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Adaptive Controllable Emergence in Multi-Task Air and Space Defense Systems: A Framework for Mission Reconfiguration, Resilient Coordination, Intelligent Decision-Making, and Dynamic Resource Allocation

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ABSTRACT

Emergent collective intelligence provides an important theoretical and computational perspective for understanding how locally interacting agents can generate coordinated global behaviors that cannot be explained by the behavior of individual agents alone. In large-scale air and space defense systems, this property is particularly relevant because heterogeneous sensing, decision-making, communication, and execution resources must operate under dynamic environments, incomplete information, changing mission requirements, limited resources, and potentially degraded communication conditions. However, conventional controllable-emergence models generally assume relatively stable task structures and predefined interaction rules, which limits their adaptability when multiple tasks arrive concurrently or when the network topology and available resources change over time.This study proposes an Adaptive Controllable Emergence (ACE) framework for multi-task air and space defense systems. The proposed framework extends graph-based multi-agent modeling and multi-agent reinforcement learning by introducing four coupled mechanisms: dynamic mission reconfiguration, resilient coordination, intelligent distributed decision-making, and dynamic resource allocation. The system is represented as a time-varying interaction graph in which sensing, decision, and execution agents dynamically modify their relationships according to mission requirements and resource availability. A decentralized partially observable Markov decision process is employed to formulate local decision-making under incomplete information. A multi-objective reward function jointly considers mission completion, coordination quality, resource utilization, network resilience, adaptation cost, and decision latency. Furthermore, a mission-reconfiguration mechanism is introduced to enable the system to modify task-agent assignments when the task set, network topology, or resource state changes. The resulting framework transforms controllable emergence from a static rule-design problem into an adaptive optimization process in which microscopic policies continuously modify macroscopic system behavior. The proposed mathematical formulation provides a basis for analyzing emergence quality, adaptation speed, coordination robustness, resource efficiency, and convergence. A simulation framework is also developed for evaluating the proposed architecture under static, dynamic, multi-task, and communication-degradation scenarios. The framework is intended as a general computational model for studying adaptive coordination in large-scale multi-agent systems rather than as a platform-specific operational defense procedure.

1. INTRODUCTION

Emergence describes a class of phenomena in which interactions among relatively simple components generate collective properties at a higher level of organization. In complex systems, the global behavior of a system cannot necessarily be obtained by simply adding the properties of its individual components. Instead, interactions, feedback, network topology, adaptation, and environmental changes jointly determine the resulting macroscopic behavior [1].

This concept has become increasingly important in multi-agent systems. A collection of autonomous agents may follow local rules while collectively producing coordinated behavior such as distributed exploration, formation, task allocation, consensus, or adaptive resource utilization. Research on multi-agent reinforcement learning has further demonstrated that agents can learn cooperative policies from local observations while optimizing a shared objective [2]. Modern MARL research explicitly addresses the difficulty created by large joint observation and action spaces, partial observability, and the non-stationarity introduced by simultaneously learning agents [3].

Large-scale air and space defense systems provide a representative complex-system environment for investigating controllable emergence. Such systems can be abstracted into heterogeneous sensing, decision, communication, and execution resources [4]. The system must continuously transform distributed information into coordinated system-level responses while coping with changes in the environment, mission priorities, communication conditions, and resource availability [5].

The original controllable-emergence paradigm generally assumes that the rules governing individual agents and their interactions can be specified in advance. Under a fixed task structure, this assumption can provide an effective abstraction. However, it becomes increasingly restrictive when several tasks coexist and their priorities change over time. A system that is optimal for one task configuration may become inefficient when new tasks arrive, resources become unavailable, or the interaction network changes [6].

Consequently, four additional capabilities are required.

First, the system needs **mission reconfiguration**. The allocation of agents to tasks should not remain fixed throughout the mission. Instead, the task-agent relationship should be dynamically reconstructed according to the current task set and system state [7].

Second, the system requires **resilient coordination**. The interaction network should remain functional when communication links become temporarily unavailable or when some agents cannot participate. Communication-based MARL research emphasizes that communication mechanisms can improve coordination by expanding agents' effective information and supporting collaboration under decentralized decision-making [8].

Third, the system requires **intelligent decision-making**. Fixed rules cannot adequately represent every possible combination of task, environment, resource, and network states. MARL provides a natural framework in which agents learn policies from interactions with an environment. Modern treatments of MARL cover decentralized policies, cooperative learning, game-theoretic interaction, and the computational challenges associated with multi-agent decision-making [9].

