

Data-Driven Model Free Adaptive Sliding Mode Control for Multi DC-Motors Speed Regulation

bim

Abstract

This paper proposes the distributed data-driven sliding mode control approach to address the consensus problem of nonlinear multi-agent systems. Firstly, the equivalent data model for each agent is constructed using the compact-form dynamic linearization (CFDL) technique. Secondly, utilizing the input-output data of agents, the novel sliding surface is employed, which ensures the boundedness of distributed error through stability-guaranteeing mechanism. Subsequently, a distributed model-free adaptive sliding mode controller is developed to ensure the reference trajectory tracking. Finally, the effectiveness of the proposed control approach is verified through experiments on multi-DC motors.

KEYWORDS

Model-free adaptive sliding mode control, compact form dynamic linearization, nonlinear multi-agent system, data-driven control.

I. INTRODUCTION

Motivated by the coordinated behaviors observed in nature, such as bird flocking or herd migration, the distributed control multi-agent systems(MASs) has been studied with interest in recent years. [1] Because of the distributed and flexible structure, the MASs based approaches have significant potential in addressing coordination challenges for complex systems [2]. The control of DC motors is essential in numerous technological applications, with single DC motor serving as the foundation for the systems in various fields, including vehicle cooperation [3], multi-robot systems and industrial machinery [4].

It is challenging to establish an accurate mathematical model for the speed regulation of multi-DC motor systems due to their nonlinear, time-varying, and multi-variable conditions [7]. Even if a relatively accurate mathematical models are developed, the associated control algorithms can become highly complex, so the model-based control approach is difficult to apply or extend to such systems. Nowadays, data-driven methods have been used to control, decision making, planing, fault diagnosis, predicting, etc. In [15]- [16], a compact form dynamic linearization (CFDL) data-driven modeling method is proposed for nonlinear systems. So far, the CFDL data-driven modeling method has proven to be highly useful in various domains [17]- [20] with different characteristics such as simplicity and particularly, a small amount of calculation, ease of implementation, and strong robustness, making it highly effective for addressing unknown nonlinear time-varying systems.

In [21], a model-free adaptive control (MFAC) approach is presented for MASs, which uses input and output data to achieve consensus tracking trajectory.

Alternatively, the sliding mode control (SMC) adapts dynamically the system operation based on the current state of the system such as the error and its derivative, ensuring the system follows a predetermined sliding surface [22]. Because the sliding surface can be designed and has the purpose to deal with the object parameters and disturbances, the SMC provides the fast response, insensitivity to parameter changes and disturbances, and simplicity in implementation. The above advantages make SMC widely used in control systems and one of main topic to focus in the ongoing research. [28]- [30]

Inspired by the abovementioned considerations, this paper studies a novel model-free adaptive sliding mode control for speed regulation of multi-DC motors. The proposed control method consists to eliminates the need for precise system models by dynamically adjusting the control law [21], where is particularly useful in systems where obtaining a detailed model is impractical or complex such as the tradition PID control method. Compared with other existing literature on multi-DC motors systems, the results of this paper have following distinct features.

- 1) The proposed method integrates encoder counts based on the well known constant elapsed time (CET) method [31] for accurate speed control in nonlinear, time-varying multi-DC motor systems. This innovation greatly enhances resolution and reliability, setting it apart from traditional methods.
- 2) The implementation of a fixed communication topology for agents interconnections, which makes the controller more applicable and flexible in real implementation.
- 3) Utilizes the pseudo partial derivative (PPD) estimation mechanism within the MFASMC scheme, which provides strong robustness

The following sections will outline the remaining content of this paper: section II provides preliminaries and problem formulation, Section III The main results, Section IV presents simulation results and performance analysis, demonstrating the efficacy of the proposed method under various operating conditions. At the end, Section V concludes the paper, summarizing the key findings potential points for future research.

II. PRELIMINARIES AND PROBLEM FORMULATION

A. Directed Graph Theory

The directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \mathcal{A})$ is employed to describe the information exchange between agents. Here, $\mathcal{A} = [a_{ij}] \in \mathbb{R}^{N \times N}$ represents the adjacency matrix, $\mathcal{V} = \{v_1, v_2, \dots, v_N\}$ is the set of vertices, and $\mathcal{E} = [(v_j, v_i) | v_i \in \mathcal{V}] \subseteq \mathcal{V} \times \mathcal{V}$ is the set of edges. Moreover, $\mathcal{N}(i) = \{j \in \mathcal{V} | (i, j) \in \mathcal{E}\}$ denotes the neighbor set of agent i , where $a_{ij} \neq 0$. No self-loop is allowed in this article, which means $(i, i) \notin \mathcal{E}$ for any $i \in \mathcal{V}$, $a_{ii} = 0$. Furthermore, the degree matrix $K = \text{diag}(k_1, \dots, k_N)$. If $k_i > 0$, agent i can directly obtain the information from the leader. The Laplacian matrix L is defined as $L = (\mathcal{D} - \mathcal{A})$, here $\mathcal{D} = \text{diag}(d_1, \dots, d_N)$ and $d_i = \sum_{j=1}^N a_{ij}$ denotes the in-degree matrix. Moreover, the graph is strongly connected if the path exists between every pair of vertices.

B. Problem Formulation

Consider the nonlinear multi-agent systems composed of N agents:

$$y_i(k+1) = f_i(y_i(k), u_i(k)), \quad i = 1, 2, \dots, N \quad (1)$$

where $u_i(k) \in \mathbb{R}$ and $y_i(k) \in \mathbb{R}$ represent the system input and output signals of agent i , respectively. $f_i(\cdot)$ signifies an unknown nonlinear function.

Assumption 1: The partial derivative of $f_i(\cdot)$ with respect to $u_i(k)$ is continuous.

Assumption 2: The system (1) satisfies the generalized Lipschitz condition, meaning that if $\Delta u_i(k) = u_i(k) - u_i(k-1) \neq 0$ then $|\Delta y_i(k+1)| \leq b|\Delta u_i(k)|$ holds for any k , where $\Delta y_i(k+1) = y_i(k+1) - y_i(k)$.

Remark 1: The assumptions above are general. As the common condition for model-free control methods, Assumption 1 is crucial in ensuring effective system performance. Assumption 2 implies that the system input rate constrains the system output rate, which is satisfied in many practical systems.

Assumption 3: The network of followers forms a strongly connected graph, ensuring each follower can directly receive information from at least one leader.

