Advanced Convergence Optimization in Consensus-Based Wireless Sensor Networks via Strategic Node Addition and Pinning Control

Francesco Lamonaca, *Senior Member, IEEE*, Luigi D'Alfonso, *Senior Member, IEEE*

***Abstract*— Wireless Sensor Networks (WSNs) require precise time synchronization to ensure coordinated monitoring operations and data coherence across distributed multi-agent systems. Consensus-based protocols offer a robust, fully distributed solution for synchronizing clock offsets and frequencies by leveraging local information exchange. The convergence speed of such algorithms is heavily dependent on the algebraic connectivity of the network graph, structurally quantified by the second smallest eigenvalue of the graph's Laplacian matrix. This paper investigates the reduction of convergence time in WSNs by strategically introducing a single dynamic node to an existing network topology. Three distinct criteria for determining the connections of the new node are proposed and mathematically analyzed: an exhaustive search for optimal positioning, a maximum degree constraint approach, and a Twin criterion that emulates the topology of an existing node. Numerical simulations establish that maximizing the second eigenvalue significantly accelerates synchronization. Furthermore, the integration of optimal node placement strategies provides a comprehensive framework for optimizing both resource cost and convergence speed.**

I. Introduction

Wireless Sensor Networks (WSNs) are widely deployed in various scenarios, including smart agriculture [1]–[3] and food processing [4], [5], smart homes [6], industrial monitoring [7], power distribution [8]–[10], critical infrastructure monitoring [11]–[13], civil infrastructure supervision [14]–[16], territorial monitoring [17], [18], education [19], and biomedical applications [20]–[23]. In these environments, independent electronic devices interact and collaborate to gather and process environmental data [24]. However, the distributed nature of WSNs introduces a critical challenge: temporal synchronization [25], [26]. When parallel operations are performed without a common time reference, significant interference and data loss can occur, leading to a breakdown in communication [27] and in the overall measurement accuracy [28]. Therefore, establishing a unified temporal reference is fundamental to coordinating network tasks, ensuring information reliability, consistency, and completeness [29], [30].

To achieve this overarching goal, networks often rely on consensus dynamics, an area of research at the intersection of systems theory and graph theory. It studies how a group of agents, such as robots, sensors, or decision-makers, interacting over a network can reach a common decision or estimate through local rules and information exchange [30]. In multi-agent systems, the goal is to ensure that all agents eventually agree on a certain quantity, despite starting with potentially different initial values. The behavior of these systems is typically modeled using an unforced dynamical system governed by the network's interconnection topology, highly beneficial in cooperative control of vehicle formations [31]–[33].

In the broader context of complex networks, synchronization is a fundamental research topic in decentralized control. It is usually described via continuous-time ordinary differential equations mapping the intrinsic dynamics of agents alongside the diffusive coupling from their neighbors [34], [35]. Recent advances explore fixed-time cluster synchronization via pinning control, where the network can achieve synchronization in finite-time [36]–[38]. In a resource-limited multi-agent system, it is of practical importance to select a fraction of nodes to provide control inputs such that consensus can be achieved with optimized performance in terms of network cost and convergence speed [39], [40].

In practical engineering scenarios, such as the deployment of coordinated unmanned aerial vehicle (UAV) swarms for distributed surveillance [41], dynamic formation control [42], and target capturing [43], as well as in robotic platooning or smart grids, the addition of a strategic relay node (e.g., a mobile UAV acting as a temporary bridge) can rapidly repair or enhance temporal coordination. Furthermore, while the structural depth of complex networks may also be approached using k-core or k-shell decomposition methods to identify globally influential nodes and suggest core additions [**?**], this work focuses on targeted microscopic interventions.

Specifically, we propose a robust mathematical methodology to accelerate the convergence of consensus-based synchronization in WSNs. By strategically adding a single dynamic node to the network, the topology is structurally modified to maximize the algebraic connectivity. Three criteria for adding this node are rigorously evaluated to balance theoretical optimality with physical implementation constraints, accounting for real-world signal interference. Fig. 1 illustrates the concept of augmenting an existing network by inserting an additional node with selected connections.

The remainder of this paper is organized as follows. Section II establishes the mathematical model for consensus. Section III details the proposed node addition criteria. Section IV presents the numerical results and, finally, the last section concludes the work and outlines future research directions.