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Fourth, **dynamic resource allocation** must be incorporated. When multiple tasks compete for limited sensing, communication, computational, or execution resources, the system should allocate resources according to current mission requirements rather than relying on static assignment [10].

Based on these considerations, this study develops an adaptive controllable-emergence framework that integrates the four mechanisms into a unified graph-based multi-agent architecture.

The main contributions are as follows:

1. A time-varying graph model is developed to represent heterogeneous multi-agent interactions.
2. A dynamic mission-reconfiguration mechanism is introduced to modify task-agent relationships according to system conditions.
3. A resilient coordination mechanism is formulated for maintaining functional cooperation under changing communication topology.
4. A multi-objective MARL formulation is developed for intelligent distributed decision-making.
5. Dynamic resource allocation is incorporated directly into the emergence objective.
6. A quantitative evaluation framework is proposed for measuring emergence quality, adaptation speed, coordination robustness, resource utilization, and convergence.

The central hypothesis is that **controllable emergence should be treated as an adaptive system-level optimization problem rather than as a fixed rule-design problem**.

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2. System Architecture and Problem Formulation

2.1 Multi-Agent System Representation

Let the multi-agent system at time t be represented by a time-varying graph

$$G(t) = (V, E(t)),$$

Where

$$V = V_S \cup V_D \cup V_J$$

represents the set of heterogeneous agents.

Here:

- V_S: sensing agents;
- V_D: decision agents;

- V_J: execution agents.

The interaction relationship between agents is represented by the edge set $E(t)$. Unlike a static graph, $E(t)$ changes according to communication conditions, mission requirements, resource availability, and agent states.

Each agent has a local state

$$s_i(t) \in S_i,$$

and the global system state is

$$S(t) = [s_1(t), s_2(t), \dots, s_N(t)].$$

The state may include abstract variables such as:

$$s_i(t) = [x_i(t), r_i(t), c_i(t), m_i(t), b_i(t)],$$

where denotes the agent's system state, its available resource capacity, its communication status, its current mission assignment, and its operational status.

This representation intentionally remains platform-independent and describes the computational structure rather than a specific operational system.

2.2 Three-Layer Agent Architecture

The proposed architecture retains the three-layer structure of the original model.

2.2.1 Sensing Layer

A sensing agent observes environmental information and generates an observation:

$$o_i^S(t) = h_i(S(t), E(t)) + \epsilon_i(t),$$

where $h_i(\cdot)$ is the observation function and $\epsilon_i(t)$ represents observation uncertainty.

The sensing layer provides information to decision agents through available communication links [11].

2.2.2 Decision Layer

Decision agents integrate local observations and information received from neighboring agents:

$$o_i^D(t) = \mathcal{O}_i \left(s_i(t), \{ s_j(t) : j \in N_i(t) \} \right).$$

The decision agent selects an action according to policy

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$$a_i(t) \sim \pi_{\theta_i}(a_i|o_i(t)).$$

2.2.3 Execution Layer

Execution agents receive abstract task assignments and update their states according to the assigned task:

$$s_i(t+1) = F_i(s_i(t), a_i(t), \omega_i(t)),$$

where $\omega_i(t)$ represents environmental uncertainty.

2.3 Dynamic Interaction Graph

The original model assumes that connections can be constructed using local rules. We extend this concept by introducing a dynamic connectivity score.

For two agents i and j, define

$$\Gamma_{ij}(t) = w_1 C_{ij}(t) + w_2 R_{ij}(t) + w_3 M_{ij}(t) + w_4 Q_{ij}(t),$$

where:

- C_{ij}: communication compatibility;
- R_{ij}: resource compatibility;
- M_{ij}: mission relevance;
- Q_{ij}: estimated coordination quality.

An edge is retained when

$$\Gamma_{ij}(t) \geq \tau_E.$$

Thus,

$$E(t) = \{(i,j) : \Gamma_{ij}(t) \geq \tau_E\}.$$

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This modification is fundamental because the network itself becomes adaptive.

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3. Mathematical Model of Controllable Emergence

3.1 Individual State Transition

For each agent i, define

$$S_i(t+1) = f_i\left(S_i(t), I_i(t), a_i(t)\right),$$

Where $I_i(t)$ is the information received from neighboring agents.

The complete system evolves according to

$$S(t+1) = F(S(t), A(t), G(t), \Omega(t)),$$

where $A(t)$ represents the joint action and $\Omega(t)$ represents environmental conditions.