Lemma 1 [8]: Consider the nonlinear multi-agent system (1) satisfying above two assumptions. If $|\Delta u_i(k)| \neq 0$ holds, then the system can be transformed into the CFDL data model as follows:

$$\Delta y_i(k+1) = \phi_i(k) \Delta u_i(k) \quad (2)$$

where $\phi_i(k)$ is called pseudo partial derivative (PPD), satisfying $|\phi_i(k)| \leq b$.

The distributed measurement error of $\xi_i(k)$ for N agents is established as:

$$\xi_i(k) = \sum_{j \in N_i} a_{ij}(y_j(k) - y_i(k)) + d_i(y_d(k) - y_i(k)) \quad (3)$$

if the agent i can receive data from the leader, then $d_i = 1$; otherwise, $d_i = 0$. Additionally, $y_d(k)$ represents the reference trajectory.

Remark 2: The CFDL technique requires no prior knowledge about the system dynamic model. Moreover, the dynamic behavior of time-varying PPD can be highly complex and more challenging to verify. Therefore a data-driven method for studying numerical characteristics is the preferred solution.

III. MAIN RESULTS

A. Model Free Adaptive Controller Design

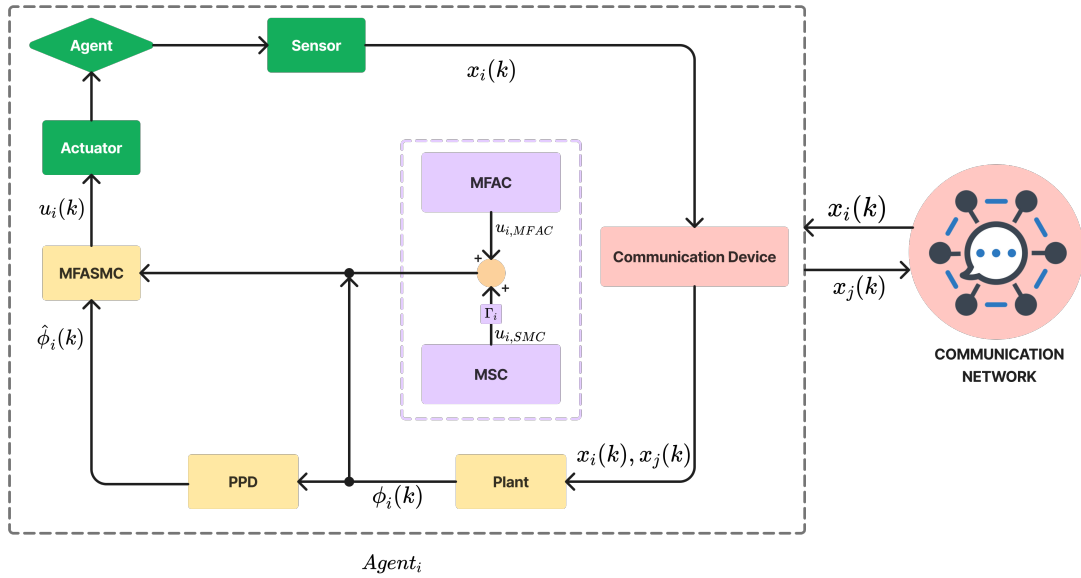


Fig. 1: Block diagram.

Consider the following PPD criterion function, which is used to evaluate the performance of the parameter $\phi_i(k)$:

$$J(\phi_i(k)) = |\Delta y_i(k) - \phi_i(k) \Delta u_i(k-1)|^2 + \mu |\phi_i(k) - \hat{\phi}_i(k-1)|^2 \quad (4)$$

By utilizing the optimal condition $\frac{\partial J(\phi_i(k))}{\partial \phi_i(k)} = 0$, then the updating law with reset algorithm can be derived as

$$\hat{\phi}_i(k) = \hat{\phi}_i(k-1) + \frac{\eta \Delta u_i(k-1)}{\mu + \Delta u_i(k-1)^2} (\Delta y_i(k) - \hat{\phi}_i(k-1) \Delta u_i(k-1)) \quad (5)$$

$$\hat{\phi}_i(k) = \hat{\phi}_i(1), \text{ if } |\hat{\phi}_i(k)| \leq \epsilon \text{ or } \text{sign}(\hat{\phi}_i(k)) \neq \text{sign}(\hat{\phi}_i(1)) \quad (6)$$

Herein, $\eta \in (0, 1)$, $\mu > 0$ the weight factor, ϵ is a small positive number and $\hat{\phi}_i(k)$ represents the estimated value of $\phi_i(k)$.

The following distributed MFAC algorithm is then presented:

$$u_{i,\text{MFAC}}(k) = u_{i,\text{MFAC}}(k-1) + \frac{\rho \hat{\phi}_i(k)}{\lambda + |\hat{\phi}_i(k)|^2} \xi_i(k) \quad (7)$$

where $\rho \in (0, 1)$ is a step-size constant, which is added to make (7) general.

B. Sliding Mode Controller Design

To design the SMC for the system, the sliding mode surface is first defined as

$$S_i(k) = \alpha \xi_i(k) - \xi_i(k-1) \quad (8)$$

herein $\alpha > 1$ represents a positive constant.

Furthermore, from (2) and (3), the formula (3) is updated as

$$\begin{aligned} \xi_i(k+1) = \xi_i(k) - \left(\sum_{j \in N_i} a_{ij} + d_i \right) \phi_i(k) \Delta u_i(k) + \sum_{j \in N_i} a_{ij} \Delta y_j(k) \\ + d_i \Delta y_d(k+1) \end{aligned} \quad (9)$$

wherein $\Delta y_j(k+1)$ is replaced with $\Delta y_j(k)$ because the data at the next moment cannot be obtained.

