A Review on DRL Approach in Unmanned Aerial Vehicle-based Networks with RSMA: Research Challenges and Future Trends

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***Abstract*—Unmanned Aerial Vehicle (UAV)-based wireless networks have emerged as a flexible solution for providing coverage in 5G/6G and beyond, but they face significant challenges in interference management, dynamic topology, and resource allocation. Rate-Splitting Multiple Access (RSMA) has recently gained attention as a powerful non-orthogonal multiple access scheme to enhance spectral efficiency and interference mitigation in multi-user communications. Meanwhile, Deep Reinforcement Learning (DRL) techniques are being leveraged to tackle the complex optimization problems inherent in UAV networks with RSMA, adapting to dynamic environments and imperfect channel state information. In this paper, we present a comprehensive review of DRL approaches applied to UAV-based networks with RSMA, covering their motivations, recent technological developments, and state-of-the-art research from 2022 to 2025. We discuss the background of UAV communications and RSMA, highlight the role of RSMA in improving UAV network performance, and survey various DRL-driven solutions for resource allocation, trajectory design, power control, and other optimizations in RSMA-enabled UAV networks. A comparative summary of recent works is provided in tabular form. Furthermore, we identify key challenges such as multi-agent coordination, real-time learning, and generalization to varying scenarios. We also outline future trends, including advanced DRL algorithms, integration with emerging technologies like reconfigurable intelligent surfaces and generative AI, and the need for robust and energy-efficient designs to fully unleash the potential of DRL-empowered RSMA in UAV networks.**

***Index Terms*—Rate-Splitting Multiple Access (RSMA), Unmanned Aerial Vehicles (UAV), Deep Reinforcement Learning (DRL), PPO, DDPG, TD3, SAC, Multi-Agent RL, 6G.**

I. Introduction and Motivation

Unmanned Aerial Vehicles (UAVs) are increasingly deployed in wireless networks as aerial base stations, relays, or user equipments to extend coverage and capacity for 5G-and-beyond systems [10], [14]. UAV-based networks offer high mobility and flexible deployment, enabling rapid restoration of communication in disaster zones and providing connectivity in rural or temporary events [8], [11]. However, these aerial networks face challenges such as severe interference, dynamic channel conditions due to UAV mobility, and limited backhaul capacity [3], [16]. Traditional Orthogonal Multiple Access (OMA) schemes suffer from limited spectrum efficiency in multi-user UAV scenarios [1], [27]. Non-orthogonal techniques like NOMA (Non-Orthogonal Multiple Access) were explored to allow multiple users on the same resource block, but NOMA's requirement that some users decode others' messages leads to performance degradation and stringent power difference requirements [2].

Rate-Splitting Multiple Access (RSMA) has emerged as a generalized multiple access strategy that splits each user's message into a common part (decodable by all users) and a private part (intended for one user), enabling successive interference cancellation (SIC) at receivers [1]. By treating part of the interference as decodable signal, RSMA strikes a balance between fully decoding interference and treating it as noise [2], [27]. Prior research demonstrated that RSMA can outperform NOMA and other multiple access techniques in throughput and fairness [1], [2]. In particular, RSMA avoids the need for one user to decode another's entire message (a drawback of NOMA) and offers more flexibility in interference management [2]. For multi-antenna downlink systems, RSMA has shown gains under both perfect and imperfect Channel State Information (CSI) conditions [3], [4]. These advantages motivate the integration of RSMA into UAV networks, where interference and dynamic channel variations are pronounced.

Despite RSMA's benefits, optimizing RSMA parameters (such as power allocation, precoding vectors, and common/private rate splits) in UAV networks is challenging. The joint design of beamforming, rate splitting, user association, and UAV trajectory leads to a non-convex, high-dimensional optimization problem [4], [16]. Traditional optimization methods (e.g., successive convex approximation or brute-force search) become intractable in these scenarios [23]. Moreover, UAV networks operate in highly dynamic environments with time-varying channels and user mobility, requiring adaptive and real-time decision-making [11].

Deep Reinforcement Learning (DRL) has emerged as a promising approach to handle such complex decision problems in communication networks. By modeling the control problem as a Markov Decision Process (MDP), DRL agents can learn policies to maximize long-term performance metrics (throughput, reliability, etc.) by interacting with the environment. DRL is well-suited for dynamic resource allocation and interference management due to its ability to learn directly from trial-and-error and handle uncertainties and partial observability [6], [7]. In multi-UAV or multi-user settings, multi-agent DRL frameworks enable distributed learning, aligning with the decentralized nature of UAV networks [10].