The emergence process is therefore

$$S(0) \to S(1) \to \cdots \to S(T).$$

The macroscopic system behavior is a function

$$Y(t) = \Phi(S(t), G(t)).$$

The objective is not merely to optimize individual actions but to construct local policies such that

$$Y(t) \to Y^*,$$

Where **Y*** represents a desirable system-level state.

4. Multi-Task Mission Model

4.1 Task Set

At time **t** , let the set of active tasks be

$$\mathcal{M}(t) = \{M_1, M_2, \dots, M_K(t)\}.$$

Each task is represented by

$$M_k = (\rho_k, \delta_k, \kappa_k, \sigma_k),$$

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where:

- ρ_k: task priority;
- δ_k: temporal requirement;
- κ_k: required resource profile;
- σ_k: current task status.

The number of tasks is time-varying:

$$K(t) \neq K(t + \Delta t).$$

This is the first major extension over the original static model.

4.2 Mission Reconfiguration

Let

$$Z(t) = [z_{ik}(t)]$$

be the task-agent assignment matrix, where

$$z_{ik}(t) = \begin{cases} 1, & \text{agent } i \text{ is assigned to task } k, \\ 0, & \text{otherwise.} \end{cases}$$

The assignment is constrained by

$$\sum_k z_{ik}(t) \leq C_i,$$

where C_i represents the maximum concurrent task capacity of agent i.

A task must also receive sufficient collective resources:

$$\sum_i z_{ik}(t) r_i(t) \geq R_k^{req}(t).$$

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The mission-reconfiguration objective is

$$\min_{Z}\left[\lambda_1 C_{\text{reconfig}} + \lambda_2 C_{\text{delay}} + \lambda_3 C_{\text{imbalance}}\right].$$

Here, C_{reconfig} represents the cost of changing assignments.

This prevents excessive reassignment and therefore avoids unstable oscillations in mission structure.

---

5. Resilient Coordination Mechanism

5.1 Communication Degradation

Let

$$c_{ij}(t) \in [0,1]$$

represent the quality of the communication relationship between agents i and j.

The effective adjacency matrix is

$$A_{ij}(t) = \begin{cases} 1, & c_{ij}(t) \geq \tau_c, \\ 0, & \text{otherwise.} \end{cases}$$

The network therefore changes dynamically:

$$G(t) \to G(t+1).$$

The objective is to preserve sufficient connectivity for distributed decision-making rather than requiring an unchanged topology.

5.2 Resilient Coordination Index

Define

$$R_C(t) = \alpha_1 C_G(t) + \alpha_2 I_G(t) + \alpha_3 P_G(t),$$

where:

- C_G: connectivity measure;

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- I_G: information availability;
- P_G: policy-consistency measure.

The overall resilience score is

$$R = \frac{1}{T} \sum_{t=1}^{T} R_C(t).$$

A resilient system should maintain a high despite moderate changes in network structure.

Recent MARL research increasingly considers communication as a mechanism for improving coordination, while graph-based communication provides a natural representation of changing inter-agent relationships [12].

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6. Intelligent Decision-Making Based on MARL

6.1 Decentralized Partially Observable Model

Because an individual agent cannot generally observe the complete system state, the proposed framework uses a decentralized partially observable formulation [13].

For agent i,

$$o_i(t) = O_i(S(t), G(t)).$$

The policy becomes

$$a_i(t) = \pi_{\theta_i}\left(o_i(t), h_i(t)\right),$$

where $h_i(t)$ represents the agent's historical information.

The joint policy is

$$\boldsymbol{\pi} = (\pi_1, \pi_2, \ldots, \pi_N).$$

The system objective is

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$$\max_{\pi} \mathbb{E}\left[\sum_{t=0}^{T} \gamma^t R(t)\right].$$

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7. Multi-Objective Reward Function

A major modification introduced by this study is that the reward is not based on a single system objective.

We define

$$R(t) = w_M R_M(t) + w_C R_C(t) + w_R R_R(t) + w_A R_A(t) + w_D R_D(t) - w_L C_L(t).$$

The components are:

Mission performance

$$R_M(t) = \frac{\sum_k \rho_k I_k(t)}{\sum_k \rho_k},$$

where $I_k(t)$ measures task completion progress.

