Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Navigating Handover Technique: A Comprehensive Review of UAV-Based Communication Systems

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ARTICLE INFO

Article history:
Received 2 February 2025
Received in revised form 30 June 2025
Accepted 10 July 2025
Available online 20 July 2025

Keywords:
Interaction, optimization, machine parameter, mechanical properties

ABSTRACT

The evolution of modern communication systems into fifth-generation (5G) and sixth-generation (6G) networks has introduced new challenges and opportunities in handover decision techniques, particularly in dynamic and heterogeneous environments. Traditional handover methods, which rely on received signal strength, often result in frequent handovers, especially for unmanned aerial vehicles (UAVs) acting as drone base stations (DBSs). This frequent handover can degrade network performance and reduce service reliability, particularly in emergency scenarios where rapid and stable connectivity is critical. The purpose of this research survey is to provide a comprehensive review of existing handover decision techniques in UAV-based communication systems, methodically analysing the advantages and limitations of each method. By reviewing recent research papers sourced from leading databases such as Web of Science, Scopus, and IEEE, this survey identifies key trends, methodologies, and performance metrics used in the field. In the analysis of categories, various performance metrics are used to evaluate handover techniques. The shortcomings identified in current research are discussed in the research gaps and issues section, offering a thorough overview of the current state of UAV-based communication systems. This survey enhances the understanding of handover decision techniques, setting the stage for the development of more efficient and reliable drone communication networks.

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1. Introduction
1.1 Research Background

Drones, or Unmanned Aerial Vehicles (UAVs), have become integral across industries such as agriculture, logistics, and surveillance due to their agility and speed. Ensuring a stable and persistent network connection is essential for their successful operation in these applications, necessitating an efficient mobility management scheme. However, cellular networks, originally designed for ground-based User Equipment (UEs), face challenges when integrating drones, particularly in managing frequent handovers due to their unique mobility patterns and high-speed, 3D movements Sing et al., [1] Zeng et al., [2] Warrier et al., [4]. The advent of 5G/6G cellular networks and beyond is expected to increase base station density within small cells to meet high data rate demands and Quality of Service (QoS) requirements. However, the proliferation of base stations and the use of higher frequencies result in smaller cell footprints and increased signalling costs due to frequent handovers, posing challenges in maintaining functional connectivity with drones Zeng et al., [2] Wang et al., [4] Fan et al., [5].

The integration of UAVs within 5G and 6G mobile networks is attracting considerable interest due to their adaptability and cost-effectiveness. Drones, functioning as Aerial Base Stations (ABSs) and relays, have the potential to improve connectivity across diverse environments. Nevertheless, challenges like power limitations, rapid mobility, and frequent handovers underscore the requirement for advanced strategies in managing mobility and handovers. Handover is a critical aspect of UAV communication systems, where a seamless transfer of communication links from one base station (BS) to another is essential to maintain connectivity as the UAV moves. The need for handover arises from several factors, including the limited coverage area of individual BSs, the high-speed movement of UAVs, and the requirement to maintain QoS as the UAV transitions between different BSs Sing et al., [1] Zeng et al., [2] Wang et al., [4]. However, unnecessary handovers can lead to increased signalling costs, latency, and service disruptions, particularly in densely populated cellular networks Wang et al., [3] Jha et al., [6]. These unnecessary handovers are often triggered by suboptimal handover decision-making processes, such as basing handover solely on signal strength without considering other network parameters or future trajectory predictions Fan et al., [5] Jha et al., [6].

In traditional mobility management, the selection of a target Base Station (BS) is based on the Received Signal Strength Indication (RSSI) for ground user equipment, a method ill-suited to drones due to their intermittent network coverage caused by weak and inconsistent side lobes of cellular antennas, often leading to ping-pong handovers Lin et al., [7]. Recent studies have highlighted the challenges of conventional handover mechanisms for drones, showing an increase in handover failure rates with higher speeds and altitudes of drones Almuallim et al., [8]. To ensure uninterrupted connectivity, handovers for drones must be executed judiciously, considering the optimal target BS Despite extensive research on drone mobility, few schemes have been proposed to enhance handover performance Banagar et al., [9].

1.2 Previous Review Paper

This section provides a brief overview of previous reviews and survey papers on UAV handover communication. It will summarize key findings and insights from existing literature, highlighting the various techniques and strategies that have been explored to manage handovers in UAV networks.

Study by Abir *et al.*, [10] Software-Defined UAV Networks for 6G Systems: Requirements, Opportunities, Emerging Techniques, Challenges, and Research Directions. This comprehensive review evaluated software-defined UAV networks (SDUAV) for 6G systems, identifying key requirements, opportunities, and emerging techniques. Despite offering valuable insights, the review lacks specific implementation guidelines necessary for practical application. The broad scope of the paper highlights the need for more focused research that provides concrete frameworks and detailed solutions. Future studies should bridge this gap by developing practical guidelines and case studies that address the identified challenges in SDUAV implementation.

Angjo *et al*., [11] explored the integral role of drones in future mobile communication networks, where they serve both as mobile users and mobile base stations in the sky, offering solutions for communication and non-communication services. However, the integration of drones into these networks poses challenges, particularly in managing handovers. Unlike terrestrial networks, drones operate in a three-dimensional environment, complicating mobility issues. The study provided an overview of handover management for connected drones, summarizing current research approaches and focusing on the complexities of the handover process. Additionally, it discussed the integration of drones into heterogeneous networks and proposes specific solutions to address potential problems. Moreover, the survey insights into upcoming research directions, guiding future studies related to connected drones in heterogeneous network environments.

Shayea *et al*., [12] conducted a comprehensive survey focusing on handover management for drone networks within future mobile networks. The study underscored the significance of intelligent handover schemes, particularly those leveraging machine learning and deep learning techniques. By reviewing existing research, the survey addressed the challenges and potential solutions for enhancing mobility management in forthcoming generations of mobile networks such as 5G, 6G, and beyond.

Alshaibani et al., [13] the impending deployment of Ultra-Dense Networks (UDNs) to manage the increasing mobile data traffic, leading to more handover scenarios and potential challenges in connectivity, stability, and reliability. It emphasized the additional complexity brought by Unmanned Aerial Vehicles (UAVs) in future networks due to their 3D mobility and unique communication characteristics. The study aimed to provide an overview of mobility management for connected UAVs in upcoming networks like 5G, 6G, and satellite networks. It discussed recent solutions and identifies challenges, serving as a foundation for future research in UAV mobility management by defining existing problems and presenting the latest research outcomes.
Table 1 shows analysis of recent survey papers on handover management in UAV communication system.

Table 1
Analysis of existing survey papers on handover management in UAV communication system

Author, Year	Title	No. of papers considered for the survey
This paper,2024	Navigating Handover Technique: A Comprehensive Review of UAV-Based Communication Systems	29
Abir et al., 2023	Software Defined UAV Network for 6G System: Requirements, Opportunities, emerging Techniques, Challenges, and Research Direction	21

W T Alshaibani et al., 2022	Mobility Management of Unmanned Aerial Vehicles in Ultra-Dense Heterogeneous Networks	29
Shayea et al., 2020	Handover Management for Drones in Future Mobile Networks – A Survey	20
Angjo J. et al., 2021	Handover Management of Drone in Future Mobile Networks: 6G Technologies	20

This review paper surveys recent advancements in handover decision techniques in UAV communication systems. Specifically, it analyzes recent handover techniques proposed from 2020 to 2024, with research papers sources from Web of Science, Scopus, and IEEE. focusing on their effectiveness in mitigating the challenges posed by the unique mobility patterns of drones and improving network performance. By analyzing existing literature from reputable sources, we seek to identify key trends, methodologies, performance metrics, and tools employed by researchers in this field. Additionally, we will discuss the challenges and opportunities in future handover decision techniques for drones, highlighting areas requiring further research and development to meet the evolving requirements of future communication networks.

This survey paper is organized as follows: Section 2 provides a review of the methodology of handover technologies in UAV communication systems, while Section 3 identifies the research gaps and issues. Section 4 is the analysis based on publication years, tools used, performance metrics, and the value of the handover rate. Section 5 discusses the challenges and opportunities, and the paper concludes with Section 6.

2. Methodology Review

This section reviews various techniques used for handover mechanisms in UAV communication systems, specifically on drone communication networks. The evolution of modern communication systems into fifth-generation (5G) and sixth-generation (6G) networks has introduced new challenges and opportunities in handover decision techniques, particularly in dynamic and heterogeneous environments. Traditional handover methods, which rely on received signal strength, often result in frequent handovers, especially for unmanned aerial vehicles (UAVs) acting as drone base stations (DBSs). This frequent handover can degrade network performance and reduce service reliability, particularly in emergency scenarios where rapid and stable connectivity is critical.

Figure 1 illustrates the architecture for heterogeneous handover techniques in these systems. Due to the high frequency used in UAV communication, which limits its range, heterogeneous networks are employed. These networks utilize multiple base stations to cover large areas, as shown in Figure 1, with each base station classified based on its transmission power. Drones can connect to multiple base stations but typically select the one with the strongest signal. **Figure 2** categorizes handover-based technologies in UAV or drone communication networks. These include reinforcement learning techniques, machine learning or AI-based techniques, optimization-based techniques, received signal strength-based techniques, and fuzzy logic-based techniques. The challenges associated with these methods are assessed to encourage researchers to develop innovative handover mechanisms for UAV or drone communication networks.