Motivation: This paper aims to review the state-of-the-art research at the intersection of DRL, UAV-based networks, and RSMA. The confluence of these areas is relatively new and rapidly evolving (most works have appeared in 2022–2025), and a coherent overview is needed to identify common approaches and open challenges. We seek to highlight how DRL algorithms have been applied to optimize RSMA in UAV networks (for tasks such as power control, beamforming, trajectory design, user association, etc.), and what performance gains they achieved. By surveying recent works, we derive insights into the research challenges unique to DRL-enabled RSMA systems (e.g., training complexity, multi-agent coordination, safety constraints) and outline future trends to guide further investigations.

The rest of this paper is organized as follows. Section 2 provides background on UAV-based communication networks and enabling technologies. Section 3 discusses the role of RSMA in UAV networks and its performance benefits. Section 4 reviews various deep reinforcement learning approaches proposed for UAV networks with RSMA, including a comparative summary of recent works in a table. Section 5 discusses key challenges and future research directions. Section 6 concludes the paper.

II. Background and Technologies

UAV-Based Communication Networks: UAV-assisted wireless networks typically consist of one or multiple UAVs serving as flying base stations (FlyBS) or relays that provide connectivity to ground users or augment coverage of terrestrial base stations [10], [14]. UAVs can be deployed quickly and repositioned on the fly, which makes them ideal for providing on-demand coverage, network offloading, and bridging connectivity in underserved areas [8], [11]. For example, UAV-BSs have been considered for emergency communication in disaster scenarios and for connecting rural areas without infrastructure [5]. UAVs operate at various altitudes: low-altitude platforms (typically tens to a few hundred meters high) are agile and inexpensive, while high-altitude platforms (e.g., HAPs/balloons at stratospheric heights) cover larger areas but are often stationary once deployed [28]. UAV networks are a component of space–air–ground integrated networks (SAGIN), envisioned in 6G to provide ubiquitous connectivity by integrating satellites, aerial platforms, and terrestrial networks [1], [13].

Challenges in UAV Networks: Unlike fixed terrestrial base stations, UAV-BSs face strict constraints in backhaul (often wireless backhaul with limited capacity) and energy (finite battery life). Interference is a major concern: UAVs often serve multiple users with line-of-sight links that cause strong inter-user interference, especially if frequency reuse is employed [16]. The UAVs' mobility leads to rapid channel variation, making it difficult to obtain accurate and timely CSI at the transmitter or receiver [4], [16]. Furthermore, when multiple UAVs are used, user association (deciding which UAV serves which user for uplink and downlink) becomes a complex problem. Traditional approaches tied each user to the same station for both uplink and downlink, but decoupling these associations can yield better rates given the differing link characteristics [10]. However, designing such decoupled associations requires careful interference management and possibly full-duplex operation with self-interference cancellation [3]. UAV networks must also meet diverse service requirements: e.g., URLLC (ultra-reliable low-latency communications) for mission-critical links, requiring stringent delay and reliability guarantees, or high-throughput for broadband applications. These requirements impose additional constraints on resource allocation and network design [26].

Enabling Technologies: Advances in antenna and transceiver technologies (multi-antenna MIMO arrays on UAVs) allow serving multiple users via spatial multiplexing. Complementary technologies like Reconfigurable Intelligent Surfaces (RIS) are being studied to assist UAV communications by intelligently reflecting signals to enhance coverage or reduce blockage effects [20]. Active RIS mounted on UAVs can even amplify signals, though they introduce higher energy consumption, creating a trade-off in system design [12]. UAV communications can benefit from such technologies, but they also increase the complexity of the system optimization (e.g., joint beamforming and RIS phase control). Moreover, Mobile Edge Computing (MEC) may be integrated with UAVs (where UAVs carry computing payloads to process data from users), introducing new variables like task offloading decisions and computing resource allocation [8]. Each of these extensions (RIS, MEC, full-duplex, etc.) introduces additional optimization dimensions that compound the difficulty of network control.

Deep Reinforcement Learning (DRL): DRL combines deep neural networks with reinforcement learning to enable an agent to learn good policies in complex, high-dimensional environments. In the context of UAV network control, DRL can be used to learn resource allocation (power, channel assignment), movement control (trajectory/path planning for UAVs), and other decisions by interacting with a simulator or real environment. Various DRL algorithms have been applied: value-based methods like Deep Q-Network (DQN) for discrete decision spaces, and policy-based or actor–critic methods like Deep Deterministic Policy Gradient (DDPG) and Proximal Policy Optimization (PPO) for continuous control [6], [7]. Multi-agent DRL (MADRL) extends these to multiple learners (e.g., multiple UAVs each as an agent) and often uses centralized training with distributed execution to handle the joint optimization while mitigating non-stationarity during learning [10] [17]. In UAV networks, DRL offers the ability to adapt policies on the fly to changing channel conditions and traffic patterns, potentially achieving near real-time optimization that classical solvers cannot [18] [19].