Authors are with the Department of Informatics, Modeling, Electronics and Systems Engineering, University of Calabria, Rende 87036, Italy (e-mail: f.lamonaca@dimes.unical.it, luigi.dalfonso@unical.it.

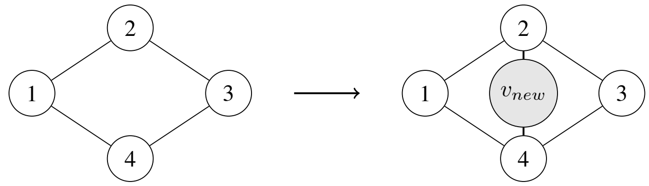

Fig. 1. Strategic insertion of a new node to improve connectivity.

II. System Model and Mathematical Formulation of Consensus Synchronization

To model the synchronization process over a network of nodes, we consider a discrete-time sequence of communication instants $t_k = t_0 + kT_s$, where T_s is the sampling interval. In a wireless sensor network, each node is equipped with a local hardware clock modeled as

$$\tau_i(t) = \alpha_i t + \beta_i, \tag{1}$$

where α_i represents the clock skew and β_i the clock offset. In order to achieve a common notion of time across the network, each node maintains a tunable software (virtual) clock defined as

$$\hat{\tau}_i(t) = \hat{\alpha}_i(t)\tau_i(t) + \hat{o}_i(t). \tag{2}$$

The synchronization mechanism considered in this work relies on iterative updates of the virtual clock offsets when nodes exchange timestamps. Let ε be a mixing parameter. When node i receives a message from node j at time t_k, the virtual clock of node i is updated according to

$$\hat{\tau}_i(t_k^+) = \hat{\tau}_i(t_k) - \varepsilon\left(\hat{\tau}_i(t_k) - \hat{\tau}_j(t_k)\right). \tag{3}$$

This update corresponds to a local consensus step that reduces the difference between the two virtual clocks. To describe the evolution of the entire network compactly, we introduce the vector of virtual clocks

$$\hat{\tau}(k) = [\hat{\tau}_1(k), \hat{\tau}_2(k), \dots, \hat{\tau}_N(k)]^T. \tag{4}$$

Let the communication topology be represented by an undirected graph with Laplacian matrix L. The collective evolution of the virtual clocks can then be written as

$$\hat{\tau}(k+1) = \hat{\tau}(k) - \varepsilon L\hat{\tau}(k) = (I - \varepsilon L)\hat{\tau}(k). \tag{5}$$

The convergence properties of this iteration depend on the spectral properties of the Laplacian matrix. For a connected undirected graph, the Laplacian matrix L is symmetric and positive semidefinite, satisfying $L\mathbf{1} = 0$, implying its ordered eigenvalues are $0 = \lambda_1(L) \le \lambda_2(L) \le \cdots \le \lambda_N(L)$. The system matrix governing the iteration is $\Phi = I - \varepsilon L$. Its eigenvalues are directly related to those of the Laplacian matrix by $\lambda_i(\Phi) = 1 - \varepsilon\lambda_i(L)$.

Because $\lambda_1(L) = 0$, the dominant eigenvalue is $\lambda_N(\Phi) = 1$, corresponding to the consensus subspace spanned by $\mathbf{1}$. The remaining eigenvalues satisfy $\lambda_i(\Phi) = 1 - \varepsilon\lambda_i(L)$ for $i = 2, \dots, N$, and determine the convergence of the disagreement dynamics. For consensus to be achieved, all eigenvalues except the one associated with the consensus subspace must lie strictly inside the unit circle, namely

$$|\lambda_i(\Phi)| < 1, \qquad i = 1, \dots, N-1. \tag{6}$$

Using the eigenvalue relation above, the most restrictive condition is associated with $\lambda_N(L)$, yielding the step-size condition

$$0 < \varepsilon < \frac{2}{\lambda_N(L)}. \tag{7}$$

Under this condition, the eigenvalue at 1 preserves the consensus subspace, while all the remaining modes asymptotically decay, ensuring convergence of the virtual clocks to a common value.

