

Survey paper

A Comprehensive Survey on Handover Management Techniques Toward Seamless Mobility in 5G and Beyond Heterogeneous Networks

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ABSTRACT

Handover failures and service interruptions remain critical challenges to seamless mobility in Fifth Generation and beyond (B5G) heterogeneous cellular networks (HetNets). In these environments, ultra-dense deployments and coexisting Radio Access Technologies (RATs) dramatically increase the complexity of mobility control. User Equipment (UE) frequently switches between macro cells, small cells, and different RATs. These frequent switches introduce risks of service disruption, excessive signaling overhead, and degraded user experience. Therefore, Handover Management (HOM) has become one of the most critical functions in modern mobile networks. This paper presents a comprehensive survey of HOM techniques designed to support seamless mobility in B5G HetNets. The survey begins by reviewing the handover mechanisms defined in recent Third Generation Partnership Project (3GPP) releases, from Release 15 through Release 18. Their operational principles and practical limitations in dense multi-tier cellular architectures are discussed. The survey then examines existing mobility optimization methods, including parameter tuning, mobility robustness optimization, and coordinated mobility control. Particular attention is given to intelligent Mobility Management (MM) approaches based on Machine Learning (ML). These approaches enable predictive mobility analysis, adaptive handover parameter adjustment, and context-aware decision-making in large-scale radio access networks. The role of Software Defined Networking (SDN) in enabling centralized and programmable handover control is also analyzed, along with joint SDN and ML frameworks that support self-optimizing network behavior. The survey further examines how emerging technologies may shape future MM frameworks. These technologies include Integrated Sensing and Communication (ISAC), Reconfigurable Intelligent Surfaces (RIS), Non-Terrestrial Networks (NTN), and Integrated Access and Backhaul (IAB) architectures. Several open challenges are also discussed. These include the scalability of mobility prediction algorithms in dense deployments, security management during handover procedures, and latency constraints for Ultra-Reliable Low-Latency Communication (URLLC) services. Finally, the survey outlines important research directions for future mobility-aware network architectures in B5G and Sixth Generation (6G) cellular systems. This survey reveals that while ML-based and SDN-assisted approaches offer significant gains in handover robustness, critical gaps remain in real-time deployment, scalability, and security-aware mobility design for next-generation networks.

1. Introduction

In the last decade, the rapid evolution of mobile communication technologies has led to an unprecedented surge in the number of connected devices and an increasing demand for high-speed, low-latency,

and reliable wireless services [1]. From smartphones and smartwatches to autonomous vehicles and industrial Internet of Things (IoT) systems, modern applications require seamless connectivity and uninterrupted service delivery. Fifth Generation and Beyond (B5G) mobile networks

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have promised to provide transformative solutions to fulfill these new demands and ensure enhanced data rates, Ultra Reliable Low Latency Communication (URLLC), and massive Machine-Type Communication (mMTC) [2,3]. In order to achieve these goals, Fifth Generation (5G) networks utilize advanced technologies, including millimeter Wave (mmWave) communication, massive Multiple-Input Multiple-Output (MIMO) systems, beamforming, and network densification through the deployment of small cells [4]. This convergence of innovations has given rise to a new concept of Heterogeneous Networks (HetNets), which integrates various types of Base Stations (BS) and Radio Access Technologies (RATs) into a unified architecture [5,6].

HetNets are considered one of the key contributors to the evolution of B5G networks, providing a cohesive framework that enhances coverage and capacity in high-density urban areas [7]. The integration of B5G and HetNets enables Multi-Radio Access Technology (Multi-RAT), such as Fourth Generation (4G) Long Term Evolution (LTE), 5G New Radio (NR), and Wireless Fidelity (Wi-Fi), to provide ubiquitous connectivity according to the user's requirements [8]. The dynamic allocation of resources not only facilitates efficient Load Balancing (LB) but also minimizes latency and enhances Quality of Service (QoS) for a wide range of applications [9]. Therefore, a proper configuration of HetNets and Multi-RATs is necessary to enhance network performance and resource utilization. It also significantly improves user experience by ensuring reliable, high-speed connectivity in an increasingly mobile and data-driven environment [10]. However, HetNets also lead to more Frequent Handovers (FHOs) due to smaller cell sizes and overlapping coverage areas, increasing signaling overhead, energy consumption, and the likelihood of Handover Failures (HOFs) and service interruptions [11].

Efficient Mobility Management (MM) is a crucial component of B5G HetNets that helps maintain robust and reliable connectivity [12]. An efficient MM framework improves user experience and allows better utilization of network resources. For this reason, MM is considered a fundamental function of future wireless communication systems. The handover procedure plays a central role in MM because it enables User Equipment (UE) to maintain continuous service while moving between neighboring cells [13]. Therefore, the development of intelligent and adaptive handover strategies for B5G HetNets is essential to achieve seamless connectivity. Such strategies must support highly mobile users and handle the complexity introduced by dense heterogeneous network architectures [14].

While B5G mobile networks promise transformative solutions, realizing their full potential, particularly in achieving truly seamless, ultra-reliable, and low-latency services, is significantly hampered by inherent complexities in Handover Management (HOM). For instance, the high rate of HOF and considerable Handover Interruption Time (HIT) remain critical obstacles to ensuring uninterrupted service delivery and meeting stringent latency requirements [15]. Therefore, novel schemes and improvements across various networking functional modules are essential, with handover and MM being a particularly critical area to satisfy future network needs. Moreover, integrating mmWave bands, while offering unprecedented throughput, introduces unique and significant handover challenges due to their inherent propagation characteristics [16]. The mmWave signals are highly susceptible to rapid attenuation and blockage, leading to frequent connection losses and increased HOF [17]. This impact is particularly pronounced in high-mobility scenarios, such as vehicular networks, where the highly directional nature of mmWave beams can cause "coverage blindness" and limit the time available for target BS discovery, necessitating specialized handover schemes [18]. The increasing densification and integration of Multi-RAT within HetNets exacerbate handover challenges. Inter-RAT HOs result in greater measurement gaps and signaling overhead, which must be meticulously optimized to ensure seamless connectivity across diverse technologies [19]. Additionally, the mobility of high-speed users in these ultra-dense environments introduces further complexities; their rapid movement through smaller cells leads

to a higher frequency of handover attempts and subsequent failures, contributing to network instability [20,21]. Beyond user-centric concerns, decisions made during HOs significantly impact network-wide performance metrics, including LB and overall resource utilization [22]. Therefore, future handover schemes must be designed not only to address user-side requirements but also to prioritize holistic network-side optimization for comprehensive performance enhancement.

Due to the dynamic and complex environment of HetNets, standalone optimization of handover parameters is often insufficient for achieving high throughput, better coverage, and high QoS [23]. Additionally, traditional handover algorithms can be used when the primary focus is on the users' received signals. These algorithms often direct UE toward cells with high transmission power, potentially causing load imbalances and suboptimal network-wide performance [24,25]. For next-generation wireless networks, the handover process will significantly impact both the network and user sides of network performance. For instance, the widespread deployment of small cells in HetNets and Ultra Dense Network (UDN) causes FHOs, not only between inter-cell layers but also within intra-cell layers [26,27]. This increased number of handovers leads to higher signaling overhead and energy consumption on both the network and user sides; most critically, it can also result in decreased user throughput [28,29]. Therefore, the main objectives of handover procedures suggested for next-generation wireless networks are to minimize specific handover Key Performance Indicators (KPIs), such as the number of ping-pong events, Handover Failure Rate (HOF), handover delay, and HIT, while maximizing the handover success rate to satisfy ultra-high reliability and low-latency requirements [11].

There are many approaches and studies aimed at solving such complications arising in HetNets and mmWave bands in B5G mobile networks [35,36]. One prominent approach is the development of novel handover decision algorithms to address B5G challenges and enhance network performance in terms of speed, reliability, and latency. Improving handover decision algorithms can be achieved by using a broader set of network parameters and by developing more sophisticated algorithms [37]. In B5G HetNets, advanced and reliable parameters can be used to perform more efficient handovers. For example, Reference Signal Received Power (RSRP), available BW, UE speed, and Bit Error Rate (BER) can be used for decision-making during handover [11]. These multidimensional parameters are crucial for making more informed decisions about the optimal handover during user mobility. This approach offers significant advantages and enhances users' Quality of Experience (QoE) compared to purely RSRP-based algorithms [38,39].

Intelligent and efficient handover decision algorithms are necessary to determine an optimal BS during handover, thereby maximizing the overall network performance [40]. Machine Learning (ML) based algorithms learn intricate patterns and features present within the network before making decisions [5,41]. For handover optimization, several ML-based algorithms are available, including Recurrent Neural Network (RNN), Reinforcement Learning (RL), clustering techniques, and decision trees [40,42]. These ML-based decision algorithms make significantly better choices, especially in complex or rapidly changing environments. Such handover decision algorithms significantly enhance network performance by reducing unnecessary handovers and HOFs, minimizing the "ping-pong" effect, and improving overall network throughput [37,43]. As a result, the problems encountered in B5G networks can be reduced by designing and developing new models that incorporate additional parameters or advanced ML algorithms [44,45].

The challenges discussed above show that mobility management remains a complex problem in heterogeneous cellular networks. Dense small cell deployments, high user mobility, and the integration of multiple radio access technologies significantly increase the complexity of handover control. At the same time, emerging technologies such as ML and SDN provide new opportunities to improve mobility management. These developments motivate a comprehensive survey of intelligent

Table 1

Comparison of representative recent survey papers on mobility and HOM in 5G and 6G networks.

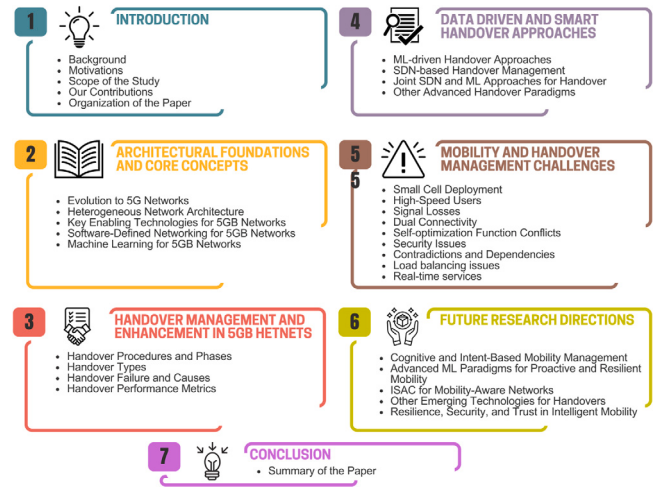
Survey paper	ML-based handover	SDN-based handover	3GPP mobility enhancements	Emerging 6G enablers
[30]	No	No	Limited	No
[31]	Yes	No	Limited	No
[32]	Limited	No	No	No
[33]	Limited	Limited	Limited	Limited
[34]	Yes	Limited	Limited	Yes
This survey	Yes	Yes	Yes	Yes

handover mechanisms for B5G heterogeneous networks. Several recent survey papers have discussed MM and handover optimization in B5G mobile systems. However, most of them focus on one side of the problem only. Some studies give a broad review of MM requirements and challenges, while others concentrate on ML, mobility robustness optimization, or general 5G and Sixth Generation (6G) mobility trends. A direct comparison is therefore needed to clarify the position of the present survey.

Jain et al. [30] discussed whether existing MM solutions are adequate for 5G and beyond. Their review mainly examined functional requirements, architectural limitations, and open research challenges. Molle et al. [31] focused on ML applications for HOM and provided a useful summary of supervised learning, unsupervised learning, and RL methods. Tashan et al. [32] reviewed mobility robustness optimization and emphasized self optimization problems such as handover failure, ping-pong events, and parameter tuning. Siddiqui et al. [33] presented a broader review of MM issues and solutions in 5G and beyond networks, but their discussion was not centered on a detailed handover taxonomy, recent 3GPP mobility enhancements, or the joint role of SDN and data driven handover control. More recently, Saoud et al. [34] reviewed mobility and HOM in 5G and 6G with attention to sustainability and innovation trends. A comparison with representative recent surveys is summarized in Table 1.

In contrast, this paper provides a comprehensive survey that brings the above mentioned directions together in one framework. This paper combines conventional handover procedures, handover types, failure causes, 3GPP Release 15 through Release 18 mobility enhancements, ML-driven methods, SDN-based solutions, and joint SDN and ML approaches. The future enabling technologies such as Integrated Sensing and Communication (ISAC), Reconfigurable Intelligent Surface (RIS), Non Terrestrial Network (NTN), and Integrated Access and Backhaul (IAB) are also presented. In this paper, performance indicators, open problems, and future research directions are also discussed in a unified way. The main contributions of this survey are summarized as follows.