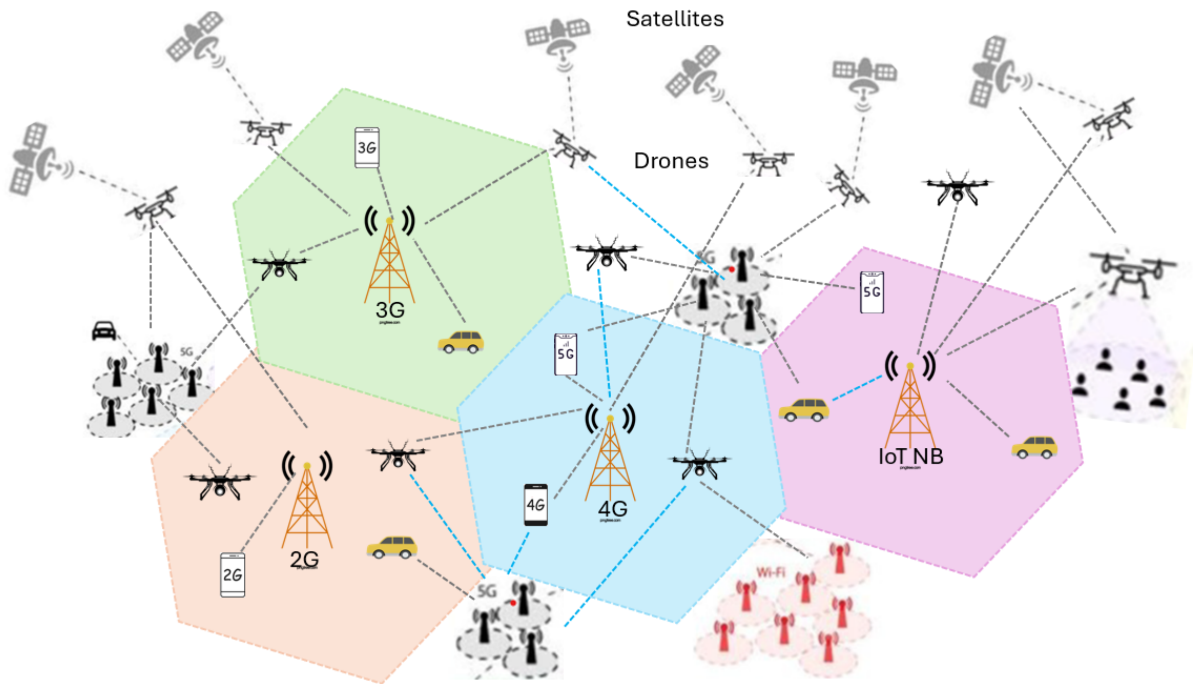

Fig. 1. Architecture of UAV Handover Network

2.1 Classification of Handover Techniques

The research examining various techniques used for handover mechanisms in UAV communication systems is described below:

2.1.1 Fuzzy Logic-Based Technique

Haghrah et al., [14] introduced handover triggering estimation based on Fuzzy Logic for LTE-A/5G Networks with Ultra-Dense Small Cells. Fuzzy logic is used to estimate and trigger handovers in ultra-dense networks. It considered multiple factors such as signal strength, user mobility, and network load to make more nuanced and accurate handover decisions. This approach reduced unnecessary handovers and improves overall network performance by adapting to the dynamic conditions of the network environment.

Singh et al., [15] addressed the complexity of managing handover (HO) in mobile communication systems involving Unmanned Aerial Vehicles (UAVs) by proposing a novel method using a multi-level fuzzy system. Their research focused on reducing the rule complexity of fuzzy systems to enhance the performance of handover systems. The methodology involved processing various parameters across three levels: at the first level, coverage, speed limit, and cost are considered; at the second level, connection time, security, and power consumption are evaluated. These parameters generated intermediate probability outputs, which were then processed at the third level to produce the final estimation level. The tools used in this study include MATLAB software, where the efficacy of the proposed multi-level fuzzy system was analysed and compared with traditional handover systems to prove its efficiency.

2.1.2 Machine Learning Based Technique

(a) Supervised Learning (using labeled data)

Zhao et al., [16] proposed UAV-Assisted Handover Scheme for Coverage Maximization against 5G Coverage Holes. This study used a Machine learning-based proactive handover scheme using Long Short-Term Memory (LSTM) networks. The technique used LSTM networks, a type of recurrent neural network (RNN), to predict future coverage holes in 5G networks. By anticipating areas with weak or no coverage, the UAV could proactively hand over to base stations with better coverage, thereby maximizing the network's overall coverage and reliability.

Anderson et al., [19] aimed to improve handover procedures in Aerial 5G and Beyond Systems by analysing different Deep Learning (DL) algorithms. Their methodology involved modelling a 5G Air-to-Ground radio channel and using DL techniques, particularly Recurrent Neural Networks (RNN), for trajectory and signal predictions. They extended the 5G Standalone (SA) libraries of the OMNeT++ simulator to implement and evaluate their approach. The goal was to enhance Quality of Service (QoS) metrics, such as reducing delay and packet loss, compared to the baseline 5G handover procedure. The tools used included the OMNeT++ simulator and various DL algorithms, with a focus on the Gated Recurrent Unit (GRU) for signal prediction, which showed the best results. This study provided insights into using DL techniques to improve handover procedures in Aerial Networks, benefiting UAV-BS networks.

Wang et al., [17] conducted Stable Matching with Evolving Preference for Adaptive Handover in Cellular-Connected UAV Networks. This study used a dynamic stable matching-based adaptive handover (DSMAH) algorithm. This technique applied a stable matching algorithm, which dynamically evolved preferences based on network conditions and UAV requirements. It ensured that handover decisions adapt to changing environments and user preferences, maintaining stable and optimal connections for UAVs in cellular networks. This tackled the issue of frequent UAV handovers in future 6G networks, which could disrupt services. The approach involved converting the handover problem into a stable matching model and expanding it to encompass the entire time-space dimension. This adaptation allowed for the representation of changing time-space information as evolving preference relations. The proposed DSMAH algorithm adjusts the preference lists' evolution to match the current network topology, ensuring efficient and stable matching in dynamic settings. The method sought to strike a balance between communication quality, handover frequency, and convergence speed, ultimately enhancing cellular-connected network stability.

(b) Reinforcement Learning Technique

A Hybrid Scheme using TOPSIS and Q-Learning for handover decision-making in UAV assisted heterogeneous network is conducted by Zhong et al., [18] This study introduced a handover decision-making algorithm that leverages the strengths of Technique for Order Preference by Similarity to An Ideal Solution (TOPSIS) and Q-Learning to enhance the performance of UAV-assisted heterogeneous networks (HetNet’s). The objective is to reduce the number of handovers and improve energy efficiency. Combining TOPSIS, which is a multi-criteria decision-making approach, with the reinforcement learning capabilities of Q-Learning, the proposed method aims to optimize handover decisions in dynamic network environments. TOPSIS was used to evaluate multiple handover candidates based on several criteria, such as signal strength and network load. Q-learning, a reinforcement learning technique, optimizes the handover decisions over time by learning from the environment. This combined approach ensures efficient and adaptive handover decisions in heterogeneous networks.

Azari et al., [20] highlighted the challenges and opportunities associated with cellular connectivity for drones, particularly focusing on communication dynamics influenced by three-dimensional mobility and line-of-sight channel characteristics, leading to increased handovers with altitude changes. The research employed cell planning simulations to assess the coexistence of aerial and terrestrial users, highlighting severe interference from drones to base stations, which poses a major challenge for uplink communications of terrestrial users. Using real geographical network data for Stockholm, the study derives analytical models for key performance indicators (KPIs), including communication delay and interference over cellular networks. Subsequently, the authors formulated the handover and radio resource management (H-RRM) optimization problem and propose a deep reinforcement learning solution to address it. The methodology involved transforming the problem into a Machine Learning (ML) problem and utilizing simulation results to demonstrate how drone speed, altitude, and interference tolerance shape the optimal H-RRM policy in the network. Specifically, the study presented heat maps of handover decisions for different drone altitudes and speeds, aiming to prompt a revision of legacy handover schemes and cell boundaries in the sky.

Yun Chen et al., [21] addressed the challenge of providing reliable wireless connectivity to drone user equipment (UEs) in cellular networks, which are primarily designed for ground UEs. They proposed a novel handover (HO) mechanism for cellular-connected drones to enhance connectivity and mobility support. The key feature of their approach is the use of a Q-learning algorithm from reinforcement learning to dynamically optimize HO decisions. This algorithm allowed the drone to learn and adapt its HO strategy based on its interactions with the network environment, aiming to minimize the number of HOs while maintaining robust connectivity. The methodology involved developing and implementing the Q-learning algorithm within the cellular-connected drone system, integrating it with the network's HO decision-making process. The tools used in this study include software and hardware components for simulating drone mobility and network connectivity scenarios, as well as programming tools for implementing the Q-learning algorithm.

Reinforcement Learning-Based Optimization for Drone Mobility in 5G and Beyond Ultra-Dense Networks is conducted by Tanveer et al., [22]. This study Q-learning to optimize handover decisions in ultra-dense networks for drones, addressing challenges like signal strength variations and co-channel interference. The proposed approach minimized handover costs while maintaining robust connectivity, demonstrating significant improvements in time-sensitive applications and high data rate communications. The study aimed to address the challenges faced by 4G and 5G cellular networks in ensuring dynamic control and safe mobility for drones, particularly in scenarios such as crowded events, disaster response, and UAV traffic management. The primary focus was on optimizing the handover process to maintain robust connectivity and minimize handover costs, which are critical when drones operate in three-dimensional space and encounter issues, such as signal strength variations and co-channel interference. The methodology employed Q-learning-based approach to enhance the handover algorithm, moving beyond the baseline greedy handover method that only ensures the strongest connection, often resulting in multiple handovers. By leveraging Q-learning, a type of machine learning technique suited for fast environment learning, the study evaluated the handover decision process in three different scenarios. This approach enabled the drone to learn optimal routes and maintain high data rates, essential for time-sensitive applications like tactile internet and haptic communication. Simulation results confirmed that the proposed Q-learning algorithm effectively reduced handover costs and enhanced connectivity, presenting a significant contribution to the optimization of drone mobility in ultra-dense network environments.

Jang et al., [23] proposed a Deep Reinforcement Learning (DRL)-based handover decision scheme. The DRL is used to optimize handover decisions by learning from the UAV's interactions with the network environment. This technique allowed the UAV to make proactive and intelligent handover decisions, minimizing the number of handovers and maintaining robust connectivity even in dynamic network conditions.

Jang et al., [24] expanded their proposal for a UAV handover decision system using deep reinforcement learning, specifically the Proximal Policy Optimization (PPO) algorithm, in a 3D UAV mobility environment. The use of PPO in UAV handover decision-making is a novel approach and shows promise in enhancing handover performance. However, the study lacked a comprehensive comparison with existing handover decision methods. It would be beneficial to see a comparison of the proposed PPO algorithm with traditional handover decision approaches in terms of handover latency, success rate, and network efficiency. Furthermore, the scalability and adaptability of the PPO algorithm to different UAV mobility scenarios need to be investigated to assess its practical utility in real-world applications.

