ISAC-Enabled Low-Altitude Economy: Game-Theoretic Learning Empowered Techniques and Future Directions

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ISAC-Enabled Low-Altitude Economy: Game-Theoretic Learning Empowered Techniques and Future Directions

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***Abstract*—Sixth-generation (6G) network has been emerging as a key support for the low-altitude economy (LAE), where the implementation of LAE is highly dependent on unmanned aerial vehicles (UAVs). Moreover, UAVs are expected to be airborne integrated sensing and communication (ISAC) platforms, thus forming the foundation for the ISAC-enabled LAE. In practice, the large-scale development of ISAC-enabled LAE relies on the collaboration of UAV swarms, where resource allocation and trajectory planning significantly determine the overall performance of ISAC-enabled LAE. However, how to optimize both resources and trajectories remains a key challenge due to the coupling of these two optimization problems in dynamic environments. Recently, game-theoretic learning approaches have gained attention due to their superiority in multi-agent dynamic interactions and distributed decision-making. Leveraging these advantages, game-theoretic learning approaches are promising for resolving the coupling problem inherent in the optimization of resources and trajectories for the ISAC-enabled LAE. In this article, the applications and challenges of ISAC-enabled LAE are first analyzed, emphasizing the significance of UAV swarm collaboration and the urgency of resource allocation and trajectory planning. Game-theoretic learning empowered approaches are then introduced, especially the multi-agent interactions for addressing the coupling problem. Subsequently, a game-theoretic deep reinforcement learning (DRL) approach is proposed, which focuses on integrating game theory's decision mechanism with DRL's adaptive capabilities to enable the joint optimization of resource allocation and trajectory planning for UAV swarms. Finally, the future research directions of ISAC-enabled LAE are introduced in detail.**

I. Introduction

LOW-ALTITUDE economy (LAE) is a novel economic application relying on airspace below 1000 meters, which includes both manned and unmanned aircraft. LAE enables a wide range of applications such as transportation, logistics, agriculture, and environmental monitoring [1]. However, the successful implementation of LAE depends on the safe operation of aircraft, which requires the capabilities of seamless wireless communication and ubiquitous sensing for a large number of low-altitude aircraft. These capabilities can expand the operational coverage of these aircraft, facilitate their trajectory planning and tracking, and enable real-time monitoring [2]. Statistically, the number of aircraft is expected to reach 9.6 million by 2030 [3], which inevitably induces interference in communication and sensing among low-altitude aircraft and heightens demand for spectrum resources. Against this background, integrated sensing and communication (ISAC) has been emerging as a promising technology to facilitate the future LAE.

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ISAC is a technology with a dual-functional design that combines both communication and sensing, which can improve the wireless spectral efficiency and enhance the coordination between communication and sensing systems [4]. However, its performance highly depends on line-of-sight (LoS) links, where communication interruption and sensing degradation will happen when the LoS is blocked. Fortunately, unmanned aerial vehicles (UAVs) in the LAE can serve as aerial platforms with enhanced LoS propagation, broad coverage, and flexible deployment, thus improving the performance in ISAC-enabled LAE systems [5].

Generally, the large-scale development of ISAC-enabled LAE relies on the collaboration of UAV swarms, where resource allocation and trajectory planning are critical. On one hand, ground users (GUs) transmit data to UAVs, which involves concurrent transmissions from multiple GUs and is constrained by limited spectrum resources. Meanwhile, with the same spectrum resource, UAVs also need to actively detect radar targets (RTs) [6]. On the other hand, UAVs' performance in serving GUs and detecting RTs can be improved through trajectory planning. Additionally, UAV swarms require trajectory planning to avoid collisions when they are operating independently. However, it is difficult to simultaneously achieve optimal resource allocation and trajectory planning for UAV swarms using conventional algorithms when a large number of UAVs are deployed.

