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Review Paper

Handover management in ultra-dense 6G networks: A comprehensive review of challenges, emerging solutions, and future directions

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ABSTRACT

The sixth generation (6G) networks represent the revolutionary processes in the field of wireless networks, such as ultra-dense network (UDN) frameworks, multi-dimensional connectivity, and network automation procured by AI. Nevertheless, the high rate of small cell and heterogeneous network environment proliferation poses severe challenges in handover management that result in higher signalling overhead, latency, and service interruptions. This review paper investigates the latest handover management solutions in 6G UDNs with some of the most significant challenges being mobility prediction, resource, and security constraints. We especially examine the new solutions, such as machine learning (ML)-based mobility prediction models Long short-term memory (LSTM) and gated recurrent unit (GRU), reinforcement learning (RL)-based handover decision models, and split federated learning (SFL) of privacy-preserving optimization. Moreover, we will look at network-slicing integration and blockchain-based security solutions as an effort to ensure an efficient and dynamic handover procedure. The paper gives a methodological future study roadmap to optimisation of handover in ultra-dense 6G networks which synthesizes existing approaches with research gaps identified. These results point to the necessity to optimise the interactions between layers and coordinate network efforts by using artificial intelligence and the proactive handover paradigm to provide seamless, low-latency, and energy-efficient mobility management in future next-generation wireless networks.

1. Introduction

The sphere of wireless communications is experiencing blistering, which is why in such a way, sixth-generation (6G) networks are identified as the next critical stage of the development of world communication technologies. According to recent peer-reviewed work, the implementation of the fifth-generation (5G) infrastructure has been growing on a global scale, and research and engineering teams already start working on the development of the next generation of wireless networking, which is expected to launch operations by 2030 [1]. 5G networks are predicted to result in a considerable improvement of performance metrics, thus making available completely new classes of applications. The ongoing investigation is in the high-tech technologies. such as terahertz (THz) communication, visible light communication (VLC), large intelligent surfaces (LIS), as well as quantum communication techniques [2, 3]. Simultaneously, new network architectures and protocols are under development to support these new technologies. One of the key research directions focuses on the development of superior machine-learning tools, in particular, split federated learning (SFL), which aims to enhance the obstacles related to data confidentiality and efficiency [4]. At the same time, new mechanisms of handover are being researched, and proactive handover has proven to be one of the most promising approaches to providing smooth connectivity over high-mobility situations. Some of the available and prospective services and technologies relevant to the 6G ecosystem would include the following:

- Tera bits per second (Tbps) peak data rates.
- Sub-millisecond ultra-reliable low-latency communication.
- Gigantic number of connections Green, energy-efficient solutions.
- Learning-enabled intelligent networking Terrestrial, aerial, and satellite (TAS).
- Three-dimensional (3D) coverage [5–7].

Many new challenges have been introduced with the introduction of sixth-generation (6G) networks. They are complex and multifaceted issues that require much research and development efforts and interdisciplinary cooperation to mitigate them. According to scholars, 6G will not only provide significant improvements to the current communication services, but it will also trigger disruptive innovation in a broad range of industries, such as (but not limited to) healthcare, mobility, industrial production, and digital entertainment [8, 9]. The vision outlined above is gradually coming into focus, due to the expected contribution of 6G to the next generation of the global communication and technological ecosystem as an intermediary to a wide range of developments based on next-generation wireless infrastructure. Although the full implementation of 6G is a goal that can be achieved at some point in the future, its technical implementation, policy-related, and societal consequences are issues that will have to be addressed through the joint effort of researchers, regulators, and industry stakeholders [10]. The context-aware handover management in 6G networks represents a paradigm shift from traditional mobility management approaches. It leverages multidimensional contextual information beyond conventional metrics, encompassing user mobility patterns, application-specific QoS requirements, network load conditions, and energy efficiency considerations. This approach enables dynamic and proactive handover decisions, crucial in ultra-dense 6G environments, Fig. 1, where handover events are frequent, and decision windows are narrow [9].