Coordination

$$R_C(t) = \frac{1}{N} \sum_i Q_i(t).$$

Resource efficiency

$$R_R(t) = 1 - \frac{R_{\text{unused}}(t)}{R_{\text{available}}(t) + \epsilon}.$$

Adaptation

$$R_A(t) = 1 - \frac{C_{\text{reconfig}}(t)}{C_{\max} + \epsilon}.$$

Decision quality

$$R_D(t) = 1 - \frac{C_{\text{decision}}(t)}{C_{\max} + \epsilon}.$$

The penalty term

$$C_L(t)$$

represents unnecessary latency or instability.

Thus, the system seeks a balanced solution rather than maximizing a single metric.

---

8. Dynamic Resource Allocation

Let the available resources be

$$\mathcal{R}(t) = \{r_1(t), r_2(t), \ldots, r_N(t)\}.$$

For task M_k, let the required resource vector be

$$R_k^{req}(t).$$

The allocation matrix is

$$X(t) = [x_{ik}(t)].$$

The constraints are

$$x_{ik}(t) \geq 0,$$

And

$$\sum_k x_{ik}(t) \leq r_i(t).$$

The allocation objective can be expressed as

$$\max_X \sum_k \rho_k U_k(X,t) - \lambda_X C_X(X,t),$$

where U_k represents task utility and C_X represents resource-allocation cost.

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This formulation allows resources to move between tasks as the system state changes.

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9. Adaptive Mission-Reconfiguration Algorithm

The proposed framework operates through five stages.

Stage 1: State perception

Agents collect local observations:

$$o_i(t) = O_i(S(t), G(t)).$$

Stage 2: Mission evaluation

The system evaluates

$$\mathcal{M}(t)$$

and determines whether the existing task structure remains suitable.

Stage 3: Reconfiguration

If

$$D_M(t) > \tau_M,$$

where D_M represents mission-structure deviation, the assignment matrix is $Z(t)$ updated.

Stage 4: Resource redistribution

The resource allocation matrix $X(t)$ is recomputed.

Stage 5: Policy execution

Each agent selects

$$a_i(t) \sim \pi_{\theta_i}.$$

The resulting system state is then evaluated and fed back into the learning process.

This produces the closed loop

$$\boxed{\text{Observation} \to \text{Mission Evaluation} \to \text{Reconfiguration} \to \text{Resource Allocation} \to \text{Coordination} \to \text{Action} \to \text{Emergence Evaluation}}$$

---

10. Adaptive Controllable-Emergence Framework

The complete architecture can be summarized mathematically as

$$\mathcal{E}(t) = \mathcal{F}\left[G(t), Z(t), X(t), \boldsymbol{\pi}(t), S(t)\right].$$

The desired emergent state satisfies

$$\mathcal{E}(t) \to \mathcal{E}^*.$$

Unlike the original static formulation, however,

$$G(t), Z(t), X(t), \boldsymbol{\pi}(t)$$

are all time-dependent.

Therefore, the proposed system is an **adaptive controllable-emergence system**.

Its core principle can be written as

$$\boxed{\text{Local Adaptation} + \text{Dynamic Interaction} + \text{Resource Reallocation} \Rightarrow \text{Controllable Global Emergence}}$$

11. Value Decomposition for Cooperative Decision-Making

For cooperative agents, a joint value function can be decomposed as

$$Q_{\text{tot}} = f(Q_1, Q_2, \ldots, Q_N).$$

Value decomposition is useful because the joint action and observation spaces can become very large as the number of agents increases. VDN introduced the idea of decomposing a team value function into agent-wise value functions[14], while QMIX later provided a monotonic factorization enabling decentralized execution from locally conditioned agent values. [15].

Accordingly, the proposed framework may employ

$$Q_{\text{tot}} = f_\phi(Q_1, \ldots, Q_N, S),$$

during centralized training while retaining

$$a_i = \arg\max_{a_i} Q_i(o_i, a_i)$$

during decentralized execution.

This separation reduces the computational burden associated with directly optimizing the full joint action space.

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12. Graph-Based Communication and Coordination

A graph neural representation can be used to aggregate neighboring information.

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For agent i,

$$h_i^{(l+1)} = \sigma\left(W_0 h_i^{(l)} + \sum_{j \in N_i} W_1 h_j^{(l)}\right).$$

The resulting representation is

$$h_i^* = \mathrm{GNN}(G(t), o_i(t)).$$

The policy becomes

$$\pi_i(a_i | h_i^*).$$

This design allows the policy to depend on local network structure rather than on a fixed number of agents.

This is particularly important because graph-based communication has become an active research direction in MARL, with recent surveys specifically examining how graph neural networks can represent and learn communication structures among agents.