Recently, game-theoretic learning, which integrates game theory and learning algorithms to address decision-making in multi-agent systems, has gained attention due to its superiority in handling multi-agent dynamic interactions. The core idea of game-theoretic learning is to enable agents to learn their strategies adaptively. Through observing the actions and feedback of other agents, as well as environment states, each agent can iteratively refine its decisions to achieve better performance [7]. In ISAC-enabled LAE scenarios, the interactions among UAVs can be modeled as a dynamic game, where each UAV can leverage learning mechanisms to adjust its resources and trajectory according to the actions of other agents and environmental variations. Therefore, game-theoretic learning has been emerging as a promising solution to optimize resource allocation and trajectory planning for UAV swarms [8].

In light of the above, we first analyze the applications and challenges of ISAC-enabled LAE, emphasizing the importance of UAV swarm collaboration and the urgency to optimize resource allocation and three-dimensional (3D) trajectories in uplink scenarios. Then, we introduce the game-theoretic learning empowered approaches, which show superiority in managing multi-agent interactions. Subsequently, we elaborate

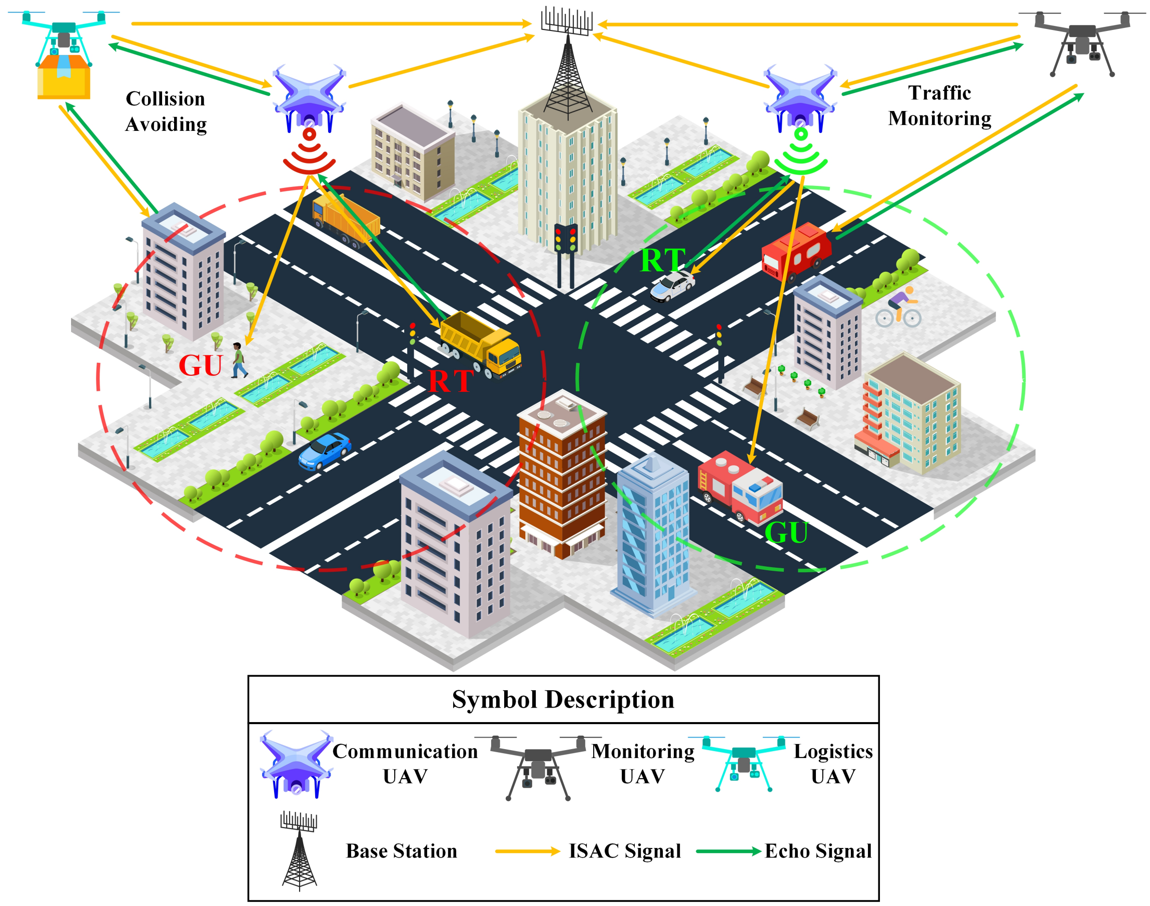

Fig. 1. The ecological environment of the considered ISAC-enabled LAE.

