Review

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Review

The Role of Artificial Intelligence in Next-Generation Handover Decision Techniques for UAVs over 6G Networks

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Abstract

The rapid integration of unmanned aerial vehicles (UAVs) into next-generation wireless systems demands seamless and reliable handover (HO) mechanisms to ensure continuous connectivity. However, frequent topology changes, high mobility, and dynamic channel variations make traditional HO schemes inadequate for UAV-assisted 6G networks. This paper presents a comprehensive review of existing HO optimization studies, emphasizing artificial intelligence (AI) and machine learning (ML) approaches as enablers of intelligent mobility management. The surveyed works are categorized into three main scenarios: non-UAV HOs, UAVs acting as aerial base stations, and UAVs operating as user equipment, each examined under traditional rule-based and AI/ML-based paradigms. Comparative insights reveal that while conventional methods remain effective for static or low-mobility environments, AI- and ML-driven approaches significantly enhance adaptability, prediction accuracy, and overall network robustness. Emerging techniques such as deep reinforcement learning and federated learning (FL) demonstrate strong potential for proactive, scalable, and energy-efficient HO decisions in future 6G ecosystems. The paper concludes by outlining key open issues and identifies future directions toward hybrid, distributed, and context-aware learning frameworks for resilient UAV-enabled HO management.

Keywords: handover optimization; mobility management; UAV communication; 6G networks; artificial intelligence; machine learning; deep reinforcement learning

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1. Introduction

Connected Unmanned Arial Vehicles (UAVs, also known as drones) are emerging as a critical technology, providing diverse services across various environments, but their mobility demands stable and seamless connectivity. A primary challenge lies in effective handover (HO) management, especially as cellular networks evolve towards 6G, which targets ultra-high data rates, ultra-low latency, and ubiquitous coverage [1]. Traditional HO approaches often prove inadequate for the dynamic and heterogeneous conditions faced by UAVs due to their inherent complexity and limited accuracy [2,3].

This paper surveys the crucial role of Machine Learning (ML) techniques in optimizing UAV HO decisions for 6G networks. ML offers intelligent and adaptive solutions to mitigate frequent HOs and ensure robust Quality of Service (QoS) for highly mobile UAVs [1,4,5]. By examining existing challenges and solutions, this review identifies key opportunities and future research directions for seamless UAV integration into advanced wireless ecosystems.

1.1. Motivation: The Transformative Potential of Cellular-Connected UAVs

UAVs are expected to profoundly transform future wireless networks and revolutionize various industries. The UAV industry itself is projected to experience substantial growth, with an expected increase from 19.3 billion USD in 2019 to 45.8 billion USD by 2025. This significant economic expansion is driven by the UAVs' inherent flexibility, low-altitude capabilities, and potential cost-efficiency, making them attractive for both academia and industry [6,7].

Cellular-connected UAVs offer versatile roles within these networks, capable of acting as flying base stations (BSs), relays, or user equipment (UEs). When deployed as airborne BSs, UAVs can intelligently adjust their position, enabling reliable and cost-effective wireless communication, enhancing network scalability, and providing ubiquitous coverage [8–10]. Their ability to adapt altitude and navigate obstacles improves the likelihood of establishing line-of-sight (LoS) communication with ground users. This makes them invaluable for diverse applications, including telecommunications, surveillance, monitoring, environmental sensing, border security, cargo delivery, visual shows, disaster management, search and rescue, and emergency response [8,11–13]. UAVs can also significantly enhance intelligent transportation systems and even offer telepresence solutions.

However, realizing the full potential of cellular-connected UAVs depends on ensuring seamless and reliable wireless connectivity, particularly during HO events. Unlike terrestrial devices, UAVs exhibit high mobility in a three-dimensional (3D) environment, leading to frequent and often unpredictable changes in signal conditions. These characteristics can result in frequent HOs, affecting connectivity and QoS [14,15]. The critical and sensitive nature of many UAV applications, such as rescue missions and medical supply delivery, further emphasizes the importance of addressing these mobility challenges to ensure robust command and control signaling and continuous data transmission [16]. Therefore, optimizing HO decisions is paramount for maximizing operational efficiency and unlocking the transformative capabilities of UAVs in future networks.

1.1.1. Emerging Applications of Cellular-Connected UAVs

Cellular-connected UAVs are transforming industries and are recognized as a highly promising technology for future wireless networks, with significant market growth anticipated. Their inherent autonomy, high mobility, and flexible deployment enable diverse and emerging applications [6,12].

These UAVs serve critical functions, acting as flying BSs or relays to extend network coverage and capacity, particularly in challenging environments, remote areas, or for rapid deployment during disaster management, search and rescue, and emergency response operations [8,17]. As user equipment (UEs) within cellular networks, they facilitate applications such as package delivery, including vital medical supplies, remote sensing, and various forms of surveillance and monitoring, encompassing industrial IoT (IIoT) platforms [18,19].

Beyond these, UAVs are integral to evolving concepts like the Internet of Things (IoT) in the sky and the broader Internet of Everything (IoE), providing real-time data for environmental sensing and civil infrastructure monitoring. Their capabilities further extend to traffic management, asset inspection, aerial imaging, and visual shows. The integration with 6G networks is expected to enable advanced services such as ultra-smart cities and Extended Reality (XR) [11]. This wide range of applications emphasizes the critical need for seamless and reliable wireless connectivity provided by cellular networks.

1.1.2. The Crucial Need for Seamless and Reliable Wireless Connectivity

Wireless communication networks are witnessing an unprecedented demand for continuous, reliable, and stable connectivity, driven by the rapid growth of smart devices and the expansion of the IoE. This need is particularly critical for UAVs in diverse applications, where safe operation and real-time data exchange are paramount [11,20–23]. The evolution towards Sixth Generation (6G) networks, with their emphasis on the next technological improvement of the Ultra-Reliable Low-

Latency Communications (URLLC), further stresses the necessity for uninterrupted and high-quality links, especially for mission-critical services [24,25].

However, achieving such seamless connectivity in dynamic environments presents significant challenges. Traditional cellular networks are primarily optimized for ground UEs, making connectivity for flying UAVs difficult [34,35]. UAVs experience volatile radio environments, higher interference, and significantly more frequent HOs than ground users due to their high mobility and operating altitudes [23]. These factors lead to issues such as Radio Link Failures (RLF), HO failures (HOF), and ping-pong HOs, which degrade service quality, increase signaling overhead, and can result in packet loss [15,22,29]. Moreover, the dense deployment of small cells and the use of Millimeter Wave (mmWave) and Terahertz (THz) bands amplify the challenge by increasing HO frequency and susceptibility to signal blockages [30]. Efficient HO management for UAVs is thus crucial to minimize service interruption to ensure consistent data rates and reliability.

1.1.3. Scope and Contributions: Bridging the Gap in UAV HO Research

UAV HO management presents significant challenges due to their inherent 3D mobility, which complicates traditional terrestrial network mobility issues. Unlike ground users, UAVs operate in a unique radio environment where altitude changes profoundly impact communication and interference, often leading to increased HO rates and failures [18]. Limited onboard battery capacity and frequent HOs also pose critical limitations, potentially causing communication disruptions and reduced mission endurance. Existing cellular systems were not optimally designed for aerial users, necessitating tailored solutions for efficient mobility management [14,19,31]. Furthermore, the narrow beamwidths of millimeter-wave (mmWave) and THz communications can result in disconnections due to antenna misalignment, further deteriorating performance.

To bridge these identified gaps, various ML-based approaches have been proposed to enhance UAV HO decisions. Reinforcement Learning (RL) frameworks, such as Q-learning, offer flexible HO decision, allowing for adaptable trade-offs between HO frequency and received signal strength (RSS)/Signal-to-Interference-plus-Noise Ratio (SINR) [32]. More advanced DRL algorithms, including Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN), have demonstrated substantial reductions in unnecessary HOs and improved communication reliability by dynamically optimizing parameters based on current conditions. For instance, the REQIBA solution leverages regression neural networks and Dueling Double DQN (D3QN) for intelligent BS association, maximizing throughput while managing HO rates effectively, particularly in interference-limited channels [15,18]. Recent contributions also address joint trajectory planning and HO management for multi-UAV systems, aiming to minimize key performance indicators (KPIs) like delay, interference, and HO numbers by considering their inter-dependencies [33]. These advancements are crucial for enabling seamless and reliable UAV integration into future 6G networks, addressing the complex challenges posed by their unique operational characteristics.

1.1.4. Focus on AI/ML-Based HO Decision for Cellular-Connected UAVs in 6G Networks

The integration of UAVs into 6G networks introduces significant mobility management challenges. Their high speeds and 3D mobility, coupled with narrow beamwidths in mmWave and THz bands, cause frequent HO and degraded QoS [34,35].

Artificial Intelligence (AI) and ML are crucial for these complexities. They enable systems to learn network behaviors, predict future conditions, and make proactive HO decisions, overcoming traditional reactive limitations [15,36,37].

RL, including Deep RL (DRL), is highly promising for UAV HO optimization, effectively minimizing HO frequency and maintaining signal quality [15,38]. In parallel, Recurrent Neural Network (RNN), a deep learning (DL) model that employs the concept of supervised learning, predict UAV trajectories and signal strength for precise HO timing [39,40].

These AI/ML-driven approaches collectively reduce unnecessary HOs, improve communication reliability, and enhance overall network performance for UAVs in the challenging 6G environment.

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1.1.5. Comprehensive Review Scope and Key Contributions

This review paper makes several key contributions to the field of UAV HO management in future wireless communication networks, including 6G.

This paper contributes to the academic discourse by providing:

- A unified and comprehensive overview of the growing research efforts in UAV HO management, consolidating existing knowledge and outlining essential directions for future investigations.
- A specific focus on ML applications for UAV HO management, differentiating it from broader mobility management surveys.
- Detailed discussions on communication requirements and design challenges for the seamless integration of cellular-connected UAVs into future wireless systems, including 6G.
- An identification of existing limitations in current research, such as the scarcity of reliable datasets, insufficient detail on ML tools, and overlooked hardware impacts, which hinder reproducibility and practical deployment.

1.2. Paper Organization

This paper is structured into nine main sections, as illustrated in Figure 1. **Section 1** introduces the motivation, objectives, and contributions of the study, emphasizing the need for intelligent HO mechanisms in UAV-assisted 6G networks. **Section 2** provides the necessary background on UAV communications, 6G architectures, and HO fundamentals, establishing the conceptual basis for subsequent discussions. **Section 3** reviews existing studies on HO optimization, categorized into non-UAV, UAVs acting as BSs (UAV-BS), and UAVs acting as UE (UAV-UE) scenarios, covering both traditional and AI/ML-based methods. **Section 4** discusses key HO challenges for cellular-connected UAVs, including mobility, interference, and dynamic topology issues. **Section 5** examines AI/ML-driven HO decision techniques, outlining learning paradigms and their application in UAV networks. **Section 6** presents performance evaluation parameters and key metrics used across the reviewed literature. **Section 7** identifies major open research challenges that limit efficient UAV HO design. **Section 8** highlights future research directions toward hybrid, distributed, and context-aware learning frameworks. Finally, **Section 9** concludes the paper with summarized findings and recommendations for advancing intelligent UAV handover management in 6G systems.