In summary, UAV-based networks bring flexibility and broad coverage but suffer from interference and dynamic changes. RSMA is introduced next as an advanced multiple access strategy particularly well-suited to such interference-limited, dynamic scenarios. DRL serves as a powerful tool to control and optimize RSMA-enabled UAV networks, as we detail in the subsequent sections.

III. Role of RSMA in UAV-Based Networks

Rate-Splitting Multiple Access (RSMA) is a novel multiple access paradigm that plays a crucial role in enhancing the performance of UAV-based networks. By allowing each user's message to be split into common and private components, RSMA provides an additional degree of freedom in interference management compared to conventional OMA or even NOMA. This flexibility is particularly beneficial in UAV networks where interference is strong and channels can be highly variable.

Interference Mitigation: In a typical UAV downlink scenario (one or more UAV-BSs serving ground users), co-channel interference between users can severely limit the sum-rate. Traditional OMA orthogonalizes users at the cost of spectral efficiency, while NOMA superposes users but forces successive decoding of complete messages, which is suboptimal if channel conditions are not highly skewed. RSMA, on the other hand, partially decodes interference: the transmitter sends a common message (intended for all users) that encodes part of each user's data, and private messages for the remaining data [1]. All receivers decode the common message first (using SIC) then their own private message [1], [2]. In doing so, RSMA can smooth out the rate disparity between users and effectively manage interference by choosing how much information to put in the common stream. This ability to treat some interference as decoded signal and the rest as noise leads to robust performance gains. Studies have shown that RSMA yields higher spectral efficiency than NOMA in multi-antenna systems, even when channel state information is imperfect [4], [27]. In UAV networks, where acquiring perfect CSI is challenging due to mobility, RSMA's robustness to CSI errors is a significant advantage [16].

Performance Benefits in UAV Networks: Early works analyzing RSMA in UAV communications reported improved throughput and capacity [21]. For instance, Jaafar et al. (2020) examined a UAV-assisted downlink and found that RSMA provides throughput gains over space-division multiple access in various UAV deployment scenarios [14], [15]. Singh et al. (2023) investigated an RSMA-enabled UAV communication system and optimized UAV placement, demonstrating increased ergodic capacity compared to OMA/NOMA baselines [15]. Another study by Singh et al. considered finite and infinite blocklength communications with RSMA on a UAV link, highlighting performance improvements even with imperfect SIC and CSI conditions [4], [16]. A recent example quantified RSMA's advantage: Huang et al. (2025) showed in simulations that a UAV-assisted downlink using RSMA achieved about 13.3% higher system throughput than a comparable NOMA scheme [24]. Such improvements are crucial for UAVs, which often serve many users within their coverage and must maximize spectral efficiency due to limited bandwidth.

Integration with UAV Operations: RSMA's flexibility aids not just in link-level performance but also in network-level decisions. For example, in multi-UAV networks, RSMA can be used in both downlink and uplink to allow more aggressive frequency reuse [22]. Ji et al. propose a network where users have uplink–downlink decoupled (UDDe) association and employ RSMA on the downlink to manage the interference from multiple UAVs transmitting simultaneously [10]. RSMA becomes a key enabler for such complex association policies by mitigating the resulting interference. Simulation results confirmed that a decoupled association strategy with RSMA outperforms conventional coupled association in sum-rate [10]. Beyond conventional communications, RSMA has found roles in advanced scenarios. For instance, in UAV-enabled mobile edge computing (MEC) systems, a UAV may serve multiple users offloading computation tasks. Truong et al. (2022) introduced HAMEC-RSMA for an aerial computing system, where RSMA improved the efficiency of task offloading by managing uplink interference among users transmitting data to the UAV [8]. Likewise, RSMA has been considered in UAV networks supporting ultra-reliable low-latency communications (URLLC). Alkanhel et al. (2025) formulated a UAV-based RSMA system explicitly targeting URLLC QoS and showed improved reliability in meeting latency and rate constraints using RSMA compared to baseline multiple access methods [26].

