

## Review

# Mobility and Handover Management in 5G/6G Networks: Challenges, Innovations, and Sustainable Solutions

Bilal Saoud <sup>1,2,\*</sup>, Ibraheem Shayea <sup>3</sup> , Mohammad Ahmed Alnakhli <sup>4,\*</sup>  and Hafizal Mohamad <sup>5</sup>

<sup>1</sup> Department of Electrical Engineering, Faculty of Applied Sciences, University of Bouira, Bouira 10000, Algeria

<sup>2</sup> LISEA Laboratory, Faculty of Applied Sciences, University of Bouira, Bouira 10000, Algeria

<sup>3</sup> Electronics & Communications Engineering Department, Faculty of Electrical and Electronics Engineering, Istanbul Technical University (ITU), Istanbul 34467, Turkey

<sup>4</sup> Electrical Engineering Department, College of Engineering, Prince Sattam Bin Abdulaziz University, Wadi Addwasir 11991, Saudi Arabia

<sup>5</sup> Faculty of Engineering and Built Environment, Universiti Sains Islam Malaysia, Bandar Baru Nilai 71800, Negeri Sembilan, Malaysia

\* Correspondence: b.saoud@univ-bouira.dz (B.S.); m.alnakhli@psau.edu.sa (M.A.A.)

## Abstract

Compared to 4G long-term evolution (LTE) networks, 5G and 6G networks provide fast data transmission with little delay, larger base station capacity, enhanced quality of service (QoS), and extensive multiple-input-multiple-output (MIMO) channels. Nevertheless, the attainment of mobility and handover (HO) in 5/6G networks has been hindered by substantial changes in intelligent devices and the high-definition applications of multimedia. Therefore, the existing cellular network is compared with difficulties in transmitting large amounts of data at a faster rate, ensuring high QoS, minimizing latency, and efficiently managing HOs and mobility. This paper primarily addresses the difficulties related to HO and mobility management in 5G/6G networks. The findings of this paper emphasize the importance of aligning mobility and HO strategies with sustainable development goals to reduce energy consumption and improve resource allocation. It focuses on integrating innovative technologies such as artificial intelligence and machine learning to enhance the sustainability and efficiency of mobility and HO management. The paper provides a comprehensive analysis of the current body of the literature and explores essential metrics for measuring performance (known as KPIs) and potential solutions for difficulties linked to HO and mobility. The analysis takes into account established standards in the field. Furthermore, it assesses the effectiveness of existing models in dealing with HO and mobility management problems, considering criteria such as energy efficiency, dependability, latency, and scalability. This survey concludes by highlighting key challenges associated with HO and mobility management in existing research models. It also offers comprehensive assessments of the proposed solutions, accompanied by suggestions for future research.

**Keywords:** 5G/6G networks; HO; HetNet; ML; resource efficiency; green technology



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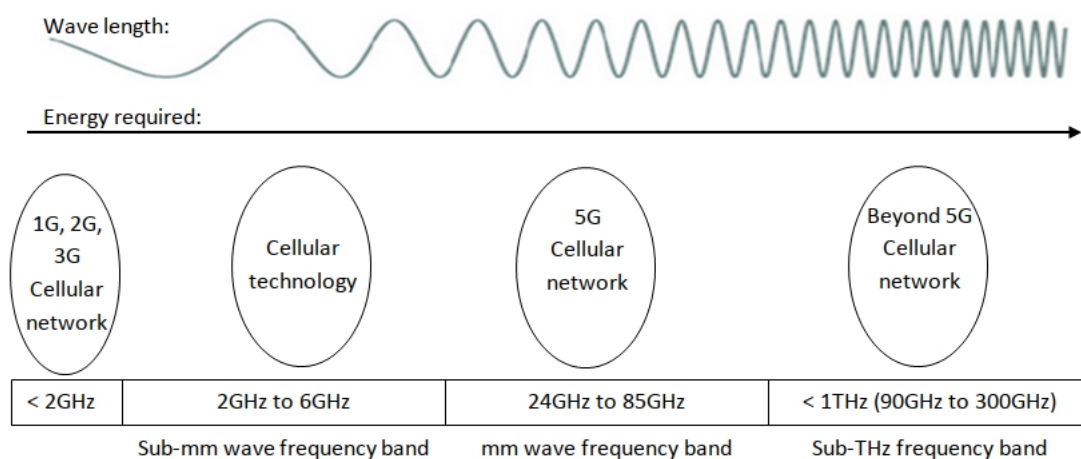
## 1. Introduction

The exponential growth in mobile user equipment (UE), data-intensive applications, and smart devices has dramatically increased global data traffic demands [1]. To address these evolving requirements, organizations such as the International Telecommunication Union (ITU) and the 3rd Generation Partnership Project (3GPP) have introduced 5G as a

transformative wireless communication standard. Enabling technologies like the Internet of Things (IoT), Device-to-Device (D2D) communication, Vehicle-to-Vehicle (V2V) networking, and Edge Computing (EC) has further emphasized the need for networks offering ultra-low latency, high spectral efficiency, and massive connectivity [2,3]. In this context, 5G promises enhanced coverage, increased data rates, minimal latency, improved energy efficiency, and seamless device interoperability [4,5].

To deliver these capabilities, 5G employs dense deployments of heterogeneous networks (HetNets), millimeter wave (mmWave) communication, and massive multiple-input multiple-output (MIMO) systems [6–10]. However, mobility management and handover (HO) performance can become increasingly complex in ultra-dense HetNets (UD-HetNets), where frequent cell transitions can severely impact quality of service (QoS) and quality of experience (QoE). Aspects such as latency, jitter, packet loss, and signal strength directly influence these metrics. Thus, efficient HO and mobility procedures are essential to maintain seamless and reliable communication.

The use of mmWave frequencies (24–84 GHz) in 5G provides high bandwidth but poses propagation challenges, such as high path loss and limited penetration [11]. To overcome coverage limitations, UD-HetNets combine macro base stations (MBSs) with small cells (micro, pico, and femto), enhancing throughput and coverage in densely populated environments [12,13]. Additionally, massive MIMO enables base stations to serve multiple UEs simultaneously, improving spectral and energy efficiency [14,15]. Despite these benefits, dense deployments introduce mobility-related issues such as increased handover frequency, ping-pong effects, and radio link failures (RLFs) [16,17]. Figure 1 illustrates the frequency spectrum across different cellular generations. Efficient HO strategies are crucial in UD-HetNets, especially considering projections such as Ericsson’s estimate of 9.1 billion cellular users by 2027 [2]. As small cells operate in limited areas, high-speed users often experience frequent HO (FHO), which leads to network congestion, increased signaling, and degraded QoE.



**Figure 1.** The various cellular networks’ frequency spectra.

The architectural advantages of 5G, like high capacity and wide coverage, are countered by challenges such as co-channel interference (CCI) and signal blockage in small cells due to mmWave constraints [18–20]. These issues are further exacerbated in dual connectivity scenarios or overlapping coverage regions, increasing the difficulty of ensuring uninterrupted service. Furthermore, environmental sustainability has become a priority in 5G and B5G network design. The deployment of energy-intensive technologies demands green strategies to manage the network’s carbon footprint. This includes dynamic power

management, energy-aware HO optimization, and AI-driven load balancing to ensure sustainable yet high-performing networks.

While several reviews address HO and mobility management in general 5G contexts, few offer a focused evaluation of HO performance and mobility challenges specific to ultra-dense HetNets under high-speed mobility and mmWave conditions. This study addresses this gap by offering a structured review and analysis of existing mobility and HO solutions, emphasizing performance indicators, sustainability, and future evolution. The key contributions of this study are the following:

- A focused survey of HO and mobility challenges in 5G UD-HetNets, identifying key problem areas such as FHO, RLF, and signaling overhead;
- A performance-based comparison of state-of-the-art HO techniques and algorithms based on relevant KPIs;
- A discussion on sustainability, AI integration, and adaptive HO strategies for improved network resilience;
- A critical analysis of open research issues and potential directions for future mobility management in B5G/6G networks.

The remaining sections of the paper are organized as follows: Section 2 encompasses the examination of previous research and provides a concise summary of pertinent survey articles. Section 3 explores the services, architecture, and technologies associated with 5G HetNet. Section 4 provides an explanation of the HO and mobility process in 5G HetNet, while Section 5 examines the existing technologies used to tackle HO and mobility management (MM) challenges in 5G HetNet. Section 6 specifically addresses the difficulties associated with HO (higher-order) and MM (multi-modal) aspects. Challenges related to 5/6G networks will be presented in Section 7. Some of the results of the evaluation of HO in mobile scenarios will be illustrated in Section 8. Ultimately, the article is brought to a close and summarized in Section 9.

## 2. Literature Review

Recent surveys have explored various strategies for HO and mobility management in 5G and beyond HetNets, including emerging paradigms like ultra-dense networks (UD-HetNets). However, a closer analysis reveals that many of these studies describe existing techniques without offering deeper critical comparisons or synthesizing trends across approaches.

### 2.1. HO in 5G Networks

The authors in [21] provide a broad overview of HO and mobility management strategies, particularly emphasizing dual connectivity (DC), software-defined networking (SDN), and machine learning (ML) techniques. Although it presents a rich catalog of solutions, the study does not quantitatively compare the effectiveness of these techniques, especially under high-speed mobility or ultra-dense deployment conditions. Moreover, it overlooks critical factors such as load balancing (LB) and inter-cell interference (ICI), both of which directly impact HO failure rates (HOFR).

In [2], the authors address the disruption caused by the COVID-19 pandemic in the rollout of 5G and evaluate current models using KPIs such as latency, energy efficiency, and scalability. Although their analysis includes a wide scope, the survey does not provide a focused evaluation of HO-specific mechanisms nor assess how models perform under UD-HetNet constraints.

## 2.2. Surveys with a Technology-Specific Emphasis

A number of studies concentrate on specific enabling technologies. For example, ref. [22] discusses the integration of unmanned aerial vehicles (UAVs) in 5G, reviewing deployment scenarios, spectrum policies, and emerging trends. While informative, the work is more UAV-centric than mobility-centric, with limited attention to HO optimization. Similarly, ref. [23] offers an in-depth examination of the evolution toward 5G, with discussions on massive MIMO, low-latency applications, and QoS. However, the study is oriented toward technology evolution rather than mobility management challenges.

The work in [24] shifts focus to the transition toward 6G and its enabling technologies, such as hierarchical cells and network slicing. Though valuable for future planning, the paper primarily provides high-level perspectives without analyzing current HO strategies or how to bridge 5G shortcomings.

## 2.3. Mobility-Specific HO

More targeted reviews, such as [25], analyze ML- and fuzzy logic-based HO decision algorithms in ultra-dense small cells. Although comparative in approach, the study is limited by not addressing the behavior of high-speed users, which is central in real-world mobility. However, energy consumption challenges related to mobility are addressed in [26], which focuses on LTE networks and the role of mobile edge computing (MEC). While the study evaluates trade-offs among energy-saving techniques, it does not directly assess their impact on HO performance in 5G or UD-HetNet scenarios.

Other general surveys provide evaluations of conventional and emerging HO mechanisms, including SDN and NFV. While they cover topics such as seamless transitions, scalability, and resource optimization, they often fall short of evaluating HO strategies under constraints like ICI, LB, and high-mobility environments. These factors are increasingly relevant in modern HetNets but under-represented in the existing literature.

## 2.4. Advanced Architectures and Optimization-Oriented Studies

In [27], the authors evaluate SDN-enabled multi-RAT architectures, including HO optimization techniques and associated limitations. Likewise, ref. [28] explores machine learning applications in maintenance and repair operations (MROs), indirectly related to HO optimization. However, neither paper provides a unified comparison framework or comprehensive performance analysis using KPIs relevant to mobility.

## 2.5. Research Gap

To summarize, although prior surveys offer foundational overviews of mobility and HO strategies, they often suffer from one or more of the following limitations:

- Lack of critical cross-comparison between strategies using common performance indicators;
- Narrow focus on specific technologies without holistic integration;
- Limited discussion of crucial challenges, like LB, ICI, and HOFR, under high-speed or ultra-dense conditions;
- Absence of comprehensive taxonomies or unified evaluation frameworks.

This review identifies the need for a focused, comparative, and holistic survey that addresses the shortcomings of current approaches, provides a taxonomy of HO strategies, and highlights performance trade-offs relevant to 5G and beyond mobility scenarios.