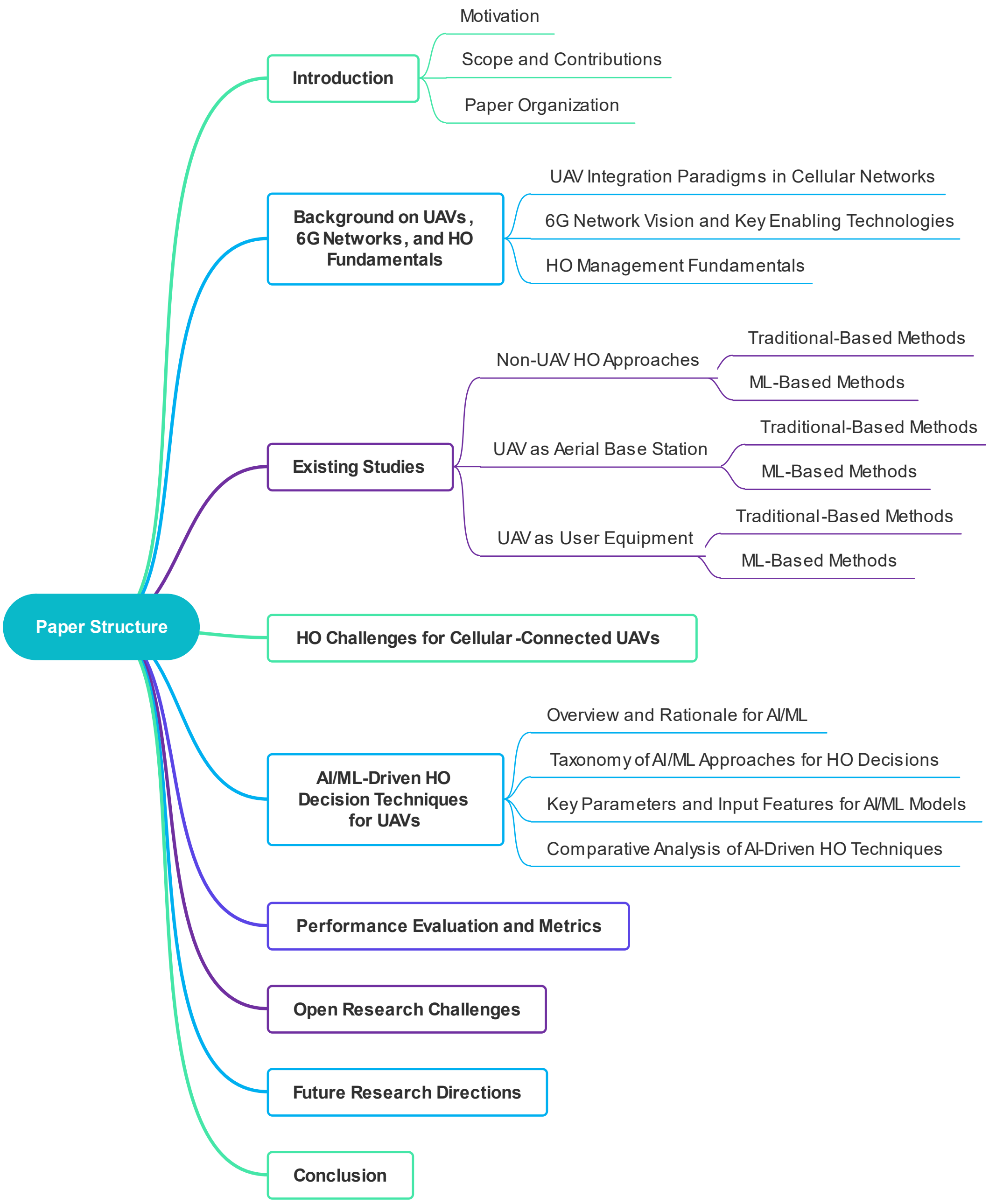

Figure 1. Organizational structure of the survey paper.

2. Background on UAVs, 6G Networks, and HO Fundamentals

The integration of UAVs into cellular networks introduces new opportunities and challenges across different deployment paradigms. UAVs may operate as UEs, facing interference and mobility issues, or serve as aerial base stations (ABSs) and relays to extend coverage. Besides, the emergence of Heterogeneous Networks (HetNets) and Ultra-Dense Networks (UDNs) further transforms the network environment. As the evolution toward 6G promises ultra-reliable, low-latency, AI-driven connectivity, HO management becomes critical to ensure seamless communication, optimize resources, and maintain service quality in increasingly complex and dynamic wireless environments [41].

2.1. UAV Integration Paradigms in Cellular Networks

UAVs are integrated into cellular networks in two primary paradigms: as UEs and as ABSs or relays as illustrated in Figure 2 [17]. When functioning as UEs, UAVs perform tasks as aerial users

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that connect to the existing terrestrial cellular network for command-and-control (C&C) and payload data exchange. However, as UEs, UAVs face significant challenges, including strong interference, frequent HOs, and throughput degradation at higher altitudes [18,42]. Conversely, when deployed as ABSs or relays, UAVs function as mobile infrastructure, extending terrestrial network coverage and providing services to terrestrial UEs [43]. Additionally, UAV-UAV communication facilitates data and control signal exchange between UAVs, often relying on intra-UAV links [12].

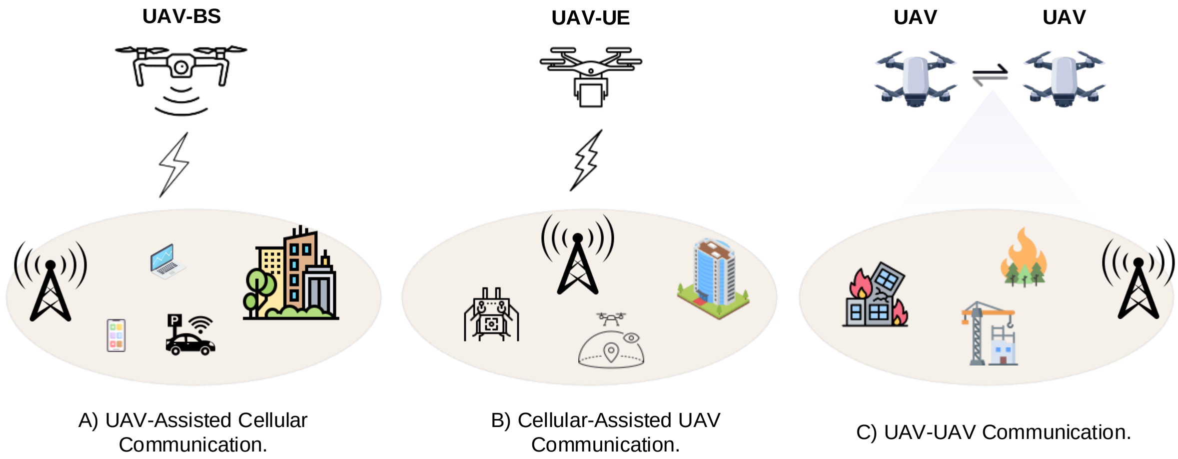

Figure 2. Integration paradigms of UAVs in future mobile networks.

2.1.1. UAV as User Equipment

UAVs operating as UEs are crucial for next-generation cellular networks, supporting applications like surveillance and package delivery, leveraging their flexible deployment. This role, however, presents challenges including limited battery capacity and frequent HOs in dynamic 3D environments, poorly handled by traditional algorithms [27]. High UAV mobility increases HO rates with speed and altitude, impacting QoS [6]. ML solutions are vital for optimizing HO decisions, trajectory, and resource allocation, aiming to improve connectivity, energy efficiency, and signal quality for UAV UEs [15,23,33].

2.1.2. UAV as Aerial Base Station or Relay

UAVs are increasingly deployed as ABSs or relay nodes, complementing ground networks in cellular systems. This offers enhanced coverage, capacity, reliability, and energy efficiency. Furthermore, their mobility and adaptive altitude enable rapid deployment in disaster areas or for high-traffic hotspots where terrestrial infrastructure is insufficient. Moreover, UAV ABSs improve LoS communication due to elevated positions, reducing signal blockage [8,44].

2.2. Heterogeneous Networks and Ultra-Dense Networks

HetNets integrate diverse wireless communication technologies, deploying various BSs such as macrocells, microcells, picocells, and femtocells to enhance network capacity and QoS [45,46]. Similarly, UDNs involve a high density of small cells to significantly improve capacity, spectral efficiency, and user experience. Both HetNets and UDNs are crucial for 5G and 6G networks. However, their reliance on small cells often leads to an increased number of HOs, potentially causing HO ping-pong, HO failures, and heightened interference and signaling overhead [47,48]. Effective HO management is therefore essential for maintaining seamless connectivity.

2.3. 6G Network Vision and Key Enabling Technologies

The 6G network vision centers on ubiquitous, ultra-low latency, and highly reliable connectivity, natively leveraging AI. Key performance indicators include ultra-high data rates, extremely low latency, ultra-high reliability, and very high mobility [49–51].

Key enabling technologies for 6G include mmWave and THz communications to address spectrum resource scarcity, non-terrestrial network (NTN) (e.g., satellites, UAV-mounted BSs) for global seamless coverage, and Mobile Edge Computing (MEC) for reduced latency. AI and ML are expected to play a crucial role in these networks [46,52,53].

2.3.1. Vision and Requirements

The vision for 6G networks transcends 5G capabilities, aiming for seamless, high-performance connectivity across environments. These networks are designed to integrate space, air, ground, and underwater communications, connecting everything with intelligence [53,54]. Key requirements of 6G include ultra-high data rates of up to 1 Tbps and end-to-end latency below 0.1 ms. Achieving 99.99999% reliability and supporting connection densities of up to 10 million devices per square kilometer are critical. Furthermore, 6G is projected to handle high mobility, up to 1000 km/h, utilizing THz frequency bands and so it is expected to deliver up to 100 times greater energy efficiency compared to 5G. Moreover, AI is fundamental to 6G, enabling autonomous network management, real-time decision, and self-optimization.

This AI-nativeness enables emerging services with stringent performance demands, such as holographic communications, tactile internet, and autonomous vehicles [49,53,55–58]. Table 1 provides a comparison of 5G and 6G in terms of mobility and HO characteristics [50].

Table 1. Key differences between 5G and 6G networks and their implications for mobility and HO performance.

Parameter	5G	6G	Impact on Mobility and HO
Operating Frequency	Sub-6 GHz + mmWave bands	mmWave and THz spectrum >10 GHz	Higher frequencies in 6G increase susceptibility to blockage and require more frequent HOs.
Available Bandwidth	Up to ~400 MHz	>1 GHz (very wide channels)	Wider bandwidth enables high data rates but increases complexity of maintaining stable links during fast mobility.
Latency	~1 ms	<1 ms (target)	Ultra-low latency demands fast and optimized HO execution mechanisms.
Node Density	~10^6 devices/km^2	~10^7 devices/km^2	Increased density leads to more interference zones and more frequent HO decisions.
Mobility Support	Up to ~500 km/h	>1000 km/h (target)	Extremely high mobility in 6G (e.g., drones, HAPS) requires predictive and AI-assisted HO strategies.
Network Architecture	Dense small cell deployments	Ultra-dense cell networks with UAV/NTN integration	- Dense deployment increases HO rate. - UAV-assisted cells introduce 3D mobility challenges.

2.3.2. Key Enabling Technologies for 6G

In next-generation wireless networks, various technologies play complementary roles in enabling high-performance connectivity. For instance, mmWave and THz bands offer high data rates but experience significant path loss and limited coverage, which leads to frequent HOs. Moreover, NTN, integrating satellites and UAVs, provides global coverage but faces complex HO due to high mobility. In addition, MEC reduces latency and enhances processing by moving computing closer to users for real-time applications; however, HO authentication remains a challenge [48,53]. Furthermore, Software-Defined Networking (SDN) and Network Function Virtualization (NFV) boost flexibility and scalability, while reducing latency, which are essential for managing complex networks and HO [46,59]. Figure 3 highlights the 6G vision, emphasizing key enabling technologies.

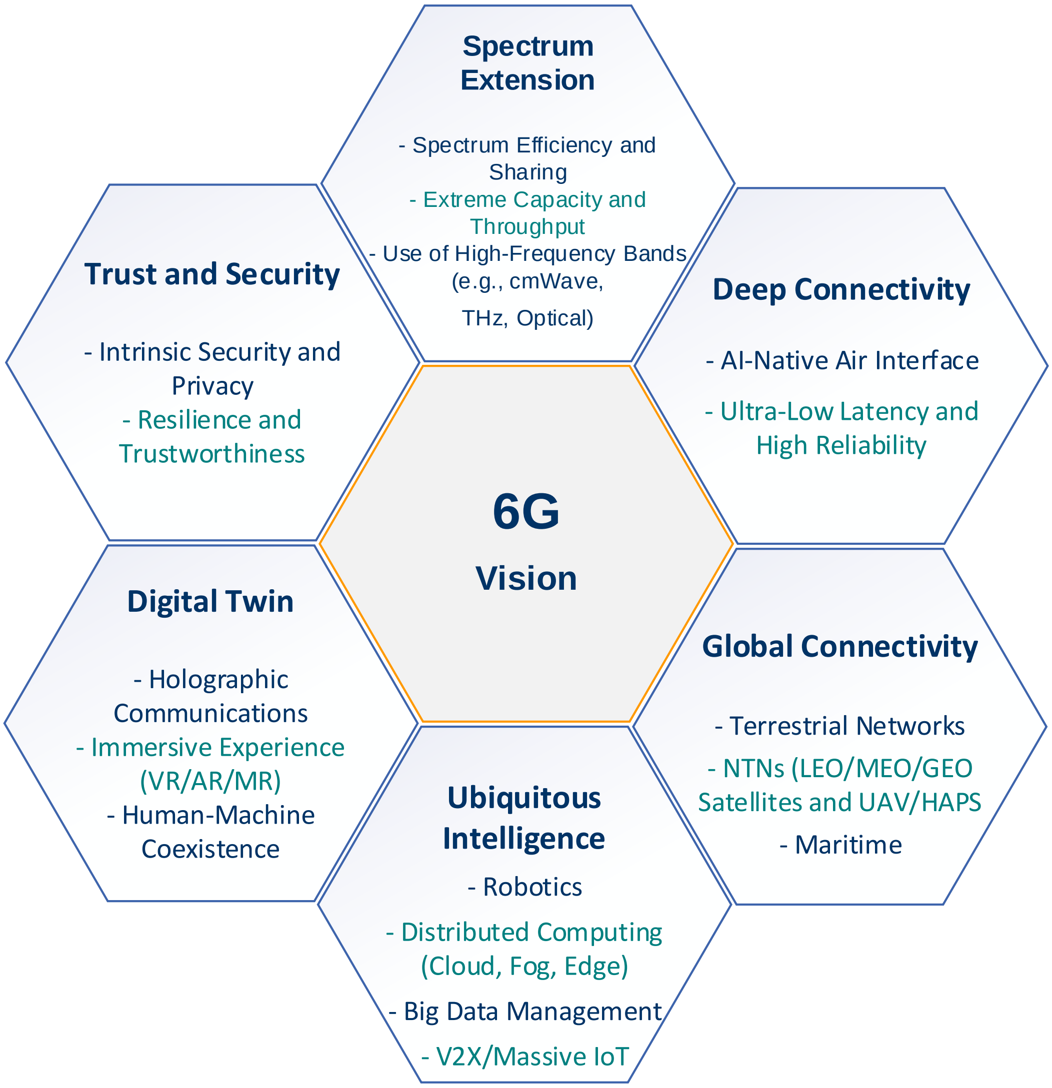

Figure 3. The 6G vision highlighting key enabling technologies.