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Nomenclature

B_{eff}	Effective Bandwidth
$b(v)$	Source slice
E_{sig}	Energy Consumed in signaling
E_{proc}	Processing Energy at the network nodes
E_{exec}	Energy consumed during handover execution
E	Total energy consumption related to handover
$f(t,\omega)$	Time-varying handover process (sec.)
K	Number of users sharing the same pilot
L	End-to-end latency
L_i	Latency components across n network layers
N_{HO}	Number of handovers
Ot	Output gate vector
$P(H)$	Overall handover performance
P_{fai}	Probability of handover failure.
R	Received power from the serving BS.
S	Reliability metric
T_i	Threshold for slice i
T_{HO}	Threshold (maximum acceptable cost) for slice i
$Tanh(ct)$	Handover interruption time
t_o	Hyperbolic tangent of the cell state
t_f	Initiation time-varying handover (sec.)
U	Completion time-varying handover (sec.)
θ_o	Non-dimensional velocity component X-direction
θ_i	Shared parameters
wb	Slice-specific parameters
U_i	Utility of slice i
W_i	Priority weight of slice i
EHO	Total energy consumption associated with handover
Abbreviations	
BS	Base Station
gNB	Next-generation node B
$SINR$	Signal-to-interference-plus-noise ratio
SNR	Signal-to-noise ratio
BER	Bit error rate
$URLLC$	Ultra-reliable low-latency communications
$eMBB$	Enhanced mobile broadband
$mMTC$	Massive machine-type communications
Greek Symbols	
α_i	Corresponding weighting factors
ε	Neighborhood of point
$\forall_i$	Specifies the constraints
α,β,γ	Scaling factors reflecting of each component
v	Velocity
θ	User movement direction
λ	BS density
$\hat{Y}$	Vector of relevant network and user metrics at time
σ	Activation function
Subscripts	
$\hat{h}$	Estimated channel
h	True channel
$\odot$	Hadamard product used to elements

By tailoring handover mechanisms to individual user needs and network conditions, context-aware management enhances overall Quality of Experience (QoE) and facilitates the realization of user-centric 6G network operations. The integration of machine learning (ML) techniques in 6G handover management processes marks a significant progress towards intelligent and adaptive networks. ML algorithm, including supervised learning, reinforcement learning, and intensive teaching architecture, provides powerful tools to process the vast amounts of multidimensional data contained in reference-utterance systems. These techniques enable user dynamics patterns and accurate predictions of network conditions, which facilitate active and customized handover decisions [5].

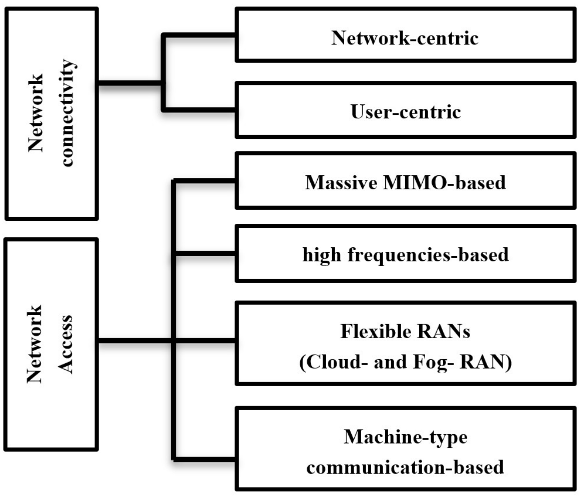

Figure 1. Taxonomy of ultra-dense networks regarding several criteria [11].