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13. Adaptive Policy Update

The policy parameters are updated according to

$$\theta_i^{t+1} = \theta_i^t + \eta \nabla_{\theta_i} J(\theta_i).$$

However, because the environment changes, the objective is not simply

$$J(\theta).$$

Instead,

$$J = J(\theta, G, Z, X, \mathcal{M}).$$

Consequently,

$$\frac{dJ}{dt} = \frac{\partial J}{\partial \theta}\frac{d\theta}{dt} + \frac{\partial J}{\partial G}\frac{dG}{dt} + \frac{\partial J}{\partial Z}\frac{dZ}{dt} + \frac{\partial J}{\partial X}\frac{dX}{dt}.$$

This equation highlights an important property of the proposed framework: **system adaptation occurs simultaneously at the policy, network, mission, and resource levels.**

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14. Emergence Quality Metric

To quantify emergence, define

$$E_Q = \beta_1 P_M + \beta_2 P_C + \beta_3 P_R + \beta_4 P_A - \beta_5 C_S,$$

where:

- P_M: mission performance;
- P_C: coordination performance;
- P_R: resource efficiency;
- P_A: adaptation performance;
- C_S: system instability.

The overall emergence quality is

$$EQ \in [0,1].$$

A high value means that the system simultaneously satisfies multiple system-level requirements.

15. Convergence and Adaptation Analysis

Let

$$D(t) = \|Y(t) - Y^*\|.$$

The adaptation time is defined as

$$T_A = \min\{t : D(\tau) \le \epsilon,\ \forall \tau \ge t\}.$$

The smaller T_A, the faster the system adapts to a change.

For network resilience, define

$$\Delta G = d(G(t), G(t + \Delta t)),$$

where $d(\cdot,\cdot)$ represents a graph-distance measure.

The resilience objective is therefore

$$\min |E_Q(G) - E_Q(G')|$$

for moderate structural perturbations

$$G \to G'.$$

This provides a mathematical interpretation of resilient emergence: **the desired macroscopic behavior should remain relatively stable even when the microscopic interaction structure changes.**

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16. Simulation Framework

The original work used a fixed multi-agent configuration to demonstrate controllable emergence. The proposed study extends this experimental structure to multiple dynamic scenarios.

16.1 Experimental Scenarios

Scenario A: Static Single-Task Environment

The task set remains constant:

$$\mathcal{M}(t) = \mathcal{M}_0.$$

This scenario establishes the baseline.

Scenario B: Multi-Task Environment

Multiple tasks coexist:

$$|\mathcal{M}(t)| > 1.$$

Agents must allocate resources across tasks.

Scenario C: Dynamic Task Arrival

At time t_c,

$$\mathcal{M}(t_c^+) \neq \mathcal{M}(t_c^-).$$

The system must reconfigure.

Scenario D: Communication Degradation

A subset of graph edges is temporarily removed:

$$E(t_c^+) \subset E(t_c^-).$$

The system must reconstruct sufficient coordination relationships.

Scenario E: Resource Reduction

The available resource changes:

$$R(t_c^+) < R(t_c^-).$$

The system must redistribute resources among tasks.

Scenario F: Combined Perturbation

Mission structure, resources, and network topology change simultaneously.

This is the most demanding test of adaptive controllable emergence.

---

17. Evaluation Metrics

The following metrics should be reported.

17.1 Task Completion Rate

$$TCR = \frac{N_{\text{completed}}}{N_{\text{total}}}.$$

17.2 Mission Reconfiguration Time.

$$MRT = t_{\text{stable}} - t_{\text{change}}.$$

17.3 Resource Utilization

$$RU = \frac{R_{\text{used}}}{R_{\text{available}}}.$$

17.4 Coordination Robustness

$$CR = \frac{E_Q^{perturbed}}{E_Q^{normal}}.$$

17.5 Decision Latency

$$DL = \frac{1}{N}\sum_{i}(t_i^{decision} - t_i^{observation}).$$

17.6 Adaptation Efficiency

$$AE = \frac{\Delta E_Q}{T_A}.$$

17.7 Emergence Quality

$$EQ = w_1 TCR + w_2 CR + w_3 RU + w_4 AE - w_5 DL.$$

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18. Baseline Algorithms

To demonstrate the contribution of the proposed framework, the following baseline configurations should be compared:

1. **Fixed-rule controllable emergence (FR-CE).**
2. **Static MARL without mission reconfiguration (MARL-S).**
3. **MARL with dynamic resource allocation (MARL-DRA).**
4. **MARL with resilient coordination (MARL-RC).**
5. **Proposed Adaptive Controllable Emergence framework (ACE).**

The comparison should use identical environmental conditions and evaluation metrics.

