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Data Driven Distributed Bipartite Consensus Tracking for Nonlinear Multiagent Systems via Iterative Learning Control

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ABSTRACT This article explores a data-driven distributed bipartite consensus tracking (DBCT) problem for discrete-time multi-agent systems (MASs) with coopetition networks under repeatable operations. To solve this problem, a time-varying linearization model along the iteration axis is first established by using the measurement input and output (I/O) data of agents. Then a data-driven distributed bipartite consensus iterative learning control (DBCILC) algorithm is proposed considering both fixed and switching topologies. Compared with existing bipartite consensus, the main characteristic is to construct the proposed control protocol without requiring any explicit or implicit information of MASs' mathematical model. The difference from existing iterative learning control (ILC) approaches is that both the cooperative interactions and antagonistic interactions, and time-varying switching topologies are considered. Furthermore, through rigorous theoretical analysis, the proposed DBCILC approach can guarantee the bipartite consensus reducing tracking errors in the limited iteration steps. Moreover, although not all agents can receive information from the virtual leader directly, the proposed distributed scheme can maintain the performance and reduce the costs of communication. The results of three examples further illustrate the correctness, effectiveness, and applicability of the proposed algorithm.

INDEX TERMS Iterative control (ILC), bipartite consensus, data-driven control (DDC), multi-agent systems (MASs), nonlinear discrete-time systems.

I. INTRODUCTION

Over the past few years, the cooperative control theories of multiagent systems (MASs) have been wildly researched. MASs have been already applied to many practical areas [1]–[3], such as vertical tank systems, automated highway systems, autonomous cars, and satellite formation. Moreover, the distributed algorithm [4], [5] which is one of the significant algorithms in the cooperative control theories can regulate agents to achieve consensus without a central control unit. Low-cost capture devices can be used to construct a high-performance system. Ning *et al.* [4] apply the edge-based fixed-time consensus approach and the Hessian matrix to formulate a distributed protocol, which can successfully guarantee the distributed optimization of MASs under both fixed and switching communication topologies. An effective control protocol of the second-order MASs is proposed in [5] to perform the formation task and maintain predictive performance.

As aforementioned, the relationship among agents is collaborative. However, cooperative and competitive relationships are coexistent among agents in natural or engineering scenarios. For instance, in economic systems, duopolistic regimes occur when agents compete for limited resources.

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In some multi-robot systems, a robot needs to cooperate with its teammates while competing with the antagonistic robots. In biological systems, a pair of genes are viewed as activators when they are in cooperative interaction, and as inhibitors when in competitive interactions. Altafini first considers bipartite consensus (BC), a class of consensus, by introducing a signed graph to represent both cooperative and competitive relationships among agents in [6]. In a signed graph, if the edge between two nodes is positive, then it means those agents are in the same alliance and have the same performance, otherwise having opposite behaviors. Here, both of the alliances could reach a consensus respectively. Hu et al present some sufficient and necessary conditions of consensus in [7].

The high-order MASs are investigated and a tow control strategy is proposed in [8], which can guarantee reducing the BC errors even if unknown disturbances exist. Time-varying cooperation-competition networks are considered for high-order MASs to realize bipartite containment control in [9]. Ren *et al.* propose an event-triggered control scheme to reduce the communication burden of bipartite leader-following consensus in [10]. Fixed-time and finite-time BC are researched in [12]–[14]. To solve the input saturation problem of MASs, both distributed event-triggered control and low-gain feedback technique are utilized in [15] to guarantee BC and successfully exclude the Zeno behavior for each agent. The measurement noises are investigated in [16] by introducing a significant function, which can reduce the influence of measurement noises to ensure mean-square BC. Ai in [17] applies the signed graph theory and proposes a distributed adaptive robust controller to address the leader-follower BC problem of MASs with uncertain dynamics. A Two-DOF robotic manipulator is researched in [18], where several distributed estimator-based control algorithms are proposed, which can guarantee all controlled robots to ultimately reach BC. Considering both competitive and cooperative relationships among agents is more attractive than only considering one of them, which is the first motivation of this article.

However, the researches above depend on explicit or implicit mathematical models of MASs to design corresponding control protocols to realize BC control, which is also called the model-based control (MBC) theory. In fact, the mathematical model of some practical systems, especially the accurate model of complicated MASs, is hard to be obtained. In addition, even if an accurate model of the controlled plant is established, it can lead to a very complicated controller with huge computations. Hence, merely utilizing the I/O data of each agent to explore BC control problems for unknown nonlinear non-affine MASs is significant. Fortunately, several intelligent algorithms have been developed to achieve consensus control or formation control. For example, Lewis *et al.* [19] apply Reinforcement Learning to cope with partially observable systems developed in [20]. A Data-driven distributed output consensus control is proposed for MASs, the Learning-based adaptive attitude control is formulated for spacecraft formation to guarantee prescribed performance in [21]. A depth control approach is proposed to track the desired depth trajectories for an autonomous underwater vehicle in [22]. It is noted that most of the schemes mentioned above need to establish neural networks to design controllers, which makes preparing the external testing signals and training processes inescapable. Recently, some useful results have been reported for unknown multiagent systems, such as Model-Free Adaptive Control (MFAC) [23], [24], Q-Learning [25]–[27], Iterative Feedback Tuning (IFT) [28], [29], Simultaneous Perturbation Stochastic Approximation (SPSA) [30], [31], Iterative Learning Control (ILC) [32]–[38], Virtual Reference Feedback Tuning (VRFT) [39].

As aforementioned, the control approaches in [19]–[42] are intelligent algorithms, which also are named as Data-Driven control (DDC) or Leaning control. Those Learning control approaches improve the control performance through understanding the additional control information from the previous time instants of the controlled systems and the external environment attained by its learning ability. In other words, using those methods to design the corresponding controller only depends on the I/O data of the controlled plant, which can sufficiently avoid difficulties with the precise mathematical model and identification process. Moreover, the learning control has two different controlled aims according to the controlled plants. One of the important systems is repetitively operating systems, where machines perform repeatable or periodic tasks in a limited time interval, such as the formation keeping and tracking the desired trajectory of quadrotors in [33]. In reality, many tasks of industrial production are repeatable over a finite tracking interval, such as IC welding and wafer manufacturing, where a quantity of agents are autonomously operating over and over again in a similar fashion. With the huge requirements of manufacturing production, to develop the control systems on a repeatable operation environment has a great business value and strategic significance, which forms the second motivation of this article.

It is worth pointing out that the ILC approach is one of the excellent schemes to control repetitively operating systems. This article proposes a new ILC algorithm to implement the distributed BC tracking scheme for MASs under a repeatable operation environment. In [32], the ILC algorithm is first applied to keep the desired formation for MASs, where the nonlinear dynamics are partially available. In [33], Hock *et al.* extend the results of [32] and design an additional consensus feedback controller to compensate for non-repetitive disturbances. In addition, the so-called Q-filter and a Kalman filter are applied to enhance the ability of disturbance estimation. Meng *et al.* [35] propose a robust formation control approach, where the global Lipschitz condition is not necessary, and also the switching topologies are also discussed for nonlinear MASs. A distributed Model-Free Adaptive Iterative Learning (MFAIL) approach is successfully utilized in [36] for MASs to perform consensus tracking, where both flex and iteration-varying topologies are discussed. Wang *et al.* [37] research the MFAILC scheme for consensus tracking, where a general dynamic linearization mold is introduced to estimate the dynamic of MASs with the disturbance input. An interesting research presented in [38] adds a space dimension, where iterative variations are compensated which can improve the tracking performance and the speed for MASs formation control. Moreover, several other novel instances are investigated in [40], [41].

From the above observations and analysis, there are still some remaining issues to be addressed. For example, introducing competitive interaction among agents in [1]–[5] could be more useful. Although the BC control approaches are extensively researched in [6]–[18] which propose many effective methods, most of them are dependent on accurate mathematical models that are hard to obtain or lead to a heavy calculation burden.

The main contributions of this work are:

(1). Propose a new data-driven DBCILC scheme for MASs to achieve BC with switching topologies and coopetition networks under a repeatable operation environment.

(2). Study fixed topology, time-varying topologies, and coopetition networks for general nonaffine nonlinear heterogeneous MASs to perform a time-vary tracking task, while learning control approaches for MASs in [19]–[42] only consider the cooperative interactions among agents and most of them require the same initial state.

(3). Only employ online measurement I/O data of MASs to construct the proposed algorithm, which can tactfully avoid the difficulties of obtaining a precise mathematical model. Meanwhile, the identical initial condition is not necessary for the proposed algorithm, while this condition is a fundamental assumption of existing ILC-based multiagent systems.