On the other hand, the study by Cao et al., [25] introduced the use of Deep Reinforcement Learning (DRL) for Multi-User Access Control in Non-Terrestrial Networks (NTNs). The approach of using a centralized agent to train parameters of a deep Q-network (DQN) was innovative and addressed the complex nature of access control in NTNs. However, the study lacked in-depth analysis and evaluation of the proposed method. The authors could provide more insights into the performance of the DQN in different scenarios, such as varying network loads or user mobility patterns. Additionally, the practical feasibility and scalability of deploying a centralized DRL agent for access control in large-scale NTN environments need to be discussed further.

Yan et al., [26] conducted multi-UAV speed control with collision avoidance and handover-aware cell association which employed Deep Reinforcement Learning (DRL) to optimize the cell association and velocity decisions of multiple UAVs. The aim was to improve transportation and communication performance by minimizing collisions and ensuring Optimal Handovers (HOs). The methodology involved training DRL models to make dynamic decisions on UAV velocities and their associations with ground cells, enhancing overall system efficiency. Simulation environments are used to test and validate the proposed solutions, demonstrating their effectiveness compared to traditional methods.

Previously, Chowdhury et al., [27], aimed to address the challenges in providing robust wireless connectivity and mobility support for cellular-connected UAVs in beyond visual line of sight scenarios. The focus was on dynamically adjusting the down tilt (DT) angles of ground base stations (GBSs) using a model-free Reinforcement Learning (RL) algorithm to ensure better connectivity and mobility support for UAVs while maintaining good throughput performance for ground users. The methodology involved leveraging tools from RL to dynamically adjust DT angles of GBSs. The RL algorithm is model-free, allowing for adaptability to changing network conditions. The technique involved optimizing the received signal quality at UAVs while ensuring good throughput performance for ground users. The study used simulation tools to evaluate the proposed RL-based mobility management technique. The simulations compared the proposed technique with a baseline scheme where the network keeps the DT angle fixed. The proposed RL-based mobility management technique shows promise in reducing the number of handovers while maintaining performance goals. By dynamically adjusting DT angles, the technique aimed to provide efficient mobility support for UAVs in complex air-to-ground path loss environments.

The study by Jang et al., [28] focused on enhancing the handover decision mechanism for UAVs by addressing the shortcomings of traditional ground-user-centric methods. Their proposed UAV Handover Decision (UHD) scheme utilized Deep Reinforcement Learning (DRL) to dynamically determine the optimal moments for UAVs to execute handovers, ensuring stable connectivity. They employed the Proximal Policy Optimization (PPO) algorithm within a simulated 3D UAV mobility environment. This advanced learning framework allows the UAVs to adaptively learn and manage handover decisions, reducing unnecessary handovers caused by signal strength fluctuations.

Deng et al. [29] aimed to minimize the challenges faced by UAVs due to overlapping coverage areas and interference with terrestrial users. Their study proposed a joint optimization approach for UAV trajectory design and handover management using a duelling double deep Q-network (D3QN) based reinforcement learning algorithm. This method optimized the UAV's path to avoid overlapping coverage areas, thereby reducing interference and the frequency of handovers. The algorithm dynamically adjusted the UAV's trajectory to balance key performance indicators such as delay, uplink interference, and handover numbers.

Almasri et al. [30] aimed to tackle the connectivity challenges faced by Unmanned Aerial Vehicles (UAVs) in cellular networks, which were increasingly vital across various sectors. The study introduced a Q-learning-based algorithm designed to optimize the number of handovers (HOs) that occured frequently due to the high speed and altitude of UAVs. This method involved simulations in rural, semi-rural, and urban settings to assess the algorithm's performance compared to a baseline where drones connected to the cell with the strongest signal. A unique aspect of this research was the consideration of decision distance, which allowed drones to make informed handover decisions based on their proximity to cell towers. While the use of reinforcement learning was innovative, there were potential limitations, such as the algorithm's scalability in dense urban areas and the generalizability of simulation results to real-world scenarios.

Supervised learning techniques using labelled data were applied by Zhao et al. [16] and Anderson et al. [19]. Reinforcement learning methods that adapt and learn from the environment were employed by Zhong et al. [18], Azari et al. [20], Yun Chen et al. [21], Tanveer et al. [22], Jang et al. [23, 24, 28], Cao et al. [25], Yan et al. [26], Chowdhury et al. [27], Deng et al. [29], and Almasri et al. [30]. Wang et al. [17] used a dynamic matching algorithm that adapts to network changes.

2.1.3 Optimization-Based Techniques

Cheung et al., [31] focused on reducing the age of information (AoI) for unmanned aerial vehicles (UAVs) by improving network selection. While previous methods often prioritize the closest or strongest signal base stations (BSs) for data rate optimization, they overlook BS queueing and handover delays. The research aims to minimize AoI in network access and handover by considering BS load and UAV flight plans. Each UAV must choose between uncongested BSs for quicker updates or BSs along its path for fewer handovers. The UAVs' decisions were modelled as a noncooperative game to minimize their cost, which included BS AoI and handover penalties. The study introduced a distributed BS association (DBA) algorithm to find a Nash equilibrium, ensuring UAVs select BSs based on load and flight plans. Simulation results demonstrated that the proposed DBA scheme reduced AoI compared to existing methods.

A Novel Cooperative Relaying-Based Vertical Handover Technique for Unmanned Aerial Vehicles was proposed by Haider et al., [32]. The research introduced a relay-based vertical handover technique for UAVs, employing multicriteria handover parameter triggering to minimize packet loss and delay. Simulation results indicated enhanced handover success rates and reduced end-to-end delay, proving the method's effectiveness in maintaining seamless connectivity during vertical handovers.

Furthermore, Hajiakhondi-Meybodi et al., [33] proposed Joint Transmission Scheme and Coded Content Placement in Cluster-Centric UAV-Aided Cellular Networks. The Technique proposed a coded content placement strategy and a coordinated multipoint (CoMP) transmission approach. This technique used a coded content placement strategy to pre-position data in the network, combined with CoMP transmission to enhance signal strength and reliability. Its improved data availability and reduces latency during handovers by coordinating transmissions from multiple base stations.

Huichen et al., [34] aimed to enhance mobility management in wireless networks for UAV inspection in a 5G-enabled smart grid, recognizing the need for high data rates, minimal latency, and robustness. Their focus was on the unique challenges posed by UAVs' agile movements and demanding communication requirements. To address these challenges, they introduced the uplink-based pre-handover scheme, comprising a pre-handover decision algorithm and signalling procedure. This scheme aimed to improve handover efficiency and reliability. The methodology involved implementing and testing the proposed scheme in simulations to compare its performance with traditional methods. Their technique cantered on developing and implementing this new scheme to optimize handover decisions and signalling for UAVs. The study likely employed simulation tools to evaluate the scheme's effectiveness in a controlled environment.

Bekkouche et al., [35] aim to address the challenges associated with managing the mobility of services in Multi-Access Edge Computing (MEC) environments, particularly for Unmanned Aerial Vehicles (UAVs). The primary objective is to ensure sustainable Quality-of-Service (QoS) as UAVs move and undergo handovers across distributed MEC hosts. To achieve this, the authors proposed using predefined UAV flight plans to develop proactive service relocation strategies. The methodology involved formulating the Proactive Service Relocation for UAV (PSRU) problem using linear programming. This approach was designed to handle asynchronous relocation processes efficiently by anticipating UAV movements and making informed decisions on where and when to relocate services.

Fonseca et al., [36] aimed to highlight the challenges faced by network operators in providing connectivity for UAVs in cellular networks. The focus was on understanding and addressing the network planning and optimization challenged that arose when UAVs become users of the network. The methodology involved analysing 3GPP specifications, existing research literature, and a publicly available UAV connectivity dataset. The study classified challenges into network planning and network optimization categories to provide a comprehensive understanding of the issues. The study used real-world datasets to support its findings about the challenges faced by network operators in providing connectivity for UAVs. It also discussed possible approaches to address these challenges. The study provided a thorough analysis of the challenges faced by network operators in enabling UAV connectivity in cellular networks. By considering network planning and optimization challenges, the study highlighted the need for network operators to adapt their planning and operation strategies to accommodate UAVs as users of the network.

2.1.4 Handover Count (HOC)- Based Techniques

Chowdhury et al., [37] aimed to estimate the velocity of cellular-connected Unmanned Aerial Vehicles (UAVs) to ensure reliable and effective mobility management. It focuses on deriving a probability mass function (PMF) of handover count (HOC) for different UAV velocities and ground base station (GBS) densities and proposes a velocity estimation method based on the HOC measurement time. The study modelled the relationship between HOC and UAV velocity and derived the Cramer-Rao lower bound (CRLB) for velocity estimation. It also provided a simple unbiased estimator for UAV velocity based on GBS density and HOC measurement time. The study evaluated the accuracy of the proposed velocity estimation method under different GBS densities and HOC measurement windows. The study provided a valuable contribution to the field of cellular-connected UAVs by proposing a method for velocity estimation based on HOC. By considering the impact of GBS density and HOC measurement time, the study addressed key challenges in mobility management for UAVs.

Again Chowdhury et al., [38] investigated the estimation of UAV speed to improve mobility management and service quality for cellular-connected UAVs. The study aimed to develop a reliable method for detecting UAV mobility states based on handover count (HOC) statistics. The authors proposed an approximation of the probability mass function of HOC considering UAV height, velocity, and ground base station (GBS) density. Using this approximation, they derived the Cramer-Rao lower bound (CRLB) for speed estimation and introduced a simple biased estimator for UAV speed, which became unbiased under specific conditions. The methodology employed statistical analysis tools to correlate handover counts with UAV speed, providing a practical approach to mobility state detection in UAV networks.

2.1.5 Others Based Techniques

Teeluck et al., [39] proposed a seamless handover mechanism for UAVs acting as base stations, utilizing an RSS (Received Signal Strength) decision algorithm. The goal was to enable continuous service provision to ground users by seamlessly swapping UAVs without introducing downtime. The methodology involved designing and implementing the handover mechanism, which included the development of the RSS decision algorithm. The technique used was based on leveraging RSS measurements to determine the optimal timing for UAV swapping, ensuring continuous coverage. The tools used likely included simulation software for testing the handover mechanism and algorithm to validate its effectiveness in maintaining uninterrupted service.

