A distributed gain-scheduled observer-based approach for the practical consensus of LPV multi-agent systems☆

Paulo Sergio Pereira Pessim [a], Pedro Henrique Silva Coutinho [b], Márcio J. Lacerda [c], Vicenç Puig [d], Reinaldo Martinez Palhares [e,*]

[a] Federal University of Minas Gerais, Graduate Program in Electrical Engineering, Brazil
[b] State University of Rio de Janeiro, Department of Electronics and Telecommunication Engineering, Brazil
[c] School of Computing and Digital Media, London Metropolitan University, UK
[d] Institut de Robòtica i informàtica Industrial (CSIC-UPC), Universitat Politècnica de Catalunya, Spain
[e] Federal University of Minas Gerais, Department of Electronics Engineering, Brazil

A B S T R A C T

This paper proposes a distributed gain-scheduled observer-based technique for the practical state consensus of linear parameter-varying (LPV) multi-agent systems (MAS). In the proposed approach, the effects of considering different scheduling parameters for each agent are modeled as an internal disturbance. By applying the concepts of the Lyapunov theory, sufficient conditions are obtained for the design of a gain-scheduled observer-based consensus protocol ensuring that the trajectories of the consensus error converge exponentially to a bounded region, achieving a practical consensus. Numerical experiments illustrate the advantages of the proposed practical consensus over the non-synchronization-based scenario usually obtained when the LPV MAS is subjected to different scheduling parameters.

1. Introduction

Influenced by the cooperative behaviors of the natural world, the study of multi-agent systems (MAS) has enabled significant advancements in practical applications of several fields, such as robotics, complex systems, and transportation (Qin, Ma, Shi, & Wang, 2017). From the control design perspective, consensus, formation, and flocking control of MAS have been the three major tasks extensively investigated in recent years. These cooperative tasks rely on the availability and transmission of local information among the agents. Consequently, control approaches that effectively address these aspects are crucial to maintaining progress in these areas (Qin et al., 2017).

Among the possible communication setups, the distributed approach stands out as it allows a trade-off between the main advantages of centralized and decentralized structures by limiting the exchange of information to only the agents within the same neighborhood (Qin et al., 2017). Meanwhile, when the agent's dynamics are not completely available for measurement, observer-based protocols can provide a suitable solution to estimate the missing information (Zuo, Defoort, Tian, & Ding, 2020). Due to the these benefits, distributed observer-based protocols have emerged in many scenarios, including MAS with high-order integrator dynamics (Zuo et al., 2020), double-integrator dynamics (Li, Du, & Lin, 2011), nonlinear dynamics (Du, Wen, Wu, Cheng, & Lü, 2020; Zhang, Wang, Sun, Li, & He, 2023), general linear dynamics (Chen, Wang, Zhao, Lai, & Lyu, 2022; Huang, Liu, Zhao, Huang, & Zhao, 2024), and linear parameter-varying dynamics (Rotondo, Ponsart, & Theilliol, 2022; Rotondo, Theilliol, & Ponsart, 2023).

The modeling and control of engineering applications often consider the class of linear parameter-varying (LPV) systems to extend linear techniques to the case of nonlinear dynamics. Thus, it is not surprising that this class of model has been considered in several approaches within the context of MAS (Chen, Huang, & Zhan, 2021; Chen, Zhang, Cao, & Chu, 2017; Fu, Zhang, Huang, Wang, & Yan, 2023; Rehan, Tufail, & Ahmed, 2021; Rehman, Shi, Wu, Huang, & Zhang, 2023; Rotondo et al., 2022, 2023; Ugrinovskii, 2014). In Ugrinovskii (2014), the synchronization of uncertain bilinear systems is investigated by constructing a gain-scheduling consensus protocol. The output synchronization of heterogeneous MAS represented by affine LPV models is studied in Fu et al. (2023). Assuming that Lipschitz nonlinearities

☆ This work was supported by the Brazilian agencies CNPq (Grant numbers: 305578/2022-7; 141252/2021-9) and FAPEMIG (Grant numbers: APQ-04310-24; APQ-00528-24). The material in this paper was not presented at any conference. This paper was recommended for publication in revised form by Associate Editor Constantino M. Lagoa under the direction of Editor Sophie Tarbouriech.

* Corresponding author.
E-mail addresses: ppessim@ufmg.br (P.S.P. Pessim), pedro.coutinho@uerj.br (P.H.S. Coutinho), m.lacerda@londonmet.ac.uk (M.J. Lacerda), vicenc.puig@upc.edu (V. Puig), rpalhares@ufmg.br (R.M. Palhares).

can be transformed into an LPV representation, the approaches in Rehan et al. (2021) and Rehman et al. (2023) design leaderless consensus protocols for MAS under input saturation and switching topologies, respectively. Fault-tolerant consensus protocols are designed in Chen et al. (2017) and Rotondo et al. (2023) for continuous-time LPV MAS. Furthermore, the state consensus for LPV MAS with communication delays is addressed in Chen et al. (2021) considering a gain-scheduled consensus protocol. The benefits of the gain-scheduled structure for the state consensus were also explored in Rotondo et al. (2022), where an observer-based consensus protocol is proposed considering that both controller and observer gains depend on the time-varying scheduling parameters.

Another interesting discussion performed in Rotondo et al. (2022), concerns the conditions under which an LPV MAS can reach a consensus. It was shown that with the proposed consensus protocol, a sufficient condition to achieve an exact leaderless state consensus is that all agents that compose the LPV MAS have equal time-varying scheduling parameters. In this case, the dynamics are entirely homogeneous once the matrix vertices of the state–space model are scheduled in the same manner in all agents. Moreover, it was also shown that a non-synchronization scenario occurs when the designed consensus protocol is implemented with different scheduling parameters. However, while Rotondo et al. (2022) acknowledge this non-synchronization scenario, it does not provide an alternative solution to assess or set bounds on the consensus error within this more intricate context. It is important to highlight that in the previously discussed works (Chen et al., 2021, 2017; Rotondo et al., 2022, 2023), the focus is on the study of fully homogeneous LPV MAS. Thus, little attention has been given to the more general case when the LPV MAS has different scheduling parameters.

Motivated by these limitations in the current literature, this paper investigates the practical consensus of LPV MAS with different scheduling parameters. Similar to Rotondo et al. (2022), our goal is to design a distributed gain-scheduled observer-based consensus protocol, where the estimated states obtained from local observers are available for neighboring agents. However, unlike the discussed approaches which assume uniform time-varying scheduling parameters for all agents, we account for the effects of differing parameters as internal perturbations. In this context, we show that a practical consensus can be achieved by guaranteeing the convergence of the consensus error to a bounded region, defined with Lyapunov stability arguments. The concept of practical consensus considered in the proposed method has been mainly employed in approaches focused on the leader-following consensus for heterogeneous MAS, where the unmatched terms between the leader and follower agents are modeled as disturbances (Ding & Zheng, 2017; Visakamoorthi, Yu, Subramanian, Chadli, & Trinh, 2023; Yang, He, & Han, 2021; Yang, Wang, Xiao, Jiang, & Huang, 2019). Disturbance-like terms are also considered in Ding, Zheng, and Guo (2018) and Yang et al. (2019) to account for saturation and quantization effects in the designed input.

Based on the above discussion, this paper provides the following original contributions:

- Sufficient conditions for designing a distributed gain-scheduled observer-based consensus protocol that ensures the practical consensus of LPV MAS with distinct time-varying scheduling parameters.
- Unlike existing techniques, we guarantee that the trajectories of consensus error, when disturbed by internal perturbations that arise due to the difference among the scheduling parameters, converge exponentially to an attractive bounding region.
- A less conservative approach than the existing gain-scheduled observer-based consensus protocols, providing the exact consensus for LPV MAS in scenarios where the existent conditions fail to obtain feasible solutions.