1. We analyze the limitations of conventional handover mechanisms in B5G HetNets. We discuss how mmWave communication, dense small cell deployments, and high-speed user mobility increase HOF rates, signaling overhead, and ping-pong events. We also explain how inter-RAT transitions further complicate handover control in heterogeneous environments.
2. We examine handover procedures, phases, and a structured taxonomy of handover types in B5G HetNets. This includes intra/inter-frequency, intra/inter-layer, intra/inter-RAT, and soft versus hard handovers. We also explain the main HOF categories and key evaluation metrics, including HOSR, HOFr, HIT, ping-pong rate, and handover latency.
3. We review 3GPP mobility enhancements from Release 15 through Release 18. We cover baseline NR handover and DC in Release 15, CHO and DAPS in Release 16, Multi-TRP mobility in Release 17, and LTM in Release 18. For each release, we explain the problem addressed, the mechanism introduced, and the relevant 3GPP specifications.
4. We classify and discuss representative ML-based and SDN-based handover approaches. For ML, we cover supervised learning, LSTM-based prediction, RL, and clustering methods. For SDN, we discuss centralized handover control, load-aware routing, and inter-RAT coordination. We also analyze joint SDN and ML frameworks that support

**Fig. 1.** The organization of the paper.

self-optimizing handover behavior. For each approach, we explain the working principle, key findings, and limitations.

5. We discuss how ISAC, RIS, NTN, and IAB may influence future MM frameworks in B5G and 6G networks. For each technology, we explain its relevance to handover management and the open research problems it introduces.

6. We identify open challenges in B5G HOM, including ML scalability, LB, high-speed user mobility, handover security, URLLC latency constraints, and SON function conflicts. We also outline future directions, including FL, XAI, GNN, digital twins, GAI, O-RAN integration, and quantum-resistant handover security.

This survey aims to provide a useful reference for researchers and practitioners working on mobility solutions for evolving wireless infrastructures and future cellular communication ecosystems. The remainder of this paper is organized as follows: Section 2 explains the architectural foundations and core concepts. Section 3 discusses HOM in B5G HetNets and provides details on enhancements to handover standards introduced in recent 3GPP releases. Section 4 explores data-driven and smart handover solutions. Section 5 identifies research challenges in mobility and HOM. Section 6 outlines future directions, and Section 7 summarizes and concludes the paper. The section-wise distribution of the paper is visualized in Fig. 1. For the convenience of the reader, the main acronyms used throughout this paper are summarized in Table 2.

2. Architectural foundations and core concepts

This section provides essential background and preliminary concepts for understanding smart handover procedures used in B5G HetNets. We begin by describing the evolution of the B5G network architecture and its core parts. The key enabling technologies, such as mmWave communication, massive MIMO, and network densification, are defined. We then explain the architecture and characteristics of HetNets, including the integration of Multi-RAT. Next, we introduce the enabling technologies, such as SDN and ML, which provide pivotal solutions to the smart handover procedures in the B5G HetNets.

Table 2

A list of abbreviations and their full forms used throughout this paper.

Abbreviation	Meaning	Abbreviation	Meaning
3GPP	Third Generation Partnership Project	MEC	Mobile Edge Computing
4G	Fourth Generation	MIMO	Multiple-Input Multiple-Output
5G	Fifth Generation	ML	Machine Learning
6G	Sixth Generation	MM	Mobility Management
AI	Artificial Intelligence	mmWave	Millimeter Wave
AP	Access Point	mMTC	Massive Machine-Type Communication
B5G	Fifth Generation and beyond	MNO	Mobile Network Operator
BER	Bit Error Rate	MRO	Mobility Robustness Optimization
BS	Base Station	Multi-RAT	Multi-Radio Access Technology
BW	Bandwidth	NG-RAN	Next Generation Radio Access Network
CHO	Conditional Handover	NH	Next Hop
CNN	Convolutional Neural Network	NR	New Radio
CoMP	Coordinated Multi-Point	NTN	Non-Terrestrial Network
DAPS	Dual Active Protocol Stack	O-RAN	Open Radio Access Network
DC	Dual Connectivity	PCA	Principal Component Analysis
DDPG	Deep Deterministic Policy Gradient	PoA	Point of Access
DL	Deep Learning	PRB	Physical Resource Block
DNN	Deep Neural Network	QoE	Quality of Experience
DRB	Data Radio Bearer	QoS	Quality of Service
DT	Digital Twin	RAN	Radio Access Network
EHF	Extremely High Frequency	RAT	Radio Access Technology
eMBB	Enhanced Mobile Broadband	RIC	RAN Intelligent Controller
FHO	Frequent Handover	RIS	Reconfigurable Intelligent Surface
FL	Federated Learning	RL	Reinforcement Learning
GAI	Generative Artificial Intelligence	RLF	Radio Link Failure
GAN	Generative Adversarial Network	RNN	Recurrent Neural Network
gNB	Next Generation NodeB	RRC	Radio Resource Control
GNN	Graph Neural Network	RSRP	Reference Signal Received Power
GTP	GPRS Tunneling Protocol	RSRQ	Reference Signal Received Quality
HAPS	High-Altitude Platform Station	SAW	Simple Additive Weighting
HCP	Handover Control Parameter	SDN	Software Defined Networking
HetNet	Heterogeneous Network	SDN-H	SDN-Handover
HIT	Handover Interruption Time	SINR	Signal-to-Interference-plus-Noise Ratio
HO	Handover	SON	Self-Organizing Network
HOF	Handover Failure	SNR	Signal-to-Noise Ratio
HOFR	Handover Failure Rate	SVM	Support Vector Machine
HOM	Handover Management	THz	Terahertz
HPO	Handover Parameter Optimization	ToA	Time of Arrival
HOSR	Handover Success Rate	TRP	Transmission and Reception Point
HTS	High-Throughput Satellite	TTT	Time-to-Trigger
IAB	Integrated Access and Backhaul	UAV	Unmanned Aerial Vehicle
IBN	Intent-Based Networking	UDN	Ultra Dense Network
IoT	Internet of Things	UE	User Equipment
ISAC	Integrated Sensing and Communication	URLLC	Ultra-Reliable Low-Latency Communication
KPI	Key Performance Indicator	V2X	Vehicle to Everything
LB	Load Balancing	VANET	Vehicular Ad hoc Network
LoS	Line-of-Sight	VoIP	Voice over IP
LSTM	Long Short-Term Memory	Wi-Fi	Wireless Fidelity
LTE	Long Term Evolution	XAI	Explainable Artificial Intelligence
LTM	Low Layer Triggered Mobility		
MADM	Multi-Attribute Decision Making		

2.1. Evolution to B5G networks

The evolution of mobile communication over the past decades has been remarkable, driven by an unrelenting demand for higher data rates, lower latency, and the capacity to support an ever-expanding array of connected devices [46]. Although 4G Long Term Evolution (LTE) networks marked a significant leap forward, they face inherent limitations in addressing the escalating traffic generated by ubiquitous smart devices and the stringent requirements of emerging applications, such as autonomous vehicles and the Industrial IoT [47]. In particular, 4G networks often experience capacity saturation in densely populated urban environments, struggle to deliver the ultra-low latencies essential for critical real-time services, and encounter challenges in efficiently connecting a vast number of low-power IoT devices [48].

B5G networks, on the other hand, introduce a paradigm shift that provides not only improved data rates and reduced latency but also facilitates the seamless integration of diverse technologies and applications. This is accomplished through the implementation of advanced enabling technologies such as massive MIMO, mmWave communications, and network densification. As a result, B5G networks can achieve

greater efficiency, flexibility, and scalability [49]. Consequently, B5G mobile networks are expected to further extend these capabilities by integrating Artificial Intelligence (AI)/ML, and SDN, as well as utilizing new spectrum bands, such as enabling Multi-RATs [50]. Ultimately, these enhancements will pave the way for brilliant and adaptive wireless communication systems capable of supporting future data-hungry applications [51].

The B5G mobile networking architecture is structured into the following logical planes to ensure efficient data delivery and service provisioning, as well as MM.

User Plane: This plane consists of all UEs that connect to the network. It encompasses a vast and diverse range of devices, each with unique requirements. Key examples are smartphones, connected cars, and smart devices.

Access Plane: This plane serves as the bridge between the users and the core network, managing the physical and link-layer connectivity. It utilizes Multi-RAT to provide ubiquitous coverage and high performance through various types of Next Generation NodeB (gNB).

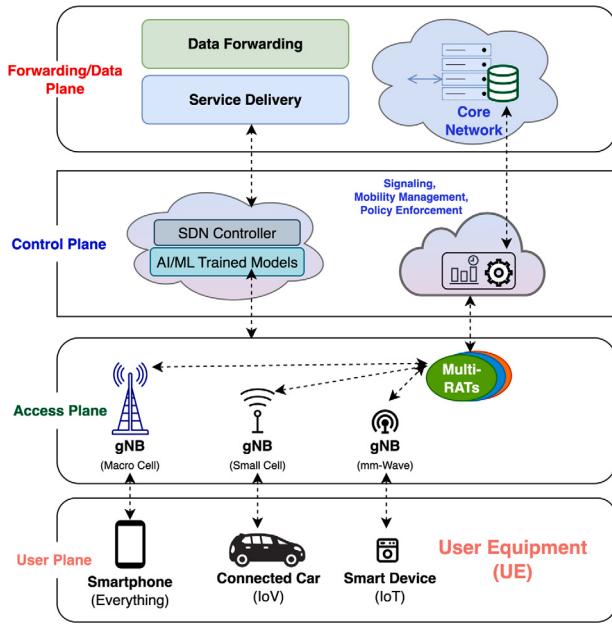


Fig. 2. A layered B5G networking architecture, comprising the user, access, control, and forwarding planes.

For example, a macro cell provides wide-area coverage for general mobile connectivity. Small cells can be deployed in urban areas to increase network capacity and density. In some cases, small cells use mmWave frequencies to deliver extremely high data rates in localized, high-demand areas.

Control Plane: This plane is responsible for critical functions such as signaling, session setup, policy enforcement, and MM (e.g., handover decisions). It leverages advanced principles to make intelligent, centralized decisions. SDN can provide a programmable, holistic view of the network, separating control logic from the underlying data-forwarding hardware. AI/ML models can analyze network data, predict traffic patterns, proactively manage resources, and optimize mobility to deliver a seamless user experience.

Forwarding/Data Plane: This plane, primarily implemented within the B5G Core Network, manages the actual transmission and routing of user data packets. Its operations, such as packet filtering, forwarding, and QoS policy enforcement, are directly guided by instructions from the Control Plane, ensuring efficient and reliable data/service delivery.

This clear separation of concerns significantly enhances the agility and efficiency of the B5G mobile networks, empowering operators to deploy services more rapidly and adapt dynamically to changing traffic patterns and diverse user demands. Fig. 2 illustrates a layered architecture that highlights the synergistic role of virtualization and programmability in enabling flexible MM.

2.2. Heterogeneous network architecture

B5G mobile networks extend their capabilities beyond traditional macro cell-based architectures to achieve ambitious performance targets, such as capacity, coverage, and QoS, across diverse environments. HetNet appears to be a promising solution to achieve these targets [52]. HetNet represents a fundamental architectural shift that integrates multiple types of BSs and Access Points (APs), each with varying transmission powers, coverage areas, and backhaul capabilities, within a unified network framework.

In a HetNet, a traditional macrocell, which provides wide-area coverage, can be layered with various low-power small cells, including microcells, picocells, and femtocells, as well as Wi-Fi APs and relays, as

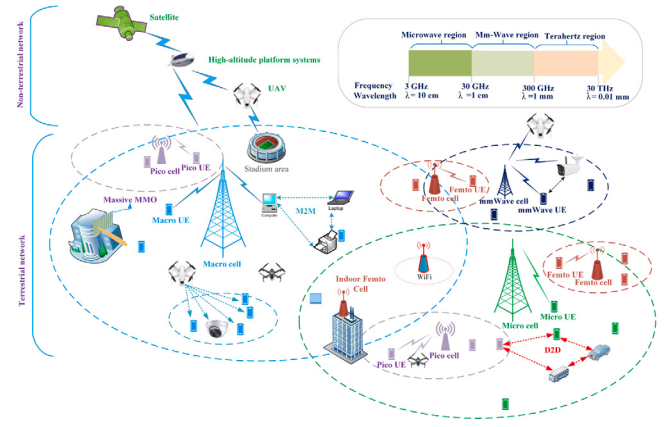


Fig. 3. Deployment scenarios of B5G HetNet, Device-to-Device, Unmanned Aerial Vehicle (UAV), and Machine to Machine (M2M) communication.

shown in Fig. 3. The Figure also demonstrates the fundamental functions of both the terrestrial and non terrestrial networks. Small cells can be strategically deployed to densify the network, which brings communication BSs closer to UE. This strategy significantly enhances network capacity, improves spectral efficiency, and reduces transmission delays, thereby directly addressing the demand for higher BW in congested areas and filling coverage gaps [53]. However, this dense, multi-layered environment also introduces significant challenges, most notably in managing co-channel interference across network layers [54].

Moreover, integrating Multi-RAT into HetNets enables simultaneous access to multiple communication technologies, such as LTE, Wi-Fi, and 5G NR. This approach allows users to perform vertical handovers, switching between different access networks dynamically to optimize connectivity based on real-time conditions and user requirements [55]. Multi-RAT enhances overall network resilience and efficiently supports a diverse range of applications, from high BW video streaming to low-power IoT communications.