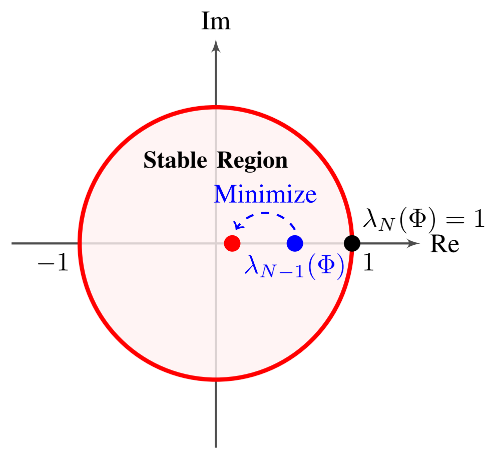

Fig. 2. Stability region for discrete-time systems. All observable eigenvalues of $(I-\varepsilon L)$ must reside strictly inside the unit circle. Pushing $\lambda_{N-1}(\Phi)$ towards the origin (from blue point to red point) increases convergence speed.

Applying the spectral theorem, since Φ is symmetric, it can be orthogonally diagonalized as $\Phi = Q\Delta Q^T$. The state evolution over k steps is $x_k = \left[\sum_{i=1}^{N} q_i q_i^T (\lambda_i(\Phi))^k\right] x_0$. Because $\lambda_N(\Phi) = 1$ and its corresponding normalized eigenvector is $q_N = \frac{1}{\sqrt{N}}\mathbf{1}$, we define the generic error e_k from the steady-state consensus point as:

$$e_k = x_k - \frac{x_0}{N}\mathbf{1} = \left[\sum_{i=2}^{N} q_i q_i^T (\lambda_i(\Phi))^k\right] x_0 \tag{8}$$

Using the properties of vector norms, the error magnitude is bounded by:

$$||e_k|| \le a|\lambda_{N-1}(\Phi)|^k \tag{9}$$

where $a > 0$ is a positive constant. The function $|\lambda_{N-1}(\Phi)|^k$ strictly decays. Therefore, structurally altering the graph to minimize $\lambda_{N-1}(\Phi)$ (pushing it closer to the origin) mathematically forces a steeper exponential decay, aggressively accelerating synchronization (see Figure 3). As a consequence, to speed-up the consensus, $\lambda_2(L)$ has to be maximized.

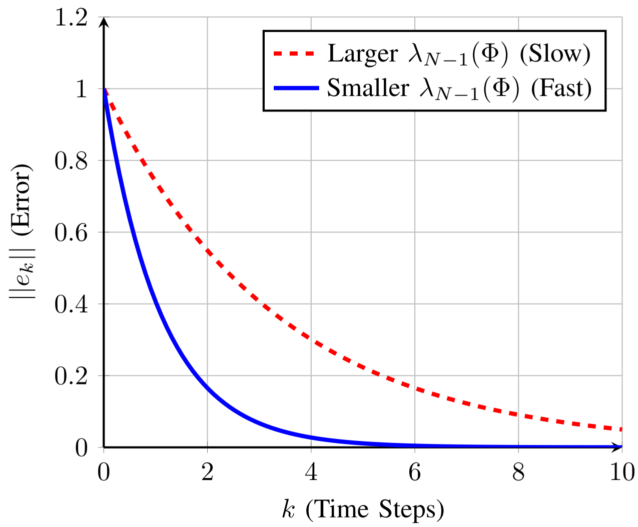

Fig. 3. Theoretical decay of the synchronization error over time steps k. A smaller magnitude of the observable eigenvalue structurally guarantees a faster exponential convergence.

III. Proposed Node Addition Criteria and Optimization Problem

The primary objective of adding a dynamic node to an existing Wireless Sensor Network is to drastically decrease the synchronization time. As mathematically established in the theory of consensus dynamics, the synchronization error decay is strictly bounded by the second smallest eigenvalue of the network's Laplacian matrix. Therefore, optimizing the network topology requires a structural modification that pushes this eigenvalue as far from the origin as possible. When a new node is introduced into the existing N-node network, an expanded Laplacian matrix L_{N+1} is created. Given an initial Laplacian $L_N = D - A$ (where elements are denoted as a_{rc}), the addition of the new node is modeled via a binary connection vector $v \in \mathbb{R}^N$. The block matrix evolution is formally defined as:

$$L_{N+1} = \begin{bmatrix} L_N & \mathbf{0} \\ \mathbf{0}^T & 0 \end{bmatrix} + \begin{bmatrix} \text{diag}(v) & -v \\ -v^T & |v| \end{bmatrix} \tag{10}$$

where $|v| = \sum_{i=1}^{N} v_i$ represents the total number of connections of the new node. To ensure that the newly added node is not completely isolated from the rest of the network, the binary vector v must satisfy $v \in \{0,1\}^N \setminus \{\mathbf{0}\}$.

The overarching goal translates into a discrete optimization problem: finding the optimal vector v^* that maximizes the algebraic connectivity (the second smallest eigenvalue, λ_2) of the augmented Laplacian $L_{N+1}(v)$.

$$v^* = \arg \max_{v \in \{0,1\}^N \setminus \{\mathbf{0}\}} \lambda_2(L_{N+1}(v)) \tag{11}$$

Three distinct criteria are proposed to solve this optimization problem and determine the optimal vector v.

A. Optimal Positioning via Exhaustive Search

The most direct approach to solve the optimization problem is through an exhaustive search across the entire solution space. For an N-node network, there are exactly $2^N - 1$ valid combinations for the binary vector v. By recursively evaluating the resulting eigenvalues, the global theoretical optimum v^* is precisely identified. Finding a sub-optimal or partially connected vector that matches the maximum possible convergence speed provides a significant advantage, as it guarantees a good synchronization time while strictly utilizing fewer hardware resources.

B. Maximum Degree Constraint

In practical WSN deployments, the theoretically optimal vector v^* identified by the exhaustive search might be physically impossible to implement. Environmental conditions, such as physical distances or structural obstacles, can severely attenuate the signal. To account for these impossibilities, the Maximum Degree Constraint restricts the optimization search space. This criterion imposes a strict constraint: the added node cannot possess a total number of connections greater than the maximum degree d_{max} found in the pre-existing network. The constrained optimization problem becomes:

$$v^*_{constrained} = \arg \max_{v} \lambda_2(L_{N+1}(v)) \tag{12}$$

$$\text{subject to:} \quad \sum_{i=1}^{N} v_i \leq d_{max}$$

C. The Twin Criterion

The Twin criterion completely bypasses the physical implementation uncertainties by dictating that the newly added node must perfectly emulate the connection profile of a target node already operating within the network. Since the emulated node has already proven that its specific communication links are physically viable, replicating them provides an absolute guarantee of feasibility. Let the target node to be emulated be denoted by index $m \in \{1, \dots, N\}$. The binary vector v is constructed by copying the m-th row of the initial adjacency matrix A_N: $v_i = (A_N)_{m,i}$ for $i \neq m$.

The criterion is strictly subdivided into two distinct topological cases:

- **Unconnected Twins:** The new node intentionally omits a direct link to the emulated node itself ($v_m = 0$).
- **Connected Twins:** A direct communication link is explicitly established between the new node and the target node ($v_m = 1$).

The Twin criterion connects the new node to the same neighbors as an existing node, effectively replicating its adjacency pattern (see Fig. 4).

IV. Numerical Results

Extensive numerical tests were conducted utilizing MATLAB to validate the mathematical models. The baseline scenario utilizes a randomly generated graph network comprising 9 nodes and 31 active links. The network is deemed synchronized when the clock delay between all nodes definitively falls within a restrictive tolerance band of ± 20 milliseconds. Assuming a discrete synchronization period $T = 3$

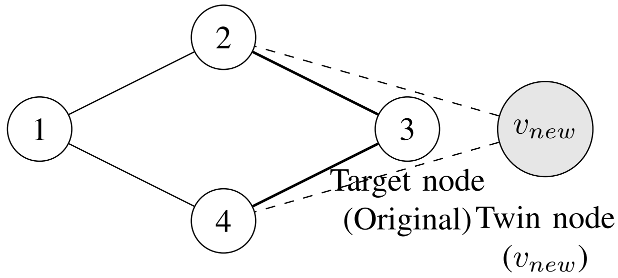

Fig. 4. Twin criterion: the new node (v_{new}) replicates the adjacency pattern of an existing target node (Node 3 in this example).

seconds, the required cycles are calculated. The summarized results for the proposed node addition criteria are presented in Table I.