IV. Reinforcement Learning Approaches in UAV Networks with RSMA

Researchers have actively explored DRL-based solutions to optimize UAV networks employing RSMA, especially in the last few years (2022–2025). The problems addressed include sum-rate maximization, energy efficiency improvement, secure communications, latency and reliability (URLLC), and more. Table 1 provides a comparative summary of representative recent works in this domain, outlining their scenario, objectives, DRL approach, and key results. We then discuss these works in detail.

Discussion of Approaches: The above works illustrate a range of DRL techniques applied to RSMA-UAV problems:

- *Multi-Agent vs Single-Agent:* When multiple UAVs or multiple decision components are present, researchers have used multi-agent DRL. For example, Ji et al. treated each UAV as an agent learning user associations [10], whereas Adam & Elhassan used multiple agents for different UAVs (or different tasks like trajectory and beamforming separately) [25]. Most multi-agent solutions adopt a centralized training phase to handle couplings, then decentralized execution (agents make decisions locally), aligning with CTDE principles. Some works (e.g., Ji et al.) explicitly address partial observability by modeling as a POMDP and using decentralized policies [7], [10]. In contrast, single-agent DRL is used when one central controller can dictate all decisions, as in a single UAV optimizing its own trajectory and resource allocation [5], [11].

TABLE I
REPRESENTATIVE DRL-BASED RSMA APPROACHES FOR UAV NETWORKS (2022–2025)

Ref.	Scenario & Objective	Decision Variables
[10]	Multi-UAV cellular; decoupled UL–DL association with RSMA; maximize sum-rate	UL/DL association, precoding
[5]	Single UAV downlink; sum-rate via 2D placement + RSMA	UAV 2D position, power/precoder
[11]	UAV downlink remote areas; 3D trajectory + RSMA	UAV 3D path, power/precoder
[9]	Energy-harvesting UAV; long-term sum-rate	Power (battery-aware), precoder
[26]	UAV downlink; URLLC (latency, reliability)	Beamforming/rate, trajectory
[25]	Multi-UAV with eavesdroppers; secrecy rate	Beamforming, rate split, trajectories
[12]	Active-RIS-assisted UAV; energy efficiency	Beamforming, RIS config, 3D flight, common rate
[20]	RIS-aided RSMA networks (aerial/terrestrial)	RIS phases, power, splits

- *Choice of DRL Algorithms:* Continuous control problems (like power levels, 2D/3D positions, beamforming vectors) naturally lend themselves to actor–critic methods like DDPG and its variants. DDPG was popular in early works (e.g., Hua et al. used DDPG for 2D trajectory optimization), but can suffer from unstable training and overestimation of Q-values [7]. To address this, later works have employed TD3 (Twin-Delayed DDPG), which adds clipped double Q-learning and other improvements for stability [11]. Nguyen et al.'s TD3-based framework explicitly outperformed DDPG in both convergence speed and achieved sum-rate [11]. PPO, a more stable policy gradient method, was adapted in multi-agent form by Ji et al. with additional stabilization heuristics [10]. For discrete decision components (like offloading decisions or discrete rate selection), Deep Q-Networks (DQN) can be used, but in RSMA literature DQN is less common due to many continuous variables.
- *Hybrid Model-Based + DRL Approaches:* A notable trend is combining deep learning with domain-specific optimization techniques. For instance, in the URLLC study by Alkanhel et al., deep unfolding was used to embed a model-driven optimization (for beamforming and rate allocation) into the learning loop [26]. This yields a hybrid where part of the problem (e.g., designing beamformers) is solved using a few iterations of an optimization algorithm unrolled as a neural network, while the DRL agent focuses on other parts (like trajectory). Similarly, Seong et al. split the problem: a DRL agent handles power control under energy harvesting constraints, and a solver (SLSQP) handles precoder design for given power [9], [20]. Such decompositions leverage the strength of both worlds: fast convergence of known algorithms for sub-problems and the adaptability of RL for global decision-making. The "DUN-DRL" (Deep Unfolding + DRL) in the secrecy context is a prime example, which showed better performance than end-to-end DRL [25].
- *Limitations:* Despite successes, these works often emphasize certain limitations. Many DRL solutions rely on a training phase in a simulated environment; generalizing to real-world or varying conditions can be an issue. Some approaches don't consider multi-agent coordination during execution (each agent may converge to a selfish policy if not carefully designed). As noted in recent RSMA-UAV works, CTDE should be incorporated more explicitly to stabilize learning in coupled environments [2], [9]. Another noted gap is that energy-efficiency optimization (rather than sum-rate) in RSMA networks via DRL was relatively overlooked until very recently [7], [12].

