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Distributed control and decision-making algorithms for open multi-agent systems: a brief overview

Guanghui WEN[1✉], Meng LUAN[2], Xiao FANG[1], Xiaodong LI[3]

[1]*School of Automation, Southeast University, Nanjing 210096, China*
[2]*Division of Industrial Data Science, School of Data Science, Lingnan University, Hong Kong, China*
[3]*School of Mathematics, Southeast University, Nanjing 211189, China*

Abstract: Open multi-agent systems (OMASs), characterized by the dynamic joining and leaving of agents, possess distinct attributes such as agent-level autonomy, time-varying network topologies, and environmental openness. These characteristics make them highly applicable to dynamic scenarios like robotic swarms, smart grids, and vehicular networks. However, such dynamism introduces core challenges in maintaining system stability, achieving efficient collaboration, and guaranteeing decision robustness. This paper presents a brief overview of recent advances in distributed control and decision-making algorithms for OMASs. First, the fundamental concepts and control strategies of OMASs are systematically reviewed. Second, distributed decision-making mechanisms encompassing distributed consensus optimization, separable resource allocation, and Nash equilibrium (NE) seeking in non-cooperative games are discussed, highlighting key technologies and typical methods. Finally, an outlook on future perspectives in the field is presented.

Key words: Open multi-agent system; Time-varying topology; Distributed control; Distributed optimization; Nash equilibrium seeking

1 Introduction

Over the past few decades, multi-agent systems (MASs) have been widely employed in areas ranging from intelligent transportation to industrial collaboration, distributed energy, and swarm robotics, thereby garnering sustained research attention (Wen et al., 2014; Shi and Yan, 2021; Qu et al., 2022; Dong JW et al., 2023; Luan et al., 2025; Sebastián et al., 2025). Within this domain, distributed control and decision-making serve as the foundational mechanisms enabling MASs to collaboratively accomplish complex tasks. Specifically, relying on the underlying communication topology, agents can execute complex tasks in a distributed manner solely through local interactions.

✉ Guanghui WEN, ghwen@seu.edu.cn
Guanghui WEN, https://orcid.org/0000-0003-0070-8597
Meng LUAN, https://orcid.org/0009-0008-7170-3287
Xiao FANG, https://orcid.org/0000-0003-2050-9894
Xiaodong LI, https://orcid.org/0000-0003-3561-9762
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Nevertheless, driven by the rapid iteration and deep integration of technologies such as artificial intelligence, the Internet of Things, and distributed computing, the requirements for MASs are escalating. The traditional closed-system paradigm, assuming a static set of agents, falls short of meeting the demands for high-level intelligence and collaboration in complex cyber-physical systems. Consequently, the development of MASs exhibits a distinct trend toward openness (Huynh et al., 2006). An increasing number of application scenarios require agents to operate in open environments rather than being confined to fixed and closed systems. Thus, conventional distributed control and decision-making methods, typically designed for fixed scales, struggle to adapt to dynamic and open scenarios. They lack the flexibility to respond to the dynamic arrival and departure of agents and real-time changes in topology, revealing inherent defects in scalability and adaptability. In contrast, open MASs (OMASs) have emerged as ideal platforms for solving complex distributed tasks through the local interaction and collaboration of multiple autonomous agents (Franceschelli and Frasca, 2021).

Among various distributed coordination tasks, consensus control serves as the cornerstone of distributed control, aiming to drive the states of all agents to a common value via local interactions (Olfati-Saber et al., 2007). However, in open environments, the dynamic migration of agents poses significant challenges to consensus. On one hand, the dynamic joining and departure of agents cause frequent changes in system topology, undermining the stability of existing consensus algorithms. Conventional algorithms designed for fixed topologies typically struggle to handle such changes, resulting in a low convergence rate or even divergence. On the other hand, incoming agents in open environments may introduce significant state discrepancies and incompatible interaction rules, which can interfere with the original consensus process of the system. Although various consensus problems in OMASs have been investigated, including proportional dynamic consensus (Franceschelli and Frasca, 2018), median consensus (Dashti et al., 2019), and maximum consensus (Abdelrahim et al., 2017), achieving global consensus and performing rigorous stability analysis while accommodating the inherent "plug-and-play (PnP)" nature of these systems remain critical open issues in distributed control.

In the field of distributed decision-making for MASs, distributed optimization stands out as one of the most active research directions. In this domain, consensus optimization (which aims to achieve global consensus on the optimal solution) and resource allocation optimization (which seeks to rationally allocate limited resources to maximize overall benefits) have garnered the most attention. Conventional distributed optimization algorithms are typically designed based on a fixed set of agents, assuming continuous agent participation in the optimization process and stable information interactions. However, in OMASs, the dynamic arrival and departure of agents induce a continuously time-varying set of optimization participants. This not only results in severe computational inefficiency due to the frequent interruption and restarting of the solution process for global optimization objectives, but also causes shifts in the global optimal solution whenever agents carrying specific local cost functions exit or when new agents introduce new resource constraints. To address these challenges, recent studies have explored distributed optimization in OMASs (de Galland et al., 2021, 2024; Hsieh et al., 2021; Vizuete et al., 2022; Liu YX et al., 2026a; Dutta and Doan, 2025; Makridis et al., 2025; Sawamura et al., 2025; Wu et al., 2026), including formulations within online settings (Hayashi, 2023; Liu YX et al., 2024; Makridis et al., 2025; Sawamura et al., 2025; Deplano et al., 2026).

Non-cooperative games represent another pivotal research direction in distributed decision-making for OMASs. In this framework, agents act as self-interested entities, where the cost function of each agent relies on the decisions of other agents in the system, and each agent is dedicated solely to maximizing its utility (Fang et al., 2022a). Unlike consensus optimization (Luan et al., 2024), where variations in the number of agents typically do not alter the local objective functions of other agents, the inherent interdependence of decision-making in non-cooperative games implies that the entry or exit of agents not only modifies the structure of other agents' local objective functions, but also changes the dimensionality of the collective decision space (Liu WT et al., 2026). To date, research on non-cooperative games in OMASs remains scarce, and the literature is limited (Chen et al., 2025; Liu YX et al., 2025, 2026b; Xu et al., 2025; Liu WT et al., 2026).

Despite the growing importance of this field, systematic reviews focusing on OMASs remain scarce, leaving the research community without a comprehensive and clear roadmap or reference framework. Compared with mature paradigms for fixed-scale, topologically stable closed MASs, existing research on distributed control and decision-making in OMASs is still in its infancy, with a complete theoretical and technical framework yet to be established. Therefore, there is an urgent need to systematically review the latest research advances in this field, deeply analyze the core characteristics, inherent limitations, and existing gaps in the literature, and discuss future research priorities and development directions. Driven by these considerations, this paper comprehensively examines the core concepts, modeling approaches, stability notions, and distributed control and decision-making strategies of OMASs. It synthesizes prevailing strategies for maintaining steady-state performance in highly dynamic settings, including stochastic descriptions of population evolution, variable-dimensional modeling frameworks, switching-frequency or dwell-time constraints, and distributed protocols for preserving stability, consensus, and optimization performance in the presence of agent turnover.

2 Distributed control in OMASs

In OMASs, the term "open" indicates that the agent set is scalable rather than fixed during system evolution. Unlike MASs with switching topologies, where the agent set remains static and communication links vary, OMASs involve the irregular arrival and departure of agents. This results in time-varying network sizes and fluctuating dimensions of the global state vector. In existing OMAS studies, the admission of new agents is typically governed by specific modeling rules or control-oriented criteria rather than being treated as entirely arbitrary. Typical examples include proximity and bounded-error requirements (Li XD et al., 2026b), stochastic replacement mechanisms (de Galland and Hendrickx, 2023), and topology constraints based on limited openness and joint robustness (Jia et al., 2026b). Although both OMASs and MASs involve time-varying network structures, OMASs additionally exhibit dimension variations induced by agent arrivals and departures. This dimensional variability limits the direct application of conventional control frameworks developed for fixed-dimensional systems. For instance, Lyapunov functions and convergence metrics defined for a fixed number of agents may no longer remain valid following agent arrivals or departures. Moreover, the consensus objective must be reformulated for a time-varying agent set, and controller design needs to account for state initialization, information integration, and stability preservation during agent entry and exit. These issues motivate the need for variable-dimensional modeling frameworks and tailored analysis tools for OMASs. This section first introduces the fundamental concepts and modeling methods used to capture the time-varying characteristics of OMASs and then reviews specific distributed control algorithms.