## 3. 5G Architecture and Services

This section provides an overview of 5G services and the fundamental structure. It also introduces 5G New Radio (5G-NR) and explores the essential technologies that contribute

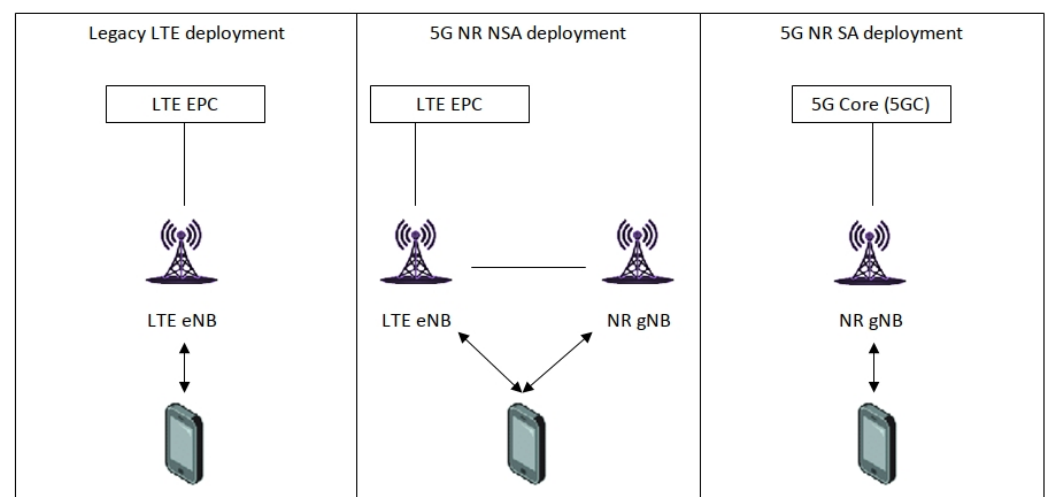
to improving network capacity, reliability, and connectivity. Additionally, it highlights the advancements that enable these enhancements in modern wireless networks.

### 3.1. 5G Architecture

5G architectures represent a major evolution from earlier wireless networks, designed to support high-speed data transmission, ultra-low latency, and massive device connectivity [28]. They incorporate advanced technologies such as network slicing, edge computing, and cloud-native infrastructures, enabling diverse service categories like enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC) [29–33].

Network slicing enables multiple virtual networks to operate on shared physical infrastructure, each tailored to specific performance needs. Edge computing complements this by processing data closer to end users, reducing latency for time-sensitive applications such as AR, VR, and industrial automation [34–36]. Additionally, the service-based architecture (SBA) of 5G offers modularity and flexibility, easing the integration of emerging technologies.

The use of massive MIMO, beamforming, and other advanced radio access technologies boosts spectral efficiency and coverage, especially in dense environments [37]. Deployment models include Non-Standalone (NSA), which relies on LTE-A for control functions, and Standalone (SA), which uses a dedicated 5G core for both control and data planes—delivering enhanced throughput and capacity [37]. Figure 2 illustrates the core components and interfaces of 5G systems.



**Figure 2.** 5G SA and NSA architecture.

### 3.2. 5G Services

5G New Radio (5G-NR) is structured around three primary service categories: enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), and ultra-reliable low-latency communications (URLLCs). Each is tailored to meet specific performance demands across a variety of applications [38].

- eMBB delivers high-speed connectivity and increased capacity for data-intensive services such as UHD video streaming, AR/VR, and other multimedia-rich applications. Technologies like massive MIMO, beamforming, and broad frequency bands ensure reliable performance even in high-density environments [39,40].
- mMTC focuses on connecting large volumes of low-power IoT devices, supporting sectors like smart cities, agriculture, and healthcare. It emphasizes coverage, energy efficiency, and the ability to manage massive device densities under constrained conditions [41].

- URLLC is designed for mission-critical applications requiring ultra-low latency (as low as 1 ms) and high reliability, such as autonomous vehicles, remote surgery, and industrial automation. It achieves these goals through network slicing, edge computing, and optimized resource management [42].

Together, these services form the foundation of the ability of 5G to address the diverse needs of next-generation connectivity.

### 3.3. 5G Technologies

Several important technologies, including HetNets, mmWave communications, massive-MIMO, beamforming, full-duplex (FD) communication, and D2D technologies, make it possible to deploy 5G cellular systems. These developments provide high capacity, improved data rates, and smooth, ubiquitous connection for user equipment (UE) in order to satisfy the demands of future networks [43].

#### 3.3.1. 5G and HetNet

HetNets are a key enabler for 5G and beyond, offering increased capacity, reduced latency, and improved coverage—especially for UE at cell edges [43–45]. By integrating macro base stations (MBSs) with small base stations (SBSs) and multiple RATs, HetNets deliver seamless connectivity and enhanced performance across diverse environments.

In urban areas with dense populations and physical obstructions, small cell deployment is vital to ensure high data rates and comprehensive coverage. These include femto-cells, picocells, and microcells, each suited for different ranges and user densities [45,46]. Small cells consume less power, are cost-effective to deploy, and can operate indoors or outdoors, offloading traffic from MBSs and enhancing the overall quality of service (QoS) through load balancing [47].

Ultra-dense HetNets further amplify network capacity, but their dense deployment introduces challenges such as inter-cell interference (ICI), especially when signals from macro cells overlap with small cell coverage, degrading the Signal-to-Interference-plus-Noise Ratio (SINR) [48,49]. Moreover, mobility management remains critical: efficient HO procedures must accommodate both high-speed (e.g., vehicular) and low-speed (e.g., pedestrian) users to maintain reliable service continuity in dynamic network conditions.

#### 3.3.2. mmWave

mmWave technology is a foundational component of 5G, operating in the 24–100 GHz frequency range [50,51]. These high-frequency bands enable ultra-fast data rates and broad bandwidth, making mmWave ideal for data-intensive applications like UHD video streaming, AR, and VR. However, the short wavelengths of mmWave result in limited range and poor penetration through obstacles. To address this, 5G networks utilize dense small cell deployments and beamforming to focus signals and enhance both coverage and reliability.

In high-density environments such as urban centers, stadiums, and airports, mmWave alleviates network congestion and boosts capacity through massive MIMO, supporting many simultaneous users. Its ultra-low latency makes it suitable for real-time applications, including autonomous vehicles, remote surgery, and industrial automation. Despite its propagation limitations, mmWave—when integrated with lower-frequency bands in HetNet architectures—offers a balanced solution that combines wide-area coverage with high-speed performance. As 5G evolves, mmWave remains essential to realizing the full potential of next-generation wireless networks.

### 3.3.3. Massive MIMO

Massive MIMO is a transformative technology in 5G, characterized by the use of dozens or even hundreds of antennas at base stations to serve multiple users simultaneously [52,53]. It significantly enhances data rates, spectrum efficiency, and network capacity through advanced beamforming, which directs signals precisely toward users while minimizing interference. This enables better coverage, improved signal quality, and support for higher user densities—particularly in dense urban environments.

A key advantage of massive MIMO is its ability to support diverse 5G use cases, including eMBB, mMTC, and URLLC. It facilitates high-speed applications like VR and 4K streaming while also ensuring reliable connectivity for IoT and mission-critical services. Moreover, by focusing transmission energy where needed, massive MIMO improves energy efficiency and reduces overall power consumption. Despite its complexity, advancements in signal processing and antenna design are making it more scalable and cost-effective, solidifying its role as a cornerstone of future-proof 5G deployments [54].

### 3.3.4. Beamforming

Beamforming is a pivotal 5G technology that directs wireless signals toward specific users rather than broadcasting them uniformly, thereby improving signal strength, reach, and quality [55]. By focusing energy in targeted directions, beamforming enhances the signal-to-noise ratio (SNR) and reduces interference—which is especially critical in dense urban environments where many devices compete for connectivity. This technique enables reliable, high-speed communication, even when user devices are in motion, by dynamically adjusting beam direction in real time [56].

5G UD-HetNets leverage both analog and digital beamforming to improve system throughput and reliability [2]. Analog beamforming, typically used in mmWave frequencies, relies on phase shifters and amplifiers to control signal phase and amplitude at the antenna level—which is ideal for high-gain directional transmission. In contrast, digital beamforming operates in the baseband using mathematical processing, offering greater flexibility in real-time beam adjustment and being better suited for sub-6 GHz bands due to lower signal gain requirements and higher computational power.

### 3.3.5. 5G HetNet and FD Communication

Full-duplex (FD) communication is a critical enabler for 5G HetNets, allowing simultaneous transmission and reception on the same frequency band. This capability significantly enhances spectrum efficiency, network capacity, and data rates by eliminating the need for separate uplink and downlink frequency bands [57,58]. It also supports real-time bidirectional communication, which is essential for latency-sensitive 5G applications, such as IoT, AR, and VR.

By removing time-division multiplexing, FD reduces latency and improves reliability by minimizing transmission errors. Its bidirectional nature also enhances network flexibility, dynamic traffic adaptation, and security through immediate identity verification. Moreover, FD reduces the demand for multiple frequency bands, leading to lower spectrum licensing costs and improved interference management. In summary, FD is a foundational component of 5G HetNets, enabling faster, more reliable, and cost-effective wireless communication to support next-generation services.

### 3.3.6. D2D Communication

D2D communication enables direct data exchange between user devices in 5G HetNets without relying on centralized infrastructure such as base stations (BSs) [59,60]. By bypassing the core network, D2D improves network efficiency, reduces congestion, and enhances

capacity, allowing more simultaneous connections and better quality of service. D2D also supports low-latency and high-speed communication, making it ideal for real-time applications such as AR/VR, online gaming, and video streaming. Moreover, it extends coverage in areas with weak or no cellular signals, benefiting remote or underserved regions. Its energy-efficient operation is especially suited for low-power IoT devices. Finally, D2D enhances the user experience by enabling context-aware and personalized services, such as social networking and local multimedia sharing.

### 3.3.7. SDN and NFV

The integration of SDN and NFV in 5G HetNets brings significant advantages for service providers aiming to meet the complex requirements of 5G and deliver high-performance services [7,13,61–63]. SDN enables centralized network control, allowing faster, more efficient deployment and management of 5G services. In parallel, NFV facilitates the virtualization of network functions, enabling dynamic resource allocation based on real-time demand. Together, these technologies improve network performance, reduce operational costs, and enhance scalability.

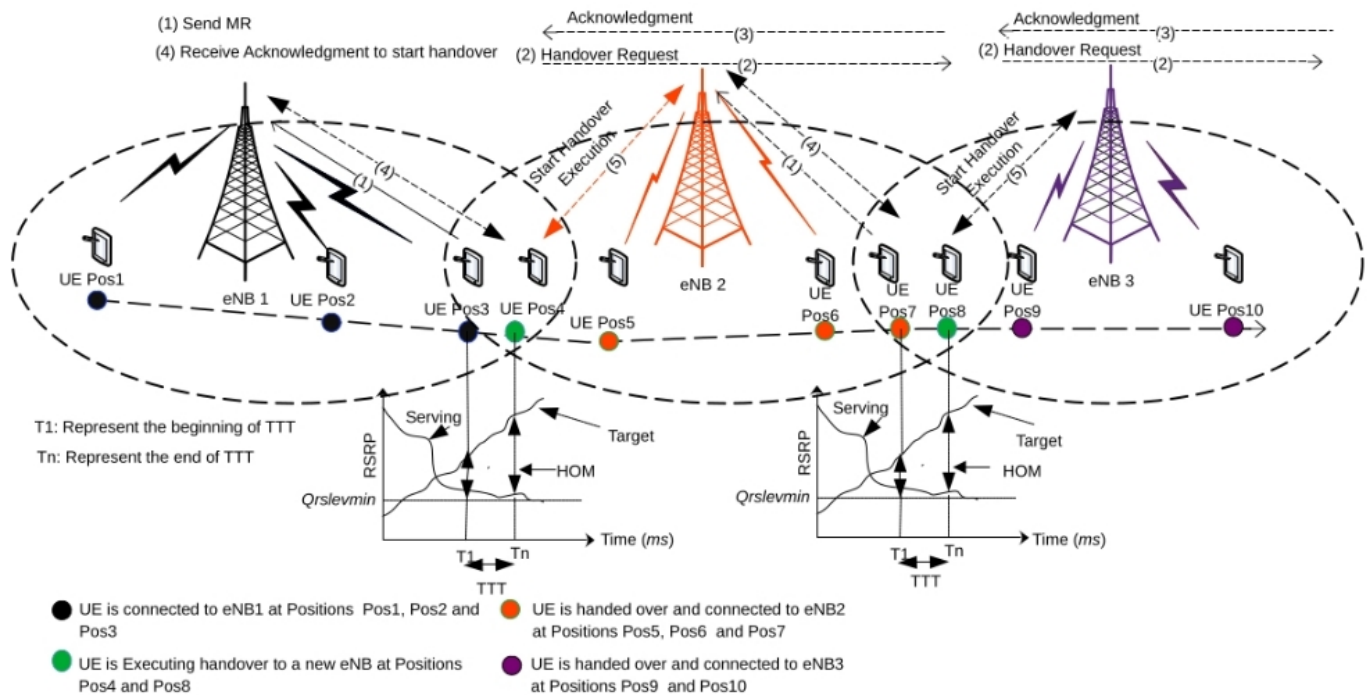
SDN provides increased visibility and centralized control, supporting simplified network management and security enforcement. Meanwhile, NFV enables the virtualization of critical security functions—such as firewalls and intrusion detection systems—enhancing overall network security. Moreover, SDN and NFV play a critical role in maintaining QoS by allowing intelligent management of resources tailored to diverse service requirements. Their combined use introduces advanced automation, elastic scalability, flexibility, and support for rapid innovation, making them essential components in the evolution of 5G HetNets.