The combination of small cells and multi-RAT capabilities within the HetNet architecture not only addresses the challenges of high user density but also enables a more adaptable, responsive network. In 5G mobile networks, the HetNet architecture, along with intelligent resource and MM schemes, is an essential component for delivering the high data rates, low latency, and reliable connectivity demanded by emerging technologies, applications, and services [56].

2.3. Key enabling technologies for B5G networks

B5G mobile networks introduce several pivotal enabling technologies. These technologies play a vital role in realizing the performance capabilities of B5G networks, notably in managing the complexity arising from frequent mobility and handovers [57]. Some of the key technologies are presented here as follows:

2.3.1. Millimeter Wave (mmWave) communication

MmWave communication operates in higher frequency bands (e.g., 30–300 GHz), offering access to a vast, contiguous spectrum. This enables remarkably high data rates and substantial capacity, making it essential for BW intensive applications [58]. However, mmWave signals are highly susceptible to severe path loss, atmospheric attenuation, and blockage from obstacles such as buildings, vehicles, and even human bodies [59]. This sensitivity demands strict line-of-sight (LoS) propagation and sophisticated beam management, posing unique challenges for maintaining continuous connectivity, particularly in high-mobility scenarios and densely populated urban environments. The management of these highly directional beams during user movement is a primary factor complicating handover procedures in mmWave systems [60]. The mmWave frequency bands with inclusion of wavelength are presented in Fig. 3.

2.3.2. Massive MIMO and beamforming

Massive MIMO systems employ a large number of antennas at the BS to serve multiple users simultaneously, significantly boosting spectral efficiency and overall system throughput [61]. Intrinsic to massive MIMO is beamforming, a technique that directs concentrated radio energy beams toward individual user devices. This targeted communication profoundly improves signal strength, extends range, and enhances interference suppression. While powerful, the highly directional nature of these beams requires precise and rapid alignment. This precision creates significant challenges for handover procedures, as UE mobility can easily lead to beam misalignment and potential service interruptions if not managed intelligently and proactively [62].

2.3.3. Network densification

B5G mobile networks employ a strategy called densification to handle the massive demand for data, particularly in densely populated areas. This means that instead of relying solely on large, traditional macro cells, numerous smaller BS, such as microcells, picocells, and femtocells, can be deployed together to form UDNs. This strategy dramatically increases network capacity and improves coverage in high-demand areas by bringing BSs closer to users [63]. However, this strategy creates a new challenge: a much higher frequency of handovers due to smaller cell sizes and overlapping coverage areas, which are inherent. Therefore, the B5G mobile network requires more intelligent and adaptive systems to manage handovers smoothly and efficiently [64].

2.4. Software-defined networking for B5G networks

SDN is one of the state-of-the-art approaches for modern networking that uses software-based controllers or application programming interfaces (APIs) to communicate with the underlying hardware infrastructure and direct traffic on a network [65]. This paradigm offers a transformative approach to traditional network design by decoupling the control plane from the data (or forwarding) plane at its fundamental level [66]. This separation enables centralized management and dynamic programmability of network resources [67], which is crucial for meeting the adaptable demands of modern mobile networks. In an SDN architecture, a logically centralized controller maintains a complete, real-time view of the entire network [68]. This SDN perspective enables operators to monitor network conditions, implement policies, and make swift configuration changes in the whole infrastructure. Therefore, implementing SDN not only enhances operational efficiency and agility but also promotes interoperability among diverse network devices and technologies, fostering innovation and mitigating vendor lock-in.

This capability, driven by SDN, is particularly crucial in HetNets, where the seamless integration of multiple access technologies and varying user demands can overwhelm traditional, rigid network management approaches [69]. Specifically, SDN enables dynamic handover control, allowing the centralized controller to proactively fine-tune handover parameters (e.g., Time-to-Trigger (TTT), hysteresis) based on granular data such as user velocity, network load, service priority, and signal quality fluctuations, leading to smoother transitions. It also enables load-aware routing, where traffic can be intelligently rerouted in real-time to circumvent congestion and balance load across various cells (including macro and small cells), thereby improving QoS and reducing the likelihood of HOFs [70].

SDN simplifies the complex integration and coordination required between different RATs (e.g., 4G LTE, 5G NR, Wi-Fi) and across different cell layers, enabling more efficient traffic offloading and seamless inter-RAT handovers [67]. It also enables policy-driven automation, allowing network policies to be consistently enforced across the entire infrastructure, ensuring uninterrupted service continuity and the desired QoE during user mobility events. Additionally, by centralizing control, the need for extensive signaling exchanges between adjacent cells during handovers is minimized, resulting in lower overhead and faster

handover completion times [71]. The integration of SDN with ML represents a critical area of focus. The architectural benefits of SDN facilitate the development of genuinely Self-Optimizing Networks (SONs) [72]. By leveraging SDN's centralized control, ML algorithms can be integrated to further enhance network performance. This synergy allows for the utilization of real-time global network data to predict mobility events, identify anomalies, and support data-driven decision-making for proactive handover execution and optimization [73].

SDN provides a foundational and indispensable framework for implementing intelligent and adaptive MM in B5G mobile networks. Its core principles of centralized control and programmability, combined with its compatibility with virtualization technologies and synergy with ML, position it as an ideal platform for developing scalable and efficient handover solutions in increasingly complex and dynamic wireless environments [74].

2.5. Machine learning for B5G networks

ML equips systems with the remarkable capability to learn from data and improve their performance over time without explicit programming [75,76]. In the context of B5G HetNets, ML enables networks to monitor, analyze, and actively model complex network behaviors and parameters [77]. ML algorithms use historical and real-time data in order to identify subtle patterns, predict future network states, and make intelligent, context-aware decisions [78]. This proactive capability is vital for optimizing various network functions, including traffic monitoring, LB, and, crucially, MM and HOM [79]. ML algorithms are divided into the following main types based on their fundamental learning approaches:

2.5.1. Supervised learning

These algorithms learn from labeled datasets, where each input is paired with a corresponding desired output (label) [80]. The objective is to build a model that can accurately predict outputs for new, unseen inputs. In MM, supervised learning is used to classify or predict handover outcomes (e.g., success/failure) based on features such as RSRP, Reference Signal Received Quality (RSRQ), and UE speed, or to forecast signal strength trends for proactive handover triggering. Standard algorithms include Support Vector Machines (SVMs), Decision Trees, and various forms of Neural Networks.

2.5.2. Unsupervised learning

Unlike supervised learning, these algorithms operate on unlabeled data, seeking to discover hidden patterns, structures, or relationships within the input information without prior knowledge of outcomes [81]. In mobility contexts, unsupervised techniques can be employed for tasks such as clustering cells or UEs with similar mobility behavior, identifying anomalous handover patterns indicative of network issues, or reducing the dimensionality of complex network data for more efficient processing. Examples include K-Means Clustering and Principal Component Analysis (PCA).

2.5.3. Reinforcement Learning (RL)

RL involves an autonomous agent learning optimal policies through iterative trial and error by interacting directly with a dynamic environment. The agent performs actions and receives feedback in the form of rewards or penalties, gradually learning which actions maximize cumulative reward over time [82]. This approach is particularly well-suited for dynamic mobility scenarios where the network must adapt its handover policies in real time to continuously changing user mobility patterns, traffic conditions, and network states. RL agents can learn to make optimal handover decisions, effectively minimize ping-pong effects, and significantly enhance overall network performance.

2.5.4. Deep Learning (DL)

As a specialized subfield of ML, DL utilizes artificial neural networks composed of multiple layers, known as Deep Neural Network (DNN) [83]. DL models, such as RNNs, Long Short Term Memory (LSTM), and Convolutional Neural Network (CNN), excel at processing large, complex datasets and automatically extracting intricate features [84]. They are increasingly employed in mobility scenarios for tasks like time-series prediction (e.g., forecasting future signal strength), spatial feature extraction, and sequential decision-making, offering advanced capabilities for complex handover optimization problems.

3. Handover management and enhancement in B5G HetNets

As the evolution of mobile networks progresses toward B5G, the need for seamless and efficient handover becomes important [85]. The increased complexity stemming from the densification of HetNets, the adoption of high-frequency bands such as mmWave, and the integration of diverse RATs has significantly complicated MM [86]. Among the core functions within this domain, the handover process plays a pivotal role in maintaining uninterrupted connectivity and service continuity as the UE moves across different cells or network layers [87]. In traditional cellular systems, handover decisions were often based on simplistic signal strength thresholds and static parameters. However, in the dynamic and diverse environments of B5G networks, such approaches are no longer sufficient. The rapid variability of signal conditions, the diverse range of user mobility patterns, and the stringent requirements of services like URLLC demand more intelligent, adaptive, and context-aware handover mechanisms [88]. This section provides a comprehensive overview of HOM in B5G HetNets. Furthermore, this section explains the enhancements to HOM introduced in recent 3GPP releases.

3.1. Handover procedures and phases

A handover is a fundamental process in cellular networks that ensures uninterrupted service continuity by seamlessly transferring a UE's active connection from a serving BS to a target BS as the UE moves. While signal quality deterioration is the most common trigger for a handover, other network-level objectives, such as LB across cells or resource utilization, can also initiate a handover.

The decision to execute a handover is typically driven by the continuous monitoring and analysis of various radio conditions, primarily the RSRP and quality from both the serving BS and potential neighboring target BSs [89].

The stability and reliability of handover decisions, particularly in dynamic B5G environments, depend on two crucial parameters: Hysteresis and TTT. Hysteresis refers to a margin that collects desirable signals from the target cell to ensure they consistently surpass the signals received from the serving cell by a specified threshold before initiating a handover [90]. This mechanism effectively prevents frequent, undesirable “ping-pong” handovers between cells with fluctuating signal strengths. TTT, conversely, acts as a timer that ensures the handover conditions (e.g., the target cell's signal meeting the hysteresis requirement) are maintained for a specified duration before the handover process is actually initiated. This prevents premature handovers triggered by momentary signal spikes.

The handover process, regardless of specific cellular generation (4G/LTE/5G), typically involves several sequential phases to ensure a smooth transition:

Handover Preparation Phase: The UE continuously monitors the signal strength and quality (RSRP, RSRQ) of its serving cell and neighboring cells. Based on predefined criteria (e.g., event A3 in LTE), the serving BS or a centralized network entity (e.g., an SDN controller)

evaluates the measurement reports to identify suitable target BSs and initiate preparatory steps.

Handover Initiation Phase: Once a target BS is selected, the serving BS sends a handover request to the chosen target BS. The target BS then reserves the necessary radio resources and responds with a handover command, which is subsequently forwarded to the UE.

Handover Execution Phase: Upon receiving the command, the UE detaches from the serving BS and begins synchronizing with the target BS. During this critical period, mechanisms such as data buffering and forwarding from the serving BS to the target BS are employed to minimize packet loss and service interruptions. Path switching within the core network also redirects data flow to the new connection.

Handover Completion Phase: After successful synchronization, the UE establishes its new connection with the target BS and resumes regular data transmission. The target BS sends a handover complete message, and the serving BS subsequently releases the resources it had allocated to the UE.

3.2. Handover types

In B5G HetNets, handovers are essential for maintaining seamless connectivity as the UE moves across various cells, frequency bands, and RATs. The inherent diversity of network deployments and the wide range of service requirements necessitate the evolution of a diverse set of handover types, each tailored to specific mobility scenarios and performance objectives. Handovers are performed not only to maintain signal quality but also to fulfill user service preferences and optimize network functions, such as LB.

Handover types are primarily categorized based on the underlying network characteristics of the serving and target BSs, and the method of connection transfer:

3.2.1. Categorization by network characteristics

Frequency-Based Handover: This classification depends on the operating frequencies of the involved BSs.

Intra-Frequency Handover: Occurs when a UE performs a handover between BSs operating on the same carrier frequency. This type is generally faster and typically requires minimal, if any, measurement gaps, as the UE can continuously monitor the target cell without switching frequencies.

Inter-Frequency Handover: Involves a handover between BSs operating on different carrier frequencies. This often necessitates a “measurement gap”, a brief period during which the UE pauses data transmission to tune to and measure the target frequency. Such gaps can impact throughput and latency, thereby affecting the user experience.

Cell Layer-Based Handover: This category distinguishes handovers based on the type of cells involved in HetNets deployments.

Intra-Layer handover: Takes place between cells of the same type (e.g., macro-to-macro, micro-to-micro, or pico-to-pico). These handovers are generally less complex as the cell characteristics are similar.

Inter-Layer Handover: Occurs between cells of different types (e.g., macro-to-pico, micro-to-femto). These often require more complex decision-making processes due to significant differences in coverage areas, transmission powers, and propagation characteristics in dense HetNets.