V. CHALLENGES AND FUTURE TRENDS

Sample Efficiency & Training Cost: DRL algorithms often require a large number of interactions with the environment to converge to good policies. Training a UAV+RSMA control agent in high-dimensional state/action space can be time-consuming. In practice, obtaining a high-fidelity environment model or simulator that captures UAV dynamics, channel variations, and network traffic is itself a challenge. Future research may explore improved sample efficiency through techniques like transfer learning (e.g., pre-training on a simpler scenario and fine-tuning in the target scenario) or model-based RL, where a learned or approximate model of the network dynamics is used to reduce the need for direct interaction.

Multi-Agent Coordination: When multiple UAVs or multiple agents (for different network functions) are involved, coordination without centralized control is difficult. Many existing works used simultaneous learning or independent learners, which can lead to non-stationary behaviors from each agent's perspective. Adopting a centralized training, distributed execution (CTDE) paradigm is promising, as it can stabilize training by giving agents access to global information (e.g., via a centralized critic) while keeping execution decentralized. Future work should integrate CTDE more explicitly into RSMA-UAV DRL frameworks to enable scalability to larger fleets of UAVs and more users. Techniques from multi-agent RL (like MADDPG, QMIX, or mean-field RL) could be customized for RSMA scenarios to ensure agents learn cooperative policies (for interference management, for example).

Robustness, Safety, Sim-to-Real: UAV networks face uncertainties like sudden channel outages, UAV hardware failures, or model mismatches (sim-to-real gap). DRL policies can be brittle if conditions deviate from training. Ensuring robustness is a key challenge. Robust or distributional RL algorithms might be used to account for uncertainties during training. Additionally, safety constraints (like avoiding collisions or ensuring a minimum quality of service at all times) are hard to guarantee with black-box policies. Future research might incorporate safe RL or constrained RL approaches, ensuring that the learning process respects critical constraints (e.g., URLLC reliability or UAV flight regulations) at all times, not just at convergence.

Incorporating Domain Knowledge: One trend seen in recent works is combining DRL with domain-specific knowledge (e.g., optimization solvers, deep unfolding of algorithms). This hybrid approach often yields better performance and faster convergence. Future systems can expand on this by, for example, using expert demonstrations or imitation learning from known good solutions (like convex optimization results for simplified scenarios) to guide the DRL agent initially. Another idea is to use meta-learning to allow the agent to quickly adapt to new environments (e.g., when the number of users changes or traffic patterns shift). We expect more work on adaptive or online learning where the agent continues to learn during deployment to handle environment non-stationarity.

Integration with other methods: Future UAV networks will likely integrate RSMA with other technologies such as Integrated Sensing and Communication (ISAC) and Reconfigurable Intelligent Surfaces (RIS). RSMA has already been investigated in an ISAC context. In UAV networks, a UAV might perform sensing (for environment mapping or surveillance) while communicating; DRL could then be used to manage the dual use of resources similar to how beamforming was managed in RSMA–ISAC via PPO. For RIS-assisted UAV networks, while initial studies used conventional optimization, DRL can be used to handle the real-time reconfiguration of RIS elements along with RSMA precoding, as seen in the AARIS meta-RL work [12]. We anticipate research on joint RIS phase shift and RSMA control via DRL, enabling UAVs to smartly reflect signals to users and maybe even self-optimize their channels.

VI. Conclusion

RSMA equips UAV networks with a robust interference-management lever via common/private splitting and SIC, outperforming OMA/NOMA especially under imperfect CSI. DRL provides the adaptive control substrate to optimize RSMA's many coupled degrees of freedom in dynamic environments. Recent works (2022–2025) demonstrate consistent gains in throughput, energy efficiency, URLLC, and secrecy by combining actor–critic/MARL with hybrid model-based tools and trajectory co-design. Key challenges remain in sample efficiency, multi-agent coordination, safety/robustness, and sim-to-real transfer. Future research should emphasize CTDE MARL at scale, meta/transfer and safe RL, energy-aware learning, and tight integration with RIS/ISAC/MEC towards AI-native, autonomous UAV communications in 6G.

VII. Acknowledgment

This work was supported by the IITP (Institute of Information & Communications Technology Planning & Evaluation) - ITRC (Information Technology Research Center) (IITP-2026-RS-2022-00156353, 50% / IITP-2026-RS-2023-00258639, 50%) grants funded by the Korea government (Ministry of Science and ICT).

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