Generally, this article is inspected by [14], [23], and [34]. The heterogeneity of MASs is considered in [14] to realize BC, however, the controller is complex. The ILC approach is applied in [34] to achieve formation control of MASs, however, it requires that the system dynamics are affine systems with an identical initial condition. Although the results in [34] are further developed in [35], both of them only consider the collaborative relationship among agents. The proposed DBCILC scheme generally solves the bequeathal problems faced by the above methods. This extension provides a new method based on the result from the above literature to formulate a DBCILC algorithm for multiagent systems by only using I/O data. Especially, it presents a new problem for repetitively operating systems.

The rest work of this article is structured as follows. Several necessary preliminaries are presented in Section II. Section III introduces the DBCILC algorithm for MASs with fixed and switching topologies. Moreover, the corresponding rigorous mathematical proofs are presented. The simulation experiments are given in Section IV. Finally, conclusions and future work are provided in Section V.

II. PROBLEM FORMULATION AND PRELIMINARIES

A. SIGNED GRAPH THEORY

In this article, R, R^N, $R^{N\times N}$ denote the set of real numbers. $\|\Theta\|$ is a Euclidean norm for a given vector $\Theta \in R$. A diagonal matrix and an identity matrix are expressed by $diag(\bullet)$ and I, respectively, and their dimension are dependent on the context. Here, the coopetition communication network considered consists of N agents and a signed graph (SG) $F = (V, \varepsilon, A_F)$, where $V = \{v_1, \cdots, v_N\}$ is the nonempty finite vertex set, $\varepsilon = \{(v_i, v_j) \,|v_i, v_j \in V\} \subseteq V \times V$ denotes the nonempty finite set of arcs, and $A_F = [a_{ij}] \in R^{N\times N}$ is a weighted adjacency matrix with -1, 0, 1 elements. $\varepsilon(i, j)$ denotes that node j can receive the information from node i, where $a_{ij} \neq 0$ and it is equivalent to $(v_j, v_i) \subseteq V \times V$. If $a_{ij} = 1$, the interactions relationship between vertexes i and j is collaborative; $a_{ij} = -1$ indicates the interactions between vertexes i and j is antagonistic; otherwise $a_{ij} = 0$. Let $N(i) = \{j|j \neq i, (v_j, v_i) \in \varepsilon\}$ denote the neighbors set of the node i. $D = diag\{d_1, \cdots, d_N\}$ is the degree matrix of the SG A_F and $d_i = \sum_{j\in N(i)} |a_{ij}|$. Hence, we can use $L = -A_F + D \in R^{N\times N}$ to calculate the Laplacian matrix of F.

The interactions between N agents and the leader are described by $\bar{F} = (\tilde{V}, \tilde{\varepsilon}, A_F)$, which is an augmented graph, and wherein $\tilde{V} = \{v_0, v_1, \cdots, v_n\}$ and $\tilde{\varepsilon} \subseteq \tilde{V} \times \tilde{V}$. Furthermore, define a diagonal matrix B, where $B = diag\{b_1, \cdots, b_N\} \in R^{N\times N}$. If $b_i > 0$, the leader can directly transmit the information to agent i. The direction of information transmission is directed such as (v_i, v_j) denotes the information flow from node v_i to node v_j and also a directed path could be obtained as $\{(v_i, v_{k1}), (v_{k1}, v_{k2}), \cdots, (v_{km}, v_j)\}$. If the coopetition network $\bar{F}$ contains a spanning tree, the information can flow from the root node to any other nodes. Meanwhile, if all nodes in the network $\bar{F}$ can be divided into two disjoint subsets such as V_1, V_2, this network $\bar{F}$ is also called structurally balanced. Generally, the structurally balanced networks satisfy the following three conditions:

(1). $V = V_1 \cup V_2$ and $V_1 \cap V_2 = \emptyset$;

(2). If $\forall i, j \in V_z \,(z \in \{1, 2\})$, $a_{ij} \geq 0$;

(3). If $\forall i \in V_z, j \in V_q, z \neq q \,(z, q \in \{1, 2\})$, $a_{ij} \leq 0$.

In order to investigate time-varying switching topologies, let $\bar{F}(k)$ denote a time-varying switching graph with a virtual leader, which is dependent on k, and $A_F(k) = [a_{ij}(k)] \in R^{N\times N}$, $d_i(k) = \sum_{j\in N(i)} |a_{ij}(k)|$, $L(k) = -A_F(k) + D(k) \in R^{N\times N}$ are corresponding adjacency matrix, degree matrix and Laplacian matrix, respectively. $N_p(i)$ denotes the neighborhood of the *ith* agent and $B(k) = diag\{b_1(k), \cdots, b_N(k)\} \in R^{N\times N}$. To describe the time-varying topology, the set of communication graph is expressed by $\bar{F}_p = \{\bar{F}_1, \bar{F}_2, \cdots, \bar{F}_\kappa\}$, where $\kappa \in Z^+$ denotes the total number of possible interaction graphs.

B. PROBLEM FORMATION

In order to discuss the bipartite consensus problem of non-affine nonlinear discrete-time MASs, the following mathematical model is defined for each agent, where i denotes that the dynamic belongs to the ith agent and the number of the agents is N.

$$y_i(l,k+1) = f_i(y_i(l,k),\cdots,y_i(l,k-n_y), u_i(l,k),\cdots,u_i(l,k-n_u)) \quad (1)$$

where l denotes the iteration number, $k \in \{0,1,\ldots,T\}$ is the time interval, $i = 1,2,\ldots,N$, n_y, n_u are unknown orders of the output and the input. The control input is expressed by $u_i(l,k) \in R^1$ and $y_i(l,k) \in R^1$ denotes the output, where k donates the kth time instant. It is noted that the nonlinear function $f(\bullet)$ is unknown, which will be established by the dynamic linearization technique in Lemma 1. Moreover, the communication topology among agents is expressed by $F = (V, \varepsilon, A_F)$.

In order to facilitate our analysis, it is assumed that agents' dynamic satisfies the following conditions.

Assumption 1 [44]: The partial derivative of $f(\bullet)$ with respect to the control input $u_i(l,k)$ is continuous.

Assumption 2 [45]: Equation (1) satisfies the generalized Lipschitz condition along the iteration axis, so that $|\Delta y_i l, k+1| \leq c|\Delta u_i l, k+1|$ holds for all $k \in \{0,1,\ldots,T\}$ and $l = 0,1,2,\ldots$, where c is a positive constant, $\Delta y_i(l,k+1) = y_i(l,k+1) - y_i(l-1,k+1)$ and $\Delta u_i(l,k) = u_i(l,k) - u_i(l-1,k) \neq 0$

Assumption 3: In this article, all of the fixed ($\bar{F}$) and time-varying switching ($\bar{F}_p, p = 1,2,\ldots,\kappa$) communication graphs are strongly connected and the trajectory information of the virtual leader can be transmitted to one or more follower agents directly.

Remark 1: The above assumptions are there fundamental assumptions of DBCILC approach and the reasonability of them have been discussed in [8], [23] and [38].

Lemma 1 [36], [42]: If Equation (1) satisfies assumptions 1 and 2, Equation (1) can be described as the following compact form dynamic linearization (CFDL) model.

$$\Delta y_i(l,k+1) = \Lambda_i(l,k)\Delta u_i(l,k), \quad \forall k \in \{0,1,\ldots,T\}, \quad l = 1,2,\ldots \quad (2)$$

where $\Lambda_i(l,k)$ is an iteration-dependent and time-varying parameter called pseudo-partial-derivative (PPD) and $|\Lambda_i(l,k)| < \bar{c}$, where $\bar{c}$ is a small positive constant, for anytime instant k and iteration l.

Remark 2: As it is pointed out in [42], the CFDL model can transform the nonlinear system of each agent into a time-varying linear systerm so that the PPD is a time-varying parameter, which includes all of the possible nonlinear behavior characteristics. Moreover, it is obvious that PPD can be estimated by utilizing the I/O data of the controlled plant. Therefore, if the I/O data is available, the PPD can be estimated and the CFDL model can be established without requiring any mathematical model information of the controlled system.

Definition 1: The distributed bipartite consensus measurement output of the ith agent at the lth iteration is defined by $\zeta_i(l,k)$ as follows:

$$\zeta_i(l,k) = \sum_{j\in N(i)} |a_{ij}|(sign(a_{ij})y_j(l,k) - y_i(l,k)) + b_i(s_i y_0(l,k) - y_i(l,k)) \quad (3)$$

where b_i denotes the connected situation between the virtual leader and agent i in the communication topologies, and $sign(\bullet)$ is a sign function. If the leader and agent i is connected directly i.e., $\{0,j\} \in \tilde{\varepsilon}$, $b_i = 1$, otherwise $b_i = 0$. Moreover, $s_i = 1$, for $i \in V_1$ and $s_i = -1$, $i \in V_2$.