2.4. HO Management Fundamentals

HO management is fundamental for maintaining seamless communication as UEs move between different cell coverage areas. Its objectives include preserving signal continuity, optimizing resource allocation, balancing network load, and conserving energy [41]. Besides, HO Control Parameters (HCPs) such as Time-To-Trigger (TTT), HO Margin (HOM), and Cell Individual Offset (CIO) are dynamically adjusted to minimize unnecessary HOs and failures The HO process typically begins with the UE monitoring signal quality and sending measurement reports to the serving base station, which then evaluates this data to select the optimal target BS for the HO [59–61].

2.4.1. Basic HO Concepts and Procedures

HO plays crucial role for mobility management in cellular networks, enabling the transfer of an active communication session from a serving BS to a target BS without service interruption. This process is essential for maintaining signal quality, ensuring service continuity, balancing network load, and optimizing resource allocation [1]. Besides, the HO procedure generally comprises three distinct stages: preparation, execution, and completion [42]. Initiation typically involves UE sending measurement reports (MRs) to the serving BS, detailing signal quality metrics such as Reference Signal Received Power (RSRP). A common triggering condition, like the 3rd Generation Partnership Project (3GPP) A3 event, is met when the target BS's RSRP exceeds that of the serving BS by a defined HOM for a specified TTT duration [1,59,62]. The HO procedure is depicted in Figure 4, where the HO decision is initiated once the received signal strength from the target cell exceeds that of the serving cell by a predefined offset threshold [48].

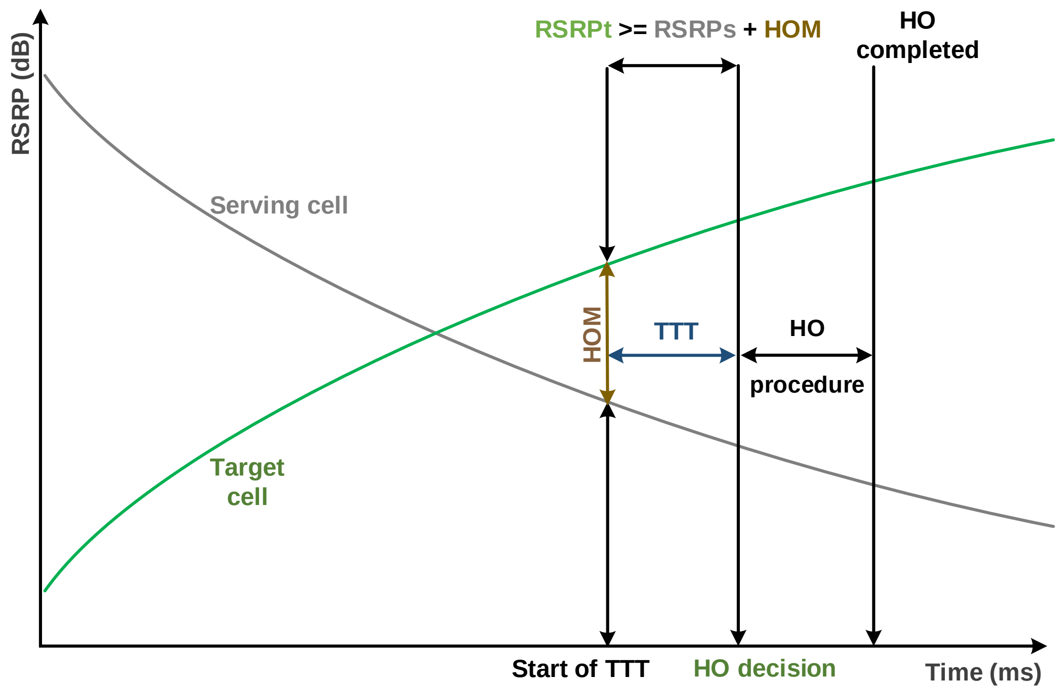

Figure 4. Description of HO Procedure.

2.4.2. HO Control Parameters

HCPs are essential for managing HO processes, ensuring stable and quality connections for UEs. The primary HCPs include HO Margin and Time-To-Trigger. These parameters determine the optimal timing for initiating a HO. In addition, incorrect HCP setting can lead to issues such as too-early or too-late HOs, increasing HO Ping-Pong (HOPP) or RLF probabilities, respectively. Moreover, adaptive adjustment of HCPs based on factors like UE speed and signal quality is crucial for network performance [30,63,64]. Table 2 presents the relationship between HO parameter configuration and corresponding HO failures [48].

Table 2. Impact of suboptimal HO parameter settings on HO performance.

HO Issue	TTT Setting	HOM Setting	Resulting Performance Degradation
Delayed HO (HO occurs later than needed)	Too long	Too long	Increased RLF due to staying too long with a weak serving cell.
Premature HO (HO occurs too early)	Too short	Too short	Increased HOPP due to frequent switching between cells.
HO to Suboptimal/Incorrect Target Cell	Improperly adjusted	Improperly adjusted	May cause RLF or HOPP, depending on whether the link breaks or cells keep switching.

2.4.3. Measurement Events

UAV HO decisions heavily rely on measurement events, which involve reporting signal quality parameters to the serving BS. Key metrics include RSRP, RSRQ, and Received Signal Strength Indicator (RSSI). Moreover, standardized 3GPP HO events, such as A2 and A3, determine when a UAV initiates measurement reports [1,65,66]. For instance, Event A3 is triggered when a neighboring BS's signal exceeds the serving BS's signal by a predefined offset, an essential aspect for maintaining connection quality. Furthermore, parameters like TTT and hysteresis margins are crucial for managing these events, preventing excessive and unnecessary HOs [66,67].

3. Existing Studies

The evolution of HO optimization mirrors the transition from rule-based mobility management to intelligent, learning-driven decision frameworks. This section synthesizes representative studies across three categories, non-UAV terrestrial systems, UAVs acting as BSs, and UAVs as user equipment, each further divided into traditional and ML-based techniques.

3.1. Non-UAV HO Approaches

3.1.1. Traditional-Based Methods

Early HO optimization relied on analytical and multi-criteria methods. In [68], mathematical analysis improved vertical HO reliability by tuning latency and block distance. A hybrid Fuzzy Logic Controller (FLC) with Weighted Function in [63] dynamically adjusted HOM and TTT, minimizing RLF to 0.006. The Weighted Function model in [69] integrated RSRP, velocity, and traffic load to significantly cut HO interruption time. Similarly, [70] applied Fuzzy–MADM methods to achieve highly reduced unnecessary HOs at low speeds. Collectively, these classical models emphasize heuristic parameter control but lack predictive or autonomous capabilities.

3.1.2. ML–Based Methods

With 5G and beyond, HO management shifted toward predictive and data-driven control. Double Deep RL (DDRL) in [34] optimized network QoS by minimizing the occurrence of frequent

HOs. DQN and Multi-Agent DRL in [71] improved proactive HO success rate under fast user movement, while Random Forest clustering in [72] demonstrated significance of the distance between a user and its cell center for decision-making, tackling mobility management complexity inherent in next-generation networks. The Long Short-Term Memory (LSTM) model in [40] efficiently predicted RSRP sequences, cutting RLF rates significantly, while Double Deep Q-Learning in [66] reduced packet loss by 25.72% per HO, significantly outperforming the A3 RSRP baseline. These works established ML as a cornerstone for adaptive, context-aware HO, yet they still face issues of training cost and scalability.

3.2. UAV as Aerial Base Station

3.2.1. Traditional-Based Methods

Traditional UAV-BS studies extended terrestrial heuristics to aerial contexts. A Fuzzy System Strategy in [6] combined parameters like user speed, RSSI, and UAV's battery level, improving QoS and QoE and ensuring more stable connectivity in dynamic aerial networks. The adaptive Cell Individual Offset (CIO) algorithm in [73] reduced HO failure ratio and HOPP by managing CIO for HO of both UAV-BS and mobile users. A hybrid framework of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) with Q-learning (TOPSIS–Q-learning) in [44] reduced the size of the action-space in Q-learning, remarkably reducing unnecessary HOs. These multi-criteria and hybrid strategies introduced adaptability but required human-tuned thresholds, limiting autonomous scalability.

3.2.2. ML–Based Methods

Recent works leverage DL for UAV-BS intelligence. A DRL-based distributed DQN framework in [74] optimized long-term throughput while reducing HO frequency. In [42], user trajectory prediction via DL minimized misjudged HOs, improving the HO success rate. The Convolutional Neural Networks (CNN)–LSTM prediction in [75] reduced ping-pong and outage rates while increasing energy efficiency and load balance. Meanwhile, [76] utilized RNN/Gated Recurrent Unit (GRU)/LSTM for trajectory-aware HO control, boosting SINR and RSSI by 165% and 118%, respectively, indicating superiority of GRU model in carrying out HO management. Advanced DRL variants such as Noisy Network (NoisyNet)-DDQN-based Sequential HO [77] minimized unnecessary HOs improving overall performance, while Multi Agent DQN (MADQN) [78] improved HO management, by trading-off between deployment cost and UAV dropouts. Collectively, these AI-driven schemes exhibit strong performance under 3D dynamic conditions, though their computational cost remains a constraint for onboard deployment.

3.3. UAV as User Equipment

3.3.1. Traditional-Based Methods

For UAV-UEs, traditional models incorporated graph and optimization logic. The generalized inter-section method with HO (GIM-HO) model in [79] used graph-based optimization, which improved UAV trajectories and HO strategies, while the Weighted Summation Model in [58] optimized terrestrial–satellite transitions, improving reliability and seamless communication in remote and challenging environments. Hybrid approaches like model-based Service Availability Mobility Robustness Optimization (SA-MRO) with DQN [80] reduced HO numbers by over 50% and improved service availability by 40%. Though effective, these designs lacked real-time learning for unpredictable UAV trajectories.

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3.3.2. ML–Based Methods

Learning-driven schemes dominate UAV-UE optimization. Q-learning [22] reduced HO frequency and ensured cost-efficient mobility by balancing RSS and signaling overhead. DRL-PPO in [15] cut unnecessary HOs by up to 76% versus greedy baselines, while lowering signaling cost. Hybrid Generative Adversarial Network (GAN)–RL in [61] autonomously tuned hysteresis and TTT, ensuring smooth soft HOs, while Dueling Double Deep Q-Network (D3QN) in [81] improved HO frequency across diverse flight scenarios. Recent edge-intelligent models, such as Semantic MobileBERT in [82], achieved near-perfect HO prediction accuracy using multi-label contextual reasoning. These AI-based UAV-UE frameworks exhibit strong adaptability and self-learning behavior, underscoring a decisive evolution toward autonomous, context-aware HO in 6G aerial networks.

Overall, across all scenarios, the literature reveals a clear paradigm shift, from static, rule-based thresholds toward AI-enabled dynamic optimization. Traditional methods provided interpretability and simplicity, while ML-based frameworks now enable proactive, multi-objective decision-making critical for ultra-reliable, low-latency, and energy-efficient HOs in next-generation UAV-integrated networks.

4. HO Challenges for Cellular-Connected UAVs

Cellular-connected UAVs face significant HO challenges due to their unique 3D mobility and high speeds, leading to frequent HOs and the HO ping-pong effect [4,83]. The complex radio environment, characterized by unpredictable signal fluctuations, exposure to antenna sidelobes, and increased interference from multiple BSs in line-of-sight conditions, further complicates HO management. These issues culminate in performance degradation, including RLF, HO failures, increased latency, packet loss, and degraded QoS [2,44,45,83]. A summary of the HO Challenges for Cellular-Connected UAVs is presented in Figure 5.