on the proposed game-theoretic deep reinforcement learning (DRL) approach. Finally, the future research directions of ISAC-enabled LAE are introduced in detail.

II. Overview of ISAC-enabled LAE

In traditional LAE, communication and sensing functionalities are typically implemented as separate subsystems, which often leads to inefficient coordination between tasks, redundant occupation of spectrum resources, and poor adaptability to dynamic low-altitude environments. To tackle the above issues, the ISAC-enabled LAE is proposed, which integrates sensing and communication functionalities. Specifically, the ISAC-enabled LAE can provide services to different types of UAVs, including logistics UAVs, communication UAVs, monitoring UAVs, etc., where ISAC is utilized as technical support to assist these UAVs to complete missions effectively [2]. By integrating sensing and communication functionalities, these UAVs can efficiently collect and transmit real-time data, including location information, low-altitude traffic conditions, and environmental parameters, thus enabling coordinated operations within dynamic low-altitude environments.

A. Application of ISAC-enabled LAE

As shown in Fig. 1, the application of ISAC in low-altitude scenarios enhances the performance of each category of UAV in specific tasks [5], which further addresses the limitations of traditional UAV operations as follows.

Logistics UAVs in ISAC-enabled LAE can concurrently sense environmental constraints and transmit real-time status data, which enables dynamic route replanning and avoids collisions or delays. By merging environmental awareness with data transmission, logistics UAVs can improve delivery efficiency, reduce mission failures, and support scalable swarm-based operations, thus providing a foundation for reliable last-mile logistics in the urban environment.

Communication UAVs in ISAC-enabled LAE can both enable stable communication with GUs and actively sense RTs. ISAC ensures that communication links remain robust even as airspace dynamics change, while also enhancing awareness of potential RTs. In complex low-altitude environments, ISAC can minimize interference between communication and sensing, thereby optimizing spectrum usage and ensuring reliable connectivity for GUs as well as accurate RT detection.

Monitoring UAVs in ISAC-enabled LAE can integrate real-time environmental sensing with instant data transmission. Sensed information can be immediately transmitted to decision-making systems, which enables rapid responses like alerting traffic control to congestion. Moreover, this capability can support data-driven management, such as coordinating real-time air quality monitoring with urban environmental control systems for pollution mitigation. By integrating sensing and communication, the situational awareness ability of monitoring UAVs can be strengthened regardless of the application scenarios.

B. Challenges of Collaborative ISAC-enabled LAE

Collaboration among different types of UAVs will facilitate the ISAC-enabled LAE significantly. However, the collaboration faces great challenges due to the conflicting objectives, resource constraints, and dynamic nature of low-altitude airspace.

Firstly, all types of UAVs rely on shared spectrum for both communication and sensing, which leads to intense competition and complex collaboration. For instance, communication UAVs are required to maintain links with GUs and actively sense RTs, which is the same as the needs of logistics UAVs and monitoring UAVs, thus leading to signal interference in dense scenarios. However, dynamically addressing such a problem is challenging because spectrum allocation must adapt to real-time changes in UAV positions, task priorities, and airspace congestion.

Secondly, each type of UAV has distinct objectives, which are typically in conflict. Logistics UAVs prioritize delivery speed and route efficiency, driving them to avoid high-traffic airspace and interrupt their connection with other types of UAVs. Communication UAVs need stable positioning to maintain GU link stability and RT sensing accuracy, which makes sudden repositioning caused by other types of UAVs harmful to their performance. Monitoring UAVs for comprehensive environmental coverage may require overlapping trajectories with other types of UAVs, raising collision risks that delay logistics operations or weaken communication signals. Different objectives could lead to fragmented coordination without a unified decision framework, i.e., UAVs optimize individually rather than collectively.