Notation $\mathbb{R}^n$ is the n-dimensional Euclidean space; $\text{diag}(A, B)$ denotes a block diagonal matrix whose elements are A and B. For given vectors $x_i \in \mathbb{R}^n$, define $(x_1, \ldots, x_N) = [x_1^\top, \ldots, x_N^\top]^\top \in \mathbb{R}^{Nn}$; I_n represent a $n \times n$ dimensional identity matrix; $\mathbf{1}$ and $\mathbf{0}$ represent respectively a column vector of ones and zeros with appropriate dimension; $\|\cdot\|$ represent the Euclidean norm for vectors or Spectral norm of matrices; $\|\cdot\|_\infty$ represent the norm-∞ of vectors or matrices.

2. Problem formulation

2.1. Preliminaries on graph theory

The communication among the agents is represented by a connected undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of vertices, and $\mathcal{E} = \{e_{ij} = (i, j) \in \mathcal{V} \times \mathcal{V}\}$ is the set of edges. The neighborhood set of an agent i is represented by $\mathcal{N}_i = \{j \in \mathcal{V} : (j, i) \in \mathcal{E}\}$. The undirected graph is connected if there is an undirected path between each pair of distinct vertices. Notice that a path of length k is a sequence of edges $(v_1, v_2), (v_2, v_3), \ldots, (v_k, v_{k+1})$.

The elements of the adjacency matrix $\mathcal{A} = [a_{ij}]$, $i, j \in \mathcal{V}$, are defined as

$$a_{ij} = \begin{cases} 0, & \text{if } i = j \text{ or } e_{ij} \notin \mathcal{E}, \\ 1, & \text{if } e_{ij} \in \mathcal{E}, \end{cases}$$

and the elements of the diagonal degree matrix $\mathcal{D} = \text{diag}(d_1, \ldots, d_N)$ are computed as $d_i = \sum_{j=1}^{N} a_{ij}$, $i \in \mathcal{V}$. Finally, the Laplacian matrix associated with the connected graph $\mathcal{G}$ is defined as $\mathcal{L} = \mathcal{D} - \mathcal{A}$. The Laplacian $\mathcal{L}$ can be written in terms of a spectral decomposition, such that $\mathcal{L} = T \Lambda T^{-1}$, where the orthogonal matrix $T \in \mathbb{R}^{N \times N}$ constitutes the eigenvectors of $\mathcal{L}$, and $\Lambda = diag(\lambda_1, \lambda_2, \ldots, \lambda_N) \in \mathbb{R}^{N \times N}$ are the eigenvalues ordered such that $\lambda_1 < \lambda_2 \leq \cdots \leq \lambda_N$, with $\lambda_1 = 0$.

2.2. Agents modeling and consensus error

Consider a MAS composed of N agents in the form

$$\begin{aligned} \dot{x}_i(t) &= A(\rho_i(t))x_i(t) + B(\rho_i(t))u_i(t), \\ y_i(t) &= C(\rho_i(t))x_i(t), \end{aligned} \tag{1}$$

where $x_i \in \mathbb{R}^{n_x}$ is the state vector, $u_i \in \mathbb{R}^{n_u}$ is the control input, $y_i \in \mathbb{R}^{n_y}$ is the output, and $\rho_i(t) \in \mathbb{R}^p$ is the vector of time-varying scheduling parameters, which are functions of measured exogenous signals.

The parameter-dependent matrices $A(\rho_i(t)) \in \mathbb{R}^{n_x \times n_x}$, $B(\rho_i(t)) \in \mathbb{R}^{n_x \times n_u}$, and $C(\rho_i(t)) \in \mathbb{R}^{n_y \times n_x}$ are functions of the scheduling parameters and belong to a polytopic domain. Then, they can be written as follows:

$$\begin{bmatrix} A(\rho_i) & B(\rho_i) \\ C(\rho_i) & \cdot \end{bmatrix} = \sum_{h=1}^{N_v} \alpha_h(\rho_i) \begin{bmatrix} A_h & B_h \\ C_h & \cdot \end{bmatrix},$$

where A_h, B_h, and C_h are the vertices of the polytopic domain, N_v is the number of vertices and $\alpha_h(\rho_i)$ satisfies the convex sum property:

$$\sum_{h=1}^{N_v} \alpha_h(\rho_i) = 1, \quad \text{and} \quad \alpha_h(\rho_i) \geq 0, \quad \forall i \in \mathcal{V}.$$

The addressed LPV-MAS (1) comprehends N same-order agents represented by homogeneous LPV models with the same vertices. That is, all agents share the same polytopic domain. However, it is assumed that each agent has independent time-varying

scheduling parameters, which can induce heterogeneity among the agents. Moreover, also notice that the agents do not share any common states, being the local open-loop dynamics completely decoupled. For preliminary discussions on LPV systems and gain-scheduling control, the reader is referred to Atoui, Sename, Milanes, and Martinez-Molina (2022) and Rugh and Shamma (2000).

Consider the following gain-scheduled observer-based distributed consensus protocol

$$u_i = K(\rho_i(t)) \sum_{j \in \mathcal{N}_i} (\hat{x}_i - \hat{x}_j), \quad \forall i \in \mathcal{V}, \tag{2}$$

where $K(\rho_i(t)) \in \mathbb{R}^{n_u \times n_x}$ is the gain-scheduled function to be designed, $\hat{x}_i \in \mathbb{R}^{n_x}$ is the estimated state of the local agent, and $\hat{x}_j \in \mathbb{R}^{n_x}$ are the estimated states of the agents that compose the neighborhood $\mathcal{N}_i$. For each agent, the local estimated states are given by

$$\begin{aligned} \dot{\hat{x}}_i(t) =& A(\rho_i(t))\hat{x}_i(t) + B(\rho_i(t))u_i(t) \\ &+ L(\rho_i(t))\Big(C(\rho_i(t))\hat{x}_i(t) - y_i(t)\Big), \end{aligned} \tag{3}$$

where $L(\rho_i(t)) \in \mathbb{R}^{n_x \times n_y}$ is the gain-scheduled observer function to be designed. The considered gain-scheduled observer-based scheme is also employed in Rotondo et al. (2022), and it is realistic since the agents' open-loop dynamics do not share any common states. To alleviate the notation, the time dependency will be omitted hereafter.