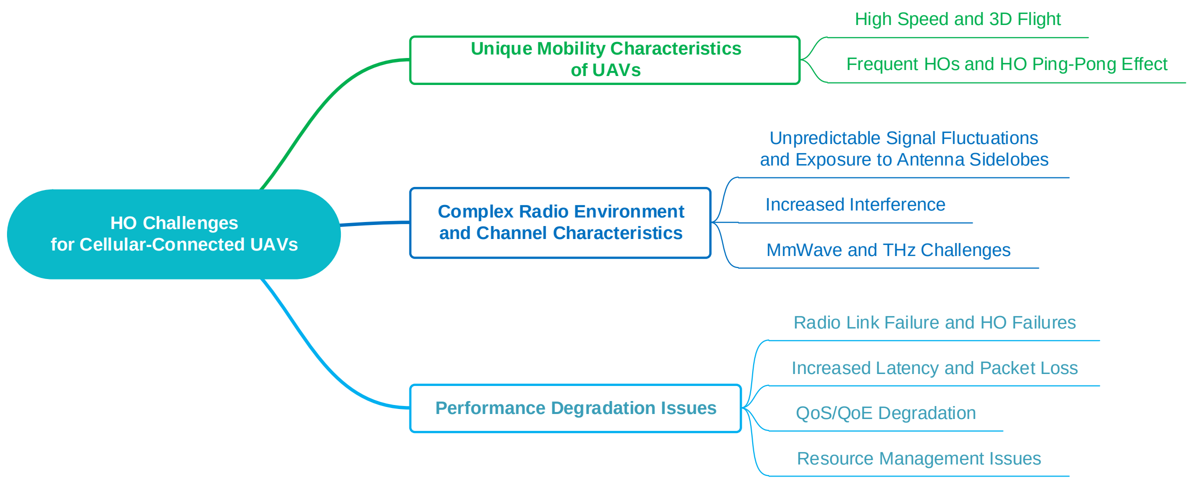

Figure 5. Summary of HO Challenges for Cellular-Connected UAVs.

4.1. Unique Mobility Characteristics of UAVs

UAVs exhibit unique mobility characteristics distinct from terrestrial UEs, primarily operating in 3D space at varying altitudes and speeds. Their unpredictable and often high-velocity trajectories can cause rapid changes in channel quality, leading to fragmented coverage and frequent HO with ground-based BSs. Unlike terrestrial scenarios, where radio conditions and HO thresholds are typically optimized for ground users, UAVs encounter unique environmental challenges. Furthermore, 3GPP models emphasize specific UAV parameters, including speeds up to 160 km/h and altitudes of 300 m, highlighting the complexities in maintaining stable connectivity [16,84,85].

4.1.1. High Speed and 3D Flight

UAVs operate at high speeds and in 3D space, profoundly affecting HO management. This inherent mobility and 3D flight lead to rapid channel quality changes and increased HO rates [83]. Traditional HO methods are often insufficient under these dynamic conditions [20]. Consequently, ML and DRL techniques are crucial for intelligent HO decision. DRL-driven schemes, for instance, optimize HOs in 3D environments, reducing unnecessary HOs and stabilizing communication links. Moreover, these systems manage complex trajectories and varying radio environments inherent to UAV operations [50,85].

4.1.2. Frequent HOs and HO Ping-Pong Effect

Frequent HOs and the HOPP effect significantly degrade network performance and user experience [88]. HOPP occurs when a mobile device frequently switches back and forth between two or more neighboring BSs, often triggered by signal fluctuations or inappropriate HO parameter settings. High UAV mobility can further worsen these frequent HOs. These unnecessary HOs lead to increased signaling overhead, latency, and energy consumption, ultimately resulting in reduced throughput and potential call drops [6,10,88,89]. Consequently, mitigating frequent HOs and the HOPP effect is crucial for maintaining seamless connectivity and QoS.

4.2. Complex Radio Environment and Channel Characteristics

UAV communication faces a complex radio environment, distinct from terrestrial settings due to varying altitudes and 3D mobility. Higher altitudes often yield LoS links, which, though reliable, also intensify interference for terrestrial users [17]. Besides, dynamic and unpredictable channel conditions, driven by UAV trajectories and velocities, cause rapid signal quality fluctuations, complicating HO management [85]. Additionally, mmWave and THz communications are highly susceptible to LoS blockage, high path loss, and antenna misalignment, resulting in frequent signal degradation and outages [18,90].

4.2.1. Unpredictable Signal Fluctuations and Exposure to Antenna Sidelobes

Unpredictable signal fluctuations significantly challenge UAV HO decisions, especially due to high mobility and dynamic mmWave/THz channels with narrow beamwidths [91]. These fluctuations are often a consequence of rapid changes in the received signal power and link quality, stemming from the UAV's high mobility, transitions between LoS and Non-Line-of-Sight (NLoS) conditions, and potential misalignment of narrow beamwidth antennas. Furthermore, UAVs often connect to BSs via antenna sidelobes, which are primarily downtilted for terrestrial users. These sidelobes offer fragmented coverage with sharp signal drops at their edges and deep nulls, frequently causing HO events and potential radio link failures [22,26,92].

4.2.2. Increased Interference

Increased interference poses a significant challenge in 6G networks, especially with UAV integration. In addition, elevated UAV operation and LoS propagation lead to broader signal coverage and reduced blockage, causing substantial uplink interference to terrestrial users and ground BSs [18,83]. Network densification with numerous small cells further intensifies inter-cell interference, degrading SINR and overall performance [93]. Therefore, effective interference management is crucial for robust communication and stability.

4.2.3. MmWave and THz Challenges

Despite spectrum benefits, mmWave and THz bands present significant challenges. In particular, high path loss, molecular absorption (mainly caused by water vapor), and susceptibility to blockages limit communication range and quality. Moreover, narrow beamwidths lead to disconnections from antenna misalignment. Consequently, these factors necessitate smaller coverage, resulting in frequent HO, increased signaling overhead, and complex HO management, often causing poor user experience [39,46].

4.3. Performance Degradation Issues

UAV HO decision faces significant performance degradation. In this regard, frequent and unnecessary HOs, including ping-pong effects, reduce reliability, throughput, QoS, and increase signaling overhead and energy consumption. Additionally, HO failures and RLF further cause service interruptions and diminish network performance. Moreover, challenges such as high altitude, signal drops, and interference intensify poor signal quality [30,94].

4.3.1. Radio Link Failure and HO Failures

RLF signifies a lost wireless connection due to poor quality or interference, interrupting communication [14,88]. Besides, HOF occurs when a UAV cannot complete the HO process. Both result from issues like too early/late HOs, wrong cell selection, or resource scarcity. Consequently, both significantly degrade network performance and user experience. Moreover, mitigation of these challenges involves optimizing HCPs, utilizing ML, and employing Conditional HO strategies [95–98].

4.3.2. Increased Latency and Packet Loss

Frequent UAV HOs significantly increase network latency and packet loss, disrupting communication and degrading QoS. This is primarily due to increased signaling overhead and HO interruption times required for re-establishing communication links. Furthermore, high user mobility and suboptimal HO parameter settings intensify these issues, potentially leading to service disruptions and data transmission errors [2,47,99]. Therefore, mitigating unnecessary HOs is crucial to reducing these delays, ensuring stable connections, and improving overall network efficiency.

4.3.3. Quality of Service/Quality of Experience Degradation

QoS and QoE are significantly degraded by frequent HO events and the resultant ping-pong effect, reducing communication quality, increasing HO delays, and raising dropping probabilities [46,88]. This degradation is getting further worse in dense network deployments and with high UAV mobility, which generate more HOs and signaling overhead [47]. Thus, optimizing HO is crucial to sustain reliable connectivity.

4.3.4. Resource Management Issues

Resource management presents significant challenges in 6G networks, particularly for UAV-assisted systems. Critical issues include the scarcity of radio, computing, storage, and energy resources. Furthermore, high UAV mobility and dynamic network conditions overwhelm conventional resource management methods, which struggle with rapid responses and generate substantial control signaling overhead. Moreover, dense deployments, coupled with diverse QoS requirements, intensify interference and resource shortages, making efficient joint optimization complex. Besides, limited onboard energy and processing capabilities further constrain UAV operations [76,100,101].

5. AI/ML-Driven HO Decision Techniques for UAVs

AI/ML techniques are essential for optimizing HO decision in UAV networks, particularly in dynamic and complex 6G environments. These approaches overcome the limitations of traditional methods by learning hidden patterns, predicting network parameters, and enabling proactive HO optimization. In addition, AI/ML algorithms offer self-learning capabilities, improving performance

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through experience without explicit programming and adaptively modelling network behavior. Furthermore, this intelligence is crucial for managing the unique challenges of UAV mobility, dynamic channel conditions, and interference. Besides, AI/ML techniques span supervised, unsupervised, and RL, including DRL which integrates DL with RL for adaptive online HO decisions [22,49]. The concept of AI-driven HO decision in UAV-integrated HetNets over 6G is illustrated in Figure 6.

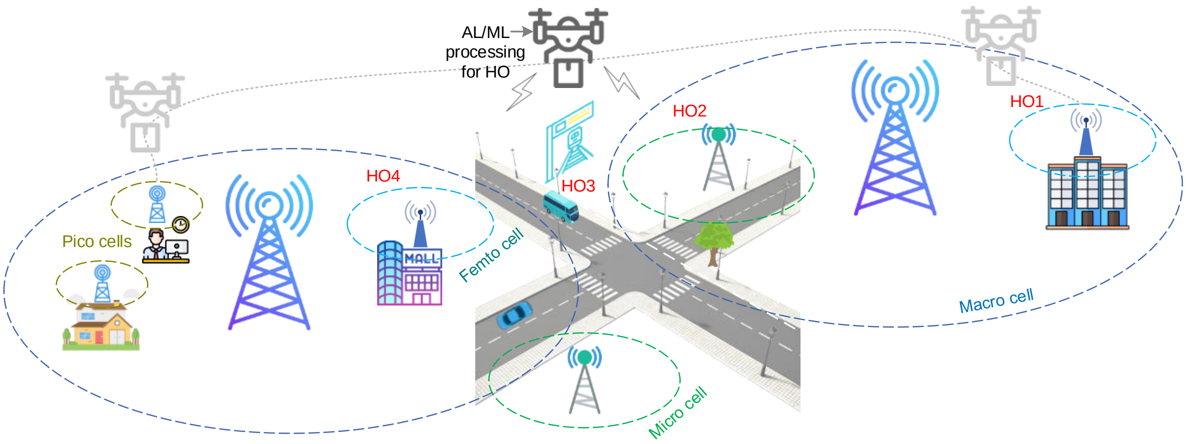

Figure 6. AI-Driven HO Decision in UAV-Integrated HetNets over 6G.

5.1. Overview and Rationale for AI/ML

AI and ML are crucial for 5G and beyond networks, enabling autonomous intelligence, dynamic optimization, and real-time HO decision [102]. Moreover, HO optimization is a decision-making problem where intelligence is essential for optimal decisions. Besides, ML algorithms learn from data or experience, enabling systems to discover patterns and proactively optimize network parameters, thus solving complex challenges. This ensures seamless connectivity and maximizes throughput [4,46].

5.1.1. Solving Challenges in Dynamic Environments

Dynamic environments, with high UAV mobility and rapid channel changes, pose HO management challenges like frequent unnecessary HOs and interference. To address these issues, ML approaches provide adaptive solutions, dynamically optimizing HO parameters [103]. Furthermore, RL frameworks, like Q-learning, offer flexible HO decisions, balancing HO frequency and signal quality. Moreover, DRL algorithms enhance reliability by learning optimal policies from real-time interactions in complex scenarios [15,22].

5.1.2. ML-Driven Capabilities for HO and Network Management

ML-based HO strategies offer advanced capabilities for network management. They can learn hidden patterns and relationships from dynamic network data, such as user movement interactions and intricate data correlations. Moreover, these strategies effectively predict critical network parameters, including future trajectories, channel quality, and HO events. This predictive power enables proactive optimization, leading to reductions in HO failures, ping-pong effects, and unnecessary HO, significantly improving system stability and performance [36].

5.1.3. Taxonomy of AI/ML Approaches for HO Decisions

AI/ML approaches for HO decisions are mainly categorized into Supervised Learning (SL), Unsupervised Learning (USL), and RL, with DL and DRL representing their neural-network-based extensions. Furthermore, hybrid approaches integrate these paradigms, often with other methods, to address complex HO challenges. A summary of the taxonomy of AI/ML approaches for HO decisions is presented in Figure 9.

