recent years, a number of novel adaptive neural or fuzzy control techniques for uncertain nonlinear systems have been developed based on the approximation capabilities of neural networks or fuzzy logic systems [9], [10]. The benefits of adaptive neural (or fuzzy) backstepping control methods lie in the fact that prior knowledge of the system's nonlinear functions is not required, nor are certain matching conditions need to be satisfied. For nonlinear systems with unknown functions, adaptive neural (or fuzzy) backstepping control, which has received a lot of attention recently, offers a systematic control mechanism [11]. For instance, the adaptive fuzzy and NN state feedback decentralized control design problem for large-scale uncertain nonlinear systems has been reported [12]. The nonlinear strict-feedback continuous-time systems with dead-zone and state constrained has investigated using an adaptive fuzzy finite-time tracking control technique [13]. For two classes of nonlinear discrete-time systems with unknown control directions, the problem of adaptive output-feedback control was investigated, and a unified method to control design has been presented via

The associate editor coordinating the review of this manuscript and approving it for publication was Min Wang.

neural networks [14]. A decentralized adaptive neural fault-tolerant control has been reported for nonlinear interconnected systems subjected input powers [15]. For nonlinear systems subjected to constrains, an adaptive neural control schemes has been reported in [16]. For multi-agent systems, distributed adaptive control problem has been reported in [17] via neural networks approximation.

Fault-tolerant control (FTC) is receiving a lot of attention since actuator faults frequently result in unsatisfactory system behavior and can even cause instability of the controlled system [18]. Tragic accidents may occur if failures arise because the stability of the systems won't be assured. In order to prevent performance degradation and to guarantee the dependability and safety of the controlled system, fault compensation is necessary [19]. Therefore, investigating fault-tolerant control (FTC) design techniques that allow for such failures while preserving acceptable system performance is important. Numerous fuzzy or neural network FTC approaches have recently been put out to address actuator fault concerns [20], [21], [22]. The proposed control method makes it possible to increase system dependability and account for the impact of faults on the system. Fuzzy and neural network approximations have been used to address adaptive fault-tolerant control problems for nonlinear switched systems and stochastic switched nonlinear systems in [23] and [24]. For large-scale systems with faulty actuators, an adaptive fault-tolerant controller has been developed in [25]. A new adaptive control has been developed utilizing the dynamic surface control (DSC) technique for uncertain nonlinear systems in the presence of actuator failures to address the issue of computations burden caused by repeating the differentiations in a virtual controller [26].

To the best of our knowledge, however, the fault-tolerant control which takes into input quantization hasn't received any attention in the current literature. Recent years have seen a rise in the prominence of quantized control in the discipline of control engineering and in hybrid, digital, and networked control systems, it has been widely used [27]. In order to create a strong nonlinear behavior during control design, a quantizer can be considered as a mapping from a continuous region to a discrete set of numbers, primarily as piecewise constant functions of time [28]. The performance of the system will suffer from this behavior, which may potentially cause instability. It is a fact that quantization occurs frequently in modern applications [29]. Since then, research into the control problem of nonlinear systems with quantization has shown to be fruitful, and a number of efficient strategies have been investigated [30], [31], [32], [33], [34]. A class of uncertain switched nonlinear systems in strict feedback form has been studied in [35] to examine the challenge of adaptive fuzzy quantized output-feedback control and a hysteretic quantizers for switched nonlinear uncertain systems have recently been studied in [36]. For interconnected fuzzy systems a finite-time adaptive control problem has been reported in [37] with quantization and network attacks. For interconnected semi-markovian systems, an adaptive quantized control problem has been reported in [38] with actuator faults and disturbances. A class of uncertain deterministic nonlinear systems is being addressed, and an adaptive fuzzy quantized control approach has been presented in [39]. An adaptive quantized controller is introduced once a switched fuzzy observer has been set up [40]. For nonlinear stochastic systems, the authors presented two adaptive fuzzy quantized control strategies [41]. For strict-feedback nonlinear systems with quantized input signals was constructed, and an adaptive control approach based on the backstepping method has been developed in [42]. The problem of adaptive event-triggered fault detection in semi-Markovian jump systems has been investigated under output quantization [43].

According to the aforementioned considerations, few works simultaneously consider nonlinear systems with actuator faults and input quantization. It is difficult to deal with this problem, which motivates us to do this research. In comparison to existing results, this paper investigates adaptive neural networks-based adaptive fault-tolerant control of nonlinear systems. Radial basis function neural networks are used to deal with uncertainty in nonlinear systems. In summary, the following are the key contributions of this work:

(i) In contrast to existing results [3], [7], [19], [30], [38], this work proposed an adaptive neural fault-tolerant control problem for strict-feedback nonlinear systems with actuator faults while considering unknown failure parameters. Although existing results [22], [25], [26] have explored control design in the presence of actuator faults, they do not account for the impact of quantization. Additionally, in [44], the issues arising from quantized input are effectively addressed through the decomposition of the hysteresis quantizer.

(ii) An adaptive fault-tolerant controller with neural network approximation capabilities is designed using Lyapunov stability theory and the backstepping approach. The proposed control strategy ensures that the close signals are bounded and that the system output tracks the reference signal with a small bounded error. To demonstrate the effectiveness of the control strategy, simulation results of an electromechanical system are provided.

The rest of the paper is organized as follows: Section II presents the formulation of the problem and preliminaries. Stability analysis is presented in Section III along with the design of an adaptive controller. Section IV presents a simulation example, and Section V presents the conclusion.

II. PROBLEM FORMULATION AND PRELIMINARIES

In this paper, the following nonlinear system is considered in strict-feedback form

$$\begin{aligned} \dot{\chi}_i &= \chi_{i+1} + \phi_i(\bar{\chi}_i), \quad 1 \le i \le n-1 \\ \dot{\chi}_n &= \Gamma(Q(\omega)) + \phi_n(\bar{\chi}_n) \\ y &= \chi_1 \end{aligned} \tag{1}$$

where $\bar{\chi}_i = [\chi_1, \chi_2, \ldots, \chi_i]^T \in \mathbb{R}^i$ with $i = 1, 2, \ldots, n$, and $y \in \mathbb{R}$ represent the state variable and system output, respectively. The functions $\phi_i(\cdot)$ represent unknown smooth nonlinear functions with $\phi_i(0) = 0$. $\Gamma(Q(\omega))$ is the system input subjected to actuator fault and quantization with ω being the control input to be designed. The system input $\Gamma(Q(\omega))$ is defined as