Finally, low-altitude airspace is dynamic with changes in interference, weather, and obstacle distribution. Effective collaboration demands that UAVs share real-time ISAC data, such as obstacle identification of logistics UAVs, RT detection of communication UAVs, and environmental change reporting of monitoring UAVs, so that they can collectively adapt to dynamic changes in the low-altitude environment. However, data synchronization across UAVs is challenging. Transmission latency can make shared information outdated, which leads to miscoordinated actions. Additionally, ISAC data from different types of UAVs may differ in accuracy, thereby resulting in a relatively low quality of the fused data.

C. Special Requirements for Uplink Optimization

Uplink scenarios in ISAC-enabled LAE impose unique constraints on communication UAVs, which arise from the requirement for concurrently transmitting data by GUs and effectively maintaining robust sensing. Optimization under such conditions should address the special requirements as follows.

- **Spectral Efficiency:** In uplink scenarios, multiple GUs transmit data to communication UAVs simultaneously, which share limited spectrum resources with the UAVs' sensing functionalities. Efficient spectrum utilization requires dynamic partitioning to avoid mutual interference between communication and sensing. Communication UAVs must adaptively allocate bandwidth based on real-time traffic loads and sensing requirements, and such allocation directly impacts data throughput and detection accuracy. Therefore, how to maximize spectral efficiency becomes critical to balance dual functionalities without performance degradation.
- **Interference Mitigation:** Concurrent uplink transmissions from GUs introduce co-channel interference that degrades communication signal quality at communication UAV receivers. Meanwhile, sensing signals for RT detection may overlap with those of communication, resulting in mutual interference that decreases detection accuracy. Additionally, the mobility of communication UAVs could further worsen the system performance because the relative distances and propagation paths change accordingly. Therefore, communication UAVs are required to suppress mutual interference between communication and sensing adaptively, which includes power control adjustments and beamforming optimization to enhance both the signal-to-interference-plus-noise ratio for GU data and the signal-to-clutter ratio for RT detection. Consequently, effective interference mitigation ensures reliable data reception and RT detection.
- **Trajectory Planning:** Communication performance relies heavily on LoS propagation between UAVs and GUs. Non-line-of-sight (NLoS) conditions could introduce significant path loss and latency, which degrade transmission reliability. Similarly, sensing accuracy is influenced under NLoS conditions due to increased measurement errors from NLoS paths. Therefore, communication UAVs should maintain stable LoS links through precise 3D trajectory planning. Specifically, 3D trajectory planning should take dynamic obstacles, GU mobility, and RT movement into consideration to prevent LoS blockages. In summary, 3D trajectory planning can reduce retransmissions in communication and minimize sensing errors, thereby saving energy and improving overall system performance.
- **Dynamic Adaptability:** Uplink scenarios in ISAC-enabled LAE are characterized by varying GU distributions, traffic fluctuations, environmental changes, and dynamic RT movements. Therefore, static optimization fails to handle these coupled dynamics, and communication UAVs need learning-driven resource allocation mechanisms that adapt to real-time network states and sensing demands. Specifically, these mechanisms should leverage observed metrics such as throughput, latency, and detection error rates to refine strategies. Overall, dynamic adaptation ensures that communication UAVs maintain optimal performance under varying operational conditions, thus balancing communication reliability and sensing precision.