5.1.4. Supervised Learning

Supervised Learning is an ML technique that relies on labelled training datasets, comprising input features and corresponding desired outputs, to learn a mapping function. This method is categorized into regression for continuous outcomes and classification for discrete outputs [46]. In the context of UAV HO management, SL algorithms can predict future UAV locations, trajectories, or serving cells to enable proactive HO optimization, thereby enhancing QoS [17,104].

a) Regression Models: As a component of SL, they are specifically designed to predict continuous numeric values, such as user coordinates or channel quality. Key regression algorithms include Linear Regression, Support Vector Regression (SVR), and Gaussian Process Regression (GPR) [49,105]. Furthermore, Bayesian regression, Random Forest, and XGBoost regressors are widely utilized for diverse applications such as HO decision and throughput estimation. These models are typically evaluated using metrics such as Mean Absolute Error and Root Mean Square Error [106–109].

b) Classification Models: Classification models, a subset of SL, are crucial for UAV HO decisions in future networks. They predict discrete outputs, aiding optimal target cell identification. Moreover, these models enhance HO performance and reduce failures. Common algorithms like Support Vector Machines (SVM) and Random Forests achieve high accuracy in relevant tasks [46,62].

5.1.5. Unsupervised Learning

Unsupervised Learning is distinguished by its ability to identify hidden structures, patterns, and correlations within unlabeled datasets [46]. This methodology is typically employed for tasks such as clustering, anomaly detection, pattern recognition, and the reduction of dataset dimensions. Common USL algorithms include K-means clustering, Principal Component Analysis (PCA), and Expectation-Maximization (EM) [49,88]. Furthermore, in the context of network management, USL algorithms offer valuable solutions for scalability and decentralization. For example, clustering techniques, such as K-means, are instrumental in grouping devices with similar mobility patterns, which can then be leveraged for efficient HO optimization, especially in ultra-dense cellular networks [46,104].

5.1.6. RL, DL and DRL

Another critical subfield of ML is RL (Figure 7) along with its advanced extension known as DRL (Figure 8). RL involves an agent learning an optimal policy via trial-and-error interaction with an environment to maximize cumulative rewards. Its problems are frequently modelled using Markov Decision Processes (MDPs) [32]. Likewise, DL represents a powerful branch of ML that employs multi-layered neural networks for automated feature extraction and complex pattern recognition [110]. Building on these capabilities, DRL integrates RL and DL, leveraging Deep Neural Networks (DNNs) to approximate value functions or policies. This combination enables DRL to address high-dimensional, complex sequential decision problems impractical for traditional RL algorithms [54,104].

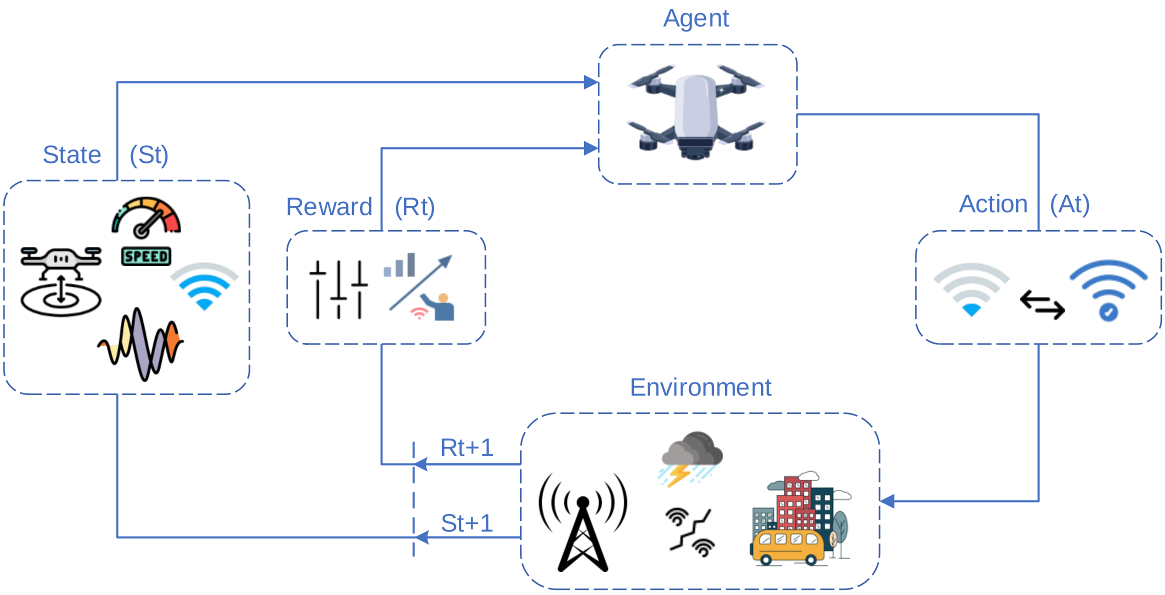

Figure 7. RL Framework for HO optimization in UAV Networks.

a) Value-Based RL: Value-Based RL algorithms, including Q-learning and SARSA, maximize the expected long-term reward by estimating the value function for states or state-action pairs. Among them, Q-learning is an off-policy method foundational to many HO optimization schemes [46,111,112]. Besides, for complex environments, DQNs approximate the Q-function using neural networks, thereby addressing the state-space explosion. In addition, the Dueling Deep Q-Network (DDQN) architecture is also frequently employed for refined HO decision [18,80].

b) Policy-Based RL: Policy-based RL methods explicitly search for and optimize the policy (π), which defines the agent's action given a state. Unlike value-based algorithms, they directly optimize policy parameters using gradient ascent [47,50]. Popular examples include Policy Gradient, PPO, and Actor-Critic (AC) methods. These techniques are generally stable and well-suited for high-dimensional or continuous action spaces [46,54].

c) Recurrent Neural Networks: RNNs are specialized architectures designed for handling sequential data, using feedback connections to model temporal dependencies. Standard RNNs often struggle with learning long-range dependencies due to the vanishing gradient problem [76,113]. Therefore, specialized variants, such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), overcome this limitation by employing sophisticated gating mechanisms to control information flow. Moreover, RNN-based models are instrumental in mobility and trajectory prediction, effectively supporting proactive HO decisions in next-generation networks [76,106,114].

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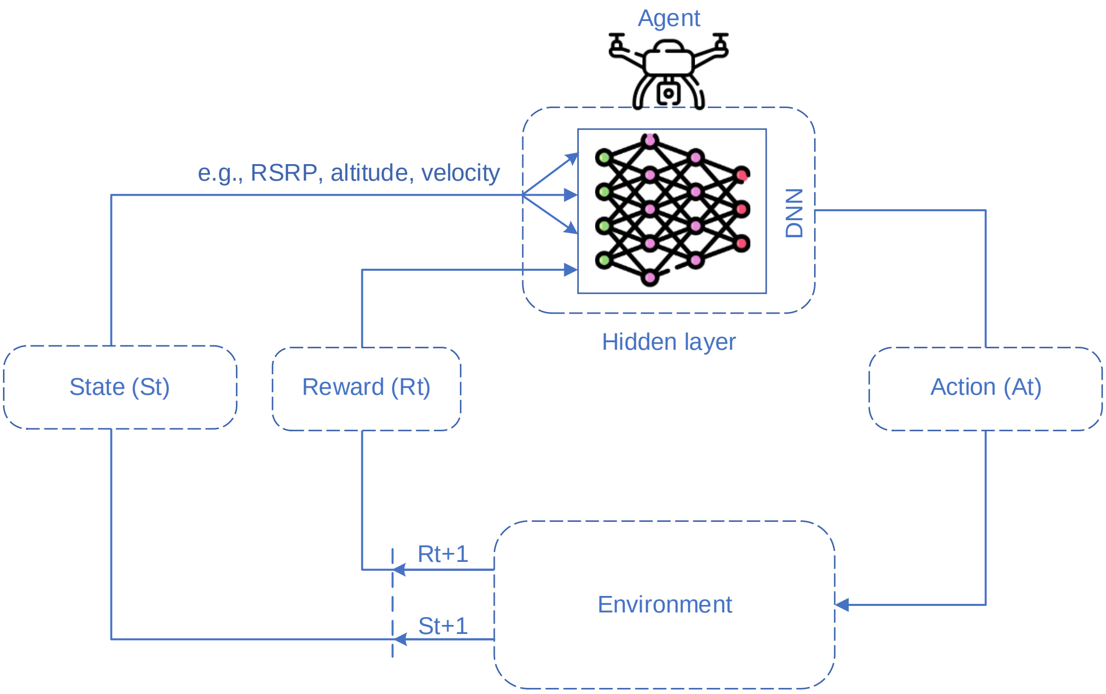

Figure 8. DRL Framework for HO optimization in UAV Networks.

d) Hybrid RL/Actor-Critic Approaches: Hybrid RL/AC approaches combine the advantages of value-based and policy-based algorithms, promoting stable learning. The AC framework utilizes an actor network to select actions based on a learned policy, and a critic network to estimate the value function, thus evaluating the actor's behavior [50,115]. As a result, this architecture offers fast convergence properties and is effective for handling large action spaces [73]. Moreover, common AC algorithms such as Deep Deterministic Policy Gradient, Advantage Actor-Critic (A2C), and Proximal Policy Optimization (PPO) are frequently applied in HO management [54,111].

e) Multi-Armed Bandit (MAB) Algorithms: The MAB algorithms, a variant of RL, are applied in HO management to balance exploitation and exploration during cell selection [54]. MAB models the selection of a BS as choosing an arm to maximize the cumulative expected reward [47]. Furthermore, Contextual MAB (CMAB) incorporates state information (context) to dynamically predict the optimal BS for HO decisions [116]. These online learning methods are employed in cellular networks to minimize unnecessary HO events and optimize beam selection, demonstrating significant effectiveness [46,117].

5.1.7. Fuzzy Logic Systems (FLSs) and Multi-Attribute Decision Making (MADM) Based Techniques

FLSs handle imprecise data in complex, non-linear systems using linguistic variables. They rely on a fuzzy inference process, which consists of fuzzification, rule-based inference, and defuzzification [20]. Moreover, fuzzy logic-based algorithms often incorporate MADM techniques, like Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and Simple Additive Weighting (SAW), to evaluate and rank candidate networks using multiple criteria in the decision phase [118,119].

a) Fuzzy Logic Controllers (FLCs): FLCs are highly accurate and complex mechanisms suited for complicated non-linear systems, crucial for UAV HO management. They manage HO decisions using the fuzzy inference process. This excels at modeling relations based on numerous dynamic parameters like speed, altitude, coverage, and signal quality. Besides, FLCs dynamically adjust HCPs, such as HO Margin and TTT, leading to improved HO performance [20,60,120].

b) Multi-Attribute Decision Making Methods: MADM provides a systematic framework for improving HO decisions by simultaneously evaluating multiple criteria or attributes, typically operating in a discrete decision space. This approach evaluates and ranks alternatives based on factors such as QoS needs, network load, and signal quality. In addition, TOPSIS and SAW are among the common MADM methods utilized in HO management [118,121].

5.1.8. Hybrid and Other AI/ML Approaches

Hybrid AI/ML approaches combine techniques like Fuzzy Logic with Q-learning or ANN to enhance decision accuracy and interpretability. For instance, models integrating TOPSIS and Q-learning reduce unnecessary HOs and improve scalability [44,97]. Moreover, multi-UAV coordination relies on advanced cooperative paradigms such as Multi-Agent RL (MARL). In addition, Genetic Algorithms (GA) optimize HCPs, and FL supports distributed resource optimization [18,112,114].

a) Game Theory: Game theory serves as a crucial analytical framework for distributed decision-making and resource management in UAV networks. It is applied to optimize HO management, coverage, and trajectory planning [8,13]. Moreover, game theory models performance where users or UAVs influence each other. Cooperative game theory, for example, is used to select the optimal UAV during HO, minimizing delay and signaling overhead [1,6,92].

b) Genetic Algorithms: Genetic Algorithms are meta-heuristic optimization methods that simulate biological evolution to find optimal solutions. It is highly effective for solving NP-hard problems, such as optimizing antenna up-tilt angles to maximize the minimum Signal-to-Interference Ratio (SIR) for UAVs. Furthermore, Genetic Algorithm is employed in hybrid methods for HO parameter tuning and trajectory optimization [30,112,122].

c) Multi-Agent Reinforcement Learning: MARL extends RL and DRL to environments involving multiple agents, making it crucial for complex distributed systems [78,123]. Agents, such as UEs or UAVs, learn individual policies within a shared environment, often formalized as a Markov Game [13]. Besides, MARL is effective for distributed HO management, resource allocation, and joint optimization tasks. In addition, implementations commonly rely on centralized training with decentralized execution [123,124].

d) Graph Neural Networks: Graph Neural Networks are DL models specifically designed to process graph-structured data, such as network topologies and vehicular connections. They leverage a message-passing mechanism to transfer information between interconnected nodes, thereby learning complex node representations and global graph structures [51]. Furthermore, Graph Neural Networks improve adaptability to changes in satellite HO directed graph topology, making them valuable for intelligent HO decision algorithms in integrated networks [58,99].

e) Federated Learning: FL is a distributed ML approach where devices jointly train a shared model, sending only trained parameters to a central entity. This strategy preserves data privacy, reduces latency, and lowers communication overhead. Consequently, FL can be used to optimize HO procedures and predict user mobility [46,125].

