SMC-Based Bounded Consensus Tracking for Multiagent Systems Under Stochastic DoS Attacks With Applications to Multiple DC Motors

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***Abstract*—This article presents a sliding mode controller to address the challenge of achieving mean-square bounded consensus tracking for leader–follower multiagent systems (MASs) under stochastic denial-of-service (DoS) attacks. Such cyber attacks can reduce the effective transmission of measurement signals by interrupting the communication between the MASs and the control station, thereby corrupting the feasibility of control. Existing descriptions of DoS attacks typically rely on two energy assumptions regarding attack frequency and duration, which introduce conservatism into the stability analysis of the system. Conversely, this article models DoS attacks using a two-mode Markov process, thereby preventing the necessity for explicit energy constraints. To ensure control feasibility under DoS attacks, a control scheme that uses the latest uncontaminated control input signal and uses it as the new primary control input signal until the DoS attack ceases is adopted to mitigate the effects of DoS attacks effectively. Based on the Lyapunov function method, it is shown that the designed sliding mode controller guarantees the reachability and mean-square bounded consensus tracking of the resulting global tracking error dynamic system under Markov-type DoS attacks. At last, the correctness and the effectiveness are verified by a web-based multiple dc motors angle coordinated control experiment.**

***Index Terms*—Bounded consensus tracking, dc motors, multiagent systems (MASs), sliding mode controller, stochastic denial-of-service (DoS) attacks.**

I. Introduction

MULTIAGENT systems (MASs), as an emerging research topic, have captured the interest of scholars across various fields due to their unique advantages and potential practical applications [1]. In contrast to single-agent systems, MASs entail multiple agents working collaboratively or interacting with each other, enabling them to collectively address problems. These systems are typically more adaptable to change and uncertainty, adjusting to environmental changes and the behavior of other agents. In addition, MASs can leverage distributed computation and processing to address large-scale and complex problems efficiently. They demonstrate robustness and can sustain operation even in the event of failure or malfunction of one of the agents in the system. Consequently, MASs have found widespread applications in fields like intelligent transportation systems [2], collaborative robots [3], and smart grids [4]. The consensus problem is a prevalent issue in MASs, and its main objective involves formulating suitable protocols and algorithms to facilitate a group of agents converging to a consistent value [5]. An interesting topic involves introducing a leader among multiple agents to achieve consensus and transforming the consensus problem into a coordinated tracking problem in the presence of a leader or a reference signal [6]. This necessitates all agents to exchange state information with their neighbors or the leader to enable tracking of the leader.

Given the nonlinear nature of system dynamics, dynamic differences between MASs, and model uncertainty, which leads to the complexity of cooperative control and target tracking. Traditional control methods like fuzzy control [7] and PID control [8], struggle to achieve stability and optimal performance in such a complex environment [9]. Sliding mode control (SMC), as a nonlinear approach, effectively addresses the complexities of MASs, providing a strategy ensuring stability and high performance [10]. Furthermore, the SMC method exhibits rapid response characteristics. By introducing a sliding surface, it enables fast adjustment of the system state, ensuring that in the face of external disturbances or parameter variations, the system state can quickly move to the desired trajectory, thereby

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guaranteeing precise control of MASs. Its fundamental concept involves introducing a sliding surface to guide the system state, facilitating the realization of desired dynamic behavior. This imparts strong robustness to parameter variations and external disturbances. Currently, there have been some studies on consensus tracking of MASs through SMC. Considering potential state transmission disruptions due to channel fading, Gu et al. in [11] proposed a feasible distributed sliding mode controller, leveraging received fading states to resolve consensus tracking problems for MASs. Yu et al.[12] developed an SMC algorithm with constant gains to address the consensus issue for MASs subject to unknown bounded disturbances. Addressing uncertain communication scenarios, Dong et al. [13] proposed an SMC approach for tackling nonlinear tracking problems with time-varying topology. Most consensus tracking issues with SMC focus on continuous-time MASs. Further comprehensive research is needed to apply SMC to address consensus tracking problems in discrete-time MASs.

The control station of MASs is typically established separately at a fixed location. This setup enables centralized management and monitoring of the entire system, enhances the efficient utilization of computing and communication resources, and facilitates equipment maintenance by staff [14]. Communication between the control station and the multiagent cluster typically occurs through a network. This approach offers the system advantages, such as flexibility, mobility, low cost, and real-time communication. These advantages improve the adaptability of the system to dynamic and complex environments while enhancing scalability and robustness. This architecture has found widespread use in engineering practice across various MASs, encompassing unmanned surface vehicles [15], quadcopter aerial vehicles [16], and autonomous ground vehicles [17]. In such MASs, the transmission network is critical to the controllability and observability of the system. The reliability of the transmission network directly affects the performance of control and estimation. It is necessary and challenging to perform control and estimation of MASs in a degraded network environment. Considering the openness and vulnerability of network transmission, it becomes susceptible to cyber attacks by adversaries. Therefore, conducting research on security control for MASs is crucial. Denial-of-service (DoS) attacks, common malicious network attacks, disrupt network transmission by flooding the target system with a large number of requests, consuming its processing power, or depleting its network bandwidth [18]. This aims to interrupt the transmission of effective information between the system and the control station. Some results on security control of DoS attacks can currently be found in [19], [20], [21]. The results in these references are based on two restrictive assumptions regarding the energy of DoS attacks, namely, the frequency and the duration of the attack, which introduces a certain conservatism to the control and estimation of the system. The Markov process is a stochastic model that describes a series of possible events, where the jump between each mode is determined by a transition probability matrix [22]. The Markov process is well-suited for modeling dynamic systems where the evolution of states over time is probabilistic. How to construct a Markov process to characterize the stochastic evolution of DoS attacks without the above energy assumptions, is one of the motivations of this article.

DoS attacks on the network can disrupt the proper transmission of sensor signals to the designed controller. Inadequate inputs may hinder the proper functioning of the control system, potentially causing system failure or degradation in the desired control performance. Therefore, the manner in which control inputs are managed during DoS attacks is crucial for controlling the entire system. Zeng et al. [23] worked out the H_∞ control problem for Markov jump systems with DoS attacks by designing a novel event-triggered approach incorporating membership functions. To provide an efficient estimation of the performance error induced by a T–S fuzzy networked control system with DoS attacks, Cai et al. converted the performance error estimation issue into a problem of searching for elliptic constraints in [24]. Zeng et al. [23], Cai et al. [24], Hu et al. [25] proposed a method that compels the control inputs to mutate to zero in the event of a DoS attack. While this configuration may eventually enable the system to achieve the desired performance, it may impact the stability of the system due to the mutation of the control input. Therefore, the pursuit of a more balanced approach to handling control inputs during DoS attacks to minimize the impact on the stability of the system is another motivation for this work.

Building on the insights from the above discussions, this article seeks to develop an SMC scheme to achieve mean-square bounded consensus tracking for MASs under stochastic DoS attacks. This task presents notable challenges, with the main difficulties outlined as follows: 1) How to propose a simplified description of DoS attacks be formulated to avoid dual constraints on the frequency and duration of the attacks? 2) How to establish a reasonable SMC law to ensure that the control input signal does not change abruptly when a DoS attack occurs, so as to mitigate the adverse impact of a DoS attack on system performance? 3) How to validate the presented SMC algorithm for MASs on a real application platform? In this work, we will provide compelling answers to each of the three difficulties mentioned above.