Advancement in capturing advanced nerve network models, such as RNN and LSTM, user dynamics, and complex temporary dependence in network dynamics. In addition, federated learning paradigms address the concerns of privacy, which enable cooperative learning in district network institutions, which is important to develop a strong and general handover model [12]. Network Slicing in Handover Management enhances flexibility in the capability to control resources allocated to a particular service and offers the flexibility to slice the network for a dedicated service, all of which improves the 6G handover management process. It allows the creation of multiple virtual networks over a common shared physical infrastructure that can dynamically adapt and allocate resources to different services [13]. With the slice-covered dynamics of network slicing, the handover management can deploy certain types of strategies with the objective that the user connects with the corresponding appropriate set of network slices that can provide that service (i.e, defined at the slice level). It is crucial for some use cases when the QoS is very strict, like URLLC and eMBB applications [14]. where maintaining specific service requirements during handover is critical. The coordination between network slicing and ML-powered handover management enables highly adaptive mobility solutions by predicting slice resource requirements and optimizing slice selection during handover events. The ML algorithm predicts slice resource requirements undefined and optimizes slice selection during handover events in the multi-slice environment [15]. This integrated approach enhances the efficiency and reliability of handover processes; it provides truly adaptive and user-focused solutions, as 6G paves the way for network operations. The advent of ultra-dense networks in the new 6G era has drawn the concern of the importance of handover management into focus. Small cells have become extremely dense, up to small orders such as 100-1000 base stations per km^2 in some cases, and conventional paradigms of the process of handover are under intense pressure. The importance of effective handover management here is both multifaceted and profound, which is overwhelmed by many aspects of critical issues of network enhancement and user experience of equipment [11]. First of all, the number of access points within UDNs is high, which significantly raises the frequency of handovers [16]. This also means that there are frequent handovers typically taking place in just a few seconds when users transit the congested urban landscape, and as such, the signalling overhead is increased, service satisfaction is reduced, and the amount of energy used is also increased. The consequences of the inappropriate management of handovers in the described situation are not only temporary system conduct but rather a prolonged effect that can destabilize networks and deteriorate the quality of services. In addition, ultra-dense networks (UDNs) have a complicated handover decision-making process that has rapidly increased its complexity [17]. Standard measures like Received Signal Strength (RSS) cannot be used in areas with a high number of candidate cells that provide a similar quality of signal [18]. This means that they need to undergo a paradigmatic change to multi-pollination, reference incredible strategies of handover, and include parameters like network load balance, application-specific QoS needs, energy savings, and complex user mobility schedules. The heterogeneous networks of ultra-dense networks (UDNs) consisting of macro cells, Micro cells and a diversity of radio access technologies (RATs) highlight the importance of a seamless vertical and inter-RAT handover [19]. Handover process is a critical area to ensure that service continuity is guaranteed through the various elements of the network and also to ensure successive generations of wireless technology can co-exist of more than one generation of wireless technologies. The role of efficient management in ultra-dense networks (UDNs) in terms of the handover process attracts considerable academic interest. The strength of the network components and the overall decrease in energy use related to a limited number of handovers can be consequential. Smart handover plans that reduce the use of the needless transition and maximize the utilization of the sleep mode in small cells can contribute significantly to the goals of green communication in the 6G ecosystem [20]. Also, the role of handover management is aggravated in UDNs by the diverse and challenging use scenarios that are expected in 6G. Figure 2 shown the Handover concept in a deployed heterogeneous networks with 5G and 6G technology, Ultra-reliable low-latency communications (URLLC) for mission-critical applications, enhanced mobile broadband (eMBB) for high-data-rate services, and massive machine-type communications (mMTC) for Internet of Things (IoT) scenarios each present unique challenges and requirements for mobility management, (HetNet) Multi-tiered network architecture integrating macro and small Cell, crucial for 6G network densification and spectrum efficiency optimization, (MIMO)Multi-antenna technology enhancing spectral efficiency and link reliability, with massive MIMO systems envisioned for 6G networks, (BER) Quantitative measure of transmission errors, with ultra-low BER ($\leq 10-9$) essential for 6G URLLC applications, (SNR) Ratio of signal power to noise power, critical for achieving terabit-per-second data rates in 6G systems, (SINR) Extension of SNR incorporating interference, pivotal for handover optimization in ultra-dense 6G networks, (Seamless Handover) Uninterrupted service continuity during inter-cell transitions, requiring sub-millisecond latency and minimal packet loss in 6G, (Mobility) User movement across network cells, necessitating advanced predictive handovers and trajectory-aware resource allocation in 6G, (gNB) Evolved base station for 6G networks, supporting higher frequency bands and advanced features like integrated sensing and communication [20].