Accordingly, resource allocation and trajectory planning are critical for communication UAVs in uplink scenarios. In par-

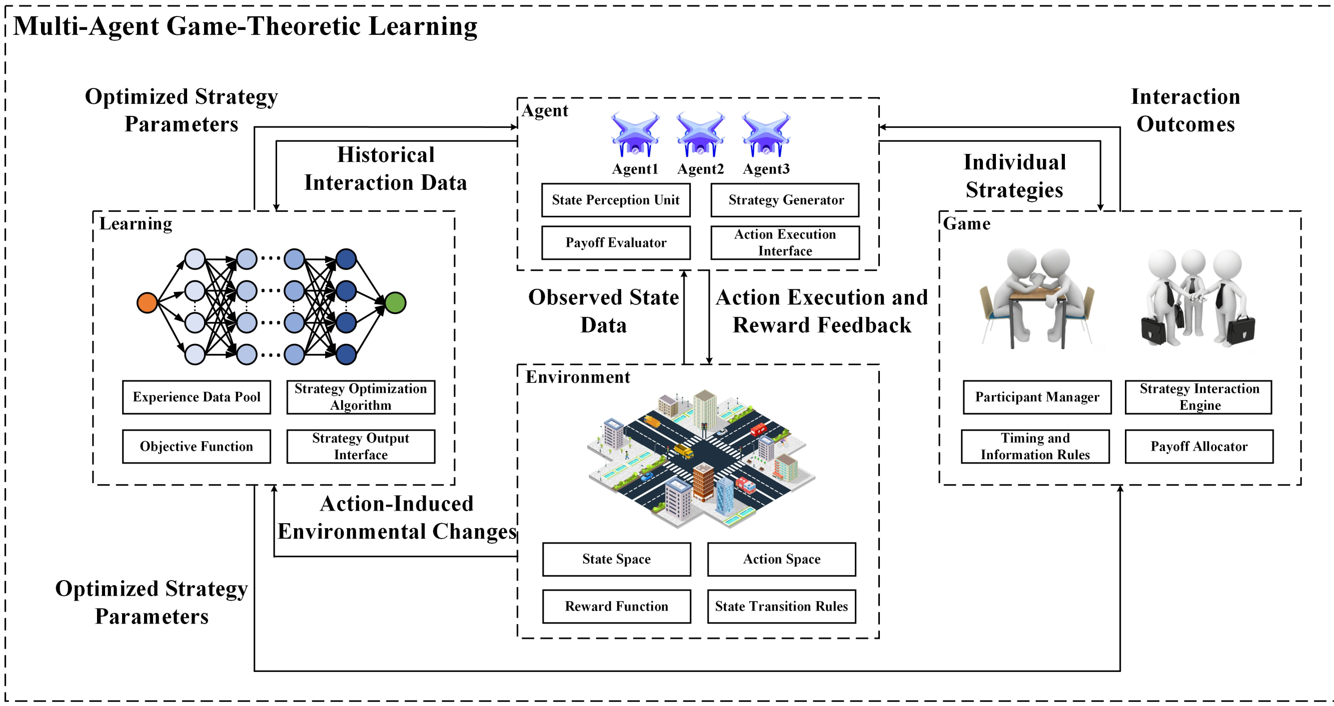

Fig. 2. The architecture of a multi-agent game-theoretic learning system.

ticular, resource allocation can balance spectrum partitioning to avoid interference, thus preserving both data throughput and sensing accuracy. Moreover, trajectory planning can maintain LoS propagation, which reduces path loss and measurement errors. The combination of resource allocation and trajectory planning can enhance spectrum and energy efficiency, ensure dual-function reliability, and improve the overall performance of ISAC-enabled LAE.

III. Overview of Game-Theoretic Learning

For ISAC-enabled LAE with a large number of UAVs, the information interactions, resource allocation, and trajectory planning are challenging [9], where individual UAV decisions will affect collaborative system performance especially in a dynamic environment. Fortunately, game-theoretic learning offers a robust approach to modeling these complex relationships, enabling effective coordination in the ISAC-enabled LAE.

A. Basic Concepts

As shown in Fig. 2, a multi-agent game-theoretic learning system comprises four modules, namely learning, agent, game, and environment. Dynamic interactions among these modules enable strategic adaptation in complex scenarios.