This research is focused on addressing the problem of mean-square bounded consensus tracking for MASs using a sliding mode controller under Markov-type DoS attacks. The primary contributions of this article are summarized as follows.

1) *A Markov process with two modes* is proposed to characterize the occurrence and cessation of a DoS attack. Leveraging the random jumping property inherent in the Markov process, it inherently captures the limitation on the frequency and duration of DoS attacks, thereby obviating the need for assumptions regarding the duration and frequency of attacks made in [19], [20], [21], [26].
2) *An SMC scheme* is proposed to achieve mean-square bounded consensus tracking for MASs under random DoS attacks. Unlike the approach in [23], [24], [25], in our proposed scheme, when a DoS attack occurs, the previous uncontaminated control input signal will be used as the new control input signal until the DoS attack stops, thus alleviating system performance loss due to the sudden change in the control input signal.

3) *A web-based experimental platform* is utilized to verify the correctness and validity of the proposed theoretical results for MASs, instead of performing simple numerical simulations as in [5], [6], [11], [12], [13]. Through cooperative control experiments with multiple motors, it is demonstrated that the proposed control algorithm can achieve consensus tracking of MASs under DoS attacks.

Notation: All matrices are assumed to have compatible dimensions unless explicitly stated otherwise in the following sections. For a real symmetric matrix P, $P > (<, \geq, \leq)\ 0$ implies that P is a positive (negative, non-negative, non-positive)-definite matrix. $\mathbb{E}\{\cdot\}$ indicates the mathematical expectation. Symbol "$*$" means the symmetric term in symmetric block matrices. $\|\cdot\|$ refers to the Euclidean norm of a vector or its induced matrix norm. 1_N denotes $N \times 1$ dimension vector and its entries are all 1. Symbol "$\otimes$" denotes the operation of the Kronecker product.

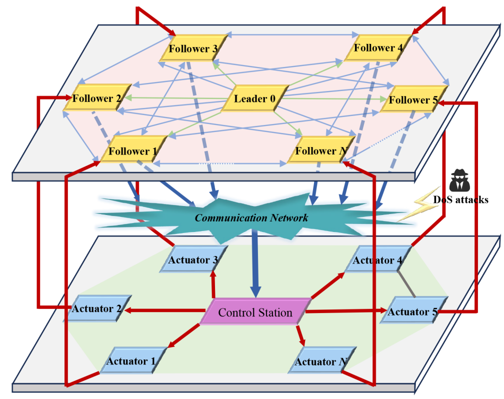

Fig. 1. Schematic diagram of the communication network between the MASs and the sliding mode controller.

II. Preliminaries

A. Graph Theory Notions

For a given undirected communication graph $\mathcal{G} = \{\mathcal{V}, \Xi, \mathcal{A}\}$ with N notes, where $\mathcal{V} = \{\mu_1, \mu_2, \ldots, \mu_M\}$, $\Xi \subseteq \mathcal{V} \times \mathcal{V}$, and $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N\times N}$ denote the node set of agents, the edge set, and the adjacency matrix, respectively. The graph $\mathcal{G}$ is said to be undirected if, and only if, $(\mu_i, \mu_j) \in \Xi$ and $(\mu_j, \mu_i) \in \Xi$, which suggests that agent i and agent j can deliver state information to each other. In addition, assume that the exclusion of self-circular edges (μ_i, μ_i). The Laplacian matrix $L = [l_{ij}] \in \mathbb{R}^{N\times N}$ with $l_{ij} = -a_{ij}$ and $l_{ii} = \sum_{j=1, j\neq i}^{N} a_{ij}$. An undirected graph $\mathcal{G}$ is said to be connected whenever an undirected path exists between any two agents. The pinning matrix for a given leader is denoted as $G = \mathrm{diag}\{g_{i0}\} \in \mathbb{R}^{N\times N}$, with $g_{i0} = 1$ if the agent i can obtain information from the leader, and $g_{i0} = 0$ otherwise.

B. Problem Formulation

Consider a linear leader–follower MAS that consists of a leader agent labeled $x_0(t)$ and multiple follower agents with the same dynamics. The dynamics are characterized as follows:

$$\begin{cases} x_i(k+1) = Ax_i(k) + Bu_i(k) + B_\omega \omega_i(k), \ i = 1, \ldots, N \\ x_0(k+1) = Ax_0(k) + Bu_0(k) \end{cases} \tag{1}$$

where $x_i(k) \in \mathbb{R}^n$ and $x_0(k) \in \mathbb{R}^n$ denote the state vectors of the followers and leader agent, respectively. $u_i(k) \in \mathbb{R}^m$ with $\|u_i(k)\| \leq \tilde{u}_0$ and $\omega_i(k) \in \mathbb{R}^\omega$ with $\|\omega_i(k)\| \leq \tilde{\omega}_0$ are the control input and the external disturbance of the followers, respectively. $u_0(k) \in \mathbb{R}^m$ with $\|u_0(k)\| \leq \tilde{u}_0$ is the control input of the leader. A, B are dimensionally compatible constant matrices. Assume that the pair (A, B) is stabilizable.

Assumption 1: The undirected communication network graph $\mathcal{G}$ is connected.

According to the topological relation of the MAS (1), the tracking error of the ith follower can be derived as follows:

$$e_i(k) = \sum_{j=1}^{N_i} a_{ij}(x_i(k) - x_j(k)) + g_{i0}(x_i(k) - x_0(k)). \tag{2}$$

Defining $\tilde{x}_i(k) = x_i(k) - x_0(k)$, we have

$$\tilde{X}(k) = X(k) - \mathbf{1}_N \otimes x_0(k) \tag{3}$$

where $\tilde{X}(k) = \mathrm{col}_N\{\tilde{x}_i(k)\}$, $X(k) = \mathrm{col}_N\{x_i(k)\}$.

Then, the global tracking error is given as follows:

$$e(k) = (T \otimes I_n)\tilde{X}(k) \tag{4}$$

where $e(k) = \mathrm{col}_N\{e_i(k)\}$ and $T = L + G$.

C. Markov-Type DoS Attacks

Due to the vulnerability of communication networks between the MAS and control stations, communication networks are at a high risk of network attacks by adversaries. As shown in Fig. 1, the communication network between the MAS and the sliding mode controller is exposed to DoS attacks, which may result in the sliding mode controller not being able to obtain sufficient measurement information for effective control.

In this study, we investigate a DoS attack driven by a Markov chain. The symbol $\theta(k) \in \{1, 2\}$ is used to represent the mode of the Markov jump process. The probability of the transition of the DoS attack behavior from time k to time $k+1$ is presented as follows:

$$\pi_{pq} = \Pr\{\theta(k+1) = q | \theta(k) = p\} \tag{5}$$

where $\pi_{pq} > 0$ with $\sum_{q=1}^{2} \pi_{pq} = 1$ for $\forall p, q \in \{1, 2\}$.

The transition probability matrix is represented as follows:

$$\Pi = \begin{bmatrix} \pi_{11} & \pi_{12} \\ \pi_{21} & \pi_{22} \end{bmatrix} = \begin{bmatrix} 1-\beta_1 & \beta_1 \\ \beta_2 & 1-\beta_2 \end{bmatrix} \tag{6}$$

where β_1 suggests that the DoS attack is in a dormant state at time k but becomes active at time $k+1$, whereas β_2 indicates that the DoS attack is active at time k but becomes dormant at time $k+1$.