Considering (8), with the assistance of reaching law $S_i(k+1) = 0$, the equivalent control law is designed as

$$\Delta u_{i,\text{SM}}^{\text{eq}} = \frac{\omega \hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \left(\frac{\xi_i(k) + \sum_{j \in N_i} a_{ij} \Delta y_j(k) + d_i \Delta y_d(k+1)}{\sum_{j \in N_i} a_{ij} + d_i} - \frac{\xi_i(k)}{\alpha (\sum_{j \in N_i} a_{ij} + d_i)} \right) \quad (10)$$

The controller consists of an equivalent control law and switching control law, which is set as

$$u_{i,\text{SM}}(k) = u_{i,\text{SM}}(k-1) + \Delta u_{i,\text{SM}}^M(k) + \Delta u_{i,\text{SM}}^s(k) \quad (11)$$

where, the switching control law $\Delta u_{i,\text{SM}}^s(k)$ is presented as

$$\Delta u_{i,\text{SM}}^s(k) = \frac{\omega \hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \tau_s \text{sign}(S_i(k)) \quad (12)$$

Taking into consideration both (10), (11) and (12), the controller is summarized as follows:

$$u_{i,\text{SM}}(k) = u_{i,\text{SM}}(k-1) + \frac{\omega \hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \left(\frac{\xi_i(k) + \sum_{j \in N_i} a_{ij} \Delta y_j(k) + d_i \Delta y_d(k+1)}{\sum_{j \in N_i} a_{ij} + d_i} \right)$$

$$- \frac{\xi_i(k)}{\alpha(\sum_{j \in N_i} a_{ij} + d_i)} + \tau_s \text{sign}(S_i(k)) \quad (13)$$

Subsequently, the final MFASMC input is designed:

$$u_i(k) = u_{i,\text{MFAC}}(k) + \Gamma_i u_{i,\text{SMC}}(k) \quad (14)$$

where the parameter Γ is a gain factor.

C. Stability Analysis

Theorem 1: For the MASs (1) satisfying assumptions 1 and 2, assuming the controller parameters establish $0 < h_0 < h_i(k) < \frac{\omega C_0}{2\sqrt{\sigma}} < 1$, then using the PPD update law (5) ensures the boundedness of $\hat{\phi}_i(k)$.

Proof: The proof is divided into two parts.

Part i: Set $\tilde{\phi}_i(k) = \hat{\phi}_i(k) - \phi_i(k)$, based on PPD estimation algorithm (5), we can obtain:

$$\begin{aligned} \tilde{\phi}_i(k) &= \tilde{\phi}_i(k-1) + \frac{\eta \Delta u_i(k-1)}{\mu + \Delta u_i(k-1)^2} (\phi_i(k-1) \Delta u_i(k-1) - \hat{\phi}_i(k-1) \Delta u_i(k-1)) \\ &= \tilde{\phi}_i(k-1) + \frac{\eta \Delta u_i(k-1)}{\mu + \Delta u_i(k-1)^2} (\phi_i(k-1) - \hat{\phi}_i(k-1)) - \phi_i(k) + \phi_i(k-1) \\ &= \left(1 - \frac{\eta \Delta u_i(k-1)^2}{\mu + \Delta u_i(k-1)^2}\right) \tilde{\phi}_i(k-1) - \Delta \phi_i(k) \end{aligned} \quad (15)$$

Denote that the term $\frac{\eta \Delta u_i(k-1)^2}{\mu + \Delta u_i(k-1)^2}$ is monotonically increasing with respect to $|\Delta u_i(k)|^2$, and its minimum value is $\frac{\eta \epsilon^2}{\mu + \epsilon^2}$.

Therefore, there must be a constant q_1 satisfying the inequalities $0 < \eta \leq 1$ and $u > 0$

$$0 < \left|1 - \frac{\eta \Delta u_i(k-1)^2}{\mu + \Delta u_i(k-1)^2}\right| \leq 1 - \frac{\eta \epsilon^2}{\mu + \epsilon^2} = q_1 < 1 \quad (16)$$

Because of $|\phi_i(k)| < \bar{b}$, and $|\Delta \phi_i(k)| < 2\bar{b}$ then the equation (15) is written as:

$$\begin{aligned} |\tilde{\phi}_i(k)| &\leq q_1 |\tilde{\phi}_i(k-1)| + 2\bar{b} \\ &\leq q_1^2 |\tilde{\phi}_i(k-2)| + 2q_1 \bar{b} + 2\bar{b} \\ &\vdots \\ &\leq q_1^{k-1} |\tilde{\phi}_i(1)| + \frac{2\bar{b}}{1 - q_1} (1 - q_1^{k-1}) \end{aligned} \quad (17)$$

which implies $\tilde{\phi}_i(k)$ is bounded. Since the boundedness of $\phi_i(k)$ is guaranteed by Lemma 1.

Part ii: In this part, mathematical induction will be utilized to prove that $\xi_i(k)$ remains bounded.

Substituting (5) into (9), then the expression for $\xi_i(k+1)$ is formulated as follows:

$$\begin{aligned} \xi_i(k+1) &= \xi_i(k) + \sum_{j \in N_i} a_{ij} \Delta y_j(k) + d_i \Delta y_d(k+1) - \frac{\omega \phi_i(k) \hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \left((1 - \frac{1}{2}) \xi_i(k) + \sum_{j \in N_i} a_{ij} \Delta y_j(k) + d_i \Delta y_d(k+1) \right) \\ &\quad + \left(\sum_{j \in N_i} a_{ij} + d_i \right) \tau_s \text{sign}(S_i(k)) \\ &= \left(1 - \frac{\omega \phi_i(k) \hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} (1 - \frac{1}{2}) \right) \xi_i(k) + \left(1 - \frac{\omega \phi_i(k) \hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \right) \left(\sum_{j \in N_i} a_{ij} \Delta y_j(k) + d_i \Delta y_d(k+1) \right) \end{aligned}$$

$$-\frac{\omega\phi_i(k)\hat{\phi}_i(k)}{\sigma + \hat{\phi}_i(k)^2} \left(\sum_{j \in N_i} a_{ij} + d_i \right) \tau_s \text{sign}(S_i(k)) \quad (18)$$

By applying the fundamentals of mathematical induction, then assuming $0 < h_0 < h_i(k) < \frac{\omega C_0}{2\sqrt{\sigma}} < 1$, where $\phi_i(k) < C_0$ and $|g_i(k)| < g_0$, the inequality is obtained by taking the absolute value of each term of (18).

$$\begin{aligned} |\xi_i(k+1)| &\leq |1 - h_i(k)(1 - \frac{1}{2})| |\xi_i(k)| + |g_i(k)| \\ &\leq |1 - h_i(k)(1 - \frac{1}{2})| |\xi_i(k)| + g_0(k) \\ &\vdots \\ &\leq 1 - h_0(1 - \frac{1}{2})^k |\xi_i(k)| + \frac{g_0(1 - (1 - h_0(1 - \frac{1}{2}))^2)}{h_0(1 - \frac{1}{2})} \end{aligned} \quad (19)$$

Therefore, the following result will be given as

$$\lim_{k \rightarrow \infty} \xi_i(k+1) = \frac{g_0}{h_0(1 - \frac{1}{2})} = \frac{\alpha g_0}{(\alpha - 1)h_0} \quad (20)$$

The proof is completed.