$$\Gamma(Q(\omega)) = \rho(t, t_\rho)Q(\omega) + \omega_r(t, t_r), \tag{2}$$

where $\rho(t, t_\rho)$ takes values within the interval [0, 1] to represent actuation effectiveness. Additionally, $u_r(t, t_r)$ accounts for uncontrollable additive actuation faults. The parameters t_ρ and t_r denote the respective time instances when the loss of actuation effectiveness fault and the occurrence of an additive actuation fault take place. $Q(\omega)$ is the hysteresis quantization [45] which is defined as

$$Q(\omega(t)) = \begin{cases} \omega_i sgn(\omega), & \text{if } 1+\delta < |\omega| \le \omega_i \text{ and } \dot{\omega} < 0, \\ & \text{or } \omega_i < |\omega| \le \omega_i(1-\delta), \\ & \text{and } \dot{\omega} > 0, \\ \omega_i(1+\delta)sgn(\omega), & \text{if } \omega_i < |\omega| \le \omega_i(1-\delta) \text{ and } \dot{\omega} < 0, \\ & \text{or } \omega_i(1-\delta) < |\omega| \\ & \le \omega_i(1+\delta)(1-\delta), \text{ and } \dot{\omega} > 0, \\ 0, & \text{if } 0 \le |\omega| < \omega_{\min}(1+\delta) \\ & \text{and } \dot{\omega} < 0, \\ & \text{or } \omega_{\min}(1+\delta) \le |\omega| \le \omega_{\min}, \\ & \text{and } \dot{\omega} > 0, \\ Q(\omega(t^-)), & \text{if } \dot{\omega} = 0, \end{cases} \tag{3}$$

where $\omega_i = \mu^{1-i} \cdot \omega_{\min}$ (for $i = 1, 2, \ldots$), $0 < \mu < 1$ determine the quantization density of $Q(\omega(t))$, and $\delta = \frac{1-\mu}{1+\mu}$, $Q(\omega(t))$ belongs to the set $\Theta = \{0, \pm\omega, \pm\omega_i(1+\delta)\}$. The dead-zone range for $Q(\omega(t))$ is $\omega_{\min}$, and $\omega_{\min} > 0$.

Remark 1: Quantization is a method that converts continuous signals into a finite set of discrete signals, therefore considerably lowering signal transmission load. The performance of the control system might be impacted, and potentially become unstable, due to the huge amount of nonlinearity and errors that quantization introduces. Hysteresis quantizers are non-uniform quantizers that have different quantization levels. These quantizers are the most basic option accessible as they reduce average communication instances and are simple to implement. The hysteresis quantizer has more quantization levels than the logarithmic quantizer, which is used to prevent chattering [30].

Control Objective: The control goal of this study is to construct an adaptive fault-tolerant controller that ensures that all of the signals in the closed-loop system are bounded and that the tracking error $z_1 = y - y_d$ converges to zero. To simplify the process of designing an adaptive fault-tolerant controller, we need to introduce the following assumptions and lemmas.

Assumption 1 [20]: The functions $\rho(t, t_\rho)$ and $\omega_r(t, t_r)$, which change over time and are not precisely known, are constrained within certain limits. Specifically, there exist positive constants $\rho_{\min}$ and $\bar{\omega}_{\max}$ such that $\rho_{\min} < \rho(t, t_\rho) \le 1$ and $|\omega_r(t, t_r)| \le \bar{\omega}_{\max}$.

Assumption 2 [6]: The reference signal y_d and its first derivative $\dot{y_d}$ are bounded and continuous.

Lemma 1 [45]: The hysteresis quantizer $Q(\omega(t))$ can be represented

$$Q(\omega(t)) = \omega(t) + h(t), \tag{4}$$

where $h(t)$ satisfies the following inequalities

$$h^2 \le \delta^2\omega^2, \text{ for} |\omega| \ge \omega_{\min} \tag{5}$$

$$h^2 \le \omega_{\min}^2, \text{ for} |\omega| \le \omega_{\min}. \tag{6}$$

Lemma 2 [12]: For all $(u, v) \in \mathbb{R}^2$, we have the following condition

$$uv \le \frac{1}{r}|u|^r + \frac{1}{s}|v|^s, \tag{7}$$

where $r > 1$, $s > 1$, and $(r-1)(s-1) = 1$.

Lemma 3 [21]: Consider a continuous function $\bar{\phi}(Z)$ defined on the compact set Ω. It is guaranteed that there exists a radial basis function neural network (RBFNN) $W^T U(Z)$ such that

$$\bar{\phi}(Z) = W^T U(Z) + \delta(Z), \tag{8}$$

where $|\delta(Z)| \le \epsilon$ with $\epsilon > 0$, the weight vector is denoted as $W = [W_1, \ldots, W_N]^T$, and $U(Z) = [U_1(Z), \ldots, U_N(Z)]^T$ is the basic function vector, where N is the number of NN nodes ($N > 1$). Each $U_i(Z)$ is a Gaussian function defined as follows

$$U_i(Z) = \exp\left(-\frac{\|Z - \mu_i\|^T}{\nu^2}\right) \tag{9}$$

where μ_i and ν represent the center and width of the Gaussian functions, respectively.

Remark 2: RBFNN are highly effective at learning complex structures and nonlinear relationships from the input data, which makes them ideal for approximating unknown functions within nonlinear systems. On the other hand, fuzzy logic systems (FLS) that depend on linguistic variables and rules are often used in studies for adaptive control of nonlinear systems. Their ability to capture complex nonlinear interactions, however, might make it more difficult to estimate unknown functions within these complex systems with accuracy.

The block diagram of proposed control scheme is presented in Fig. 1.

III. ADAPTIVE FAULT-TOLERANT CONTROLLER DESIGN AND STABILITY ANALYSIS

This section introduces a backstepping-based adaptive controller design for system (1). The backstepping-based adaptive control architecture consists of n steps. Before

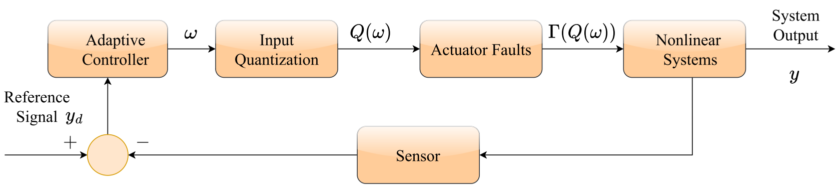


FIGURE 1. The block diagram of proposed control scheme.

continuing with the control design, the following coordinates need to be changed:

$$z_1 = \chi_1 - y_d, \tag{10}$$
$$z_i = \chi_i - \zeta_{i-1}, \quad i = 2, \dots, n \tag{11}$$

where ζ_{i-1} denotes a virtual control signal that will be designed subsequently.