Defining $z_i = \hat{x}_i - x_i$, as the local estimation error, $z = (z_1, z_2, \ldots, z_N)$, and $\rho = (\rho_1, \rho_2, \ldots, \rho_N)$, it is possible to write

$$\dot{z} = \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes (A_h + L_l C_h)\big) z,$$

where $\alpha_{hl}(\rho) = \operatorname{diag}\big(\alpha_h(\rho_1)\alpha_l(\rho_1), \ldots, \alpha_h(\rho_N)\alpha_l(\rho_N)\big)$,and L_l are the vertices of $L(\rho_i(t))$. By substituting the consensus protocol (2) into (1), we have that

$$\dot{x}_i = A(\rho_i)x_i + B(\rho_i)K(\rho_i) \sum_{j \in \mathcal{N}_i} \big((z_i + x_i) - (z_j + x_j)\big).$$

Therefore, the global dynamics of all agents $x = (x_1, x_2, \ldots, x_N)$ can be written as

$$\begin{aligned} \dot{x} = & \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes A_h + \mathcal{L} \otimes B_h K_l\big) x \\ & + \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(\mathcal{L} \otimes B_h K_l\big) z, \end{aligned}$$

being K_l the vertices of $K(\rho_i(t))$. Let the consensus error be defined as $\delta_i = x_i - \bar{x}$, being $\bar{x} = (1/N)\sum_{j=1}^{N} x_j$. Then, the relation between the global consensus error $\delta = (\delta_1, \delta_2, \ldots, \delta_N)$, and the states x is given by $\delta = \Upsilon x$, with $\Upsilon = (\bar{\Upsilon} \otimes I_{n_x})$ and $\bar{\Upsilon} = (I_N - (1/N)\mathbf{1}\mathbf{1}^\top)$. Hence, the consensus error can be defined as

$$\begin{aligned} \dot{\delta} = & \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \Upsilon \Big\{ \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(\mathcal{L} \otimes B_h K_l\big) z \\ & + \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes A_h + \mathcal{L} \otimes B_h K_l\big) x \Big\}. \end{aligned}$$

Provided that $\big(\mathcal{L} \otimes B_h K_l\big)x = \big(\mathcal{L} \otimes B_h K_l\big)\delta$, and $x = \delta + (\mathbf{1} \otimes \bar{x})$, it is possible to write

$$\begin{aligned} \dot{\delta} = & \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \Upsilon \Big\{ \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(\mathcal{L} \otimes B_h K_l\big) z \\ & + \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes A_h + \mathcal{L} \otimes B_h K_l\big)\delta + f_{hl}(\rho, \bar{x}) \Big\}, \end{aligned}$$

being $f_{hl}(\rho, \bar{x}) = \big(\alpha_{hl}(\rho)\mathbf{1} \otimes A_h \bar{x}\big)$.

Finally, defining the augmented error systems as $e = (z, \delta)$ we obtain

$$\dot{e} = \bar{A}(\rho)e + B_\omega\, \omega, \tag{4}$$

with

$$\begin{aligned} \bar{A}(\rho) &= \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \begin{bmatrix} \bar{A}_{hl}^{11} & 0 \\ \bar{A}_{hl}^{21} & \bar{A}_{hl}^{22} \end{bmatrix}, \quad B_\omega = \begin{bmatrix} 0_{Nn_x} \\ I_{Nn_x} \end{bmatrix}, \\ \bar{A}_{hl}^{11} &= \alpha_{hl}(\rho) \otimes (A_h + L_l C_h)\,, \\ \bar{A}_{hl}^{21} &= \big(\bar{\Upsilon}\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(\mathcal{L} \otimes B_h K_l\big), \\ \bar{A}_{hl}^{22} &= \big(\bar{\Upsilon}\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes A_h + \mathcal{L} \otimes B_h K_l\big), \\ \omega &= \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \Upsilon\, f_{hl}(\rho, \bar{x}). \end{aligned}$$

Remark 1. Notice that the augmented error system is subject to an internal perturbation ω due to the difference among the time-varying parameters of the agents. From the definition of (4), it is possible to conclude that $e = 0$ if and only if $\omega = 0$, and $\hat{x}_i = x_i = \bar{x}, \forall i \in \mathcal{V}$. Similarly to Rotondo et al. (2022), an exact consensus (or *synchronization* scenario) can be achieved by selecting $\rho_1 = \rho_2 = \cdots = \rho_N$. If all agents have the same scheduling parameters, then $\bar{\Upsilon}\alpha_{hl}(p)\mathbf{1} = \mathbf{0}\ \forall h, l = 1, \ldots, N_v$, which is a sufficient condition to ensure $\omega = 0$. For the case where the scheduling parameters are different, the trajectories of w depend on the vertices A_h of the system matrices, on the mean of the states $\bar{x}$, and on the difference time-varying among the scheduling functions $\alpha_{hl}(\rho)$. Since in general $\omega \neq 0$, the exact consensus cannot be achieved, resulting in the *non-synchronization* scenario discussed in Rotondo et al. (2022). For this reason, the development of a practical consensus approach for LPV MAS is the main goal of this work.

2.3. Practical consensus

Defining the ellipsoid

$$\mathcal{E}(P, \epsilon) \triangleq \{e \in \mathbb{R}^{2Nn_x} : e^\top P\, e \leq \epsilon\},$$

where $P > 0$ is a symmetric positive definite matrix, and $\epsilon > 0$ is a given positive scalar, the notion of practical consensus is established as follows.

Definition 1 (*Ding & Zheng, 2016, 2017*)**.** Given any positive scalar $\epsilon > 0$, the MAS (1) is said to achieve practical leaderless consensus if

$$\lim_{t \to \infty} d(e(t, e_0), \mathcal{E}(P, \epsilon)) = 0,$$

where $e(t, e_0)$ represents the trajectory of the error system (4) with initial condition $e_0 \in \mathbb{R}^{2Nn_x}$, and $d(e(t, e_0), \mathcal{E}(P, \epsilon))$ represent the distance between $e(t, e_0)$ and $\mathcal{E}(P, \epsilon)$.

Moreover, we have that

$$\|\omega\|_\infty \leq \sum_{h=1}^{N_v} \sum_{l=1}^{N_v} \|\Upsilon f_{hl}(\rho, \bar{x})\|_\infty,$$

from which we can define $\gamma \triangleq \sup_{t \geq 0}(\|\omega(t)\|_\infty)$, that it is important for the following analysis conditions.

Lemma 1 (*Adapted from Ding & Zheng, 2017; Fridman & Dambrine, 2009*)**.** *If there exist positive scalars $a > 0$, $b > 0$, and symmetric positive definite matrices $P_1 \in \mathbb{R}^{n_x \times n_x}$ and $P_2 \in \mathbb{R}^{n_x \times n_x}$such that the Lyapunov function*

$$V(e) = e^\top P\, e, \quad P = \operatorname{diag}\big((I_N \otimes P_1), (I_N \otimes P_2)\big), \tag{5}$$

satisfies

$$\dot{V}(e) + aV(e) - b\,\omega^\top \omega < 0, \tag{6}$$

the trajectories $e(t, e_0)$ of the error system will converge exponentially to the attractive region

$$\mathscr{X}_\infty \triangleq \left\{ e \in \mathbb{R}^{2Nn_x} : e^\top P e \leq \frac{\gamma^2 b}{a} \right\}, \tag{7}$$

with a decay rate of $a/2$.

Proof. The proof follows the same reasoning performed in Ding and Zheng (2017) and Fridman and Dambrine (2009). Therefore, the proof is omitted. ■

Considering the previous modeling and definitions, the problem addressed in this work is stated as follows.

Problem 1. Given the LPV MAS described in (1), determine a condition to design both the distributed observer-based gain-scheduled consensus protocol (2), and the gain-scheduled state-observer (3) such that the trajectories $e(t, e_0)$ of the error system (4) converge exponentially toward the attractive region (7), and the practical consensus is achieved.

3. Main results

The LMI-based design conditions of the distributed gain-scheduled observer-based consensus protocol are presented in the next theorem.