## 4. HO in 5G Networks

HO is the seamless transition of a UE from one cell's coverage to another one without losing connection (interruption). Efficient and punctual HO within any communication network is crucial for uninterrupted communication. Within the context of wireless communication systems, HO can be primarily classified into two categories: Hard HO (H-HO) and Soft HO (S-HO), often referred to as break-before-make and make-before-break HO, respectively. During the H-HO procedure, the UE promptly disconnects from the current cell (serving cell) and establishes a connection with the new cell (target cell) without any interruptions. On the other hand, the S-HO method entails creating a fresh connection to the next cell prior to ending the current connection [2,12]. Additionally, Horizontal handover (HHO) and Vertical Handover (VHO) are alternative forms of HO. The HHO procedure involves the HO of a UE from one cell to another inside the same network, utilizing the same frequency. VHO facilitates smooth UE movement across diverse networks. HHO refers to HO occurring between homogeneous BSs, while VHO refers to HO happening between HetNet BSs [2,21]. Because the deployment scenarios of many RATs, including mmWave and Sub-6 GHz, overlap, the HO process in 5G HetNet is carried out via VHO. Figure 3 presents mobility management with HO initiation.

To control UE mobility across cells, LTE-Advanced uses a beam-based mobility handover or hard handover method, which may lead to higher latency, longer handover interruption periods (HOIT), and more packet loss. HetNets and ultra-dense HetNet deployments are essential to future wireless systems like 5G/B5G in order to increase system capacity and offer seamless connectivity. Because of the lower cell sizes in HetNets, it is anticipated that the HO process will become more rapid and repetitive. Reducing HOIT, latency, and packet loss—all of which are crucial elements in 5G and B5G networks—is the primary objective of putting VHO and S-HO approaches into practice. Measurement

reporting (MR), HO initiation, HO execution, and HO completion are the four steps of the HO process in 5G-NR, which is comparable to that in 4G (LTE-A) [64].

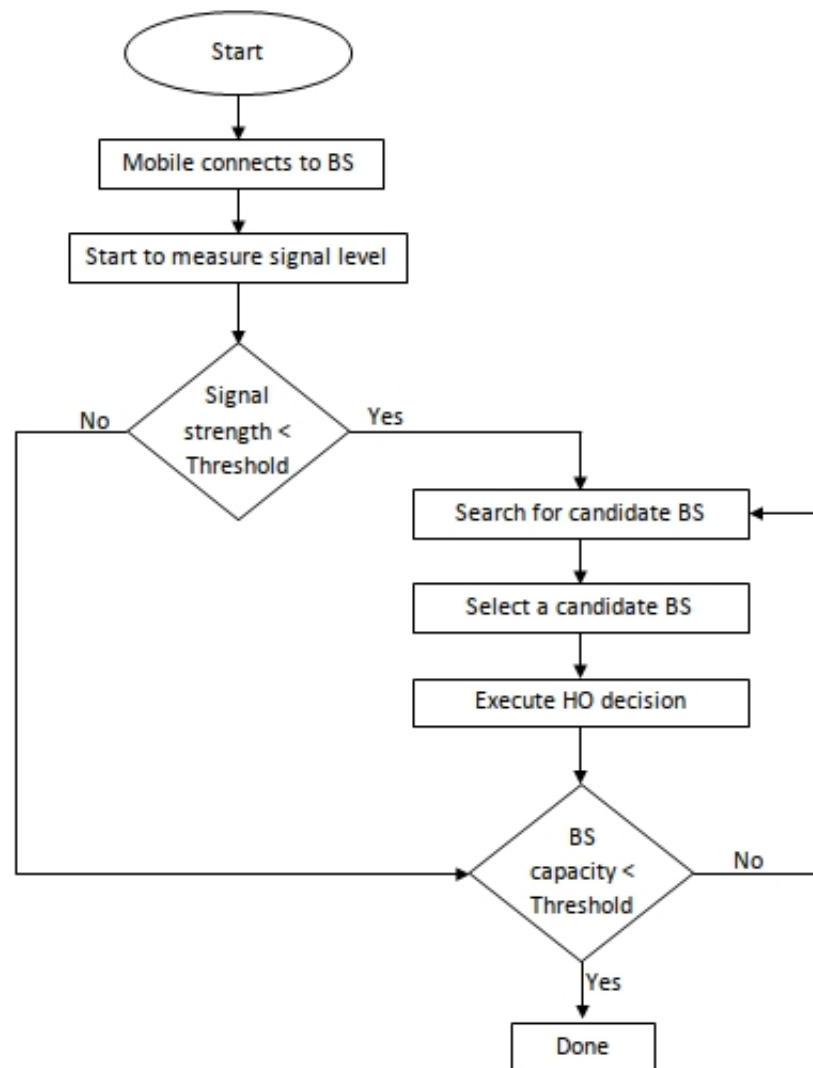


**Figure 3.** HO concept in cellular communication networks.

In 5G-NR, the HO procedure comprises multiple processes that facilitate the uninterrupted switching of UEs from one cell's coverage to another. Below is an enumeration of the sequential phases that outline this procedure:

- UE continuously measures key parameters such as Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), and Signal-to-Interference-plus-Noise Ratio (SINR) from both the serving cell (s-gNB) and neighboring cells (T-gNB). These measurements are reported to the serving gNB to assist in the HO decision-making process.
- Based on the measurement reports, network conditions, and predefined policies, the serving gNB determines whether a handover is necessary. Factors such as signal strength, cell load, and UE mobility patterns are considered to select the most suitable target cell (T-gNB).
- The serving gNB initiates communication with the target gNB to prepare for the handover. This involves exchanging necessary information, such as UE context and resource allocation, to ensure a seamless transition. The target gNB reserves resources and configures itself to accommodate the incoming UE.
- Once preparation is complete, the serving gNB sends a HO command to the UE, instructing it to switch to the target gNB. The UE detaches from the serving cell and synchronizes with the target cell, establishing a new connection.
- After successfully connecting to the target gNB, the UE sends a confirmation message to the network. The target gNB notifies the serving gNB of the successful handover, and the serving gNB releases the resources previously allocated to the UE.
- The core network updates the data path to route traffic through the target gNB instead of the serving gNB. This ensures that data transmission continues without interruption.
- Post-handover, the network may perform optimization procedures to fine-tune parameters and ensure optimal performance. This could include adjusting radio resources or re-evaluating handover thresholds based on network conditions.

Figure 4 presents the process of HO. The HO is usually triggered when the signal quality from the serving gNB (S-gNB) is low and the interference from the target gNB (T-gNB) is significant. During the HO beginning phase, the UE may encounter high RLFs caused by fast HO, which is the most susceptible stage in the initial HO procedure. If the HO control messages are not successfully transmitted or if RLF happens during the HO operation, the HO may fail [2,12,64].



**Figure 4.** Concept of HO decisions in cellular communication networks.

In 5G networks, HO events are crucial for ensuring seamless and efficient connectivity as mobile devices move within the coverage area. Several conditions trigger HO events in 5G systems. One primary factor is the signal strength or signal quality of the current serving cell. If the signal strength falls below a certain threshold, indicating a potential deterioration in connection quality, the network initiates a HO to a neighboring cell with a stronger and more reliable signal. Additionally, LB plays a key role; when a cell becomes congested or experiences high traffic, HOs may be triggered to distribute the load evenly among adjacent cells. QoS requirements, such as latency and data rate, also influence HOs. If the current cell cannot meet the required QoS parameters, the network may initiate a HO to another cell that can better fulfill these criteria, ensuring a smooth and uninterrupted user experience in 5G environments.

## 5. HO Parameters in 5G

HO parameters in 5G are critical settings that govern the process of transferring a mobile device's connection from one cell to another to maintain continuous and optimal connectivity. Furthermore, KPIs, HO decision parameters (HODPs), and HO control parameters (HCPs) can be seen as the three crucial parameters taken into account for the HO procedure in 5G HetNet for controlling user mobility and improving HO performance. Table 1 gives a classification of HO parameters. Classifying the HO parameters into HODPs, HCPs, and key KPIs provides a structured understanding of their roles in the HO process. However, the classification is not always strict, as some parameters may serve multiple purposes. For instance, Signal Strength Thresholds can be considered both HODPs (for HO initiation) and KPIs (for monitoring network performance). Similarly, LB Parameters can be seen as both HCPs (for controlling HOs) and KPIs (for assessing network load distribution). This classification provides a framework for understanding the distinct roles of each parameter in the context of HO decision-making and control and overall network performance monitoring [21,65].

**Table 1.** HO parameters decision.

| HODPs                               | HCPs                                                                              |
|-------------------------------------|-----------------------------------------------------------------------------------|
| Signal Strength Thresholds          | Signal Strength Thresholds (used for HO initiation)                               |
| LB Parameters                       | LB Parameters (control HOs for traffic distribution)                              |
| QoS Parameters                      | QoS Parameters (control HOs based on service requirements)                        |
| Measurement Reporting Configuration | Measurement Reporting Configuration (controls frequency of measurement reporting) |

### 5.1. HCPs

For 5G HetNet to maintain the quality of the network connection between the serving and target cells, the HCPs are essential for controlling and optimizing the HO process. In order to ensure continuous connectivity with the best cellular network available, HCPs can control when and how a UE must execute a HO. Three often-used HCPs in the context of 5G HetNet are Cell Individual Offset (CIO), TTT, and HO margin (HOM). These HCPs are essential to maintaining the quality of UE connections. The difference in RSS or signal quality between the current cell and the intended cell for HO is shown by HOM, which stands for HOM and is measured in decibels (dB). To avoid HO that occurs too late, it is preferable to have a lower HOM in high-speed scenarios. On the other hand, a higher HOM is more suited in low-speed settings to avoid HO occurring too soon. Because it directly affects HO performance, the HOM is an essential component of 5G HetNet. In contrast to previous generations, 5G requires lower settings to achieve its high-speed and low-latency requirements. To attain equilibrium among the HO rate, HOFR, and HO interruption time, HOM should also be adjusted. TTT is the amount of time that a UE must stay below the trigger threshold in order for a HO to be started. In 5G HetNets, the TTT parameter significantly affects both the overall QoS and HO performance. Although a shorter TTT can improve user experience and HO rate, it can also raise HOFR. A longer TTT, on the other hand, can lower the HO rate, but it might have a detrimental effect on the user experience and QoS. The specific use case and network requirements should be carefully taken into account when determining the ideal value for TTT [21].

The HO decision criteria are then adjusted in accordance with the assessment of the CIO of a neighboring cell's signal intensity relative to the serving cell. Making sure the

UE is routed to the best cell based on the user's location and network conditions is crucial in 5G HetNets, which have numerous cells of various sizes and technologies. The value of the CIO is frequently established during the network design phase and is predicated on the particular needs of the network. It is not sufficient to optimize a single HCP in order to significantly improve the HO process. To improve the HO KPIs, all HCPs must be optimized in compliance with UE standards. It is essential to have low values for HCPs, including HOM and TTT, for high-speed UEs and high values for UEs traveling at low speeds in order to reduce the rates of HO failure and HO ping-pong in 5G HetNets. In order to achieve high capacity in terms of UE connection and dependability, as well as to improve HO performance in terms of HO failure and HO ping-pong, HetNets purposefully set the HCPs to be as low as feasible.

Two crucial tactics for enhancing HO performance are load-balancing optimization (LBO) and mobility robustness optimization (MRO). MRO entails modifying HCPs to improve mobile devices' capacity to stay connected while in motion. To guarantee optimal performance, LBO concentrates on moving users to a nearby cell with the highest QoS. While LBO significantly increases user equipment throughput, the primary goal of MRO is to prevent premature, delayed, and unwanted or incorrect HOs [63]. The UE sends an early HO to neighboring cells with less traffic during LBO. This is accomplished by altering HCP values between 85 and 87 while making sure there are enough resources available. Different types of mobile users, such as walkers, drivers, and high-speed users, pose different mobility and connectivity challenges in a 5G HetNet. High-speed users may experience more RLFs due to their rapid mobility and the short time it takes for the network to establish and maintain connections, while pedestrian users may have Handover Probability Problems (HOPPs) because of their slower pace. A number of factors, such as network congestion, insufficient signal strength, and interference from nearby cells, can lead to incorrect HO in HetNets.

## 5.2. HO Decision Parameters for HO

The HO choice is an important step in the beginning of a communication system. By boosting reliability and guaranteeing continuous connectivity, optimizing and choosing the best HO choices can greatly enhance 5G HetNet performance. Numerous factors, such as RSRP, reference signal received quality (RSRQ), RSS indicator (RSSI), UE location, UE speed and direction (mobility pattern), cell load, SINR value, radio resource availability, UE battery level, RAT, and HO priority based on user behavior and channel state information (CSI) influence the HO decision in 5G HetNet [12,65].

When there is no noise or interference present, RSRP measures the strength of the reference signal that the UE receives. The parameter, which is frequently expressed in decibels milliwatts (dBm), is used to show how strong the connection is between the UE and BS. Stronger received signal quality is indicated by a higher RSRP number, while the opposite is suggested by a lower one. By taking into account the whole strength of the received signal, including any undesired noise and interference, RSSI calculates the cellular signal's intensity. Conversely, RSRQ, which is the ratio of RSRP to RSSI, is used to assess the quality of the reference signal that the UE has received. In 5G HetNet setups, these three HODPs are mainly used in tandem to determine the best cell for HO. Furthermore, by considering factors like signal strength and coverage, the position of the UE can be used to determine the best target cell for HO. Future HO requirements can be predicted, and the HO process can then be optimized by using the users' mobility patterns, such as their velocity and trajectory. Frequent HOs are caused by the connection between the UE and the source cell weakening and its connection with the target cell strengthening as it approaches

the target cell quickly. To guarantee safe and prompt HO, the UE from the heavily loaded cell may be moved to a nearby cell with less load (LB), depending on the cell load or traffic.