5.2. Key Parameters and Input Features for AI/ML Models

AI/ML models for HO decisions tend to rely on diverse input features, including signal quality metrics such as RSRP, RSRQ, and SINR [108,126]. Crucially, UAV mobility characteristics, like altitude, speed, and location, are also incorporated. Moreover, inputs may include network state information, such as cell load or available radio resources, to potentially optimize the decision-making process [30,38].

5.2.1. Signal Quality Metrics

Signal Quality Metrics are conventionally recognized as essential inputs for AI/ML HO strategies, typically including RSRP, RSRQ, SINR, RSSI, and RSS [1]. Besides, RSRP primarily reflects signal strength to guide HO initiation [127]. Conversely, metrics like RSRQ and SINR can offer a more comprehensive measure of channel quality, generally accounting for interference and noise [104,121].

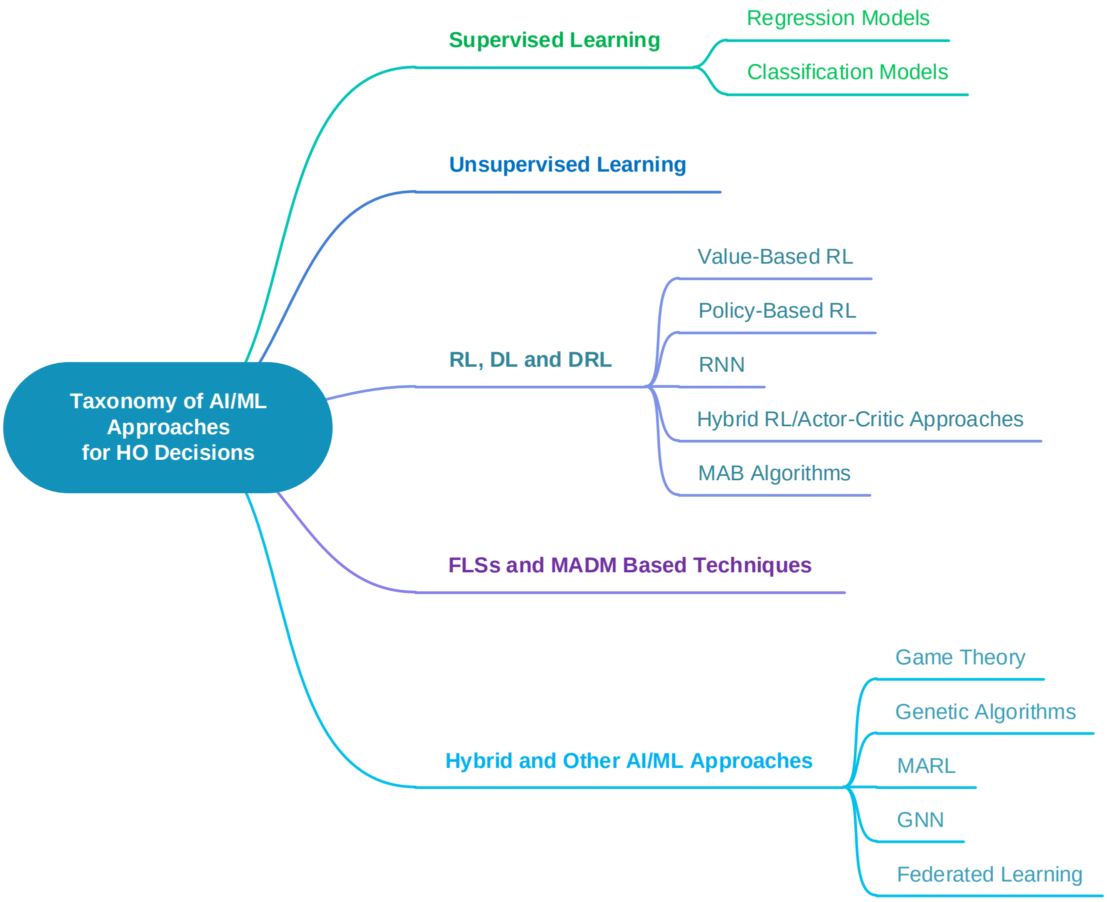

Figure 9. Taxonomy of AIML Approaches for HO Decisions.

5.2.2. UAV Mobility Characteristics

UAV mobility significantly differs from conventional networks, primarily operating in a 3D pattern rather than 2D. UAVs possess high mobility speed, which often makes control challenging. Consequently, this rapid movement may cause fast channel fluctuations, resulting in frequent HOs and ping-pong effects. Moreover, UAV flight paths are typically predictable based on missions [14,26].

5.2.3. Network State Information

Accurate HO decisions rely on comprehensive Network State Information, which typically comprises diverse metrics. Essential parameters often include signal quality indicators such as RSRP, SINR, and RSRQ. Furthermore, network resource status, like cell load, is routinely monitored. Moreover, mobility factors, including UE velocity or dwell time, may also be incorporated to enable proactive optimization [47,128].

5.2.4. Other Context-Aware Parameters

Other context-aware parameters augment HO decision capability by incorporating operational and user-centric metrics. These parameters may include the UAV's buffer queue state information to facilitate adaptive decision-making [38]. Moreover, factors such as remaining flight range or energy consumption are often considered inputs to optimize operational longevity and avoid premature HOs. Furthermore, user requirements, including QoE preferences, influence target BS selection [1,6].

5.3. Comparative Analysis of AI-Driven HO Techniques

AI-driven HO techniques present critical trade-offs. FLCs are notably lightweight and offer interpretability, effectively handling imprecise data, but they sometimes lack scalability for highly dynamic or complex inputs. In contrast, DRL methods deliver superior performance and adaptability in complex scenarios; however, they generally incur significant computational overhead, require vast training data, and face the black-box challenge regarding decision transparency [38,129].

5.3.1. Performance vs. Traditional HO Mechanisms

Traditional HO mechanisms, such as those relying primarily on RSS, typically represent the least complex systems, although they tend to be the least accurate. Consequently, advanced strategies often demonstrate significantly enhanced performance across critical metrics [98]. For instance, employing multiple criteria methods, specifically network priority, has been shown to potentially reduce the number of HOs by up to 60% compared to conventional RSS-based HO schemes [120]. Furthermore, sophisticated DRL algorithms have been observed to reduce the HOPP rate and yield substantial increases in throughput compared to traditional approaches [130]. Moreover, advanced multi-level fuzzy systems demonstrate superior Packet Delivery Ratio (up to 93.11%) and throughput (up to 95.3450%) compared to conventional fuzzy methods. Generally, improved techniques aim to maintain high QoS while mitigating unnecessary HO events that frequently affect conventional, fixed-threshold approaches [2,126].

5.3.2. Strengths and Limitations of Different AI/ML Paradigms

FLCs offer key advantages, including interpretability, transparency, and the potential to handle uncertainty well due to their rule-based reasoning. However, FLCs implementation is seemingly complex, sometimes requiring human expertise to define optimal rules and membership functions. Furthermore, its scalability is limited, as increasing the number of input criteria appears to reduce reliability and potentially introduces delays. Conversely, RL, particularly DRL, is prized for its adaptability and ability to make real-time decisions in dynamic environments, such as 5G and B5G networks [1,30,126]. Nevertheless, RL algorithms may face challenges such as long convergence times, the inherent problem of dimensionality in large state spaces, and potential overestimation of action values, particularly in conventional DQN [47,131].

Moreover, DL models appear effective in handling complex network scenarios and can continuously improve performance. Their major limitation, however, lies in the need for large training datasets, coupled with significant computational complexity, and the challenge of model interpretability associated with the black-box nature of deep architectures [132].

6. Performance Evaluation and Metrics

Performance metrics are essential for establishing the reliability and efficiency of HO management in UAV networks. This section explores the KPIs utilized for HO evaluation, in addition to the necessary simulation environments and real-world validation methods. Furthermore, the discussion covers relevant datasets and benchmarks necessary for comprehensive assessment.

6.1. Key Performance Indicators for HO in UAV Networks

KPIs are crucial for measuring connectivity and managing UAV mobility, which necessitates robust solutions to maintain seamless service. In addition, comprehensive evaluation typically encompasses metrics for Mobility Robustness Optimization, QoS and QoE, energy efficiency, and resource management [133]. These metrics are integral to designing optimized HO decision algorithms, particularly those leveraging advanced techniques like ML, to ensure reliable, high-quality, and energy-efficient connectivity for UAVs in complex 3D environments.

6.1.1. MRO Metrics

MRO algorithms are designed to automatically optimize the HCPs, such as HOM and TTT, that are critical for determining the initiation and execution criteria of the HO decision. Its performance is typically assessed using key KPIs that usually include HOF, RLF, HOPP, and unnecessary HO. Moreover, metrics such as HO Rate and Call Drop Ratio are widely used for comprehensive evaluation [30,121].

6.1.2. QoS and QoE Metrics

QoS defines service performance, whereas QoE measures the user's quality perception. Maintaining high QoS and QoE are crucial for effective HO management. Key metrics typically comprise Throughput or Spectral Efficiency, Latency (including HO Interruption Time), Packet Loss Rate, and Service Availability. Furthermore, technical parameters like SINR and RSRQ significantly influence the perceived quality [16,133–136].

6.1.3. Energy Efficiency and Power Consumption

UAV operations can be heavily constrained by limited onboard energy, making energy efficiency vital for mission longevity. Typically, propulsion consumes the primary share of this budget. Additionally, frequent HO events generate signaling overhead and increase device power utilization. Therefore, jointly managing trajectory and HO decisions is essential for maximizing energy efficiency [8,19,23].

6.1.4. Resource Fairness and Load Balancing

Load balancing appears crucial in dense HetNets, stemming primarily from erratic traffic that may cause unequal cell loads and resource congestion [29,130]. The core objective generally involves the fair distribution of mobile devices and traffic, commonly quantified using metrics such as Jain's fairness index. Consequently, optimal HO decisions should certainly integrate cell load data to enhance resource fairness and mitigate potential QoS degradation [46,75,120].

6.2. Simulation Environments and Real-World Testbeds

Evaluating UAV mobility solutions generally relies on extensive software simulations or dedicated real-world testbeds. Simulations, leveraging platforms such as NS-3 or MATLAB, are widely used to model network behavior and generate data for training ML algorithms. In addition, experimental testbeds offer crucial validation of practical operational constraints [9,17,83].

6.2.1. Simulation Tools

To rigorously evaluate HO mechanisms, researchers generally rely on detailed simulation platforms. Key software tools typically involve MATLAB, which is commonly employed for algorithmic modeling, Monte Carlo simulations, and FLC implementations [2]. Besides, sophisticated network simulators such as NS-3 and OMNeT++ are often utilized to model complex network behaviors. Moreover, many studies leverage Python libraries (e.g., Keras and TensorFlow) for implementing DRL models [47,71,76].

6.2.2. Real-World Data and Flight Trials

Field trials and measurement campaigns can provide crucial practical insights into integrating UAVs into cellular networks, offering more realistic validation environments than simulation alone. Consequently, although real-world datasets are often scarce, they are highly valuable for validating AI/ML models and deriving predictive HO decisions [17,114]. Subsequently, DQN-based mobility management schemes have been successfully validated using real-world LTE data collected from

UAV flight trials, sometimes achieving over 80% HO reduction compared to conventional methods [38].

6.2.3. Mobility Models and Scenario Types

Performance analysis often relies on simulating diverse mobility models, including the Random Waypoint and Flight Plan (FP) mobility models. These models, furthermore, are crucial for designing heterogeneous network environments. Besides, common scenario types such as vehicular connectivity, urban communications, and high-speed mobility are extensively investigated [137,138].

6.2.4. Simulation Parameters

Simulation configurations encompass environmental factors such as area size, network topology (e.g., BS locations), and radio specifications (e.g., carrier frequency and transmit power). Furthermore, parameters related to UE or UAV mobility, including speed and altitude, are routinely considered. For HO optimization, critical control parameters, such as TTT, HOM, learning rate, and discount factor, are frequently utilized [19,73].

6.2.5. Datasets and Benchmarks

Large-scale benchmarks and real-world datasets appear highly influential for evaluating AI/ML algorithms in UAV HO management [17]. However, acquiring sufficient and effective real-world data seems challenging, possibly due to data protection regulations. Consequently, synthetic or simulated datasets tend to dominate existing research. Moreover, this reliance on artificial data may potentially limit the generalizability of findings [114].