The central experimental hypothesis is:

$$EQ_{ACE} > EQ_{MARL-DRA}, EQ_{MARL-RC}, EQ_{MARL-S}, EQ_{FR-CE}.$$

The exact numerical values should be obtained from actual simulation rather than inserted theoretically.

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19. Ablation Study

A rigorous study should remove one mechanism at a time.

ACE without mission reconfiguration

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$$ACE - MR$$

ACE without resilient coordination

$$ACE - RC$$

ACE without dynamic resource allocation

$$ACE - DRA$$

ACE without adaptive policy learning

$$ACE - APL$$

The performance difference can be measured as

$$\Delta_i = EQ_{ACE} - EQ_{ACE-i}.$$

A large indicates that the corresponding mechanism contributes substantially to controllable emergence.

---

20. Discussion

The proposed framework changes the interpretation of controllable emergence in three important ways.

First, emergence is no longer considered a static property of a fixed network. Instead,

$$E_Q = E_Q(t).$$

The emergent behavior can therefore evolve as the environment changes.

Second, the network topology itself becomes part of the decision process:

$$G(t+1) = \mathcal{G}(G(t), S(t), \mathcal{M}(t), R(t)).$$

This means that coordination is not merely performed over a predefined network; the interaction structure can adapt to system requirements.

Third, mission assignment and resource allocation are coupled with policy learning:

$$\pi \leftrightarrow Z \leftrightarrow X \leftrightarrow G.$$

This coupling is essential in multi-task systems because optimizing one component independently can produce undesirable global behavior.

For example, maximizing task completion without considering resource constraints may lead to resource concentration. Conversely, maximizing resource utilization without considering mission priorities may reduce overall system effectiveness. Similarly, maximizing communication connectivity without considering decision relevance can produce unnecessary communication overhead.

The proposed multi-objective formulation addresses this problem by explicitly incorporating these factors into a common optimization framework.

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21. Theoretical Significance

The theoretical contribution of this work lies in connecting three levels of system description:

$$Microsoft\ agent\ policy \rightarrow mesoscopic\ interaction\ network \rightarrow macroscopic\ emergen\ behavior$$

At the microscopic level, agents select actions.

At the mesoscopic level, agents form dynamic relationships.

At the macroscopic level, the system exhibits mission-level behavior.

The proposed framework therefore considers controllable emergence as a hierarchical mapping:

$$\mathcal{P} \times \mathcal{G} \times \mathcal{Z} \times \mathcal{X} \rightarrow \mathcal{Y},$$

where

- $\mathcal{P}$: policy space;
- $\mathcal{G}$: graph space;
- $\mathcal{Z}$: mission-assignment space;
- $\mathcal{X}$: resource-allocation space;
- $\mathcal{Y}$: emergent-behavior space.

The controllability problem can therefore be written as

$$\exists(\mathcal{P}, \mathcal{G}, \mathcal{Z}, \mathcal{X}) : \mathcal{Y} \approx \mathcal{Y}^*.$$

This provides a general mathematical definition of adaptive controllable emergence.

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22. Practical Computational Implications

The framework is also compatible with centralized-training/decentralized-execution architectures. Such architectures are widely used because centralized information can be available during training

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while decentralized policies are required during execution. QMIX, for example, explicitly addresses this relationship through monotonic value factorization.

The framework can therefore be implemented using several algorithmic families, including:

- value decomposition;
- actor-critic methods;
- graph-based MARL;
- attention-based communication;
- multi-objective reinforcement learning;
- evolutionary optimization for resource assignment.

The appropriate algorithm should depend on the size of the agent population, degree of observability, computational budget, and degree of cooperation.

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23. Limitations

Several limitations should be recognized.

First, the mathematical model remains an abstraction of a real air and space defense system. Real systems involve heterogeneous physical dynamics, regulatory constraints, cybersecurity considerations, hardware limitations, and highly uncertain environments.

Second, the proposed framework assumes that the reward components can be appropriately normalized and weighted. In practice, determining the optimal values of

$$w_M, w_C, w_R, w_A, w_D$$

is itself a multi-objective optimization problem.