One important metric that can be used to determine whether a UE has enough power to carry out the HO process is its battery level. The choice of various RATs must consider the RAT of the serving and target cells when working in a 5G HetNet environment, which is intended to serve both macro cells and small cells UE. In order to guarantee the optimal target cell selection, this parameter is essential to the HO decision-making process. Nevertheless, during the HO process, it is essential to consider the SINR of the UE. A considerable distance between the UE and the BS results in a low SINR, particularly when it is situated close to the cell edge. A HO will be sent to the appropriate nearby cell as a result of the increased interference level. By taking into account the resources that are available in both the target and current cells, such as computing power or bandwidth, the optimal timing for HO in a HetNet can be established.

### 5.3. KPIs in HO Studies

KPIs are a group of measurements used in a HetNet to evaluate network performance with respect to mobility and HO. The KPIs include a number of measurements. These include packet loss, energy consumption, signaling overhead, HO rate (HOR), HOFR, HO success rate (HOSR), HO delay (HOD), HOPP, HO Ping-Pong Probability (HPPP), RLF rate, HO execution time (HOET), HOIT, and packet loss due to unnecessary HO failure. These KPIs are crucial for assessing how well the network satisfies user needs and identifying areas that need improvement. KPIs offer many benefits, including enhanced user experience, dependability, and network efficiency. These KPIs have inherent limitations in addition to their advantages, which need to be recognized and taken into account.

Inadequate reflection of network performance or user experience, a lack of consistency in the definition and measurement of key performance indicators, poor KPI selection, and an incomplete evaluation of network performance are some of the difficulties. To improve the performance of 5G, specifically in terms of HO and mobility, the research community must recognize these limitations and aggressively explore several approaches to successfully overcome these obstacles [21].

## 6. HO Management in 5G Ultra-Dense Small Cell Networks

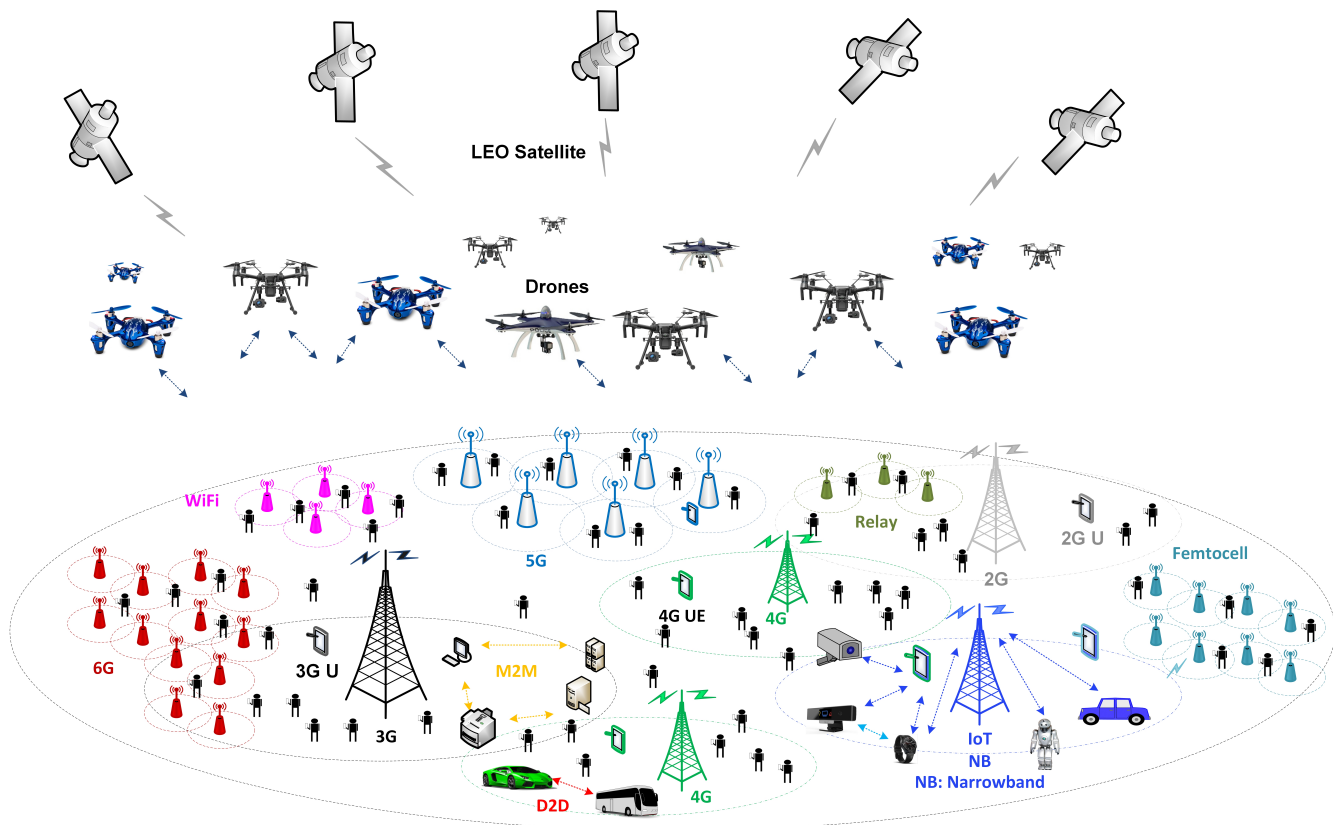
HO management is an important aspect of 5G ultra-dense small cell networks [6,21,25,42], as it helps to maintain good QoS and continuous communication, improving overall network performance. In 5G, HO is necessary to handle the higher data rates, increased number of mobile devices, and greater bandwidth required for transmission. The integration of UAVs into intelligent mobility and HO management/prediction with 5G and beyond using artificial intelligence (AI) techniques can help to address the challenges of frequent HOs with reliability and coverage. However, different challenges are associated with HO in B5G networks, such as ensuring no service interruption, improved routing, minimum latency, and security. Moreover, advanced HO solutions are increasingly tailored to specific use cases such as autonomous vehicles, UAVs, smart cities, and industrial IoT, where mobility patterns, latency sensitivity, and service continuity requirements vary widely. Recent research and real-world trials emphasize the need for dynamic and context-aware mobility management strategies to ensure seamless connectivity and optimal performance in these application domains. An example of an ultra-dense small cell is illustrated in Figure 5.

It is important to consider the different types of HOs that may occur. Intra-macrocell HO occurs within the same macrocell, while inter-macrocell HO occurs between two different macrocells. Multi-RAT HO occurs between different types of RATs, such as between 2G, 3G, and 4G networks. In dense HetNets, HO is still an open issue, as there is a

trade-off between handoff rates and interference levels in the network. This can lead to different types of interference affecting other user equipment.

The use of interference coordination techniques is another important aspect of HO management in 5G ultra-dense small cell networks. These techniques can help to reduce the interference caused by HOs, improving the overall performance of the network. For example, ICIC techniques can be used to reduce interference between cells, while intra-cell interference coordination techniques can be used to reduce interference within a single cell. Finally, HO management is an important aspect of 5G ultra-dense small cell networks, as it helps to maintain good QoS and continuous communication for users. To optimize the HO process, various techniques, such as ML and intelligent HO schemes, can be used, as well as interference coordination techniques to reduce the interference caused by HOs.

The following subsections summarize key studies focused on HO and mobility management in 5G networks. These works employ various approaches and methodologies to tackle challenges associated with HO procedures, especially in scenarios characterized by high user mobility and dense network environments. By reviewing these studies, we gain valuable insights into the advancements and strategies developed to enhance connectivity and optimize user experiences in next-generation mobile networks.



**Figure 5.** Future wireless networks will use overlapping, extremely dense HetNets with a variety of connection kinds.

### 6.1. Measurement-Based and Experimental Studies

These works focus on improving the understanding and practical management of handovers (HOs) in real-world and femtocell-based 5G network scenarios. A key trend is the detailed analysis of HO behaviors through experimental measurements or simulation-based validation to identify challenges such as excessive handovers, signaling overhead, and energy consumption.

The authors of [66] investigated the complexities of 5G mobility management, particularly focusing on the HO process through extensive measurements conducted during

a cross-country driving trip across the US. It analyzed the HO mechanisms utilized by major carriers and quantified the effects of mobility on application performance, power consumption, and signaling overheads, revealing significant challenges in current NSA deployments. The authors designed a HO prediction system called Prognos, which demonstrated improved QoE for 5G applications like 16K panoramic video on demand and real-time volumetric video streaming.

Ref. [67] focused on improving energy efficiency and QoS in femtocell-based ultra-dense networks (UDNs) by addressing uplink handovers (UL-HOs). The study confirmed the UL-HO mechanism and compared its performance with downlink handovers (DL-HOs) regarding various parameters, including power consumption, HO rate, and packet loss rate (PLR). Through simulation, the researchers demonstrated that a new target cell determination algorithm, which considers uplink RSRP (UL-RSRP), available bandwidth, and user equipment direction, significantly reduced HOR and ping-pong rate, offering a practical solution for enhancing UL-HO schemes in 5G networks.

The authors of [68] tackled the challenges of user mobility management in femtocell deployments within macrocell 5G networks, focusing particularly on HO decision-making processes. The research identified limitations in existing decision algorithms, such as neglecting cell selection in single-macrocell and multiple-femtocell scenarios and overlooking user retention parameters, which led to unnecessary HOs. To address these issues, the authors proposed a novel HO decision algorithm that incorporates factors like user speed, RSS, duration of stay, and the femtocell access policy, resulting in a significant reduction in unwanted HOs and improving network energy efficiency by over 85% compared to traditional methods.

These studies emphasize the critical role of precise measurement and context-aware handover strategies in optimizing mobility management, reducing signaling overhead, and enhancing energy efficiency in dense 5G deployments.

## 6.2. Optimization Techniques for HO and Mobility Management

A significant trend in enhancing handover and mobility management in 5G networks is the application of advanced optimization techniques. These methods aim to tackle the complex challenges of frequent handovers, ping-pong effects, handover failures, and latency in dense and heterogeneous network environments. Commonly used approaches include the following:

- Fuzzy logic controllers: Utilized for their ability to handle uncertainty and imprecision in network parameters such as signal strength, user velocity, and load, enabling dynamic adaptation of handover thresholds and timers.
- Metaheuristic algorithms: Techniques like Bayesian Optimization, Ant Lion Optimization, and hybrid methods (e.g., combining Kinetic Gas Molecular Optimization with other algorithms) are leveraged to solve multi-objective optimization problems, balancing trade-offs like reducing handover rates while maintaining QoS.
- Bayesian and machine learning-based optimization: These approaches enable the proactive tuning of handover parameters by learning from network state and user behavior, improving decision accuracy with fewer trial-and-error cycles.

Specifically, ref. [69] highlights the increasing importance of mobility management in 5G and B5G mobile networks due to factors like mmWave and terahertz technology, a higher density of small cells, and the demand for ultra-low latency. It introduced a Robust HO Optimization Technique with a fuzzy logic controller (RHOT-FLC) aimed at improving HCPs through automatic adjustments based on RSRP, RSRQ, and user equipment velocity. The proposed technique was validated across various mobility scenarios, demonstrating

significant performance improvements compared to existing algorithms, achieving up to 95% reductions in HO probability, failure, ping-pong, latency, and interruption time.

Ref. [70] addressed the challenge of frequent HOs in densely populated networks, which can negatively impact QoS, particularly in environments with stringent latency, reliability, and robustness requirements. It proposed an innovative approach for optimizing HO thresholds using Bayesian Optimization (BO), formulating a multi-objective optimization problem aimed at minimizing both early and late HOs in indoor factory scenarios. The results demonstrated that multi-objective Bayesian Optimization (MOBO) successfully identified Pareto optimal solutions with minimal samples, effectively ensuring service continuity through the safe exploration of new data points.

The authors of [71] addressed the challenges posed by frequent HOs in 5G networks due to the extensive use of SBSs, which increases the likelihood of HO ping-pong and RLFs. To enhance mobility management and ensure uninterrupted communication, the study proposed a weighted function tailored to various mobile speed scenarios alongside a trigger timer designed to reduce unnecessary HOs. The simulation results demonstrated that the proposed algorithm significantly improved system performance regarding HOPP, achieving a reduction in HOPP probability of 0.001 and 0.004 at 150 s and 400 s, respectively, outperforming existing solutions, including a fuzzy logic controller (FLC) algorithm.

Ref. [72] examined the increasing demands of mobile data traffic and recognized network densification as a crucial factor in the evolution of cellular networks, particularly through the implementation of UD-HetNet in 5G. It proposed an optimization-based mobility management technique that combined Kinetic Gas Molecular Optimization (KGMO) with Ant Lion Optimization (ALO) to improve network performance by addressing interference and HO challenges. The researchers measured metrics such as throughput, delay, and HO rates in a simulated MATLAB environment, demonstrating the effectiveness of the KGMO-ALO approach compared to other meta-heuristic techniques.