TABLE I
SUMMARY OF SIMULATION RESULTS FOR NODE ADDITION CRITERIA

Node Addition Criterion	Topology	Opt. $\lambda_2(L)$	Time t_c (s)	Cycles
Exhaustive Search	Random	5.6972	81	27
Maximum Degree Constraint	Random	5.6972	81	27
Twin Criterion (Connected)	Lattice	3.2679	141	47
Twin Criterion (Unconnected)	Lattice	3.2679	141	47
Twin Criterion (Connected)	Random	5.6972	81	27
Twin Criterion (Unconnected)	Random	5.6972	81	27

A. Exhaustive Search Results

Executing the Exhaustive Search methodology across $2^9 - 1$ binary configurations, the maximum second eigenvalue mapped to the Laplacian was evaluated to be $\lambda_2(L) \approx 5.6972$. Under this optimal configuration, the required synchronization time t_c exponentially dropped to 81 seconds, necessitating exactly 27 synchronization cycles. Noticeably, this mathematically optimal vector is not fully connected.

B. Maximum Degree Constraint Results

Applying the Maximum Degree Constraint to the identical 9-node baseline network (where the maximum existing node degree was 8) identified valid connection arrays complying with the established restrictions. The analysis successfully returned the same constrained optimal $\lambda_2(L) \approx 5.6972$ and $t_c = 81$ seconds.

C. Twin Criterion Results

Tests employing the Twin Criterion were executed on both deterministic lattice structures and randomly generated graph topologies. For a lattice topology of 9 nodes, emulating the most highly connected node (node 5) reduced the synchronization time to 141 seconds (47 cycles). When applied to the baseline random graph topology, the Twin Criterion achieved an exceptional convergence time of 81 seconds, yielding $\lambda_2(L) \approx 5.6972$. This mirrors the absolute optimum discovered in the exhaustive search, providing empirical evidence that duplicating existing high-degree communication paths is a highly efficient optimization strategy.

V. CONCLUSION

This paper addressed the critical issue of long synchronization convergence times in Wireless Sensor Networks by introducing a dynamic node to the network. By mapping the continuous network dynamics to a discrete-time system, it was proven that the decay of the synchronization error is tightly bounded by the second eigenvalue of the system matrix. Maximizing the algebraic connectivity of the Laplacian matrix directly forces a steeper exponential decay. While an exhaustive search discovers the absolute theoretical optimum, the Maximum Degree and Twin criteria provide robust alternatives that account for physical signal interference. These criteria demonstrate high relevance for emerging engineering applications requiring transient connectivity boosts, such as UAV bridging or ad-hoc smart grid restoration. Future research will focus on integrating fully mobile dynamic nodes to continually optimize the network topology in real-time.

REFERENCES

[1] F. Adamo, F. Attivissimo, L. Fabbiano, N. Giaquinto, and M. Spadavecchia, “Soil moisture assessment by means of compressional and shear wave velocities: Theoretical analysis and experimental setup,” *Measurement: Journal of the International Measurement Confederation*, vol. 43, no. 3, p. 344 – 352, 2010.

[2] F. Adamo, L. Fabbiano, F. Attivissimo, and N. Giaquinto, “Velocity-moisture relationships for sandy soils: Experimental results and data analysis,” *IEEE Transactions on Instrumentation and Measurement*, vol. 58, no. 2, p. 311 – 317, 2009.

[3] F. Attivissimo, G. Cannazza, A. Cataldo, E. De Benedetto, and L. Fabbiano, “Enhancement and metrological characterization of an accurate and low-cost method based on seismic wave propagation for soil moisture evaluation,” *IEEE Transactions on Instrumentation and Measurement*, vol. 59, no. 5, p. 1216 – 1223, 2010.

[4] S. Siciliano *et al.*, “Optical gas sensors in smart food bio-packaging: Innovation for monitoring the product freshness and safety,” *Measurement: Food*, vol. 19, 2025.