The learning module, which consists of an experience data pool, an objective function, strategy optimization algorithms, and a strategy output interface, enables policy iteration and data-driven adaptation [10]. The experience data pool captures interaction histories to inform learning processes, and the objective function guides the direction of strategy optimization. Furthermore, strategy optimization algorithms implement iterative strategy refinement, and the strategy output interface delivers optimized strategy parameters to support the formulation of agents' decision-making strategies and the dynamic game processes of the game module.

The agent module consists of multiple autonomous agents, where each agent is equipped with a state perception unit, a strategy generator, a payoff evaluator, and an action execution interface. Specifically, the state perception unit allows agents to sense environmental and interaction states, and the strategy generator formulates decision-making strategies based on the sensed information. Moreover, the payoff evaluator assesses the outcomes of agent actions, and the action execution interface translates generated strategies into specific actions.

The game module typically consists of a participant manager, a strategy interaction engine, a payoff allocator, and timing and information rules, which can model the process of strategic interaction [11]. The participant manager identifies and organizes agents involved in strategic interactions, and the strategy interaction engine facilitates the interaction of agents' decision-making strategies. Furthermore, timing and information rules define the sequence of action selection and the visibility of states and actions among agents, and the payoff allocator evaluates and distributes interaction outcomes.

The environment module defines the interaction environment, consisting of a state space, an action space, a reward function, and state transition rules. The state space outlines all possible states agents may confront, and the action space constrains the feasible actions agents can execute. Moreover, the reward function provides feedback on the outcomes of agents' actions, and state transition rules model how the environment transforms in response to agents' actions.

It can be seen that the multi-agent game-theoretic learning framework forms a closed-loop interaction among its four

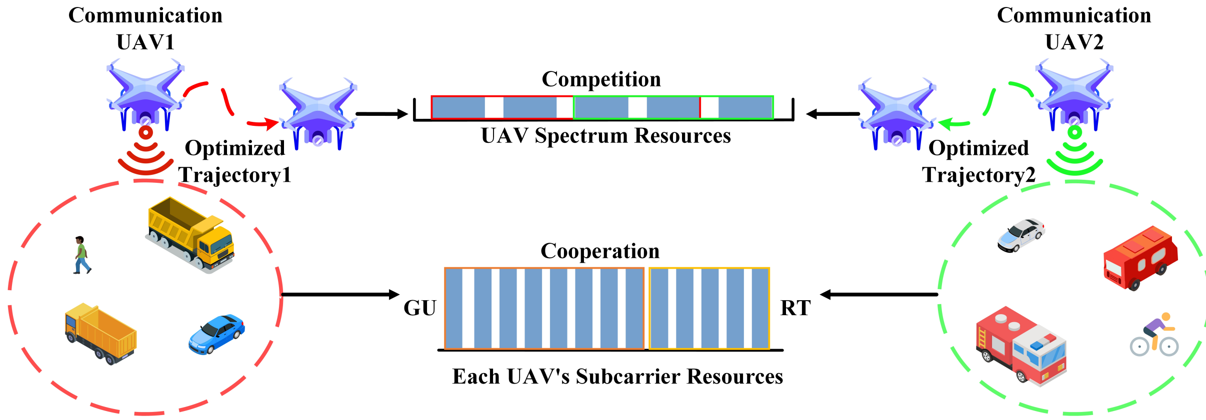

Fig. 3. Spectrum resource interaction in ISAC-enabled LAE uplink scenario: Hierarchical competition, cooperation, and trajectory coupling.

modules. Specifically, the learning module delivers optimized strategy parameters to both agents and the game module. Agents leverage these parameters to generate individual strategies, which are based on observed state data from the environment. These individual strategies are also transmitted to the game module, and the strategy interaction engine processes them with the optimized parameters from the learning module to determine interaction dynamics. Subsequently, the resulting outcomes are fed back to agents' payoff evaluators. Meanwhile, agents execute actions through their action interfaces, which usually leads to changes in the environmental states. The environment in turn returns rewards through the reward function and updated state observations through state transition rules to agents. Moreover, critical data streams are collected by the learning module, which include agents' historical interaction data and environmental feedback on state changes. With the help of optimization algorithms, the learning module refines strategies and then circulates updated parameters back to agents and the game module.

