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

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

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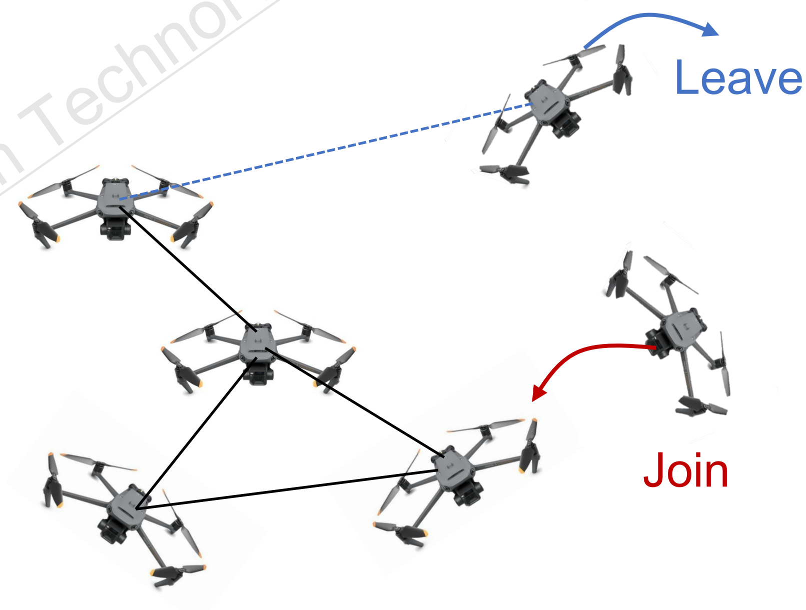
Motivation

- Traditional closed systems with a fixed number of agents struggle to adapt to the dynamic openness of the real world. In contrast, open multi-agent systems (OMASs) allow agents to join and leave, driving high-level intelligence and robust collaboration in complex cyber-physical systems through local information interactions.

Closed MAS



Open MAS

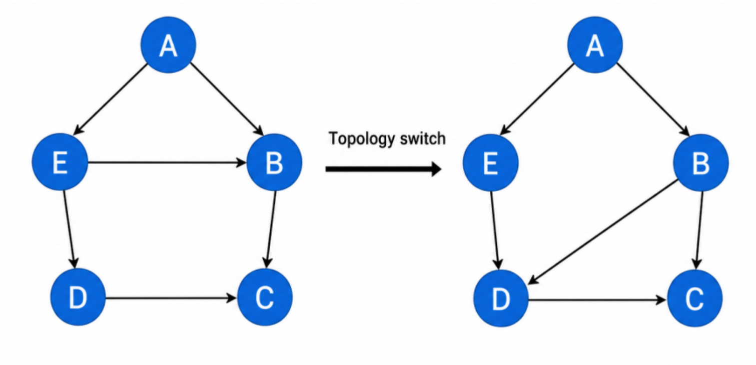
Challenges

- The dynamic joining and departure of agents cause frequent changes in system topology, undermining the stability of existing consensus algorithms.
- Within distributed decision-making frameworks, agent plug-and-play behaviors perturb the objective function structures and decision variable dimensions, thereby causing optimal or equilibrium solutions to shift.

Impact factor	Closed MAS	Open MAS	Challenges
Agent membership	Fixed	Time-varying	Non-convergence due to frequent topology switching
Decision space dimension	Constant	Dynamic dimensional fluctuation	Curse of dimensionality & mapping inconsistency
Objective function	Fixed form	Structure evolves via membership	Computational difficulty in tracking moving optima

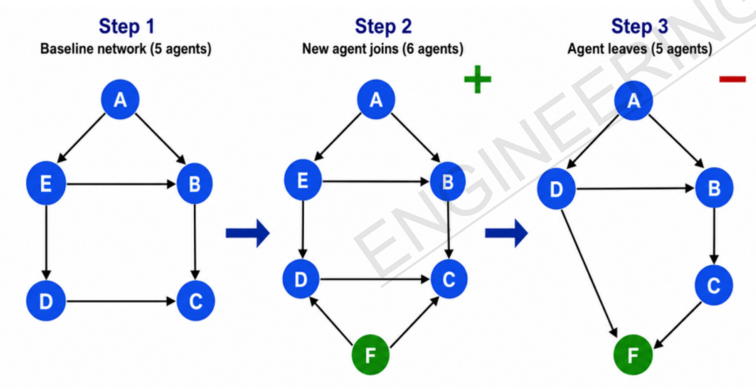
1) OMAS modeling & fundamentals

Closed MAS



Fixed agent set, varying topology

OMAS



Agent joining or leaving causes dimension change

☐ Dynamic modeling [1]

1. statistical/probabilistic modeling
2. variable-dimensional modeling
3. topology/neighborhood-based modeling

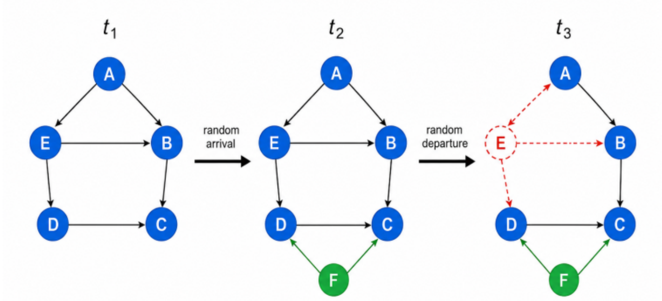
☐ Consensus concept [2]