In this article the bipartite tracking error is expressed by $e_i(l,k) = s_i y_0(l,k) - y_i(l,k)$. The goal of this article is to design a novel control protocol for MASs with fixed and time-varying switching topologies to perform bipartite consensus tracking tasks with accurately control. In order to solve the above bipartite consensus tracking problem, a DBCILC scheme is proposed as follows.

$$u_i(l,k) = u_i(l,k) + \frac{\rho\hat{\Lambda}_i(l,k)}{\lambda + \left|\hat{\Lambda}_i(l,k)\right|^2}\zeta_i(l-1,k+1) \quad (4)$$

where $\hat{\Lambda}_i(l,k)$ is the estimated value of $\Lambda_i(l,k)$ and $\lambda > 0$ denotes the weighting factor, which will affect stability of the controlled plant. ρ denotes the controller parameter of the control protocol (4) and it directly affects the convergence properties. In the next section, we will discuss how to select an appropriate value of ρ. Moreover, the value of $\hat{\Lambda}_i(l,k)$ is calculated by the following estimation approach.

$$\hat{\Lambda}_i(l,k) = \hat{\Lambda}_i(l-1,k) - \frac{\eta\Delta u_i(l-1,k)}{\mu + |\Delta u_i(l-1,k)|^2} \times \left(\hat{\Lambda}_i(l-1,k)\Delta u_i(l-1,k) - \Delta y_i(l-1,k+1)\right) \quad (5)$$

$$\hat{\Lambda}_i(l,k) = \hat{\Lambda}_i(1,k), \quad \text{if} \left|\hat{\Lambda}_i(l,k)\right| \leq \sigma \text{ or } |\Delta u_i(l-1,k)| \leq \sigma \text{ or } sign\left(\hat{\Lambda}_i(l,k)\right) \neq sign\left(\hat{\Lambda}_i(1,k)\right) \quad (6)$$

where $u > 0$ and $0 < \eta < 1$ are the weighting factor and the step factor, respectively. In the practical application, σ is usually selected as 10^{-4} or 10^{-5}, and a small σ leads to a small $\Delta u_i(l-1,k)$. The reset value of $\hat{\Lambda}_i(l,k)$ is expressed by $\hat{\Lambda}_i(1,k)$, which can improve the tracking performance of the parameter updated law (5).

Remark 3: It is noted that the distributed measurement output $\zeta_i(l-1,k+1)$ for agent i is employed to update the control input $u_i(l,k)$ in the control protocol (4), so that this approach is a distributed learning control scheme. On the other hand, the control approaches (4)-(6) are data driven schemes, since their updating only relies on the I/O data of each agent. Hence, this is a data driven distributed ILC approach of combining (4)-(6). It is designed to solve the bipartite consensus problem for nonlinear MASs, which is named as DBCILC. To the best of our knowledge, the existing results of ILC for MASs only consider the cooperative interactions between agents, while both cooperative and antagonistic interactions among agents are discussed in the proposed DBCILC approach.

Remark 4: Algorithm (6) is a reset method, which is utilized to improve the robustness of the parameter updated algorithm (5). It is noted that the learning rate of Equation (4) can be adaptively tuned by iteratively adjusting the value of $\hat{\Lambda}_i(l,k)$. Nevertheless, it is difficult to realize in the existing ILC for MASs, where its learning rate cannot be updated automatically when the controlled system encounters unknown disturbances so the laws (5) and (6) can improve the robustness of the law (4).

III. MAIN RESULTS

A. MASs WITH FIXED TOPOLOGIES

In this section, the MASs with a fixed strongly connected graph to perform time-varying tracking tasks is discussed. First of all, we provide the coming assumption and lemma.

Assumption 4: For any $k \in \{0,1,\ldots,T\}$ and $l = 0,1,2,\ldots$, the PPD $\Lambda_i(l,k)$ satisfies that $\Lambda_i(l,k) > \bar{\sigma} > 0\,(\Lambda_i(l,k) < -\bar{\sigma} < 0)$ for all $i = 0,1,2,\ldots,N$, where $\bar{\sigma}$ is an arbitrarily small positive constant. In this article, it is assumed $\Lambda_i(l,k) > \bar{\sigma} > 0$ without loss of generality.

Lemma 2 [23]: An iteration varying irreducible substochastic matrix is expressed by $\Phi(i)$, where its diagonal element is positive. Moreover, a compact form of $\Phi(i)$ is described by Φ, where the set of all possible of $\Phi(i)$ is included.

$$\|\Phi(w)\,\Phi(w-1)\cdots\Phi(1)\| \le \delta$$

where $0 < \delta < 1$ and $\Phi(i)$, $i = 0,1,2,\ldots,w$ are w matrices arbitrarily chosen from Φ.

Remark 5: According to Assumption 4, we conclude that the control direction of the DBCILC approach is determined and the output of MASs doesn't increase when the input of MASs decreases. This assumption is also applied in the model-based control theory in addressing some practical systems, for instance, temperature control systems, pressure control systems, etc.

Theorem 1: If the unknown nonlinear MASs (1) satisfies Assumptions 1-4 and the parameter ρ of the DBCILC satisfies the condition of the following inequality.

$$\rho < \frac{1}{\max_{i=1,\ldots,N}\sum_{j=1}^{N}|a_{ij}| + b_i}$$

there exists a $\lambda_{\min}$ $(\lambda > \lambda_{\min} > 0)$ such that $\lim_{l\to\infty} e_i(l,k) = 0$ for all $i = 0,1,2,\ldots,N$, which implies that $\lim_{l\to\infty} y_i(l,k) = y_0(l,k)$ for all $k \in \{0,1,\ldots,T\}$, $i = 0,1,2,\ldots,N$.

Proof: The first step is to analyze the bound of the PPD estimated value $\hat{\Lambda}\_i(l,k)$.

According to the reset method (6), when $|\Delta u_i(l-1,k)| \le \sigma$, the bound of $\hat{\Lambda}_i(l,k)$ is obvious. On the other hand, when $|\Delta u_i(l-1,k)| \ge \sigma$ and let the PPD estimation error as $\tilde{\Lambda}_i(l,k) = \hat{\Lambda}_i(l,k) - \Lambda_i(l,k)$, the following equation can be obtained.

$$\begin{aligned}\tilde{\Lambda}_i(l,k) &= \tilde{\Lambda}_i(l-1,k) - (\Lambda_i(l,k) - \Lambda_i(l-1,k)) \\ &\quad + \left(\Delta y_i(l-1,k+1) - \hat{\Lambda}_i(l-1,k)\Delta u_i(l-1,k)\right) \\ &\quad \times \frac{\eta\Delta u_i(l-1,k)}{\mu + |\Delta u_i(l-1,k)|^2}\end{aligned} \tag{7}$$

Letting $\Delta\Lambda_i(l,k) = \Lambda_i(l,k) - \Lambda_i(l-1,k)$ and using Lemma 1, (7) becomes

$$\begin{aligned}\tilde{\Lambda}_i(l,k) &= \left(1 - \frac{\eta|\Delta u_i(l-1,k)|^2}{\mu + |\Delta u_i(l-1,k)|^2}\right)\tilde{\Lambda}_i(l-1,k) \\ &\quad - \Delta\Lambda_i(l,k).\end{aligned} \tag{8}$$

Since $|\Delta u_i(l-1,k)| \ne 0$, by properly selecting η, μ, for example $0 < \eta < 1$ and $u > 0$, the function $\left(\eta|\Delta u_i(l-1,k)|^2/\left(\mu + |\Delta u_i(l-1,k)|^2\right)\right)$ is monotonically increasing with respect to $|\Delta u_i(l-1,k)|^2$. Thus, there exists a constant q such that

$$0 < \left|\left(1 - \frac{\eta|\Delta u_i(l-1,k)|^2}{\mu + |\Delta u_i(l-1,k)|^2}\right)\right| \le q < 1 \tag{9}$$

From Lemma 1 and Assumption 4, we can obtain $0 < \Lambda_i(l,k) < \bar{c}$. According to Assumption 4

$$\begin{aligned}|\Delta\Lambda_i(l,k)| &= |\Lambda_i(l,k) - \Lambda_i(l-1,k)| \\ &\le |\Lambda_i(l,k)| \le \bar{c}\end{aligned} \tag{10}$$

Hence, from (8), (9) and (10) the following inequality can be obtained.