Remark 3: Theorem 1 guarantees the boundedness of $\hat{\phi}_i$ and the distributed measurement error for the MASs described by (1) under assumptions 1 and 2. The proof employs the PPD update law (5) to ensure that $\tilde{\phi}_i(k)$ remains bounded, as demonstrated through the application of the factor $q_1 < 1$. The mathematical induction confirms that $\xi_i(k)$ is bounded. Thus, this result shows the effectiveness of the proposed controller in achieving stable performance for the MASs.

Consider the network comprising:

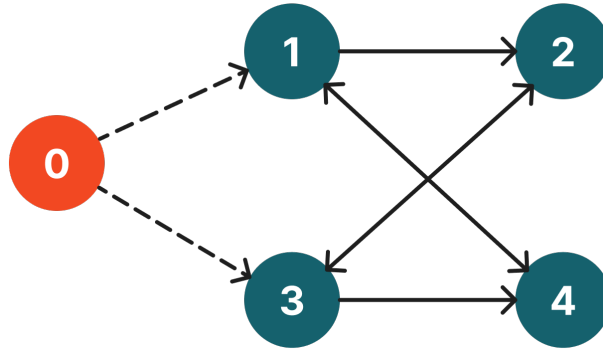


Fig. 2: Communication topology among agents.

IV. SIMULATION EXAMPLE

This section describes the usefulness of the provided control approach, which is validated by numerical simulations and physical experiments results.

The output data model of each agents is governed by:

$$\begin{aligned} \text{Agent 1 : } y_1(k+1) &= 0.5 * y_1(k) * u_1(k) + 1.2 * \frac{m}{(rT*0.2)} - 0.03 * y_1(k)^3 + 0.45 \\ \text{Agent 2 : } y_2(k+1) &= 0.5 * y_2(k) * u_2(k) + 1.2 * \frac{m}{(rT*0.2)} - 0.01 * y_2(k)^2 + 0.45 \\ \text{Agent 3 : } y_3(k+1) &= 0.5 * y_3(k) * u_3(k) + 1.2 * \frac{m}{(rT*0.2)} - 0.02 * y_3(k)^3 + 0.45 \\ \text{Agent 4 : } y_4(k+1) &= 0.5 * y_4(k) * u_4(k) + 1.2 * \frac{m}{(rT*0.2)} - 0.01 * y_4(k)^2 + 0.45 \end{aligned}$$

It is evident that the agents considered are heterogeneous, as the dynamics differ from one another. In this scenario, the dynamics are assumed to be unknown and are only used to generate the I/O data for the MASs.

As illustrated in Fig. 2, the virtual leader is designated as vertex 0. It can be observed that only agents 1 and 3 can receive information from the leader, forming a strongly connected communication graph. Assume that the information exchange among agents is directed and fixed. The Laplacian matrix of the graph is given as follows:

$$L = \begin{bmatrix} 1 & 0 & 0 & -1 \\ -1 & 2 & -1 & 0 \\ 0 & -1 & 1 & 0 \\ -1 & 0 & -1 & 2 \end{bmatrix}$$

with $D = \text{diag}(1, 0, 1, 0)$, we consider the following two different desired trajectories.

Example 1: The expression for $y_d(k)$ is:

$$y_d(k) = 6$$

as k in the range $0 \leq k \leq 200$.

The initial parameters are chosen as $u_i(1) = 0.01$, $y_i(1) = 0.6$ and $\phi_i(0) = 4$ for all agents in this simulation, $\Gamma_1 = \Gamma_3 = 0.45$ and $\Gamma_2 = \Gamma_4 = 0.15$, with $\tau_s = 10^{-5}$, $m = 200$, sampling rate $rT = 1024$, $\eta = 1$, $\mu = 0.005$, other parameters are given as $\rho = 7.5$, $\lambda = 350$, $\omega = 10$, $\sigma = 95$, $\alpha = 15$ with $\epsilon = 10^{-5}$.

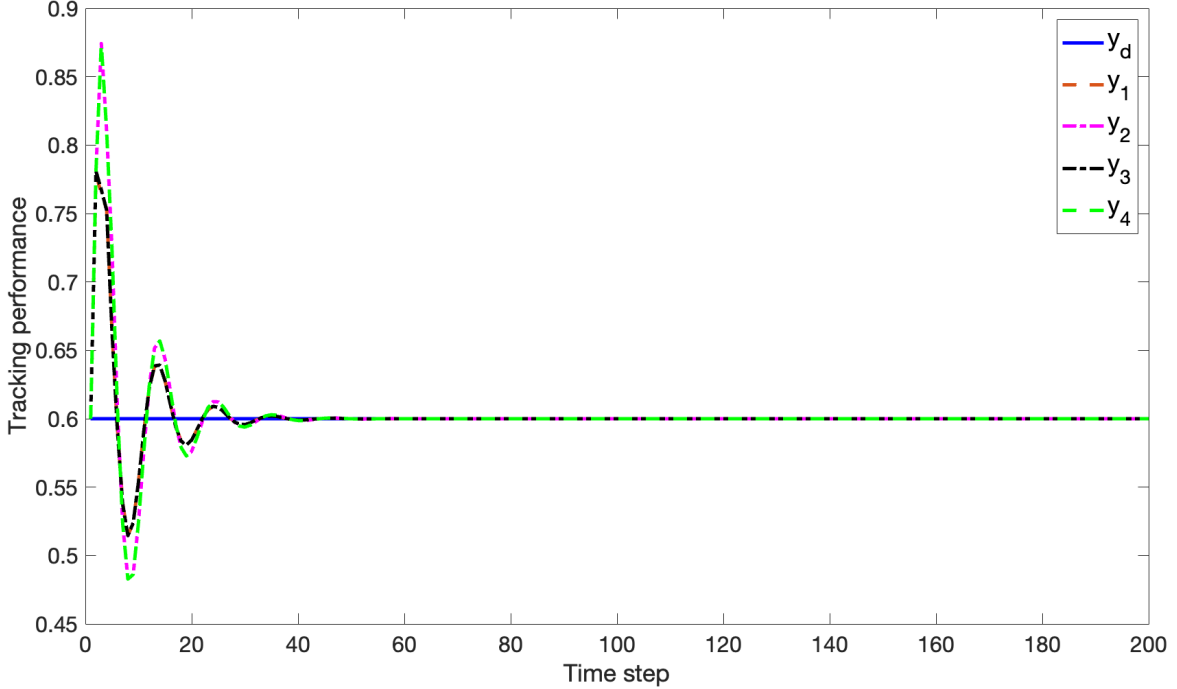


Fig. 3: Tracking performance of all agents under the time-invariant reference trajectory.