Remark 1: In [27], the durations of consecutive successful DoS attacks are employed as modes of the Markov jump system, with the number of modes describing the maximum attack duration. However, the increasing number of modes in the Markov jump system with different durations complicates the transition probability matrix, posing computational challenges.

In contrast, our method simplifies the modeling by employing only two modes to depict the occurrence and cessation of a DoS attack. Furthermore, the transition probability matrix in this work constrains the energy of DoS attacks, providing a more realistic representation of DoS attacks in practice.

D. Problem of Interest

Definition 1. (see [28]): For the MAS (1) with one leader and N followers, the mean-square bounded consensus tracking under the SMC law (10) is achieved, if for any initial values, there exists a bound $c > 0$, such that the global tracking error $e(k)$ satisfies

$$\lim_{k\to\infty} \mathbb{E}\left\{\|e(k)\|^2\right\} \leq c. \tag{7}$$

Now, our goal is to propose a suitable SMC law $u(k)$ that guarantees the reachability and mean-square bounded consensus tracking of the resulting global tracking error dynamical system under Markov-type DoS attacks.

III. SMC Under Markov-Type DoS Attacks

A. Design of Sliding Mode Surface and SMC Law

Given the tracking error $e_i(k)$, the sliding mode surface function $s_i(k) \in \mathbb{R}^m$ is designed as follows:

$$s_i(k) = He_i(k) - H(A + BK)e_i(k-1) \tag{8}$$

where $H \in \mathbb{R}^{m\times n}$ is a given parameter matrix, $K \in \mathbb{R}^{m\times n}$ is the unknown controller gain to be designed.

According to (4)–(8), we have

$$\begin{aligned} s(k+1) &= (I_N \otimes H)e(k+1) - [I_N \otimes H(A+BK)]e(k) \\ &\quad - (I_N \otimes HBK)e(k) \end{aligned} \tag{9}$$

where $s(k) = \mathrm{col}_N\{\tilde{s}_i(k)\}$, $u(k) = \mathrm{col}_N\{\tilde{u}_i(k)\}$, $\omega(k) = \mathrm{col}_N\{\tilde{\omega}_i(k)\}$, $\bar{u}_0(k) = [u_0^{\mathrm{T}}(k), u_0^{\mathrm{T}}(k), \ldots, u_0^{\mathrm{T}}(k)]^{\mathrm{T}}$.

SMC is a widely used control method that comprises two phases: *the reaching phase* and *the sliding motion phase*. In this article, a suitable SMC law is developed to guide the system trajectories toward the vicinity of the predesigned sliding mode surface during the reaching phase, as expressed follows:

$$u(k) = [T^{-1} \otimes K]e(k) + I_{Nm} \otimes \psi(k)\mathrm{sgn}(s(k)) \tag{10}$$

where $\psi(k)$ denotes a robust term with $\|\psi(k)\|^2 \leq \bar{\psi}_0^2$ and $\bar{\psi}_0$ is a given scalar, and $\mathrm{sgn}(s(k))$ is a sign function satisfying $\mathrm{sgn}(s(k)) = \mathrm{col}_N\{\mathrm{sgn}(s_i(k)\}$.

Due to the disruptive nature of Markov-type DoS attacks on communication networks, the controller is unable to acquire real-time state updates from MASs. The actual control input is represented as follows:

$$\tilde{u}(k) = v_{1\,k}u(k) + v_{2\,k}\tilde{u}(k-1), v_{1\,k} \in \{0, 1\} \tag{11}$$

where $v_{2\,k} = 1 - v_{1\,k}$. $v_{1\,k} = 1$ in (11) means that the controller can acquire input from the sensors, while $v_{1\,k} = 0$ in (11) signifies that when a DoS attack occurs, the actual control input from the previous time step will be maintained as the new actual control input until the DoS attack subsides.

Remark 2: The acknowledgment character technique is employed for detecting data dropout, a principle derived from transmission control protocol [29]. Upon receiving information, the controller transmits an acknowledgment signal to the sender, verifying the successful transmission. Conversely, in the event of a DoS attack on the communication network facilitating data transmission from the MASs to the controller, no acknowledgment signal is returned. Consequently, the controller identifies the occurrence of a DoS attack on the communication network. Utilizing the acknowledgment signal, the value $v_{1\,k}$ in (11) can be readily determined.

Remark 3: Very recently, the issue of secure control in networked control systems facing DoS attacks has been examined in a series of papers [23], [24], [25]. These papers describe that, in the event of a DoS attack, the control input is forcibly reset to zero. This places the system in an uncontrolled state, which may result in severe damage to the system control performance. To more significantly mitigate the damage of DoS attacks, we preserve the most recent uncontaminated control input signal and employ it as the new control input until the DoS attack ceases.

By applying the SMC law (10) into the sliding mode surface (9), we obtain

$$\begin{aligned} &s(k+1) \\ &\quad = v_{1\,k}[I_N \otimes HBK]e(k) + v_{1\,k}T \otimes HB\psi(k)\mathrm{sgn}(k) \\ &\qquad + v_{2\,k}(T \otimes HB)\tilde{u}(k-1) + T \otimes HB_\omega\omega(k) \\ &\qquad - (T \otimes HB)\bar{u}_0(k) - (I_N \otimes HBK)e(k) \\ &\quad = -v_{2\,k}(I_N \otimes HBK)e(k) + v_{2\,k}(T \otimes HB)\tilde{u}(k-1) + \Omega \end{aligned} \tag{12}$$

where $\Omega = (T \otimes HB_\omega)\omega(k) - (T \otimes HB)\bar{u}_0(k) + v_{1\,k}(T \otimes HB\psi(k))\mathrm{sgn}(s(k))$.

The global tracking error dynamic system is given as:

$$\begin{aligned} &e(k+1) \\ &\quad = (T \otimes I_n)[X(k+1) - \mathbf{1}_N \otimes x_0(k+1)] \\ &\quad = I_N \otimes (A + v_{1\,k}BK)e(k) + v_{2\,k}T \otimes B\tilde{u}(k-1) + \Delta \end{aligned} \tag{13}$$

where $\Delta = T \otimes B_\omega\omega(k) - (T \otimes B)\bar{u}_0(k) + v_{1\,k}T \otimes B\psi(k)\mathrm{sgn}(s(k))$.

B. Reachability Analysis

Next, we will perform a reachability analysis of the global tracking error dynamic system (13) under the action of the SMC law (10).