$$\begin{aligned}\left|\tilde{\Lambda}_i(l-1,k)\right| &\le q\left|\tilde{\Lambda}_i(l-1,k)\right| + \bar{c} \\ &\le q\left|q\left|\tilde{\Lambda}_i(l-2,k)\right| + \bar{c}\right| + \bar{c} \\ &\le q^2\left|\tilde{\Lambda}_i(l-2,k)\right| + q\bar{c} + \bar{c} \\ &\quad \cdots \\ &\le q^{l-1}\left|\tilde{\Lambda}_i(1,k)\right| + q^{l-2}\bar{c} \\ &\quad + q^{l-3}\bar{c} + \cdots + \bar{c} \\ &\le q^{l-1}\left|\tilde{\Lambda}_i(1,k)\right| + \frac{\bar{c}\left(1 - q^{l-1}\right)}{1-q}\end{aligned} \tag{11}$$

so that $\tilde{\Lambda}_i(l,k)$ is bounded, i.e. $\lim_{l\to\infty}\left|\tilde{\Lambda}_i(l,k)\right| \le \frac{\bar{c}}{1-q}$. Then, for any $k \in \{0,1,\ldots,T\}$ and $l = 0,1,2,\ldots$, the boundedness of $\hat{\Lambda}_i(l,k)$ is also guaranteed because $\Lambda_i(l,k)$ is bounded. Define the following collective stack vectors:

$$\begin{aligned}y(l,k) &= [y_1(l,k), y_2(l,k), \cdots, y_N(l,k)]^T \\ u(l,k) &= [u_1(l,k), u_2(l,k), \cdots, u_N(l,k)]^T \\ \zeta(l,k) &= [\zeta_1(l,k), \zeta_2(l,k), \cdots, \zeta_N(l,k)]^T\end{aligned}$$

$$e(l,k) = [e_1(l,k), e_2(l,k), \cdots, e_N(l,k)]^T$$
$$\bar{y}_0(l,k) = [y_0(l,k), y_0(l,k), \cdots, y_0(l,k)]^T$$
$$S(l,k) = [s_1(l,k), s_2(l,k), \cdots, s_N(l,k)]^T$$

The convergence of bipartite tracking error of MASs can be analyzed by employing the $\zeta_i(l,k)$ with tracking errors as below:

$$\begin{aligned}\zeta_i(l,k) &= \sum_{j\in N(i)} |a_{ij}|(sign(a_{ij})y_j(l,k) - y_i(l,k)) \\ &\quad + b_i(s_i y_0(l,k) - y_i(l,k)) \\ &= \sum_{j\in N(i)} \left(a_{ij}y_j(l,k) - |a_{ij}|\, y_i(l,k)\right) + b_i e_i(l,k) \\ &= \sum_{j\in N(i)} \left(a_{ij}y_j(l,k) - |a_{ij}|\, y_i(l,k)\right) + b_i e_i(l,k) \\ &\quad + \sum_{j\in N(i)} \left(|a_{ij}|\, s_i y_0(l,k) - |a_{ij}|\, s_i y_0(l,k)\right) \\ &= \sum_{j\in N(i)} \left(a_{ij}y_j(l,k) - |a_{ij}|\, s_i y_0(l,k)\right) \\ &\quad + \sum_{j\in N(i)} \left(|a_{ij}|\, e_i(l,k)\right) + b_i e_i(l,k) \\ &= \sum_{j\in N(i)} \left(a_{ij}y_j(l,k) - a_{ij}s_j y_0(l,k)\right) \\ &\quad + \sum_{j\in N(i)} \left(|a_{ij}|\, e_i(l,k)\right) + b_i e_i(l,k) \\ &= \sum_{j\in N(i)} \left(|a_{ij}|\, e_j(l,k) - a_{ij}e_i(l,k)\right) + b_i e_i(l,k)\end{aligned}$$

Then, a compact form of $\zeta_i(l-1,k+1)$ can be obtained

$$\zeta(l-1,k+1) = (B+L)e(l-1,k+1) \tag{12}$$

where $B = diag(b_1, b_2, \cdots, b_N)$ and $L = -A_F + D$.

According to Equation (12) and the control protocol (4), the following equation can be obtained.

$$\begin{aligned}\Delta u(l,k) &= \rho\hbar(l,k)\zeta(l-1,k+1) \\ &= \rho\hbar(l,k)(L+B)e(l-1,k+1)\end{aligned} \tag{13}$$

where $\Delta u(l,k) = u(l,k) - u(l-1,k)$, $\hbar(l,k) = diag(\theta_1, \theta_2, \cdots, \theta_N)$, and $\theta_i = \frac{\hat{\Lambda}_i(l,k)}{\lambda + |\hat{\Lambda}_i(l,k)|^2}$. According Lemma 1, we obtain the following compact form of (2):

$$\Delta y(l,k+1) = \Omega(l,k)\Delta u(l,k) \tag{14}$$

where $\Delta y(l,k+1) = y(l,k+1) - y(l-1,k+1)$ and $\Omega(l,k) = diag(\Lambda_1(l,k), \cdots, \Lambda_N(l,k))$. According to the definitions of $y_i(l,k)$ and $e_i(l,k)$, the following equation can be obtained.

$$\Delta y(l,k+1) = -\Delta e(l,k+1) \tag{15}$$

where $\Delta e(l,k+1) = e(l,k+1) - e(l-1,k+1)$. According to (13) and (14), (15) can be rewritten as following.

$$e(l,k+1) = (I - \rho\bar{\lambda}(l,k))\, e(l-1,k+1) \tag{16}$$

where

$$\psi(l,k) = \Omega(l,k)\hbar(l,k) = diag(\Gamma_1(l,k), \cdots, \Gamma_N(l,k)),$$
$$\Gamma_i(l,k) = \frac{\Lambda_i(l,k)\hat{\Lambda}_i(l,k)}{\lambda + \left|\hat{\Lambda}_i(l,k)\right|^2}, \quad i = 1, 2, \ldots, N$$

and $\bar{\lambda}(l,k) = \psi(l,k)(L+B)$. From (16), we can obtain that if $\|I - \rho\bar{\lambda}(l,k)\| < 1$ for all $k \in \{0, 1, \ldots, T\}$, $l = 0, 1, 2, \ldots$, then $\lim_{l\to\infty} ||e(l,k+1)|| = 0$.

In this step, the convergence condition of MASs will be derived.

Since $\hat{\Lambda}_i(l,k)$ is bounded and $0 < \Lambda_i(l,k) < \bar{c}$ for all $i = 0, 1, 2, \ldots, N$, also $\lambda + \left|\hat{\Lambda}_i(l,k)\right|^2 \geq 2\sqrt{\lambda}\left|\hat{\Lambda}_i(l,k)\right|$, we can obtain a bounded constant $\lambda_{\min} > 0$ ($\lambda > \lambda_{\min}$) such that the following inequality sequences holds:

$$0 < \Gamma_i(l,k) \leq \frac{\bar{c}\hat{\Lambda}_i(l,k)}{2\sqrt{\lambda}\left|\hat{\Lambda}_i(l,k)\right|} \leq \frac{\bar{c}}{2\sqrt{\lambda}} \leq \frac{\bar{c}}{2\sqrt{\lambda_{\min}}} < 1$$

First of all, it is noted that the communication graph satisfies Assumption 3 so that $I - \rho\bar{\lambda}(l,k)$ is an irreducible matrix. Moreover, $0 < \Gamma_i(l,k) < 1$ for all $i = 0, 1, 2, \ldots, N$ and ρ satisfies following inequation.

$$\rho < \frac{1}{\max_{i=1,\ldots,N} \sum_{j=1}^{N} |a_{ij}| + b_i}$$

This means that ρ is less than the reciprocal of the greatest diagonal entry of $L + B$. Hence, the existing row sum of $I - \rho\bar{\lambda}(l,k)$ is strictly less than one, which implies that $I - \rho\bar{\lambda}(l,k)$ is an irreducible substochastic matrix. Moreover, its diagonal entries are positive. According to (16), following inquisition can be obtained.

$$\begin{aligned}\|e(l,k+1)\| &\leq \|I - \rho\bar{\lambda}(l,k)\|\, \|e(l-1,k+1)\| \\ &\leq \|I - \rho\bar{\lambda}(l,k)\|\, \|I - \rho\bar{\lambda}(l-1,k)\| \\ &\quad \times \|e(l-2,k+1)\| \\ &\quad \cdots \\ &\leq \|I - \rho\bar{\lambda}(l,k)\|\, \|I - \rho\bar{\lambda}(l-1,k)\| \\ &\quad \cdots \|I - \rho\bar{\lambda}(2,k)\|\ \|e(1,k+1)\|\end{aligned} \tag{17}$$

By utilizing Lemma 2, the product sequence of (17) can be assigned to several set and for each set we have Φ matrices so that we can obtain the following inequality.

$$\|e(l,k+1)\| \leq \delta^{\left\lfloor \frac{l-1}{\Phi} \right\rfloor} \|e(1,k+1)\|$$

in which $\lfloor \bullet \rfloor$ demotes the floor function. $\lfloor (l-1)/\Phi \rfloor$ demotes that the value is the smaller but the nearest integer to the real number $(l-1)/\Phi$. Finally, limitation of $\lim_{l\to\infty} \|e(l,k+1)\| = 0$ is obtained.