Fig. 3 demonstrates that all agents successfully track the time-invariant reference trajectory.

As shown in Fig. 4 and 6, the distributed errors for all agents are relatively small and converge to zero over time. However, the individual agents exhibit varying levels of tracking error, suggesting that their unique dynamics or initial conditions may influence the performance.

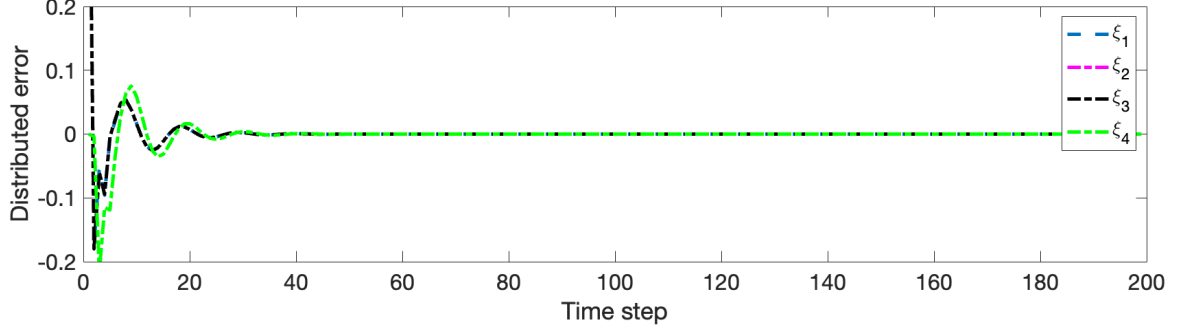


Fig. 4: Distributed error of all agents under the time-invariant reference trajectory.

Example 2: The expression for $y_d(k)$ is:

$$y_d(k) = 0.5 \sin\left(\frac{k\pi}{30}\right) + 0.3 \cos\left(\frac{k\pi}{10}\right)$$

as k in the range $0 \leq k \leq 200$.

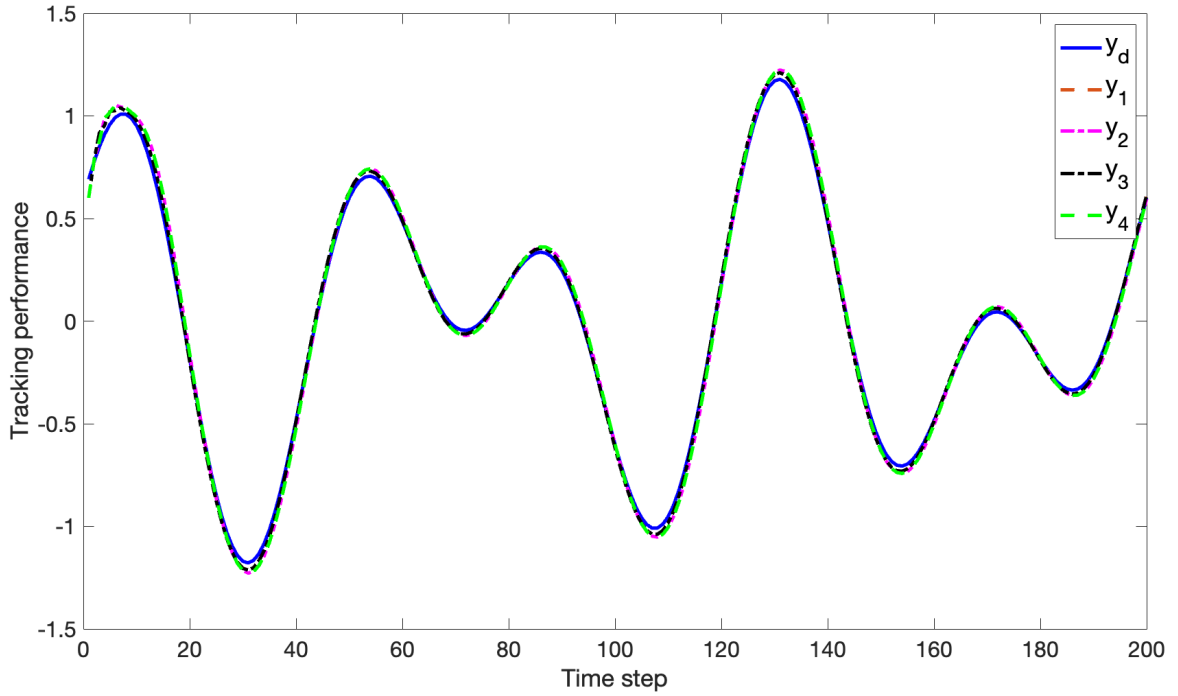


Fig. 5: Tracking performance of all agents under the time-varying reference trajectory.

Fig. 5 presents a detailed analysis of the tracking performance for all agents. All agents successfully track the time-varying desired trajectory, confirming the effectiveness of the proposed control system. While minor variations in individual trajectories are evident, each agent generally adheres to the desired path. Factors such as agent dynamics, communication delays, and environmental disturbances could potentially influence the tracking performance.

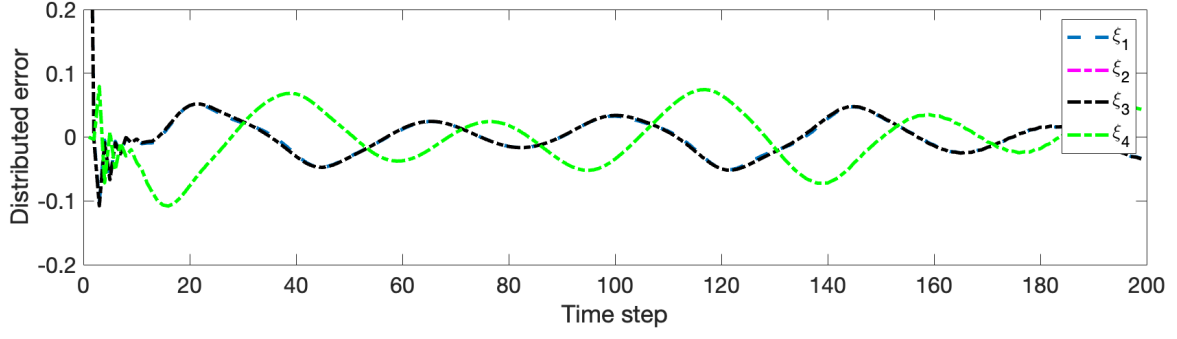


Fig. 6: Distributed error of all agents under the time-varying reference trajectory.