2.1 Preliminaries and system modeling of OMASs

Agent arrivals and departures may result in dimensional changes, impulsive state transitions, and persistent perturbations in group behaviors, making standard asymptotic convergence analysis insufficient. This subsection reviews modeling methods for variable-dimensional state spaces, categorizes consensus objectives for dynamic agent groups, and elaborates on stability definitions tailored to open networks.

For brevity, in certain parts of this paper, we omit the time argument t (or k) from time-dependent variables and vectors.

2.1.1 Dynamic modeling

To mathematically formalize the continuous variation of agents, several primary modeling frameworks have been developed.

The first category comprises statistical or probabilistic modeling approaches, which characterize the aggregate evolution of the agent population rather than deterministic trajectories at the individual agent level. These approaches are particularly useful when individual-level trajectory tracking becomes impractical under frequent agent turnover. Consequently, several studies have employed statistical models to analyze them at the system level. For example, de Galland and Hendrickx (2023) initiated this line of inquiry by modeling agent arrivals and departures as random events driven by Poisson clocks. In their framework, system evolution is viewed as a sequence of discrete events (specifically, gossip, arrival, and replacement), which facilitates the derivation of expected performance bounds rather than deterministic trajectory tracking. To further capture the fluctuations in population size $N(t)$, de Galland et al. (2020) modeled the number of agents as a birth–death process. By defining explicit arrival rates λ_{a} and departure rates λ_{d}, this probabilistic approach enables a rigorous analysis of the asymptotic size distribution of the system around a nominal value.

The second category focuses on variable-dimensional modeling approaches, which explicitly describe how agent entry and exit change the dimension of the global state space. Unlike statistical models, which primarily characterize open systems at the collective level, these approaches directly address the dimensional variability of the system state. To capture this feature, OMASs are formalized as hybrid dynamical systems, where the dimension of the state space itself is a function of a switching signal. Xue et al. (2022) established the framework of multi-mode multi-dimensional ($\mathrm{M^3D}$) systems, where the state transition at a switching instant t_k is governed by an affine mapping $x(t_k^+) = \varXi_k x(t_k^-) + \varPhi_k$. Here, $\varXi_k$ denotes a special $0-1$ matrix handling dimension reduction or expansion, and $\varPhi_k$ captures impulsive effects, such as the initialization of new agents. A similar impulsive framework was adopted by Zhu et al. (2025) to characterize abrupt changes in network scale. To ensure the well-posedness and stability of these systems, explicit constraints on the frequency of agent turnover are often required. Jia et al. (2026a) introduced specific variables, such as the cumulative frequency of agent arrivals and departures and the duration of disconnected topologies, to mathematically bound the switching frequency of agents and the dwell-time of disconnected graphs, distinguishing between stable and unstable intervals.

The third category includes topology- and neighborhood-based modeling approaches, where agent arrivals and departures are reflected by variations in communication links, sensing relationships, and local coordination structures. These approaches focus on how openness dynamically reshapes network topologies and local interaction patterns among agents. For instance, Restrepo et al. (2022) defined the network topology using dynamic vertex sets $\mathcal{V}_\phi$ and edge sets $\mathcal{E}_\phi$ governed by local sensing ranges. In this model, new communication links are established not only by agent arrival but also by agents entering the interaction zone $\varDelta_k$ of other agents. To differentiate between stable and disruptive agents, Jia et al. (2026b) proposed the concept of "f-limited open set" $\mathcal{O}_f(k)$. This modeling approach categorizes agents based on their potential to disrupt the network, providing a granular view of how new entrants influence the existing topology. Dong LJ and Nguang (2021) introduced a relay mechanism that defines a logical handover of tracking responsibilities as agents enter or leave the communication range, ensuring task continuity through the design of an impulse-time-dependent average Lyapunov function.

2.1.2 Consensus concepts in open environments

In OMASs, the classical definition of asymptotic consensus (i.e., $x_i \to x^*$ as $t \to \infty$) is often unattainable due to persistent state perturbations induced by agent arrivals and departures. Recent literature has proposed several alternative consensus concepts tailored to such open environments.

Earlier studies focused on relaxing the convergence requirement from a single equilibrium point to a bounded region. For instance, Zhu et al. (2025) termed this relaxed objective "quasi-consensus," where the error norm between each follower and the leader converges to a bounded neighborhood, i.e., $\lim_{t\to\infty} \|x_i(t) - x_0(t)\| \le \epsilon$. Similarly, Xue et al. (2022) analyzed this asymptotic behavior within the framework of global uniform practical stability (GUPS), revealing that the bound ϵ is typically a function of the arrival rate and the perturbation magnitude of new agents. From a stochastic perspective, de Galland and Hendrickx (2023) quantified the consensus performance via the expected mean-squared error (MSE), formulated as $C(t) := \frac{1}{N}\sum_{i=1}^{N}(\bar{x}(t) - y_i(t))^2$, where $\bar{x}(t) = \frac{1}{N}\sum_{i=1}^{N} x_i(t)$. They rigorously proved that under random agent replacements, this error exhibits a fundamental non-zero lower bound, representing a hard performance limitation for open systems.

Beyond relaxed state consensus, practical functional requirements have driven the development of additional robust consensus definitions. Jia et al. (2026b) introduced the concept of non-disruptive consensus, which requires that newly joined agents converge to the state of the existing group without perturbing the transient trajectories or asymptotic stability of active agents. This property is particularly critical for precision applications, such as clock synchronization. To facilitate global computations under time-varying network sizes, Dashti et al. (2022) proposed an average-preserving consensus framework. This concept uses auxiliary variables to compensate for the state mass entering or leaving the system, ensuring that the global "sum" or "average" remains invariant or reconstructible. In addition, for heterogeneous systems where internal states differ, Liu XM et al. (2024) and Li XD et al. (2026b) defined the output consensus of heterogeneous OMASs.

2.1.3 Stability concepts in control

Standard stability analysis tools (e.g., common Lyapunov functions) often fall short under fluctuating system dimension conditions. Recent literature has introduced specialized stability concepts for addressing the switching and impulsive nature of OMASs.

To prevent system destabilization caused by frequent agent turnover, stability criteria are typically linked to the timing of events using dwell-time methods. For instance, Xue et al. (2022) developed a transition-dependent average dwell-time (ADT) condition for M^3D systems. This concept extends standard ADT by allowing for different switching frequency constraints depending on the "direction" of the dimension change (e.g., distinguishing between adding and removing an agent). For systems that may temporarily enter unstable modes (such as periods with disconnected interaction topologies), Liu XM et al. (2024) applied the concept of persistent dwell-time (PDT). PDT strictly bounds the allowable ratio of time that the system spends in unstable configurations while ensuring that overall stability is maintained.

Complementing time-domain analysis, generalized energy concepts are employed to handle state-space variations and physical constraints. To accommodate dimension variations, Xue et al. (2022) constructed parametric multiple Lyapunov functions, where the matrix parameters adapt to the active mode $\sigma(t)$. This formulation ensures that the generalized "energy" of the system strictly decreases across dimension jumps. Moreover, to enforce state constraints (such as collision avoidance) during topology transitions, Restrepo et al. (2022) employed barrier Lyapunov functions (BLFs) to formally define safety manifolds. These functions characterize the boundaries of inter-agent constraints, ensuring that both global collision avoidance and local connectivity are rigorously guaranteed, even under fluctuating system dimension conditions caused by the addition of new agents or communication edges.

Finally, stability in open environments has also been framed using the concepts of robustness and invariance. Franceschelli and Frasca (2021) formalized a theoretical framework for OMASs by treating agent arrivals and departures as system disturbances. To accommodate the time-varying dimension of the global state vector, they introduced a normalized open distance function that enables a consistent comparison of states across different Euclidean spaces. Using this framework, they established sufficient conditions for the open stability of a trajectory of points of interest (TPI), and demonstrated that the tracking error of the system remains bounded within a stability radius determined by the bounded variation of the TPI and the intensity of the agent arrival process. From a topological perspective, Jia et al. (2026b) introduced the concept of joint robustness to ensure the necessary connectivity within the time-varying network, along with limited openness to constrain the influence of disruptive newly joined agents. Additionally, these concepts characterize the ability of the network to maintain non-disruptive consensus (NDC). Based on decentralized model predictive control (MPC), Riverso et al. (2013) defined PnP invariance conditions under which a subsystem can join a network without violating the robust invariant sets of its neighbors. This concept was subsequently extended by Riverso et al. (2015) to provide decentralized voltage and frequency regulation in islanded microgrids.