7. Open Research Challenges

Although AI/ML approaches show promise for optimizing UAV HO decisions in complex 6G environments, substantial research challenges remain. These obstacles often stem from the unique high mobility and 3D flight characteristics of UAVs, demanding further innovation for seamless integration into future wireless networks [13,83].

7.1. UAV-Specific Mobility and Channel Modeling

UAV-specific mobility and channel characteristics present profound challenges that must be addressed for reliable 6G integration, necessitating dedicated research into accurate modeling of complex 3D movement patterns and high speeds, the dominant LoS Air-to-Ground channel properties, and the specific propagation issues arising from mmWave and THz frequencies [26,46].

7.1.1. Complex 3D Movement Patterns and High Speeds

UAV mobility is inherently complex as it typically operates in a 3D pattern, diverging from traditional 2D movement. Furthermore, high speeds, sometimes exceeding 500 km/h in 5G and B5G systems, may significantly amplify HO challenges. Consequently, this high mobility and 3D flight often lead to rapid channel fluctuations, prompting the occurrence of frequent HOs and ping-pong effects [88].

7.1.2. Air-to-Ground (A2G) Channel Characteristics

The A2G channel properties fundamentally differ from terrestrial channels because of the UAV's altitude and 3D movement. Consequently, propagation often exhibits dominant LoS conditions, particularly as altitude increases. However, this favorable LoS link may increase the vulnerability to interference from numerous neighboring BSs in the downlink direction. Furthermore, precise path loss modeling typically necessitates accounting for elevation angle, 3D distance, and the surrounding environment [8,17,83].

7.1.3. MmWave and THz Challenges

MmWave and THz spectrum utilization, though offering high bandwidth, suffers from high propagation loss and molecular absorption, severely restricting the transmission range. In addition, narrow beamwidths are typically necessary for achieving high SNR. Consequently, UAV mobility, including small-scale uncertainties, may cause antenna misalignment, potentially leading to communication disconnections and performance deterioration up to 50%. Therefore, advanced error control mechanisms and beamwidth adaptation protocols should be investigated [39,46,139].

7.2. Computational Complexity and Scalability

Computational challenges are undeniably crucial in complex networks, particularly concerning scalability and efficiency in heterogeneous and ultra-dense scenarios. Besides, high-dimensional environments tend to lead to the curse of dimensionality, which therefore necessitates efficient models for real-time decision making. Moreover, constraints on computational resources may impose significant limitations on on-device AI deployment [37,47,125].

7.2.1. Curse of Dimensionality

The curse of dimensionality fundamentally limits tabular Q-learning in complex UAV HO problems, causing computational requirements and storage to increase exponentially with the state space. Consequently, DRL methods, such as DQN, are employed, leveraging neural networks to approximate the Q-value function and mitigate this constraint [11,47,119].

7.2.2. Real-Time Decision Making

Real-time HO decision-making is paramount, particularly for highly mobile UAVs operating in dynamic environments [92,132]. Moreover, ML and DRL models are essential as they facilitate low-latency decision processes, which are critical for service continuity in latency-sensitive applications [21,46,125].

7.2.3. On-Device AI

On-device AI, achieved via local processing, may significantly reduce latency for HO decisions. Nevertheless, computational resource constraints inherent to UAVs restrict the permissible complexity of models and can strain battery life and overall performance [106]. Consequently, efficient deployment often necessitates developing lightweight AI models, utilizing specialized techniques such as TinyML or quantization, to meet real-time operational demands [54,140].

7.3. Data Management and Training Challenges

Implementing ML solutions for UAV HO optimization invariably encounters practical barriers related to data logistics and model training. These challenges often stem from difficulties in obtaining adequate, high-quality datasets and managing subsequent data sparsity. In addition, substantial issues arise concerning model generalization across diverse operational environments and effectively mitigating the inevitable simulation-to-reality gap when deploying learned policies in the real world [13,36,46].

7.3.1. Data Acquisition

Data acquisition is critical for training ML-based HO algorithms. In addition, input data typically encompasses wireless network metrics, such as RSRP and cell load, and sometimes visual data for blockage detection [46,141]. Owing to the scarcity of real-world measurements, however, many approaches often leverage synthetic or simulation-based datasets for training and validation.

7.3.2. Data Sparsity

Data sparsity presents a major constraint for ML approaches, which require extensive, reliable, and representative datasets for robust training. Besides, limited or skewed data may cause ML models to exhibit overfitting or suboptimal performance. Moreover, a core challenge remains the lack of real-world UAV operational data, necessitating reliance on synthetic or simulated sources, which could potentially compromise generalization [76,93,114].

7.3.3. Generalization Across Diverse Environments

Generalization remains a persistent challenge, as ML solutions often struggle to maintain performance across diverse operating environments. Consequently, policies trained effectively in one scenario may lead to notably compromised HO performance when transferred to varied settings (e.g., urban versus rural deployment) [46,134,141].

7.3.4. Simulation-to-Reality Gap

Despite the widespread reliance on simulations for training AI models, deploying effective HO solutions often faces the simulation-to-reality gap. Furthermore, this challenge arises because complex real-world dynamics and channel behavior may be imperfectly captured in simulated environments, frequently relying on simplified models [13].

7.4. Multi-UAV Coordination and Resource Management

To ensure seamless connectivity in multi-UAV systems, addressing intense aerial interference through robust interference management seems vital. Moreover, achieving optimal performance often relies on joint optimization of functions like HO, power allocation, trajectory, or task offloading [123].

7.4.1. Interference Management

UAV integration arguably introduces severe interference challenges, primarily due to their elevated position and LoS propagation, which tend to amplify interference compared to terrestrial networks. In addition, UAVs are susceptible to strong downlink interference. Conversely, they might also generate substantial uplink interference for terrestrial users and ground BSs [83]. Therefore, effective interference management is crucial for network stability.

7.4.2. Joint Optimization with Other Network Functions

To address inherent complexity, sophisticated methods often involve the joint optimization of HO with other network functions. For instance, ML frameworks are frequently leveraged to coordinate HO with Power Allocation, Trajectory Optimization, or Task Offloading decisions. These joint approaches typically seek to maximize system capacity, while concurrently minimizing negative outcomes such as latency, energy consumption, and HO frequency [18,88,91,105].

7.5. Security and Privacy

Security and privacy are crucial for highly connected 5G and B5G/6G networks due to sensitive data concerns. Ensuring continuous, reliable operation demands robust Secure HO Authentication mechanisms. In addition, ML integration introduces challenges concerning Data Privacy During ML Model Training and Deployment, often mitigated using techniques such as FL [1,25,46].

7.5.1. Secure HO Authentication

The high frequency of HOs in 5G and future UAV networks demands robust security and authentication mechanisms. Consequently, novel protocols often incorporate blockchain technology, potentially enhancing authentication procedures and mitigating security threats like spoofing [1,25,61].

7.5.2. Data Privacy During ML Model Training and Deployment

Data privacy presents a crucial challenge for ML-based HO management, arguably because obtaining adequate user mobility datasets is difficult due to regulations, where providers must protect personal user identity. Consequently, privacy-preserving methods, such as FL, are highly promoted. Additionally, FL maintains confidentiality by transferring only trained model parameters [25,46,106].

7.6. Regulatory and Ethical Considerations

Integrating cellular-connected UAVs necessitates navigating complex legal regulations and addressing critical societal concerns inherent to widespread deployment [17,142]. These include harmonizing airspace operations, especially Beyond Visual Line of Sight (BVLoS) activities and Air Traffic Control integration, and ensuring the trustworthiness and interpretability of autonomous AI decisions governing UAV HO [38,143].

7.6.1. Air Traffic Control Integration and BVLoS

The coexistence of UAVs with piloted vehicles in the National Airspace System (NAS) necessitates integration with Air Traffic Control operations. This integration is paramount as UAV operations increase, requiring coordination and adherence to communication standards for safe BVLoS operations. Moreover, careful consideration must be given to ensuring seamless HO between communication standards during flight [143,144].

7.6.2. Ethical Implications of Autonomous AI Decision-Making

Autonomous AI systems for HO introduce ethical concerns due to their opaque nature, which limits interpretability and trust, especially for safety-critical operations. Besides, achieving explainability and algorithm robustness is crucial for regulatory compliance and addressing potential legal liability arising from autonomous AI decisions [38,54,101].

8. Future Research Directions

The full commercialization and integration of cellular-connected UAVs into future communication networks is still pending, requiring substantial time and effort. Consequently, despite promising solutions already proposed, a number of major research directions should be efficiently addressed to enable widespread employment. A summary of the Future Research Directions is presented in Figure 11.

8.1. Advanced AI/ML Techniques and Paradigms

Advanced AI/ML approaches, including DRL and DL, appear central to the 6G vision for managing complex UAV mobility challenges. Furthermore, future development focuses on advancing these paradigms through improved real-time adaptation, hybrid models, and introducing explainable AI (XAI) for trustworthiness [46,71].

8.1.1. Explainable AI for Trust and Interpretability

XAI is widely regarded as crucial for mitigating the inherent black-box nature associated with DL-based HO solutions. It generally provides transparency and insight into AI decision-making, thereby helping to validate model reasoning and foster necessary trust among network stakeholders. For instance, techniques like Shapley Additive Explanations can facilitate generating comprehensible, natural language explanations for complex HO policies [16,38,123].

8.1.2. Real-Time Learning

Real-time learning, often utilizing DRL, permits AI-based HO models to adapt continuously to dynamic network conditions and user mobility. Moreover, this continuous interaction typically facilitates online exploitation, driving decisions aimed at maximizing long-term rewards [74,116].

8.1.3. Hybrid AI/ML Models

Hybrid AI/ML models are necessary to overcome single-paradigm limitations, typically balancing learning capability with interpretability. Therefore, future studies often explore coordinating DNN prediction with DRL optimization to mitigate accumulated errors and enhance HO accuracy. In addition, hybrid approaches should address increased complexity and integration overhead [91,145].

8.2. Integration with Emerging 6G Technologies

The evolution toward 6G networks generally mandates the seamless integration of various enabling technologies, such as NTN and THz communication, which are key to supporting pervasive UAV operations. Furthermore, these emerging features typically introduce unique complexities that necessitate advanced solutions for maintaining reliable connectivity and achieving efficient HO management [26,91].

8.2.1. Seamless Handover in TN-NTN

The integration of Terrestrial Networks (TN) and NTN is essential for realizing global connectivity, yet it poses challenges to seamless mobility due to high propagation delays and frequent HO events. Besides, novel AI/ML mechanisms can strengthen TN-NTN mobility by dynamically optimizing HO triggering, minimizing unnecessary HOs, and enhancing service continuity for UAVs in these complex domains [52,146].

8.2.2. Reconfigurable Intelligent Surfaces

As illustrated in Figure 10, RISs are appealing for 6G networks, enabling optimized reflection of signals to enhance cellular-connected UAV coverage and link quality [26,48,53]. Furthermore, RIS integration can mitigate downlink interference and is promising for proactive HO management, especially in THz networks. These surfaces may also help prevent RLFs by enabling a new path during HO when mmWave signals are blocked [1,39,48].

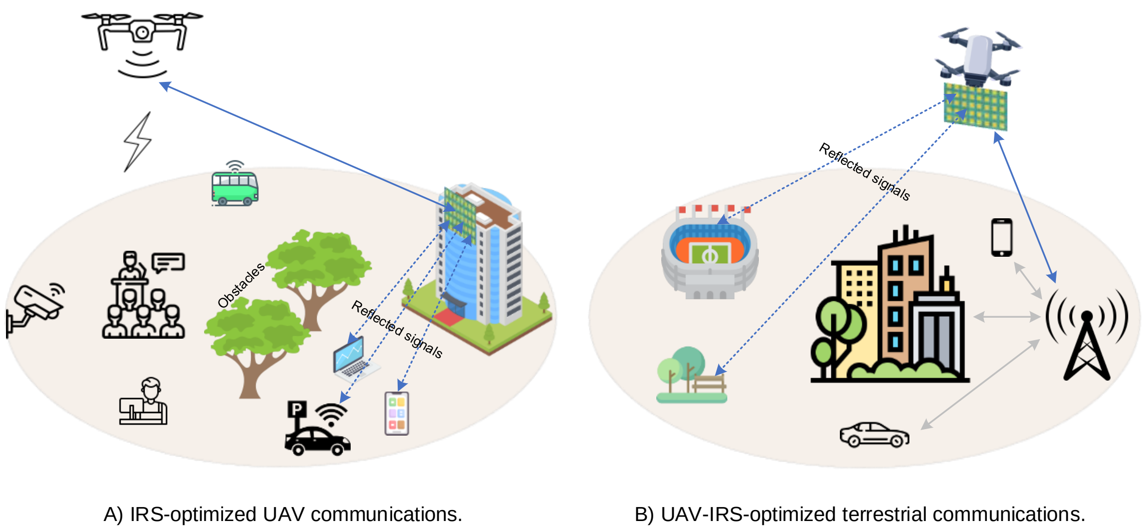

Figure 10. RIS-assisted UAV communication for enhanced terrestrial coverage.