To verify the proposed consensus tracking control methodology, the experimental validation is conducted using a multi-DC motor system, as illustrated in Fig. 8. The system consists of three DC motors equipped with Hall encoders and reduction gears, an STM32F407 main control chip, two motor drive modules, and an LCD display module. The microcontroller unit (MCU) STM32F407ZGT6 is used for high-resolution pulse width modulation (PWM) output generation to achieve precise motor speed control. The timer module is utilized for this purpose.

In addition, the controller code is written in C language using STM32CubeIDE, while STM32CubeMX is used for pin configuration. The main purpose of the experiment is to ensure that the three motors accurately track the reference trajectory:

$$y_d(k) = 0.5 \sin(0.07\pi(k)) + 0.7 \cos(0.04\pi(k))$$

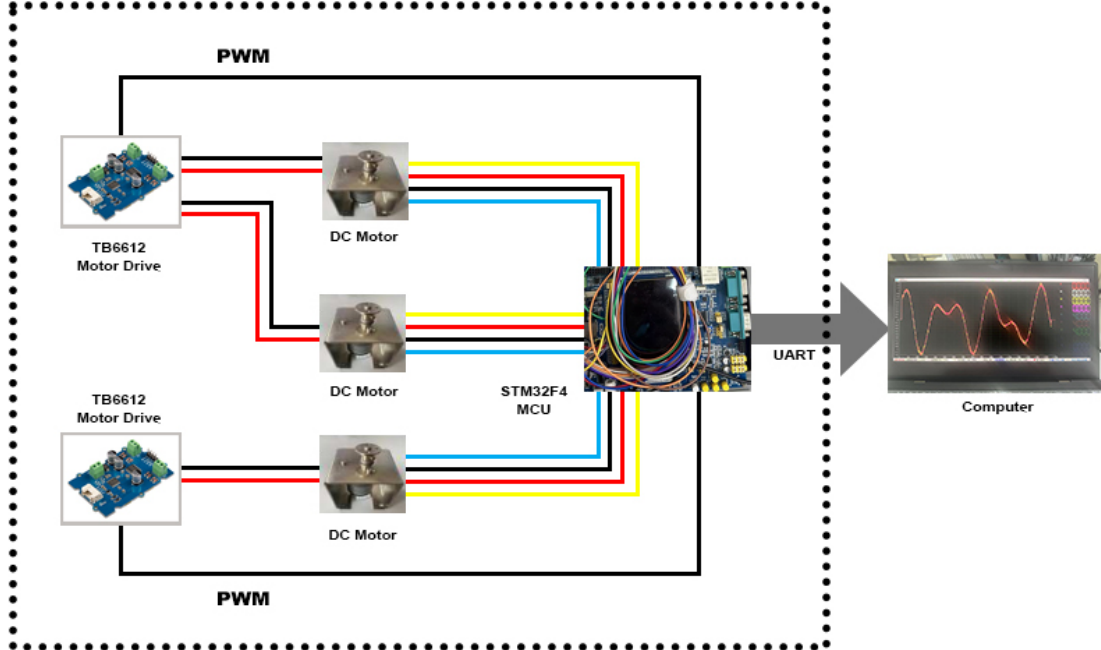


Fig. 7: System connection diagram of multi-DC motors consensus tracking control.

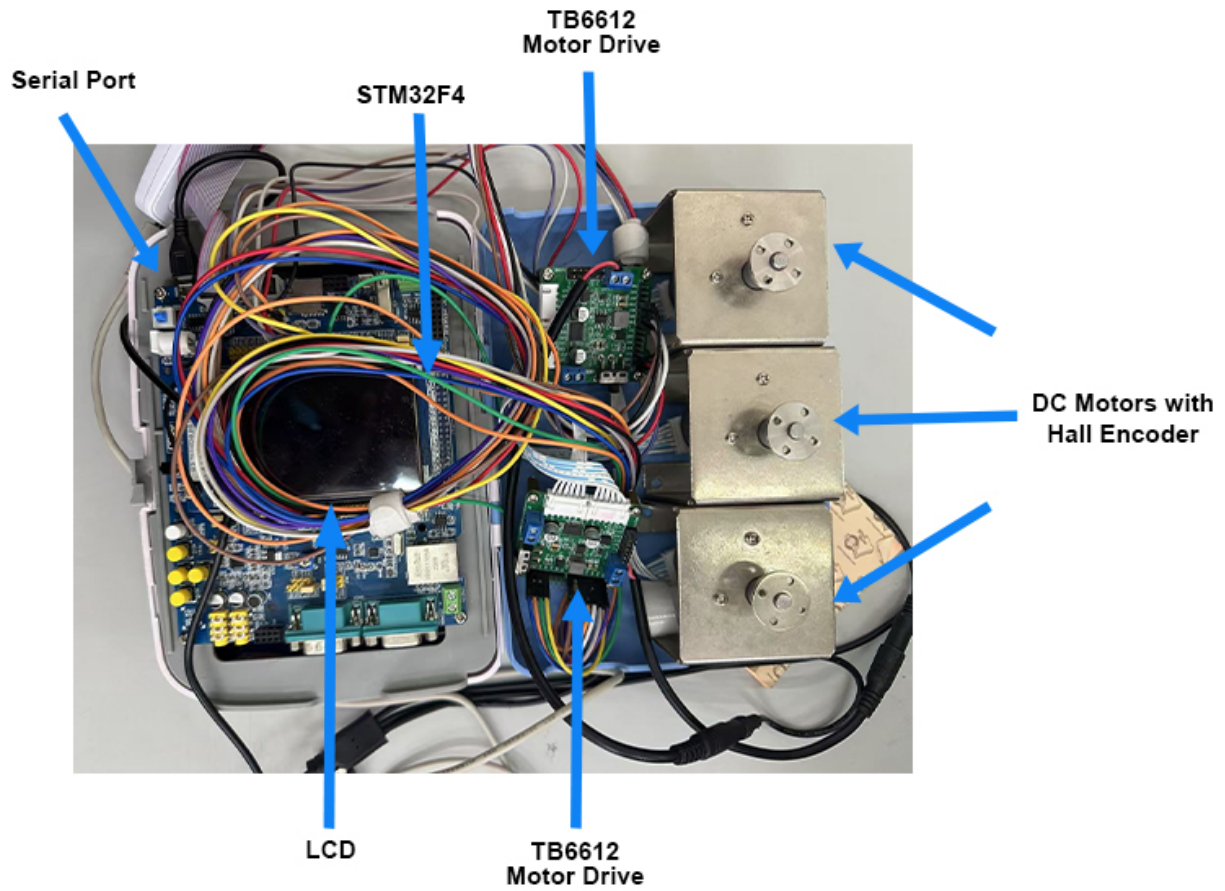


Fig. 8: Multi-DC motors system.