Theorem 1: Consider a linear leader-following MAS (1) subject to Markov-type DoS attacks, if there exist positive-definite symmetric matrices $W_p \in \mathbb{R}^{m\times m}$, $Y_p \in \mathbb{R}^{n\times n}$, $Q_p \in \mathbb{R}^{m\times m}$, $p = 1, 2$ to satisfy

$$\Pi = \begin{bmatrix} \Pi_{11} & \Pi_{12} \\ * & \Pi_{22} \end{bmatrix} < 0 \tag{14}$$

where

$\Pi_{11} = -\mathrm{diag}\{\mathcal{Y}_p, \mathcal{Q}_p\}, \Pi_{12} = [\Pi_{12}^1 \ \ \Pi_{12}^2 \ \ \Pi_{12}^3 \ \ \Pi_{12}^4]$

$\Pi_{12}^1 = \mathrm{diag}\{\sqrt{3\pi_{p2}}I_N \otimes (HBK)^{\mathrm{T}}, \sqrt{3\pi_{p2}}T^{\mathrm{T}} \otimes B^{\mathrm{T}}H^{\mathrm{T}}\}$

$\Pi_{12}^2 = \mathrm{diag}\{\sqrt{3\pi_{p2}}I_N \otimes A^{\mathrm{T}}, \sqrt{3\pi_{p2}}T^{\mathrm{T}} \otimes B^{\mathrm{T}}\}$

$\Pi_{12}^3 = [\sqrt{3\pi_{p2}}I_N \otimes (A+BK) \ \ 0]^{\mathrm{T}}$

$\Pi_{12}^4 = \mathrm{diag}\{\sqrt{2\pi_{p1}}(T^{-1} \otimes K)^{\mathrm{T}}, \sqrt{\pi_{p2}}I_{Nm}\}$

$\Pi_{22} = -\mathrm{diag}\{\mathcal{W}_2^{-1}, \mathcal{W}_2^{-1}, \mathcal{Y}_2^{-1}, \mathcal{Y}_2^{-1}, \mathcal{Y}_1^{-1}, \mathcal{Q}_1^{-1}, \mathcal{Q}_2^{-1}\}$

$\mathcal{W}_p = I_N \otimes W_p, \mathcal{Y}_p = I_N \otimes Y_p, \mathcal{Q}_p = I_N \otimes Q_p$

then, under the action of the SMC law (10), the trajectories of the global tracking error dynamic system (13) will be driven into the following sliding region:

$$\Theta \triangleq \{s(k) \mid \|s(k)\| \leq \tilde{b}(k)\} \tag{15}$$

where $\tilde{b}(k) \leq \sqrt{\frac{b(k)}{\lambda_{\min}(\mathcal{W}_q}})$ with $b(k) = (6 + 3\pi_{p1})N \max\{\lambda_{\max}(\mathcal{W}_q, \lambda_{\max}(Y_q)\}(\|T \otimes HB_\omega\|^2\tilde{\omega}_0^2 + \|T \otimes HB\|^2\tilde{u}_0^2) + 9N\pi_{p1} \max\{\lambda_{\max}(\mathcal{W}_q, \lambda_{\max}(Y_q)\}\|T \otimes HB_\omega\|^2\bar{\psi}_0^2 + 2N\pi_{p1}\lambda_{\max}(Q_{11})\|I_N \otimes \psi(k)\|^2$.

Proof: Consider a Lyapunov function as follows:

$$V_r(k) = \sum_{t=1}^{3} V_{rt}(k) \tag{16}$$

where $V_{r1}(k) = s^{\mathrm{T}}(k)\mathcal{W}_p s(k)$, $V_{r2}(k) = e^{\mathrm{T}}(k)\mathcal{Y}_p e(k)$, $V_{r3}(k) = \tilde{u}(k-1)^{\mathrm{T}}\mathcal{Q}_p\tilde{u}(k-1)$.

From (12), the expectation of the difference of $V_{r1}(k)$ is obtained as follows:

$$\begin{aligned}
&\mathbb{E}\{\Delta V_{r1}(k)\}\\
&\quad\leq 3\pi_{p2}e^{\mathrm{T}}(k)(I_N \otimes K^{\mathrm{T}}B^{\mathrm{T}}H^{\mathrm{T}})\mathcal{W}_2(I_N \otimes HBK)e(k)\\
&\qquad + 3\pi_{p2}\tilde{u}^{\mathrm{T}}(k-1)(T^{\mathrm{T}} \otimes B^{\mathrm{T}}H^{\mathrm{T}})\mathcal{W}_2(T \otimes HB)\tilde{u}(k-1)\\
&\qquad + 3\pi_{p1}\Omega_1^{\mathrm{T}}\mathcal{W}_1\Omega_1 + 3\pi_{p2}\Omega_2^{\mathrm{T}}\mathcal{W}_1\Omega_2 - s^{\mathrm{T}}(k)\mathcal{W}_p s(k)
\end{aligned} \tag{17}$$

where $\Omega_1 = (T \otimes HB_\omega)\omega(k) - (T \otimes HB)\bar{u}_0(k) + T \otimes HB\psi(k)\mathrm{sgn}(s(k))$, $\Omega_2 = (T \otimes HB_\omega)\omega(k) - (T \otimes HB)\bar{u}_0(k)$.

The expectation of the difference of $V_{r2}(k)$ can be represented as follows:

$$\begin{aligned}
&\mathbb{E}\{\Delta V_{r2}(k)\}\\
&\quad\leq 3\pi_{p1}e^{\mathrm{T}}(k)[I_N \otimes (A+BK)]^{\mathrm{T}}\mathcal{Y}_1(I_N \otimes (A+BK))e(k)\\
&\qquad + 3\pi_{p2}e^{\mathrm{T}}(k)(I_N \otimes A^{\mathrm{T}})\mathcal{Y}_2(I_N \otimes A)e(k)\\
&\qquad + 3\pi_{p2}\tilde{u}^{\mathrm{T}}(k-1)(T^{\mathrm{T}} \otimes B^{\mathrm{T}})\mathcal{Y}_2(T \otimes B)\tilde{u}(k-1)\\
&\qquad + 3\pi_{p1}\Delta_1^{\mathrm{T}}\mathcal{Y}_1\Delta_1 + 3\pi_{p2}\Delta_2^{\mathrm{T}}\mathcal{Y}_2\Delta_2 - e^{\mathrm{T}}(k)\mathcal{Y}_p e(k)
\end{aligned} \tag{18}$$

where

$\Delta_1 = (T \otimes B_\omega)\omega(k) + (T \otimes B))\bar{u}_0(k) + T \otimes H\psi(k)\mathrm{sgn}(s(k))$

$\Delta_2 = (T \otimes B_\omega)\omega(k) + (T \otimes B)\bar{u}_0(k)$.

Likewise, the expectation of the difference of $V_{r3}(k)$ is given as follows:

$$\begin{aligned}
&\mathbb{E}\{\Delta V_{r3}(k+1)\}\\
&\quad\leq 2\pi_{p1}e^{\mathrm{T}}(k)(T^{-1} \otimes K)^{\mathrm{T}}\mathcal{Q}_1(T^{-1} \otimes K)e(k)\\
&\qquad + 2\pi_{p1}\mathrm{sgn}^{\mathrm{T}}(s(k))(I_N \otimes \psi^{\mathrm{T}})\mathcal{Q}_1(I_N \otimes \psi(k)\mathrm{sgn}(s(k))\\
&\qquad + \pi_{p2}\tilde{u}^{\mathrm{T}}(k-1)\mathcal{Q}_2\tilde{u}(k-1)) - \tilde{u}(k-1)^{\mathrm{T}}\mathcal{Q}_p\tilde{u}(k-1).
\end{aligned} \tag{19}$$