1. quasi-consensus
2. expected mean-squared error
3. average-preserving consensus
4. non-disruptive consensus

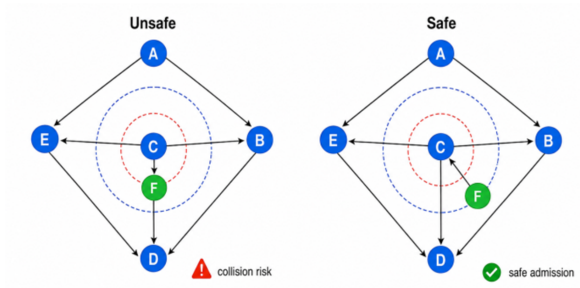
☐ Stability concepts [3]

1. dwell-time methods
2. multiple Lyapunov functions
3. robustness and invariance

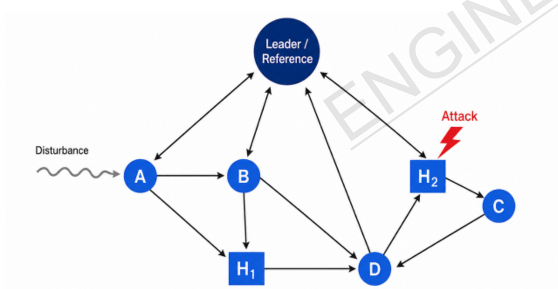
2) Distributed control for OMASs



Random joining/leaving events change network size unpredictably.



Safe admission requires collision avoidance and connectivity preservation.



Coordinated tracking under heterogeneity, disturbance, and attacks

☐ Random arrivals and departures [4]

1. randomized gossip algorithms
2. saturated impulsive control
3. relay tracking control

☐ Safety constraints [5]

1. BLF-embedded control

☐ Heterogeneous dynamics, disturbances, and attacks [2]

1. fuzzy cooperative control
2. distributed adaptive control
3. resilient control and observers
4. E-MSR filtering

3) Distributed consensus optimization for OMASs

- Distributed consensus optimization aims to cooperatively minimize the sum of local objective functions through local information exchange while achieving a common decision among all agents.
- Challenges in OMASs: time-varying global objective, gradient loss and dimension variation, consensus tracking of a drifting optimizer.

Representative methods

Ref.	Cost function	Constraint	Topology graph	Method
[6]	Time-varying, convex	Unconstrained	Undirected, connected	Open ADMM
[7]	Time-varying, convex	Set constraint	Undirected, time-varying,	Distributed subgradient-based algorithm
[8]	Time-varying, convex, Lipschitz continuous	Set constraint	Undirected, time-varying	GS-DDA, WM-DDA

ADMM: alternating direction method of multipliers; GS-DDA: gradient storage-based distributed dual averaging; WM-DDA: weighting matrix-based distributed dual averaging

4) Distributed resource allocation for OMASs

- Distributed resource allocation aims to optimize local decisions through distributed coordination while satisfying global coupling constraints on shared resources.
- Challenges in OMASs: dynamic coupling constraints, feasibility disruption under agent turnover, online recovery of resource balance and optimality.

Representative methods

Ref.	Cost function	Constraint	Topology graph	Method
[9]	Time-invariant, strongly convex, smooth	Equality constraint	Undirected, connected	Distributed RCD algorithm
[10]	Time-varying, convex, Lipschitz continuous	Set constraint, equality constraint	Undirected, vertex-connected	GS-SPD
[11]	Time-varying, convex	Set constraint, inequality constraint	Directed, strongly connected	Distributed primal-dual push-sum algorithm

RCD: random coordinate descent; GS-SPD: gradient storage-based saddle point dynamics

5) NE seeking of non-cooperative games

- In non-cooperative games, the objective function of each agent depends on the decisions of other players, and each individual solely aims to minimize its own cost.
- 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.

Representative methods

Ref.	Cost function	Constraint	Topology graph	Method
[12]	Convex, continuously differentiable, strongly monotone, smooth	Set constraint	(Jointly) strongly connected	Three-part gradient play
[13]	Twice continuously differentiable, convex	Equality constraint	Undirected, connected	Incremental consensus-based distributed algorithm
[14]	Time-varying, convex, continuously differentiable, Lipschitz continuous, smooth, strongly monotone	Set constraint	_	Online best-response algorithm

Future research

Direction	Outlook
High-order nonlinear control	• Unified stability analysis for dimension-varying nonlinear systems • Koopman operator-based representations for heterogeneous dynamics • Transient control barrier functions tailored to OMASs
Resilient & secure control	• Resilient control under FDI and DoS attacks • Privacy-preserving information exchange during plug-and-play operations • Joint attack detection and topology adaptation
Online optimization & game theory	• Algorithms with provable non-asymptotic guarantees • Adaptive/Dynamic regret analysis under agent turnover • Fast recovery and transient performance after topology changes
Embodied online decision-making	• Integration of optimization and control • Distributed MPC with dynamic agent sets • Safe real-time decision-making
Data-driven intelligent OMASs	• Dimension-adaptive MARL for dynamic populations • Openness-aware replay mechanisms • Stable GNN-based distributed decision-making

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Biography

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