Queiroz et al., [40] aimed to address the challenges of handover procedures for ground users assisted by a network of Unmanned Aerial Vehicles (UAVs) acting as base stations (UAV-BSs) in 5G and beyond (B5G) systems. The focus was on developing intelligent handover strategies using Deep Learning (DL) algorithms to improve Quality of Service (QoS) metrics for ground users. The study models a 5G Air-to-Ground radio channel and proposes DL techniques for handover management based on Recurrent Neural Networks (RNNs) for trajectory and signal predictions. The techniques were implemented and evaluated using the OMNeT++ simulator, with new modules added to extend the 5G Standalone (SA) libraries. The study used the OMNeT++ simulator with extended 5G SA libraries to implement and evaluate the proposed DL-based handover management techniques. The study provided a novel approach to improving handover procedures in aerial 5G and beyond systems using DL algorithms. By focusing on trajectory and signal predictions, the study addressed key challenges in maintaining service continuity for ground users in UAV-BS networks.

The study in Goudarzi et al., [41] aimed to improve handover processes in heterogeneous wireless networks, particularly in future 5G cellular networks, using cooperative game theory. The focus was on selecting the best UAV during the handover process to optimize handover among UAVs, reducing end-to-end delay, handover latency, and signalling overheads. The study proposed a method based on cooperative game theory to optimize handover among UAVs. The method utilized the software-defined network (SDN) design with media-independent handover as forwarding switches to achieve seamless mobility. The study employed cooperative game theory and SDN design principles as theoretical frameworks for optimizing handover among UAVs. The study introduced a novel approach to improving handover processes in UAV-assisted communications using cooperative game theory. By focusing on optimizing handover among UAVs, the study addressed key challenges in maintaining QoS for mobile devices.

Meer I. A, et al. [42] explored the challenges of mobility management for cellular-connected UAVs, emphasizing the need to maintain service availability while minimizing unnecessary handovers. They highlighted that the traditional Mobility Robustness Optimization (MRO) procedures, optimized for terrestrial users, fail to address the unique challenges faced by aerial users such as frequent handovers due to line-of-sight conditions with multiple ground base stations (BSs). To address this, the authors proposed two approaches: a model-based service availability-aware MRO and a deep Q-network based model-free approach. Both approaches aimed to reduce handovers and increase service availability, with simulation results showing over a 40% increase in service availability and a 50% reduction in handovers compared to traditional methods.

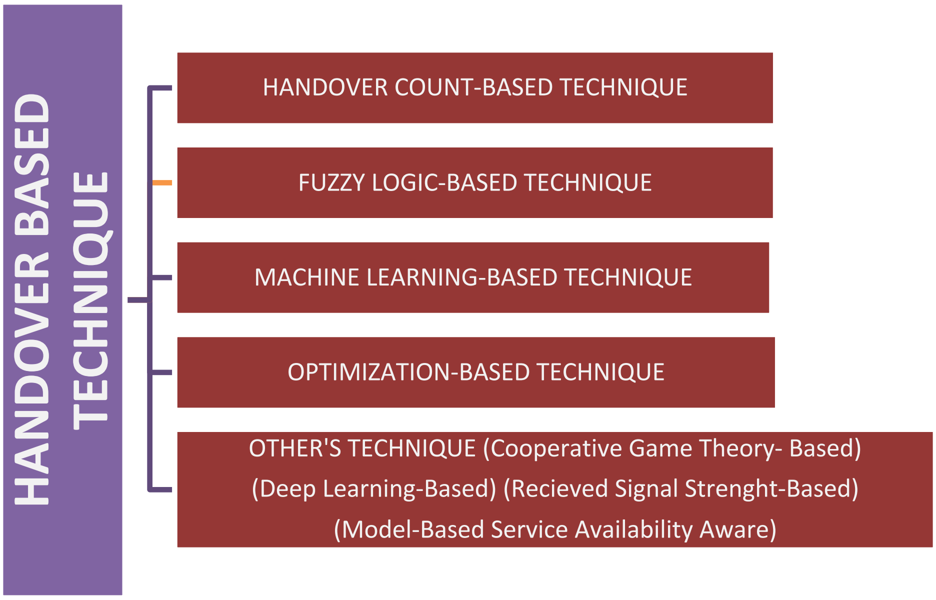

Fig. 2. Classification of Handover Based Techniques

3. Research Gap Issues

This section highlights the research gaps and issues encountered by previous handover approaches in UAV communication systems.

Handover Triggering Estimation Based on Fuzzy Logic for LTE-A/5G Networks with Ultra-Dense Small Cells was conducted by Haghrah et al., [14]. The study improved handover performance and radio link quality in ultra-dense small cell networks using a fuzzy logic-based handover triggering mechanism. Despite these improvements, the method's dependency on accurate positional data remains a significant drawback. Inaccurate positional information can lead to suboptimal handover decisions. Future work should focus on developing adaptive algorithms capable of handling positional inaccuracies, thereby enhancing the reliability and applicability of the handover mechanism in real-world scenarios.

Singh et al., [15] demonstrated the effectiveness of their multi-level fuzzy system in managing handover (HO) in mobile communication systems with UAVs. The results showed that their approach reduced the complexity of the HO decision-making process while enhancing system performance. By considering parameters such as coverage, speed limit, cost, connection time, security, and power consumption, their system provided more efficient and reliable HO decisions compared to traditional methods. However, the study did not delve deeply into the practical implementation of the proposed system in real-world scenarios, leaving a gap in understanding its scalability and adaptability to dynamic environments. Despite this, the research represented a significant step towards improving

HO management in mobile communication systems with UAVs, highlighting the potential of fuzzy logic in enhancing system performance. Nevertheless, the inherent complexity of fuzzy systems themselves presented a challenge, potentially offsetting the benefits of reduced overall system complexity. The trade-off between system simplification and the complexity of the fuzzy logic approach needed careful consideration. Future work could aim to streamline the fuzzy inference process, perhaps through hybrid models that combine fuzzy logic with other, simpler decision-making techniques.

Zhao et al., [16] proposed a Machine Learning-based proactive handover scheme using LSTM to enhance network performance by minimizing handover delays. The results showed a reduction in ping-pong rates and end-to-end delays. However, the study did not detail specific performance gaps, which are crucial for understanding the method's limitations. Future research should include comprehensive empirical testing across diverse environments to identify and address potential performance issues, ensuring the robustness of the proposed scheme.

Wang et al., [17] proposed stable matching with evolving preference for adaptive handover in cellular-connected UAV networks. The study utilized a Dynamic Stable Matching Algorithm (DSMAH) to improve network stability for cellular-connected UAVs. The results showed improvements in communication quality and reduced handover frequency. However, the frequent handovers and ping-pong effects observed indicate a need for further refinement. Simulation results showcased the algorithm's superiority over standard schemes, with the study utilizing simulation tools to assess the algorithm's performance in dynamic conditions. Integrating predictive mechanisms to pre-emptively address potential handover triggers could reduce the frequency of handovers and mitigate the ping-pong effect, leading to a more stable network.

Study by Zhong et al., [18] aimed to reduce the number of handovers and improve energy efficiency in UAV-assisted heterogeneous networks by employing a combined approach of TOPSIS and Q-learning algorithms. The results demonstrated a significant reduction in handover numbers and an improvement in average energy efficiency. However, the approach was heavily dependent on a large volume of training data, which introduced significant challenges and complexities, particularly in real-time implementation scenarios. This reliance on extensive data sets poses a barrier to practical deployment, making the system less agile and more resource intensive. To enhance the real-time applicability and efficiency of the proposed method, future research could focus on developing algorithms that require less data or employ data-efficient training techniques.

The finding of Anderson et al., [19] study indicated significant improvements in Quality of Service (QoS) metrics for handover procedures in Aerial 5G and Beyond Systems. By using Deep Learning (DL) algorithms, particularly the Gated Recurrent Unit (GRU) for signal prediction, they were able to reduce delay and packet loss compared to the baseline 5G handover procedure. However, the study did not specify the exact extent of improvement achieved. One issue arose was the complexity and computational overhead of implementing DL algorithms for real-time handover decision-making in UAV-BS networks. Additionally, the research gap lied in the lack of exploration into the scalability and robustness of the proposed DL-based handover strategies across different network scenarios and deployment environments. A critical review suggested that while DL showed promise in improving handover procedures, further research was needed to address these issues and validate the scalability and practicality of DL-based approaches in real-world Aerial Network deployments.

Azari et al., [20] study revealed significant insights into the challenges and dynamics of cellular connectivity for drones, particularly emphasizing the interference issues between drones and terrestrial users. By providing analytical models and proposing a Machine Learning solution, the research offered a systematic approach to optimize handover and resource management in such networks. However, the study also highlighted the need for further research to address remaining challenges and gaps, such as the practical implementation of proposed solutions and the adaptation of existing network infrastructure to accommodate drone communications. A critical review suggested that future studies could focus on real-world validation of proposed algorithms and explore additional factors influencing handover decisions in diverse environmental conditions. Additionally, recommendations included the development of standardized protocols and guidelines for integrating drones into cellular networks effectively.

Yun Chen et al., [21] developed a novel handover (HO) mechanism for cellular-connected drones, utilizing a Q-learning algorithm to dynamically optimize HO decisions. Their results demonstrated a significant reduction of up to 80% in the number of HOs compared to a baseline scheme, highlighting the potential of their approach to improving connectivity and mobility support for drone user equipment (UEs) in cellular networks. However, while the study's findings were promising, several critical aspects warranted further investigation. Firstly, the performance of the proposed HO mechanism should be validated through real-world experiments to assess its practical feasibility and scalability. Additionally, the impact of reduced HOs on other performance metrics, such as network throughput and latency, needed to be thoroughly evaluated to understand the trade-offs involved. Furthermore, the study's focus on reducing the number of HOs might overlook other important aspects of HO optimization, such as the quality of service (QoS) experienced by drone UEs. Future research could explore these aspects to provide a more comprehensive understanding of the implications of HO optimization in cellular-connected drone systems.