B. Main Advantages

Conventional algorithms are hard to handle such scenarios due to dynamic interactions and competing interests in resource utilization and strategy planning. Comparatively, game-theoretic learning can model these interactions as strategic games, which enables each agent to adapt its strategies according to other agents' actions and environmental variations. The core advantages of game-theoretic learning are as follows.

- Game-theoretic learning can enhance adaptability to varying environments. Complex systems are characterized by variations in resource availability, external disturbances, and channel conditions, which create a need for flexible decision-making among agents. Fortunately, game-theoretic learning can address this need by providing agents with learning mechanisms to refine their decisions. Based on feedback from other agents and the environment, agents can adjust their strategies in real time.
- Game-theoretic learning can balance individual objectives with collective performance. Agents in multi-agent systems pursue conflicting goals such as maximizing individual gains versus maintaining overall system efficiency. Fortunately, game-theoretic learning drives the system toward a strategic balance where individual actions contribute to overall system optimization, which prevents fragmented operations and suboptimal resource use.
- Game-theoretic learning can support expandability for large-scale agent networks. Many complex systems rely on the collaborative operation of numerous agents, where game-theoretic learning can offer a flexible framework that accommodates increasing numbers of such agents without significant performance degradation. By leveraging distributed decision-making, game-theoretic learning can avoid the limitations of centralized control in practical scenarios.

IV. Proposed Game-Theoretic DRL Approach

During the uplink transmission of ISAC-enabled LAE, UAV swarms must coordinate resource allocation and trajectory planning under dynamic interference and time-varying channels, which is highly suitable for game-theoretic learning. Therefore, this article proposes a game-theoretic DRL approach, which integrates game-theoretic modeling and DRL to enable adaptive decision-making [12]. The proposed game-theoretic DRL approach focuses on the joint optimization of spectrum resources and flight trajectories for UAV swarms, which can enhance communication and sensing performance as well as improve system resource efficiency within the dynamic low-altitude uplink scenarios.

A. Scenario and Motivation

As shown in Fig. 3, the ISAC-enabled LAE uplink scenario involves communication UAVs, GUs, and RTs, demonstrating dual interaction mechanisms in spectrum resource management. On one hand, multiple UAVs compete for shared spectrum resources during uplink transmission. On the other hand, GUs and RTs cooperate on subcarrier resources by leveraging orthogonal subcarrier allocation to enhance spectral efficiency.

The interaction between spectrum competition at the UAV layer and ground cooperation at the subcarrier layer, as well as the interconnections between trajectory planning and resource allocation, requires complex distributed decision-making. However, conventional approaches struggle to jointly

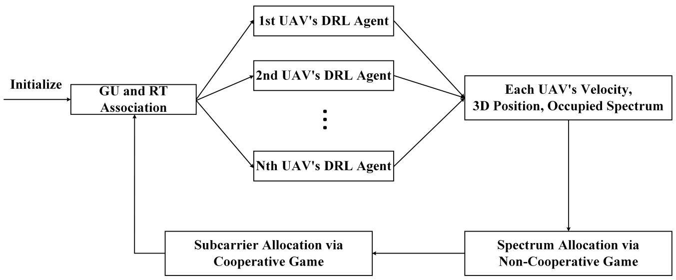

Fig. 4. The framework of a proposed game-theoretic DRL approach.

optimize these coupled aspects in dynamic scenarios, which motivates us to propose a game-theoretic DRL framework.

B. Framework Design and Analysis

As shown in Fig. 4, the proposed framework is initiated by associating GUs and RTs with different UAVs separately, which is based on initial channel conditions, GU distributions, and RT positions. Each UAV deploys an independent DRL agent to learn strategies over velocity, 3D position, and occupied spectrum. These agents operate in a dynamic environment where channel conditions change due to UAV mobility, atmospheric interference, and fading, while other UAVs' actions directly affect available resources. To support decision-making, they continuously process real-time observations, including neighbor positions, channel quality, and interference levels. Furthermore, agents predict the movements of other nodes during each iteration to balance short-term system performance and long-term resource sustainability. Their outputs include UAV velocities, positions, and spectrum resources, thus reflecting the coupled optimization of spectrum and trajectory.