The above discussions show that dynamic modeling, consensus concepts, and stability concepts address different but closely related challenges caused by openness in OMASs. Dynamic modeling focuses on describing the changes in agent population, interaction topology, and global state dimension induced by agent arrivals and departures. These changes make it necessary to model random population evolution, dimension expansion or reduction, and impulsive state transitions within a unified framework. Consensus concepts are required because persistent agent turnover may continuously perturb the group state, introduce non-zero steady-state errors, or disrupt the information quantities that classical consensus protocols aim to preserve. Accordingly, alternative notions such as quasi-consensus, expected error bounds, average-preserving consensus, and NDC have been introduced to characterize achievable coordination in open environments. Stability concepts further address the effects of dimensional jumps, impulsive state changes, disconnected topologies, and perturbations introduced by newly joining agents, thereby providing conditions under which the system remains bounded or stable despite these effects. Therefore, these three research directions address how to represent open-system dynamics, define coordination objectives, and guarantee bounded or stable behavior under agent turnover, respectively.

2.2 Distributed control algorithms for OMASs

Building on the aforementioned modeling, consensus, and stability notions, this subsection reviews distributed control algorithms for OMASs. These algorithms are designed to maintain consensus or tracking performance under agent turnover and handle heterogeneous dynamics, safety constraints, limited communication, and unknown disturbances.

To cope with the randomness of agent arrivals and departures, many control protocols adopt adaptive, randomized, or event-driven mechanisms rather than relying solely on fixed-gain feedback. For instance, Hendrickx and Martin (2017) proposed randomized gossip algorithms, where agents update their states via pairwise averaging with randomly selected neighbors. This asynchronous protocol is robust to frequent agent replacements, as it relies on statistical convergence rather than rigid topology maintenance. Based on this statistical approach, de Galland et al. (2020) analyzed gossip interactions in variable-size systems, showing that the system variance converges to a non-zero steady state determined by the ratio of interaction to replacement rates. Moreover, de Galland and Hendrickx (2023) formally established fundamental performance limitations for any averaging algorithm in open systems, proving that a non-zero lower bound on the MSE is unavoidable due to the continuous information loss and state perturbations caused by agent turnover. To accommodate limited communication resources and physical constraints, Zhu et al. (2025) developed a distributed saturated impulsive control strategy. Instead of continuous feedback, agents update their states only at discrete instants (impulses). This method is particularly effective for OMASs as it allows the system to tolerate the "shocks" caused by topology switching while explicitly handling input saturation constraints. To maintain tracking performance when agents leave the network, Dong LJ and Nguang (2021) introduced a relay tracking controller. This strategy employs an impulse-time-dependent average Lyapunov function to mitigate the impact of discontinuous tracking errors caused by the switching of active agents, thereby ensuring global stability despite the time-varying network size. Furthermore, Dashti et al. (2022) proposed an average-preserving consensus procedure to compute the "mode" (most frequent value) of agent opinions. This protocol introduces auxiliary variables to compensate for the state mass lost or gained during the process of changing the number of agents, ensuring that global properties of the system are preserved despite local changes. Restrepo et al. (2025) proposed a passivity-preserving framework for multi-dimensional switched systems, specifically addressing the destabilizing "energy jumps" inherent in the autonomous addition and removal of robotic agents. This work introduces a distributed energy-tank-based strategy, where each agent maintains a virtual reservoir to buffer impulsive energy variations. By satisfying a state-dependent switching condition based on local energy budgets, agents can autonomously regulate network membership without the need for a centralized supervisor or global reconfiguration.

In open environments, the addition of new agents introduces critical risks of inter-agent collisions and connectivity loss. To mitigate such risks, control architectures must explicitly incorporate safety constraints. Specifically, Restrepo et al. (2022) synthesized a consensus control protocol by embedding the gradient of a BLF directly into the system dynamics. This formulation establishes a scalar potential field that diverges as the relative edge states approach the singular boundaries of the admissible region (i.e., the minimum safety distance δ for collision avoidance and the maximum sensing range Δ_k for connectivity maintenance). By ensuring the forward invariance of the constrained set $\mathcal{D}_\phi$, the controller guarantees that the system trajectories remain strictly within the safety manifold, even under impulsive disturbances and dimensional variations triggered by the addition of new agents or communication edges.

To facilitate modularity in large-scale systems such as critical infrastructure, PnP architectures allow subsystems to join or leave without necessitating a global retuning of the network. Riverso et al. (2013) proposed a PnP decentralized MPC architecture, where each agent solves a local optimization problem subject to coupling constraints. When a new agent requests to join, a "plug-in" operation is executed: the neighbors evaluate whether the coupling effects of the new agent violate their robust invariant sets. Upon successful verification, the agent is admitted without triggering a global controller redesign. This PnP paradigm was subsequently adapted by Riverso et al. (2015) for islanded microgrids with meshed topologies. In this specific application, the control scheme ensures voltage and frequency stability by treating additions or removals of distributed generation units (DGUs) as localized physical reconfigurations, requiring that only the directly connected units should update their control laws based on the principle of neutral interactions.

In practical applications, OMASs often involve agents with diverse dynamic models (inherent heterogeneity, nonlinearity) or face unknown disturbances (such as system uncertainties or cyber-attacks). To address these complexities, several control architectures have been developed. Specifically, Liu XM et al. (2024) formulated a fuzzy cooperative control architecture for accommodating nonlinear and heterogeneous dynamics. By characterizing the nonlinear agents using Takagi–Sugeno (T-S) fuzzy models, this framework synthesizes a distributed reference generator capable of estimating the state of the exosystem. Local fuzzy controllers are then deployed to drive the outputs of the heterogeneous agents to track this reference, thereby guaranteeing cooperative output regulation even under PDT switching topologies. Li CC et al. (2017) proposed a switched tracking strategy to study the tracking consensus problem of nonlinear OMASs. Li XD et al. (2024) addressed the leader-following consensus problem of open multi-unmanned aerial vehicle systems under directed topology.

To counteract the effects of actuator attacks, Li XD et al. (2023) proposed a distributed resilient control protocol to achieve the tracking consensus of OMASs under these attacks. Subsequently, Li XD et al. (2026b) designed two classes of distributed resilient control protocols that integrate attack-free state observers with dynamic compensators to achieve output consensus tracking for heterogeneous OMASs. To protect existing agents from being destabilized by new entrants with arbitrary states, Jia et al. (2026b) proposed the estimation-based mean subsequence reduced (E-MSR) algorithm. This control logic acts as a dynamic filter: it allows existing agents to ignore "disruptive" values from newly joined agents until these agents converge to a safe range (the "consistent interval"). This ensures NDC, guaranteeing that the stability of the incumbent cluster is preserved during network expansion. To avoid reliance on global topological information, two types of adaptive control protocols were developed in Li XD et al. (2026a) and Li XD and Wen (2026) to achieve tracking consensus of homogeneous OMASs and output consensus of heterogeneous OMASs, respectively.

Based on the above discussions, which are summarized in Tables 1 and 2, distributed control algorithms for OMASs can be distinguished according to the effects of agent entry and exit that they are designed to handle. Gossip-based methods are suitable for random replacements and asynchronous interactions, where fixed communication patterns and global synchronization are difficult to maintain. Average-preserving and compensation-based methods address the injection or loss of state information induced by agent arrivals and departures, thereby preserving global quantities such as averages, sums, and tracking references. PnP, barrier-function-based, and invariant-set-based methods are used when new agents may affect connectivity, safety constraints, and local stability. Resilient and adaptive protocols further handle disruptive entrants, heterogeneous dynamics, unknown disturbances, and adversarial behaviors. In particular, under high agent churn, gossip- and compensation-based methods are generally more tolerant of frequent turnover because their local-update and information-balancing mechanisms may accommodate agent replacements without requiring global reconfiguration.