Radio Access Technology (RAT)-Based Handover: This classification differentiates handovers by the underlying radio technology. Fig. 4 further illustrates different types of handovers in a HetNets as follows:

Intra-RAT Handover (Horizontal Handover): Involves a handover between BSs utilizing the same RAT (e.g., 5G NR to 5G NR, or LTE

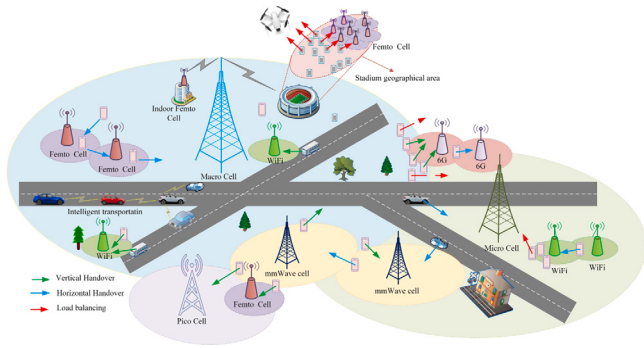


Fig. 4. Handover scenarios with LB using various mobile network deployments.

to LTE-Advanced). These are fundamental for mobility within a single technology domain.

Inter-RAT Handover (Vertical Handover): Occurs between BSs employing different RATs, e.g., LTE to NR, NR to Wi-Fi, or LTE to Wi-Fi. This type of handover is crucial in HetNets for seamless connectivity and intelligent traffic steering, enabling users to switch dynamically between technologies to optimize performance or conserve battery power.

3.2.2. Soft vs. Hard handover

Handover types can also be classified based on the interruption in data flow during the transition:

Soft Handover: In a soft handover, the UE maintains simultaneous connections with both the serving and target BSs for a period during the handover process. This “make-before-break” approach significantly improves reliability and minimizes service interruption time, making it highly desirable for real-time and critical services. However, it typically increases signaling overhead and network resource consumption.

Hard Handover: Conversely, a hard handover follows a “break-before-make” approach, where the UE completely disconnects from the serving BS before establishing a connection with the target BS. While simpler to implement and less resource-intensive, hard handovers inevitably introduce a brief but perceptible service interruption time. This interruption can negatively impact user experience, particularly for latency-sensitive applications. In B5G, while efforts are made to minimize its duration, hard handover is often the only option for inter-frequency or inter-RAT scenarios where simultaneous connections are not feasible.

3.3. Handover failures and causes

In B5G mobile networks, achieving seamless handover is paramount for maintaining uninterrupted service continuity and a high QoE, especially given the complexities of ultra-dense and high-mobility environments. However, due to the inherent intricacies of HetNets, the increased frequency of handovers, and the challenging propagation characteristics of high-frequency bands, such as mmWave, the risk of HOFs has increased dramatically [91].

A HOF occurs when a UE is unable to successfully establish or maintain a connection with the target BS during the handover process. Failure to maintain the connection arises from inappropriate configurations of the Handover Control Parameters (HCP) such as TTT and HOM shown in Fig. 5. Such failures directly result in service interruptions, including dropped calls, interrupted data sessions, and a marked degradation in user QoE. HOFs are commonly categorized into three primary types based on the timing or decision error:

Too Late Handover: This failure occurs when the handover is triggered after the signal quality from the serving cell has already deteriorated

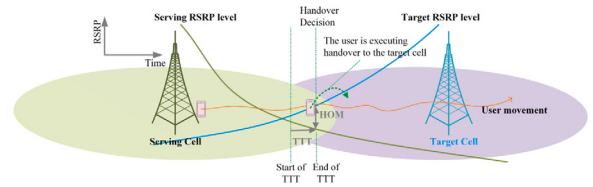


Fig. 5. Handover mechanism between serving BS and target BS.

below a usable or acceptable threshold. Consequently, the UE experiences a Radio Link Failure (RLF) before the handover procedure can be completed, leading to a sudden service interruption.

Too Early Handover: Conversely, a too early handover results when the UE is handed over to a target cell prematurely. At the time of connection, the signal quality of the target cell is not yet sufficiently strong or stable to sustain a reliable link. This often leads to immediate disconnection from the new cell or a rapid subsequent handover back to the original (or another) cell, known as the “ping-pong effect”.

Handover to Wrong Cell: This type of failure arises when the UE is handed over to a cell that is not optimal or cannot reliably sustain the connection. This can occur due to inaccurate measurement, erroneous target cell selection, or dynamic changes in the radio environment. This is particularly likely to happen near cell edges or in areas with overlapping coverage, where multiple candidate cells may appear suitable but are suboptimal.

Beyond these timing and decision-related categories, several underlying factors contribute to the occurrence of HOFs in B5G HetNets:

High Mobility: Rapid changes in UE location and speed make it challenging for the network to acquire accurate, up-to-date measurements and execute timely handover decisions. The signal quality can fluctuate rapidly, leading to missed handover opportunities or late handovers.

Measurement Gaps: In inter-frequency and inter-RAT handovers, the UE may need to temporarily pause data transmission to perform measurements on the target frequency or RAT. These “measurement gaps” increase the risk of missed handover opportunities, particularly in fast-fading or dynamic environments.

Beam Misalignment: In mmWave deployments, the use of highly directional, narrow beams means that even minor UE movements or temporary blockages (e.g., by obstacles or the human body) can lead to sudden and severe beam misalignment. This can result in abrupt signal drops and an increased likelihood of HOF.

Propagation Challenges: Factors like severe path loss, atmospheric attenuation, and signal blockage (e.g., by buildings, foliage) in dense urban environments directly impact signal quality, making reliable handover prediction and execution more difficult.

Load Imbalance and Resource Availability: An overloaded target cell might reject an incoming handover request, forcing the UE to remain connected to a suboptimal or failing serving cell. Insufficient available resources, e.g., Physical Resource Blocks (PRBs) in the target cell, can also directly lead to HOF.

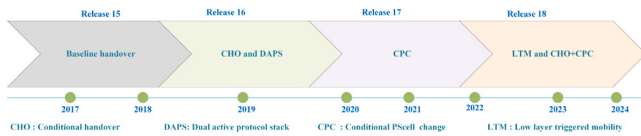
Interference Management: In ultra-dense HetNets, complex interference patterns can distort signal quality measurements, leading to inaccurate handover decisions or preventing the UE from reliably decoding the target cell’s signals.

HOFs in B5G mobile networks are multifaceted, stemming from complex interactions between network dynamics, UE mobility, and environmental factors. Effectively mitigating these failures requires a combination of predictive, adaptive, and context-aware strategies, often leveraging advanced technologies like SDN and ML, which are crucial for achieving the promised seamless connectivity of B5G mobile networks.

Table 3

Key mobility enhancements standardized by 3GPP.

Release	Feature	Problem addressed	Key mechanism	Primary specification(s)
Rel-15 [92]	Baseline NR Handover/DC	Foundational 5G mobility and enhancing reliability through DC.	Standard L3-based handover procedure; simultaneous connection to LTE and NR nodes.	TR 21.915
Rel-16 [93]	CHO	High HOFR, “Too Late” handovers, and reducing HIT.	Decoupling of handover preparation and execution; UE-based execution based on pre-configured conditions.	TS 38.300, TS 38.331
Rel-16 [94]	DAPS	High HIT, ensuring URLLC service continuity by enabling make-before-break transitions.	“Make-before-break” handover; UE maintains simultaneous user plane connection to source and target cells.	TS 38.300, TR 21.916
Rel-17 [95]	Multi-TRP mobility enhancements	HOFs due to beam misalignment and blockage in coordinated deployments, crucial for mmWave and dense networks.	Enhanced signaling and beam management for seamless transitions between coordinated transmission points.	TS 38.300, TR 21.917
Rel-18 [96]	LTM	High HIT and signaling overhead of L3 handovers; reducing complexity compared to DAPS for certain scenarios.	Handover trigger moved from L3 Radio Resource Control (RRC) to L1/L2 (e.g., MAC-CE); combines CHO concepts with fast signaling.	TR 21.918, TS 38.300

**Fig. 6.** Timeline of 3GPP handover enhancements for future mobile networks.

3.4. 3GPP enhancements for 5G handover

To directly address these challenges and reduce the incidence of HOFs, 3GPP has introduced several key enhancements across its releases (15 to 18) as shown in Fig. 6, building upon the foundational handover types discussed in Section 3.2:

Baseline 5G NR Handover (Release 15): Established the foundational 5G NR handover procedures, including initial support for inter-RAT handover between LTE and NR, and early Dual Connectivity (DC) features for enhanced mobility robustness.

Conditional Handover (CHO) (Release 16): By pre-configuring multiple target cells and allowing the UE to execute the handover when specific radio conditions are met autonomously, CHO helps mitigate too late or wrong-cell handovers by providing more flexibility and reducing network signaling latency at the point of decision.

Dual Active Protocol Stack (DAPS) (Release 16): This feature significantly reduces HIT by enabling the UE to maintain simultaneous active connections with both the serving and target BSs during the handover. This “make-before-break” approach drastically lowers the risk of service interruption, thereby decreasing the perceived HOF rate.

Multi Transmission and Reception Point (TRP) - Release 17: In environments with multiple coordinated transmission points, Multi-TRP enhances coverage and reliability, especially crucial for mmWave. Supporting seamless transitions between these points inherently reduces the likelihood of HOFs due to beam misalignments or sudden signal drops.

Low Layer Triggered Mobility (LTM) (Release 18): By initiating handover decisions based on faster Layer 1/2 events, this mechanism enables much quicker and more accurate handovers, directly addressing the “too late handover” problem and improving overall mobility robustness.

These continuous advancements, coupled with new KPIs for monitoring handover performance (e.g., “handover per beam-cell pair” and “mean interruption time interval for 5QI” in Release 18), underscore the industry’s commitment to mitigating HOFs through more innovative and resilient MM mechanisms (see Table 3).

3.5. Handover performance metrics

Evaluating the effectiveness of handover mechanisms in B5G mobile networks requires a robust and comprehensive set of performance metrics. These indicators are crucial for assessing the quality, reliability, and efficiency of MM strategies, particularly in the complex environments of HetNets and ultra-dense deployments. They are widely utilized in network simulations and real-world deployments to measure, compare, and optimize various network configurations and handover algorithms.

Traditionally, handover performance has been quantified using several KPIs that directly reflect both user experience and network behavior during mobility events [97]. The Handover Success Rate (HOSR), for instance, represents the percentage of successful handovers among total handover attempts and serves as a primary measure of effective MM. Conversely, the HOFR indicates the proportion of handovers that fail due to issues such as signal degradation, incorrect target cell selection, or signaling errors, directly impacting service continuity (as discussed in Section 3.3). Another critical metric is the Ping-Pong Rate, which quantifies the frequency of rapid back-and-forth handovers between two cells. A handover is typically classified as a ping-pong event when the UE returns to a previously serving BS within a time interval shorter than a defined threshold, often around 2 s, indicating suboptimal handover parameter tuning or unstable radio conditions. Furthermore, the HIT measures the duration during which the UE is unable to transmit or receive data while transitioning between cells, a critical consideration for real-time and URLLC applications. Finally, handover latency is the total delay incurred throughout the handover process, from initiation to successful completion. Minimizing this latency is essential for maintaining seamless connectivity and a high QoE.

Recent advancements in 3GPP releases have progressively refined and expanded the set of handover-related metrics to support the evolving and more stringent requirements of B5G mobile networks, particularly with features such as massive MIMO and mmWave. In Release 15, baseline KPIs for handover success and failure rates were established, alongside initial measurements for LTE-NR interworking. Release 16 then introduced specific metrics for CHO performance, including success/failure rates of conditionally triggered handovers and their impact on latency and reliability. With the release of Release 17, support for Multi Transmission and Reception Point (TRP) and DC scenarios introduced new metrics to monitor simultaneous connections and the effectiveness of transitions between multiple transmission points. Finally, Release 18 notably introduced a comprehensive set of new KPIs and measurements designed for advanced mobility features. These include Handover per Beam-Cell Pair, which tracks handover events at the highly granular level of individual beam transitions, crucial

for precise MM in mmWave and massive MIMO deployments. The Mean Interruption Time Interval for 5QI measures the average service disruption time for specific 5G QoS Identifier (5QI) flows, enabling fine-grained QoE analysis tailored to service requirements. Additionally, metrics like Conditional PSCell Change Metrics evaluate the performance of conditional primary–secondary cell changes in DC scenarios. At the same time, Packet Delay and Loss Metrics (e.g., downlink GPRS Tunneling Protocol (GTP) packet delay, uplink delay between Next Generation Radio Access Network (NG-RAN) and UE, and DL packet loss rate on Uu interface) and UE Throughput and Buffering Metrics (e.g., average downlink throughput per Data Radio Bearer (DRB) and buffering delays) provide a holistic view of end-to-end performance.

Therefore, the continuous evolution and diversification of handover performance metrics directly reflect the increasing complexity and diversity of 5G mobile network services. Accurate, comprehensive, and granular measurement is indispensable for designing, tuning, and validating the intelligent and adaptive handover mechanisms required to meet the stringent demands of next-generation mobile applications, ensuring a truly seamless user experience.

4. Data driven and smart handover approaches

Due to the complexities inherent in 5G HetNets and the stringent demands for seamless connectivity, ultra-low latency, and enhanced Mobile Broadband (eMBB), a paradigm shift in HOM is necessary. Traditional, rule-based handover algorithms often struggle to adapt to the dynamic, unpredictable nature of these networks, leading to inefficiencies such as FHOs, higher failure rates, and suboptimal resource utilization. Consequently, intelligent approaches, particularly those leveraging ML and SDN, have emerged as pivotal solutions for optimizing handover performance and ensuring robust MM. This section explores various intelligent handover solutions, detailing how ML algorithms are used for predictive and adaptive decision-making, how SDN enables centralized, programmable control, and how their synergistic combination offers a path toward self-organizing, self-optimizing networks.