When $s(k) \geq b(k)$, this indicates that the system trajectories have not yet entered the sliding region Θ. Conversely, if inequality (14) leads to $\Delta V_r(k) < 0$, it indicates that the sliding variable $s(k)$ is strictly decreasing outside the sliding region, and the system trajectories will ultimately converge to the sliding region. This concludes the proof. ■

C. Mean-Square Bounded Consensus Tracking

At the point where the system trajectory enters the sliding region, i.e., the system state enters the quasi-sliding mode. By the relationship $s(k+1) = s(k) = 0$, this fact can deduce that

$$\begin{aligned}
&(T \otimes HB)u(k) + (T \otimes HB_\omega)\omega(k)\\
&\quad - (T \otimes HB)\tilde{u}_0(k) - (I_N \otimes HBK)e(k) = 0.
\end{aligned} \tag{20}$$

From (20), the equivalent control law is derived as follows:

$$u_{eq}(k) = -(I_N \otimes B^{-1}B_\omega)\omega(k) + \tilde{u}_0(k) + [T^{-1} \otimes K]e(k). \tag{21}$$

Given the impact of the Markov-type DoS attacks, the actual equivalent law $\tilde{u}_{\mathrm{eq}}(k)$ should be formulated as follows:

$$\tilde{u}_{\mathrm{eq}}(k) = v_{1\,k}u_{\mathrm{eq}}(k) + v_{2\,k}\tilde{u}_{\mathrm{eq}}(k-1), v_{1\,k} \in \{0,1\} \tag{22}$$

where $v_{1\,k}$ and $v_{1\,k}$ play an identical role as in (11).

Taking the equivalent control law $\tilde{u}_{\mathrm{eq}}(k)$ into the $e(k+1)$, one has

$$\begin{aligned}
&e(k+1)\\
&\quad= [I_N \otimes (A + v_{1\,k}BK)]e(k) + v_{2\,k}T \otimes B_\omega\omega(k)\\
&\qquad - v_{2\,k}T \otimes B\bar{u}_0(k) + v_{2\,k}T \otimes B\tilde{u}_{eq}(k-1).
\end{aligned} \tag{23}$$

Theorem 2: Consider a linear leader-following MAS (1) subject to Markov-type DoS attacks, if there exist a positive scalar α, positive-definite symmetric matrices $W_p \in \mathbb{R}^{m\times m}, Y_p \in \mathbb{R}^{n\times n}$, $Q_p \in \mathbb{R}^{m\times m}$, $p = 1, 2$ to satisfy

$$\Phi_0 = \begin{bmatrix} \Phi_{11} & \Phi_{12} \\ * & \Phi_{22} \end{bmatrix} < 0 \tag{24}$$

where

$\Phi_{11} = -\mathrm{diag}\{\alpha\mathcal{Y}_p, \alpha\mathcal{Q}_p\}, \Phi_{12} = [\Phi_{12}^1 \ \ \Phi_{12}^2 \ \ \Phi_{12}^3]$

$\Phi_{12}^1 = [2\sqrt{\pi_{p1}}(I_N \otimes (A+BK)) \ \ 0]^{\mathrm{T}}$

$\Phi_{12}^2 = \mathrm{diag}\{2\sqrt{\pi_{p2}}(I_N \otimes A^{\mathrm{T}}), 2\sqrt{\pi_{p2}}(T^{\mathrm{T}} \otimes B^{\mathrm{T}})\}$

$\Phi_{12}^3 = \mathrm{diag}\{\sqrt{3\pi_{p1}}(T^{-1} \otimes K)^{\mathrm{T}}, \sqrt{\pi_{p2}}I_{Nm}\}$

$\Phi_{22} = -\mathrm{diag}\{\mathcal{Y}_1^{-1}, \mathcal{Y}_2^{-1}, \mathcal{Y}_2^{-1}, \mathcal{Q}_1^{-1}, \mathcal{Q}_2^{-1}\}$

then the global tracking error dynamic system (13) can achieve mean-square bounded consensus tracking.

Proof: Consider a Lyapunov function as follows:

$$V_c(k) = V_{c1}(k) + V_{c2}(k) \tag{25}$$

where $V_{c1}(k) = e^{\mathrm{T}}(k)(I_N \otimes Y_p)e(k)$, $V_{c2}(k) = \tilde{u}_{\mathrm{eq}}^{\mathrm{T}}(k-1)(I_N \otimes Q_p)\tilde{u}_{\mathrm{eq}}(k-1)$.

Considering the bounded energy of the external disturbance and the control input, one has

$$\mathbb{E}\{V_c(k+1)\} - \alpha V_c(k) \leq \xi^{\mathrm{T}}(k)\Psi_0\xi(k) + c_1 \tag{26}$$

where $\Psi_1 = 4\pi_{p2}(T^{\mathrm{T}} \otimes B_\omega^{\mathrm{T}})\mathcal{W}_2(T \otimes B_\omega) + 3\pi_{p1}(I_N \otimes (B^{-1}B_\omega)^{\mathrm{T}})\mathcal{Q}_1(I_N \otimes (B^{-1}B_\omega))$, $\Psi_2 = 4\pi_{p2}(T^{\mathrm{T}} \otimes B^{\mathrm{T}})\mathcal{Y}_2(T \otimes B) + 3\pi_{p1}\mathcal{Q}_1$, $c_1 = N\|\Psi_1\|\tilde{\omega}_o^2 + N\|\Psi_2\|\tilde{u}_o^2$.

For $\alpha > 1$, it yields

$$\begin{aligned}&\mathbb{E}\{V_c(k+1)\} - \alpha V_c(k)\\ &\quad\leq -\frac{\gamma_1}{\alpha\lambda_{\max}(\mathrm{diag}\{\mathcal{Y}_p, \mathcal{Q}_p\})}\alpha V_c(k) + c_1\end{aligned} \tag{27}$$

where $\gamma_1 = \lambda_{\min}\{-\Psi_0\}$.

Thus, one has

$$\mathbb{E}\{V_c(k+1)\} \leq \gamma_2\alpha V_c(k) + c_1 \tag{28}$$

where $\gamma_2 = \left(1 - \frac{\gamma_1}{\alpha\lambda_{\max}(\mathrm{diag}\{\mathcal{Y}_p, \mathcal{Q}_p\})}\right)$.

Above inequality can be further involved into

$$\mathbb{E}\{V_c(k)\} \leq \gamma_2^k\alpha^k V_c(0) + \frac{1-\gamma_2^k\alpha^k}{\gamma_2\alpha}c_1. \tag{29}$$

Due to $\gamma_2\alpha \in (0,1)$, we can obtain when $k \to \infty$, one has

$$\mathbb{E}\{\|e(k)\|^2\} \leq \frac{1}{\lambda_{\min}(\mathcal{Y}_p)\gamma_2\alpha}c_1 \leq c. \tag{30}$$

According to Definition 1, one can assert that the global tracking error dynamic system (13) is mean-square bounded consensus tracking, which ends the proof. ■

D. Synthesis of SMC Law

To simultaneously ensure the reachability and mean-square bounded consensus tracking of the global tracking error dynamic system (13) under Markov-type DoS attacks, the controller gain matrix K in the proposed SMC scheme (10) is to be identified based on Theorems 1 and 2. Subsequently, we will establish some sufficient conditions for the synthetic SMC law scheme (10).