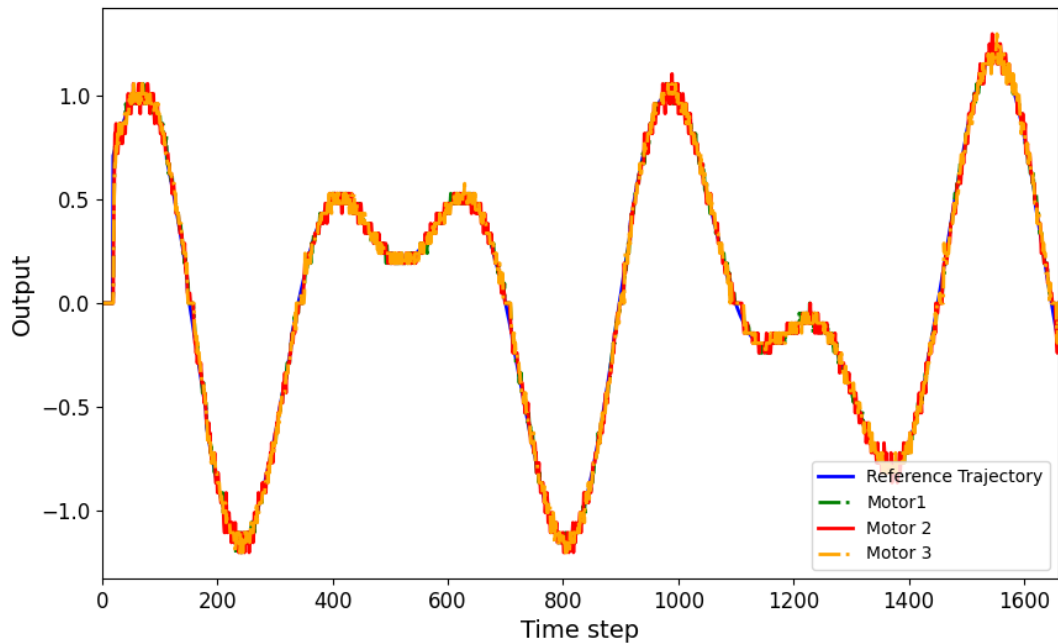


Fig. 9: Tracking performance of 3 DC motors for time-invariant desired trajectory.

Fig.9 shows the tracking performance of multi-DC motors. As presented, all DC motors successfully track the desired trajectory, demonstrating the effectiveness of the proposed control method. Where the reference trajectory is presented by blue. Overall, the simulation results suggest that the proposed control system is capable of tracking a constant desired trajectory for multiple agents. While initial transient errors may occur, the system eventually reaches a steady-state condition with minimal tracking error. The variations in tracking performance among the agents highlight the potential influence of individual characteristics and external factors.

V. CONCLUSION

In this study, the model-free adaptive sliding mode control approach is presented to address the consensus problem of MASs. Firstly, the equivalent data model for each agent is obtained using the CFDL method. Secondly, a novel sliding surface is presented to ensure that the distributed error remains bounded. Finally, the effectiveness of the proposed control approach is verified through physical experiments on multi-DC motor system.

REFERENCES

- [1] Lewis, F.L.; Zhang, H.; Hengster-Movric, K.; Das, A. Cooperative Control of Multi-Agent Systems: Optimal and Adaptive Control Design; Springer Science and Business Media: Berlin/Heidelberg, Germany, 2014.
- [2] Bu, XH; Hou, ZS and Zhang, HW. Data-Driven Multiagent Systems Consensus Tracking Using Model Free Adaptive Control. *IEEE Transactions on Neural Networks and Learning Systems*, May 2018, 29(5): 1514-1524.
- [3] Ren, W. Consensus strategies for cooperative control of vehicle formations. *IET Control Theory Appl.* 2007, 1, 505–512.
- [4] Dong, S.; Wang, C.; Wen, S.; Gang, F. A synchronization approach to trajectory tracking of multiple mobile robots while maintaining time-varying formations. *IEEE Trans. Robot.* 2009, 25, 1074–1086.
- [5] Z. Hou and S. Jin, "A novel data-driven control approach for a class of SISO nonlinear systems," *IEEE Transactions on Control Systems Technology*, vol. 19, no. 6, pp. 1549-1558, 2011.
- [6] R. Olfati-Saber, J. A. Fax, and R. M. Murray, "Consensus and cooperation in networked multi-agent systems," *Proceedings of the IEEE*, vol. 95, no. 1, pp. 215-233, 2007.
- [7] M. Sampei, T. Tamura, T. Kobayashi, and N. Shibui, "Arbitrary path tracking control of articulated vehicles using nonlinear control theory," *IEEE Trans. Control Syst. Technol.*, vol. 3, no. 1, pp. 125–131, Mar. 1995.
- [8] W. Ren, R. W. Beard, and E. M. Atkins, "Information consensus in multivehicle cooperative control," *IEEE Control Systems*, vol. 27, no. 2, pp. 71-82, 2007.
- [9] D. Xu, B. Jiang, and P. Shi, "Adaptive observer based data-driven control for nonlinear discrete-time processes," *IEEE Transactions on Automation Science and Engineering*, vol. 11, no. 4, pp. 1037-1045, 2014.
- [10] R. Chi, Z. Hou, S. Jin, D. Wang, and C.-J. Chien, "Enhanced data-driven optimal terminal ILC using current iteration control knowledge," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 26, no. 11, pp. 2939-2948, 2015.
- [11] Ren, Y.; Hou, Z. Robust model-free adaptive iterative learning formation for unknown heterogeneous non-linear multi-agent systems. *IET Control Theory Appl.* 2020, 14, 654–663.
- [12] C. L. P. Chen, G.-X. Wen, Y.-J. Liu, and F.-Y. Wang, "Adaptive consensus control for a class of nonlinear multiagent time-delay systems using neural networks," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 25, no. 6, pp. 1217-1226, 2014.
- [13] Zhou, N (Zhou, Ning); Deng, WX (Deng, Wenxiang); Yang, XW (Yang, Xiaowei); Yao, JY (Yao, Jianyong), "Continuous adaptive integral recursive terminal sliding mode control for DC motors," *International Journal of Control*, vol. 96, no. 9, pp. 2190-2200, June 2022.
- [14] X. Liu, J. Lam, W. Yu, and G. Chen, "Finite-time consensus of multiagent systems with a switching protocol," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 27, no. 4, pp. 853–862, Apr. 2016.
- [15] Z. Hou and Z. Wang, "From model-based control to data-driven control: Survey, classification and perspective," *Inf. Sci.*, vol. 235, pp. 3–35, 2013.
- [16] Z. Hou and S. Jin, "A novel data-driven control approach for a class of discrete-time nonlinear systems," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 6, pp. 1549–1558, Nov. 2011.
- [17] D. Xu, B. Jiang, and F. Liu, "An improved data driven MDEL free adaptive constrained control for a solid oxide fuel cell," *IET Control Theory Appl.*, vol. 10, no. 12, pp. 1412–1419, 2016.
- [18] D. Xu, B. Jiang, and P. Shi, "A novel model free adaptive control design for multivariable industrial processes," *IEEE Trans. Ind. Electron.*, vol. 61, no. 11, pp. 6391–6398, Nov. 2014.