Tanveer et al., [22] revealed that the Q-learning-based approach significantly reduces handover costs and improves connectivity for drones in 5G networks. The simulation results demonstrated the algorithm's effectiveness in providing efficient mobility support, high data rates, and robust connections, especially in time-sensitive applications like the tactile internet and haptic communication. However, the research identified issues, such as the increased handover cost due to variations in the received signal strength indicator, co-channel interference, and abrupt signal drops caused by antenna nulls. These challenges highlighted the need for more sophisticated algorithms to manage drone mobility in ultra-dense network environments. Despite its promising findings, the study had some limitations, such as the scope of scenarios evaluated and the potential need for real-world testing to validate the simulation results. A critical review suggested that future research could explore hybrid approaches combining Q-learning with other machine learning techniques or investigate adaptive algorithms that respond to dynamic network conditions in real-time. Additionally, expanding the testing environment to include more diverse and complex scenarios would provide a more comprehensive understanding of the proposed algorithm's capabilities and limitations.

Jang et al., [23] aimed to prevent unnecessary handovers while maintaining stable connectivity using a Deep Reinforcement Learning (DRL)-based scheme. The results showed reduced unnecessary handovers and maintained stable RSSI. However, the approach is not suitable for ground users, limiting its applicability. Future work should integrate ground user considerations into the model to provide a more comprehensive solution that addresses both aerial and terrestrial connectivity needs.

Furthermore, Jang et al., [24] proposed a DRL-based UAV handover decision scheme to manage stable connectivity. The results indicated reduced handover frequency and maintained signal strength. However, frequent fluctuations in signal strength due to UAV mobility present challenges. Stabilizing signal strength through advanced prediction models could improve overall performance and reliability. Future work should focus on developing algorithms that can dynamically adjust to maintain consistent signal strength despite UAV mobility.

Cao et al., [25] proposed a UE-driven DRL-based scheme to optimize multi-user access control in non-terrestrial networks. The results demonstrated improvements in long-term system throughput and reduced handover frequency. However, the dynamic environment of non-terrestrial networks poses unique challenges, such as the mobility of NT-BSs. Adapting the model to better handle these dynamic conditions could improve its robustness and applicability. Future work should focus on enhancing the algorithm to manage the mobility and variability of non-terrestrial networks more effectively.

Yan et al., [26] demonstrated significant improvements in both collision avoidance and communication performance, with reduced handover rates and better connectivity. However, the complexity of implementing DRL in real-time environments remained a critical issue, along with the scalability of the solution in dense UAV networks. The research gap included the need for real-world validation and addressing the computational overhead associated with DRL. Critically, while the approach showed promise in simulations, its real-world application could be constrained by the current technological limitations in processing power and real-time learning capabilities.

Chowdry et al., [27] found that the Reinforcement Learning-based approach significantly reduces the number of handovers without compromising the quality of service (QoS). It ensured robust connectivity and efficient mobility management for UAVs in cellular networks. However, issues, such as computational complexity and the need for real-time learning pose challenges. The research gap lied in the lack of extensive real-world testing and the need for more efficient algorithms to handle large-scale deployments. Critically, while the study demonstrated potential, its practical applicability was limited by the high computational demands and the need for more extensive real-world validation.

The experimental results in Jang et al., [28] of the UHD scheme showed a significant reduction in handovers, up to 76% compared to conventional methods and 73% compared to other target methods, while maintaining stable signal strength. This indicated a substantial improvement in the efficiency and reliability of UAV communications. However, the study highlighted the need for further optimization of the DRL algorithms to handle more complex and dynamic UAV environments. Future research should focus on refining these algorithms and conducting real-world validations to ensure robustness and applicability in practical scenarios.

Deng et al., [29] The results demonstrated that the proposed D3QN-based approach could reduce handover numbers by 90% and interference by 18%, with only a minor increased in transmission delay. Additionally, incorporating trajectory design into the D3QN policy reduced interference by 29% and handover numbers by 33%. Despite these promising outcomes, the study suggested that further refinement was needed to optimize the balance between transmission delay and interference reduction. Future research should explore more sophisticated trajectory planning and resource allocation strategies to enhance the overall performance of UAV communication systems.

Almasri et al., [30] found that the Q-learning-based algorithm significantly reduced the average number of HOs compared to the baseline, enhancing quality of service and reducing energy consumption for UAV operations. The findings also emphasized the importance of hyper-parameters in different environments. However, the study did not fully explore the effects of varying drone speeds and altitudes on handover performance or the long-term adaptability of the algorithm to dynamic network conditions. These gaps highlighted the need for further research, including extensive real-world testing and the development of adaptive algorithms that could optimize continuously in changing environments. Additionally, integrating Machine Learning with predictive analytics for network load balancing could further improve UAV connectivity's efficiency and reliability across diverse operational scenarios.

Cheung et al., [31] provided valuable insights into minimizing the age of information (AoI) for UAVs in cellular networks, addressing a critical need for reducing latency in real-time status updates. By focusing on optimizing network selection to consider both BS load and UAV flight plans, the research introduced a novel approach that could significantly improve the efficiency of UAV communication. However, despite its innovative contributions, the study lacked a detailed analysis of the practical implementation challenges and scalability of the proposed DBA algorithm. Additionally, the research gap lied in the limited consideration of factors, such as network congestion, varying UAV speeds, and dynamic network conditions, which could impact the effectiveness of the proposed approach in real-world scenarios. Further research could explore these factors to enhance the applicability and robustness of the proposed solution in complex UAV communication environments.

Haider et al., [32] focused on addressing the challenges of vertical handover in UAV communication by proposing a relay-based technique. Results indicated that the proposed method enhances connectivity and performance during the handover process. However, the study lacked a detailed discussion on the specific scenarios or conditions under which the relay-based technique outperformed existing methods. Additionally, the research gap lied in the absence of a thorough analysis of the impact of environmental factors, such as weather conditions or interference, on the proposed technique's effectiveness. Moreover, the critical review suggested further investigation into the scalability and adaptability of the relay-based approach in different UAV communication scenarios. It is recommended to conduct field trials or real-world simulations to validate the proposed technique's performance in practical UAV deployment scenarios. Furthermore, incorporating Machine Learning or AI algorithms could potentially enhance the relay selection process, leading to more efficient vertical handover in UAV communication networks.

Joint Transmission Scheme and Coded Content Placement in Cluster-Centric UAV-Aided Cellular Networks was developed by Hajiakhondi-Meybodi et al., [33]. This research focused on increasing content diversity and managing user requests efficiently using a coded content placement and coordinated multipoint (CoMP) approach. The results indicated improvements in cache-hit-ratio, SINR, and access delay. However, the method's efficiency dropped significantly in indoor environments due to signal attenuation and UAV battery constraints. Future research should explore hybrid solutions that combine both indoor and outdoor strategies to enhance overall network efficiency and content delivery performance.

Huichen et al., [34] The study introduced a novel uplink-based pre-handover scheme for UAV inspection in a 5G-enabled smart grid, aiming to enhance transmission rates, reduce latency, and improve reliability. Simulation results indicated a 38% decrease in handover failure compared to traditional schemes, demonstrating the effectiveness of the proposed approach. However, the study lacked a detailed discussion on the specific performance metrics used to evaluate the scheme's effectiveness, such as throughput, latency, and reliability metrics. Additionally, the research could benefit from a more comprehensive comparison with existing handover schemes to establish its superiority more convincingly. Despite these limitations, the study focused on optimizing handover decisions for UAVs in 5G-enabled smart grids was crucial for enhancing communication network performance in such scenarios. Further research could delve deeper into specific optimization algorithms or consider real-world implementation challenges to validate the scheme's practicality and effectiveness.

Bekkouche et al., [35] proposed proactive service relocation for UAVs in MEC. This research introduced a proactive service relocation method using linear programming to manage MEC service mobility efficiently. While the results showed improvements in service relocation efficiency, the complexity of decision-making processes remained a significant challenge. Simplifying the algorithm and enhancing decision-making efficiency were crucial for practical deployment. Future studies should focus on streamlining the relocation process to make it more feasible for real-world applications.

Fonseca et al., [36] identified several key challenges, including network coverage planning, PCI collision and confusion, automatic neighbouring relation (ANR), and handover issues. These challenges were important considerations for network operators as UAV technology becomes more prevalent. The study suggested possible approaches to address these challenges, but further research was needed to validate these approaches and develop practical solutions for network operators.

Simulation in Chowdhury et al., [37] introduced an approximate probability mass function (PMF) for handover count (HOC) in UAVs, considering different velocities and ground base station (GBS) densities. The researchers derived the Cramer-Rao lower bound (CRLB) for UAV velocity estimation and proposed an unbiased estimator dependent on GBS density and HOC measurement time. Simulation results showed that higher GBS densities and longer HOC measurement windows improved velocity estimation accuracy. However, issues included the dependency on GBS density, which might vary, and assumptions about consistent HOC measurements, potentially affected by interference and environmental factors. The study also did not fully address the impact of other network parameters on accuracy. The study presented a valuable approach to UAV velocity estimation but was limited by its reliance on GBS density, which might not be uniform across different areas. Future research should explore adaptive algorithms to handle varying GBS densities and incorporate additional data sources, such as GPS or onboard sensors, to enhance accuracy. Field tests in diverse environments were recommended to validate the method and identify areas for improvement, ensuring reliable connectivity and effective mobility management for UAVs in various scenarios.

Further research by Chowdhury et al., [38] indicated that the proposed estimator could accurately estimate UAV speed under various conditions, with the CRLB providing a theoretical lower bound for estimation accuracy. However, the study identified several issues and research gaps, such as the potential for biased estimates under high handover conditions and the needed for further validation in diverse operational environments. The research suggests that future work should explore more sophisticated estimation techniques that can account for varying UAV trajectories and environmental factors. Additionally, integrating this estimator with real-time network data could enhance its practical applicability, leading to more effective mobility management solutions for cellular-connected UAVs.

Teeluck et al., [39] proposed a new method for seamless handover of UAV base stations in fifth-generation mobile networks to ensure continuous coverage. Their approach aimed to address the challenge of limited UAV flight time due to battery constraints by swapping UAVs acting as base stations without downtime. The study demonstrated the effectiveness of the proposed method in maintaining uninterrupted service during UAV swapping, giving the impression of perpetual UAV flight. While the study was a significant advancement, it lacked an in-depth exploration of practical implementation challenges and their impact on network performance. Future research could focus on addressing these issues and comparing the proposed method with existing techniques. Despite these potential limitations, this work was a promising step toward improving the reliability and continuity of UAV-based communication systems.