Theorem 3: Consider a linear leader-following MAS (1) subject to Markov-type DoS attacks, if there exist a positive scalar α, positive-definite symmetric matrices $\tilde{W}_p \in \mathbb{R}^{m\times m}$, $\tilde{Y}_p \in \mathbb{R}^{n\times n}$, $\tilde{Q}_p \in \mathbb{R}^{m\times m}$, $p = 1, 2$, and matrices $\tilde{J}_1 \in \mathbb{R}^{n\times n}$, $\tilde{J}_2 \in \mathbb{R}^{m\times m}$ to satisfy the following linear matrix inequalities (LMIs):

$$\tilde{\Pi} = \begin{bmatrix}\tilde{\Pi}_{11} & \tilde{\Pi}_{12}\\ * & \tilde{\Pi}_{22}\end{bmatrix} < 0 \tag{31}$$

$$\tilde{\Phi}_0 = \begin{bmatrix}\tilde{\Phi}_{11} & \tilde{\Phi}_{12}\\ * & \tilde{\Phi}_{22}\end{bmatrix} < 0 \tag{32}$$

where

$\tilde{\Pi}_{11} = -\mathrm{diag}\{\tilde{\mathcal{Y}}_p - J_1^{-1} - J_1, \tilde{\mathcal{Q}}_p - J_2^{-1} - J_2\}$
$\tilde{\Pi}_{12} = [\tilde{\Pi}_{12}^1\ \ \tilde{\Pi}_{12}^2\ \ \tilde{\Pi}_{12}^3\ \ \tilde{\Pi}_{12}^4]$
$\tilde{\Pi}_{12}^1 = \mathrm{diag}\{\sqrt{3\pi_{p2}}I_N \otimes (HB\tilde{K})^{\mathrm{T}}, \sqrt{3\pi_{p2}}T^{\mathrm{T}} \otimes (HB\bar{Q}_q)^{\mathrm{T}}\}$
$\tilde{\Pi}_{12}^2 = \mathrm{diag}\{\sqrt{3\pi_{p2}}I_N \otimes \tilde{Y}_p^{\mathrm{T}}A^{\mathrm{T}}, \sqrt{3\pi_{p2}}T^{\mathrm{T}} \otimes \bar{Q}_q^{\mathrm{T}}B^{\mathrm{T}}\}$
$\tilde{\Pi}_{12}^3 = [\sqrt{3\pi_{p2}}I_N \otimes (A\tilde{Y}_p + B\tilde{K})\ \ 0]^{\mathrm{T}}$

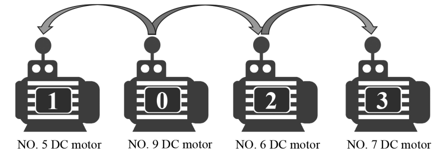

Fig. 2. Communication configuration of the leader–follower multiple dc motor servo system.

$\tilde{\Pi}_{12}^4 = \mathrm{diag}\{\sqrt{2\pi_{p1}}(T^{-1} \otimes \tilde{K})^{\mathrm{T}}, \sqrt{\pi_{p2}}\tilde{\mathcal{Q}}_p\}$
$\tilde{\Pi}_{22} = -\mathrm{diag}\{\tilde{\mathcal{W}}_2, \tilde{\mathcal{W}}_2, \tilde{\mathcal{Y}}_2, \tilde{\mathcal{Y}}_2, \tilde{\mathcal{Y}}_1, \tilde{\mathcal{Q}}_1, \tilde{\mathcal{Q}}_2\}$
$\tilde{\Phi}_{11} = -\mathrm{diag}\{\alpha\tilde{\mathcal{Y}}_p, \alpha\tilde{\mathcal{Q}}_p\}$, $\tilde{\Phi}_{12} = [\tilde{\Phi}_{12}^1\ \ \tilde{\Phi}_{12}^2\ \ \tilde{\Phi}_{12}^3]$
$\tilde{\Phi}_{12}^1 = [2\sqrt{\pi_{p1}}(I_N \otimes A\tilde{Y}_p + B\tilde{K})\ \ 0]^{\mathrm{T}}$
$\tilde{\Phi}_{12}^2 = \mathrm{diag}\{2\sqrt{\pi_{p2}}(I_N \otimes \tilde{Y}_p^{\mathrm{T}}A^{\mathrm{T}}), 2\sqrt{\pi_{p2}}(T^{\mathrm{T}} \otimes \tilde{Q}_p^{\mathrm{T}}B^{\mathrm{T}})\}$
$\tilde{\Phi}_{12}^3 = \mathrm{diag}\{\sqrt{3\pi_{p1}}(T^{-1} \otimes \tilde{K})^{\mathrm{T}}, \sqrt{\pi_{p2}}\tilde{Q}_p\}$
$\tilde{\Phi}_{22} = -\mathrm{diag}\{\tilde{\mathcal{Y}}_1, \tilde{\mathcal{Y}}_2, \tilde{\mathcal{Y}}_2, \tilde{\mathcal{Q}}_1, \tilde{\mathcal{Q}}_2\}$
$\tilde{\mathcal{W}}_p = I_N \otimes \tilde{W}_p$, $\tilde{\mathcal{Y}}_p = I_N \otimes \tilde{Y}_p$, $\tilde{\mathcal{Q}}_p = I_N \otimes \tilde{Q}_p$

then, under the proposed SMC scheme (10), the reachability and mean-square bounded consensus tracking of the global tracking error dynamic system (13) can be guaranteed. Besides, the controller gain matrix K can be solved by $K = \tilde{K}J_1^{-1}$.

Proof: Define $\tilde{Y}_p = Y_p^{-1}$, $\tilde{Q}_p = Q_p^{-1}$, $\tilde{W}_p = W_p^{-1}$. Executing a congruence transformation to inequality (31) with $\mathrm{diag}\{J_1, J_2, I, I, I, I, I, I\}$ and to inequality (32) with $\mathrm{diag}\{J_1, J_2, I, I, I, I, I\}$, and considering the relationship $J_1^{\mathrm{T}}\tilde{Y}_p^{-1}J_1 \geq J_1^{\mathrm{T}} - \tilde{Y}_p + J_1$ and $J_2^{\mathrm{T}}\tilde{Q}_p^{-1}J_2 \geq J_2^{\mathrm{T}} - \tilde{Q}_p + J_2$, then, we can find inequalities (14) and (24) can be converted into LMIs (31)–(32). The proof is complete. ■

IV. Experiment

In this section, we consider a coordinated control experiment of multiple dc motors based on a web platform called NCSLab. The communication configuration of the leader–follower multiple dc motor servo system, comprising one leader and three followers, is illustrated in Fig. 2. The real-time angle and velocity are considered as the system states, and using the least mean-square method, the multiple dc motor servo system can be modeled as the MAS (1) subject to the following system parameters [30]:

$$A = \begin{bmatrix}1 & 0.01\\ 0 & 0.8669\end{bmatrix},\quad B = \begin{bmatrix}0\\ 71.896\end{bmatrix}$$

$$B_\omega = \begin{bmatrix}0.1\\ 0.1\end{bmatrix},\quad C = [1\ \ 0].$$

The experimental test setup is depicted in Fig. 3 and the configuration is presented in Fig. 4. The experimental test setup is composed of a computer with MATLAB and multiple browsers and four dc motor servo plants. Each plant includes a dc motor, a 2-million-pixel IP camera, a 12 V 4.2 A power supply, and a controller (RaspberryPi Model 4B) with a 10 ms cycle. The experimental step is performed as follows.