Hence, the trajectory error of each agent can be reduced and the bipartite consensus tracking can be guaranteed. □

Remark 6: This part proposes a novel Data-driven distributed bipartite consensus tracking scheme for heterogeneous MASs with fixed topology and the sufficient conditions are studied. To the best of our knowledge, this is the first time employing PPD technology to solve the bipartite consensus problem for unknown dynamics MASs. Although some results of PPD technology are researched, a few of them focus on Multi-systems. The proposed scheme sufficiently empowers Data-driven approaches to solve the more complicated consensus tasks for MASs, which has an important enlightening significance.

B. MASs WITH TIME-VARYING TOPOLOGIES

Time-varying topologies are considered in this part. Meanwhile, the stability and convergence of MASs to perform time-varying trajectory tracking tasks are investigated.

The graph theory of this part is discussed in the end of section II and Definition 1 becomes

$$\zeta_i(l,k) = \sum_{j\in N(i)} \left(a_{ij}(k)\, y_j(l,k) - \left|a_{ij}(k)\right| y_i(l,k)\right) + b_i(k)\left(s_i(k)\, y_0(l,k) - y_i(l,k)\right) \quad (18)$$

Theorem 2: When nonlinear MASs satisfies Assumptions 1-4 above, especially all of the communication graph satisfies Assumption 3, the laws (4)-(6) of the DBCILC scheme can be used, if the value of ρ is selected as

$$\rho < \frac{1}{\max_{i=1,\ldots,N,p=1,2,\ldots,\kappa} \sum_{j=1}^{N} \left|a_{ij}^{p}(k)\right| + b_i^{p}(k)}$$

and a $\lambda_{\min} > 0$ with $\lambda > \lambda_{\min}$ is available such that $\lim_{l\to\infty} e_i(l,k) = 0$ and $\lim_{l\to\infty} y_i(l,k) = y_0(l,k)$, for all $k \in \{0, 1, \ldots, T\}$, $i = 0, 1, 2, \ldots, N$.

Proof: According to (12)-(16) and (18), the bipartite tracking error of the DBCILC scheme in (16) becomes.

$$e(l,k+1) = (I - \rho\psi(l,k)\, G(k))\, e(l-1,k+1) \quad (19)$$

where $G(k) = (L(k) + B(k))$ and all the reciprocals of the diagonal entry in $L(k) + B(k)$, $p = 1, 2, \ldots, \kappa$ are larger than ρ. Hence, using the similar analytical approach of fixed topology, we can obtain that $I - \rho\psi(l,k)\, G(k)$ is an irreducible substochastic matrix and its diagonal entries are positive. We can use the similar methods in proving Theorem 1 to prove this and can also select an appropriate $\lambda_{\min} > 0$ and $\lambda > \lambda_{\min}$ to guarantee the $\lim_{l\to\infty} e_i(l,k+1) = 0$ for all $i = 0, 1, 2, \ldots, N$.

Hence, performing the bipartite consensus tracking tasks with time-varying switching topologies can reduce the trajectory error of each agent.

This completes the proof. □

Remark 7: In the existing bipartite consensus or formation algorithms for MASs, most the majority of them are dependent on the assumption that an accurate mathematical model information is available to analyze the convergence and stability of controlled systems. However, it is that the mathematical model is not a requirement in the DBCILC scheme. Moreover, the existing data-driven ILC designs don't consider the coopetition communication interactions among the agents and the time-varying switching topologies problem.

IV. SIMULATION RESULTS

A. FIXED TOPOLOGIES

In this example, the performances of seven follower agents with fixed topologies to perform a bipartite consensus time-varying trajectory tracking task is discussed and the nonlinear dynamics of each agent is given as

$$y_1(l,k+1) = \frac{y_1^2(l,k-1)u_1(l,k-1)}{1 + y_1(l,k-1)y_1(l,k-2) + y_1^2(l,k-3)} + \frac{(1 + (k/150)u_1(l,k-1))}{1 + y_1(l,k-1)y_1(l,k-2) + y_1^2(l,k-3)}$$

$$y_2(l,k+1) = \frac{y_2^2(l,k-2)u_2(l,k-2)}{1 + y_2(l,k-1)y_2(l,k-2) + y_2^2(l,k-3)} + \frac{(1 + (k/150)u_2(l,k-1))}{1 + y_2(l,k-1)y_2(l,k-2) + y_2^2(l,k-3)}$$

$$y_3(l,k+1) = \frac{y_3^3(l,k-3)u_3(l,k-3)}{1 + 2y_3^2(l,k-3)} + \frac{(1 + (k/150)u_3(l,k-1))}{1 + 2y_3^2(l,k-3)}$$

$$y_4(l,k+1) = \frac{y_4^3(l,k-2)u_4(l,k-2)}{1 + y_4^2(l,k-1) + y_4^2(l,k-2)} + \frac{(1 + (k/150)u_4(l,k-1))}{1 + y_4^2(l,k-1) + y_4^2(l,k-2)}$$

$$y_5(l,k+1) = \frac{y_5^4(l,k-2)u_5(l,k-2)}{1 + 2y_5(l,k-1)y_5(l,k-2)} + \frac{(1 + (k/150)u_5(l,k-1))}{1 + 2y_5(l,k-1)y_5(l,k-2)}$$

$$y_6(l,k+1) = \frac{y_6^4(l,k-1)u_6(l,k-2)}{1 + y_6^2(l,k-1) + y_6^2(l,k-2)} + \frac{(1 + (k/150)u_6(l,k-1))}{1 + y_6^2(l,k-1) + y_6^2(l,k-2)}$$

$$y_7(l,k+1) = \frac{y_7^3(l,k-1)u_7(l,k-2)}{1 + 2y_7(l,k-1)y_7(l,k-2)} + \frac{(1 + (k/150)u_7(l,k-1))}{1 + 2y_7(l,k-1)y_7(l,k-2)}$$

It is noted that all of the seven agents have a different dynamics system model, so the considered MASs is heterogeneous, which consists of different structures and time-varying parameters. Furthermore, dynamics system models above are only applied to produce the I/O data for the MASs, while the DBCILC algorithm doesn't utilize any model information. During designing this algorithm process, the dynamics of MASs are all unknown.

The communication topology of the considered MASs is shown in Fig. 1. we can observe that the virtual leader is denoted by using vertex 0 and the followers are distributed

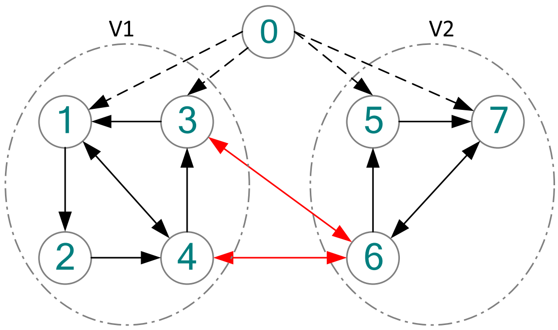

FIGURE 1. Communication topology among agents of example 1.

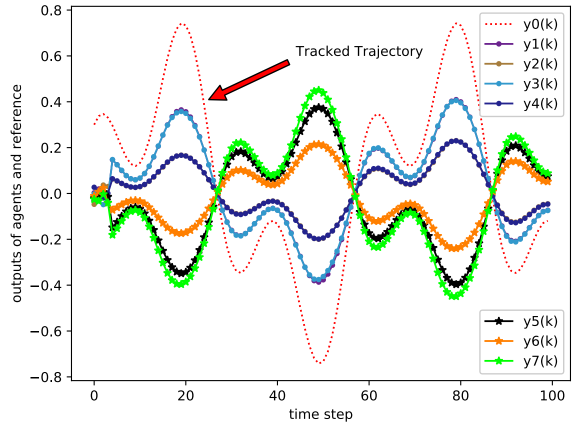

FIGURE 2. Tracking performances of each agent at 10th (example 1).

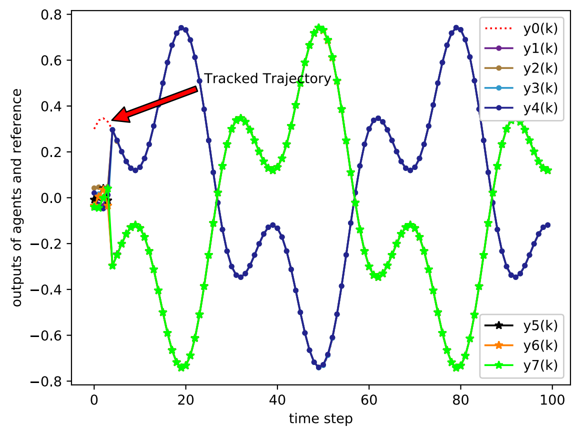

FIGURE 3. Tracking performances of each agent at 246th (example 1).