Following DRL decision-making, the non-cooperative game module models UAV competition for shared spectrum. In this game, each UAV acts as a self-interested player with a utility function quantifying communication and sensing performance. Driven by the goal of selecting strategies that are both self-optimizing and collectively stable, UAVs iteratively adjust their spectrum strategies to realize a Nash equilibrium. In this equilibrium state, no UAV can improve its utility by unilaterally changing its strategy.

Subsequently, the cooperative game module manages subcarrier allocation for GUs and RTs to maximize ground-layer spectral efficiency. To satisfy the requirement of collaborative orthogonal subcarrier allocation, GUs and RTs form temporary alliances based on shared needs to mitigate interference, thus improving the system performance. Under the guidance of the fair distribution principle, alliance outcomes are fed back to the initial association module, enabling the system topology to evolve dynamically with UAV trajectories and spectrum changes.

This closed-loop interaction shown in Fig. 4 establishes a hierarchical framework, which integrates UAVs' spectrum competition and ground subcarrier cooperation, thus enabling multi-layer resource management. Notably, the optimization of subcarriers will be influenced by the adjustment of UAV trajectories and spectrum allocation. Therefore, the association of GUs and RTs will be updated, which will be input to the DRL agents. The above process reaches convergence when interactions stabilize, i.e., UAVs stop actively adjusting their trajectories and spectrum resources to obtain larger utility gains, while subcarrier allocations for GUs and RTs remain constant.

V. Future Research Directions

The proposed game-theoretic DRL framework provides a foundational mechanism for ISAC-enabled LAE optimization, but its practical deployment in real-world complex scenarios still faces significant challenges. The future research directions are as follows.

- **Adaptability and Overhead Reduction:** The proposed game-theoretic DRL framework cannot meet the requirements for adaptability to extreme dynamic environments, such as extreme weather, strong electromagnetic interference, sudden obstacles, or massive UAV swarms. To solve this problem, meta-learning-based rapid strategy transfer mechanisms can be explored [13], thus enabling UAVs to adjust decision models through minimal interactions in new environments. Additionally, how to combine distributed training with federated learning to reduce communication overhead in large-scale swarms is a promising direction.
- **Security and Privacy:** In UAV swarm collaboration, the transmission of real-time data such as positions and spectrum usage may pose risks of privacy leakage or malicious attacks. It is necessary to study game strategy optimization based on privacy to maintain group decision-making efficiency while protecting individual data privacy. Meanwhile, anti-jamming mechanisms should be designed to prevent spectrum occupation or false information injection from malicious nodes, which will enhance system robustness [14].
- **Ubiquitous Network Connectivity:** The LAE involves multiple types of nodes, which include UAVs, GUs, RTs, and satellites. However, the model in this article primarily focuses on optimization within UAV swarms. It is necessary to extend the game-theoretic framework to heterogeneous network scenarios, where spectrum sharing strategies among UAVs, ground base stations, and satellites, as well as cross-layer space-air-ground collaborative sensing and communication decision mechanisms should be investigated to enhance global service capabilities [15].

VI. Conclusions

In this article, the applications and challenges of ISAC-enabled LAE were comprehensively investigated, as well as the significance of UAV swarm collaboration and the urgency of optimizing resource allocation and 3D trajectories in uplink scenarios. Subsequently, game-theoretic learning empowered approaches were introduced, showing superiority in handling multi-agent interactions. Furthermore, a game-theoretic DRL approach was proposed to achieve efficient joint optimization of resource allocation and trajectory planning for

UAV swarms, focusing on integrating game theory and DRL. Finally, the future research directions of ISAC-enabled LAE were introduced.

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