Theorem 1. *Consider the closed-loop error dynamics (4) computed with the LPV MAS (1), the distributed gain-scheduled consensus protocol (2), and the gain-scheduled observer (3). Given positive scalars $a, b \in \mathbb{R}$, $\xi \in \mathbb{R}$, and the $\lambda_{\mathbf{m}}$ non-zero eigenvalues of the Laplacian matrix $\mathcal{L}$, $\forall \mathbf{m} = 2, \ldots, N$, if there exist symmetric positive definite matrices $P_1 \in \mathbb{R}^{n_x \times n_x}$, $\widetilde{P}_2 \in \mathbb{R}^{n_x \times n_x}$, matrices $X_1 \in \mathbb{R}^{n_x \times n_x}$, $X_2 \in \mathbb{R}^{n_x \times n_x}$, $\widetilde{K}_l \in \mathbb{R}^{n_u \times n_x}$, and $\widetilde{L}_l \in \mathbb{R}^{n_x \times n_y}$, such that the following inequalities hold*

$$\Phi_{hh} < 0, \qquad \text{if } h = l, \tag{8}$$

$$\Phi_{hl} + \Phi_{lh} < 0, \qquad \text{if } h < l, \tag{9}$$

$$\Psi_{hh\mathbf{m}} < 0, \qquad \text{if } h = l,\ \forall\, \mathbf{m} = 2, \ldots, N, \tag{10}$$

$$\Psi_{hl\mathbf{m}} + \Psi_{lh\mathbf{m}} < 0, \qquad \text{if } h < l,\ \forall\, \mathbf{m} = 2, \ldots, N, \tag{11}$$

with

$$\Phi_{hl} = \begin{bmatrix} -\xi \mathrm{He}(X_1) & \star \\ \xi \widetilde{\Theta}_{hl}^\top + P_1 - X_1 & aP_1 + \mathrm{He}(\widetilde{\Theta}_{hl}) \end{bmatrix}, \tag{12}$$

$$\Psi_{hl\mathbf{m}} = \begin{bmatrix} -\xi \mathrm{He}(X_2) & \star & \star \\ \xi \widetilde{\Gamma}_{hl\mathbf{m}}^\top + \widetilde{P}_2 - X_2 & a\widetilde{P}_2 + \mathrm{He}(\widetilde{\Gamma}_{hl\mathbf{m}}) & \star \\ \xi I_{nx} & I_{nx} & -bI_{nx} \end{bmatrix}, \tag{13}$$

$$\widetilde{\Theta}_{hl} = X_1 A_h + \widetilde{L}_l C_h, \tag{14}$$

$$\widetilde{\Gamma}_{hl\mathbf{m}} = A_h X_2 + \lambda_m B_h \widetilde{K}_l, \tag{15}$$

for all $h, l \in \{1, 2, \ldots, N_v\}$. Then, the trajectories of the error dynamics (4) converge exponentially to the attractive region $\mathscr{X}_\infty$ defined in (7) with a decay rate of $a/2$. Moreover, the gains of the consensus protocol (2), the gains of the observer (3), and the matrices of the Lyapunov function (5) are given, respectively, by $K_l = \widetilde{K}_l X_2^{-1}$, $L_l = X_1^{-1}\widetilde{L}_l$, P_1, and $P_2 = X_2^{-\top}\widetilde{P}_2 X_2^{-1}$.

Proof. Firstly by applying a separation principle argument, we have that the exponential convergence of (4) to the attractive region (7) can be analyzed considering the subsystems

$$\dot{z} = \sum_{h=1}^{N_v}\sum_{l=1}^{N_v} \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes (A_h + L_l C_h)\big) z, \tag{16}$$

$$\dot{\delta} = \sum_{h=1}^{N_v}\sum_{l=1}^{N_v} \big(\bar{\Upsilon}\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes A_h + \mathcal{L} \otimes B_h K_l\big)\delta + \omega. \tag{17}$$

Notice that the internal perturbation ω does not affect the state-estimation subsystem (16). Moreover, considering $V(z) = z^\top (I_N \otimes P_1) z$ it is possible to compute

$$\dot{V}(z) = \dot{z}^\top (I_N \otimes P_1) z + z^\top (I_N \otimes P_1)\dot{z}, \tag{18}$$

that can be written as

$$\dot{V}(z) = 2\sum_{h=1}^{N_v}\sum_{l=1}^{N_v} z^\top \big(\alpha_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes P_1 (A_h + L_l C_h)\big) z.$$

Replacing (14) in (12), and performing the exchange of variables $X_1 L_l = \widetilde{L}_l$, we have $\Theta_{hl} = X_1 A_h + X_1 L_l C_h$, and

$$\Phi_{hl} = \begin{bmatrix} -\xi \mathrm{He}(X_1) & \star \\ \xi \Theta_{hl}^\top + P_1 - X_1 & aP_1 + \mathrm{He}(\Theta_{hl}) \end{bmatrix}. \tag{19}$$

Multiplying (19) by $[A_h^\top + C_h^\top L_l^\top \quad I_{n_x}]$ on the left, and its transpose in the right, results in

$$\Phi_{hl} = \mathrm{He}\left(P_1 (A_h + L_l C_h)\right) + aP_1. \tag{20}$$

Considering the convex property of the time-varying parameters, it is possible to write (20) as

$$\sum_{h=1}^{N_v}\sum_{l=1}^{N_v} \alpha_{hl}(\rho)\Phi_{hl} = \sum_{h=1}^{N_v} \alpha_{hh}(\rho)\Phi_{hh} + \sum_{h=1}^{N_v}\sum_{l>h}^{N_v} \alpha_{hl}(\rho)\left(\Phi_{hl} + \Phi_{lh}\right),$$

from which it is possible to conclude that the LMIs (8)–(9) are sufficient to guarantee that $\dot{V}(z) + aV(z) < 0$, with $\dot{V}(z)$ as in (18).

Now considering the consensus-error (17), and choosing $V(\delta) = \delta^\top (I_N \otimes P_2)\delta$, it is possible to compute $\dot{V}(\delta)$ similarly to (18). Moreover, from the spectral decomposition $\mathcal{L}$, it is possible to define the exchange of coordinates $\widetilde{\delta} = (T^{-1} \otimes I_{n_x})\delta$. Applying the exchange of coordinates in (17) and in $\dot{V}(\delta)$, we obtain

$$\dot{\widetilde{\delta}} = \sum_{h=1}^{N_v}\sum_{l=1}^{N_v} \big(\widetilde{\alpha}_{hl}(\rho) \otimes I_{n_x}\big)\big(I_N \otimes A_h + \Lambda \otimes B_h K_l\big)\widetilde{\delta} + \widetilde{\omega},$$

where $\widetilde{\alpha}_{hl}(\rho) = T^{-1}\bar{\Upsilon}\alpha_{hl}(\rho)T$, $\widetilde{\omega} = (T^{-1} \otimes I_{n_x})\omega$, and

$$\dot{V}(\widetilde{\delta}) = 2\sum_{h=1}^{N_v}\sum_{l=1}^{N_v} \widetilde{\delta}^\top \big(\widetilde{\alpha}_{hl}(\rho) \otimes I_{n_x}\big)\Big\{ \big(I_N \otimes P_2 A_h\big)\widetilde{\delta} + \big(\Lambda \otimes P_2 B_h K_l\big)\widetilde{\delta} \Big\} + 2\widetilde{\delta}^\top (I_N \otimes P_2)\widetilde{\omega}. \tag{21}$$

Replacing (15) in (13), multiplying (13) on the left by $\mathrm{diag}(X_2^{-\top}, X_2^{-\top}, I_{n_x})$ and its transpose on the right, and performing the exchange of variables $\widetilde{K}_l = K_l X_2$, and $P_2 = X_2^{-\top}\widetilde{P}_2 X_2^{-1}$, we have $\Gamma_{hlm} = X_2^{-\top} A_h^\top + \lambda_m X_2^{-\top} B_h K_l$, and

$$\Psi_{hl\mathbf{m}} = \begin{bmatrix} -\xi \mathrm{He}(X_2^{-1}) & \star & \star \\ \xi \Gamma_{hl\mathbf{m}}^\top + P_2 - X_2^{-\top} & aP_2 + \mathrm{He}(\Gamma_{hl\mathbf{m}}) & \star \\ \xi X_2^{-1} & X_2^{-1} & -bI_{n_x} \end{bmatrix}. \tag{22}$$