Table 1 Distributed control methods of OMASs over undirected topology graphs

Reference	Problem	Topology graph	Method
Jia et al. (2026a)	Consensus analysis and convergence rate optimization	Undirected, disconnected	Average-preserving distributed consensus procedure
de Galland et al. (2020)	Behavior of all-to-all pairwise gossip interactions	Undirected, fully connected	Gossip interactions
de Galland and Hendrickx (2023)	Average consensus fundamental limits	Undirected, connected	Gossip algorithm
Dong LJ and Nguang (2021)	Trajectory tracking	Undirected, connected	Relay tracking controller
Dashti et al. (2022)	Average consensus	Undirected, connected	Average-preserving consensus framework
Restrepo et al. (2022)	Consensus with collision avoidance and connectivity	Undirected, connected	BLF-embedded gradient control
Riverso et al. (2015)	Voltage and frequency stability	Undirected, connected	PnP control architectures
Li CC et al. (2017)	Tracking consensus	Undirected, connected	Switched tracking strategy
Li XD et al. (2023)	Resilient tracking consensus	Undirected, connected	Distributed resilient control protocol
Li XD et al. (2026a)	Adaptive tracking consensus	Undirected, connected	Fully distributed adaptive protocol
Li XD and Wen (2026)	Resilient output consensus tracking	Undirected, connected	Fully distributed adaptive resilient control protocol
Restrepo et al. (2025)	Passivity-preserving energy-aware design	Undirected, biconnected	Distributed energy-tank-based strategy

PnP: plug-and-play; BLF: barrier Lyapunov function

Table 2 Distributed control methods of OMASs over directed topology graphs

Reference	Problem	Topology graph	Method
Xue et al. (2022)	Global uniform practical stability	Directed, disconnected	Parametric multiple Lyapunov functions
Liu XM et al. (2024)	Cooperative output regulation	Directed, disconnected	Fuzzy cooperative control
Jia et al. (2026b)	NDC	Directed, fully connected	E-MSR algorithm
Hendrickx and Martin (2017)	Average consensus	Directed, fully connected	Randomized gossip algorithms
Zhu et al. (2025)	Quasi-consensus under input saturation	Directed, connected	Distributed saturated impulsive control
Li XD et al. (2026b)	Resilient output consensus tracking	Directed, connected	Distributed resilient control protocols with attack-free state observers
Franceschelli and Frasca (2021)	Trajectory tracking	Directed, connected	OPDC algorithm
Riverso et al. (2013)	Decentralized stabilization	Directed, connected	PnP decentralized MPC
Li XD et al. (2024)	Leader-following consensus	Directed, connected	Distributed control protocol

NDC: non-disruptive consensus; E-MSR: event-triggered mean subsequence reduced; OPDC: open proportional dynamic consensus; PnP: plug-and-play; MPC: model predictive control

3 Distributed decision-making algorithms for OMASs

Building on the distributed control frameworks discussed in the previous section, which primarily ensure system stability and fundamental consensus, this section focuses on higher-level decision-making processes in OMASs. While control algorithms provide the necessary coordination and convergence under time-varying dimensions, decision-making algorithms including distributed optimization and game theory aim to optimize collective performance while reconciling individual objectives (Fang et al., 2022b; Wen et al., 2022). The transition from control to decision-making is essential in open environments because the irregular arrival and departure of agents not only perturb the dynamic stability of the system but also shift the optimal equilibrium and the feasible solution set. The following subsections scrutinize how OMASs handle complex decision-making problems, including consensus optimization, separable resource allocation, and NE seeking in non-cooperative games, under persistent structural fluctuations.

3.1 Distributed consensus optimization for OMASs

Consider a fundamental distributed consensus optimization problem for MASs consisting of n active agents, i.e.,

$$\min \sum_{i=1}^{n} f_i(x_i) \tag{1a}$$

$$\text{s.t.}\quad x_i = x_j,\ \forall i, j = 1, 2, \ldots, n, \tag{1b}$$

where $f_i(\cdot): \mathbb{R}^d \to \mathbb{R}$ denotes the local objective function, and $x_i \in \mathbb{R}^d$ is the decision vector associated with agent i. The constraint (1b) enforces network-wide consensus on local decision vectors across all participating agents. In conventional closed systems, this formulation assumes a static agent set. However, in open systems, the dynamic turnover of agents induces abrupt variations in both the dimensionality of the decision space and the global objective function. This inherent volatility renders classical asymptotic convergence guarantees inapplicable, necessitating the development of tailored analytical frameworks.

To tackle these structural perturbations, initial efforts focused on analyzing the sensitivity of standard optimization methods in open environments. For instance, Hendrickx and Rabbat (2020) investigated the stability of the following general decentralized gradient descent (DGD) algorithm over undirected graphs:

$$x_i^{k+1} = x_i^k - \eta\left(\nabla f_i(x_i^k) + \rho\sum_{j=1}^{n} a_{i,j}(x_i^k - x_j^k)\right), \tag{2}$$

where x_i^k denotes the decision vector of agent i at iteration k, $\nabla f_i(x_i^k)$ is the local gradient for agent i at x_i^k, $a_{i,j}$ represents the adjacency weight satisfying $a_{i,j} > 0$ if and only if agent i receives information from agent j, and η and ρ denote the step size and penalty parameters, respectively. By assuming smoothness and strong convexity of the objective functions, Hendrickx and Rabbat (2020) quantified the sensitivity of the global optimum to variations in individual objective functions during agent replacements. They established that the iterative trajectories remain confined within a bounded neighborhood despite such replacements, precluding unbounded divergence.

While the aforementioned works assume a fixed state dimension, Wu et al. (2026) tackled a more challenging scenario where agent arrivals and departures trigger dimensional fluctuations within the decision space, formulated as

$$\min_{p\in\mathbb{R}^{n_{\max}}} f(p) = \min_{p\in\mathbb{R}^{n_{\max}}} \sum_{i\in V(\tau)} f_i(p), \tag{3}$$

where $f_i(p)$ represents the local convex objective function of agent i, $\mathbb{R}^{n_{\max}}$ characterizes the decision space subject to dimensional fluctuations, with the index $n_{\max}$ bounding the maximum possible scale of these dynamic variations, and $V(\tau)$ is the agent set at instant τ drawn from the set $\{1, 2, ..., n_{\max}\}$. To mitigate the gradient information loss induced by agent departures, Wu et al. (2026) proposed an open consensus algorithm equipped with an auxiliary compensation variable and a diminishing step-size scheme. This approach achieves asymptotic convergence to the exact optimal solution under certain conditions, despite a continuous network reconfiguration. Alternatively, rather than compensating for lost gradient information, Dutta and Doan (2025) leveraged an S-redundancy condition within a client–server architecture to transform the time-varying optimization problem into a static equivalent, guaranteeing the exact convergence of the local stochastic gradient descent (SGD) algorithm.

Beyond the aforementioned dimensional fluctuations at the agent level, the inherent openness of OMASs exacerbates network-level challenges, such as asynchronous communication and time-varying interaction topologies. To tackle asynchronous updates subject to communication delays, Hsieh et al. (2021) formulated the problem as minimizing the average instantaneous loss of active agents at time t:

$$f_t^{\text{inst}}(x) = \frac{1}{m_t}\sum_{i\in\mathcal{V}_t} f_i(x), \tag{4}$$

where m_t represents the number of active agents at time t, and $\mathcal{V}_t$ denotes the set of active agents. The proposed dual averaging for open network (DAERON) algorithm proposed by Hsieh et al. (2021) updates the decision variables by projecting the accumulated network gradients as follows:

$$x_{i,t} = \Pi_{\mathcal{X}}\left(x_1 - \eta_{i,t}\sum_{(j,s)\in\mathcal{S}_{i,t}} g_{j,s}\right), \tag{5}$$

where $\Pi_{\mathcal{X}}$ denotes the projection onto the shared constraint set $\mathcal{X}$, x_1 is a common initialization point, $\eta_{i,t} > 0$ is a potentially time- and agent-dependent learning rate, and $\mathcal{S}_{i,t}$ denotes the index set of subgradients available to agent i at time t. To evaluate algorithmic performance under such continuous agent turnover, its convergence is theoretically characterized by a running loss metric that measures the average suboptimality of the network over a time horizon T:

$$\overline{\text{Loss}}(T) = \frac{1}{M_T}\left(\sum_{t=1}^{T}\sum_{i\in\mathcal{V}_t} f_i(x_t^{\text{ref}}) - \min_{u\in\mathcal{X}}\sum_{t=1}^{T}\sum_{i\in\mathcal{V}_t} f_i(u)\right),$$

where x_t^{ref} represents the reference point at time t, $M_T = \sum_{s=1}^{T} m_s$ denotes the cumulative number of participating agents up to time T, and m_s represents the number of active agents at time s.