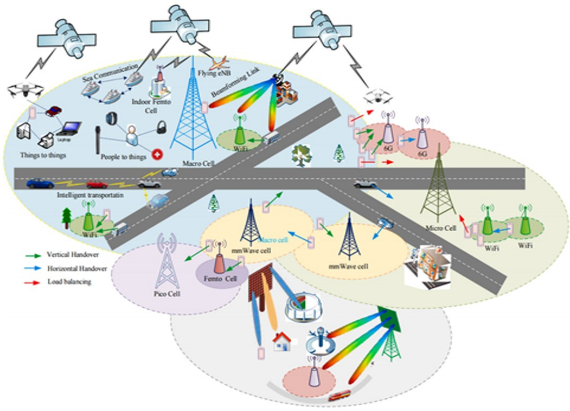

Figure 2. Handover concept in a deployed heterogeneous network with 5G and 6G technology [21].

In conclusion, handover management in ultra-dense networks plays a fundamental role in realizing the full potential of 6G technologies. In 6G networks, this line of research is particularly important due to the increasing complexity of security requirements and emerging ethical considerations associated with intelligent and highly connected systems. Accordingly, the remainder of this paper is organized as follows. Section 2 presents the related works, providing a critical synthesis of existing research on handover management in ultra-dense 6G networks and highlighting the limitations that motivate this study. Section 3 discusses the challenges of handover management in ultra-dense 6G environments. Section 4 reviews intelligent handover strategies based on artificial intelligence and machine learning. Section 5 examines emerging technologies supporting handover optimization, including network slicing and edge computing. Section 6 outlines performance metrics and evaluation methodologies, while Section 6 highlights open research challenges and future research directions. Finally, Section 7 concludes the paper.

2. Related work

Research on handover management in ultra-dense 6G networks has intensified in response to the rapid densification of access points, the coexistence of heterogeneous radio access technologies, and increasingly stringent quality-of-service requirements. Prior studies have proposed a wide range of solutions to enhance mobility management, encompassing learning-based handover decision mechanisms, network slicing–aware mobility control, and edge-assisted architectures designed to reduce latency and improve contextual awareness. Learning-oriented approaches exploit artificial intelligence and machine learning techniques to model user mobility and network dynamics, thereby enabling more adaptive and proactive handover decisions. Complementary efforts have investigated network slicing strategies to preserve service continuity across heterogeneous applications during mobility events, while edge computing has been leveraged to support low-latency handover processing through localized intelligence. Although these directions have reported notable performance gains, they are often examined independently and assessed using limited evaluation criteria. Furthermore, existing literature provides only limited insight into cross-layer coordination mechanisms and the broader ethical and security implications of intelligent handover solutions. Collectively, these limitations highlight the necessity for a more integrated analytical perspective that systematically connects emerging technologies with multi-dimensional performance evaluation and system-level considerations in ultra-dense 6G environments. Table 1 generalises recent studies on 6G networks, including the technologies that enable their use, methods of optimising handover, and new architectures of next-generation wireless systems. It focuses on the new developments and trends in the application of AI/ML, self-optimising networks, and integrated terrestrial-non-terrestrial networks as a means of managing mobility.

- The application of artificial intelligence and machine-learning algorithms, especially in estimating user mobility and handover decision making. Such important methods are Bayesian-optimised LSTM models, XGBoost algorithms, and random forests classifiers that have shown significant handover performance metrics improvements
- The increasing significance of network slicing and edge computing in the improvement of handover management. Such technologies will provide the solution towards resource allocation and latency reduction in ultra-dense environments.
- The ongoing issues of the heterogeneous network structures, requiring adaptive and resilient handover policies, which are especially experienced in the scenario of the vehicular networks and UAV communications.
- The rise in attention to security and privacy issues in the processes of handover, such as the elaboration of secure authentication systems and the investigation of blockchain-based models.