1) *Step 1:* Choose $\alpha = 0.11$, and the Markov-type DoS attack behavior is characterized by the probabilities $\pi_{11} = 0.78$, $\pi_{12} = 0.22$, $\pi_{21} = 0.88$, $\pi_{22} = 0.12$. The

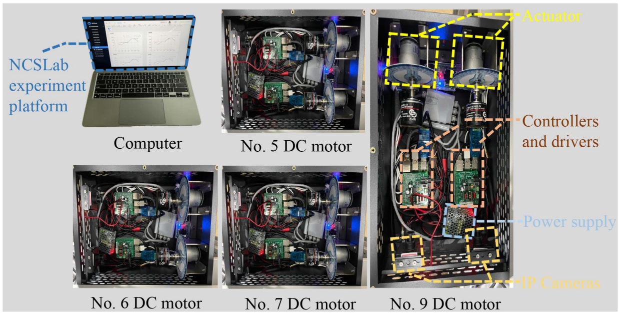

Fig. 3. Experimental test setup.

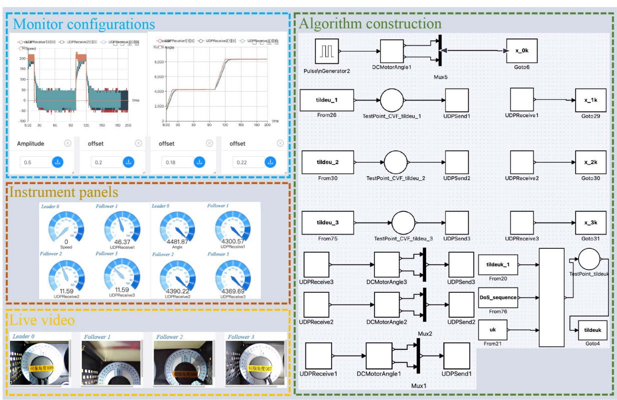

Fig. 4. Configuration of the experimental platform.

Matlab LMI toolbox is employed to solve the LMIs (31)–(32), and the controller gain can be found to be $K = [0.0082 \quad 0.0024]$.

2) *Step 2:* Login to the NCSLab experiment platform, use the simulation module provided by the platform to build the experimental simulation control algorithm of each agent, and add communication modules, such as the UDP module.
3) *Step 3:* Convert the control algorithms into real-time programs on the RaspberryPI platform through the model-based code generation technology.
4) *Step 4:* Download the motor angle reset algorithm to the leader (No. 9 dc motor) and three followers (No. 5-7 dc motors). The communication between the leader and the followers is realized through the UDP protocol.
5) *Step 5:* Design the monitoring configuration, which includes four IP cameras and graphs of key signals such as motor angle and speed.
6) *Step 6:* Running the real-time program, the monitoring of the status of four dc motors can be realized in the monitoring platform through the self-defined protocol of the platform.

The external disturbance is a band-limited white noise with a noise power of 0.1. The control input $u_0(k)$ of the leader is a pulse signal with a period of 100 steps and an amplitude of 0.5. Besides, the time of each dc motor servo plant is calibrated in advance through a network time protocol, so that the synchronization error between each two motors is less than 1 ms, which is smaller than the sampling period in this experiment.

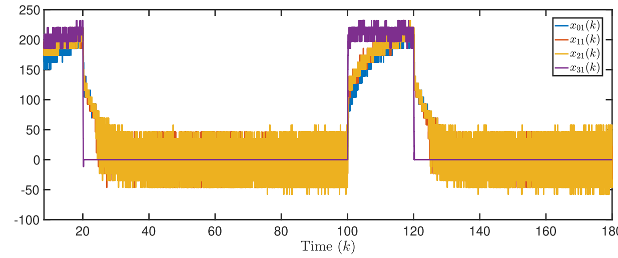

Fig. 5. Speed of the multiple dc motor servo system without DoS attacks.

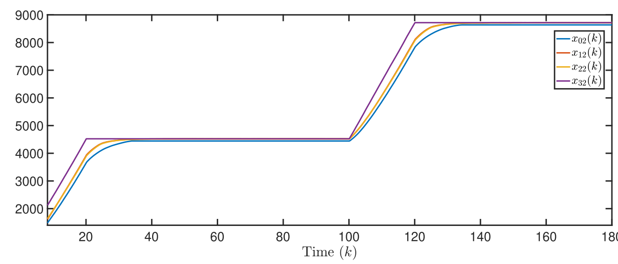

Fig. 6. Angle of the multiple dc motor servo system without DoS attacks.

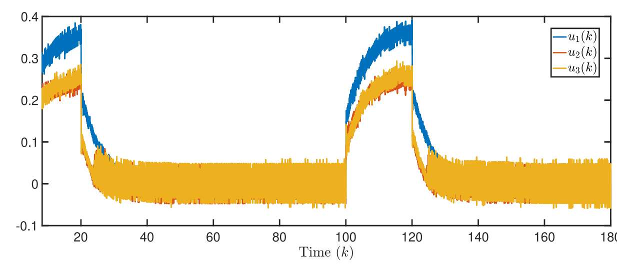

Fig. 7. SMC law $u(k)$ without DoS attacks.

To reflect the impact of DoS attacks on system control performance and to demonstrate the correctness and superiority of our proposed method, we divide the experimental section into three parts.

1) In the Absence of DoS Attacks: With the application of the SMC law (10), the speed and the angle of the multiple dc motor servo system without DoS attacks are depicted in Figs. 5 and 6, respectively. It is evident that the designed sliding mode controller effectively accomplishes the mean-square bounded consensus tracking of the MAS well without DoS attacks. Fig. 7 portrays the SMC law $u(k)$ without DoS attacks.

2) In the Presence of DoS Attacks: The experiment results of the multiple dc motor servo system under DoS attacks are illustrated in Figs. 8–12. During a DoS attack, the controller struggles to accurately obtain speed and angle information from the multiple dc motor servo system. As illustrated in Figs. 8–9,

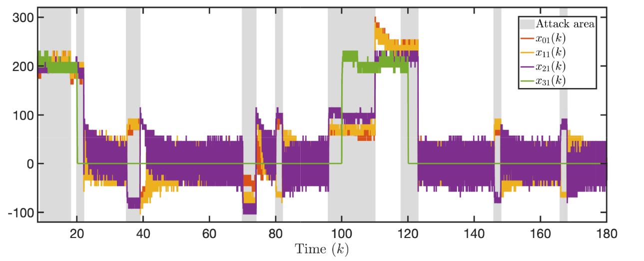

Fig. 8. Speed of the multiple dc motor servo system with DoS attacks under the action of the SMC law (10).

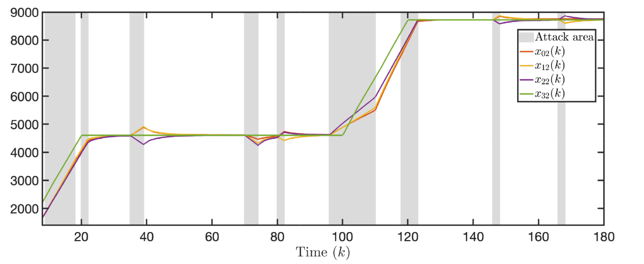

Fig. 9. Angle of the multiple dc motor servo system with DoS attacks under the action of the SMC law (10).