The authors of [73] introduced a hybrid optimization-based mobility management strategy that combined Kinetic Gas Molecular Optimization (KGMO) with Ant Lion Optimization (ALO). Initially, KGMO utilized kinetic energy principles to calculate particle properties, but its limitations led to the incorporation of ALO, which adjusted the inertia weight of KGMO. The proposed KGMO-ALO approach was validated in a MATLAB environment and compared against various meta-heuristic techniques, demonstrating advancements in performance metrics such as throughput and HO efficiency, ultimately aiming to enhance mobility management in heterogeneous LTE cellular networks.

Mobility challenges in UD-HetNet, particularly in scenarios involving high-speed trains and connected drones, were studied in [74]. To reduce unnecessary HOs, a trigger timer was proposed alongside a weighted algorithm for automatically optimizing HCPs based on network conditions such as mobile speed, traffic load, and signal strength measurements. The simulation results demonstrated that the proposed algorithm significantly outperformed existing methods, achieving reductions in RLF, HO ping-pong, handover probability, and HOIT by 8.8%, 6.9%, 6.7%, and 344%, respectively.

Ref. [75] proposed an intelligent HO management algorithm for 5G ultra-dense small cell heterogeneous networks, utilizing a fuzzy logic controller (FLC) to optimize HO decisions. The FLC dynamically adjusted the TTT and handover margin (HOM) based on user velocity and other factors such as RSRP and cell load, enhancing the responsiveness to user movement. Evaluation metrics, including HOR, handover failure, RLF, and HO ping-pong, showed that the proposed algorithm significantly outperformed existing methods, resulting in improved overall system performance.

These studies demonstrate that optimization techniques—especially those integrating fuzzy logic and metaheuristic algorithms—are highly effective in addressing mobility

management challenges by providing adaptive, efficient, and scalable solutions suitable for the dynamic nature of 5G networks.

### 6.3. AI/ML-Based Approaches

ML techniques have become increasingly prominent in mobility management for 5G and beyond networks, enabling more intelligent and proactive handover decision-making. These methods leverage historical and real-time data to predict user mobility patterns, handover events, and network conditions, thereby improving QoS and reducing unnecessary handovers. Key trends in ML-based mobility management include the following:

- Sequence-to-sequence and time series prediction: These are used to forecast handover cells, dwell times, and user trajectories, helping to anticipate network resource requirements and optimize handover timing;
- Reinforcement learning and deep learning: These are applied to learn optimal handover policies in dynamic network environments, balancing trade-offs like handover frequency, latency, and throughput;
- Hybrid and ensemble models: Combining multiple ML algorithms to improve prediction accuracy and robustness in varying mobility scenarios.

Specifically, ref. [76] introduced an AI-based method employing sequence-to-sequence modeling to improve mobility management in B5G networks, which operate at high frequencies and wide bandwidths. It addressed the challenge of high path loss and the need for dense network deployments, proposing a proactive scheme that utilizes historical trajectory data to predict HO cells and beams for UEs. The results demonstrated that the method achieved over 90% accuracy in HO cell estimation and a low mean absolute error for dwell time, effectively enhancing mobility support in dense network environments.

The authors of [77] addressed the challenges of user mobility management in emerging cellular networks, highlighting that current paradigms are inadequate for achieving the desired QoE and resource efficiency. To facilitate a shift from reactive to proactive mobility management, the authors proposed an Advanced Mobility Management and Utilization Framework (A-MMUF), which utilizes mobility prediction models (MPMs) to forecast user mobility attributes and traffic patterns, thereby improving the HO process and enabling proactive automation. Through three case studies—proactive HO, proactive mobility LB, and proactive energy savings—the results demonstrated significant performance gains while also providing insights into the trade-off between agility and accuracy, which is crucial for selecting optimal ML models for A-MMUF deployment.

The authors of [78] proposed an ML approach to optimize resource management in mobile networks by predicting demands for mobility management tasks, such as HOs and tracking area updates (TAUs), which are essential for user mobility. Given the dynamic nature of user behavior and its impact on the control plane, traditional time series analysis was found to be inadequate; thus, the study utilized real-life HO and TAU message records to forecast their occurrence in future time windows. By comparing various prediction models, including a baseline, linear regression, a convolutional neural network (CNN), and a Long Short-Term Memory network (LSTM), the research aimed to provide more accurate estimates of expected network demands for specific functions in LTE and 5G NSA architecture environments.

Ref. [79] introduced the early-scheduled HO preparation scheme aimed at enhancing the HO procedure in 5G-NR systems, particularly in high mobility and dense small cell environments. It focused on optimizing the timing of the HO preparation phase by applying ML techniques to predict the earliest possible trigger points for HO events, which helps reduce channel quality degradation during the process. The findings demonstrated that

this proactive and user-aware approach could significantly improve the robustness and efficiency of the HO procedure by minimizing execution time.

The authors of [80] addressed the challenges of mobility management in network-sliced 5G environments, where users move across various BSs and slices while sharing the existing 4G infrastructure. They proposed a solution to improve network performance by minimizing the number of HOs through the application of Deep Reinforcement Learning (DRL) using the Proximal Policy Optimization (PPO) method. The simulation results indicated that the PPO approach significantly reduced the number of HOs compared to other algorithms, enhancing overall network efficiency.

ML approaches enable more predictive and adaptive mobility management strategies by learning from data, which can significantly reduce handover failures and latency while optimizing resource utilization in complex 5G network scenarios.

#### 6.4. SDN/NFV and Network Slicing-Based Solutions

Emerging architectural paradigms such as SDN and NFV are playing a pivotal role in enhancing mobility management in 5G and beyond networks. These technologies decouple control and data planes, enabling centralized, programmable, and dynamic network management that can adapt in real time to mobility events, improving handover performance and service continuity.

Ref. [81] addressed the challenges of mobility management in 5G networks, particularly for mobile roaming users, by leveraging network slicing and MEC to enhance service delivery. It proposed a HO mobility management architecture that utilizes network slicing to enable seamless HO between 5G and 4G networks while minimizing QoS disruptions. The evaluation of this architecture demonstrated significant improvements, including reduced HODs and increased average throughput compared to traditional RSS-based and CMaaS HO approaches.

Ref. [82] introduced an SDN-based dynamic mobility management framework for B5G networks, specifically designed to enhance seamless connectivity for high-speed railways and address challenges related to frequent service migrations and network management. By leveraging the capabilities of the SDN controller to dynamically install flow rules, the proposed solution offers centralized control and fine-grained visibility, incorporating Kalman Filter-based algorithms to predict user trajectories and adapt to high mobility conditions. Extensive simulations demonstrated that the framework significantly improved service migration efficiency, reducing migration time by 30% (to less than 6 ms) and achieving a 40% reduction in end-to-end delay while maintaining high throughput.

Ref. [83] presents a novel VHO mechanism for 5G networks, addressing challenges such as limited coverage and high rates of ineffective handovers, which can degrade service quality and waste network resources. By integrating IEEE 802.21 with SDN, the mechanism leverages centralized control and programmability alongside standardized information exchange. This approach enhances decision-making, minimizes unnecessary VHOs, and improves overall network performance. The primary objectives include maintaining efficient resource utilization, ensuring QoS requirements, and reducing new call blocking and HO call dropping probabilities. The simulation results demonstrate that the proposed mechanism significantly decreases the number of required HOs in 5G networks compared to existing algorithms.

The authors of [84] proposed a fuzzy logic controller system for enhancing smart mobility management in 5G wireless communication networks, addressing mobility management as a critical issue for future all-IP mobile networks. They introduced a new VHO algorithm that integrates the IEEE 802.21 Media Independent Handover (MIH) standard with Proxy Mobile IPv6 (PMIPv6) to anticipate the HO process more efficiently, overcoming

limitations in existing protocols regarding latency and signaling. The simulation results indicated a significant reduction in HOD, packet loss, HO blocking probability, and signaling overhead, demonstrating the effectiveness of the proposed approach.

SDN and NFV architectures enable more flexible, adaptive, and efficient mobility management by centralizing control, supporting service customization, and proactively handling user mobility, which is critical for meeting the stringent performance requirements of next-generation mobile networks.

#### 6.5. Vehicular and High-Speed Mobility Management

High-speed mobility scenarios such as connected autonomous vehicles, high-speed trains, and UAVs introduce unique challenges to 5G mobility management. These environments require ultra-reliable, low-latency connectivity while managing frequent and rapid handovers due to high velocities and dynamic network conditions. Among these, we can find frequent and rapid Ho, energy efficiency and resource optimization, reliable channel allocation and resource reuse, and the integration of EC and network slicing. Representative studies include ref. [85], which explored the development of energy-aware 5G and Wi-Fi 6 wireless networks in response to the growing demand for sustainable smart cities and intelligent vehicular networks. It focused on the internet of energy-based technology aimed at efficiently managing energy resources within these complex systems, emphasizing the need to adapt and optimize mobility management and communication protocols for next-generation networks. The authors reviewed recent mobility management protocols for 5G-enabled vehicular networks, analyzing their efficiency, design, and limitations and proposing future research directions to enhance these systems in support of greener transportation solutions.

Ref. [86] proposed a novel, user-centric channel allocation scheme called the Vehicular Frequency Reuse (VFR) scheme for high-speed terrestrial users in 5G networks operating in the millimeter-wave band, particularly for Connected Autonomous Vehicles (CAVs). It introduced a new mobility management function aimed at reducing HO rates and control plane signaling while enhancing link reliability and channel reuse ratios, supported by a Distance-Threshold (DT) metric to determine frequency reuse. Additionally, the paper outlined a cell reselection procedure for high-speed users, distinguishing between low-speed and high-speed users, with a Velocity-Threshold (VT) metric calculated using a K-Means ML approach, demonstrating that the VFR scheme can achieve over 99% reduction in HO rates compared to traditional channel allocation methods through extensive simulations.

The authors of [87] introduced a user-centric channel allocation scheme called the Vehicular Frequency Reuse (VFR) scheme for high-speed users in the Fifth Generation (5G) network operating in the millimeter-wave band, particularly targeting Connected Autonomous Vehicles (CAVs). To enhance performance and reduce HOs in Vehicle-to-Network (V2N) services, a new mobility management function was developed, which significantly decreased HO rates and control plane signaling while improving link reliability and channel reuse ratios. The proposed framework included a Distance-Threshold (DT) metric for frequency reuse and a cell reselection procedure for high-speed users, resulting in an over 99% reduction in HO rates compared to traditional channel allocation methods, and it was designed to be easily integrated into existing 5G networks with minimal software updates.

Ref. [88] introduced a novel energy-efficient mobility management protocol, NEMa, designed for vehicular networks in the context of advancing 5G and emerging 6G technologies. This protocol aimed to optimize network resources and onboard vehicle sensing to reduce energy consumption while ensuring a high packet delivery ratio and minimal interruption time. Performance evaluations indicated that NEMa outperformed exist-

ing benchmark solutions in terms of network overhead, latency, and energy efficiency, thus addressing critical challenges in energy consumption and network performance for next-generation vehicular networks.

These works demonstrate that addressing vehicular and high-speed mobility requires specialized algorithms and architectures capable of rapid decision-making, predictive handovers, and efficient resource utilization to ensure robust and continuous connectivity in challenging environments.

#### *6.6. Mobility Management in mmWave, THz, and Ultra-Dense Networks*

The deployment of mmWave and terahertz frequency bands, combined with ultra-dense network architectures, offers tremendous capacity and data rate enhancements for 5G and beyond networks. For instance, ref. [89] proposed a novel mechanism to enhance mobility management in ultra-dense networks (UDNs) operating in millimeter-wave (mmWave) and terahertz (THz) bands, which face challenges from shrinking cell coverage and severe penetration loss. By leveraging wireless signals and on-road surveillance systems, the approach predicts potential blockages and facilitates timely HOs using computer vision to identify obstacles and track user locations and speeds. The simulation results demonstrated that the new blockage event (BLK) detection and proactive HO algorithm achieved a 40% improvement in maintaining user connectivity and QoE compared to conventional networks lacking blockage prediction.

The authors of [90] introduced a HO scheme aimed at enhancing link connectivity in 5G mobile communication networks that utilize millimeter-wave (mmWave) bands, which are vulnerable to irregular cell patterns caused by user and topographic dynamics. To address these challenges, the proposed scheme employs Game Theory (GT) in conjunction with Jump Markov Linear Systems (JMLSs) to predict target link deterioration patterns, allowing for the selection of the most reliable mmWave link for mobile users. The simulation results demonstrated that the GT-JMLS HO scheme significantly improved throughput, energy efficiency, and reliability and increased the dwell time between HOs compared to traditional HO methods, ultimately reducing the risk of link failures.

Ref. [70] applies Bayesian Optimization for the multi-objective tuning of handover thresholds in indoor factory UDN scenarios, effectively balancing early and late handover decisions to maintain service continuity. Ref. [67] focuses on uplink HOs in femtocell-based ultra-dense networks, proposing a target cell determination algorithm that reduces handover rates and energy consumption. Ref. [68] develops a HO decision algorithm incorporating user speed, signal strength, and femtocell policies to minimize unnecessary handovers and improve energy efficiency in macro-femto deployments.