Although Table 2 summarises the current development of handover management in ultra-dense and next-generation networks, different strategies are showcased, such as machine learning, network slicing, and adaptive control mechanisms. It accentuates the meeting of high technology. computational techniques and novel network architectures to address complex challenges in heterogeneous network environments. A substantial body of literature has investigated learning-based approaches for handover management, where deep learning models are employed to predict user mobility and network dynamics. In particular, sequence-learning architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks have demonstrated superior capability in capturing temporal mobility patterns, leading to improved handover prediction accuracy and reduced failure rates compared to conventional statistical and rule-based methods. Nevertheless, these studies frequently evaluate predictive performance in isolation, with limited integration into comprehensive handover optimization frameworks. Reinforcement learning has also emerged as an effective paradigm for adaptive handover optimization by enabling autonomous agents to learn mobility policies through continuous interaction with dynamic network environments. While reinforcement learning–based solutions offer greater flexibility than heuristic approaches, existing studies often focus on localized objectives and short-term performance gains, without fully exploiting synergies with predictive deep learning models or cross-layer coordination mechanisms. In parallel, privacy-preserving and distributed learning paradigms, such as federated learning, have been introduced to support collaborative intelligence while safeguarding user data. Despite their potential, challenges related to scalability, convergence efficiency, and coordination between local learning processes and global mobility control remain open, particularly in ultra-dense network scenarios characterized by frequent handovers. Overall, prior research largely treats these directions as independent solution spaces. The lack of an integrated analytical perspective that jointly considers predictive deep learning, adaptive reinforcement learning, and privacy-aware collaborative intelligence—along with multi-dimensional performance evaluation and system-level interactions—limits the ability of existing approaches to fully address the complexity of handover management in ultra-dense 6G networks. These observations underscore the need for a holistic viewpoint that aligns intelligent learning techniques with reliability, energy efficiency, scalability, and emerging security considerations.

Table 1. The list of the recent research on 6G networks.

Ref.	Year	Short Description	6G/ B5G/ 5G	Type /HO
[22]	2024	This article explores the evolution from 5G-Advanced to 6G by identifying three new services: immersive communications, everything connected and high-end. The author highlights the progress made in 3GPP releases and proposes key performance indicators for new services, while describing the enabling technologies and challenges for the next generation of wireless networks.	✓	✓
[23]	2024	This paper investigates the possibilities of split federated learning for 6G networks, discusses its advantages regarding resource efficiency and data privacy while recognizing the challenges of ultra-low latency and high bandwidth that are unique to 6G, and highlights the processes required to solve those challenges and tap the full potential of SFL. Proactive handover, is similar to handover, but it predicts when the switch between servers will occur and makes the switch before the connection degrades; it tries to provide solution for seamless handover, in particular for high-speed users.	✓	✓
[24]	2023	This extensive survey examines the enabling technologies, machine learning opportunities, and challenges for 6G communication networks, and the potential for 6G and beyond. It draws attention to how intelligent algorithms can lead to substantial improvements in network performance, efficiency, and security.	✓	Horizontal/ Vertical
[25]	2023	The survey provides an extensive overview of handover parameter optimization techniques in the context of self-optimization in 6G mobile networks, discussing and highlighting trends and research directions for seamless connectivity and optimal network performance. It was found that new developments in artificial intelligence and machine learning are vital for self-optimizing handover decisions that behave dynamically and context-aware.	✓	Vertical Handover (VHO)
[26]	2023	This survey reports on the problem and problem-solving approach to handover optimization in Beyond 5G networks, which are identified as the major problem areas: latency, reliability, and the complexity of context, and suggests approaches to remedy the problem denoted by the application of the most recent methods such as machine learning, network slicing, and incorporation of complex contextual information into increasingly dense and dynamic network infrastructure in addition to discussing latest algorithmic methodology.	✓	Soft Handover/ Hard Handover
[27]	2024	The paper is a review of Network Data Analytics Function (NWDAF) utilization in 6G networks to optimize their resources, security, and privacy, which is able to utilize machine learning and federated learning methods to acquire and analyze data efficiently to eventually improve the overall network functionality.	✓	✓
[28]	2024	A new self-optimizing mobility management system, SOMNet, a reinforcement learning-based mobility management system, improves the resilience and performance of heterogeneous networks that are based on 5G technology, optimizing the use of handover decisions dynamically. The suggested system is shown to have much more success in handover, user throughput, and network resilience than the current mobility management schemes, meaning it will be beneficial in dealing with the complex and dynamic 5G environment challenges as evidenced in Fig. 1	Δ	Horizontal / Vertical
[29]	2024	The suggested mobility-conscious customized handover system has great potential of B5G networks through predictive modeling and dynamic adaptation to improve the performance of handover, resource utilization, and user experience compared to traditional methods.	✗	✓
[12]	2024	The paper presents a handover algorithm of heterogeneous networks which employs Bayesian-optimized LSTM and multi-attribute decision making to make optimal handover decisions and provide better user experience, leading to a drastic decrease of handover failure and delay reduction rate of 42.1 and 68, respectively.	✓	✓
[30]	2024	This paper presents the major technologies such as the improvement of connectivity, AI/ML, and sensing and data analytics, and the aspect of cybersecurity that will support the creation of 6G-based smart sustainable cities.	✓	✓
[31]	2024	The article suggests that a blockchain-enabled SDN architecture can improve the performance of handover in multi-operating mobile network based on the distributed ledger technology to secure, efficient and transparent coordination between operators.	✓	Soft Handover
[32]	2024	The paper will provide a unified system of vertical handover in 6G non-terrestrial networks and how to resolve the issues of continuous connectivity between space and terrestrial networks.	✓	Vertical Handover