Step 1: By using (1) and $z_1 = \chi_1 - y_d$, one has

$$\dot{z}_1 = \chi_2 + \phi_1 - \dot{y}_d = z_2 + \zeta_1 + \phi_1 - \dot{y}_d. \tag{12}$$

Take the Lyapunov function as

$$V_1 = \frac{1}{2}z_1^2 + \frac{1}{2\zeta_1}\eta_1^2, \tag{13}$$

where ζ_1 is a positive design parameter, and η_1 represents the estimation error, with $\hat{\eta}_1$ being the estimated value of η_1.

Now, differentiate (13) with respect to time, we have

$$\begin{aligned}\dot{V}_1 &= z_1(z_2 + \zeta_1 + \phi_1 - \dot{y}_d) - \frac{1}{\alpha_1}\eta_1\dot{\hat{\eta}}_1\\ &= z_1\left(z_2 + \zeta_1 + \bar{\phi}_1(Z_1)\right) - \frac{1}{2}z_1^2 - \frac{1}{\alpha_1}\eta_1\dot{\hat{\eta}}_1,\end{aligned} \tag{14}$$

where $\bar{\phi}_1(Z_1) = \phi_1 - \dot{y}_d + \frac{1}{2}z_1$.

To address the challenge posed by the unknown nonlinear function ϕ_1 within $\bar{\phi}_1(Z_1)$, RBFNN is using for approximating this function. For any $\epsilon_1 > 0$, one has

$$\bar{\phi}_1(Z_1) = W_1^T U_1(Z_1) + \delta_1(Z_1), |\delta_1(Z_1)| \le \epsilon_1, \tag{15}$$

where $Z_1 = [\chi_1, \chi_2, \dots, \chi_n, y_d, \dot{y}_d]^T$.

By utilizing the concept of completion of squares, we have

$$\begin{aligned}z_1\bar{\phi}_1(Z_1) &= z_1(W_1^T U_1(Z_1) + \delta_1(Z_1))\\ &\le \frac{1}{2\beta_1^2}z_1^2\|W_1\|^2 U_1^T(Z_1)U_1(Z_1) + \frac{\beta_1^2}{2} + \frac{z_1^2}{2} + \frac{\epsilon_1^2}{2}\\ &\le \frac{1}{2\beta_1^2}z_1^2\eta_1 U_1^T(X_1)U_1(X_1) + \frac{\beta_1^2}{2} + \frac{z_1^2}{2} + \frac{\epsilon_1^2}{2},\end{aligned} \tag{16}$$

where $X_1 = [\chi_1, y_d, \dot{y}_d]^T$, $\beta_1 > 0$ is a design parameter, $\eta_1 = \|W_1\|^2$.

The virtual controller ζ_1 is designed as

$$\zeta_1 = -c_1 z_1 - \frac{1}{2\beta_1^2}z_1^2\hat{\eta}_1 U_1^T(X_1)U_1(X_1), \tag{17}$$

and the adaptation law is the designed as

$$\dot{\hat{\eta}}_1 = \frac{\alpha_1}{2\beta_1^2}z_2^2 U_1^T(X_1)U_1(X_1) - \varrho_1\hat{\eta}_1, \tag{18}$$

where $c_1 > 0$, $\varrho_1 > 0$ represent the positive design parameters.

Substituting equations (16)-(18) into (14), we have

$$\dot{V}_1 \le -c_1 z_1^2 + z_1 z_2 + \frac{\varrho_1}{\beta_1}\eta_1\hat{\eta}_1 + \frac{1}{2}\beta_1^2 + \frac{1}{2}\epsilon_1^2. \tag{19}$$

Step i ($2 \le i \le n-1$). By using (1) and (11), one has

$$\dot{z}_i = z_{i+1} + \zeta_i + \phi_i(\chi) - \dot{\zeta}_{i-1}. \tag{20}$$

The following Lyapunov function is chosen as

$$V_i = V_{i-1} + \frac{1}{2}z_i^2 + \frac{1}{2\alpha_1}\tilde{\eta}_i^2. \tag{21}$$

Taking the time derivative of (21), we get

$$\begin{aligned}\dot{V}_i \le &-\sum_{j=1}^{i-1} c_j z_j^2 + z_{i-1}z_i + \sum_{j=1}^{i-1}\frac{\varrho_j}{\alpha_1}\tilde{\eta}_j\hat{\eta}_j + \sum_{j=1}^{i-1}\frac{\alpha_j^2}{2} + \frac{\epsilon_j^2}{2}\\ &+ z_i(z_{i+1} + \zeta_i + \bar{\phi}_i(Z_i)) - \frac{1}{2}z_i^2,\end{aligned} \tag{22}$$

where

$$\bar{\phi}_i(Z_i) = z_{i-1} + \phi_i - \dot{\zeta}_{i-1} + \frac{1}{2}z_i. \tag{23}$$

The unknown function $\bar{\phi}_i(Z_i)$ can be approximated by RBFNN as

$$\bar{\phi}_i(Z_i) = W_i^T U_i(Z_i) + \delta_i(Z_i), |\delta_i(Z_i)| \le \epsilon_i, \tag{24}$$

where $Z_i = [\chi_1, \chi_2, \dots, \chi_n, \bar{\hat{\eta}}_{i-1}^T, \bar{y}_d^{(i)T}]^T$.

By using Young's inequality, we get

$$\begin{aligned}z_i\bar{\phi}_i(Z_i) &= z_i(W_i^T U_i(Z_i) + \delta_i(Z_i))\\ &\le \frac{1}{2\beta_i^2}z_i^2\|W_i\|^2 U_i^T(Z_i)U_i(Z_i) + \frac{\beta_i^2}{2} + \frac{z_i^2}{2} + \frac{\epsilon_i^2}{2}\\ &\le \frac{1}{2\beta_i^2}z_i^2\eta_i U_i^T(X_i)U_i(X_i) + \frac{\beta_i^2}{2} + \frac{z_i^2}{2} + \frac{\epsilon_i^2}{2},\end{aligned} \tag{25}$$

where $X_i = [\chi_1, \chi_2, \dots, \chi_i, \bar{\hat{\eta}}_{i-1}^T, \bar{y}_d^{(i)T}]^T$ with $\bar{\hat{\eta}}^{i-1} = [\hat{\eta}^1, \dots, \hat{\eta}^{i-1}]^T$ and $\bar{y}_d^{(i)T} = [y_d, \dots, y_d^{(i)}]^T$, $\eta_i = \|W_i\|^2$, and $\beta_i > 0$ is a design parameter.