- [19] D. Xu, B. Jiang, and P. Shi, "Adaptive observer based data-driven control for nonlinear discrete-time processes," *IEEE Trans. Autom. Sci. Eng.*, vol. 11, no. 4, pp. 1037–1045, Oct. 2014.
- [20] Z. Pang, G. Liu, D. Zhou, and D. Sun, "Data-based predictive control for networked nonlinear systems with network-induced delay and packet dropout," *IEEE Trans. Ind. Electron.*, vol. 63, no. 2, pp. 1249–1257, Feb. 2016.
- [21] H. Zhang and F. L. Lewis, "Adaptive cooperative tracking control of higher-order nonlinear systems with unknown dynamics," *Automatica*, vol. 48, no. 7, pp. 1432–1439, 2012.
- [22] J. Liu, S. Vazquez, L. Wu, A. Marque, H. Gao, and L. G. Franquelo et al., "Extended state observer based sliding mode control for three-phase power converters," *IEEE Trans. Ind. Electron.*, vol. 64, no. 1, pp. 22–31, Jan. 2017.
- [23] Z.-G. Hou, L. Cheng, and M. Tan, "Decentralized robust adaptive control for the multiagent system consensus problem using neural networks," *IEEE Transactions on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol. 39, no. 3, pp. 636–647, Jun. 2009.
- [24] Z. Hou and W. Huang, "The model-free learning adaptive control of a class of SISO nonlinear systems," *Proceedings of the American Control Conference*, Albuquerque, NM, USA, Jun. 1997, pp. 343–344.
- [25] H. Su, G. Chen, X. Wang, and Z. Lin, "Adaptive second-order consensus of networked mobile agents with nonlinear dynamics," *Automatica*, vol. 47, no. 2, pp. 368–375, Feb. 2011.
- [26] D. Xu, B. Jiang, and P. Shi, "Adaptive observer based data-driven control for nonlinear discrete-time processes," *IEEE Transactions on Automation Science and Engineering*, vol. 11, no. 4, pp. 1037–1045, Oct. 2014.
- [27] H. Zhang and F. L. Lewis, "Adaptive cooperative tracking control of higher-order nonlinear systems with unknown dynamics," *Automatica*, vol. 48, no. 7, pp. 1432–1439, Jul. 2012.
- [28] Z. Wu, X. Wang, and X. Zhao, "Backstepping terminal sliding mode control of DFIG for maximal wind energy captured," *Int. J. Innovative Comput. Inf. Control*, vol. 12, no. 5, pp. 1565–1579, 2016.
- [29] X. Yan and C. Edwards, "Adaptive sliding-mode-observer-based fault reconstruction for nonlinear systems with parametric uncertainties," *IEEE Trans. Ind. Electron.*, vol. 55, no. 11, pp. 4029–4036, Nov. 2008.
- [30] J. Liu, W. Luo, X. Yang, and L. Wu, "Robust model-based fault diagnosis for PEM fuel cell air-feed system," *IEEE Trans. Ind. Electron.*, vol. 63, no. 5, pp. 3261–3270, May 2016.
- [31] A. Anuchin, A. Dianov and F. Briz, "Synchronous Constant Elapsed Time Speed Estimation Using Incremental Encoders," in *IEEE/ASME Transactions on Mechatronics*, vol. 24, no. 4, pp. 1893–1901, Aug. 2019, doi: 10.1109/TMECH.2019.2928950.
- [32] S. Qin and T. Badgwell, "A survey of industrial model predictive control technology," *Control Eng. Pract.*, vol. 11, pp. 733–764, 2003.
- [33] A. Sharafian, V. Bagheri, and W. Zhang, "RBF neural network sliding mode consensus of multi-agent systems with unknown dynamical model of leader-follower agents," *International Journal of Control, Automation and Systems*, vol. 16, no. 2, pp. 749–758, 2018.
- [34] X. Ma, F. Sun, H. Li, and B. He, "Neural-network-based integral sliding-mode tracking control of second-order multi-agent systems with unmatched disturbances and completely unknown dynamics," *International Journal of Control, Automation and Systems*, vol. 15, no. 4, pp. 1925–1935, 2017.
- [35] R. Rahmani, H. Toshani, and S. Mobayen, "Consensus tracking of multi-agent systems using constrained neural-optimiser-based sliding mode control," *International Journal of Systems Science*, vol. 51, no. 14, pp. 2653–2674, 2020.
- [36] Z. Peng, G. Wen, A. Rahmani, and Y. Yongguang, "Distributed consensus-based formation control for multiple nonholonomic mobile robots with a specified reference trajectory," *International Journal of Systems Science*, vol. 46, no. 8, pp. 1447–1457, 2015.