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8.2.3. Cell-Free Massive MIMO and VLC

Cell-Free Massive MIMO (CF-mMIMO), employing distributed antennas, is anticipated to offer reliable, wide-scale UAV support and can mitigate HO due to its inherent low interference. Nonetheless, challenges include complex 3D beam tracking and managing signaling overhead. Moreover, Visible Light Communication (VLC) provides high data rates (400–800 THz), but its blockage susceptibility requires hybrid RF integration to ensure consistent connectivity in 6G [3,26,50].

8.2.4. Digital Twins

Digital Twins function as virtual replicas of physical networks and are potentially essential for 6G and beyond systems. They can employ real-time data, simulations, and ML to monitor performance and anticipate network conditions. This approach helps optimize HO procedures and parameters, accelerating DRL model training for UAV mobility management [30,147].

8.2.5. AI-Native Network Architectures

AI-native network architectures, perceived as a central future research direction, are fundamental to the 6G vision, transforming networks from static, conventional systems into intelligent, self-managing ecosystems. This approach typically embeds AI/ML as core architectural components, enabling capabilities such as self-optimization, self-learning, and real-time adaptation. Consequently, this architectural shift is essential for managing complexity and achieving truly autonomous HO functionality [25,49,55,148,149].

8.2.6. Cross-Layer and Joint Optimization

The inherent complexity of UAV HO demands sophisticated solutions beyond reactive triggering. Consequently, research has focused on proactive prediction, jointly optimizing conflicting objectives, and explicitly integrating QoS/QoE demands [37,46,84].

8.2.7. Proactive HO

Proactive HO schemes certainly constitute a paradigm shift, utilizing intelligence, often via AI/ML, to predict mobility and anticipate HO events well before the current link terminates [37,150]. This advanced preparation, which can include pre-connection strategies, aims to significantly reduce disruption and optimize timing [71,104,108].

8.2.8. Joint Optimization of HO

Joint optimization in HO decisions typically seeks to maximize communication metrics, while concurrently mitigating the undesirable cost of frequent HO events [92,151]. This balancing act often relies on weighted reward functions within DRL frameworks, allowing for the precise tuning of the trade-off between signal quality and connection stability. Moreover, adjusting these weights usually helps curb redundant HO activity [22,32,103,152].

8.2.9. QoS/QoE Aware HO

QoS and QoE are highly susceptible to degradation stemming from the frequent UAV HO events [47,132]. Accordingly, ML strategies can incorporate QoS-related metrics, such as data rate, delay, or buffer status, into HO decision to achieve robust connectivity and minimize undesirable transitions [83,91].

8.3. Real-World Deployment and Standardization

Successful real-world deployment of cellular-connected UAVs seems to mandate strict adherence to ongoing standardization and regulatory frameworks. Moreover, rigorous validation through testbeds is essential for practical solutions [13,17].

8.3.1. Standardization Efforts

Standardization efforts by the 3GPP are crucial for integrating cellular-connected UAVs into future mobile networks, providing a unified platform for design innovations. Studies began with enhanced LTE support in Release 15, progressing through 5G enhancements in Releases 16 and 17 [11,12,17]. These activities will continue into the 6G era, focusing intently on mobility management, NTN integration, and defining enhanced requirements for UAV applications [54].

8.3.2. Field Trials and Benchmarking for Validation and Datasets

Field trials, though complex and potentially costly, are paramount for practical validation and closing the gap between simulation and deployment [17]. Furthermore, benchmarking against established or competitive algorithms is required for comprehensive performance evaluation. Consequently, because real-world mobility data is often restricted, researchers frequently rely on synthetic or simulation-based datasets for ML training [114,119,125,141].

8.3.3. Societal and Ethical Considerations Beyond Regulatory Aspects

Societal acceptance of UAV technology is often challenged by privacy concerns related to aerial surveillance and potential job security impacts. Besides, ensuring the safety and reliable control of UAV operations, especially against malicious intrusion, appears critical. Moreover, environmental and economic sustainability considerations, such as minimizing energy consumption, are important for wide-scale deployment [17,123,153].

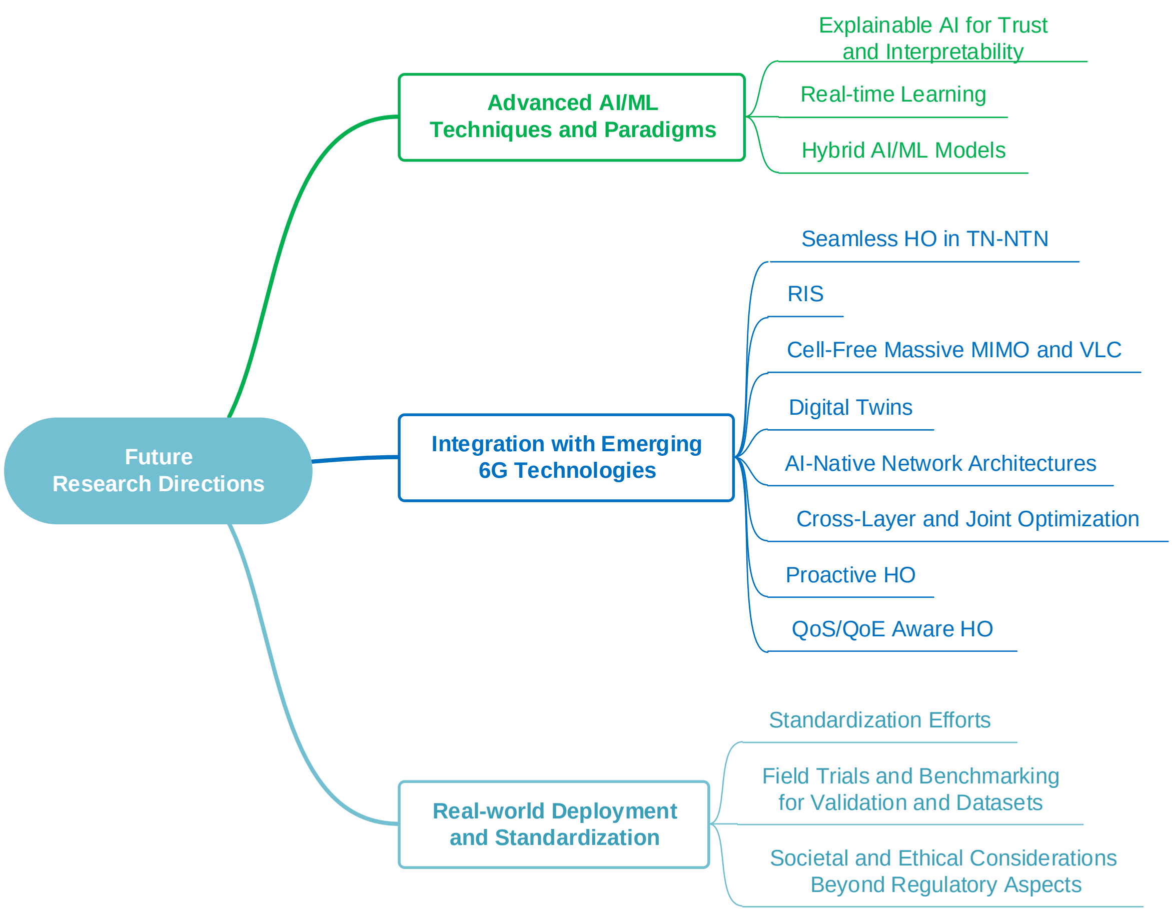

Figure 11. Summary of Future Research Directions.

9. Conclusions

The rapid evolution of UAV-assisted 6G networks demands seamless and intelligent HO mechanisms capable of sustaining ultra-reliable, low-latency, and energy-efficient communication. This comprehensive survey has reviewed AI-driven HO decision techniques for UAVs, encompassing traditional, rule-based, and modern learning-based paradigms. By categorizing the existing body of work across non-UAV, UAV-BS, and UAV-UE scenarios, this study has highlighted the transformative role of AI/ML in overcoming the limitations of deterministic HO strategies. Compared with conventional threshold- or geometry-based methods, AI/ML approaches, particularly DRL and FL, demonstrate superior adaptability, proactive optimization, and robustness in highly dynamic, 3D environments.

The review emphasized that DRL frameworks, such as DQN, DDQN, and PPO, effectively balance exploration and exploitation to minimize unnecessary HOs and RLFs, while hybrid and distributed learning paradigms improve scalability and privacy preservation. Nevertheless, these intelligent solutions face persistent challenges, including high computational complexity, limited generalization across heterogeneous environments, and data scarcity due to the scarcity of real-world UAV flight datasets. Furthermore, achieving real-time decision-making under resource-constrained conditions remains an open issue, especially for lightweight, on-device AI deployment in energy-limited UAV platforms.

Beyond algorithmic innovation, the survey identified several systemic gaps that require attention. Accurate 3D channel and mobility modeling, efficient multi-UAV coordination, and robust interference management are essential to ensure reliable connectivity in dense aerial networks. Similarly, security, privacy, and ethical considerations, particularly those related to autonomous AI decision-making and BVLoS operations, must be integrated into future HO frameworks to ensure safety, trust, and regulatory compliance.

Looking forward, several research frontiers hold promise for advancing UAV mobility management in 6G. Future studies should focus on XAI to enhance transparency and interpretability; hybrid and cross-layer optimization that jointly considers trajectory, energy, and QoS/QoE metrics; and AI-native architectures capable of real-time learning and self-optimization. Moreover, the convergence of NTN, RIS, cell-free massive MIMO, and digital twins will redefine how UAVs maintain connectivity and perform predictive, context-aware HOs across multi-domain environments.

In summary, AI-driven HO decision techniques constitute a central enabler for the next generation of UAV communications. By bridging learning-based intelligence with emerging 6G technologies, future networks can achieve seamless, resilient, and autonomous mobility management, realizing the vision of a truly intelligent, ubiquitous, and self-optimizing aerial communication ecosystem.

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Abbreviations

The following abbreviations are used in this manuscript:

3D	Three-Dimensional
3GPP	3rd Generation Partnership Project
5G	Fifth Generation
6G	Sixth Generation
ABS	Aerial Base Station
AC	Actor-Critic
AI	Artificial Intelligence
ANN	Artificial Neural Network
A2G	Air-to-Ground
BVLOS	Beyond Visual Line of Sight
BS	Base Station
CF-MMIMO	Cell-Free Massive Multiple Input Multiple Output
CIO	Cell Individual Offset
CNN	Convolutional Neural Network
D3QN	Dueling Double Deep Q-Network
DDQN	Double Deep Q-Network
DL	Deep Learning
DNN	Deep Neural Network
DRL	Deep Reinforcement Learning
DQN	Deep Q-Network
FLC	Fuzzy Logic Controller
FL	Federated Learning
FLS	Fuzzy Logic System
GA	Genetic Algorithm
GAN	Generative Adversarial Network
GNN	Graph Neural Network
GRU	Gated Recurrent Unit
HETNET	Heterogeneous Network
HCP	Handover Control Parameter
HO	Handover
HOF	Handover Failure
HOPP	Handover Ping-Pong
KPI	Key Performance Indicator
LOS	Line of Sight
LSTM	Long Short-Term Memory
MADM	Multi-Attribute Decision Making
MARL	Multi-Agent Reinforcement Learning
MAB	Multi-Armed Bandit
MEC	Mobile Edge Computing
ML	Machine Learning
MMWAVE	Millimeter Wave
MRO	Mobility Robustness Optimization
MDP	Markov Decision Process
NLOS	Non-Line of Sight

NTN	Non-Terrestrial Network
PPO	Proximal Policy Optimization
QOE	Quality of Experience
QOS	Quality of Service
Q-LEARNING	Quality Learning
RLF	Radio Link Failure
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RIS	Reconfigurable Intelligent Surface
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
SA-MRO	Service Availability Mobility Robustness Optimization
SDN	Software-Defined Networking
SINR	Signal-to-Interference-plus-Noise Ratio
SL	Supervised Learning
SVM	Support Vector Machine
THZ	Terahertz
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
TTT	Time-To-Trigger
UAV	Unmanned Aerial Vehicle
UAV-BS	UAV acting as Base Station
UAV-UE	UAV acting as User Equipment
UE	User Equipment
UDN	Ultra-Dense Network
URLLC	Ultra-Reliable Low-Latency Communication
USL	Unsupervised Learning
VLC	Visible Light Communication
XAI	Explainable Artificial Intelligence

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