The authors of [91] examined the mobility management challenges in 5G HetNets, which combine macro cells and densely distributed small cells to meet increasing data demands. They identified several issues associated with the complexity of 5G network topology, including frequent HOs, failures, delays, and ping-pong HOs that arise from dense small cell deployment. The authors focused on radio resource control as a critical aspect of 5G HetNet mobility management and outlined the key challenges that need to be addressed for effective mobility management in this evolving architecture.

Together, these works demonstrate that overcoming the intrinsic vulnerabilities of mmWave, THz, and ultra-dense networks requires intelligent, context-aware handover strategies, predictive models, and optimization techniques tailored for rapid, reliable mobility management in challenging radio environments.

### 6.7. HO Algorithms for D2D, MIAB, and Integrated Systems

Emerging paradigms in 5G mobility management, such as D2D communication, Mobile Integrated Access and Backhaul (MIAB), and integrated resource optimization, introduce unique HO challenges that differ from conventional cellular scenarios. These systems require specialized algorithms to maintain connectivity, optimize resource usage, and reduce signaling overhead.

The authors of [92] proposed a Ping-Pong effect Reduction (PPR) algorithm to enhance HO performance for D2D communication in 5G networks, addressing issues related to mobility that lead to HO failures and unreliable communication. Utilizing the Reference Point Group Mobility (RPGM) model, the authors also introduced a mode selection algorithm to optimize transmission for D2D users in the 5G cellular network. The performance evaluations demonstrated that the PPR algorithm reduced unnecessary HOs by up to 80% while maintaining a stable throughput of 12 Mbps, ultimately contributing to reduced power consumption compared to existing algorithms.

Ref. [93] proposed a novel HO scheme for Mobile Integrated Access and Backhaul (MIAB) networks, addressing the challenges of HOIT and RLF, which affect user QoS in high-density mobile environments. It examined various HO scenarios, including intra-gNB, inter-gNB, and parent MIAB node HOs, and developed probabilistic models based on the velocities of both parent and child MIAB nodes. The simulation results demonstrated that the proposed scheme, featuring low-latency uplink control plane data transmission and a RACH-less HO procedure, significantly outperformed the baseline HO scheme in terms of reduced HOD and overhead.

The authors of [94] focused on the importance of effective mobility management in HetNet to ensure seamless HOs among various cell types as users navigate between macrocells, small cells, and femtocells. They proposed a self-optimization algorithm designed to reconcile the conflicting optimization tasks of MRO and LBO, aiming to enhance user communication during movement. Through comprehensive simulations, the proposed algorithm demonstrated significant reductions in HO ping pong and handover failures (HOFs), indicating its potential to improve network performance and user experience in next-generation wireless networks.

Ref. [95] proposed a profile-based predictive HO strategy (PBPHS) aimed at improving the HO process in 5G mobile networks. By utilizing a predictive model that analyzed previous user resource utilization and mobility tracking, the strategy aimed to select the optimal small cell BS for HOs, thereby enhancing QoS and minimizing unnecessary HOs. The simulation results demonstrated that the PBPHS achieved a HO reduction rate that outperformed existing methods by an average of 13% to 26%.

These studies collectively highlight the need for adaptive, context-aware handover algorithms tailored for integrated and emerging 5G network paradigms, ensuring seamless mobility while optimizing network performance and energy consumption.

To provide a clearer comparison of the various HO strategies developed for emerging 5G paradigms, such as D2D communication, MIAB, and integrated HetNet, Table 2 summarizes the methodologies and key findings of the representative studies. These works collectively emphasize the importance of predictive, context-aware, and adaptive handover mechanisms tailored to the unique requirements of next-generation mobility scenarios.

**Table 2.** Summary of measurement-based and experimental studies on 5G HO management.

| Ref  | Focus                                                                    | Methodology                                                                                                      | Key Findings                                                                                                              |
|------|--------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
| [66] | 5G HO process and mobility impact                                        | Extensive measurements during cross-country drive                                                                | Identified challenges in NSA deployments; Prognos HO prediction system improves QoE for 5G applications (e.g., 16K video) |
| [67] | Energy efficiency in femtocell UDNs                                      | Simulation of UL and DL HO mechanisms                                                                            | New target cell algorithm based on UL-RSRP reduces HO rate and ping-pong rate; improves power consumption and packet loss |
| [68] | HO decision algorithms in femtocell-macrocell setups                     | Algorithm development and simulation                                                                             | Novel HO decision algorithm reduces unnecessary handovers and improves energy efficiency by over 85%                      |
| [69] | Robust HO optimization with fuzzy logic                                  | RHOT-FLC validated across mobility scenarios                                                                     | Up to 95% reduction in HO probability, failure, ping-pong, latency, and interruption time                                 |
| [70] | Bayesian Optimization for HO thresholds                                  | Multi-objective Bayesian Optimization for indoor factory                                                         | Efficiently identifies Pareto-optimal HO thresholds, minimizes early/late HOs                                             |
| [71] | Weighted function and trigger timer for HO ping-pong                     | Simulation with speed-aware weighted functions                                                                   | Significant reduction in HO ping-pong probability, outperforming fuzzy logic controllers                                  |
| [72] | Metaheuristic optimization combining KGMO and ALO                        | Simulation in MATLAB environment                                                                                 | Improved throughput, delay, and HO rates compared to other metaheuristics                                                 |
| [73] | Hybrid KGMO-ALO optimization algorithm                                   | MATLAB simulations comparing metaheuristic techniques                                                            | Enhancements in throughput and HO efficiency for heterogeneous LTE networks                                               |
| [74] | HO optimization for high-speed trains and drones                         | Trigger timer and weighted algorithm based on network parameters                                                 | Reduced RLF, HO ping-pong, HO probability, and HO interruption time significantly                                         |
| [75] | Fuzzy logic controller for HO decisions in UD-SCN                        | FLC dynamically adjusting TTT and HOM                                                                            | Significant improvement in HO rate, failure, RLF, and ping-pong compared to existing methods                              |
| [76] | Sequence-to-sequence modeling for HO prediction                          | Predicts HO cells and dwell times using historical trajectory data                                               | Achieved over 90% HO cell estimation accuracy and low mean absolute error for dwell time                                  |
| [77] | Proactive mobility management framework                                  | Advanced Mobility Management and Utilization Framework (A-MMUF) using mobility prediction models                 | Significant improvements in HO process, mobility load balancing, and energy savings                                       |
| [78] | ML prediction of mobility management tasks                               | Compared baseline, linear regression, CNN, and LSTM models on HO and TAU message data                            | LSTM and CNN provided more accurate demand forecasts for LTE and 5G NSA architectures                                     |
| [79] | Early-scheduled HO preparation in 5G-NR                                  | ML-based prediction of earliest HO trigger timing                                                                | Reduced channel quality degradation and improved HO robustness and efficiency                                             |
| [80] | DRL for HO minimization in network slicing                               | Deep reinforcement learning with Proximal Policy Optimization (PPO)                                              | PPO approach significantly reduced HO numbers and improved network efficiency                                             |
| [81] | Network slicing and MEC for HO management                                | HO mobility management architecture leveraging network slicing for seamless HO between 5G and 4G                 | Reduced handover disruptions (HODs) and increased average throughput compared to RSS-based and CMaaS HO methods           |
| [82] | SDN-based dynamic mobility for high-speed railways                       | SDN controller with Kalman Filter-based user trajectory prediction for seamless service migration                | Migration time reduced by 30%, end-to-end delay reduced by 40%, improved throughput                                       |
| [83] | VHO mechanism integrating IEEE 802.21 with SDN                           | Centralized SDN control combined with Media Independent Handover for optimized vertical handovers                | Significantly fewer unnecessary handovers, improved resource utilization and QoS                                          |
| [84] | Fuzzy logic-based VHO with MIH and PMIPv6 integration                    | Proposed new VHO algorithm to reduce latency and signaling overhead                                              | Significant reduction in handover delay, packet loss, HO blocking probability, and signaling overhead                     |
| [85] | Energy-aware mobility management for smart cities and vehicular networks | Review of mobility management protocols for 5G-enabled vehicular networks with focus on sustainable energy usage | Identified design limitations and proposed future research for greener vehicular networks                                 |

Table 2. Cont.

| Ref  | Focus                                                                     | Methodology                                                                                                                    | Key Findings                                                                                                              |
|------|---------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------|
| [66] | 5G HO process and mobility impact                                         | Extensive measurements during cross-country drive                                                                              | Identified challenges in NSA deployments; Prognos HO prediction system improves QoE for 5G applications (e.g., 16K video) |
| [86] | Vehicular Frequency Reuse (VFR) for mmWave 5G CAVs                        | User-centric channel allocation with Distance-Threshold and Velocity-Threshold metrics; K-Means ML for velocity classification | Over 99% reduction in HO rates; improved link reliability and channel reuse                                               |
| [87] | VFR scheme for high-speed users in mmWave 5G                              | Similar to [86], with a focus on V2N services and minimal software update integration                                          | Significant reduction in HO rates and control plane signaling; easy integration with existing 5G networks                 |
| [88] | Energy-efficient mobility management protocol NEMa for vehicular networks | Protocol optimizing network and vehicle sensing for energy efficiency and packet delivery                                      | Outperformed benchmarks in network overhead, latency, and energy consumption                                              |
| [89] | Blockage prediction and HO in mmWave/THz UDNs                             | Wireless signals combined with computer vision from on-road surveillance to predict blockages and trigger proactive HO         | Achieved 40% improvement in connectivity and QoE by predicting and mitigating blockage events                             |
| [90] | HO scheme for mmWave links using Game Theory and JMLS                     | Prediction of link deterioration via Game Theory and Jump Markov Linear Systems for optimal link selection                     | Improved throughput, energy efficiency, reliability, and dwell time, reducing link failures                               |
| [70] | Multi-objective HO threshold tuning in indoor factory UDN                 | Bayesian Optimization to balance early and late HOs for service continuity                                                     | Efficient tuning of HO parameters to reduce unnecessary handovers                                                         |
| [67] | Uplink HO in femtocell UDN                                                | Target cell determination algorithm considering UL-RSRP, bandwidth, and user direction                                         | Reduced HO rates, ping-pong, and energy consumption                                                                       |
| [68] | HO decision algorithm in macro-femto deployments                          | Incorporates user speed, RSS, duration of stay, and femtocell policy                                                           | Reduced unwanted handovers and improved energy efficiency by 85%                                                          |
| [91] | Mobility challenges in 5G HetNets                                         | Analysis of RRC challenges due to dense small cells, HO failures, delays, and ping-pong effects                                | Highlighted critical challenges for efficient mobility management in dense HetNets                                        |
| [92] | HO in D2D communication                                                   | Ping-Pong effect Reduction (PPR) algorithm; Reference Point Group Mobility (RPGM) model; mode selection algorithm              | Reduced unnecessary HOs by up to 80%; stable throughput of 12 Mbps; lower power consumption                               |
| [93] | HO in MIAB networks                                                       | Probabilistic modeling of HO scenarios; RACH-less HO procedure; low-latency uplink control plane transmission                  | Significantly reduced HO delay and overhead; improved QoS in dense mobile environments                                    |
| [94] | Seamless HO in HetNets among macrocells, small cells, femtocells          | Self-optimization algorithm balancing MRO and LBO optimization objectives                                                      | Reduced HO ping-pong and handover failures; improved network performance and user experience                              |
| [95] | Predictive HO strategy based on user profiles                             | Profile-Based Predictive HO Strategy (PBPHS) using mobility and resource utilization data                                      | HO reduction rate improved by 13–26% over existing methods; enhanced QoS                                                  |

### 6.8. Mobility Prediction Techniques in 5G Networks

Mobility prediction has emerged as a crucial component of HO management and overall mobility strategies in 5G networks. As ultra-dense small cell deployments, high user mobility, and diverse service requirements place increasing strain on network resources, the ability to anticipate user movement and resource demands offers significant advantages. Accurate mobility prediction can enhance HO decision-making, reduce call drops, enable proactive resource allocation, and improve energy efficiency.

A variety of methods have been proposed to tackle mobility prediction challenges. Traditional approaches such as Markov chains, Hidden Markov Models (HMMs), and Bayesian networks have evolved with the integration of ML and deep learning (DL) techniques. These learning-based solutions can effectively capture non-linear mobility patterns, especially in highly dynamic urban environments.

In [96], a comprehensive survey of mobility prediction techniques highlights how learning-based approaches—ranging from neural networks to data mining—offer improved accuracy in anticipating user trajectories. The paper emphasizes key prediction dimensions, including movement predictability, performance metrics, and outputs (e.g., next-cell prediction), and identifies open research challenges under 5G contexts.

A more focused application of deep learning is presented in [97], where mobility data is encoded as images are fed into a convolutional neural network (CNN) for next-cell prediction. This technique leverages the strength of CNNs in spatial pattern recognition and achieves high accuracy in anticipating the next cell during user movement, a critical aspect of minimizing call drops and HO latency in dense deployments.