Multiplying (22) by

$$\mathcal{B}^\top = \begin{bmatrix} A_h^\top + \lambda_m K_l^\top B_h^\top & I_{n_x} & 0 \\ I_{n_x} & 0 & I_{n_x} \end{bmatrix},$$

on the left, and $\mathcal{B}$ on the right results in

$$\Psi_{hl\mathbf{m}} = \begin{bmatrix} \mathrm{He}\left(P_2 (A_h + \lambda_m B_h K_l)\right) + aP_2 & \star \\ P_2 & -bI_{n_x} \end{bmatrix}. \tag{23}$$

Finally, performing a dimension adjustment and then multiplying (23) by $\varpi^\top = [\widetilde{\delta}^\top \ \widetilde{\omega}^\top]$ on the left, and its transpose on the right, we obtain

$$\begin{aligned}\varpi^\top \Psi_{hl\mathbf{m}} \varpi = \widetilde{\delta}^\top \left(\mathrm{He}\left(I_N \otimes P_2 \left(A_h + \lambda_m B_h K_l\right)\right)\right) \widetilde{\delta} \\ + \widetilde{\delta}^\top (I_N \otimes aP_2) \widetilde{\delta} + \widetilde{\omega}^\top (I_N \otimes P_2) \widetilde{\delta} \\ + \widetilde{\delta}^\top \left(I_N \otimes P_2^\top\right) \widetilde{\omega} - b \widetilde{\omega}^\top \widetilde{\omega}.\end{aligned}$$

Considering the convex property of the time-varying parameters, and exploring the fact that $\lambda_1 = 0$ and $\widetilde{\delta}_1 = 0$ in the transformed subsystem, it is possible to conclude that the LMIs (10)–(11) are sufficient to guarantee that $\dot{V}(\widetilde{\delta}) + aV(\widetilde{\delta}) - b\widetilde{\omega}^\top \widetilde{\omega} < 0$, with $\dot{V}(\widetilde{\delta})$ as in (21).

Moreover, notice that since P_1 and P_2 are symmetric positive definite matrices, we have $V(z) > 0$ and $V(\delta) > 0$, for all $z, \delta \neq 0$. Thus, it is possible to conclude that $V(e) = V(z) + V(\delta)$ as in (5) is positive definite. Furthermore, from the previously performed steps, it is possible to conclude that if the LMIs (8)–(11) hold, the derivative $\dot{V}(e) = \dot{V}(z) + \dot{V}(\delta)$ satisfies (6). Thus, all the conditions of Lemma 1 hold and the trajectories of the error system will converge exponentially to the attractive region (7). This concludes the proof. ■

Remark 2. Note that differently from Rotondo et al. (2022), the observer gains of Theorem 1 are recovered independently of the Lyapunov function (5). Therefore, in the proposed approach, the design can be performed without imposing particular structures on the Lyapunov matrices in (5).

4. Numerical examples

4.1. Example 1

In this example, we present a comparison with the method developed in Rotondo et al. (2022) to demonstrate the advantages of the proposed approach. First, we present simulations to illustrate that the proposed practical consensus approach can improve the state consensus and reduce the consensus error for LPV MAS with different time-varying parameters. Moreover, we show that the observer-based gain-scheduled approach in Theorem 1 achieves feasible results in cases where the observer-based gain-scheduled method developed in Rotondo et al. (2022) fails.

Consider the LPV MAS presented in Rotondo et al. (2022). The system is composed of four agents with a two-vertex polytopic representation. For more information about the system and communication topology, the reader is referred to Rotondo et al. (2022).

Considering $p = 0.49$ (the maximum value of p such that the conditions of Rotondo et al. (2022) are feasible), $a = 0.9526$, $b = 1.6554$, and $\xi = 0.001$, the solution of the gain-scheduled observer based practical consensus protocol proposed in Theorem 1 is given by:

$$L_1^\top = \begin{bmatrix}-1.1236 & -0.6837\end{bmatrix}, \ L_2^\top = \begin{bmatrix}-0.3373 & -0.2873\end{bmatrix},$$
$$K_1 = \begin{bmatrix}-2.4882 & -0.7343\end{bmatrix}, \ K_2 = \begin{bmatrix}-1.0936 & -0.2344\end{bmatrix}.$$

The values of the scalar parameters a, b, and ξ were defined by a grid search. Similarly to the non-synchronization scenario of Rotondo et al. (2022), we perform simulations starting from the initial conditions $x_1(0) = [1 \ 1]^\top$, $x_2(0) = [1 \ 3]^\top$, $x_3(0) = [3 \ 1]^\top$, $x_4(0) = [3 \ 3]^\top$, and with different scheduling parameters, $\alpha_1(\rho_1(t)) = (1 + \sin(2t))/2$; $\alpha_1(\rho_2(t)) = (1 + \cos(0.1t))/2$; $\alpha_1(\rho_3(t)) = (1 + \sin(0.5t))/2$; $\alpha_1(\rho_4(t)) = (1 + \cos(0.05t))/2$; and $\alpha_2(\rho_i(t)) = (1 - \alpha_1(\rho_i(t)))$, $\forall i \in \mathcal{V}$. The simulation results are depicted in Figs. 1–2.

From Fig. 1, it is clear that closed-loop LPV MAS achieves practical consensus, even in the case of different scheduling parameters. Notice that the agents are maintaining the practical

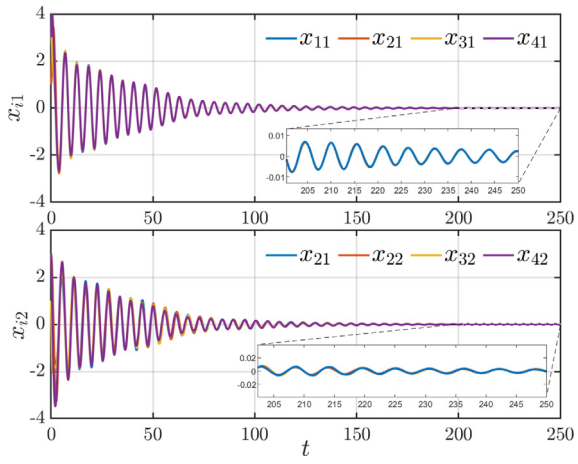

Fig. 1. State trajectories of the closed-loop LPV MAS with the proposed practical consensus for $p = 0.49$ — Example 4.1.

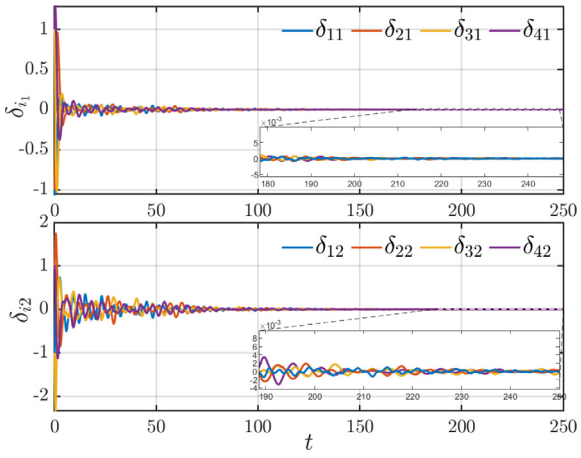

Fig. 2. Trajectories of the consensus error obtained with the proposed gain-scheduled observer-based practical consensus — Example 4.1.

consensus while converging together toward the origin. Moreover, from Fig. 2, it is possible to see the oscillations of the consensus error around the zero equilibrium, confirming once again that the practical consensus is achieved. When the agents are close to the origin, we have that $\bar{x} \approx 0$. Consequently, the internal perturbation that depends on $\bar{x}$ is also $w \approx 0$ even with different scheduling parameters.