The virtual controller ζ_i is define as

$$\zeta_i = -c_i z_i - \frac{1}{2\beta_i^2}z_i\hat{\eta}_i U_i^T(X_i)U_i(X_i), \tag{26}$$

and the adaptation law is define as

$$\dot{\hat{\eta}}_i = \frac{\alpha_i}{2\beta_i^2}z_i^2 U_i^T(X_i)U_i(X_i) - \varrho_i\hat{\eta}_i, \tag{27}$$

where c_i, ϱ_i are positive design parameters.

Substituting equations (25)-(27) into (22), one has

$$\dot{V}_i \leq -\sum_{j=1}^{i} c_i z_j^2 + z_i z_{i+1} + \sum_{j=1}^{i} \frac{\varrho_j}{\alpha_j}\tilde{\eta}_j\hat{\eta}_j + \sum_{j=1}^{i}\left(\frac{\beta_j^2}{2} + \frac{\epsilon_j^2}{2}\right). \tag{28}$$

Step n: By using (1), (2), (4) (11) and by taking the time derivative of z_n, we obtain

$$\begin{aligned}\dot{z}_n &= \Gamma(Q(\omega)) + \phi_n(x) - \dot{\zeta}_{n-1}\\ &= \big(\rho(t,t_\rho)\omega(t)\\ &\quad + \rho(t,t_\rho)h(t) + \omega_r(t,t_r)\big) + \phi_n(x) - \dot{\zeta}_{n-1}.\end{aligned} \tag{29}$$

Choose the following Lyapunov function as

$$V_n = V_{n-1} + \frac{1}{2}z_n^2 + \frac{1}{2\alpha_n}\tilde{\eta}_n^2. \tag{30}$$

The time derivative of (30) gives

$$\begin{aligned}\dot{V}_n \leq& -\sum_{j=1}^{n-1} k_j z_j^2 + z_{n-1}z_n + \sum_{j=1}^{n-1}\frac{\varrho_j}{\alpha_j}\tilde{\eta}_j\hat{\eta}_j + \sum_{j=1}^{n-1}\frac{\beta_j^2}{2} + \frac{\epsilon_j^2}{2}\\ &+ z_n\left(\big(\rho(t,t_\rho)\omega(t) + \rho(t,t_\rho)h(t) + \omega_r(t,t_r)\big) + \bar{\phi}_n(Z_n)\right)\\ &- \frac{1}{2}z_n^2,\end{aligned} \tag{31}$$

where

$$\bar{\phi}_n(Z_n) = z_{n-1} + \phi_n(x) - \dot{\zeta}_{n-1} + \frac{1}{2}z_n. \tag{32}$$

The unknown function $\bar{\phi}_n(Z_n)$ can be approximated by the RBFNN such that for any $\epsilon_n > 0$, we get

$$\bar{\phi}_n(Z_n) = W_n^T U_n(Z_n) + \delta_n(Z_n), \ |\delta_n(Z_n)| \leq \epsilon_n, \tag{33}$$

where $Z_n = [\chi_1, \chi_2, \ldots, \chi_n, \bar{\hat{\eta}}_{n-1}^T, \bar{y}_d^{(n)T}]^T$.

Moreover, we have

$$\begin{aligned}z_n\bar{\phi}_n(Z_n) &= z_n(W_n^T U_n(Z_n) + \delta_n(Z_n))\\ &\leq \frac{1}{2\beta_n^2}z_n^2\|W_n\|^2 U_n^T(Z_n)U_n(Z_n) + \frac{\beta_n^2}{2} + \frac{z_n^2}{2} + \frac{\epsilon_n^2}{2}\\ &\leq \frac{1}{2\beta_n^2}z_n^2\eta_n U_n^T(X_n)U(X_n) + \frac{\beta_n^2}{2} + \frac{z_n^2}{2} + \frac{\epsilon_n^2}{2},\end{aligned} \tag{34}$$

where $X_n = Z_n$, $\eta_i = \|W_n\|^2$, and $\beta_n > 0$ is a design parameter.

The real control law is define as

$$\omega = -c_n z_n - \frac{1}{2\beta_n^2\rho_{\min}} z_n\eta_n U_n^T(X_n)U_n(X_n). \tag{35}$$

By Lemma 2 and Assumption 1, one has

$$z_n\omega_r(t,t_r) \leq \frac{1}{2}z_n^2 + \frac{1}{2}\bar{\omega}_{\max}^2. \tag{36}$$

From Assumptions 1, Lemma 2, and (35), one has

$$\rho(t,t_\rho)\omega \leq -c_n\rho_{\min}z_n^2 - \frac{1}{2\beta_n^2}z_n^2\eta_n U_n^T(X_n)U_n(X_n), \tag{37}$$

$$\rho(t,t_\rho)h(t) \leq \frac{1}{2}z_n^2 + \frac{1}{2}\omega_{\min}^2\rho_{\min}^2. \tag{38}$$

The adaptation law is defined as

$$\dot{\hat{\eta}}_n = \frac{\alpha_n}{2\beta_n^2}z_n^2 U_n^T(X_n)U_n(X_n) - \varrho_n\eta_n, \tag{39}$$

where k_n and ϱ_n are positive design parameters.

Using (34)-(39) into (38), we have

$$\begin{aligned}\dot{V}_n \leq& -\sum_{j=1}^{n-1} c_n z_j^2 - c_n\rho_{\min}z_n^2 + \sum_{j=1}^{n}\frac{\varrho_j}{b_j}\tilde{\eta}_j\hat{\eta}_j + \sum_{j=1}^{n}\left(\frac{\beta_j^2}{2} + \frac{\epsilon_j^2}{2}\right)\\ &+ \frac{1}{2}\bar{\omega}_{\max}^2 + \frac{1}{2}\omega_{\min}^2\rho_{\min}^2.\end{aligned} \tag{40}$$

Theorem 1: Consider the non-strict-feedback system (1) with Assumptions 1-2 taken into account, along with actuator faults (2) and hysteresis quantizer (3). Given bounded initial conditions, the proposed control approach, comprising the actual controller ω (35), virtual control law ζ_i (17), (26), and adaptive laws $\hat{\eta}_i$ (18), (27), and (39), ensures the boundedness of all signals within the closed-loop system. Furthermore, the tracking error $z_1 = y - y_d$ satisfies

$$\lim_{t\to\infty} z_1(t) = 0. \tag{41}$$

Proof: First, it was established that

$$\tilde{\eta}_i\eta_i \leq -\frac{1}{2}\tilde{\eta}_i^2 + \frac{1}{2}\eta_i^2. \tag{42}$$