Queiroz et al., [40] indicated the effectiveness of the DL-based approach in improving QoS metrics for ground users compared to baseline 5G handover procedures. However, the study did not address the scalability and complexity of implementing DL algorithms in real-world UAV-BS networks. Further research was needed to address these implementation challenges and validate the proposed techniques in practical scenarios.

The results in Goudarzi et al., [41] demonstrated the effectiveness of the proposed approach in reducing the number of handovers, cost, and delay. However, the study did not consider practical implementation issues and scalability challenges in real-world networks. Further research was needed to validate the proposed approach and develop practical solutions for network operators.

Irshad A. Meer et al., [42] study's significant contribution lied in its dual-approach methodology, providing both a model-based and a learning-based solution to UAV mobility management. By fine-tuning handover control parameters in the model-based approach and leveraging Deep Reinforcement Learning in the model-free approach, the research offered robust strategies to enhance the service reliability of UAVs in cellular networks. The findings underscored the importance of adapting existing terrestrial mobility management techniques to accommodate the distinct characteristics of aerial users, thus paving the way for more efficient UAV integration into future cellular networks.

In conclusion, while significant strides have been made in optimizing UAV handover and connectivity, each study highlighted areas needing further exploration. Addressing these specific gaps with adaptive and simplified algorithms, enhanced predictive mechanisms, and a focus on practical deployment challenges will be crucial.

4. Analysis and discussion

This section outlines the study and discussion of handover techniques in unmanned aerial vehicle (UAV) communication systems, categorized by method, publication year, and performance evaluation metrics.

4.1 Analysis in Terms of Publication Year

This section categorizes the review according to the publication year, focusing on 29 articles discussing handover techniques in drone communication systems. The breakdown by publication year is summarized in Table 2. Among the 29 surveyed articles, a higher number of articles journal were published in 2022 and a higher number of conference papers were published in 2020, compared to 2023 and 2024.

Table 2
Analysis based on the publisher's year

Years	No. of Articles Journal	No. of Conference Paper
2024	3	-
2023	5	1
2022	7	2
2021	4	2
2020	2	3

4.2 Analysis Based on Techniques

Based on the analysis of 29 recent articles published between 2020 and 2024, various techniques were used for handover in UAV communication systems, as depicted in Figure 3. The most widely used techniques were Machine Learning Based Technique which accounting for 34% with Reinforcement learning method indicating their potential and promising role in the field. Optimization-based approaches at 21%. Fuzzy logic-based techniques and Handover Count-based approaches were used by 7% of researchers. Additionally, other techniques, such as Deep Learning, cooperative game theory, model-based, and Received Signal Strength-based techniques constitute 14% of the surveyed articles. Thus, the analysis indicates that Reinforcement Learning as one of the

Machine Learning Based type, predominantly favoured for handover mechanisms in UAV communication systems, followed by an optimization-based technique. On the other hand, Fuzzy Logic-based techniques and Handover count-based approaches were also among the less frequently used. Machine Learning-based techniques specifically on Reinforce were increasingly favoured by researchers as a potential future choice for handover management in UAV communication systems, Fonseca et al., [36] driven by the advancements in Artificial Intelligence.

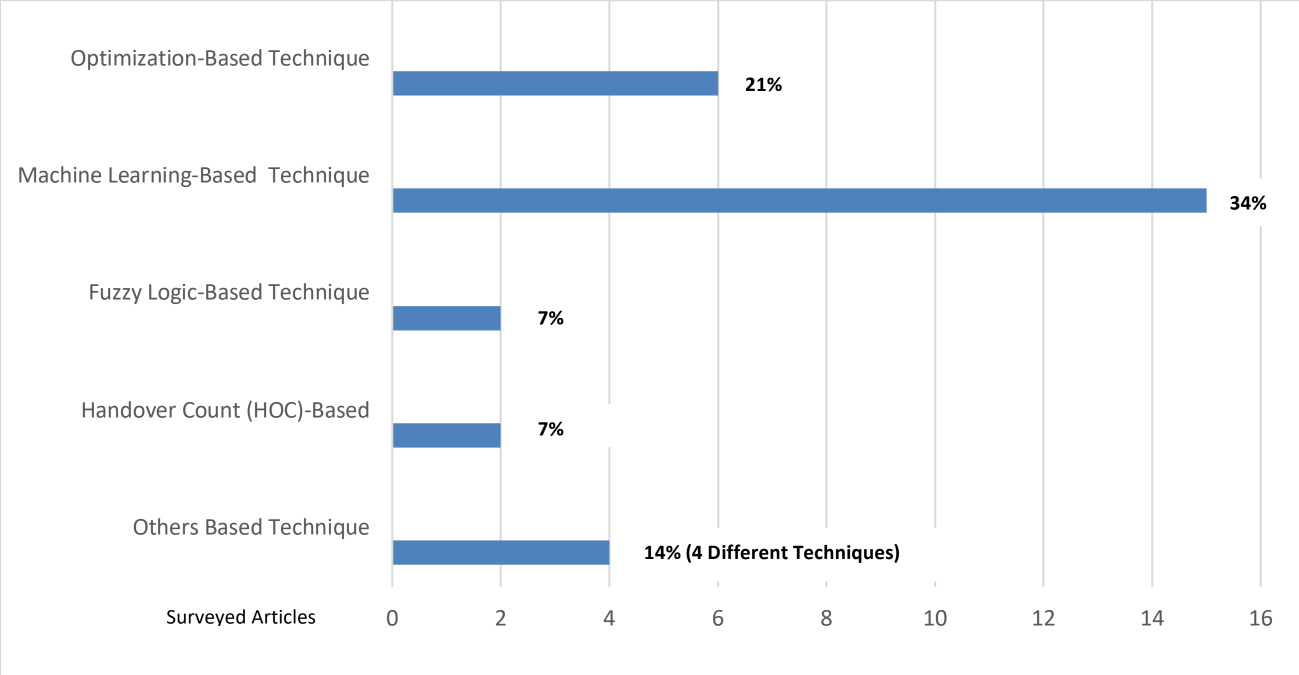

Fig. 3. Analysis based on techniques.

The most widely used techniques were Machine Learning Based Technique with RL method indicating their potential and promising role in the field. RL techniques emerged as the predominant method used in UAV-related in this study, particularly in handover decision-making, due to several compelling reasons. These reasons highlighted the adaptability and efficacy of RL in dynamic and complex environments typical of UAV operations. RL enabled UAVs to learn optimal handover strategies by interacting with the environment and adapting to changes in real-time. This adaptability was crucial in UAV operations where conditions such as signal strength, interference, and mobility patterns varied frequently (Zhong et al., [18]).

Unlike supervised learning, which relied on static labelled data, RL could continuously update its policies based on new data and experiences. This dynamic decision-making capability was essential for UAVs to maintain robust connectivity and minimize handovers in fluctuating network conditions (Azari et al., [20]). RL techniques, particularly Q-learning and deep reinforcement learning (DRL), could optimize multiple performance criteria simultaneously. For instance, they could balance minimizing handover frequency with maintaining strong signal strength and reducing energy consumption (Yun et al., [21]). RL algorithms were highly scalable and could handle the complexity of UAV networks, which often involved numerous variables and large state spaces. Studies had shown RL's effectiveness in scenarios ranging from ultra-dense networks to non-terrestrial networks (NTNs), demonstrating its robustness across different environments (Jang et al., [12]). RL allowed UAVs to make proactive and intelligent decisions. For example, the use of DRL with Proximal Policy Optimization (PPO) enabled UAVs to anticipate and react to future network conditions, thereby reducing unnecessary handovers and enhancing overall network performance (Cao et al., [25]). Many RL-based studies had demonstrated practical applicability through simulations and real-world data, such as the use of geographical network data to model interference and delay in UAV operations. This practical validation underlined RL's potential for deployment in actual UAV networks (Deng et al., [29]). Reinforcement learning's ability to continuously learn and adapt, optimize multiple criteria, and make proactive decisions made it an ideal technique for managing the complexities of UAV networks. These attributes enabled RL to address the dynamic nature of UAV operations more effectively than traditional supervised learning methods, which were limited by static datasets and lacked adaptability in real-time environments.

RL techniques could broadly be classified into three main categories based on their approach to learning and decision-making: value-based, policy-based, and model-based RL. The RL classification being used by the researchers is shown in Table 3.

Table 3

Classification of RL	Research articles
Value-based	Zhong et al., 2024; Y Chen et al., 2021; Tanveer et al.,2022, Deng et al., 2020;
Policy-based	Azari et al., 2019; Jang et al., 2021; Cao et al., 2020; Jang et al., 2023; Yan et al., 2022;
Model- Free	Chowdhury et al., 2021;
Other	Wang et al., Wang et al., 20

Value-based RL methods learn a value function that estimates the expected return (cumulative reward) of being in a particular state and following a certain policy. The value function helps the agent to make decisions by selecting actions that maximize the expected return. Examples of value-based RL algorithms include Q-learning, Deep Q-Networks (DQN), and Double Deep Q-Networks (DDQN). Zhong et al. [18] used Q-learning to optimize handover decisions in UAV-assisted heterogeneous networks.

Policy-based RL methods directly learn an optimal policy, which is a mapping from states to actions without explicitly estimating the value function. Policy-based methods can handle large and continuous action spaces more effectively than value-based methods. Examples include policy gradient methods, Proximal Policy Optimization (PPO), and Deterministic Policy Gradient (DPG). Jang et al. [12] utilized the PPO algorithm for UAV handover decision-making in a 3D mobility environment.

Model Free-based RL methods involve learning an internal model of the environment to predict outcomes of actions. These methods use the learned model to plan actions and make decisions. Model-based RL can potentially reduce the number of interactions needed with the real environment compared to model-free approaches include Dyna-Q and Model Predictive Control (MPC) combined with RL. Chowdhury et al. [27] employed model-free RL to dynamically adjust down tilt angles of ground base stations for cellular-connected UAVs.