To further capture the dynamism of open environments, recent research has shifted its focus toward scenarios involving time-varying objective functions within OMASs. For instance, Deplano et al. (2026) investigated the minimization of such time-varying local objective functions, formulated as the following optimization problem:

$$\min_{y\in\mathbb{R}^p} \sum_{i\in\mathcal{V}_k} f_k^i(y), \tag{6}$$

where $p \in \mathbb{N}$ denotes the dimension of variable y, $\mathcal{V}_k$ denotes the time-varying set of agents, and $f_k^i(\cdot): \mathbb{R}^p \mapsto \mathbb{R}$ represents the local objective function of agent $i \in \mathcal{V}_k$ in the network at time k.

To address this, Deplano et al. (2026) proposed an open ADMM algorithm, establishing convergence through the novel "theory of open operators." This theoretical framework extends standard operator concepts to accommodate time-varying state spaces, allowing operators to act on sequences of points with fluctuating dimensions and compositions. Crucially, this analysis establishes a general framework for evaluating algorithms in open networks, shifting the performance metric from cumulative regret over a finite horizon to the instantaneous distance from the dynamic optimal solution. Furthermore, operating under these time-varying functional conditions often coincides with severe topological vulnerabilities. In this context, Makridis et al. (2025) investigated distributed optimization in OMASs where agent departures may physically fragment the network into disjoint clusters. The problem is formulated as minimizing the cluster-wide objective for each dynamically formed cluster q: $\min \sum_{v_j \in \mathcal{V}_k^q} f_{j,k}(x)$, where each agent v_j holds a possibly time-varying convex local cost function $f_{j,k}(\cdot) : \mathbb{R}^d \to \mathbb{R}$ at time k, and $\mathcal{V}_k^q$ is the active agent set of cluster q at time k. To tackle this, Makridis et al. (2025) introduced the open distributed optimization algorithm with gradient tracking (OPEN-GT), which employs acknowledgment messages to dynamically detect active out-neighbors and a max-consensus mechanism to coordinate departure information. The theoretical analysis establishes cluster consistency and stability, demonstrating that agents maintain coherence within the dynamically formed clusters and asymptotically converge to their respective cluster-wide optimal solutions, conditional on the eventual stabilization of the network topology.

It should be noted that, unlike closed MASs with a fixed population in which one can directly analyze the asymptotic convergence of agent states to a static optimal solution, the continuous arrival and departure of agents in OMASs fundamentally challenge the applicability of classical asymptotic stability and steady-state convergence concepts. Each agent admission or departure simultaneously changes the dimension of the global decision vector, alters the aggregate cost function, and reshapes the communication topology, so that the optimal solution itself drifts over time and a fixed equilibrium to which all agents could globally converge does not generally exist. As a result, the dominant analytical strategy for distributed online decision-making in OMASs is to evaluate the algorithmic performance through a regret minimization framework, in which the cumulative loss incurred by the distributed algorithm is compared with the loss of an appropriate dynamic or static benchmark over a finite horizon. This perspective shifts the analytical focus from achieving exact convergence to bounding the time-averaged optimality gap, and provides a meaningful performance measure even when no globally stable equilibrium can be attained under high dynamism.

To systematically evaluate algorithmic performance under such continuously evolving objective functions and network structures, researchers frequently employ online optimization frameworks. Hayashi (2023) considered a constrained online optimization problem in OMASs, aiming to minimize cumulative local cost functions over a finite-time horizon, formulated as

$$\min_{x \in \mathcal{X}} \sum_{k=0}^{T-1} f_k(x), \tag{7}$$

where agent i has a convex and possibly time-varying local cost function $f_{i,k} : \mathcal{X} \to \mathbb{R}$ at time k with $\mathcal{X} \subset \mathbb{R}^m$ being a convex constraint set, and $f_k(x) = \sum_{i \in \mathcal{V}_k} f_{i,k}(x)$ represents the aggregate cost function of active agents $\mathcal{V}_k$. A distributed consensus-based projected subgradient algorithm was proposed where each agent updates its estimation via

$$x_i(k+1) = \Pi_{\mathcal{X}} \left[\sum_{j \in \mathcal{N}_{i,k}} p_{ij}(k) x_j(k) - s(k) g_{i,k}(x_i(k)) \right], \tag{8}$$

using a time-varying step size $s(k)$, the local subgradient $g_{i,k}$, and edge weights $p_{ij}(k)$ for the communication link $\{j,i\} \in \mathcal{E}_k$. The theoretical evaluation is conducted within a regret minimization framework, where the dynamic regret for agent i is defined as

$$\mathrm{Reg}_i = \sum_{k=t_i^{\mathrm{i}}}^{t_i^{\mathrm{o}}-1} f_k(x_i(k)) - \sum_{k=t_i^{\mathrm{i}}}^{t_i^{\mathrm{o}}-1} f_k(x^*),$$

where t_i^{i} and t_i^{o} are the arriving and departing times of agent i, respectively, satisfying $0 \le t_i^{\mathrm{i}} < t_i^{\mathrm{o}} \le T$, and $x^* \in \mathcal{X}$ is an optimal fixed strategy implying $\sum_{k=0}^{T-1} f_k(x^*) \le \sum_{k=0}^{T-1} f_k(\xi)$ for all $\xi \in \mathcal{X}$. Based on this metric, the proposed method achieves a sublinear regret bound under appropriate step-size rules and assumptions of bounded agent turnover. Additionally, Liu YX et al. (2026c) explored distributed optimization over partially free-in and free-out (FIFO) networks. Table 3 summarizes the key features of the aforementioned literature.

3.2 Distributed separable resource allocation for OMASs

Transitioning from distributed consensus optimization problems, distributed resource allocation emerges as another pivotal class of decision-making problems in OMASs. This paradigm is relevant to practical applications such as energy dispatch and load balancing, where agents must optimize local decisions while satisfying global coupling resource constraints.

A fundamental distributed separable resource allocation problem in an OMAS can be formulated as follows (de Galland et al., 2021, 2024; Vizuete et al., 2022):

$$\min_{x \in \mathbb{R}^{nd}} \sum_{i \in \mathcal{V}} f_i(x_i) \quad \text{s.t.} \sum_{i \in \mathcal{V}} a_i x_i = b, \tag{9}$$

where $a_i > 0$ is the weight of agent i for satisfying the constraint, $x_i \in \mathbb{R}^d$ is the decison of agent i, $x = [x_1^{\mathrm{T}}, \ldots, x_n^{\mathrm{T}}]^{\mathrm{T}}$, n is the number of agents, and $b \in \mathbb{R}^d$ is the budget. The objective is to minimize the sum of local cost functions subject to an equality constraint on the weighted sum of the states $\sum_{i \in \mathcal{V}} a_i x_i = b$. The predominant challenge in OMASs arises from the dynamic entry and exit of agents, which inherently disrupts the global equality constraint. To address this, building on the initial studies of de Galland et al. (2021) and Vizuete et al. (2022), de Galland et al. (2024) proposed a distributed random coordinate descent (RCD) algorithm over undirected graphs for open environments, where agents may be replaced during the process. Rather than relying on network-wide simultaneous updates, the RCD algorithm randomly selects a pair of connected agents (i,j) at each iteration to execute a localized pairwise update:

$$x^+ = x - hQ^{ij} \nabla f(x), \tag{10}$$

where Q^{ij} is a specifically designed projection matrix, and $h \ge 0$ denotes a nonnegative step size. This pairwise mechanism guarantees a monotonic reduction of the global objective while strictly preserving the coupled resource constraint, thereby effectively isolating the update process from the disruptive effects of non-participating agents' replacements. From a time-varying optimization perspective, this research characterizes the expected distance to the minimizer over time. Under the assumption of smooth and strongly convex local functions, the theoretical analysis establishes that the algorithm converges linearly to a steady-state expected error neighborhood, effectively quantifying the trade-off between convergence speed and robustness to agent replacements.