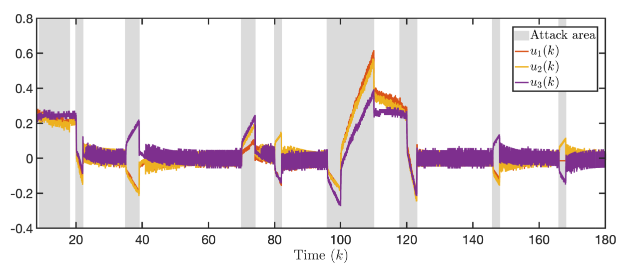

Fig. 10. SMC law $u(k)$ with DoS attacks under the action of the SMC law (10).

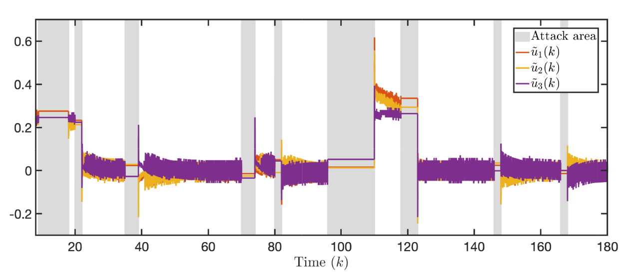

Fig. 11. Actual control input $\tilde{u}(k)$ with DoS attacks under the action of the SMC law (10).

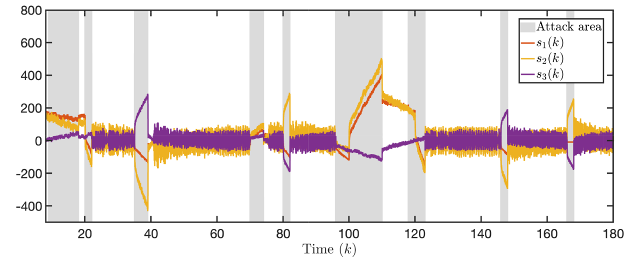

Fig. 12. Sliding mode surface function $s(k)$ with DoS attacks under the action of the SMC law (10).

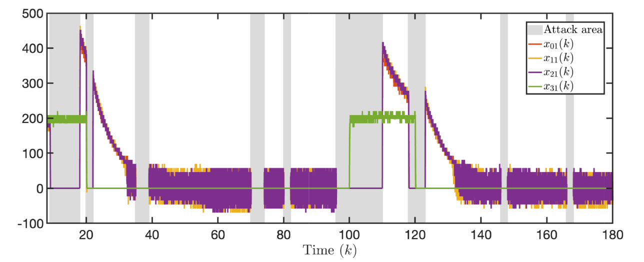

Fig. 13. Speed of the multiple DC motor servo system with DoS attacks by the control scheme in [23], [24], [25].

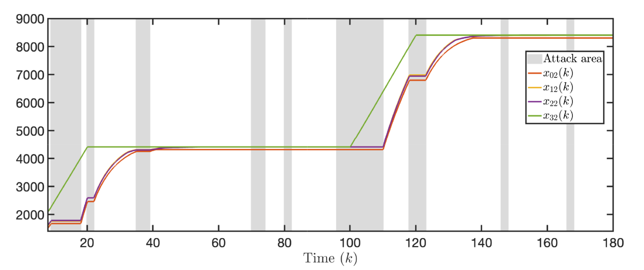

Fig. 14. Angle of the multiple dc motor servo system with DoS attacks by the control scheme in [23], [24], [25].

within the attack area, the state behavior of followers will rapidly deviate from that of the leader, resulting in deteriorated tracking performance of followers towards the agent. This reflects the disruptive impact of DoS attacks on system stability and consensus. In this article, we adopt the most recent uncontaminated control input signal and employ it as the new control input until the DoS attack ceases. With this control scheme, as evident from Figs. 8 and 9, the multiple dc motor servo system can achieve the mean-square bounded consensus even in the presence of DoS attacks. The SMC law $u(k)$ and the actual control input $\tilde{u}(k)$ are described in Figs. 10 and 11, respectively. By comparing Figs. 10 and 11, we observe that within the same attack area, the actual control input $\tilde{u}(k)$ is equal to the most recent uncontaminated magnitude of the SMC $u(k)$; outside of the attack region, they are the same. This is consistent with the setting in (11). Furthermore, as depicted in Fig. 12, the sliding mode surface function $s(k)$ ultimately reaches a bounded region.

3) Comparison of the Zero Control Input Scheme in [23], [24], [25] with Our Proposed Scheme: To demonstrate the superiority of our presented scheme, we implemented a zero control input scheme employed in [23], [24], [25] in the same attack scenario. Zeng et al. [23], Cai et al. [24], Hu et al. [25] forced the control input to zero when the DoS attack occurs. The corresponding experimental results are presented in Figs. 13–15. By observing Figs. 13 and 14, it is clear that DoS attacks have a significant impact on the evolution of the state of followers. Although

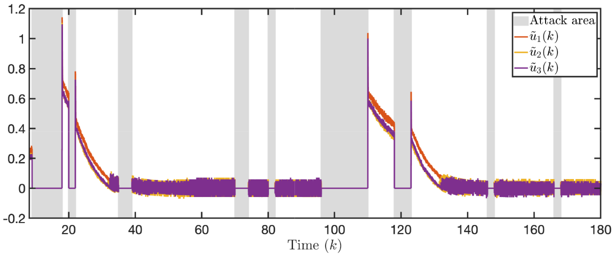

Fig. 15. Actual control input $\tilde{u}(k)$ with DoS attacks by the control scheme in [23], [24], [25].

the control strategy in [23], [24], [25] enables the multiple dc motor servo system to eventually achieve mean-square bounded consensus tracking, this then results in a larger tracking error relative to our proposed control strategy. As shown in Fig. 15, when a DoS attack occurs, the actual control input $\tilde{u}(k)$ by the control scheme in [23], [24], [25] is forced to 0.

Remark 4: In this experiment, the coordinated control of multiple dc motors is implemented based on the NCSLab web platform. This platform supports various classical experiments, including motor angle control, motor speed control, slide table position control, and water tank water level control, allowing researchers to conduct theoretical validation. It has excellent scalability, offering rich custom experiments and self-recovery capabilities [30]. Using HTML5 technology, researchers can remotely control the experimental targets through a web browser. Real-time experimental data and live monitoring screens are displayed on the page, enabling researchers to conduct experiments at any time. In addition, the NCSLab web platform is equipped with a cluster of hundreds of experimental devices, making it easier to validate experiments for MASs and providing a better alternative to traditional numerical simulations.

V. Conclusion

In this work, a sliding mode controller is developed to solve the mean-square bounded consensus tracking for MASs under stochastic DoS attacks. A Markov process with two modes is proposed to characterize stochastic DoS attacks, which avoids the limitations on the duration of DoS attacks. The data not affected in the previous moment is continuously used as input until the end of the attack. Using the Lyapunov function method, we present a sufficient condition for mean-square bounded consensus tracking for the MAS. Finally, we validate our approach through a coordinated control experiment involving multiple dc motors on the NCSLab platform.

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