To illustrate the benefits of the proposed practical consensus, we will directly compare the norm of the augmented error vector $e(t)$, which comprises the estimation and consensus errors, with the norm of error in the non-synchronization scenario obtained with the approach proposed in Rotondo et al. (2022). From the results presented in Fig. 3, we observe that, as expected, the convergence error obtained with the proposed approach in (—) is upper-bounded by the convergence error of the approach in Rotondo et al. (2022) (- - -). This result clearly demonstrates the superiority of the designed consensus protocol in dealing with the presence of different scheduling parameters when compared to the current literature. It is important to highlight that, unlike the proposed method, the conditions of Rotondo et al. (2022) were not designed to deal with this more general case, which makes clear the contribution and importance of the result in Theorem 1.

Now consider the LPV MAS with $p = 1$. In this case, the approach in Rotondo et al. (2022) fails to provide feasible solutions. However, selecting by grid-search: $a = 1$, $b = 0.1$, and

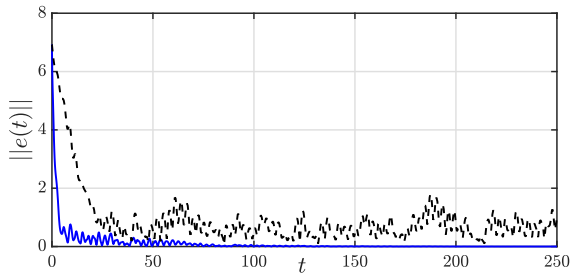

Fig. 3. Norm of the augmented error system considering the proposed approach (—) and the method of Rotondo et al. (2022) (- - -) — Example 4.1. .

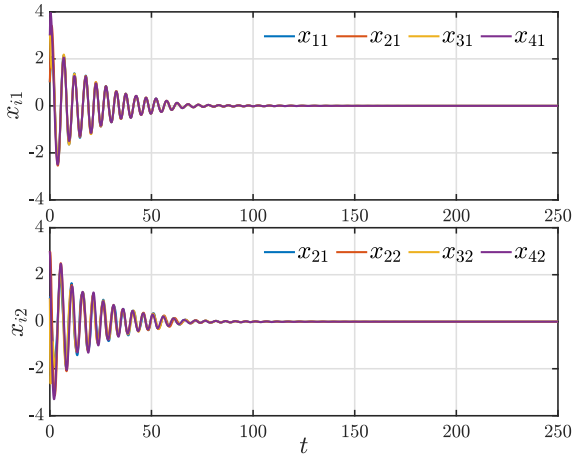

Fig. 4. State trajectories of the closed-loop LPV MAS for the case of $p = 1$ and different parameters — Example 4.1.

$\xi = 0.001$, it is possible, via Theorem 1, to have a solution to the gain-scheduled observer-based practical consensus protocol, namely:

$$L_1^\top = \begin{bmatrix} -1.2200 & -0.7220 \end{bmatrix}, \; L_2^\top = \begin{bmatrix} -0.2873 & -0.1977 \end{bmatrix},$$
$$K_1 = \begin{bmatrix} -5.2191 & -1.0451 \end{bmatrix}, \; K_2 = \begin{bmatrix} -1.4950 & -0.2352 \end{bmatrix}.$$

Similarly to Rotondo et al. (2022), if the scheduling parameters are equal, we have that $\gamma = 0$, and the protocol proposed in Theorem 1 can achieve the exact consensus. Therefore, it is possible to conclude that the proposed approach also contributes to improving the completely homogeneous case, since it proposes less conservative design conditions, that obtain feasible solutions for bigger values of p compared to Rotondo et al. (2022). To illustrate this fact, Figs. 4–5 depict the state trajectories obtained with a simulation considering the solution for $p = 1$, with different parameters, and with $\alpha_1(\rho_i(t)) = (1 + \sin(2t))/2$, $\alpha_2(\rho_i(t)) = (1 - \alpha_1(\rho_i(t)))$, $\forall i \in \mathcal{V}$, respectively.

It can be seen that practical consensus is successfully achieved as depicted in Fig. 4, and that exact consensus occurs as depicted in Fig. 5. Similar to the previous case, when different parameters are considered in the simulations, the trajectories of the agents maintain the practical consensus while converging toward the origin. This behavior is possible because the combination of the proposed protocol with different parameters results in stable heterogeneous dynamics. Meanwhile, when considering the same parameter for all agents, the closed-loop MAS is completely homogeneous and the exact consensus is achieved.

4.2. Example 2

Consider an adaptation of the LPV MAS presented in Example 1 of Chen et al. (2017). We assume that the matrices $A(\eta)$ and

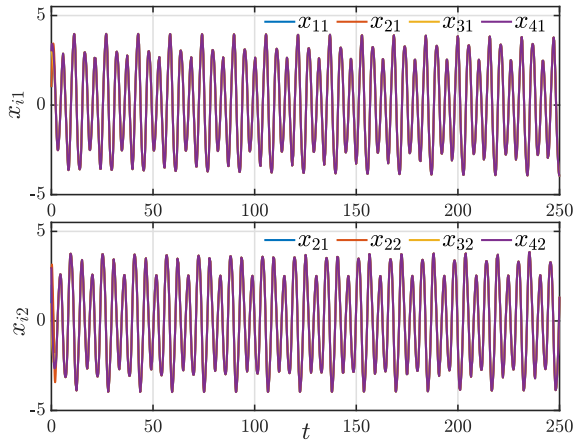

Fig. 5. State trajectories of the closed-loop LPV MAS for the case of $p = 1$ and equal parameters — Example 4.1.

$B(\eta)$ are kept the same, but the output matrix is replaced by $C(\eta) = [1 \; 0]$. The system is composed of a four-vertex polytopic representation, obtained with the same bounds presented in Chen et al. (2017). Moreover, consider that the system has $N = 10$ agents and the Laplacian matrix encompasses the following neighborhood: $\mathcal{N}_1 = \{2\}, \mathcal{N}_2 = \{1, 3, 4\}, \mathcal{N}_3 = \{2, 5\}, \mathcal{N}_4 = \{2, 5\}, \mathcal{N}_5 = \{3, 4, 6\}, \mathcal{N}_6 = \{5, 7, 8\}, \mathcal{N}_7 = \{6, 9\}, \mathcal{N}_8 = \{6, 9\}, \mathcal{N}_9 = \{7, 8, 10\}, \mathcal{N}_{10} = \{9\}$.

In this example, the complexity of the problem in terms of the number of vertices and agents increases in comparison with Example 1. The main computational cost of the proposed approach is the one required to solve the LMI conditions of Theorem 1. The complexity of the conditions can be evaluated in terms of the number of scalar decision variables N_{var} and the number of LMI rows N_{rws} given by

$$N_{var} = 3{n_x}^2 + n_x + N_V(n_x(n_y + n_u)),$$
$$N_{rws} = n_x(2 + N_V + {N_V}^2) + \frac{3n_x(N-1)(N_V + {N_V}^2)}{2}.$$

Notice that N_{var} and N_{rws} increase with the increment of the number of vertices and agents. In the first example, we have $N_{var} = 22$ and $N_{rws} = 70$. Meanwhile, in this example we have $N_{var} = 30$ and $N_{rws} = 584$. Although the complexity is much higher than in the first example, the proposed design can still be efficiently performed offline with semi-definite programming toolboxes.