Table 3 Distributed consensus optimization algorithms for OMASs

Reference	Problem	Cost function	Constraint	Topology graph	Method
Hendrickx and Rabbat (2020)	Consensus optimization	Time-invariant, strongly convex, smooth	Unconstrained	Undirected, connected	DGD
Wu et al. (2026)	Consensus optimization	Time-invariant, strongly convex, bounded gradient	Unconstrained	Undirected, connected	Diminishing gradient descent scheme
Dutta and Doan (2025)	Consensus optimization	Time-invariant, smooth, strongly convex	Unconstrained	Client–server architecture with redundancy	Local SGD
Hsieh et al. (2021)	Consensus optimization	Time-invariant, convex, Lipschitz	Set constraint	Undirected, jointly vertex-connected	DAERON
Deplano et al. (2026)	Consensus optimization	Time-varying, convex, semicontinuous	Unconstrained	Undirected, connected	Open ADMM
Makridis et al. (2025)	Consensus optimization	Time-varying, Lipschitz gradient, strongly convex	Unconstrained	Directed, jointly strongly-connected cluster	OPEN-GT
Hayashi (2023)	Consensus optimization	Time-varying, convex	Set constraint	Undirected, time-varying, jointly vertex-connected	Distributed subgradient-based algorithm
Liu YX et al. (2026c)	Consensus optimization	Time-varying, convex, Lipschitz continuous	Set constraint	Undirected, time-varying	GS-DDA, WM-DDA

DGD: decentralized gradient descent; SGD: stochastic gradient descent; DAERON: dual averaging for open network; OPEN-GT: open distributed optimization algorithm with gradient tracking; GS-DDA: gradient storage-based distributed dual averaging; ADMM: alternating direction method of multipliers; WM-DDA: weighting matrix-based distributed dual averaging

To address more intricate scenarios involving time-varying cost functions and local feasible sets, Liu YX et al. (2024) investigated the following distributed online resource allocation problem:

$$\min_{x_1 \in \Omega_1, \ldots, x_T \in \Omega_T} \sum_{t=1}^{T} f_t(x_t) \tag{11a}$$

$$\text{s.t.} \sum_{i \in \mathcal{V}_t} (x_{i,t} - d_{i,t}) = 0,\ \forall t = 1, 2, \ldots, T, \tag{11b}$$

where $x_t \in \mathbb{R}^{|\mathcal{V}_t|}$ is the concatenated column vector of local decisions $x_{i,t}$, $\Omega_t \triangleq \prod_{i \in \mathcal{V}_t} \mathcal{X}_i$ denotes the feasible set, with $\mathcal{X}_i$ being the local constraint set for agent i, $f_t(x_t) \triangleq \sum_{i \in \mathcal{V}_t} f_{i,t}(x_{i,t})$ denotes the global objective function, and $d_{i,t} \in \mathbb{R}$ denotes the local demand of agent i at time t. The constraint (11b) enforces, at each time step t, the balance between the total amount of resources allocated by active agents and the total demand within the active agent set $\mathcal{V}_t$. Because the cardinality $|\mathcal{V}_t|$ varies over time, both the dimension of x_t and the aggregate demand $\sum_{i \in \mathcal{V}_t} d_{i,t}$ are time-dependent, thereby reflecting the openness of the resource allocation problem. To handle the inherent openness of the network, where agents are allowed to join and leave freely, Liu YX et al. (2024) proposed a gradient storage-based saddle point dynamics (GS-SPD) algorithm. Agents update their decision variables via a projected gradient method and dual variables via dual averaging. This primal-dual method uses auxiliary variables to store the sum of gradients and record the number of stored gradients for each agent. Convergence analysis is conducted by quantifying the dynamic regret $\mathrm{Reg}^{\mathrm{d}}(T)$ regarding the optimal sequence $\{x_t^*\}_{t=1,2,\ldots,T}$ and the accumulation of constraint violation $\mathrm{CV}(T)$, defined as

$$\mathrm{Reg}^{\mathrm{d}}(T) = \sum_{t=1}^{T} \left(f_t(x_t) - f_t(x_t^*)\right),$$

$$\mathrm{CV}(T) = \left\| \sum_{t=1}^{T} \sum_{i \in \mathcal{V}_t} (x_{i,t} - d_{i,t}) \right\|.$$

It is demonstrated that both the dynamic regret and the accumulation of constraint violation increase sublinearly, provided that the number of departing agents at each iteration does not exceed the connectivity degree of the communication graph.

Furthermore, Sawamura et al. (2025) investigated distributed constrained convex optimization problems over directed communication graphs. In this setting, active agents collaboratively solve an online optimization problem aimed at minimizing the cumulative cost subject to a cumulative constraint over the horizon $\mathcal{K} = \{0, 1, \ldots, T\}$:

$$\min \sum_{t \in \mathcal{K}} F_t(x(t)) \quad \text{s.t.} \sum_{t \in \mathcal{K}} G_t(x(t)) \le 0, \tag{12}$$

where $x_i(t) \in \mathcal{X}_i$ denotes the decision variable of active agent i, $x(t) \in \mathcal{X}(t)$ is the stacked vector of $\{x_i(t)\}_{i \in \mathcal{N}(t)}$, and $\mathcal{X}(t) = \prod_{i \in \mathcal{N}(t)} \mathcal{X}_i \subset \mathbb{R}^{n(t)}$ with $n(t) = \sum_{i \in \mathcal{N}(t)} n_i$. The aggregate cost function $F_t(x(t)) = \sum_{i \in \mathcal{N}(t)} f_{i,t}(x_i(t))$ and the global inequality constraint $G_t(x(t)) = \sum_{i \in \mathcal{N}(t)} g_{i,t}(x_i(t))$ are composed of the local convex cost functions $f_{i,t} : \mathcal{X}_i \to \mathbb{R}$ and constraint functions $g_{i,t} : \mathcal{X}_i \to \mathbb{R}^m$ of each active agent i at time $t \in \mathcal{K}$. To this end, Sawamura et al. (2025) introduced a consensus-based distributed primal-dual push-sum algorithm that allows agents to estimate the dual variables associated with the coupled constraints. Rigorous theoretical analysis establishes sublinear upper bounds for both dynamic regret and cumulative constraint violation, validating the ability of the algorithm to achieve cost optimality and constraint satisfaction within time-varying and directed open networks. The above discussions are summarized in Table 4.

Overall, the algorithmic frameworks reviewed in Sections 3.1 and 3.2 can be compared from a methodological perspective. Gradient-tracking and DGD-type methods are suitable for unconstrained or lightly constrained problems, where openness induces mainly gradient information loss and dimensional variations of the decision space. Primal-dual and dual averaging methods suit problems with coupled equality or inequality constraints, since the dual variables can compensate for constraint perturbations caused by agent turnover. ADMM-type methods, exemplified by the open ADMM scheme, are preferred for separable composite structures, while gossip-based and pairwise-update schemes are more appropriate under asynchronous communication and frequent agent replacements. In particular, under high agent churn, gossip-based schemes are generally more tolerant of frequent turnover because their asynchronous and pairwise local-update structure does not require global synchronization, whereas gradient tracking, primal-dual, and ADMM schemes typically rely on bounded-turnover conditions to retain their convergence or sublinear regret guarantees and are therefore more sensitive to high churn rates.

3.3 Distributed NE seeking for non-cooperative games of OMASs

A typical non-cooperative game with a fixed number of agents can be formulated as

$$\min_{x_i\in\mathbb{R}^n} f_i(x_i, x_{-i}),\quad \forall i\in\mathcal{V}, \tag{13}$$

where $\mathcal{V}=\{1,2,\ldots,N\}$ denotes the set of agents. For each agent i, $x_i\in\mathbb{R}^n$ represents its decision variable (action), and $x_{-i}=[x_1^{\mathrm{T}},\ldots,x_{i-1}^{\mathrm{T}},x_{i+1}^{\mathrm{T}},\ldots,x_N^{\mathrm{T}}]^{\mathrm{T}}$ denotes the action profile of all other players. The function $f_i(x_i,x_{-i})$ is the cost function of agent i, which seeks to minimize its own cost in a self-interested manner. An action profile $x^*=(x_i^*,x_{-i}^*)$ is called an NE if it satisfies

$$f_i(x_i^*, x_{-i}^*)\le f_i(x_i, x_{-i}^*),\ \forall i\in\mathcal{V},\ \forall x_i\in\mathbb{R}^n. \tag{14}$$

Since no agent can reduce its cost through unilateral action at the NE, it serves as a critical solution concept for reconciling the conflicting interest of individual agents. Motivated by this, researchers have developed various distributed NE seeking algorithms (Wen et al., 2025).