[5] ——, “From traditional packaging to smart bio-packaging for food safety: a review,” *Euro-Mediterranean Journal for Environmental Integration*, vol. 9, no. 4, p. 1971 – 1986, 2024.

[6] N. A. Ismail, S. M. Abu Khadra, G. M. Attiya, and S. E. S. E. Abdulrahman, “Secure and sustainable smart home networks with blockchain-based iot framework for privacy and energy efficiency,” *Discover Internet of Things*, vol. 6, no. 1, 2026.

[7] N. Cerone, F. Zimbardi, L. Contuzzi, S. Tosti, L. Fabbiano, G. D. Zito, M. O. Carnevale, and V. Valerio, “Pre-pilot scale study of hydrogen production from biomass syngas via water-gas shift in pd–ag catalytic membrane reactor and dedicated hydrogen permeation unit,” *International Journal of Hydrogen Energy*, vol. 95, p. 1204 – 1214, 2024.

[8] D. L. Carní and F. Lamonaca, “Local distributed node for power quality event detection based on multi-sine fitting algorithm,” *Sensors*, vol. 24, no. 8, 2024.

[9] D. L. Carnì and F. Lamonaca, “Automatic power quality events classifier based on hybrid cnn–lstm network and multisine fitting algorithm,” *Measurement: Journal of the International Measurement Confederation*, vol. 270, 2026.

[10] R. Morello, G. Fulco, S. Mukhopadhyay, L. Fabbiano, and C. De Capua, “Time synchronized power meters for advanced smart distribution of energy in smart grids,” *IEEE Sensors Journal*, vol. 24, no. 19, p. 30909 – 30919, 2024.

[11] A. F. Gentile *et al.*, “A performance analysis of security protocols for distributed measurement systems based on internet of things with constrained hardware and open source infrastructures,” *Sensors*, vol. 24, no. 9, 2024.

[12] L. Angrisani, F. Bonavolontà, A. Tocchi, and R. S. L. Moriello, “Frequency domain measurement node based on compressive sampling for sensors networks,” 2015, p. 48 – 52.

[13] A. Liccardo, F. Bonavolontà, M. Balato, and C. Petrarca, "Lora-based smart sensor for pd detection in underground electrical substations," *IEEE Transactions on Instrumentation and Measurement*, vol. 71, 2022.

[14] F. Lamonaca, A. Carrozzini, D. Grimaldi, and R. S. Olivito, "Improved monitoring of acoustic emissions in concrete structures by multi-triggering and adaptive acquisition time interval," *Measurement: Journal of the International Measurement Confederation*, vol. 59, p. 227 – 236, 2015.

[15] D. L. Carni *et al.*, "Damage analysis of concrete structures by means of b-value technique," *International Journal of Computing*, vol. 16, no. 2, p. 82 – 88, 2017.

[16] C. Scuro *et al.*, "Experimental and numerical analysis on masonry arch built with fictile tubules bricks," *Measurement: Journal of the International Measurement Confederation*, vol. 130, p. 246 – 254, 2018.

[17] A. Vitale and F. Lamonaca, "Enhancing geoai land cover classification via hyperparameter tuning and cross-validation: A case study in ravenna, italy," *Measurement: Journal of the International Measurement Confederation*, vol. 257, 2026.

[18] A. Vitale *et al.*, "Advancing built-up area monitoring through multi-temporal satellite data fusion and machine learning-based geospatial analysis," *Remote Sensing*, vol. 17, no. 11, 2025.

[19] A. Liccardo *et al.*, "Digital twins based on augmented reality of measurement instruments for the implementation of a cyber-physical system," *Acta IMEKO*, vol. 11, no. 4, 2022.

[20] F. Lago *et al.*, "A cost-oriented and user-friendly performance assessment procedure for passive upper limb exoskeletons," *Journal of Bionic Engineering*, 2026.

[21] B. Pichon, E. Benoit, S. Perrin, A. Benoit, N. Berton, D. Coves, J. Cruvieux, and Y. Faye, "A low-cost machine learning process for gait measurement using an electrostatic sensors network," *Acta IMEKO*, vol. 13, no. 1, 2024.

[22] Y. Kurylyak *et al.*, "Photoplethysmogram-based blood pressure evaluation using kalman filtering and neural networks," 2013, p. 170 – 174.