4.1. ML-driven handover approaches

ML techniques are increasingly used to support MM in modern cellular systems. These methods help network controllers analyze large volumes of measurement data and learn patterns related to user movement, signal fluctuations, and network congestion. As a result, ML models can assist several stages of the handover process. These stages include mobility prediction, parameter optimization, anomaly detection, and network reliability improvement. Recent surveys confirm that ML has become an important tool for handover optimization in heterogeneous mobile networks [98,99].

One early application of ML in MM is anomaly detection for self-organizing networks. Self-organizing networks require automatic mechanisms that detect malfunctioning or overloaded BSs and take corrective actions. Omar et al. [100] investigated the use of supervised learning models for network self-healing. Their work analyzes several KPIs collected from BSs and access points. These indicators are used to classify the operational condition of each node as normal, congested, or under performing. ML models such as SVMs and Decision Forests are trained using these labeled data sets. The trained models help the network controller detect abnormal conditions and guide UE toward reliable target cells. This process helps reduce handover failure events and improves the overall stability of the radio access network.

Predictive mobility analysis represents another important direction. Accurate prediction of signal quality and user movement allows the network to trigger handover decisions before link degradation occurs. Vankayala et al. [101] proposed a proactive handover mechanism based on LSTM networks. These models are able to capture temporal

relationships in historical radio measurements. By learning the evolution of RSRP values over time, the model can estimate future signal conditions for both serving and candidate cells. Such prediction allows the network to initiate handover procedures earlier and reduce the probability of radio link failure.

ML can also improve network reliability through early detection of communication problems. Islam et al. [102] introduced a DNN model that predicts potential communication failures within the 5G radio access network. The model analyzes measurement reports and traffic indicators collected from network elements. When the model detects patterns associated with possible communication disruption, preventive actions can be triggered. These actions may include early handover execution or adaptive resource allocation. Consequently, the prediction of communication failures indirectly supports proactive MM.

RL has also attracted attention for dynamic mobility optimization. In RL systems, an agent interacts with the network environment and gradually learns optimal decision policies. Tanveer et al. [103] applied RL to optimize drone mobility in ultra dense networks. The algorithm evaluates different movement strategies and selects actions that improve communication quality for aerial users. Although the study focuses on drone mobility, the approach demonstrates how RL can adapt mobility decisions according to changing network conditions.

ML techniques are also useful for large scale network analysis. Liu et al. [104] proposed a cell clustering scheme that groups cells according to their mobility characteristics. The clustering process relies on parameters such as user location information and handover statistics. Cells with similar mobility behavior are grouped together. This grouping supports network level functions such as LB and energy efficient operation. By understanding the mobility patterns within each cluster, the network can improve handover coordination among neighboring cells.

Another important research direction focuses on optimizing handover control parameters. In conventional systems parameters such as Handover Margin and Time to Trigger are often configured using static values. However, static configuration may not perform well in highly dynamic environments. Zhang et al. [105] proposed a RL method based on Q learning to adjust these parameters dynamically. The learning agent evaluates network performance indicators such as throughput, handover count, and signaling cost. The algorithm then updates the parameter values to achieve improved system performance while reducing unnecessary handover events. In most studies that investigate RL based mobility optimization, the performance of learning algorithms is evaluated relative to the conventional handover procedure defined in 3GPP cellular standards. In particular, the baseline mechanism typically follows the Event A3 handover triggering rule introduced in 3GPP Release 15, where a handover is initiated when the signal strength of a neighboring cell exceeds that of the serving cell by a predefined hysteresis margin for a specified TTT interval. RL algorithms are therefore designed to dynamically adjust parameters such as the hysteresis margin or TTT values in order to improve mobility robustness and reduce unnecessary handover events when compared with this standardized baseline [106].

Despite these advantages, RL based mobility control may encounter scalability challenges in large heterogeneous networks. When the number of neighboring cells and UEs increases, the dimensionality of the state space grows rapidly. This phenomenon is commonly referred to as the curse of dimensionality. In such situations, classical tabular RL methods may experience slow convergence and increased computational overhead, particularly in ultra-dense cellular deployments [107].

Several research directions have been proposed to mitigate this limitation. One approach is state abstraction, where only the most relevant network indicators such as candidate cells with the strongest signal measurements or aggregated load information are used to represent the system state. Another promising strategy is hierarchical RL, where high-level controllers determine global mobility policies while lower-level agents manage local handover actions. Hierarchical deep

Table 4

Representative ML-driven handover optimization approaches in heterogeneous mobile networks.

Reference	Learning type	Mobility scenario	Problem addressed	Main contribution
[100]	Supervised learning	Network self healing and reliability monitoring	Detection of abnormal BS or Access Point (AP) operational states	Classifies BS conditions using KPIs and helps guide users toward reliable target cells to reduce handover failures
[101]	DL (LSTM)	High mobility environments and predictive MM	Proactive prediction of signal strength and handover triggers	Uses historical RSRP measurements to forecast future signal conditions and enable proactive handover decisions
[102]	DNN	Radio access network reliability monitoring	Prediction of communication failures in the Radio Access Network (RAN)	Detects early indicators of communication disruption and supports proactive MM
[103]	RL	Drone mobility and aerial user communication	Optimization of drone movement in ultra dense networks	Learns adaptive mobility strategies that improve connectivity for aerial users
[104]	Clustering learning	Network wide mobility pattern analysis	Cell clustering for LB and mobility optimization	Groups cells according to mobility characteristics to improve resource management and handover coordination
[105]	RL (Q learning)	Ultra dense cellular deployments	Dynamic optimization of handover parameters	Adjusts Time to Trigger and Handover Margin values to reduce ping pong handovers and increase throughput
[111]	Clustering and prediction models	Operational network monitoring	Detection of abnormal handover patterns	Combines clustering and prediction models to identify abnormal handover behavior in real networks

RL frameworks have recently been investigated to improve scalability and decision efficiency in wireless MM [108].

Multi-agent RL architectures also provide a scalable solution for dense heterogeneous networks. In such frameworks, multiple learning agents operate at distributed network entities such as BSs or edge controllers. Each agent learns local mobility policies while exchanging limited coordination information with neighboring nodes. This decentralized learning paradigm significantly reduces the complexity of the global decision process and improves scalability in ultra-dense cellular environments [109].

More recently, deep RL techniques have been explored to approximate value functions using neural networks instead of large lookup tables. These models can generalize across similar network states and therefore mitigate the dimensionality problem in large-scale wireless environments. Several studies have demonstrated that deep RL can learn adaptive handover policies and improve mobility performance in dense cellular deployments [110].

ML can also support anomaly detection in mobility statistics. Singh et al. [111] analyzed long term handover records collected from operational networks. Their approach first applies clustering methods to group cells according to their handover behavior. After clustering, prediction models such as Gaussian Processes are used to estimate expected handover patterns. When the observed behavior deviates significantly from predicted values, the system raises an alarm for potential network issues. This process enables early detection of abnormal mobility events and helps maintain network stability. Table 4 summarizes the main ML approaches used for handover optimization in HetNets.

The studies summarized in Table 4 show that ML techniques can improve several aspects of the handover process in heterogeneous cellular networks. However, different algorithms perform better under different mobility conditions. Therefore, selecting a suitable learning model depends strongly on the deployment scenario and the available computational resources.

DL models, particularly LSTM networks, are well suited for mobility prediction tasks. These models analyze sequential radio measurements such as RSRP and RSRQ and learn the temporal behavior of signal variations. This capability is useful in high mobility environments such as high-speed railways or vehicular communication systems where signal quality changes rapidly [112].

An important practical consideration in predictive MM is the relationship between the inference latency of learning models and the coherence time of the wireless channel. In mmWave communication systems, the channel may vary rapidly due to user mobility, beam

misalignment, and blockage effects. However, most learning based mobility prediction mechanisms operate at the network control level rather than the physical layer signal processing level. Consequently, prediction models such as LSTM networks process radio measurements collected over longer observation windows, for example, sequences of RSRP or beam quality measurements, instead of instantaneous channel coefficients.

Recent studies indicate that inference latency of lightweight DL models executed at edge controllers or BSs is typically on the order of a few milliseconds, which is compatible with MM timescales used in cellular networks [113]. In practice, handover decisions are triggered based on measurement reporting intervals and MM timers that operate at tens to hundreds of milliseconds. Therefore, the prediction latency of LSTM networks generally remains within acceptable limits for proactive mobility decision support.

Furthermore, several recent works have demonstrated that learning based mobility prediction can successfully anticipate signal degradation and beam switching events in high frequency communication systems [114]. These results suggest that DL assisted mobility prediction can complement traditional measurement based handover mechanisms even in rapidly varying radio environments such as mmWave cellular networks.

RL approaches provide a different advantage in dense cellular deployments. In ultra-dense small cell environments the network state changes frequently because of user mobility and load variations. RL agents can observe these network states and gradually learn optimal handover policies. For example, RL algorithms can dynamically adjust handover parameters such as hysteresis margin and TTT in order to reduce unnecessary handover events and improve long term network performance [110].

Clustering methods and lightweight supervised learning models provide a lower computational burden compared with DL approaches. These techniques are useful for network monitoring tasks such as mobility pattern identification, anomaly detection, and cell grouping. Although their prediction capability is limited compared with DNN, they are easier to deploy in operational radio access networks where real-time decision making is required.

Overall, the design of ML based handover mechanisms involves a balance between prediction accuracy and computational complexity. DL models provide strong predictive capability for complex mobility scenarios, while RL offers adaptability in dynamic network environments. Lightweight algorithms remain useful for operational monitoring tasks and large-scale network analysis. Therefore, future MM architectures are expected to combine multiple learning techniques operating at different layers of the network control framework.

4.2. SDN-based handover management

SDN plays a transformative role in HOM by decoupling the control and data planes, which provides a centralized, programmable control plane with a global view of the network. This architecture addresses the limitations of traditional distributed control mechanisms, enabling more efficient and adaptive handover decisions. For instance, an SDN controller can leverage Multi Attribute Decision Making (MADM) algorithms to enhance handover optimization. SDN's centralized control and programmability offer significant advantages for optimizing handovers across diverse network environments, from dense small cells to satellite communications. Cicioğlu et al. [69] proposed an Entropy-based Simple Additive Weighting (SAW) decision-making method for multi-criteria handover in SDN-based B5G small cells. The centralized, proactive, and multi-metric architecture leverages parameters, such as BW, user density, and Signal-to-Interference-plus-Noise Ratio (SINR), to select the most suitable evolved NodeB (eNB). The proposed method demonstrated notable improvements of 15% in handover delay, 48% in blocking probability, and 22% in throughput when compared to conventional LTE handover mechanisms.

In multi-criteria handover decision frameworks, the evaluation parameters often have different physical units and numerical ranges. For example, received signal strength is measured in dBm, while BW availability is expressed in MHz and latency is measured in milliseconds. Therefore, the decision matrix must be normalized before calculating the weighted score of each candidate cell.

Let $X = [x_{ij}]$ denote the decision matrix, where x_{ij} represents the value of criterion j for candidate cell i . In the Simple Additive Weighting (SAW) method, each element of the decision matrix is first normalized to obtain dimensionless values. For benefit criteria, where a higher value is preferable, a commonly used normalization function is expressed as:

$$r_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \quad (1)$$

For cost criteria, where the smallest value is considered optimal, a typical normalization form is

$$r_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \quad (2)$$

However, a more robust and frequently utilized linear normalization for cost criteria, which ensures the normalized values are scaled relative to the entire range of the criterion, is given by:

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (3)$$

After normalization, the weighted score of each candidate cell can be calculated by combining the normalized parameters with their corresponding entropy-derived weights. This normalization step ensures that heterogeneous network indicators contribute fairly to the final decision metric and prevents parameters with larger numerical ranges from dominating the handover decision process [115].

Similarly, Emran et al. present an SDN-based centralized solution for HOM in LTE networks [67]. This approach enables the SDN controller to oversee the entire network and direct flow entries to OpenFlow switches, significantly enhancing network performance. While an initial delay may occur due to the absence of initial flow entries, subsequent packets experience reduced delays, resulting in overall improved data rates and handover efficiency compared to traditional LTE handovers. For complex scenarios, such as satellite networks, SDN also plays a crucial role. In [116], the authors proposed an SDN implementation for Smart Gateway Diversity (SGD) management in High-Throughput Satellite (HTS) systems. Their novel approach addresses the "graceful degradation" of feeder links by dynamically reallocating portions of user beams among gateways based on different Signal-to-Noise Ratio (SNR) thresholds. This SDN-enabled, granular resource allocation and

traffic-balancing method demonstrated a 40% gain in the system's aggregated capacity.