Survey-based work in [98] provides a taxonomy of next-cell prediction methods, categorizing them into Current Movement State-based, Historical Movement Pattern-based, and Hybrid Approaches. This framework aids in understanding the appropriate method based on available mobility data and illustrates practical applications such as HO optimization and resource provisioning.

The practical viability of predictive strategies in ultra-dense, small cell networks is discussed in [99], which shows that femto/nano-cell deployments inherently generate detailed mobility traces. These traces can fuel predictive models for future 5G and 6G systems. The integration of such models into network control planes could enable proactive mobility and resource management.

From an architectural perspective, ref. [100] proposes an intra-cluster federated learning (FL) model for traffic prediction in networks with computational asymmetry. Low-computation-power subnets benefit from model transfer mechanisms trained on more capable clusters, all while preserving data privacy—underscoring a scalable approach for mobility and traffic prediction in decentralized network environments.

Mobility prediction is not only beneficial for performance but also essential for energy-efficient network design. In [101], a reinforcement learning-based framework is used to predict bus ridership patterns in a HetNet architecture. The system achieves high prediction accuracy and significant CO<sub>2</sub> emission reductions, demonstrating how mobility prediction can align with sustainable networking goals.

Moreover, ref. [102] introduces a novel spectral approach based on predictive wavelet analysis for optimizing mobility sampling frequency. This ensures that critical movement events are captured without unnecessary energy expenditure—a particularly relevant consideration for dense urban deployments with mobile IoT devices.

Lastly, resource reservation strategies incorporating prediction mechanisms are examined in [103], which introduces a stochastic framework for evaluating trade-offs between prediction error and resource wastage. Metrics such as cell stay time and directional

movement probabilities are used to guide bandwidth pre-reservation, with demonstrated improvements in resource efficiency.

Mobility prediction in 5G networks is a rapidly advancing area, underpinning enhancements in HO reliability, resource allocation, and energy management. The incorporation of ML/DL techniques, federated learning, and predictive analytics not only addresses current challenges but also aligns with the anticipatory needs of 6G systems.

#### *6.9. Emerging Mobility Mechanisms in 5G-Advanced: Layer 1/Layer 2 Triggered Mobility (LTM)*

As 5G continues to evolve toward 5G-Advanced and eventually 6G, mobility management mechanisms are being revisited to better support ultra-dense deployments, high user mobility, and reduced latency. One of the key innovations in this direction is Layer 1/Layer 2 LTM, currently under discussion and development within 3GPP standards [104,105]. LTM introduces a lower-layer-centric approach to handover management by leveraging physical layer (Layer 1) and MAC layer (Layer 2) triggers to initiate handovers proactively. This stands in contrast to traditional mobility mechanisms, which primarily rely on higher-layer measurement reports and signaling. By utilizing real-time metrics like signal quality degradation, beam failure events, or scheduling gaps at Layer 1/2, LTM can drastically reduce handover latency and improve reliability, especially in ultra-dense small cell networks or mmWave/THz environments where link instability is more frequent.

This mechanism is also aligned with the service-aware and context-aware architecture of 5G-Advanced, where mobility decisions are increasingly expected to be more dynamic, granular, and responsive. Early evaluations suggest that LTM can improve HO success rates and reduce radio link failure (RLF) events, particularly for high-speed users and time-sensitive applications [106,107]. As LTM continues to mature, it represents a critical direction for future research and practical deployment, with implications for cross-layer design, AI-based mobility optimization, and coordination with network slicing and edge computing frameworks.

## **7. Research Challenges**

The evolution of 5G and the ongoing development of 6G networks represent significant advancements in wireless communication. However, they also introduce many research challenges, which must be addressed in order to have a sustainable network. These challenges span technical, infrastructural, and societal domains. These challenges need to be addressed based on innovative solutions to ensure their functionality in terms of seamless connectivity, sustainability, security, and smooth switching into next-generation networks. In this section, some research challenges will be introduced.

#### *7.1. Network Complexity and Scalability*

One of the primary challenges in 5/6G networks is managing the increasing complexity and scalability of the network infrastructure. 5G networks already rely on ultra-dense HetNets, massive MIMO systems, and mmWave frequencies to deliver high data rates and low latency. However, as the number of connected devices grows exponentially with the IoT and smart applications, scaling these networks while maintaining performance becomes a significant challenge [108,109]. In 6G, the integration of emerging technologies like terahertz (THz) communication and quantum networking will further complicate the architecture. Solutions based on advanced algorithms based on AI will be the best option in order to ensure efficient network management [110].

#### *7.2. Energy Efficiency and Sustainability*

The energy consumption of 5/6G networks is a critical concern. It could be more critical in the case of the demand for high-speed connectivity and data processing, which is

rising continuously. The deployment of small cells, massive MIMO, and energy-intensive mmWave technologies contributes to higher power consumption, which not only increases operational costs but also has a significant environmental impact [111]. Research efforts are focused on developing energy-efficient hardware, optimizing resource allocation, and integrating renewable energy sources into network infrastructure [112,113]. For 6G, sustainability will form a core design principle by taking into consideration some aspects, such as energy-harvesting devices and AI-based dynamic power management. These aspects play a key role in reducing the carbon footprint of next-generation networks [114].

### *7.3. Spectrum Management and Interference*

The use of higher frequency bands, such as mmWave in 5G and THz in 6G, could present challenges. They are related to spectrum availability and interference management [115]. While these frequencies offer wider bandwidths for faster data transmission, they are prone to high path loss, signal attenuation, and limited penetration through obstacles. Additionally, the dense deployment of small cells in 5G networks increases the risk of co-channel interference, which might lower network performance. Researchers are exploring techniques like beamforming, advanced modulation schemes, and cognitive radio to optimize spectrum utilization and mitigate interference [112,116]. In 6G, dynamic spectrum sharing and AI-driven spectrum management are essential to accommodate the growing demand for wireless connectivity.

### *7.4. Security and Privacy*

As 5/6G networks enable a wide range of applications (including critical infrastructure, autonomous vehicles, and healthcare), ensuring robust security and privacy becomes vital. An increased attack surface (due to the proliferation of connected devices) and the reliance on software-defined networking and network function virtualization introduce new vulnerabilities [117,118]. Threats such as data breaches, DoS attacks, and eavesdropping pose significant risks to users and network operators. Research is focused on developing advanced encryption methods, intrusion detection systems, and blockchain-based solutions to enhance security. In 6G, quantum cryptography and AI-driven threat detection are expected to play a crucial role in safeguarding next-generation networks.

### *7.5. Latency and Mobility Management*

Achieving ultra-low latency and seamless mobility is a key requirement for 5/6G networks, particularly for applications like autonomous driving, AR, and remote surgery. While 5G aims to deliver latency as low as 1 ms, achieving this in real-world scenarios with high-speed mobility remains a challenge [2,5]. Frequent HOs in ultra-dense networks and the limited coverage of small cells can lead to an increase in latency and connection interruption. Researchers are investigating techniques like edge computing, predictive HO algorithms, and network slicing to improve mobility management in order to reduce latency. In 6G, the integration of AI and the use of ML in network operations can be a good option to reach real-time decision-making and enhance the QoE by users. The transition to 5G and the development of 6G networks bring transformative opportunities for connectivity and innovation. However, they also present significant research challenges. Addressing these challenges requires a multidisciplinary approach. Solutions can be based on combining advancements in hardware and software. In addition, network architecture with a focus on sustainability, security, and scalability must be taken into consideration by the solutions posed. By overcoming these hurdles, researchers and industry stakeholders can pave the way for a future where next-generation networks deliver unparalleled performance and reliability, enabling a wide range of applications.

### 7.6. Future Challenges in 6G Mobility

The transition from 5G to 6G introduces transformative paradigms that will reshape mobility management and handover procedures. Among the most prominent are AI-native networking, integrated sensing and communication (ISAC), and pervasive intelligence—each introducing new capabilities and challenges.

In 6G, AI and ML are expected to be natively embedded into network architecture [119]. This opens up possibilities for predictive, self-optimizing mobility management. Handover decisions could be autonomously made using context-aware models that adapt in real time to user behavior, traffic load, and environmental changes. However, challenges such as data privacy, computational overhead, and distributed learning remain critical research issues.

6G networks are expected to support joint wireless communication and environmental sensing. These sensing capabilities—e.g., location, velocity, and gesture recognition—could significantly enhance mobility prediction accuracy and beam management in dynamic environments like vehicular networks or smart cities [120]. Still, integrating these signals efficiently into mobility algorithms requires new frameworks and cross-layer optimization strategies.

With intelligence distributed across the edge, core, and devices, future mobility systems will need to coordinate multiple intelligent agents [121]. This decentralized intelligence enables localized decision-making (e.g., edge-assisted HO) but introduces new problems like consistency, trustworthiness, and the need for lightweight models suitable for energy-constrained nodes.

Together, these 6G pillars present both opportunities and challenges for next-generation mobility and HO management systems, calling for cross-disciplinary research in AI, sensing, networking, and edge computing.

### 7.7. Emerging Architectures: Non-Terrestrial and Digital Twin Networks

The evolution toward 6G and beyond envisions a more integrated and intelligent network fabric that includes both terrestrial and non-terrestrial components. Non-Terrestrial Networks (NTNs)—comprising Low Earth Orbit (LEO) satellites, High-Altitude Platforms (HAPs), and UAVs—extend connectivity to remote and underserved regions while enhancing resilience and reliability [22,122,123]. However, NTNs introduce unique challenges for mobility and HO management due to dynamic topology, variable propagation delays, and intermittent link availability. Efficient HO algorithms must consider the trajectory of aerial nodes, Doppler shifts, and cross-layer coordination to maintain service continuity. Additionally, Digital Twin Networks (DTNs) are emerging as a transformative concept where real-time virtual replicas of physical network elements are created to simulate, predict, and optimize network behavior. DTNs enable proactive HO decision-making by forecasting user mobility, network congestion, and service demands through real-time analytics and AI-driven modeling. This digital mirroring of network environments supports self-optimization and facilitates seamless mobility, especially in ultra-dense and mission-critical applications.

The integration of NTNs and DTNs poses both opportunities and open research challenges in terms of architecture design, resource management, and standardization. Future research must explore hybrid HO models that can intelligently switch between terrestrial and non-terrestrial links and leverage digital twin analytics to enhance HO robustness, latency minimization, and energy efficiency in dynamic and heterogeneous environments.

## 8. Performance Analysis

The gathered findings from the simulation study are shown in this section. Following a discussion of the suggested algorithm's performance outcomes, three other algorithms

chosen from the literature are contrasted. To demonstrate how well each algorithm performs under diverse circumstances, six distinct mobile speed scenarios have been used for investigation. Simulations utilizing the 5G network are used to evaluate and validate the algorithms. The findings displayed are all average values derived from the 15 users who were taken into account during the measurements. Each user's performance is tested separately during each 50 ms simulation cycle. The average value for all users who were measured during each simulation cycle is then calculated. As a result, the results that are displayed are the average values for all 15 users. In addition, the Handover Parameter Self-Optimization (HPSO) based on distance (Dis) [124–129], HPI [130], and FLC [131] algorithms are contrasted with the outcomes of the suggested algorithm. Because they primarily concentrate on enhancing the HPSO function, the Dis, HPI, and FLC algorithms were selected from the literature. The simulation experiments were conducted using MATLAB 2020a software to evaluate the performance of the comparison algorithms. As a result, the findings show how the created algorithm affects the RLF, HPPP effect, HOP, and RSRP.

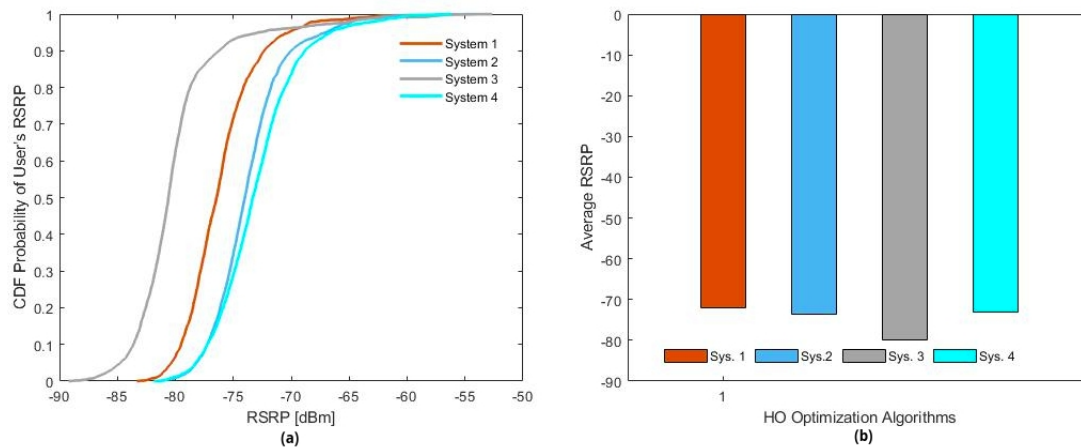
HPSO based on distance (Dis) is an adaptive technique that dynamically adjusts HO-related parameters, such as hysteresis margin and TTT based on the user's distance from the serving and target cells [124–129]. Unlike static configurations, distance-aware HPSO leverages the real-time spatial position of the user to optimize the handover timing and reduce the likelihood of unnecessary or failed HOs. For instance, when a user is near the cell edge, the system can proactively fine-tune HO thresholds to anticipate the degradation in signal quality, thus ensuring a seamless transition. This method is particularly beneficial in dense 5G deployments, where frequent HOs occur due to smaller cell sizes. By incorporating distance into the optimization loop, HPSO enhances mobility robustness and user experience while minimizing signaling overhead and handover failures.