Other RL model is proposed by Wang et al., [17] involves a stable matching algorithm to manage adaptive handover in cellular-connected UAV networks. Stable matching is a mechanism where two sets of elements (in this case, UAVs and ground base stations) have preferences for one another, and the goal is to find a stable matching where there are no two elements that would prefer to swap partners. This approach adapts handover decisions based on the evolving preferences and conditions in the network. The study aims to adapt handover decisions dynamically by evolving the preference relations between UAVs and ground base stations. This technique is different from traditional RL methods like value-based, policy-based, or model-based RL, as it focuses on matching preferences and ensuring stable connectivity rather than directly optimizing actions based on reward signals.

4.3 Analysis Based on Used Tools

This subsection describes the tools used in existing handover mechanisms for UAV communication systems. Figure 4 provides an analysis based on these toolsets. The software tools employed in the research papers include MATLAB, MATLAB Simulink, Python, NS-3, and TensorFlow. According to Figure 4, MATLAB was the most frequently used tool for handover mechanisms in UAV communication systems, followed by Python, TensorFlow, and NS-3. On the other hand, OMNeT++ and MATLAB Simulink were the least used software tools, as depicted in the graph. It is also noted that many researchers used multiple tools in combination, such as MATLAB with Python, MATLAB with NS-3, MATLAB with OMNeT++, and TensorFlow with Python.

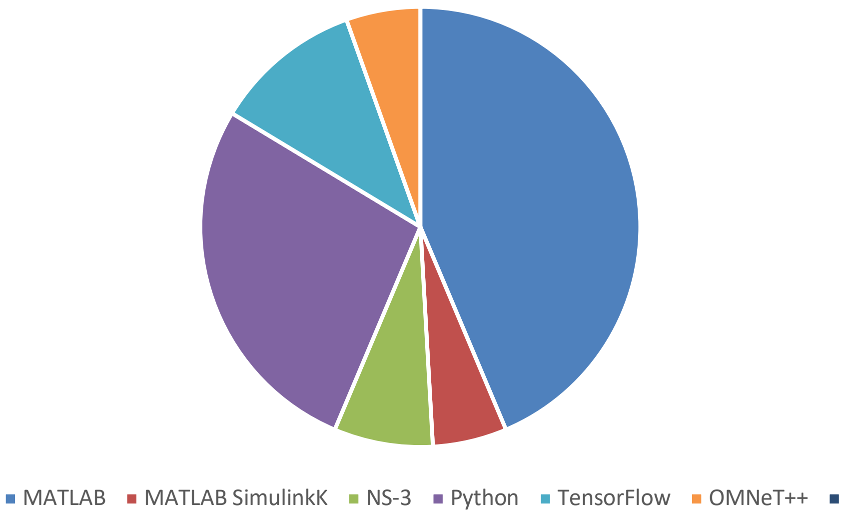

Fig. 4. Analysis based on the toolset

4.4 Analysis Using Performance Metrics

The analysis based on performance metrics is detailed in this section. The performance metrics evaluated include signalling cost, throughput, handover number, handover success rate, handover failure rate, accuracy, handover success probability, ping pong rate, packet delivery ratio, unnecessary handover, handover trigger, energy efficiency, interference, signal-to-noise ratio (SINR), and packet loss. According to Table 4, handover rate, handover failure probability, ping pong handover, and packet delivery ratio were the most frequently considered metrics. Accuracy was the least frequently considered metric. Authentication latency and throughput were the next most frequently considered metrics after accuracy. Overall, the handover rate was the most preferred metric in UAV communication systems. High handover success rates were reported in studies by Goudarzi et al.,[41] Tanveer et al., [22]; Cheung et al., [31]; Chowdhury et al., [38]; Meer et al.,[42].

Table 4
Analysis based on performance metrics.

Performance metrics	Research articles
Handover (HO) number	Singh et al., 2024; Fonseca et al., 2021; Goudarzi et al.,2021, Zhong et al., 2024; Almasri et al., 2022; Y Chen et al.,2020;
HO trigger HO failure rate Cost HO success rate	Kyun Nam Park et al., Huichen et al., 2021. Cheung et al., 2020. Goudarzi et al.,2021 Tanveer et al.,2021; Cheung et al., 2020; Chowdhury et al., 2023; Meer et al.,2024.
Unnecessary HO Ping pong rate	Z Haider et al., 2024; Jung et al., 2022; Haghrah et al.,2023 H Jung et al., 2023; Wang et al., 2024; Haghrah et al., 2023.
Throughput Energy efficiency	Cao et al., 2021; Singh et al., 2022. Zhong et al., 2024; Bekkoucheo et al., 2021; Almasri et al., 2022.
Signal strength	Anderson Queiroz et al., 2023; Goudarzi et al.,2021; Teeluck et al., 2023; A Haghrah et al., 2023; Jung et al., 2022; Y Jang et al., 2022
Delay	HajiAkhondi et al., 2022 H Jung et al., 2023. Z Haider et al., 2024; Singh et al.,2023; Azari et al., 2020; Zhao et al.,2021; Chowdhury et al.,2020, 2023
Interference Packet loss SINR	Azari et al., 2020. Z Haider et al., 2024; Azari et al., 2020. Z HajiAkhondi et al., 2022

4.6 Comparison of Existing Handover Decision Technique

Table 5 presents the advantages and disadvantages of current handover techniques in UAV communication systems. Describing the pros and cons of various techniques used in different methods is crucial for better comprehension. Fuzzy Logic-based techniques, Machine Learning-based techniques, Optimization-based techniques, Received Signal Strength-based techniques, Handover Count-based techniques, and others techniques are surveyed, and their benefits and drawbacks are outlined in the following table for clarity.

Table 5
Critical Review on Comparison of Existing Handover Decision Technique

Technique	Advantages	Disadvantages
Fuzzy Logic- Based	**Robustness:** Fuzzy logic can handle imprecise input data and uncertainty, making it robust in real-world UAV communication scenarios. **Flexibility:** These techniques can accommodate multiple input parameters and make decisions based on fuzzy rules. **Simplicity:** Fuzzy logic systems are often straightforward to implement and can be tuned through heuristic methods. **Interpretability:** Fuzzy logic systems provide transparent decision-making processes, making it easier to understand and trust the system.	**Complexity:** Designing and optimizing fuzzy logic rules and membership functions can be complex and require domain expertise. **Performance:** Fuzzy logic may not always achieve the same level of performance optimization as more sophisticated machine learning or optimization techniques. **Limited Adaptation:** Fuzzy logic systems may struggle to adapt to rapidly changing network conditions compared to adaptive learning techniques. **Scaling Issues:** Scaling fuzzy logic systems to large networks or complex environments can be challenging and may lead to reduced performance.
Machine Learning (ML)-Based	**Adaptability:** Machine Learning techniques can adapt to changing network conditions and learn optimal handover decisions without explicit programming. **Real-time Decision Making:** Some machine learning models can make decisions in real-time, improving responsiveness in dynamic UAV communication scenarios. **Efficiency:** These techniques can optimize handover decisions to improve performance metrics such as latency, throughput, and energy efficiency. **Scalability:** Once trained, machine learning models can scale to large networks and diverse environments, making them suitable for UAV communication systems.	**Data Dependency:** Machine Learning models require large amounts of training data, which may not always be available or representative of real-world conditions. **Generalization Issues:** Models may not generalize well to unseen scenarios, leading to potential performance degradation in novel environments. **Complexity:** Developing and training machine learning models can be complex and require expertise in both Machine Learning and network optimization. **Interpretability:** Machine Learning models are often "black-box" algorithms, making it difficult to understand and interpret how decisions are made, which can be a barrier to trust and adoption.
(ML) Reinforcement Learning	**Adaptability and Learning:** RL techniques can adapt to changing network conditions and learn optimal handover decisions based on environmental factors such as UAV speed, signal strength, and network load. **Performance Optimization:** RL algorithms can optimize handover decisions to improve performance metrics such as latency, packet loss, and throughput. **Real-time Decision Making:** RL techniques can make decisions in	**Complexity of Implementation:** Developing and training RL models for handover decisions can be complex and requires expertise in both reinforcements learning and network optimization. **Dependency on Training Data:** RL models require large volumes of training data to learn optimal policies, which can be challenging to obtain and may not always be representative of real-world conditions. **Performance Variability:** The performance of RL-based handover techniques heavily relies on the quality and relevance of the training data. Poorly

	real-time, which is crucial for dynamic UAV communication scenarios where network conditions can change rapidly. **Efficient Resource Management:** RL can help in efficient resource management by reducing unnecessary handovers, which in turn can save energy and extend UAV flight time. **Scalability:** Once trained, RL models can scale to large networks and complex environments, making them suitable for deployment in various UAV communication systems.	trained models can lead to suboptimal decisions. **Computational Overhead:** RL algorithms can be computationally intensive, especially during the training phase, which may introduce latency and overhead in real-time decision-making scenarios. **Interpretability:** RL models are often considered "black box" algorithms, making it difficult to interpret how decisions are made, which can be a barrier to trust and adoption in critical UAV applications. **Generalization Issues:** RL models may struggle to generalize across diverse and unseen scenarios, leading to potential performance degradation in novel environments.
Optimization-Based	**Mathematical Rigor:** Optimization techniques provide a rigorous mathematical framework to minimize handover latency, packet loss, and other performance metrics. **Efficiency:** These techniques can efficiently allocate resources and manage handovers based on predefined objectives and constraints. **Flexibility:** Optimization algorithms can be customized to adapt to different network conditions and scenarios, offering flexibility in deployment. **Real-time Adaptation:** Some optimization-based techniques can make decisions in real-time, enhancing their applicability in dynamic UAV environments.	**Complexity:** Implementing and configuring optimization algorithms can be complex and may require expertise in mathematical modelling and network optimization. **Dependency on Models:** These techniques often rely on accurate models of the network and UAV dynamics, which can be difficult to obtain and maintain. **Computational Overhead:** Optimization algorithms can be computationally intensive, leading to increased latency and energy consumption, which may not be suitable for real-time applications. **Sensitivity to Assumptions:** The performance of optimization techniques can be sensitive to the assumptions made during the modelling phase, affecting their robustness in real-world scenarios.
Received Signal Strength -Based	**Simplicity:** RSS-based techniques are relatively simple and easy to implement compared to other methods. **Real-time Decision Making:** RSS can provide real-time feedback on signal strength, enabling quick decisions during handovers. **Low Overhead:** These techniques typically have low computational overhead and energy consumption. **Widely Adopted:** RSS is a standard metric used in many communication systems, making it widely understood and implemented.	**Accuracy:** RSS measurements can be inaccurate due to factors like multipath interference, shadowing, and fading, leading to suboptimal handover decisions. **Dynamic Environment:** RSS values can fluctuate rapidly in dynamic UAV environments, making it challenging to maintain reliable connectivity. **Limited Information:** RSS alone may not capture other critical factors affecting handover decisions, such as network load or interference. **Threshold Setting:** Setting RSS thresholds for handover decisions can be challenging and may not always be optimal across different scenarios.