Addressing challenges in heterogeneous wireless networks, Abu-Ain et al. introduced an SDN-Handover (SDN-H) framework [117]. The SDN-H framework shifts the computational burden of the handover procedure to the SD-Switch and SD-Controller, integrating multiple parameters beyond signal strength, including SINR, delay, BW, UE trajectory, and UE speed, to optimize Point of Access (PoA) selection. Their proposed method achieved significant improvements, including reductions in handover count, packet delay ratio, and packet loss ratio, as well as a remarkable 75% reduction in signaling message overhead compared to previous studies. Furthermore, integrating SDN with emerging technologies, such as blockchain, enhances capabilities in multi-operator environments.

Specifically for highly dynamic vehicular networks, Duo et al. [118] proposed a seamless handover scheme for hybrid vehicular networks (Cellular/IEEE 802.11p). This approach leverages a two-level SDN controller architecture and Mobile Edge Computing (MEC) to achieve its objectives. The SDN provides a global view and centralized control, maintaining transport-layer connections during handovers to adapt to dynamic topology changes. MEC proactively caches data at the new BS, thereby reducing packet loss and minimizing the delay in resuming standard communication. The results indicated significant improvements in network performance, including more stable throughput, especially in scenarios with frequent topology changes. Similarly, Okon et al. [119] present the synergy of SDN and blockchain technology to facilitate seamless roaming across multiple Mobile Network Operators (MNOs). They proposed using smart contracts on a blockchain for handover authentication, evaluating various consensus mechanisms. Their findings indicate that the Raft consensus mechanism offers superior performance, reducing end-to-end delays by 10.7% and 18.7% over Practical Byzantine Fault Tolerance (PBFT) and Paxos, respectively, and decreasing handover delays by 12.32% and 25.73% when femtocell spacing increases. This highlights the potential of combined SDN and blockchain approaches for robust and trustworthy mobility solutions in future multi-operator networks. A summary of SDN-based handover approaches is presented in Table 5.

4.3. Joint SDN and ML approaches for handover

The true power of intelligent HOM often emerges when SDN and ML are combined, forming synergistic frameworks that leverage the strengths of both paradigms. The centralized control and network-wide visibility of SDN provide the ideal platform for ML algorithms to gather comprehensive data, learn from global network states, and implement intelligent decisions across the entire infrastructure. This integration moves beyond localized optimizations to enable truly adaptive and Self-Optimizing Network (SON) functionalities for mobility [120,121].

For instance, SDN controllers can collect vast amounts of real-time network telemetry, including traffic patterns, load distribution, signal strength measurements, and user mobility profiles, which ML algorithms can then process. This global dataset allows ML models to develop more accurate predictions of future network conditions or user behavior than would be possible with local, isolated data. The insights derived from these ML models, such as optimal handover decisions, dynamic parameter adjustments, or predicted traffic surges, can then be swiftly and precisely enforced across the network by the SDN controller, overriding traditional, rigid configurations. This tightly coupled feedback loop creates an intelligent control plane that can react proactively to changing network dynamics, leading to significantly enhanced resource utilization, reduced signaling overhead, and a superior QoE for users [121–123].

Researchers often focus on developing comprehensive architectures where an ML module, either residing within the SDN controller or communicating with it, performs the intelligence. At the same time, the SDN infrastructure handles the data collection and policy enforcement.

Table 5
Summary of SDN-based handover approaches in B5G HetNets.

Reference	Problems addressed	Approach	Key findings/Results	Year
[118]	Frequent network topology changes in Vehicular Ad hoc Networks (VANETs) due to high vehicle mobility.	SDN (two-level controller architecture) and MEC for proactive data caching.	Improving network performance, reducing data loss, and minimizing delay.	2020
[69]	Latency, HOFs, frequent handover, and ping-pong effect in dense/ultra-dense B5G small cells.	SDN-based Multi-criteria HOM using Entropy-based SAW method (using Bandwidth (BW), user density, SINR).	Achieved 15% improvement in handover delay, 48% in blocking probability, and 22% in throughput compared to conventional LTE handover.	2021
[116]	Signal degradation on feeder-links in Extremely High Frequency (EHF) satellite networks; inefficient “on-off” SGD traffic re-routing.	SDN implementation for SGD management with “graceful degradation” logic based on SNR thresholds.	Achieved a 40% gain in aggregated capacity by optimizing resource exploitation and maximizing overall operational capacity in HTS systems.	2021
[67]	Decentralized HOM in traditional LTE networks and improving UE mobility.	SDN-based centralized handover solution for LTE networks, with SDN controller managing flow entries.	Reduces handover delay and increases data rate, showing improved performance through centralized control.	2022
[117]	Handover issues in HetNets regarding QoS, inaccurate target PoA selection, and high signaling overhead.	SDN-H framework, shifting handover cost to SD-Switch/Controller; uses multi-parameters (SINR, delay, BW, UE trajectory, UE speed).	Improved performance in reducing handovers, packet delay/loss ratio, and average signaling messages overhead (over 75% reduction).	2023
[119]	Seamless roaming and efficient handover across multiple MNOs; trust-related issues.	Blockchain-Enabled SDN Architectures, integrating SDN and blockchain with smart contracts for handover authentication.	Raft consensus showed superior performance, reducing end-to-end delays (10.7%/18.7%) and handover delays (12.32%/25.73%) over PBFT/Paxos.	2024

Such integrated frameworks are crucial for implementing Intent-Based Networking (IBN) concepts in MM, where high-level service requirements (e.g., “ensure uninterrupted low-latency video streaming for this user”) are translated by the ML component into specific handover policies and then dynamically executed by the SDN plane. These joint approaches are particularly beneficial for complex inter-RAT and inter-layer handovers in HetNets, where a global orchestration capability is vital [124].

Several recent studies highlight the effectiveness of integrating SDN and ML for handover optimization. For example, Shayea et al. present a centralized SDN controller, empowered by AI algorithms in [12], in order to achieve significant improvements in handover performance by optimizing LB and reducing HOFs in ultra-dense B5G environments. Their work emphasizes the role of AI in providing a holistic view for decision-making across diverse network elements. Similarly, Liu et al. [125] propose a joint self-optimization method that combines RL with Fuzzy Logic within an SDN-enabled framework. This approach allows for dynamic adjustment of handover parameters to minimize ping-pong effects and improve overall network throughput, showcasing how ML can refine traditional handover algorithms under SDN control. Kwong et al. [126] present an autonomous Handover Parameter Optimization (HPO) scheme that leverages Deep Deterministic Policy Gradient (DDPG), an advanced RL technique, integrated with SDN principles. Their solution enables proactive and intelligent adjustment of HCP, leading to reduced unnecessary handovers and improved network stability in complex B5G scenarios. This work exemplifies how SDN provides the necessary infrastructure for deploying sophisticated ML models that learn and adapt in real-time.

Another promising direction is seen in multi-operator networks. For example, Okon et al. examined the integration of SDN with blockchain technology to facilitate seamless roaming and handover across multiple MNOs [119]. In their work, they presented the underlying SDN architecture that provides the programmable control plane essential for integrating advanced authentication and management mechanisms, which ML-driven insights can further enhance. The key findings are to reduce delays and improve performance in complex multi-operator handover scenarios by applying the integrated frameworks. Thus, the synergy between SDN and ML provides a robust foundation for developing highly adaptive, intelligent, and self-optimizing MM solutions that can meet the stringent demands of B5G mobile networks.

4.4. Other advanced handover paradigms

Several other advanced handover paradigms are being explored to address specific challenges and enhance mobility in B5G mobile networks. These approaches often incorporate elements of intelligence, context-awareness, or novel architectural designs to move beyond traditional reactive, signal-strength-based handovers. Context-aware handovers represent a significant advancement, moving beyond simple signal strength to incorporate a broader range of contextual information. This can include factors such as user velocity, current service type (e.g., distinguishing between URLLC, eMBB, or mMTC requirements), device capabilities, battery status, and user preferences. Haijun Zhang et al. [127] highlighted that integrating contextual data, such as traffic conditions and user QoS requirements, can lead to more intelligent mobility decisions in highly dynamic environments. Similarly, Hsiao-Wen Kao et al. in [128] highlighted the importance of QoE-driven context, accounting for factors such as application type and user behavior to ensure seamless service delivery. The network can make more intelligent handover decisions that prioritize specific service requirements or optimize for energy efficiency, rather than just maximizing signal strength. For example, a user streaming high-definition video might be kept on a macro cell even if a nearby small cell offers a slightly better signal, if the macro cell can guarantee consistent throughput and avoid frequent, disruptive handovers.

Predictive handovers are a broader concept that focuses on anticipating future network states or user locations before handover attempts occur. This proactive approach aims to prepare the target cell resources, pre-establish connections, or pre-configure beams (especially vital in mmWave networks) to minimize interruption time and reduce the likelihood of HOF. Panitsas Ioanniset et al. [129] employed a deep and transfer learning method to predict user movement and network conditions, enabling truly proactive handover in future wireless systems. The goal is to initiate the handover process at the most opportune moment, rather than reactively when the serving signal has already deteriorated significantly. This proactive preparation is particularly beneficial for high-mobility scenarios, where rapid changes in radio conditions can quickly lead to service degradation. Furthermore, for mmWave deployments, sophisticated beam prediction algorithms are crucial. Abdulkadir Kose et al. utilized the RL approach for dynamic beam switching and HOM, relying on accurate beam prediction to maintain connectivity in highly directional environments, as described [130].

Furthermore, novel architectural designs and protocol enhancements continue to emerge to bolster handover performance. This includes advancements in multi-connectivity (like DAPS features discussed in 3GPP Release 16), where devices maintain simultaneous connections to multiple BSs. Vigneswara Rao Gannapathy et al. [131] studied the performance of DAPS handover, demonstrating its effectiveness in significantly reducing interruption time and enhancing reliability, especially crucial for URLLC applications in mmWave environments. Its role as an advanced handover paradigm is critical in ensuring ultra-reliable and seamless mobility by providing redundant paths and enabling intelligent LB across multiple links. Future research also explores more dynamic beam management strategies for mmWave and even Terahertz (THz) handovers, where the handover decision is closely tied to the steering and switching of narrow beams. Workeneh Geleta Negassa et al. [132] investigate advanced algorithms for dynamic beam management and handover optimization in THz bands, highlighting the challenges and solutions for maintaining connectivity in these ultra-high frequency scenarios. These solutions often rely on sophisticated positioning and prediction algorithms to maintain connectivity as the UE moves through a highly directional radio environment.

The evolution of HOM in B5G mobile networks is a continuous journey, moving toward increasingly sophisticated, self-governing systems that can adapt to the diverse and demanding requirements of future mobile communications.

5. Mobility and handover management challenges

MM particularly HOM presents formidable challenges in B5G HetNets due to the escalating number of users and the ever-rising demands for high data rates, diverse applications, and seamless communication. While emerging wireless technologies and sophisticated network architectures are instrumental in meeting the requirements of future wireless networks, each introduces specific complexities that pose significant hurdles for efficient mobility, especially for the handover decision optimization problem. This section delineates the fundamental research problems associated with key emerging technologies and paradigms that directly impact HOM in future wireless networks.

5.1. Small cell deployment

Future wireless networks are characterized by the imperative to provide ubiquitous coverage and significantly higher capacity to accommodate burgeoning data traffic. Small cell deployment emerges as a primary enabler, fundamentally transforming traditional network architectures into HetNets. These low-power nodes, encompassing relays, femtocells, and picocells, can be incorporated into networks in various configurations: non overlapping deployments to extend coverage into dead zones; overlapping deployments to enhance network capacity by offloading traffic from macrocells and improving QoS; and dense deployments to tackle ultra-high data traffic in localized areas. Conversely, sparse deployments can increase overall capacity while minimizing interference between nodes. Small cells also serve specific purposes, like providing superior indoor connectivity, as is the case with femtocells. Furthermore, deployments can be classified by frequency bands: intra-frequency, where small cells and macrocells operate on the same carrier frequency, or inter-frequency, where they utilize different bands.

Despite HetNets' undeniable benefits in boosting capacity and coverage, the proliferation of small cells introduces distinct challenges for HOM. The handover process between small cells and macrocells becomes an intricate problem due to their disparate signal transmission environments and varying cell radii. For instance, the smaller cell radius of femtocells, coupled with their lower transmission power compared to macrocells, inherently leads to an increased number of handovers, including frequent unnecessary handovers and the undesirable ping-pong effect. These rapid and often redundant transitions

significantly escalate signaling interactions within the B5G core network, involving extensive communications between the UE, serving BSs, and target BSs. Such heightened signaling directly contributes to increased handover delays and a reduction in effective data throughput, a problem exacerbated by the unique features of femtocell handovers, such as specific access modes and richer measurement report data [133, 134].

Moreover, interference presents a critical challenge, particularly in intra-frequency deployments where small cells and macrocells share the same carrier frequency. This can lead to unpredictable radio frequency conditions, especially at the cell boundaries of indoor-deployed small cells, which are affected by interference from outdoor macrocells. While LB is a key advantage of small cell deployment, promoting handovers from overloaded cells to other less loaded cells, as shown in Fig. 4, this might occur even if it means operating under lower signal quality for the UE. Before handover execution, accurate cell detection and discovery are essential. When macro and small cells operate on separate carrier frequencies (inter-frequency deployment), the UE must often switch its communication frequency to perform measurements and generate reports. These "measurement gaps" lead to performance losses, increased power consumption for the UE, and reduced maximum throughput [133]. Consequently, the strategic deployment of HetNets, while vital for B5G capacity, introduces a diverse set of challenges in HOM that must be meticulously addressed to enhance user experience.