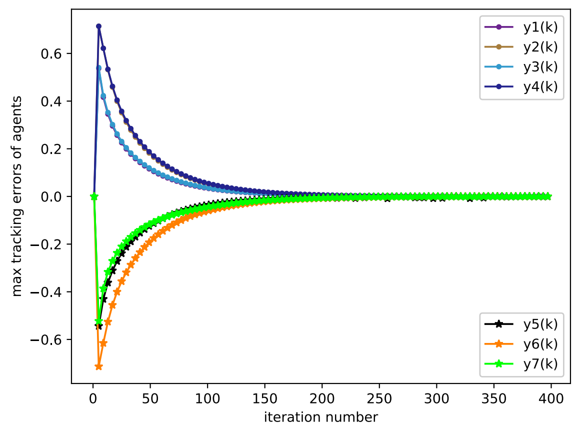

FIGURE 4. Max tracking errors of each agent (example 1).

into two alliances (agents 1, 2, 3, 4 belong to the alliance V_1, agents 5, 6, 7 belong to the alliance V_2). Moreover, the black solid lines are used to express the cooperative relationships among agents, and the competitive relationships are denoted by the red one. In this case, only the agents 1, 3, 5 and 7 can acquire commands from the leader directly. Even though other agents don't have a direct path to access the commands from the leader, the communication graph satisfies Assumption 3, so the leader can intervene in the two competitive alliances. Furthermore, the information among agents only transmits along with the arrows, and the direction is fixed. Then, the L, B and S matrix of the graph are given as follows:

$$L = \begin{bmatrix} 2 & 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 2 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 1 & 1 & 3 & 0 & -1 & 0 \\ 0 & 0 & 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 0 & -1 & 0 & 2 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 & 1 \end{bmatrix}$$

$$B = diag\begin{pmatrix} 1 & 0 & 1 & 0 & 1 & 0 & 1 \end{pmatrix}$$

$$S = diag\begin{pmatrix} 1 & 1 & 1 & 1 & -1 & -1 & -1 \end{pmatrix}$$

As above matrixes show, the reciprocal of the greatest diagonal entry of $L + B$ is about 0.33. In order to satisfy the convergence condition for all $i = 1, 2, 3, 4, 5, 6, 7$ in Theorem 1, we choose the controller parameters as $\rho = 0.24$. The following desired trajectory is considered.

$$y_0(l, k) = 0.5 \sin(k\pi/30) + 0.3 \cos(k\pi/10) \quad 0 \le k \le 100$$

In this example, the initial conditions are chosen as $u_i(0, k) = 0$, $\hat{\Lambda}_i(1, k) = 2$, $y_i(l, 0) = 0$ and $y_i(l, p) = rand(-0.05, 0.05)$, $p = 1, 2, 3, 4$. The values of the DBCILC's parameters are chosen as $\mu = 0.5$, $\eta = 1$, $\lambda = 0.5$, $\sigma = 10^{-4}$. The simulation results of tracking performances at 10*th* and the 245*th* iterations are plotted in Figs. 2-3, respectively. The max bipartite consensus tracking errors of each agent are shown in Fig. 4.

From Figs. 2-4 we can see that the outputs between followers and the virtual leader have an extreme variation at the beginning iteration, but the bipartite tracking errors decrease radically and the bipartite consensus tracking is well achieved after the 246th iterations. Besides, Fig. 3 also shows that each agent keeps the same trajectory in the same alliance, but different alliances have counter-performance.

B. TIME-VARYING SWITCHING TOPOLOGIES

In this part, the simulation of MASs with time-varying switching topologies are discussed. Here, the dynamics of each agent and directed trajectory are the same as the previous

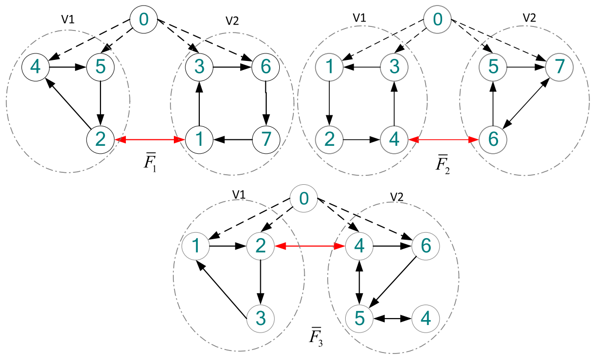

FIGURE 5. Time-varying communication topologies (examples 2 and 3).

case, and the three communication topologies are presented in Fig. 5. In order to receive a clear result of switching communication topologies simulation, a piecewise function is given as follows:

$$\begin{cases} \bar{F}_1, & 0 \leq k \leq 30 \\ \bar{F}_2, & 30 < k \leq 60 \\ \bar{F}_3, & 60 < k \leq 100 \end{cases}$$

where the topology of MASs is dependent on time iteration number k. The parameters of the laws (4)-(6) are the same values as the previous case.

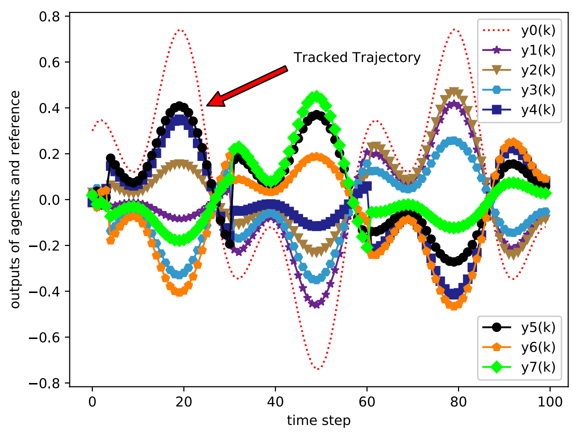

FIGURE 6. Tracking performances of each agent at 10th (example 2).

From Figs. 6-7, we can observe that the communication topology is changed at $k = 30$ and $k = 60$. Especially, the alliances of agents 1, 3 and 5 are changed at $k = 30$, which can be clearly seen in Figs. 6-7. The max bipartite consensus tracking errors of all agents are presented in Fig. 8, which further illustrates the correctness and effectiveness of proposed bipartite consensus tracking scheme.

C. REALISTIC DC LINEANR MOTORS

In this part, we will employ seven permanent magnet DC linear motors to verify the effectiveness and practicability of the proposed DBCILC scheme. Furthermore, the mathematical model of this DC is investigated in [23], [36] and [43], which

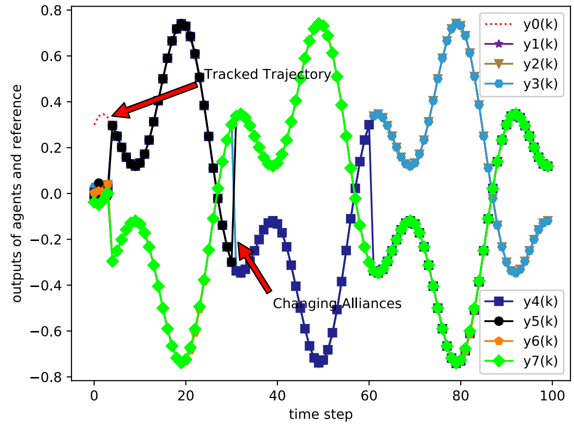

FIGURE 7. Tracking performances of each agent at 246th (example 2).