Then (40), becomes

$$\begin{aligned}\dot{V}_n \leq& -\sum_{j=1}^{n-1} c_n z_j^2 - c_n\rho_{\min}z_n^2 + \sum_{j=1}^{n}\frac{\varrho_j}{b_j}\tilde{\eta}_j\hat{\eta}_j + \sum_{j=1}^{n}\left(\frac{\beta_j^2}{2} + \frac{\epsilon_j^2}{2}\right)\\ &+ \frac{1}{2}\bar{\omega}_{\max}^2 + \frac{1}{2}\omega_{\min}^2\rho_{\min}^2,\end{aligned} \tag{43}$$

where $a_0 = \min\{2c_i, \ldots, 2c_{n-1}, 2c_n\rho_{\min}, \beta_1, \ldots, \beta_n\}$, and $b_0 = \sum_{j=1}^{n}\left(\frac{\beta_j^2}{2} + \frac{\epsilon_j^2}{2}\right) + \frac{1}{2}\omega_{\max}^2 + \frac{1}{2}\omega_{\min}^2\rho_{\min}^2 + \sum_{i=1}^{n}\frac{\varrho_j}{2\beta_j}\eta_j^2$.

Using these notations, one has

$$\dot{V} \leq -a_0 V + b_0. \tag{44}$$

Furthermore, we have

$$V(t) \leq \left(V(0) - \frac{b_0}{a_0}\right)e^{-a_0 t} + \frac{b_0}{a_0}. \tag{45}$$

Equation (45) ensures that all signals in the closed-loop system remain bounded. Specifically, we have

$$z_1^2 \leq 2\left(V(0) - \frac{b_0}{a_0}\right)e^{-a_0 t} + 2\frac{b_0}{a_0}. \tag{46}$$

As a result, equation (41) follows immediately. The proposed control approach not only achieves closed-loop system stabilization but also assures precise tracking performance for nonlinear systems in the face of actuator faults and input quantization. Hence, the proof is completed.

Remark 3: The choices made for design parameters c_i, ϱ, and β_i can have a substantial influence on the tracking error, as demonstrated by inequality (46) and the expressions for the design parameters a_0 and b_0. Increasing c_i and ϱ while decreasing β_i can reduce tracking error but raises control input. Thus, choosing the appropriate design parameters in simulations is important for enhancing control performance.

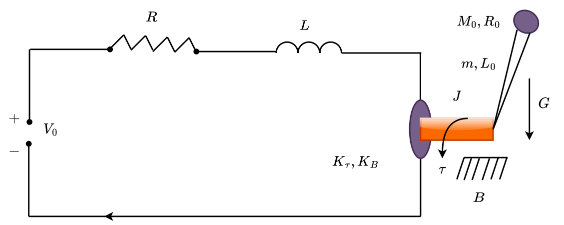


FIGURE 2. The electromechanical system.

IV. SIMULATION RESULTS

To evaluate the effectiveness of the developed control algorithm, an electromechanical system [46] is employed, as depicted in Figure 2. The system's mathematical model is expressed by the following equations:

$$\begin{cases} M\ddot{q} + B\dot{q} + N\sin(q) = I \\ \dot{I} = V_0 - RI - K_T\dot{q}, \end{cases} \tag{47}$$

where the parameters are defined as $M = \frac{J}{K_T} + \frac{mL_0^2}{3K_T} + \frac{M_0L_0^2}{K_T} + \frac{2M_0R_0^2}{5K_T}$, $B = \frac{B_0}{K_T}$, and $N = \frac{mL_0G}{2K_T} + \frac{M_0L_0G}{K_T}$, where m represents the link mass, the rotor inertia is J, the load mass is M_0, the armature inductance is L, the viscous friction coefficient is B_0, the link length is L_0, the armature resistance is R, and the back EMF coefficient is K_T, the load radius is R_0, the armature inductance is L, and the link length is L_0. q is the angular motor position, $\dot{q}$ represents the angular motor velocity, $\ddot{q}$ represents the angular motor acceleration. The term $I(t)$ stands for the motor armature current, K_T stands for the coefficient describing the electromechanical conversion of armature current to torque, and G stands for the gravitational constant. The values for the parameters are same as in [46]. Equation (47) can be recast as follows by taking into account the electromechanical system and adding the variable changes $\chi_1 = q$, $\chi_2 = \dot{q}$, $\chi_3 = I$, and $u = \frac{V_0}{M}$

$$\begin{aligned} \dot{\chi}_1 &= \chi_2, \\ \dot{\chi}_2 &= \frac{\chi_3}{M} - \frac{N}{M}\sin(\chi_1) - \frac{B}{M}\chi_2, \\ \dot{\chi}_3 &= \frac{u}{L} - \frac{K}{L}\chi_2 - \frac{R}{L}\chi_3, \end{aligned}$$

where $y = \chi_1$. Additionally, the reference signal is chosen as $y_d = 0.5\sin(t) - \cos(0.5t)$.

The virtual control signals, the actual control law, and the adaptive laws are defined as

$$\zeta_i = -c_i z_i - \frac{1}{2\beta_i^2} z_i \hat{\eta}_i U_i^T(X_i)U_i(X_i), \quad i = 1, 2 \tag{48}$$

$$\omega = -c_n z_n - \frac{1}{2\beta_n^2 \rho_{\min}} z_n \eta_n U_n^T(X_n)U_n(X_n), \tag{49}$$

$$\dot{\hat{\eta}}_i = \frac{\alpha_i}{2\beta_i^2} z_i^2 U_i^T(X_i)U_i(X_i) - \varrho_i \hat{\eta}_i, \quad i = 1, 2, 3. \tag{50}$$

In the simulation, the quantized parameters are set as $\delta = 0.3$, $\mu = 0.2$ and $\mu_{\min} = 0.8$. The actuator fault is selected as $\rho(t, t_\rho)Q(\omega) + \omega_r(t, t_r)$ where $\rho(t, t_\rho) = 0.2 + 0.8exp(-0.2t)$ and $\omega_r(t, t_r) = \cos^2(\chi_1)\chi_2$. In the simulation, the controller design parameters are selected through a trial-and-error approach. The controller design parameters are chosen as $c_1 = 10$, $c_2 = 20$ $\beta_1 = \beta_2 = \beta_3 = 1$, $\alpha_1 = \alpha_2 = \alpha_3 = 0.5$, $\varrho_1 = \varrho_2 = \varrho_3 = 0.05$. The width ν and centres μ_i of the Gaussian functions are chosen as 2 and $[-2, 2]$, respectively.The initial conditions are $\chi_1(0) = 0.5$ $\chi_2(0) = 0.4$, $\chi_3(0) = 0.2$, $\hat{\eta}_1(0) = 0$, $\hat{\eta}_2(0) = 0$, $\hat{\eta}_3(0) = 0$.