According to (13), any variation in the number of agents changes the dimensionality of the global decision variable $x=(x_i,x_{-i})$ and structurally alters the cost functions. Consequently, solving the NE seeking problem in OMASs presents significant challenges. To date, only a few studies have conducted preliminary investigations into non-cooperative games in such dynamic environments. Table 5 presents representative studies on non-cooperative games of OMASs.

Specifically, Chen et al. (2025) studied the NE seeking problem in non-cooperative games with a time-varying number of agents. In this work, the cost functions remained fixed while agents were active. By imposing constraints on the frequency of agent arrivals and departures, the authors ensured that the overall system eventually converged to the NE. In Xu et al. (2025), an incremental consensus-based distributed algorithm was developed for dynamic NE seeking in constrained non-cooperative games over OMASs. The proposed algorithm guarantees that agents can rapidly converge to a new NE whenever the system scale changes. In Liu YX et al. (2026b), a status estimation mechanism was introduced to accommodate the dynamic entry and exit of agents, enabling finite-time identification of their active or inactive status. It was demonstrated that, under strongly connected communication topologies, the actions of the agents converged linearly to a small neighborhood of the new NE whenever the player set changed.

Liu YX et al. (2025) investigated a specific class of non-cooperative games in OMASs, known as aggregative games. The mathematical formulation was given by

$$\min_{x_{i,t}\in\mathcal{X}_i} f_i(x_{i,t},\hat{v}_t),\quad t\in[t_i^{\mathrm{in}},t_i^{\mathrm{out}}], \tag{15}$$

where $x_{i,t}$ is the action of agent i at time t, $\mathcal{X}_i$ is the action set, $\hat{v}_t=x_{i,t}+\sum_{j\in\mathcal{V}_t,j\neq i}x_{j,t}$ with $\mathcal{V}_t$ being the set of active agents, and $[t_i^{\mathrm{in}},t_i^{\mathrm{out}}]$ is the active time interval of agent i. A distributed strategy for aggregative games within FIFO networks was developed in Liu YX et al. (2025). To evaluate the performance of the proposed strategy, the following static regret metric was introduced:

$$\mathcal{R}_i^s=\sum_{t=t_i^{\mathrm{in}}}^{t_i^{\mathrm{out}}}\left(f_i(x_{i,t},\hat{v}_t)-f_i\left(x_i^*,x_i^*+\sum_{j\in\mathcal{V}_t,j\neq i}x_{j,t}\right)\right), \tag{16}$$

where $x_i^*\in\arg\min_{x_i\in\mathcal{X}_i}\sum_{t=t_i^{\mathrm{in}}}^{t_i^{\mathrm{out}}}f_i(x_i,x_i+\sum_{j\in\mathcal{V}_t,j\neq i}x_{j,t})$. Through algorithm design and analysis, it was ultimately proved that

$$\mathcal{R}_i^s\le\left(K^2D_i+\frac{\left\|x_i^*-x_i^0\right\|^2}{2D_i}\right)\sqrt{2M+1}\sqrt{T_i}, \tag{17}$$

where $K, D_i>0$ are constants, M is a pre-designed parameter, and $T_i=t_i^{\mathrm{out}}-t_i^{\mathrm{in}}+1$.

Liu WT et al. (2026) developed an online best-response algorithm for non-cooperative games with a time-varying set of agents, allowing for autonomous entry and exit. In this study, the index set of active agents at time step k was denoted by $\mathcal{A}_k=\{i|k_i^{\mathrm{in}}\le k, k_i^{\mathrm{out}}>k\}$ with k_i^{in} and k_i^{out} being the time instants when player i joined and left the system, respectively. At each time step, the remaining agents updated their strategies $s_{i,k+1}$ using the following algorithm:

$$s_{i,k+1}=\mathrm{argmin}_{s_i\in S_i}J_{i,k}(s_i,s_{-i,k}), \tag{18}$$

where $J_{i,k}(s_i,s_{-i,k})$ is the time-varying cost function of agent i. The following adaptive dynamic regret of agent i during the interval was defined as a metric for algorithm performance:

$$\begin{aligned}\mathrm{Reg}_i^{\mathrm{d}}&=\sum_{k=k_i^{\mathrm{in}}}^{k_i^{\mathrm{out}}-1}J_{i,k}(s_{i,k},s_{-i,k})\\&\quad-\sum_{k=k_i^{\mathrm{in}}}^{k_i^{\mathrm{out}}-1}\min_{s'_{i,k}\in\mathcal{S}_i}J_{i,k}(s'_{i,k},s_{-i,k}).\end{aligned} \tag{19}$$

The upper bound of adaptive dynamic regret was established, thereby verifying the no-regret characteristic of the algorithm.

Table 4 Distributed optimization algorithms for resource allocation in OMASs

Reference	Problem	Cost function	Constraint	Topology graph	Method
de Galland et al. (2021)	SRA	Time-invariant, strongly convex, smooth	Equality constraint (homogeneous)	Undirected, fully connected	RCD algorithm
Vizuete et al. (2022)	SRA	Time-invariant, strongly convex, smooth	Equality constraint (homogeneous)	Undirected, complete	Distributed RCD algorithm with online optimization analysis
de Galland et al. (2024)	SRA	Time-invariant, strongly convex, smooth	Equality constraint (heterogeneous)	Undirected, connected	Distributed RCD algorithm
Liu YX et al. (2024)	SRA	Time-varying, convex, Lipschitz continuous	Set constraint, equality constraint (homogeneous)	Undirected, vertex-connected	GS-SPD
Sawamura et al. (2025)	SRA	Time-varying, convex	Set constraint, global inequality constraint	Directed, strongly connected	Distributed primal-dual push-sum algorithm

SRA: separable resource allocation; RCD: random coordinate descent; GS-SPD: gradient storage-based saddle point dynamics

Table 5 Distributed NE seeking algorithms for OMASs

Reference	Problem	Cost function	Constraint	Topology graph	Method
Liu YX et al. (2026b)	Non-cooperative game	Convex, continuously differentiable, strongly monotone, smooth	Set constraint	(Jointly) strongly connected	TPGP
Xu et al. (2025)	Non-cooperative game	Twice continuously differentiable, convex	Equality constraint	Undirected, connected	ICBD algorithm
Chen et al. (2025)	Non-cooperative game under DoS attacks	Convex, Lipschitz continuous, strongly monotone	Unconstrained	Undirected, connected (switched)	Adaptive NE seeking strategy
Liu YX et al. (2025)	Aggregative game	Convex, continuously differentiable	Set constraint	Directed, vertex-connected	DSAGF
Liu WT et al. (2026)	Non-cooperative game	Time-varying, convex, continuously differentiable, Lipschitz continuous, smooth, strongly monotone	Set constraint		Online best-response algorithm

DoS: denial-of-service; TPGP: three-part gradient play; ICBD: incremental consensus-based distributed; NE: Nash equilibrium; DSAGF: distributed strategy for aggregative games in FIFO networks

Additionally, the stability of the open game system was rigorously proven. The analysis in Liu WT et al. (2026) revealed that the stability radius was determined by the fluctuation of the equilibrium trajectory and the relative proportions of entering and exiting agents compared to the total active agents.

Across the three previous subsections, distributed consensus optimization, separable resource allocation, and NE seeking in non-cooperative games differ substantially in their types of inter-agent coupling, manifestation of openness, and dominant algorithmic families. In consensus optimization, agents are coupled through a consensus constraint on a common decision vector. Openness induces mainly gradient information loss and dimensional variations of the decision space. Current algorithms include gradient-tracking and DGD-type methods for unconstrained problems, primal-dual and dual averaging methods for problems with set constraints, ADMM-type methods for composite or time-varying objectives, and gossip-based schemes for asynchronous and high-churn scenarios. In separable resource allocation, agents are coupled through a global equality or inequality constraint on resources, so that openness simultaneously perturbs the decision dimension and the global resource constraint, and the dominant algorithms are primal-dual based, such as random coordinate descent and gradient-storage saddle-point dynamics, which exploit the dual variable to compensate for the constraint perturbations induced by agent turnover. In NE seeking, the coupling is non-cooperative through the payoff dependence of each agent on the actions of other agents, openness affects both the dimension of the joint action profile and the structural form of the payoff function of each agent, and the dominant algorithms focus on tracking the time-varying NE, including finite-time status estimation, incremental consensus-based dynamic NE seeking, and online best-response algorithms equipped with active-time regret analyses. Therefore, although the three directions share the common challenge of time-varying decision spaces under agent turnover, they differ substantially in the type of coupling they enforce, the optimality concept they target, and the algorithmic mechanisms they use to cope with the openness of OMASs.