Selecting $a = 1$, $b = 0.001$ and $\xi = 0.001$, the solution of Theorem 1 results in the observer-based practical consensus protocol given by:

$$K_1 = \begin{bmatrix} -3.0498 & -6.5706 \end{bmatrix}, \quad K_2 = \begin{bmatrix} -3.0663 & -6.5793 \end{bmatrix},$$
$$K_3 = \begin{bmatrix} -3.0625 & -6.5809 \end{bmatrix}, \quad K_4 = \begin{bmatrix} -3.0829 & -6.6023 \end{bmatrix},$$
$$L_1^\top = \begin{bmatrix} -1.2118 & 2.8951 \end{bmatrix}, \quad L_2^\top = \begin{bmatrix} -1.2118 & 2.8551 \end{bmatrix},$$
$$L_3^\top = \begin{bmatrix} -1.2118 & 2.8651 \end{bmatrix}, \quad L_4^\top = \begin{bmatrix} -1.2118 & 2.8251 \end{bmatrix}.$$

To evaluate the effectiveness of the proposed consensus protocol, we have performed temporal simulations with initial conditions within the range $x_1, x_2 \in [-5, 5]$. Similarly to Example 4.1, we have considered a different trigonometric variation for the parameters $\eta_1^i(t)$ and $\eta_2^i(t)$ inside its specific bounds. The state trajectories of the closed-loop LPV MAS, equipped with the proposed distributed observer-based consensus protocol and considering different scheduling parameters are depicted in Fig. 6. From the simulation results presented in Fig. 6, it is possible to conclude that the practical consensus is successfully achieved.

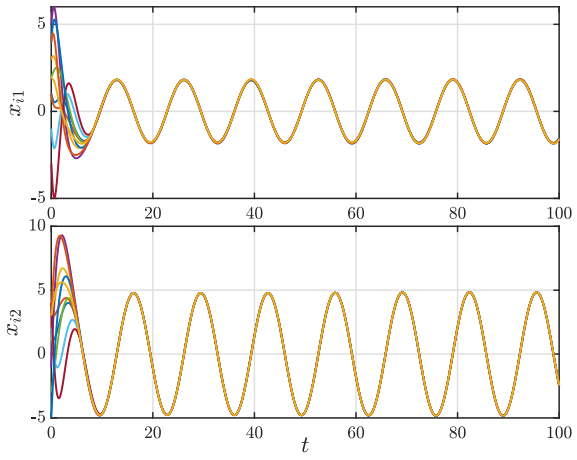

Fig. 6. State trajectories of the closed-loop LPV MAS — Example 4.2.

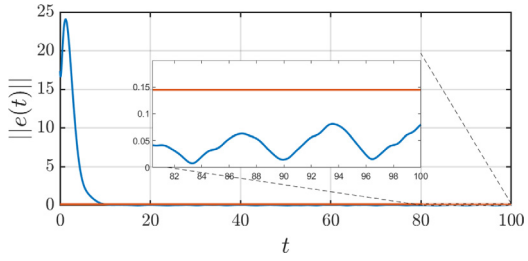

Fig. 7. Norm of the consensus error with the obtained bound for the attractive region — Example 4.2.

Furthermore, with the simulated state trajectories, we can compute the internal perturbation $\omega(t)$ and γ, for $0 \leq t \leq 100$. Thus, an estimate of the attractive region (7) can be performed with an upper bound $r = \sqrt{\frac{\gamma^2 b}{\lambda_{\min}(P)}}$ for the norm of the augmented error system. The trajectory of the norm and the obtained upper bound r are presented in Fig. 7. Since that exact consensus is not achieved, the norm of the error system does not converge to the origin. However, notice that as expected, the norm in steady state is constrained in the estimated attractive region.

5. Conclusions

This paper has presented a novel distributed gain-scheduled observer-based approach for the practical consensus of multi-agent systems represented by LPV models. It has been shown that, unlike the existing methods in the literature, the proposed approach provides a bounded practical consensus to deal with the presence of different scheduling parameters among the agents. Furthermore, it was illustrated through examples that the proposed protocol improves the design performance in comparison with the existent gain-scheduled observer-based approaches for LPV MAS with synchronized scheduling parameters. Future research may consider the presence of a directed communication among the agents, and the case of completely heterogeneous LPV MAS.

References

Atoui, H., Sename, O., Milanes, V., & Martinez-Molina, J. J. (2022). Toward switching/interpolating LPV control: A review. *Annual Reviews in Control*, *54*, 49–67.

Chen, Y., Huang, X., & Zhan, J. (2021). Gain-scheduled robust control for multi-agent linear parameter-varying systems with communication delays. *International Journal of Robust and Nonlinear Control*, *32*(2), 792–806.

Chen, K., Wang, J., Zhao, Z., Lai, G., & Lyu, Y. (2022). Output consensus of heterogeneous multiagent systems: A distributed observer-based approach. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *52*(1), 370–376.

Chen, J., Zhang, W., Cao, Y.-Y., & Chu, H. (2017). Observer-based consensus control against actuator faults for linear parameter-varying multiagent systems. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, *47*(7), 1336–1347.

Ding, L., & Zheng, W. X. (2016). Consensus tracking in heterogeneous nonlinear multi-agent networks with asynchronous sampled-data communication. *Systems & Control Letters*, *96*.

Ding, L., & Zheng, W. X. (2017). Network-based practical consensus of heterogeneous nonlinear multiagent systems. *IEEE Transactions on Cybernetics*, *47*(8), 1841–1851.

Ding, L., Zheng, W. X., & Guo, G. (2018). Network-based practical set consensus of multi-agent systems subject to input saturation. *Automatica*, *89*, 316–324.

Du, H., Wen, G., Wu, D., Cheng, Y., & Lü, J. (2020). Distributed fixed-time consensus for nonlinear heterogeneous multi-agent systems. *Automatica*, *113*, Article 108797.

Fridman, E., & Dambrine, M. (2009). Control under quantization, saturation and delay: An LMI approach. *Automatica*, *45*(10), 2258–2264.

Fu, C., Zhang, H., Huang, C., Wang, Z., & Yan, H. (2023). Fully distributed cooperative output regulation for heterogeneous linear parameter-varying systems with directed graphs. *IEEE Transactions on Control of Network Systems*, *10*(3), 1350–1361.

Huang, N., Liu, M., Zhao, Z., Huang, D., & Zhao, X. (2024). Practical prescribed-time consensus under unavailable state measurements. *IEEE Transactions on Circuits and Systems II: Express Briefs*, 1.

Li, S., Du, H., & Lin, X. (2011). Finite-time consensus algorithm for multi-agent systems with double-integrator dynamics. *Automatica*, *47*(8), 1706–1712.

Qin, J., Ma, Q., Shi, Y., & Wang, L. (2017). Recent advances in consensus of multi-agent systems: A brief survey. *IEEE Transactions on Industrial Electronics*, *64*(6), 4972–4983.

Rehan, M., Tufail, M., & Ahmed, S. (2021). Leaderless consensus control of nonlinear multi-agent systems under directed topologies subject to input saturation using adaptive event-triggered mechanism. *Journal of the Franklin Institute*, *358*(12), 6217–6239.