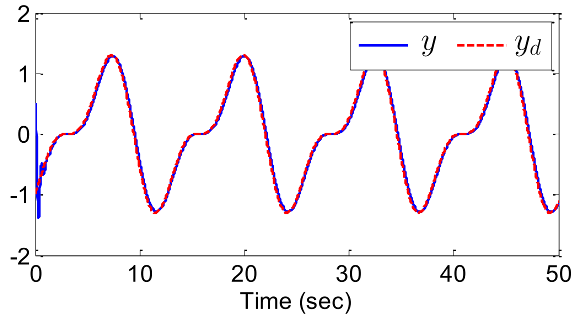


FIGURE 3. Trajectories of y and y_d.

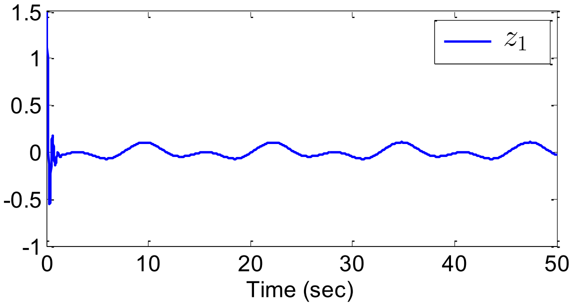


FIGURE 4. Tracking error z_1.

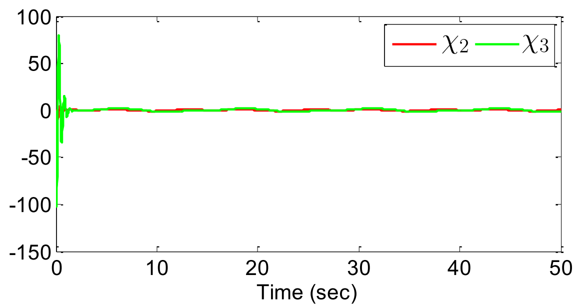


FIGURE 5. The state variable χ_2 and χ_3.

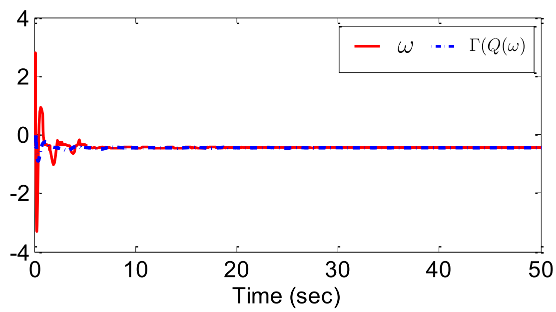


FIGURE 6. Trajectories of ω and $\Gamma(Q(\omega))$.

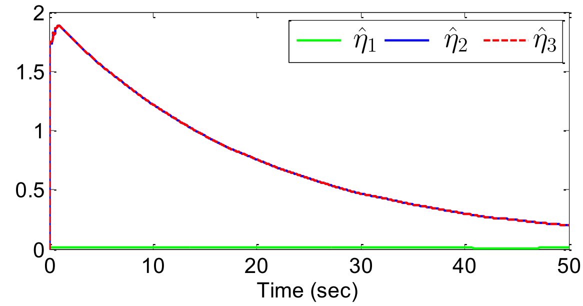


FIGURE 7. The responses of adaptive laws $\hat{\eta}_1$, $\hat{\eta}_2$ and $\hat{\eta}_3$.

The simulation results are shown in Figs. 3-7. The output y and desired signal y_d trajectories are shown in Fig. 3. It displays effective tracking performance is achieved. Fig. 4 provides an illustration of the tracking error z_1. The trajectories of the states χ_2 and χ_3 are shown in Fig. 5. Fig. 6 shows the responses to system input $\Gamma(Q(\omega))$ and control input ω. The adaptive laws $\hat{\eta}_1$, $\hat{\eta}_2$, and $\hat{\eta}_3$ are shown to be bounded in Figure 7. Figures 3-7 show that by employing the developed controller, all closed-loop system signals are bounded by suitably enhancing the parameters. This signifies that the simulation results validate the suggested controller.

V. CONCLUSION

This work investigates the adaptive fault-tolerant control problem of a class of nonlinear systems with actuator faults and input quantization. Radial basis function neural networks (RBFNN) are used in the control system to approximate nonlinear functions. In addition, utilizing the backstepping approach and Lyapunov stability theory, an adaptive fault-tolerant controller for nonlinear systems is proposed to compensate for the impacts of input quantization and actuator faults. With the proposed control method, all signals in the closed-loop system are semi-globally uniformly ultimately bounded, and the tracking error converges to an arbitrarily small area of origin. To validate the control strategy, simulation results of an electromechanical system are provided. The limitation of the proposed method resides in the selection of appropriate design parameters and initial conditions during simulation, often determined via trial and error. This iterative process can be time-consuming. The proposed control scheme demonstrates applicability across various real-world systems, including inverted pendulum control systems and chemical reactor systems. In the future, we will investigate the stochastic nonlinear systems with sensor faults and quantization by apply the proposed control method to real-world engineering issues.

REFERENCES

[1] H. Wang, H. R. Karimi, P. X. Liu, and H. Yang, "Adaptive neural control of nonlinear systems with unknown control directions and input dead-zone," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 48, no. 11, pp. 1897–1907, Nov. 2018.

[2] F. Hong, S. S. Ge, and T. H. Lee, "Practical adaptive neural control of nonlinear systems with unknown time delays," *IEEE Trans. Syst., Man Cybern. B, Cybern.*, vol. 35, no. 4, pp. 849–854, Aug. 2005.

[3] B. Chen, H. Zhang, X. Liu, and C. Lin, "Neural observer and adaptive neural control design for a class of nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 9, pp. 4261–4271, Sep. 2018.

[4] M. Chen, S.-Y. Shao, and B. Jiang, "Adaptive neural control of uncertain nonlinear systems using disturbance observer," *IEEE Trans. Cybern.*, vol. 47, no. 10, pp. 3110–3123, Oct. 2017.