5.2. High-speed users

The increasing deployment of high-speed trains and vehicular networks worldwide has led to a significant rise in the speed of mobile users, profoundly complicating HOM in HetNets, as a large number of handovers will occur [135]. High-speed mobility fundamentally degrades link quality due to rapid and frequent changes in radio conditions, negatively impacting user experience. Traditional A3 event-based handover algorithms, designed for slower mobility, prove unsuitable for high-speed users, as signal quality deteriorates too rapidly, triggering a higher number of handovers. The problems stemming from high-speed mobility are diverse, encompassing too early handovers, too late handovers, unnecessary handovers, ping-pong handovers, and handovers to the wrong cell [136]. While advancements like velocity-based self-optimization handover schemes [137] and Bayesian regression-based handover decision schemes [138] have been proposed to mitigate these issues by predicting cell boundaries and reducing RLF probability, the efficient accomplishment of lower HOF and RLF rates in real-world high-speed scenarios remains an open challenge.

A distinct set of challenges arises when mobile users are inside vehicles, such as train wagons. The metallic body of such vehicles introduces significant signal penetration loss, severely weakening external signals. This, combined with the inherently high-speed movement, results in frequent handovers and considerable difficulty in effective beam management, especially in small cell deployments. Despite various novel approaches developed to cope with high-speed users, such as enhanced handover algorithms for smart railways that evaluate B5G technologies like massive MIMO, beamforming, network slicing, and mmWave [139], or the use of mobile relays on train surfaces to mitigate penetration loss [140], these environments continue to pose complex HOM problems. The preference of users for frequently visited cells, even if they result in degraded handover delay, further complicates the optimization process. Overall, the challenges associated with high-speed mobility in B5G mobile networks continue to degrade link quality and user experience, demanding more robust and predictive handover solutions.

5.3. Signal losses

The 5G telecommunication standard's ability to utilize mmWave signals, while offering wider BW and higher carrier frequencies for increased throughput, introduces substantial challenges related to signal propagation. The mmWave signals suffer from significantly higher free-space path loss and shadowing loss compared to lower-frequency bands. This inherent characteristic results in a narrow coverage area, making mmWave signals highly susceptible to blockage by various objects, including foliage, buildings, and even the human body. In crowded environments such as offices, conference rooms, or auditoriums, the susceptibility to blockage can lead to precarious link quality. This intermittency in signal strength directly triggers more FHOs, which can degrade user experience and consume network resources. Although solutions like multi-agent deep RL frameworks have been proposed to increase network throughput and reduce handover events by intelligently managing resources and mobility [141], effectively ensuring stable connectivity in dynamic mmWave environments, especially with moving UEs and unpredictable blockages, remains a significant research hurdle. The rapid fluctuations in mmWave channel conditions also complicate the collection of reliable measurement data for ML models, adding another layer of complexity to developing truly adaptive handover solutions.

5.4. Dual connectivity

DC and multi-connectivity have been widely adopted in 5G to enhance network capacity and improve reliability, particularly in the context of sensitive mmWave bands susceptible to channel intermittency, transmission losses, fast variations, and blocking by building materials. Multi-connectivity allows a UE to maintain simultaneous connections with multiple cells (e.g., a macrocell and one or more small cells), providing alternative paths for data transmission in case one link is blocked. DC, a more advanced form, commonly involves concurrent connections to an LTE eNB (acting as a master node for control plane establishment and user plane fallback) and a mmWave gNB (for enhanced data rates). The LTE eNB can also play a crucial coordinator role, potentially leveraging ML algorithms to forecast channel quality and select optimal secondary nodes [36].

Despite their benefits in providing robust connectivity and practical mmWave band usage, DC and multi-connectivity introduce new layers of complexity into MM. These complex handover cases arise from users maintaining simultaneous connections across different carrier frequencies (e.g., 4G LTE and 5G NR), resulting in novel handover scenarios and an increase in overall handover probability [142]. The requirement for UEs to switch communication frequencies to observe and form measurement reports during inter-frequency handovers, inherent in DC, further complicates the process. Consequently, DC is foreseen to significantly increase the complexity of HOM in B5G HetNets, leading to higher signaling overheads, increased battery energy consumption for the user, and the challenge of inefficient resource allocation across multiple cells for a single user device. Managing the coordination between master and secondary nodes, ensuring seamless data path switching, and optimizing resource distribution across diverse RATs in a dynamic environment are ongoing research challenges.

5.5. Self-optimization function conflicts

SONs are conceptualized as adaptive and autonomous network models designed to simplify network management by enabling continuous learning and operation without extensive human intervention [143]. A fundamental component within SONs is the suite of self-optimization functions, which encompasses various optimization tasks across different network layers. HPO is a crucial function that dynamically adjusts HCP parameters, such as Hysteresis and TTT, to ensure robust and efficient handovers. For instance, increasing TTT can prevent HOFs in

specific scenarios. Concurrently, the LB function optimizes traffic distribution by shifting overload from congested cells to adjacent ones, often by modifying handover parameters to steer UEs toward less-utilized cells.

A significant research challenge arises from the inherent conflicts between these self-optimization modules, particularly HPO and LB, as they often influence overlapping network parameters. For example, an HPO function might aim to decrease hysteresis to reduce HOFs at cell edges, while an LB function might simultaneously increase hysteresis in an overloaded cell to deter new handovers. These conflicting objectives, executed under a seemingly centralized control over the network, can lead to suboptimal or even hazardous actions for individual user devices and overall network performance [144]. The challenge lies in developing intelligent coordination mechanisms and multi-objective optimization frameworks that can resolve these conflicts in real-time, ensuring that optimization for one KPI (e.g., HOF rate) does not inadvertently degrade another (e.g., load distribution) in a dynamic HetNets environment. This necessitates sophisticated learning algorithms capable of understanding complex interdependencies and achieving a global optimum across conflicting objectives.

5.6. Security issues

The advent of B5G technologies, particularly their support for a massive number of diverse IoT devices and various network types, has made security a paramount concern in MM, demanding innovative solutions to maintain high QoS [145,146]. In the B5G handover process, a handover key mechanism is employed to ensure data integrity and facilitate a seamless connection during transitions [147]. However, maintaining forward security with these keys presents a significant challenge. In 5G and B5G architectures, the serving gNB typically derives the target base station key (K_{gNB}^*) from the current K_{gNB} using a horizontal key derivation process involving a Next Hop (NH) parameter or a chaining counter [148]. This mechanism ensures that the target base station does not share its root keys with the source. Hence, managing these FHOs across dense HetNets needs high computational efficiency and robust security management in order to prevent signaling delays or potential vulnerabilities during rapid transitions.

More to this, the sheer diversity of networks resulting from the integration of various IoT devices further complicates security management within B5G HetNets. While traditional cryptographic mechanisms were often sufficient for managing the security procedures of IoT devices in previous generations, the massive scale and heterogeneous nature of B5G deployments demand more resource-efficient and lightweight security architectures. Existing mechanisms may incur excessive resource utilization and computational load, potentially impacting the low-latency requirements crucial for high-speed trains and real-time communication. Research is actively exploring more sophisticated, lightweight, and adaptable security schemes, including distributed ledger technologies (e.g., blockchain) and zero-trust architectures for mobility, to ensure robust authentication, authorization, and data privacy during frequent and complex handovers in future wireless networks.

An additional challenge arises from the interaction between handover security procedures and the strict latency requirements of URLLC services. During handover execution, the network must perform security operations such as key derivation, security context transfer, and authentication signaling between the serving and target BSs. Although these procedures are essential for maintaining communication security, they introduce additional control signaling and processing delay.

For URLLC applications such as industrial automation, autonomous driving, and mission-critical communication, end-to-end latency requirements are extremely stringent. Consequently, excessive signaling delays during security key exchange may degrade the continuity of service during mobility events. Recent studies therefore emphasize the need for lightweight authentication mechanisms and fast security context transfer techniques in order to support seamless mobility in latency-sensitive network slices [149,150].

5.7. Contradictions and dependencies

The number of self-organizing network functions has increased, along with the associated conflicts and interdependencies. Integrating multiple functions can lead to goal conflicts because they rely on the same performance metrics, which can cause conflicts. For instance, mobility robustness optimization and LB optimization are interconnected, as both utilize the HOM for adjustments [151]. However, when joint functions with differing objectives share the same KPI, there is a risk that the function with the highest priority will dominate the others. Additionally, the trade-off between handover parameters needs further investigation to develop an effective handover decision algorithm. Addressing too-late handovers may result in handover ping-pong due to its conflict with the TTT interval. Similarly, reducing RLF requires a lower HOM, while minimizing handover ping-pong requires a higher HOM.

However, an additional coordinating entity is required to resolve potential conflicts between these individual functions, helping to reduce overall system complexity. Its primary role is to adjust network parameters to serve various objectives while maintaining high-quality connections between users and BSs [152]. However, when both functions independently attempt to optimize the same parameter without a defined priority, conflicting decisions may occur. This dual optimization process introduces the risk of inconsistency, necessitating the implementation of mechanisms to address such conflicts.

5.8. Load Balancing (LB) issues

Mobility LB in future mobile networks, such as B5G and beyond, presents a significant challenge due to the increasing complexity and heterogeneity of network environments. These networks comprise a diverse mix of macro cells, small cells, mmWave BSs, and even aerial or satellite nodes, each with varying coverage areas and capabilities [153]. Balancing user traffic across such diverse infrastructures becomes challenging, especially when users are mobile and services have different QoS requirements. Additionally, traffic patterns are becoming more dynamic and unpredictable due to high user density, varied application demands, and the rise of machine-type communications [154]. Moreover, achieving a balance between energy efficiency and network performance is another concern, as LB actions might activate low-power cells, increasing energy consumption. While AI and ML offer promising solutions to enhance mobility LB by enabling predictive and adaptive decision-making, they require reliable, real-time data and robust models. Therefore, addressing balancing issues is essential for ensuring seamless connectivity, optimal resource utilization, and enhanced user experience in future mobile networks.

5.9. Real-time services

Real-time services require a seamless handover within a very short timeframe to prevent service interruptions or disconnections. HIT poses a critical challenge for real-time services and low-latency applications in mobile networks. This interruption refers to the short time period during a handover when a user device switches its connection from one cell to another and temporarily loses the data link. However, for applications such as voice over IP (VoIP), video conferencing, online gaming, and remote surgery, even a millisecond delay or packet loss during this transition can significantly degrade user experience or lead to service failure. Furthermore, the demand for URLLC in B5G further strengthens this issue, as such applications require end-to-end latencies of less than one millisecond with near-zero packet loss [87]. Moreover, as signal attenuation increases and cell coverage areas become smaller, mobile nodes will require more FHOs to connect to new BSs. This requires the rapid and secure establishment of connections to ensure uninterrupted service. Without effective handover optimization algorithms, this challenge could become a major limiting factor, particularly

for services that rely on low end-to-end latency [155]. Additionally, traditional handover mechanisms, particularly in HetNets with varying coverage and backhaul conditions, may not meet these high requirements. However, reducing HIT while maintaining handover success and network stability is a complex task. It requires enhancements in Radio Resource Management (RRM), faster signaling procedures, and potentially the use of predictive handover algorithms based on AI.

6. Future research directions

The continuous evolution of B5G mobile networks toward 6G necessitates a proactive approach to HOM, aiming not only to alleviate radio link interruptions and ensure superior link quality but also to anticipate and adapt to unprecedented network complexities and service demands. Future studies will focus on developing fundamentally new handover mechanisms and significantly enhancing existing processes by establishing deeper associations between diverse handover KPIs and intricate network parameters, often modeled using advanced data-driven techniques. This section outlines promising future research directions, emphasizing how intelligent paradigms will evolve to tackle the next generation of mobility challenges.

6.1. Cognitive and intent-based mobility management

The future of HOM lies in achieving fully autonomous and cognitive orchestration, moving beyond current intelligent solutions to truly self-governing networks. SDN, with its foundational concepts of control and data plane decoupling, centralized visibility, and network programmability, will serve as a crucial enabler for this evolution. While SDN has already demonstrated benefits in simplifying network management and enabling dynamic reconfiguration for handover decision optimization, its future trajectory in mobility will focus on realizing IBN. This involves translating high-level business objectives and user experience requirements (e.g., “ensure uninterrupted 8K video streaming for VIP users” or “maintain ultra-low latency for autonomous vehicle platoons”) directly into automated, real-time handover policies that require no manual intervention.

Future research will explore how SDN controllers, augmented with advanced AI, can dynamically orchestrate handover processes across increasingly fragmented HetNets, encompassing diverse RATs, network slices, and edge computing infrastructures. This includes the development of more sophisticated programmable data planes (e.g., leveraging P4 language) to enable finer-grained control over traffic forwarding during handovers, ensuring service continuity and optimal resource utilization. Furthermore, the integration of SDN with Open Radio Access Network (O-RAN) architectures presents a significant future direction. O-RAN's open interfaces and disaggregated components will enable greater flexibility and vendor neutrality in deploying and managing advanced handover functionalities, allowing for more agile development and deployment of intelligent handover control loops, and facilitating real-time data collection and policy enforcement directly at the RAN intelligent controller (RIC).