Rehman, A., Shi, P., Wu, X., Huang, T., & Zhang, W. (2023). Robust leaderless consensus control of multiagent systems with Lipschitz nonlinearity via LPV scheme under fixed and switching topologies. *IEEE Systems Journal*, 1–12.

Rotondo, D., Ponsart, J.-C., & Theilliol, D. (2022). Gain-scheduled observer-based consensus for linear parameter varying multi-agent systems. *Automatica*, *135*, Article 109979.

Rotondo, D., Theilliol, D., & Ponsart, J.-C. (2023). Virtual actuator and sensor fault tolerant consensus for homogeneous linear multi-agent systems. *IEEE Transactions on Circuits and Systems. I. Regular Papers*, 1–11.

Rugh, W. J., & Shamma, J. S. (2000). Research on gain scheduling. *Automatica*, *36*(10), 1401–1425.

Ugrinovskii, V. (2014). Gain-scheduled synchronization of parameter varying systems via relative H_∞ consensus with application to synchronization of uncertain bilinear systems. *Automatica*, *50*(11), 2880–2887.

Visakamoorthi, B., Yu, S. S., Subramanian, K., Chadli, M., & Trinh, H. (2023). Practical consensus for heterogeneous multi-agent systems with gain fluctuations via resilient sampled-data control. *European Journal of Control*, *71*, Article 100803.

Yang, Y., He, W., & Han, Q.-L. (2021). Quasi-synchronization of heterogeneous LC circuits in grid-connected systems with intentionally time-varying lumped delays. *IEEE Transactions on Circuits and Systems. I. Regular Papers*, *68*(5), 2148–2157.

Yang, H., Wang, Z., Xiao, M., Jiang, G.-P., & Huang, C. (2019). Quasi-synchronization of heterogeneous dynamical networks with sampled-data and input saturation. *Neurocomputing*, *339*, 130–138.

Zhang, Y., Wang, G., Sun, J., Li, H., & He, W. (2023). Distributed observer-based adaptive fuzzy consensus of nonlinear multiagent systems under DoS attacks and output disturbance. *IEEE Transactions on Cybernetics*, *53*(3), 1994–2004.

Zuo, Z., Defoort, M., Tian, B., & Ding, Z. (2020). Distributed consensus observer for multiagent systems with high-order integrator dynamics. *IEEE Transactions on Automatic Control*, *65*(4), 1771–1778.

Paulo Sergio Pereira Pessim received his B.Sc., in 2019, and Master degrees, in 2021, all in Electrical Engineering from the Federal University of São João del-Rei (UFSJ), Brazil. He is currently a Ph.D. candidate with the D!FCOM Laboratory at Federal University of Minas Gerais (UFMG) under the supervision of Prof. R. M. Palhares. During his Ph.D., he was a visiting scholar at the Universitat Politècnica de Catalunya (UPC), Spain, from October of 2023 to July of 2024. His main research interests include Robust Control; Distributed Control; Multi-agent systems; and Cyber–Physical Systems.

Pedro Henrique Silva Coutinho is an Assistant Professor at the State University of Rio de Janeiro, Rio de Janeiro, Brazil. He received his Ph.D. degree in Electrical Engineering from the Federal University of Minas Gerais, Brazil, in 2021. He received the IFAC Young Author Award at the 4th Conference on Embedded Systems, Computational Intelligence, and Telematics in Control (CESCIT 2021). Prof. Coutinho has been serving as Associate Editor for Fuzzy Sets and Systems since 2024. He is a member of the IFAC Technical Committee Non-Linear Control Systems (TC 2.3). His main research interests include Robust and Nonlinear Control; Cyber–Physical Systems; Process Monitoring; and Real-Time Artificial Intelligence.

Márcio J. Lacerda is a Reader in Control Engineering and Cyber–Physical Systems at London Metropolitan University. Previously, he was with the Federal University of São João del-Rei, Brazil (2016–2023) and held postdoctoral positions at UNICAMP and the University of Minnesota. He earned his Ph.D. in Electrical Engineering from UNICAMP in 2014. He is a Senior Member of the IEEE and holds editorial roles on the Conference Editorial Board and Technology Conference Editorial Board of the IEEE Control Systems Society. Additionally, he serves as an Associate Editor for the Journal of Control Automation and Electrical Systems. His research focuses on constrained control, robust control, and cyber–physical systems.

Vicenç Puig received the telecommunications engineering Bsc/Msc degree in 1993 and the Ph.D. degree in Automatic Control in 1999, both from Universitat Politècnica de Catalunya (UPC). He is Full Professor of the Automatic Control Department and a Researcher at the Institut de Robòtica i Informàtica Industrial, both from the UPC. He is currently the Director of the Ph.D. Programme in Automatic Control and Robotics and Head of the Research Group in Advanced Control Systems at UPC. Formerly, he was the Director of the Automatic Control Department at UPC. He has developed important scientific contributions in the areas of fault diagnosis and fault tolerant control using interval and linear-parameter-varying models using set-based approaches. He has participated/leaded more than 20 European and national research projects in the last decade. He has also led many private contracts with several companies and has published more than 200 journal articles and more than 500 in international conference/ workshop proceedings. He has supervised over 35 Ph.D. dissertations and over 100 master?s theses/final projects. He is currently the chair of the IFAC Safeprocess TC Committee 6.4 (2020–until now) and was the vicechair (2014–2017). He has been the general chair of the IEEE Conference on Control and Fault-Tolerant Systems (Systol 2016 and 2021) and the IPC chair of the IFAC Safeprocess 2018, IEEE EDGE 2022 and IEEE MED 2023.

Reinaldo Martinez Palhares is currently a Full Professor at the Federal University of Minas Gerais, Belo Horizonte, Brazil. Palhares received his Ph.D. degree in Electrical Engineering from the UNICAMP in Brazil, in 1998. His main research interests include Intelligent Control; Cyber–Physical Systems; Data-driven Control; Cyber-attack-tolerant Control; Fault-tolerant Control; Fault Diagnostics and Prognostics; and Artificial Intelligence applications. Currently, Prof. Palhares is serving as Associate Editor for the IEEE Transactions on Fuzzy Systems (since 2021). He had also served as Associate Editor for the IEEE Transactions on Industrial Electronics (2014–2023) and as Guest Editor for: IEEE Transactions on Industrial Electronics — SS on "Artificial Intelligence in Industrial Systems"; IET Control Theory & Applications — SS on: "Resilient Fuzzy Control Synthesis of Nonlinear Networked Systems Against Various Cyber-Attacks"; IEEE/ASME Transactions on Mechatronics Focused Section on "Real-time Monitoring, Diagnosis, and Prognosis and Health Management for Electric Vehicles" and on "Health Monitoring, Management and Control of Complex Mechatronic System"; and also for Journal of The Franklin Institute — SS on "Recent Advances on Control and Diagnosis via Process Measurements". Since 2020 Palhares has been a member of the Conference Board of the IFAC (terms 2020–2023 and 2023–2026). Currently, Palhares is a member of the: IFAC Technical Committee on Computational Intelligence in Control (TC 3.2); IFAC Technical Committee on Fault Detection, Supervision Safety of Technical Processes — SAFEPROCESS (TC 6.4); and IEEE-IES Technical Committee on Data-Driven Control and Monitoring (TC-DDCM). Since 2006, Palhares has been engaged in consulting activities with financial support from Petrobras, a leading Brazilian multinational energy company specializing in oil and gas.