Third, MARL training can suffer from non-stationarity because every agent's policy may change simultaneously. Multi-agent actor-critic research has identified non-stationarity and increasing policy-gradient variance as important challenges in multi-agent learning.

Fourth, the exponential growth of the joint state-action space remains a fundamental limitation.

If each **q** agent has possible states and there are **N** agents,

$$|\mathcal{S}| = q^N.$$

This exponential relationship motivates value decomposition, graph representations, parameter sharing, and hierarchical decision-making.

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24. Future Research

Future research should focus on five directions.

24.1 Hierarchical Emergence

A hierarchical architecture could separate:

24.2 Meta-Learning

Meta-learning could allow agents to rapidly adapt to previously unseen task configurations.

24.3 Graph-Structure Learning

Instead of manually defining G(t), the system could learn the most useful interaction topology.

24.4 Safe and Explainable MARL

Decision-making should include constraints that prevent unstable or undesirable behaviors and provide interpretable explanations for major policy changes.

24.5 Digital-Twin Evaluation

A high-fidelity digital simulation environment could be used to test the framework under diverse system configurations before any physical implementation.

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25. Conclusion

This study developed an **Adaptive Controllable Emergence (ACE)** framework for multi-task air and space defense systems. The framework extends conventional controllable-emergence models by integrating four additional mechanisms: **mission reconfiguration, resilient coordination, intelligent decision-making, and dynamic resource allocation**.

The system is represented as a time-varying heterogeneous graph in which sensing, decision, and execution agents interact through dynamically changing relationships. Multi-task mission requirements are represented through a dynamic assignment matrix, while resource allocation is modeled as a constrained optimization problem. Resilient coordination is achieved by allowing the interaction topology to adapt to changes in communication and system conditions. Intelligent decision-making is formulated through decentralized partially observable multi-agent reinforcement learning.

The central mathematical innovation is the coupling of policy, network, mission, and resource spaces:

$$\boxed{\pi \leftrightarrow G \leftrightarrow Z \leftrightarrow X \rightarrow E_Q}$$

where represents agent policies, the interaction network, mission assignment, resource allocation, and the resulting emergent-system quality.

This formulation changes controllable emergence from a static problem of designing fixed local rules into an adaptive process in which the system continuously reorganizes its microscopic policies and interactions in response to changing macroscopic requirements.

The resulting framework provides a unified basis for investigating how large-scale multi-agent systems can achieve stable, efficient, and adaptive collective behavior under multiple simultaneous tasks. Its principal scientific value is not restricted to air and space defense; the same framework can be generalized to other complex distributed systems involving heterogeneous agents, dynamic tasks, partial observability, limited resources, and changing interaction networks.

The proposed framework should therefore be regarded as a **general theoretical and computational architecture for adaptive controllable emergence in complex multi-agent systems**.

List of Abbrevation

(UAV): unmanned aerial vehicle.

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest with respect to the research, authorship, and/or publication of this article.

AUTHORS CONTRIBUTION

All authors contributed equally to the main contributor to this paper. All authors read and approved the final paper.

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References

[1] A Holland,Thomas. (2018)Foundations for the modeling and simulation of emergent behavior systems, P.218. https://books.google.jo/books?hl=en&lr=&id=5DgPEAAAQBAJ&oi=fnd&pg=PA217&dq=Emergence+describes+a+class+of+phenomena+in+which+interactions+among+relatively+simple+components+generate+collective+properties+at+a+higher+level+of+organization&ots=wr4ivu6sj-&sig=xIq0vNcuddmv39ZE880hqLpogsE&redir_esc=y#v=onepage&q&f=false

[2] Zhang, D., Yuan, Q., Meng, L. et al. Reinforcement learning for single-agent to multi-agent systems: from basic theory to industrial application progress, a survey. Artif Intell Rev 59, 46 (2026). https://doi.org/10.1007/s10462-025-11439-9

[3] Huh, D., & Mohapatra, P. (2023). Multi-agent Reinforcement Learning: A Comprehensive Survey. ArXiv, abs/2312.10256. https://www.semanticscholar.org/paper/Multi-agent-Reinforcement-Learning%3A-A-Comprehensive-Huh-Mohapatra/4768692b14a86edc398199a089e2e35ab271e2ca

[4] Del Canto Viterale, F. (2025). An Examination of the Complexity of the Large Sociotechnical Space System. Aerospace, 12(6), 491. https://doi.org/10.3390/aerospace12060491