[5] H. Li, L. Bai, L. Wang, Q. Zhou, and H. Wang, "Adaptive neural control of uncertain nonstrict-feedback stochastic nonlinear systems with output constraint and unknown dead zone," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 8, pp. 2048–2059, Aug. 2017.

[6] T. Wang, J. Qiu, and H. Gao, "Adaptive neural control of stochastic nonlinear time-delay systems with multiple constraints," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 8, pp. 1875–1883, Aug. 2017.

[7] Y. Zhang and F. Wang, "Observer-based fixed-time neural control for a class of nonlinear systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 33, no. 7, pp. 2892–2902, Jul. 2022.

[8] M. Wang and A. Yang, "Dynamic learning from adaptive neural control of robot manipulators with prescribed performance," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 47, no. 8, pp. 2244–2255, Aug. 2017.

[9] S. Zhang, Y. Dong, Y. Ouyang, Z. Yin, and K. Peng, "Adaptive neural control for robotic manipulators with output constraints and uncertainties," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 11, pp. 5554–5564, Nov. 2018.

[10] Y. Sun, B. Chen, C. Lin, and H. Wang, "Finite-time adaptive control for a class of nonlinear systems with nonstrict feedback structure," *IEEE Trans. Cybern.*, vol. 48, no. 10, pp. 2774–2782, Oct. 2018.

[11] Z. Namadchian and M. Rouhani, "Observer-based adaptive neural control for switched stochastic pure-feedback systems with input saturation," *Neurocomputing*, vol. 375, pp. 80–90, Jan. 2020.

[12] S. Tong, K. Sun, and S. Sui, "Observer-based adaptive fuzzy decentralized optimal control design for strict-feedback nonlinear large-scale systems," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 2, pp. 569–584, Apr. 2018.

[13] H. Li, S. Zhao, W. He, and R. Lu, "Adaptive finite-time tracking control of full state constrained nonlinear systems with dead-zone," *Automatica*, vol. 100, pp. 99–107, Feb. 2019.

[14] C. Yang, S. Sam Ge, C. Xiang, T. Chai, and T. Heng Lee, "Output feedback NN control for two classes of discrete-time systems with unknown control directions in a unified approach," *IEEE Trans. Neural Netw.*, vol. 19, no. 11, pp. 1873–1886, Nov. 2008.

[15] J. Zhu, Q. Shen, and T. Zhang, "Neural network-based decentralized adaptive fault-tolerant control for a class of nonlinear interconnected systems with unknown input powers," *Int. J. Adapt. Control Signal Process.*, vol. 37, no. 7, pp. 1693–1715, Apr. 2023.

[16] Q. Shen, P. Shi, R. K. Agarwal, and Y. Shi, "Adaptive neural network-based filter design for nonlinear systems with multiple constraints," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 7, pp. 3256–3261, Jul. 2021.

[17] Q. Shen, P. Shi, J. Zhu, S. Wang, and Y. Shi, "Neural networks-based distributed adaptive control of nonlinear multiagent systems," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 3, pp. 1010–1021, Mar. 2020.

[18] J. Guo, Y. Bo, J. H. Park, and J. Ma, "Adaptive neural control for nonlinear systems with actuator faults and unknown control directions via command filter," *Int. J. Robust Nonlinear Control*, vol. 32, no. 4, pp. 2100–2118, Mar. 2022.

[19] K. Lu, Z. Liu, Y. Wang, and C. L. P. Chen, "Resilient adaptive neural control for uncertain nonlinear systems with infinite number of time-varying actuator failures," *IEEE Trans. Cybern.*, vol. 52, no. 6, pp. 4356–4369, Jun. 2022.

[20] S. Tong, C. Liu, and Y. Li, "Fuzzy-adaptive decentralized output-feedback control for large-scale nonlinear systems with dynamical uncertainties," *IEEE Trans. Fuzzy Syst.*, vol. 18, no. 5, pp. 845–861, Oct. 2010.

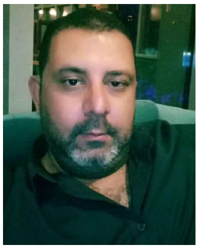
[21] Y. Zhang and F. Wang, "Adaptive neural control of non-strict feedback system with actuator failures and time-varying delays," *Appl. Math. Comput.*, vol. 362, Dec. 2019, Art. no. 124512.

[22] H. Liu, Y. Pan, J. Cao, H. Wang, and Y. Zhou, "Adaptive neural network backstepping control of fractional-order nonlinear systems with actuator faults," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 12, pp. 5166–5177, Dec. 2020.

[23] D. Cui, B. Niu, H. Wang, and D. Yang, "Adaptive fuzzy output-feedback fault-tolerant tracking control of a class of uncertain nonlinear switched systems," *Int. J. Syst. Sci.*, vol. 50, no. 14, pp. 2673–2686, Oct. 2019.

[24] D. Cui, B. Niu, D. Yang, T. Hayat, and F. E. Alsaadi, "Adaptive neural fault-tolerant control for a class of stochastic switched nonlinear systems," *IEEE Access*, vol. 7, pp. 93219–93228, 2019.