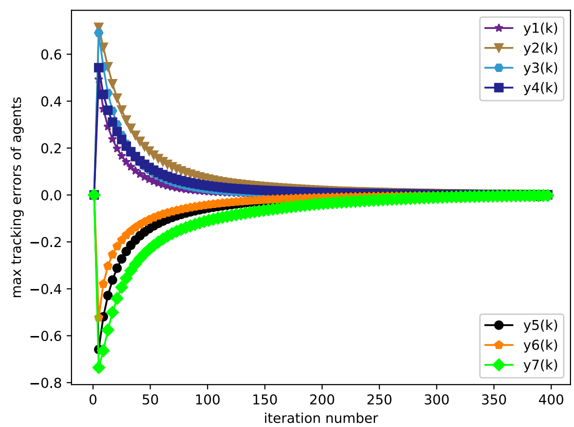

FIGURE 8. Tracking errors of each agent at 246th (example 2).

is identified as the following model.

$$\begin{cases} \dot{x}(t) = v(t) \\ v(t) = \dfrac{u(t) - f_{friction}(t) - f_{ripple}(t)}{m} \\ y(t) = v(t). \end{cases} \tag{20}$$

where $x(t)$, $v(t)$ express the position (m) and the speed (m/s), respectively. The m denotes the combined mass of the translator and load and $u(t)$ denotes the developed force (N). $f_{friction}(t)$ and $f_{ripple}(t)$ are the friction force (N) and the ripple force (N), respectively. Meanwhile, the model of the friction and ripple forces are expressed by following equations.

$$f_{friction}(t) = \left(f_c + (f_s - f_c)\, e^{-\left(\dot{x}/\dot{x}_\delta\right)^{\delta}} + f_v \dot{x} \right) sn(\dot{x})$$

$$f_{ripple}(t) = b_1 \sin(w_0 x(t))$$

where $sn(\bullet)$ is the sign function, f_c denotes the minimum level of the Coulomb friction, f_s denotes the level of the static friction, δ is an additional empirical parameter. $\dot{x}_\delta$ and f_v are lubricant and load parameters. In this example, these parameters are selected as: $m = 0.59kg$, $\dot{x}_\delta = 0.1$, $\delta = 1$, $f_c = 10N$, $f_s = 20N$, $f_v = 10N \cdot s \cdot m^{-1}$, $b_1 = 8.5N$,

$w_0 = 314s^{-1}$. The desired velocity is given as

$$y(t) = 0.5\sin(t\pi/30) + 0.3\cos(t\pi/10), \quad t \in [0, 100]$$

Using the Euler Formula to discretize the above model (20) and selecting sampling time as $h = 0.001$, we have $T = 100$. For this example, we consider three different situations. The first one is the output measurement without any noises. In the second one, we consider the output measurement with random noise, and the values of random noise belong to $[-0.03, 0.03]$. In the third one, we consider the switching topologies and random noise of the seven DC motors system. Here, we use the same parameters and the communication topology in section IV.A to conduct the first and the second one. The parameters and communication topologies of the third one are the same as IV.B.

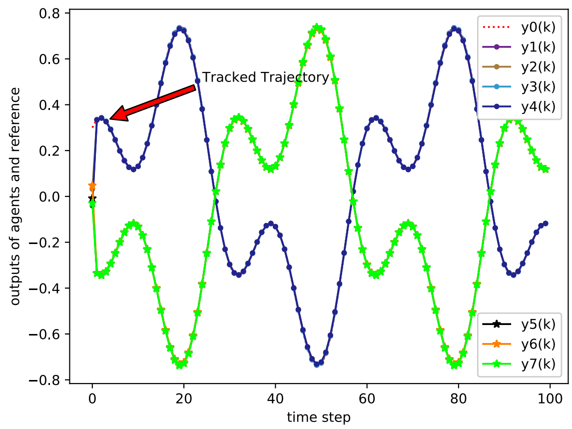

FIGURE 9. Outputs of agents without noises (example 3).

Fig. 9 shows the tracking performance of seven DC motors without output measurement noises and Fig. 10 shows the tracking performance of seven DC motors with random noise. Besides, the random noise and the switching topologies are considered in Fig. 11. By comparing Figs. 9-11, it is noted that the waveforms in Figs. 10-11 have some deviations under fixed and switching topologies, respectively. Hence, we aim to design a filter or compensator to obtain a better performance in the future. Generally, the proposed bipartite consensus control protocol can control the realistic DC linear motors to perform the bipartite consensus time-varying trajectory tracking tasks under fixed or switching topologies.

It is noted that the proposed DBCILC approach doesn't consider the disturbance observer and compensator to deal with the noises of the MASs but from Fig. 10-11 we observe that the stochastic disturbance doesn't destabilize the systems. It further demonstrates the robustness of the proposed scheme. However, to improve the robustness of the proposed algorithm, we will consider more complex environments of MASs for instance unknown disturbance, output quantized, and sensor saturation problems in the future.

As shown and analyzed above, the proposed DBCILC is correctness and effectiveness.

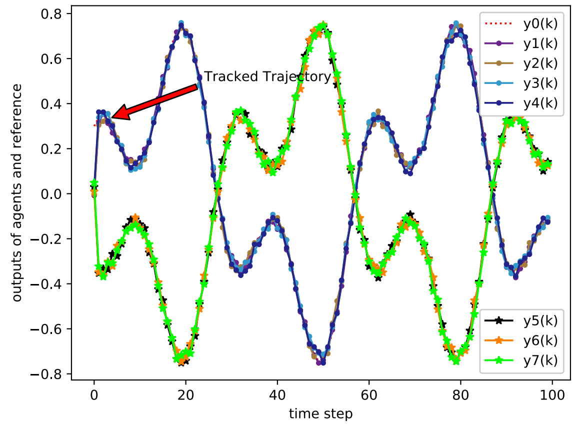

FIGURE 10. Outputs of agents with noises (example 3).

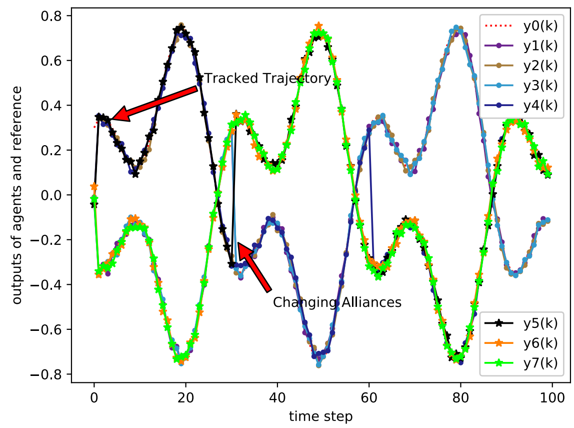

FIGURE 11. Agents under noises and switching topologies (example 3).

Remark 8: It is noted that all of the mathematical models of MASs are unknown in our simulation, where the mathematical models are merely employed to produce the I/O data for the corresponding controlled plant.

V. CONCLUSION

In this work, a data-driven distributed bipartite consensus tracking scheme has been proposed for unknown nonaffine nonlinear discrete-time MASs with fixed and switching topologies. This algorithm is dependent on the I/O data of each agent, which can ensure that bipartite tracking errors of each agent can be dramatically reduced, and realize the good bipartite consensus tracking. Compared with the model-based control algorithms, the significant feature in our design is that the agents' dynamics are no longer needed. Moreover, both the cooperative and competitive relationships among multiagent systems are considered and the convergence and stability of the algorithm are proved through rigorous mathematical analysis. Meanwhile, the corresponding simulation studies of the bipartite consensus tracking algorithm have demonstrated the effectiveness of the designed DBCILC algorithm. In our future efforts, we will further investigate the bipartite consensus problem for MASs with delay, disturbances, or sensor faults.

REFERENCES

[1] M.-B. Radac, R.-E. Precup, and R.-C. Roman, "Data-driven model reference control of MIMO vertical tank systems with model-free VRFT and Q-learning," *ISA Trans.*, vol. 73, pp. 227–238, Feb. 2018.

[2] S. Liu, Z. Hou, T. Tian, Z. Deng, and Z. Li, "A novel dual successive projection-based model-free adaptive control method and application to an autonomous car," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 30, no. 11, pp. 3444–3457, Nov. 2019.

[3] Y. Huang and Y. Jia, "Adaptive fixed-time six-DOF tracking control for noncooperative spacecraft fly-around mission," *IEEE Trans. Control Syst. Technol.*, vol. 27, no. 4, pp. 1796–1804, Jul. 2019.

[4] B. Ning, Q.-L. Han, and Z. Zuo, "Distributed optimization for multiagent systems: An edge-based fixed-time consensus approach," *IEEE Trans. Cybern.*, vol. 49, no. 1, pp. 122–132, Jan. 2019.

[5] X. Xie, H. Yao, J. Xi, and B. Hu, "Consensus-based adaptive guaranteed-performance formation control for second-order multi-agent systems," *Adv. Mech. Eng.*, vol. 11, no. 10, pp. 1–9, Oct. 2019.

[6] C. Altafini, "Consensus problems on networks with antagonistic interactions," *IEEE Trans. Autom. Control*, vol. 58, no. 4, pp. 935–946, Apr. 2013.

[7] J. Hu and W. X. Zheng, "Emergent collective behaviors on coopetition networks," *Phys. Lett. A*, vol. 378, nos. 26–27, pp. 1787–1796, May 2014.

[8] Y. Wu, Y. Zhao, and J. Hu, "Bipartite consensus control of high-order multiagent systems with unknown disturbances," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 49, no. 10, pp. 2189–2199, Oct. 2019.