[5] Yu, Youshan.(2025).Managing Complex Intelligent Systems: The Coexistence of Generativity and criticality. linkoping university. https://books.google.jo/books?hl=en&lr=&id=0iBCEQAAQBAJ&oi=fnd&pg=PR3&dq=Large-scale+air+and+space+defense+systems+provide+a+representative+complex-system+environment+for+investigating+controllable+emergence.+&ots=pV2X9Nw3Me&sig=jpKpGKYtwIOi1ZfoGCwxYFNlZ58&redir_esc=y#v=onepage&q&f=false

[6] Yusen Lin. (2025). Emergence as a Universal Phase Transition: From Mathematical Inevitability to Predictive Control Across AI, Physical, and Social Systems, 03 October 2025, PREPRINT (Version 1) available at Research Square https://doi.org/10.21203/rs.3.rs-7718584/v1

[7] Yong Liu, Marwan A. Simaan, Jose B. Cruz Jr, An application of dynamic Nash task assignment strategies to multi-team military air operations, Automatica, Volume 39, Issue 8, 2003, Pages 1469-1478, ISSN 0005-1098, https://doi.org/10.1016/S0005-1098(03)00122-5

[8] Simon Banbury, Michelle Gauthier, and Andrea Scipione.(2007).Intelligent Adaptive Systems Literature-Research of Design Guidance for Intelligent Adaptive Automation and Interfaces . Defence R & D Canada – Toronto Contract Report. DRDC Toronto CR 2007-075 . file:///C:/Users/DELL/Downloads/Intelligent_Adaptive_Systems_Literature-Research_o.pdf

[9] Zhang, K., Yang, Z., Başar, T. (2021). Multi-Agent Reinforcement Learning: A Selective Overview of Theories and Algorithms. In: Vamvoudakis, K.G., Wan, Y., Lewis, F.L., Cansever, D. (eds) Handbook of Reinforcement Learning and Control. Studies in Systems, Decision and Control, vol 325. Springer, Cham. https://doi.org/10.1007/978-3-030-60990-0_12

[10] Wei Li, Flávia C. Delicato, Paulo F. Pires, Young Choon Lee, Albert Y. Zomaya, Claudio Miceli, Luci Pirmez, (2014).Efficient allocation of resources in multiple heterogeneous Wireless Sensor Networks, Journal of Parallel and Distributed Computing, Volume 74, Issue 1,2014, Pages 1775-1788, ISSN 0743-7315, https://doi.org/10.1016/j.jpdc.2013.09.012

[11] Feng Zhao, Leonidas J. Guibas, (2004). Wireless Sensor Networks: An Information Processing Approach. Murgan kaufmann publisher, elsevier, https://books.google.jo/books?hl=en&lr=&id=BkaQkhkWGfoC&oi=fnd&pg=PP2&dq=2.2.1+Sensing+Layer+A+sensing+agent+observes+environmental+information+and+generates+an+observation:+++where++is+the+observation+function+and++represents+observation+uncertainty.+The+sensing+layer+provides+information+to+decision+agents+through+available+communication+links.&ots=HXaFbFv3Za&sig=rZNhHTgJ4mPa2w5TB6L9wIcWIXQ&redir_esc=y#v=onepage&q&f=false

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Vol. 2, No. 1, 2025, pp. 1-8

[12] Liu, Y., Wu, D., & Liang, Y. (2025). Survey on Graph-Based Reinforcement Learning for Networked Coordination and Control. Automation, 6(4), 65. https://doi.org/10.3390/automation6040065

[13] Omidshafiei, S., Pazis, J., Amato, C., How, J.P. & Vian, J.. (2017). Deep Decentralized Multi-task Multi-Agent Reinforcement Learning under Partial Observability. <i>Proceedings of the 34th International Conference on Machine Learning</i>, in <i>Proceedings of Machine Learning Research</i> 70:2681-2690 Available from https://proceedings.mlr.press/v70/omidshafiei17a.html

[14] Zhou, X., Xiong, J., Zhao, H. et al. Joint UAV trajectory and communication design with heterogeneous multi-agent reinforcement learning. Sci. China Inf. Sci. 67, 132302 (2024). https://doi.org/10.1007/s11432-023-3906-3

[15] Anqi Huang, Zhiqun Pan, Xiaoliang Zhou, 2026. RRQ: Relative residual potential functions with knowledge-distilled value decomposition for MARL,Neurocomputing, Volume 685,2026, 133676, ISSN 0925-2312, https://doi.org/10.1016/j.neucom.2026.133676.

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