The Handover Performance Indicator (HPI) is a composite metric used to evaluate the effectiveness of handover decisions by integrating multiple performance criteria, such as handover success rate, ping-pong rate, call drop rate, and signaling overhead. The Weighted Performance Handover Parameter Optimization (WPHPO) algorithm leverages HPI to guide the dynamic tuning of HO control parameters [130]. In WPHPO, each performance metric contributing to HPI is assigned a weight based on its importance to the overall network objectives (reliability, efficiency, and user experience). By continuously monitoring network performance and recalibrating the weights and parameters, the algorithm ensures adaptive optimization in real time. This approach enables a balanced trade-off among competing goals, such as minimizing unnecessary handovers while ensuring seamless connectivity, particularly in ultra-dense 5G environments. Ultimately, WPHPO enhances mobility management by aligning HO decisions with actual network conditions and service quality expectations (HPI is used as the label in the results figure).

Fuzzy logic controllers (FLCs) have been widely employed in HO management for their ability to handle the uncertainties and imprecise information typically encountered in wireless environments [131]. Unlike traditional HO algorithms that rely on fixed thresholds, FLCs utilize linguistic variables and a set of fuzzy rules to make more adaptive and context-aware decisions. By incorporating multiple input parameters such as RSS, user velocity, signal quality trends, and cell load, FLC can evaluate the overall HO desirability in a more nuanced manner. This results in smoother transitions between cells, reduced ping-pong effects, and improved QoE, particularly in HetNet or ultra-dense 5G networks where mobility conditions are highly dynamic. In all the results figures, Systems 1, 2, 3 and 4 represent Dis, FLC, HPI and WPHPO, respectively.

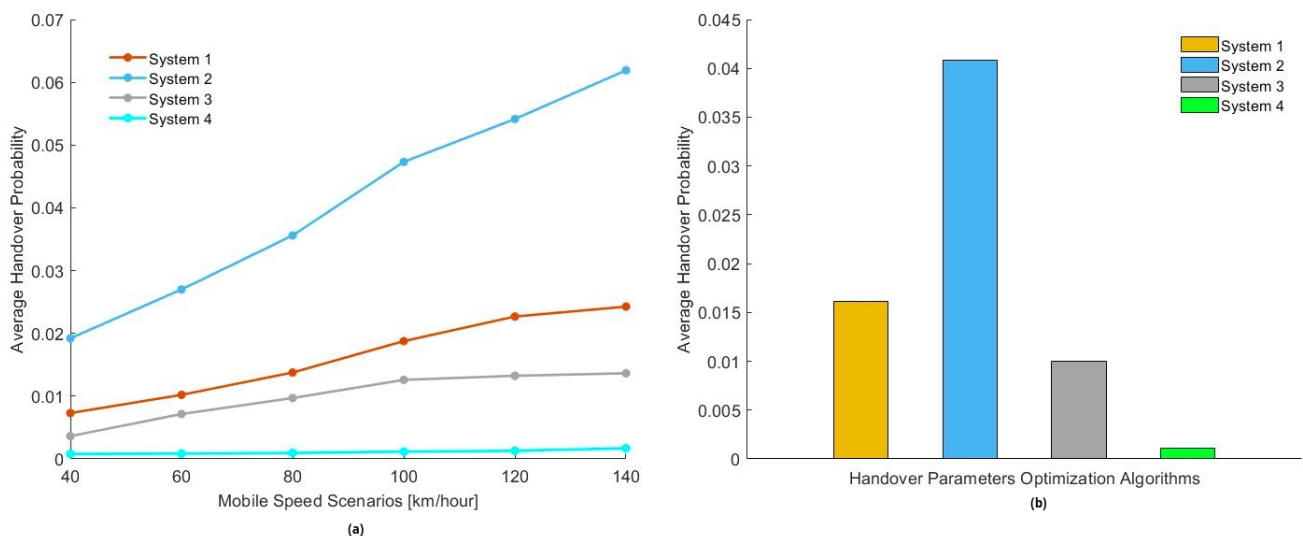
The mean RSRP across all assessed users and mobile speed conditions is shown in Figure 6. The average RSRP across all assessed users and across all mobile speed circumstances is displayed in the form of CDF in Figure 6a. The average RSRP for all

measured users across all simulation timeframes and then for all mobile speed scenarios is shown in Figure 6b. Particularly when contrasted with HPI and FLC, these figures show that the suggested approach offers substantial improvements. It was just 1 dBm lower than the Dis algorithm despite being lower overall. However, as will be demonstrated later, the suggested algorithm performs better than the Dis method based on the other KPIs.



**Figure 6.** (a) RSRP mean vs. (b) mobile speed scenarios.

Figure 7 displays the handover probability as an average rate across all mobile speed circumstances and all measured users.

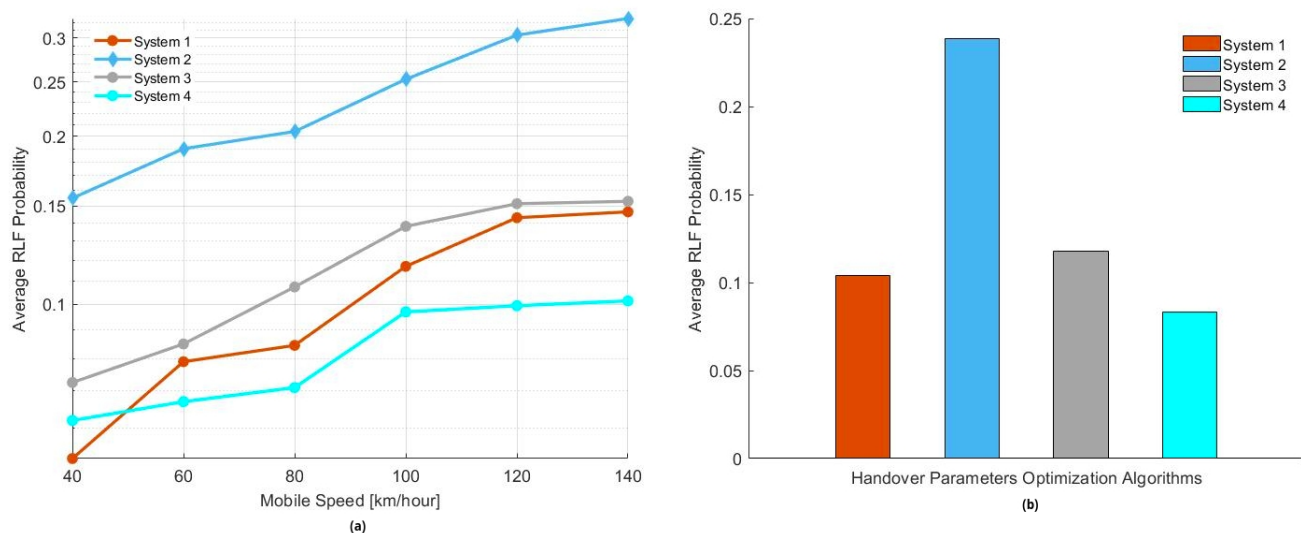


**Figure 7.** (a) Time vs. (b) average HO probability for all mobile speed conditions.

The findings generally show that there is a significant chance of handover during the first operation period. This is particularly noticeable for the average handover probability across all mobile speed situations (Figure 7b) and for lower mobile speed scenarios below 100 kmph. This problem happens as a result of the network starting up according to the HCP parameters that were first specified. Eventually, the algorithms under consideration optimize and update the HCP settings automatically. As a result, the HO probability is affected differently depending on how responsive and resilient the operating optimization algorithm is.

Figure 8 displays the RLFs as an average rate across all users and mobile speed scenarios that were measured.

For all mobile speed scenarios, the results usually show that the RLFs are variable with time. The outcomes also show that all algorithms respond constantly over time. The findings in Figure 8 show that these algorithms do not clearly distinguish from one another. In contrast to the other algorithms, the suggested technique shows a discernible decrease in the RLF rate in Figure 8. On average, the HPI results in the highest RLF rate across all mobile speed scenarios. As a result, the suggested algorithm's average reduction gains are roughly 6%, 17%, and 62% less than those of the Dis, FLC, and HPI methods, respectively. This is a noteworthy accomplishment made by the suggested algorithm.



**Figure 8.** (a) Average RLF vs. (b) time for all mobile speed scenarios.

## 9. Conclusions

In this paper, we discussed the concept, techniques, and operation of HO management in 5G networks. We also reviewed various approaches and techniques that have been proposed in the literature for optimizing HO in 5G networks, including ML algorithms, network slicing, and virtual reality technology. We also discussed the challenges involved in HO management in 5G networks, including the complexity of the HO process, efficient algorithms and techniques, maintaining high performance and low latency, HetNet, device power consumption, and LB. Finally, we discussed the potential of ML applications to optimize HO management in 5G networks. The challenges and opportunities of HO management in 5G ultra-dense small cell networks have also been illustrated in this study. There is still a need for ongoing research and development to address the various issues and challenges involved in HO management in 5G networks.

Overall, HO management is a critical aspect of 5G networks, as it plays a key role in optimizing network performance and user experience. The use of advanced approaches and techniques, such as ML and AI algorithms, network slicing, and virtual reality technology, can significantly improve HO management in 5G networks. However, there are also various challenges and issues that must be addressed to successfully implement and maintain HO management in 5G networks. Future research and development efforts should focus on addressing these challenges and developing innovative approaches and techniques for optimizing HO management in 5G networks.

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## Abbreviations

The following abbreviations are used in this manuscript:

|           |                                           |
|-----------|-------------------------------------------|
| UE        | user equipment                            |
| 3GPP      | 3rd generation partnership project        |
| ITU       | International Telecommunication Union     |
| IoT       | Internet of things                        |
| D2D       | device-to-device                          |
| V2V       | vehicle-to-vehicle                        |
| EC        | edge computing                            |
| MEC       | mobile edge computing                     |
| HetNet    | heterogeneous network                     |
| UD-HetNet | ultra-dense heterogeneous network         |
| mmWave    | millimeter wave                           |
| MIMOs     | multiple-input-multiple-outputs           |
| B5G       | beyond-5G                                 |
| QoS       | quality of service                        |
| QoE       | quality of experience                     |
| HO        | handover                                  |
| RSS       | received signal strength                  |
| MBS       | macro base station                        |
| SBS       | small base station                        |
| BS        | base station                              |
| RLF       | radio link failure                        |
| CCI       | co-channel interference                   |
| KPIs      | key performance indicators                |
| LTE-A     | LTE-advanced                              |
| 5G-NR     | 5G New Radio                              |
| CoMPs     | coordinated multiple points               |
| eNB       | Node B                                    |
| ICIC      | inter-cell interference coordination      |
| CN        | core network                              |
| EPC       | evolved packet core                       |
| RAN       | radio access network                      |
| NR        | new radio                                 |
| SDN       | software-defined networking               |
| ML        | machine learning                          |
| LB        | load balancing                            |
| LTE       | long-term evolution                       |
| UAVs      | unmanned aerial vehicles                  |
| IoE       | internet of everything                    |
| SA        | standalone                                |
| NSA       | non-standalone                            |
| eMBB      | enhanced mobile broadband                 |
| mMTCs     | massive machine-type communications       |
| URLLCs    | ultra-reliable low-latency communications |
| M2M       | machine-to-machine                        |
| FD        | full-duplex                               |
| RATs      | radio access technologies                 |

|       |                                         |
|-------|-----------------------------------------|
| ICI   | inter-cell interference                 |
| SINR  | signal-to-interference-plus-noise ratio |
| SNR   | extremely-high frequency                |
| SNR   | signal-to-noise ratio                   |
| NFV   | network function virtualization         |
| H-HO  | hard HO                                 |
| S-HO  | soft HO                                 |
| HHO   | horizontal handover                     |
| VHO   | vertical Handover                       |
| HOIT  | handover interruption time              |
| MR    | measurement report                      |
| HODPs | handover decision parameters            |
| HCPs  | handover control parameters             |
| TTT   | time-to-trigger                         |
| RSRP  | reference signal received power         |
| RSRQ  | reference signal received quality       |
| RSSI  | RSS indicator                           |
| CSI   | channel state information               |
| HOM   | HO margin                               |
| CIO   | cell individual offset                  |
| MRO   | mobility robustness optimization        |
| LBO   | load-balancing optimization             |
| HOPPs | handover probability problems           |
| HPPP  | handover ping-pong probability          |
| HOR   | HO rate                                 |
| HOFR  | HO failure rate                         |
| HOSR  | HO success rate                         |
| HOD   | HO delay                                |
| HOET  | HO execution time                       |
| HPSO  | handover parameter self-optimization    |
| CDF   | cumulative distribution function        |
| NTNs  | non-terrestrial networks                |
| LEO   | low Earth orbit                         |
| HAPs  | high-altitude platforms                 |
| DTNs  | digital twin networks                   |

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