[9] X. Meng and H. Gao, "High-order bipartite containment control in multi-agent systems over time-varying cooperation-competition networks," *Neurocomputing*, vol. 359, pp. 509–516, Sep. 2019.

[10] J. Ren, Q. Song, and G. Lu, "Event-triggered bipartite leader-following consensus of second-order nonlinear multi-agent systems under signed digraph," *J. Franklin Inst.*, vol. 356, no. 12, pp. 6591–6609, Aug. 2019.

[11] Q. Deng, J. Wu, T. Han, Q.-S. Yang, and X.-S. Cai, "Fixed-time bipartite consensus of multi-agent systems with disturbances," *Phys. A, Stat. Mech. Appl.*, vol. 516, pp. 37–49, Feb. 2019.

[12] Q. Xiao, H. Liu, X. Wang, and Y. Huang, "A note on the fixed-time bipartite flocking for nonlinear multi-agent systems," *Appl. Math. Lett.*, vol. 99, Jan. 2020, Art. no. 105973.

[13] X. Shi, J. Cao, G. Wen, and M. Perc, "Finite-time consensus of opinion dynamics and its applications to distributed optimization over digraph," *IEEE Trans. Cybern.*, vol. 49, no. 10, pp. 3767–3779, Oct. 2019.

[14] J. Duan, H. Zhang, Y. Liang, and Y. Cai, "Bipartite finite-time output consensus of heterogeneous multi-agent systems by finite-time event-triggered observer," *Neurocomputing*, vol. 365, pp. 86–93, Nov. 2019.

[15] J. Qin, W. Fu, W. X. Zheng, and H. Gao, "On the bipartite consensus for generic linear multiagent systems with input saturation," *IEEE Trans. Cybern.*, vol. 47, no. 8, pp. 1948–1958, Aug. 2017.

[16] M. Xing, F. Deng, B. Zhang, and X. Liu, "Observer-based bipartite consensus of linear multi-agent systems with measurement noises," *IEEE Access* vol. 7, pp. 75360–75366, 2019.

[17] X. Ai, "Adaptive robust bipartite consensus of high-order uncertain multi-agent systems over cooperation-competition networks," *J. Franklin Inst.*, vol. 357, no. 3, pp. 1813–1831, Feb. 2020.

[18] T.-F. Ding, M.-F. Ge, C.-H. Xiong, and J. H. Park, "Bipartite consensus for networked robotic systems with quantized-data interactions," *Inf. Sci.*, vol. 511, pp. 229–242, Feb. 2020.

[19] F. L. Lewis and K. G. Vamvoudakis, "Reinforcement learning for partially observable dynamic processes: Adaptive dynamic programming using measured output data," *IEEE Trans. Syst. Man, Cybern. B, Cybern.*, vol. 41, no. 1, pp. 14–25, Feb. 2011.

[20] H. Jiang and H. He, "Data-driven distributed output consensus control for partially observable multiagent systems," *IEEE Trans. Cybern.*, vol. 49, no. 3, pp. 848–858, Mar. 2019.

[21] C. Wei, J. Luo, H. Dai, and G. Duan, "Learning-based adaptive attitude control of spacecraft formation with guaranteed prescribed performance," *IEEE Trans. Cybern.*, vol. 49, no. 11, pp. 4004–4016, Nov. 2019.

[22] H. Wu, S. Song, K. You, and C. Wu, "Depth control of model-free AUVs via reinforcement learning," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 49, no. 12, pp. 2499–2510, Dec. 2019.

[23] X. Bu, Z. Hou, and H. Zhang, "Data-driven multiagent systems consensus tracking using model free adaptive control," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 29, no. 5, pp. 1514–1524, May 2018.

[24] C.-J. Li and G.-P. Liu, "Data-driven consensus for non-linear networked multi-agent systems with switching topology and time-varying delays," *IET Control Theory Appl.*, vol. 12, no. 12, pp. 1773–1779, Aug. 2018.

[25] C. Mu, Q. Zhao, Z. Gao, and C. Sun, "Q-learning solution for optimal consensus control of discrete-time multiagent systems using reinforcement learning," *J. Franklin Inst.*, vol. 356, no. 13, pp. 6946–6967, Sep. 2019.

[26] Y. Xu, J. Xia, H. Wu, and L. Fan, "Q-learning based physical-layer secure game against multiagent attacks," *IEEE Access*, vol. 7, pp. 49212–49222, 2019.

[27] W. Zhao, Z. Fang, and Z. Yang, "Four-dimensional trajectory generation for UAVs based on multi-agent Q learning," *IEEE Access*, vol. 7, pp. 49212–49222, 2019.

[28] Y. Xie, J. Jin, X. Tang, B. Ye, and J. Tao, "Robust cascade path-tracking control of networked industrial robot using constrained iterative feedback tuning," *IEEE Access*, vol. 7, pp. 8470–8482, 2019.

[29] W. Meng, S. Q. Xie, Q. Liu, C. Z. Lu, and Q. Ai, "Robust iterative feedback tuning control of a compliant rehabilitation robot for repetitive ankle training," *IEEE/ASME Trans. Mechatronics*, vol. 22, no. 1, pp. 173–184, Feb. 2017.

[30] D.-A. Ciupageanu, L. Barelli, A. Ottaviano, D. Pelosi, and G. Lazaroiu, "Innovative power management of hybrid energy storage systems coupled to RES plants: The simultaneous perturbation stochastic approximation approach," in *Proc. IEEE PES Innov. Smart Grid Technol. Eur. (ISGT-Europe)*, Sep. 2019, pp. 1–5.

[31] X. Ros-Roca, L. Montero, and J. Barceló, "Investigating the quality of Spiess-like and SPSA approaches for dynamic OD matrix estimation," *Transp. A Transp. Sci.*, vol. 9935, 2020, doi: 10.1080/23249935.2020.1722282.

[32] H. S. Ahn and Y. Chen, "Iterative learning control for multi-agent formation," in *Proc. ICCAS-SICE*, 2009, pp. 3111–3116.

[33] A. Hock and A. P. Schoellig, "Distributed iterative learning control for multi-agent systems," *Auton. Robots*, vol. 43, no. 8, pp. 1989–2010, 2019.

[34] D. Meng, Y. Jia, J. Du, and J. Zhang, "On iterative learning algorithms for the formation control of nonlinear multi-agent systems," *Automatica*, vol. 50, no. 1, pp. 291–295, Jan. 2014.

[35] D. Meng and K. L. Moore, "Robust cooperative learning control for directed networks with nonlinear dynamics," *Automatica*, vol. 75, pp. 172–181, Jan. 2017.

[36] X. Bu, Q. Yu, Z. Hou, and W. Qian, "Model free adaptive iterative learning consensus tracking control for a class of nonlinear multiagent systems," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 49, no. 4, pp. 677–686, Apr. 2019.

[37] Y. Wang, H. Li, X. Qiu, and X. Xie, "Consensus tracking for nonlinear multi-agent systems with unknown disturbance by using model free adaptive iterative learning control," *Appl. Math. Comput.*, vol. 365, Jan. 2020, Art. no. 124701.

[38] Y. Hui, R. Chi, B. Huang, and Z. Hou, "3-D learning-enhanced adaptive ILC for iteration-varying formation tasks," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 31, no. 1, pp. 89–99, Jan. 2020.

[39] M.-B. Radac and R.-E. Precup, "Data-driven model-free tracking reinforcement learning control with VRFT-based adaptive actor-critic," *Appl. Sci.*, vol. 9, no. 9, p. 1807, Apr. 2019.

[40] H. Ren, H. Zhang, H. Su, and Y. Mu, "Data-based stable value iteration optimal control for unknown discrete-time systems with time delays," *Neurocomputing*, vol. 382, pp. 96–105, Mar. 2020.

[41] X. Jin, "Nonrepetitive leader–follower formation tracking for multiagent systems with LOS range and angle constraints using iterative learning control," *IEEE Trans. Cybern.*, vol. 49, no. 5, pp. 1748–1758, May 2019.

[42] X. Bu, Q. Wang, Z. Hou, and W. Qian, "Data driven control for a class of nonlinear systems with output saturation," *ISA Trans.*, vol. 81, pp. 1–7, Oct. 2018.

[43] B. Armstrong-Hélouvry, P. Dupont, and C. C. De Wit, "A survey of models, analysis tools and compensation methods for the control of machines with friction," *Automatica*, vol. 30, no. 7, pp. 1083–1138, Jul. 1994.

[44] 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.

[45] X. Bu, Z. Hou, Q. Yu, and Y. Yang, "Quantized data driven iterative learning control for a class of nonlinear systems with sensor saturation," *IEEE Trans. Syst., Man, Cybern. Syst.*, early access, Sep. 24, 2018, doi: 10.1109/TSMC.2018.2866909.

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