Handover Count-Based	**Simplicity:** Handover count-based techniques are straightforward to implement and do not require complex algorithms. **Real-time Decision Making:** These techniques can make quick decisions based on the number of handovers, which is beneficial in dynamic UAV communication scenarios. **Low Overhead:** They typically have low computational overhead and energy consumption. **Efficiency:** Handover count-based techniques can optimize handover decisions to reduce unnecessary handovers and improve network efficiency. **Widely Applicable:** They are applicable across various UAV communication systems and environments.	**Lack of Context:** Handover count alone may not consider other critical factors affecting handover decisions, such as network load, signal strength, or interference. **Threshold Setting:** Setting thresholds for handover counts can be challenging and may not always be optimal across different scenarios. **Dynamic Environment:** Handover counts may fluctuate rapidly in dynamic UAV environments, leading to suboptimal decision-making. **Limited Adaptability:** These techniques may not adapt well to rapidly changing network conditions or diverse UAV communication scenarios.
Model-Based Service Availability Aware	**Increased Service Availability:** The model-based approach is designed to enhance service availability for cellular-connected UAVs. By considering unique aerial user challenges like line-of-sight conditions with multiple ground base stations (BSs), this approach can significantly increase service availability. **Reduced Handovers:** The model-based approach aims to minimize unnecessary handovers. This is crucial for UAVs that experience frequent handovers due to their mobility and line-of-sight conditions with BSs. **Optimized for Aerial Users:** Traditional mobility robustness optimization (MRO) procedures, which are typically optimized for terrestrial users, do not adequately address the specific challenges faced by UAVs. The model-based approach is tailored to meet the unique needs of aerial users, resulting in more efficient operation. **Performance Improvement:** According to simulation results provided by the authors, the model-based service availability-aware MRO approach shows significant improvements. This includes over a 40% increase in service availability and a 50% reduction in handovers compared to traditional methods.	**Complexity of Implementation:** Implementing a model-based approach can be complex and may require sophisticated mathematical modelling and simulation techniques. **Dependency on Models:** The performance of model-based techniques heavily depends on the accuracy of the underlying assumptions and models of the network dynamics. If these models are inaccurate, the performance of the approach may suffer. **Computational Overhead:** Model-based approaches may introduce computational overhead, particularly during the modelling and simulation phases, which can affect real-time decision-making capabilities. **Interpretability:** Model-based techniques can sometimes be challenging to interpret, especially in complex scenarios. This can limit the understanding of how decisions are made, which may be a barrier to trust and adoption. **Generalization Issues:** While the model-based approach shows significant improvements in simulations, it may face challenges in generalizing to diverse and unseen scenarios. The real-world application may vary from simulation results.

	Scalability and Adaptability: Model-based techniques can scale to large networks and heterogeneous environments, making them suitable for diverse UAV communication systems.	
Cooperative Game Theory-Based	**Resource Allocation:** Cooperative game theory can optimize resource allocation and enhance cooperation among UAVs and base stations during handover. **Fairness:** It can ensure fairness in resource allocation and minimize conflicts during handover processes. **Performance Optimization:** These techniques can optimize performance metrics such as latency and throughput by cooperative decision-making. **Scalability:** Cooperative game theory can scale to large networks and heterogeneous environments. **Real-time Decision Making:** Some cooperative game theory-based techniques can make decisions in real-time, improving responsiveness in dynamic UAV communication scenarios.	**Complexity:** Implementing cooperative game theory-based techniques can be complex and may require sophisticated mathematical modelling. **Communication Overhead:** The cooperative decision-making process can introduce communication overhead between UAVs and base stations. **Dependency on UAV Cooperation:** Performance heavily depends on the cooperation level among UAVs and base stations, which may not always be optimal. **Model Assumptions:** The performance may vary based on the accuracy of the underlying assumptions and models of the network dynamics.
Deep Learning-Based	**Adaptability:** Deep learning techniques can adapt to changing network conditions and learn complex patterns from large amounts of data. **Real-time Decision Making:** Some deep learning models can make decisions in real time, improving responsiveness in dynamic UAV communication scenarios. **Performance Optimization:** These techniques can optimize handover decisions to improve performance metrics such as latency, throughput, and energy efficiency. **Scalability:** Once trained, deep learning models can scale to large networks and diverse environments, making them suitable for UAV communication systems. **Complexity Reduction:** Deep learning can automate the decision-making process and reduce the complexity of handover algorithms.	**High Computational Requirements:** Deep learning models require significant computational power and resources, both for training and real-time execution. This can be a limitation in UAV systems with constrained hardware capabilities. **Complexity and Overhead:** Implementing and maintaining deep learning models is complex and requires specialized knowledge. The computational overhead can also lead to increased latency, which may affect real-time performance. **Data Dependency:** The performance of deep learning models heavily depends on the quality and quantity of training data. Inadequate or biased data can lead to poor handover decisions, impacting network reliability and user experience. **Training Time:** Training deep learning models can be time-consuming, especially for large datasets. This can delay deployment and updates, making it challenging to keep up with rapidly changing network conditions. **Vulnerability to Adversarial Attacks:**

		Deep learning models can be susceptible to adversarial attacks, where manipulated inputs lead to incorrect handover decisions. Ensuring robustness against such attacks adds another layer of complexity to the system.

5. Challenges and Opportunity

The methodologies and techniques presented for handover decision-making in UAV systems offer various challenges and opportunities. Fuzzy Logic-Based Techniques, as showcased by Haghrah et al. [14] and Singh et al., [15] demonstrated the challenge of balancing multiple factors like signal strength, user mobility, and network load to make nuanced handover decisions. The opportunity lied in reducing unnecessary handovers and improving network performance by adapting to dynamic network conditions. Machine Learning techniques, such as those proposed by Zhao et al. [16] and Wang et al., [17] faced the challenge of predicting future coverage holes and optimizing handover decisions based on evolving preferences.

There is an opportunity to maximize network coverage and reliability by proactively handing over to base stations with better coverage. Reinforcement Learning techniques, exemplified by studies from Yun Chen et al. [21] and Tanveer et al., [22] faced the challenge of ensuring reliable wireless connectivity for drones in cellular networks. The opportunity was to dynamically optimize handover decisions, minimize handover costs, and maintain robust connectivity, especially in time-sensitive applications. Optimization-based techniques, like those introduced by Cheung et al. [31] and Haider et al., [32] faced the challenge of reducing the age of information (AoI) for UAVs and ensuring seamless connectivity during vertical handovers. The opportunity was to minimize AoI in network access and handover, enhance handover success rates, and reduce end-to-end delay. Handover Count (HOC)- Based Techniques, as investigated by Chowdhury et al., [38] aim to estimate UAV velocity and speed to improve mobility management and service quality, facing the challenge of detecting UAV mobility states based on HOC statistics. The opportunity lied in developing reliable methods for detecting UAV mobility states and estimating speed based on HOC. Other techniques, such as those proposed by Teeluck et al. [39] and Queiroz et al., [40] faced the challenge of providing seamless handover mechanisms for UAVs acting as base stations and improving handover procedures for ground users assisted by a network of UAVs acting as base stations in 5G and beyond systems. The opportunity was to develop intelligent handover strategies using Deep Learning algorithms, cooperative game theory, and software-defined network (SDN) design principles to improve QoS metrics for ground users and optimize handover among UAVs.

The research in handover decision techniques for UAV communication systems revealed several key challenges and opportunities for future research. One of the primary challenges identified was the reliance on extensive training data for Machine Learning algorithms, such as Q-learning and Deep Reinforcement Learning (DRL), to make accurate handover decisions. This reliance introduces complexities and challenges for real-time implementation, as large datasets may not always be readily available or practical to use. Future research should focus on developing algorithms that require less data or employ more data-efficient training techniques to enhance real-time applicability and efficiency.

There is a need for a more comprehensive analysis and consideration of practical implementation challenges, such as network congestion, environmental factors, and scalability issues. Many studies have shown promising results in simulation environments, but their effectiveness in real-world scenarios remains unclear. Future research should conduct field trials or real-world simulations to validate the proposed techniques' performance and address practical deployment challenges. Furthermore, there is a need for algorithms that can dynamically adjust to handle dynamic network conditions and ensure consistent performance. By addressing these challenges, researchers can unlock opportunities to improve UAV communication systems' efficiency, reliability, and overall performance in various operational scenarios.

6. Conclusions

This review, based on 29 research works, explores handover decision techniques in UAV communication systems. It critically reviews the methodology, categorizes handover approaches, discusses the findings and research gaps critically, and analyses them in terms of publication year, tools, techniques, and performance metrics. collected papers are categorized into approaches such as reinforcement-based techniques, Machine Learning-based techniques, optimization-based techniques, Fuzzy Logic-based techniques, handover count-based techniques, deep learning, cooperative game theory, model-based, and received signal strength-based techniques. All research articles are accessed from platforms, such as Scopus, Web of Science, and IEEE. This survey suggests potential extensions for the handover decision mechanisms in drone communication systems by addressing the gaps and issues from the articles reviewed. The analysis and discussion are organized by classification approaches, toolsets used, and performance metrics. The analysis reveals that the Reinforcement Learning-based approach which is Machine Learning-based technique was the most used technique in research papers. Moreover, delay, handover number, handover success rate, and signal strength were the most frequently used performance metrics. To further advance this field, future research should focus on developing groundbreaking handover techniques for drone communication systems using a variety of algorithms to optimize long-term communication stability and efficiency.

Acknowledgment
This paper is part of research work supported by FRGS Grant file no.: FRGS/1/2024/TK07/UITM/02/6 and Universiti Teknologi MARA Shah Alam.

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