[23] I. U. Haq *et al.*, "Measurement uncertainty and traceability in upper limb rehabilitation robotics: A metrology-oriented review," *Journal of Sensor and Actuator Networks*, vol. 15, no. 1, 2026.

[24] V. Gazi and K. M. Passino, *Swarm stability and optimization*. Springer Science & Business Media, 2011.

[25] F. Lamonaca, P. Sciammarella, C. Scuro, D. Carni, and R. Olivito, "Synchronization of iot layers for structural health monitoring," 2018, p. 89 – 94.

[26] E. Garone *et al.*, "Clock synchronization for wireless sensor network with communication delay," 2013, p. 771 – 776.

[27] F. Lamonaca, D. L. Carni, M. Riccio, D. Grimaldi, and G. Andria, "Preserving synchronization accuracy from the plug-in of nonsynchronized nodes in a wireless sensor network," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 5, p. 1058 – 1066, 2017.

[28] F. Lamonaca and D. Grimaldi, "Trigger realignment by networking synchronized embedded hardware," *IEEE Transactions on Instrumentation and Measurement*, vol. 62, no. 1, p. 38 – 49, 2013.

[29] L. M. Pecora and T. L. Carroll, "Master stability functions for synchronized coupled systems," *Physical review letters*, vol. 80, no. 10, p. 2109, 1998.

[30] R. Olfati-Saber and R. M. Murray, "Consensus problems in networks of agents with switching topology and time-delays," *IEEE Transactions on automatic control*, vol. 49, no. 9, pp. 1520–1533, 2004.

[31] J. A. Fax and R. M. Murray, "Information flow and cooperative control of vehicle formations," *IEEE transactions on automatic control*, vol. 49, no. 9, pp. 1465–1476, 2004.

[32] A. Jadbabaie, J. Lin, and A. S. Morse, "Coordination of groups of mobile autonomous agents using nearest neighbor rules," *IEEE Transactions on automatic control*, vol. 48, no. 6, pp. 988–1001, 2003.

[33] W. Ren and R. W. Beard, "Consensus seeking in multiagent systems under dynamically changing interaction topologies," *IEEE Transactions on automatic control*, vol. 50, no. 5, pp. 655–661, 2005.

[34] L. Xiao and S. Boyd, "Fast linear iterations for distributed averaging," *Systems & Control Letters*, vol. 53, no. 1, pp. 65–78, 2004.

[35] Y. Hong, G. Chen, and L. Bushnell, "Distributed observers design for leader-following control of multi-agent networks," *Automatica*, vol. 44, no. 3, pp. 846–850, 2008.

[36] X. Liu and T. Chen, "Fixed-time cluster synchronization for complex networks via pinning control," *arXiv preprint arXiv:1509.03350*, 2015.

[37] T. Chen, X. Liu, and W. Lu, "Pinning complex networks by a single controller," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 54, no. 6, pp. 1317–1326, 2007.

[38] Y. Shen and X. Xia, "Semi-global finite-time observers for nonlinear systems," *Automatica*, vol. 44, no. 12, pp. 3152–3156, 2008.

[39] W. Yang, X. Wang, and H. Shi, "Optimal control nodes selection for consensus in multi-agent systems," *IFAC Proceedings Volumes*, vol. 47, no. 3, pp. 11 697–11 702, 2014.

[40] X. Li, X. Wang, and G. Chen, "Pinning a complex dynamical network to its equilibrium," *IEEE Transactions on Circuits and Systems I: Regular Papers*, vol. 51, no. 10, pp. 2074–2087, 2004.

[41] L. D'Alfonso, G. Fedele, and A. Bono, "Distributed region following and perimeter surveillance tasks in star-shaped sets," *Systems & Control Letters*, vol. 172, p. 105437, 2023.

[42] G. Fedele and L. D'Alfonso, "A coordinates mixing matrix-based model for swarm formation," *International Journal of Control*, vol. 94, no. 3, pp. 711–721, 2021.

[43] G. Fedele, L. D'Alfonso, A. Bono, and V. Gazi, "Swarm trajectories generation for target capturing with uncertain information," *IEEE Transactions on Control of Network Systems*, vol. 10, no. 4, pp. 1986–1996, 2023.