[25] C.-H. Xie and G.-H. Yang, "Decentralized adaptive fault-tolerant control for large-scale systems with external disturbances and actuator faults," *Automatica*, vol. 85, pp. 83–90, Nov. 2017.
[26] L. Cao, Q. Zhou, G. Dong, and H. Li, "Observer-based adaptive event-triggered control for nonstrict-feedback nonlinear systems with output constraint and actuator failures," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 3, pp. 1380–1391, Mar. 2021.
[27] L. Zheng, Z. Liu, C. L. P. Chen, and Y. Zhang, "Adaptive neural control for uncertain switched nonlinear systems with a switched filter-contained hysteretic quantizer," *Inf. Sci.*, vol. 581, pp. 345–361, Dec. 2021.
[28] T. Zhang, M. Wang, M. Xia, and Y. Yang, "Observer-based decentralized adaptive neural control for uncertain interconnected systems with input quantization and time-varying output constraints," *Int. J. Robust Nonlinear Control*, vol. 30, no. 13, pp. 4979–5003, Jun. 2020.
[29] F. Wang, B. Chen, C. Lin, J. Zhang, and X. Meng, "Adaptive neural network finite-time output feedback control of quantized nonlinear systems," *IEEE Trans. Cybern.*, vol. 48, no. 6, pp. 1839–1848, Jun. 2018.
[30] H. Wang, S. Liu, D. Wang, B. Niu, and M. Chen, "Adaptive neural tracking control of high-order nonlinear systems with quantized input," *Neurocomputing*, vol. 456, pp. 156–167, Oct. 2021.
[31] D. Zeng, Z. Liu, C. L. P. Chen, and Y. Zhang, "Adaptive neural tracking control for switched nonlinear systems with state quantization," *Neurocomputing*, vol. 454, pp. 392–404, Sep. 2021.
[32] Z. Liu, B. Chen, and C. Lin, "Adaptive neural quantized control for a class of switched nonlinear systems," *Inf. Sci.*, vol. 537, pp. 313–333, Oct. 2020.
[33] H. Wang, P. Xiaoping Liu, X. Xie, X. Liu, T. Hayat, and F. E. Alsaadi, "Adaptive fuzzy asymptotical tracking control of nonlinear systems with unmodeled dynamics and quantized actuator," *Inf. Sci.*, vol. 575, pp. 779–792, Oct. 2021.
[34] S. G. Jang and S. J. Yoo, "Quantized-state-feedback-based neural control for a class of switched nonlinear systems with unknown control directions," *IEEE Access*, vol. 10, pp. 78384–78397, 2022.
[35] F. Wang, L. Zhang, S. Zhou, and Y. Huang, "Neural network-based finite-time control of quantized stochastic nonlinear systems," *Neurocomputing*, vol. 362, pp. 195–202, Oct. 2019.
[36] S. Sui and S. Tong, "Fuzzy adaptive quantized output feedback tracking control for switched nonlinear systems with input quantization," *Fuzzy Sets Syst.*, vol. 290, pp. 56–78, May 2016.
[37] Y. Tan, Q. Liu, D. Du, B. Niu, and S. Fei, "Observer-based finite-time H_∞ control for interconnected fuzzy systems with quantization and random network attacks," *IEEE Trans. Fuzzy Syst.*, vol. 29, no. 3, pp. 674–685, Mar. 2021.
[38] Q. Liu, Y. Tan, X. Xie, D. Du, and S. Fei, "Composite anti-disturbance quantized control for interconnected semi-Markovian systems with multiple disturbances and actuator faults," *J. Franklin Inst.*, vol. 360, no. 16, pp. 12729–12749, Nov. 2023.
[39] H. Zhang, X. Zhao, L. Zhang, B. Niu, G. Zong, and N. Xu, "Observer-based adaptive fuzzy hierarchical sliding mode control of uncertain under-actuated switched nonlinear systems with input quantization," *Int. J. Robust Nonlinear Control*, vol. 32, no. 14, pp. 8163–8185, Jul. 2022.
[40] Y.-X. Li and G.-H. Yang, "Observer-based adaptive fuzzy quantized control of uncertain nonlinear systems with unknown control directions," *Fuzzy Sets Syst.*, vol. 371, pp. 61–77, Sep. 2019.
[41] X. Huo, L. Ma, X. Zhao, and G. Zong, "Observer-based fuzzy adaptive stabilization of uncertain switched stochastic nonlinear systems with input quantization," *J. Franklin Inst.*, vol. 356, no. 4, pp. 1789–1809, Mar. 2019.
[42] H. Ma, Q. Zhou, L. Bai, and H. Liang, "Observer-based adaptive fuzzy fault-tolerant control for stochastic nonstrict-feedback nonlinear systems with input quantization," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 49, no. 2, pp. 287–298, Feb. 2019.
[43] L. Zhang, H. Liang, Y. Sun, and C. K. Ahn, "Adaptive event-triggered fault detection scheme for semi-Markovian jump systems with output quantization," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 4, pp. 2370–2381, Apr. 2021.
[44] J. Zhou, C. Wen, and G. Yang, "Adaptive backstepping stabilization of nonlinear uncertain systems with quantized input signal," *IEEE Trans. Autom. Control*, vol. 59, no. 2, pp. 460–464, Feb. 2014.
[45] J. Wu, W. Sun, S.-F. Su, and J. Xia, "Neural-based adaptive control for nonlinear systems with quantized input and the output constraint," *Appl. Math. Comput.*, vol. 413, Jan. 2022, Art. no. 126637.
[46] L. Ma and L. Liu, "Adaptive neural network control design for uncertain nonstrict feedback nonlinear system with state constraints," *IEEE Trans. Syst., Man, Cybern., Syst.*, vol. 51, no. 6, pp. 3678–3686, Jun. 2021.



MOHAMED KHARRAT received the Ph.D. and Habilitation degrees in mathematics from the University of Sfax, Tunisia, in 2014 and 2021, respectively. He is currently an Assistant Professor with the College of Science, Jouf University, and a member of the Research Laboratory of Probability and Statistics LR18ES28, Faculty of Sciences, University of Sfax. His main research interests include stochastic differential equations, fractional differential equations, nonlinear systems, mathematical finance, adaptive control, and the study of stability.

MOEZ KRICHEN (Member, IEEE) received the Ph.D. degree in computer science from Joseph Fourier University, Grenoble, France, in 2007, and the HDR (Ability to Conduct Research) degree in computer science from the University of Sfax, Sfax, Tunisia, in 2018. He is currently an Associate Professor in computer science with Al-Baha University and a member of the Research Laboratory on Development and Control of Distributed Applications (REDCAD), Sfax. Currently, he is also working on formal aspects related to deep learning, data mining, blockchain, smart contracts, and optimization. His main research interests include model-based conformance, load, and security testing methodologies for real-time, distributed, and dynamically adaptable systems. Moreover, he works on applying formal methods to several modern technologies like smart cities, the Internet of Things (IoT), smart vehicles, drones, and healthcare systems.

LOAY ALKHALIFA received the B.Sc. degree in mathematics from Qassim University, Ar Rass, Saudi Arabia, the M.Sc. degree in mathematics from the Royal Military College of Canada, with a focus on location theory, and the Ph.D. degree in applied mathematics from Arizona State University, with a focus on applied optimization. He continued the research work after that in different applied mathematics areas. He is currently an Assistant Professor with the Department of Mathematics, College of Sciences and Arts, Qassim University. Alongside mathematical expertise, he possesses advanced computer skills, including proficiency in Python, MATLAB, and LATEX. He serves as the Vice Dean of the College of Business Administration, Qassim University, where he continues to contribute to the academic community.

KARIM GASMI received the bachelor's degree in computer science, in 2008, and the master's and Ph.D. degrees in computer science from the University of Sfax. He is currently an Assistant Professor with Jouf University, Saudi Arabia. He is also a member of the Research Laboratory on Development and Control of Distributed Applications (ReDCAD). His research interests include information retrieval and medical image processing.