4 Future perspectives

Although several distributed control, optimization, and game algorithms applicable to OMASs have been reviewed herein, several open challenges remain in this domain. Future research on OMASs is expected to evolve across the following five key dimensions:

1. Control architectures for high-order nonlinear dynamics. Current control strategies for OMASs predominantly rely on linear or low-order simplified models. However, in open environments, the stochastic arrival and departure of agents cause abrupt topological and dimensional shifts. These structural jumps interact intricately with high-order nonlinearities (e.g., chaotic transients, bifurcations, or non-Lipschitz behaviors), severely compromising the system's fragile invariant sets and stability manifolds. To address this, future research should establish unified stability criteria that couple dimension-varying topologies with nonlinear dynamic constraints. Leveraging tools like Koopman operators or transient control barrier functions will be crucial to safely bound the highly complex transitional dynamics. In particular, Koopman-operator-based representations may lift heterogeneous nonlinear dynamics into a common, possibly infinite-dimensional space of observables, in which the entry or exit of an agent corresponds to the activation or deactivation of a subset of observables rather than a change in the underlying state-space dimension. This perspective offers a promising route to derive consistent linear surrogates and stability certificates across dimension jumps. Moreover, transient control barrier functions tailored to OMASs need to be redesigned so that the forward invariance of safety sets can be preserved through agent admission and departure events, for example, by adapting the barrier parameters to the instantaneous network size and switching frequency.

2. Resilient control of OMASs under attacks. In cyber-physical environments, OMASs are inherently vulnerable to severe security threats, including stealthy false data injection (FDI) attacks and denial-of-service (DoS) attacks. A fundamental challenge arises when adversaries exploit the PnP mechanisms of the open framework, deliberately camouflaging malicious data injections or compromised agent entries within the transient dynamic noise generated by benign dimensional fluctuations. Moreover, the arrival of new agents often requires information exchange with existing agents, such as state estimates, neighbor information, local objectives, and topology-related data, which may expose sensitive system information in the absence of privacy-preserving mechanisms. To address this, future research should prioritize developing dimension-adaptive, resilient, and privacy-preserving mechanisms that dynamically integrate attack detection, privacy protection, and time-varying topologies, thereby ensuring reliable system operation despite simultaneous structural transitions and adversarial perturbations.

3. Distributed online optimization and game algorithms with provable performance guarantees. Current research on decision-making for OMASs primarily focuses on basic stability or sublinear regret. However, existing online optimization and game frameworks typically rely on sublinear growth of the equilibrium's path length and impose restrictive constraints on the frequency of agent turnover. Such assumptions are often violated in highly dynamic OMASs where agent population and objective functions fluctuate drastically, leading to discrete structural jumps. To address these challenges, future work should prioritize developing algorithms with explicit, non-asymptotic performance guarantees that remain robust under rapidly shifting network dimensions and high-magnitude variations in objective landscapes. Beyond traditional regret, it is crucial to establish adaptive and dynamic regret bounds that can decouple the impact of environmental non-stationarity from agent-induced structural changes. Furthermore, for open non-cooperative games, quantifying transient convergence rates and recovery time following membership updates is essential. This involves characterizing how time-varying network topologies and the loss of historical information during agent departure disrupt the stability of NE. Ultimately, providing provable metrics that accommodate non-smooth equilibrium trajectories is fundamental to ensuring the reliability of autonomous systems in unpredictable, open-world environments.

4. Distributed embodied online decision-making frameworks. To bridge the gap between high-level algorithmic planning and low-level physical execution, the development of embodied online decision-making frameworks represents a critical frontier. Future research should prioritize the integration of closed-loop optimization-control paradigms and unified game-control mechanisms. Such frameworks must simultaneously address fluctuations in system dimension resulting from agent arrivals and departures while satisfying the strict physical constraints of the underlying dynamics. By incorporating techniques like MPC or control barrier functions, high-level collaborative solutions can be mapped onto safe, reliable control inputs, ensuring seamless coordination and robust real-time responses in highly dynamic and open environments. Beyond this layered integration, a further open question is how to embed agent set variation directly into the prediction horizon and the safety filter of the underlying controller. Distributed online MPC formulations, in which each agent rolls out a finite-horizon prediction conditioned on its instantaneous neighborhood, can in principle absorb agent admissions and departures by reassembling the local prediction graph at each step. Coupling such schemes with adaptive control barrier functions whose parameters react to the instantaneous network size and switching frequency offers a concrete route toward provably safe and physically realizable embodied coordination of OMASs.

5. Data-driven distributed intelligent decision-making in dynamic environments. In OMASs where precise models are unavailable and system dynamics is highly uncertain, data-driven approaches offer a promising alternative to conventional model-based methods. Most existing OMAS control and decision-making methods are not directly compatible with mainstream multi-agent reinforcement learning (MARL) frameworks (Yang et al., 2025). Conventional MARL paradigms, such as centralized-training-decentralized-execution with parameter sharing, typically assume a fixed number of agents and a stationary underlying Markov decision process, whereas agent arrivals and departures in OMASs induce time-varying joint state–action dimensions and render the transition kernel non-stationary from the local perspective of each surviving agent, breaking the standard convergence and policy improvement arguments. Moreover, prevailing OMAS analysis tools such as dwell-time conditions and average Lyapunov functions are tightly coupled with

explicit dynamical models and are difficult to embed into MARL updates, motivating the development of dimension-adaptive policy architectures consistent with the dynamic agent set. Additionally, agent churn poses non-trivial challenges to the off-policy components of MARL. Replay buffers store transitions collected under specific joint observations, action dimensions, and neighbor configurations, so that when the agent set changes, the buffered experience corresponds to a different joint policy and effective game, leading to systematic distributional mismatch with the current environment. Future research can therefore investigate openness-aware replay mechanisms, such as dimension-conditioned importance reweighting, lifetime-based experience tagging, and population-stationary policy regularizers, to maintain policy consistency under high agent churn. Furthermore, the use of graph neural networks (GNNs) as topology-aware encoders in OMASs faces the issue of embedding drift caused by fluctuating node sets. Since standard message-passing GNNs aggregate neighbor information through permutation-invariant operations whose normalization and aggregation statistics depend on the node count and degree distribution, agent arrivals or departures abruptly change the aggregation neighborhoods of nearby agents and cause the learned embeddings to shift even for agents whose intrinsic states have not changed, degrading the downstream control or decision policy. Ensuring that GNN-based OMAS controllers remain stable and transferable across different population sizes and agent turnover regimes constitutes an important open challenge for data-driven coordination of OMASs.

5 Conclusions

This paper has provided a brief yet systematic overview of recent advances in distributed control and decision-making algorithms for OMASs. Unlike conventional closed systems, OMASs are characterized by dynamic agent arrival and departure, time-varying topologies, and environmental openness, making them widely applicable to dynamic practical scenarios. To this end, this review primarily focuses on consensus control as the cornerstone of distributed control, alongside two core decision-making paradigms, namely distributed optimization and NE seeking in non-cooperative games. Finally, we discuss several promising future research directions aimed at addressing current theoretical and practical challenges in the field.

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Author contributions

Guanghui WEN conceptualized and designed the review, and supervised the overall project. Meng LUAN, Xiao FANG, and Xiaodong LI conducted literature retrieval, and organized and synthesized the related works. All the authors drafted, revised, and finalized the paper.

Conflict of interest

Guanghui WEN is a Deputy Director of the Junior Editorial Board of *ENGINEERING Information Technology* & *Electronic Engineering*, and he was not involved with the peer review process of this paper. All the authors declare that they have no conflict of interest.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used DeepSeek to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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