6.2. Advanced ML paradigms for proactive and resilient mobility

While ML has already proven its efficacy in various aspects of HOM, from prediction to parameter optimization, future directions will explore more sophisticated ML paradigms to enhance adaptability, robustness, and efficiency. The escalating growth of mobile users and the intrinsic diversity of B5G HetNets necessitate highly adaptive, data-driven handover algorithms that can operate with minimal human intervention [156].

One key future direction is the application of Federated Learning (FL) to handover optimization. Given the privacy concerns associated with centralizing vast amounts of user mobility data, FL enables the distributed training of ML models across multiple UEs or BSs without

sharing raw data, allowing for privacy-preserving, collaborative learning for handover decision-making, such as predicting mobility patterns or optimizing local handover parameters. Another critical area is Explainable AI (XAI) for handover. As ML models become more complex (e.g., DNNs making critical handover decisions), understanding why a particular handover decision was made becomes crucial for network operators to build trust, troubleshoot issues, and ensure regulatory compliance. Future research will focus on developing XAI techniques that provide transparency and interpretability for ML-driven handover algorithms.

Furthermore, Graph Neural Networks (GNNs) are emerging as a powerful tool for MM. Unlike traditional ML models that treat data points independently, GNNs can directly leverage the inherent graph-like structure of cellular networks (where nodes are BSs and edges represent connectivity or proximity). This enables GNNs to make more informed handover decisions by considering global topological relationships and traffic flows, resulting in more robust and network-aware optimizations. The combination of RL with digital twins and advanced simulation environments offers another promising avenue. By creating high-fidelity virtual replicas of the network, RL agents can explore and learn optimal handover policies in a risk-free environment, allowing for rapid iteration and identification of highly performing strategies before real-world deployment. Few-shot and meta-learning techniques will be crucial for enabling handover algorithms to adapt rapidly to new network environments, new types of UEs, or sudden changes in traffic patterns with minimal training data, a vital capability in highly dynamic and unpredictable B5G mobile networks.

Another emerging direction is the use of Generative Artificial Intelligence (GAI) in wireless network optimization. Unlike conventional ML models that mainly perform classification, regression, or policy learning, generative models can learn the statistical structure of network data and create new samples that follow similar distributions. This property is useful in mobile networks where collecting large and diverse mobility datasets is often difficult.

Although the direct use of GAI for HOM is still at an early stage, recent studies show that generative models can support next-generation wireless optimization by generating realistic network states, enabling offline exploration of unseen scenarios, and assisting proactive decision-making in large-scale radio environments [157]. In the context of MM, such capability may help create synthetic radio measurements, user mobility traces, and traffic patterns for training handover prediction and parameter optimization models. Large generative models are also increasingly viewed as promising tools for telecom automation and intelligent network control in future systems [158]. Therefore, GAI is expected to become an important future research direction for mobility-aware network management in 5G and 6G wireless networks.

In MM research, generative models may assist the training of handover decision algorithms by generating realistic radio measurements, user mobility traces, and traffic patterns. These synthetic datasets can improve the robustness of ML models used for handover prediction and parameter optimization. Generative models can also support digital twin environments where RL agents are trained using realistic network scenarios. Although the use of GenAI in handover optimization is still limited, recent studies on AI-enabled 6G networks indicate that generative models may become an important tool for future MM frameworks [159,160].

6.3. ISAC for mobility-aware networks

ISAC is becoming an important enabling technology for future 6G wireless systems. It allows the network to use the same radio platform for data transmission and environmental sensing. This unified operation can provide additional context about user movement, surrounding objects, blockage conditions, and propagation changes. Such information is highly valuable for MM because handover decisions in dense

and high-frequency networks are strongly influenced by fast channel variation and sudden signal obstruction.

One promising direction is the use of ISAC in vehicular communication systems. In high-mobility environments, conventional handover procedures rely mainly on radio measurements collected from serving and neighboring cells. However, sensing-assisted communication can further improve mobility support by tracking the motion of vehicles and detecting nearby objects in real time. Recent studies on joint communication and radar for vehicular systems show that integrated waveforms can support cooperative perception and enhance situational awareness in future Vehicle to Everything (V2X) networks [161]. This capability can help future cellular systems anticipate mobility changes and improve handover preparation in fast-varying road environments.

Another important research direction is ISAC-based environmental imaging. By exploiting wireless channel information and advanced signal processing methods, future networks may reconstruct environmental features and identify possible obstacles around users and infrastructure. Recent work in this area shows that wireless signals can be used for high-resolution imaging and environment reconstruction in 6G mobile networks [162]. For MM, this type of environmental awareness can be useful for predicting signal blockage, identifying vulnerable links, and enabling proactive handover before severe quality degradation occurs.

ML is also expected to play a major role in ISAC-enabled mobility support. Learning-based sensing methods can estimate channel and spatial parameters with high precision and lower processing burden. Recent studies have shown that DL models can assist ISAC systems in parameter estimation and sensing-oriented signal interpretation [163, 164]. In future mobile networks, such learning-based sensing frameworks may improve mobility prediction, beam tracking, and target cell selection, especially in complex heterogeneous deployments where conventional handover rules are often insufficient.

Security and beamforming design are also critical in ISAC systems. Since sensing and communication share the same spectral and hardware resources, the network must jointly optimize reliability, sensing performance, and communication secrecy. Recent research on secure beamforming and RIS assisted ISAC systems highlights the importance of joint optimization under strict wireless constraints [165]. These issues are directly relevant to future MM because secure and reliable beam control will influence the continuity of service during handover in B5G and 6G cellular networks.

Overall, ISAC introduces a new dimension to mobility-aware wireless networking. By combining sensing, communication, and intelligent signal processing, future heterogeneous networks may support more accurate mobility prediction, earlier handover preparation, and more reliable service continuity in challenging propagation environments.

6.4. Other emerging technologies for handovers

Beyond the evolution of intelligent control, future research must also address new mobility requirements emerging in 6G wireless systems. In particular, the ability of legacy mobility protocols to support extremely low-latency handover operations remains an open question. Conventional handover procedures used in LTE and 5G networks involve several sequential stages, including measurement reporting, handover decision, context preparation, and execution signaling between serving and target BSs. Although these mechanisms have been progressively optimized in recent 3GPP releases, the resulting HIT typically remains on the order of several milliseconds. However, many envisioned 6G services, such as immersive extended reality, autonomous systems, and tactile internet applications, may require mobility support approaching sub-millisecond service continuity. Consequently, future research must explore new mobility paradigms capable of reducing signaling delay and improving service continuity in highly dynamic wireless environments.

Reconfigurable Intelligent Surface (RIS): The use of extremely high frequencies, including millimeter-wave and terahertz bands, will introduce severe propagation challenges such as signal blockage and rapid beam misalignment. RIS can act as programmable reflectors that dynamically redirect radio signals toward intended receivers. By intelligently controlling the propagation environment, RIS may assist beam tracking and link recovery during user mobility. However, this capability also introduces new challenges for MM, since handover decisions must consider both the connection with BS connectivity and the configuration state of nearby RIS elements.

Non Terrestrial Networks (NTN) and Multi-Layer Mobility: Future mobile networks will integrate terrestrial infrastructure with satellite systems and High-Altitude Platform Station (HAPS). This multi-layer architecture will create new mobility scenarios where user devices may transition between ground-based cells, aerial platforms, and satellite coverage. Such mobility patterns introduce challenges related to propagation delay, coverage discontinuities, and rapidly changing link characteristics. As a result, seamless handover across terrestrial and non-terrestrial networks will require advanced mobility coordination and predictive handover mechanisms.

Vehicle to Everything (V2X) Communication Evolution: Next generation vehicular communication systems will support highly dynamic mobility scenarios involving connected vehicles, roadside infrastructure, and cloud services. Future V2X applications, including cooperative driving and autonomous vehicle coordination, require ultra-reliable and low-latency connectivity [166]. In these environments, handover mechanisms must operate predictively and cooperatively in order to maintain continuous communication links. Leveraging vehicle sensor information and cooperative awareness messages may enable proactive handover decisions that improve connectivity reliability in high-speed mobility scenarios [167,168].

Integrated Access and Backhaul (IAB) Handover: IAB architectures allow wireless links to simultaneously support user access and backhaul connectivity between relay nodes and the core network. While this approach improves deployment flexibility in dense urban environments, it also introduces new mobility challenges. During handover, the network must coordinate user transitions across multiple wireless hops while maintaining both access connectivity and backhaul stability. Designing efficient handover procedures for IAB-enabled networks, therefore, requires joint optimization of access links and backhaul routing paths.

6.5. Resilience, security, and trust in intelligent mobility

Handover control is becoming more intelligent in modern cellular infrastructures. ML models are now used to assist mobility decisions in heterogeneous wireless environments. As a result, the resilience, security, and trust of these intelligent mechanisms become an important research topic in B5G and 6G cellular networks.

The use of learning based decision models may introduce new security risks. Malicious entities may attempt to manipulate the input data used by mobility algorithms. Such actions may force unnecessary handover operations or degrade the quality of connectivity. In extreme cases, they may even cause service interruption. Future studies must therefore investigate robust learning frameworks that can resist adversarial manipulation and maintain stable mobility decisions.

Intelligent mobility control requires large amounts of mobility data collected from UE and network elements. These data sets are useful for training predictive handover models. However, they also raise privacy concerns. Sensitive information about user movement patterns may be exposed if not handled properly. Future research should explore privacy preserving learning mechanisms that allow mobility optimization without revealing personal information.

Mobility decisions supported by learning models must remain reliable in real operational environments. Highly dynamic wireless conditions may affect the behavior of intelligent decision algorithms. It is therefore necessary to develop mechanisms that verify the correctness

of learning based handover decisions. In addition, fallback procedures must be available when the learning model produces unexpected results. Such mechanisms will help maintain stable mobility control in complex radio ecosystems.

Future communication infrastructures will also face new security risks introduced by quantum computing technologies. Current cryptographic mechanisms used for handover key exchange may become vulnerable to quantum attacks. Research on quantum resistant cryptographic techniques will therefore be important for protecting mobility procedures in future wireless infrastructures.

Overall, future smart handover mechanisms will depend on the integration of advanced learning techniques, flexible network architectures, and emerging radio technologies. At the same time, strong attention must be given to resilience, security, and trust in mobility control. These elements will be essential for maintaining reliable service continuity in highly dynamic next generation wireless environments.

7. Conclusion

Mobility support remains a central function in heterogeneous mobile networks. In Fifth Generation and beyond (B5G) Heterogeneous Networks (HetNets), UE frequently moves across macro cells, small cells, and different Radio Access Technologies (RATs). This dynamic behavior increases the complexity of Mobility Management (MM) and Handover Management (HOM) systems. Reliable handover procedures are therefore essential to preserve service continuity and stable connectivity. In this survey paper, we presented a comprehensive review of HOM mechanisms designed for B5G HetNet environments. We first examined the standardized mobility procedures defined in recent 3GPP specifications. We then discussed existing mobility optimization approaches including parameter adaptation, mobility robustness mechanisms, and coordinated mobility strategies. We mainly discussed the ML based mobility control where predictive models support adaptive handover decisions and anomaly detection in large scale networks. We also discussed several emerging technologies that may influence mobility frameworks in future cellular ecosystems. These include Integrated Sensing and Communication (ISAC), RIS, Non Terrestrial Networks (NTN), and Integrated Access and Backhaul (IAB) architectures. Such technologies may enable more proactive and context aware mobility decisions in next generation cellular networks. Despite these advancements, several challenges still remain open issues. For example, accurate mobility prediction in highly dynamic environments is still a challenge. The scalability of learning algorithms in dense network deployments also requires further investigation. Security management during handover procedures must also satisfy strict latency requirements for Ultra Reliable Low Latency Communication (URLLC) services. In the final section, we provided future research directions such as intelligent mobility architectures that integrate learning driven decision models, cross layer coordination, and emerging wireless technologies. These directions are important to support efficient handover operations in B5G and Sixth Generation (6G) cellular networks.

CRedit authorship contribution statement

Sajjad Ahmad Khan: Writing – review & editing, Writing – original draft, Visualization, Validation, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Waheeb Tashan:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Conceptualization. **Ibraheem Shayea:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Kerem Küçük:** Writing – review & editing, Validation, Supervision, Software, Project administration, Methodology, Formal analysis. **Sultan Aldırmaz-Çolak:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Methodology, Investigation, Conceptualization. **Shehzad Ashraf Chaudhry:** Writing – review & editing, Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Data curation. **Khalid Yahya:** Writing – review & editing, Validation, Software, Resources, Methodology.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used Grammarly Pro for language proofreading, clarity, readability, and typo correction. The authors also used Gemini, a large language model from Google, to improve conciseness and refine the text for adherence to the journal's formatting requirements. The authors reviewed and verified all content modified by these tools and take full responsibility for the accuracy, integrity, and scientific content of this publication.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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