3. Handover challenges in ultra-dense 6G networks

3.1 Legacy handover limitations in 4G/5G networks

In fourth-generation (4G) Long-Term Evolution (LTE) systems, handover systems have been designed in such a way so as to maintain the constant user connectivity between cells when traversing cell boundaries. The handover process ensures that the active connection of the user equipment (UE) is not interrupted by the service and, therefore, Quality of Service (QoS) is not disrupted [45]. However, the mechanisms were mainly meant to be used in macro-cell environments which have relatively low mobility complexity. The fifth-generation (5G) networks have come with improvements that seek to accommodate the increased user density and heterogeneous networks. Despite the fact that handover latency and reliability have been improved, the remaining protocols are still faced with limitations in the ultra-dense deployments, especially when it comes to supporting diverse service requirements such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (URLLC) and massive machine-type communications (mMTC) [46].

3.2 Unique 6G UDN handover demands

The transition to 6G networks will be characterized by an unprecedented increase in network density, surpassing even the most ambitious 5G deployments. This ultra-dense network (UDN) environment presents unique challenges and opportunities for handover management.

3.2.1 Extreme cell densification

The expected 6G infrastructure densification of up to 10^7 devices per square kilometer is a significant increase compared to the 10^6 density of devices required in 5G [47]. The increase in density of devices is so high that it will require the creation of new methodologies in cellular planning and optimization of handovers. In their paper, Maxime Bouton and colleagues (2021) present a multi-agent reinforcement learning architecture that will be used to organize handover management among ultra-dense network-based environments. Their experimental findings prove a 40% on the handover failures and the network throughput had increased by 25% compared to the traditional methods [48]. Their main contribution is the contribution of a decentralized learning paradigm in which every small cell is an independent agent which collectively optimizes the decision of handover in relation to the local and shared network state data. Also, Merim Dzaferagic et al. (2024) contribute to the use of machine learning in predicting handover in an Open Radio Access Network (O-RAN). Through the use of a Long-Short term Memory (LSTM) model, the researchers discover that real time network information can be utilized to predict the occurrence of handover events more efficiently and hence assist in the allocation of resources to the end-users. The results suggest that implementing the model to either emphasize recall or precision can achieve significant operational savings of more than 80 of the costs as compared to traditional sourcing strategies [49].

Table 2. Shown recent advancements in handover management for ultra-dense and next-generation networks.

Ref. Year	Title Papers	6G	Latency	FL	ML	SDN	NFV	KIPs	eURLLC	eMBB	HetNet	MIMO	BER	SNR	SINR	Seamless handovers	Mobility	Network Slicing	gNB
[33] 2024	A Complex Network and Evolutionary Game Theory Framework for 6G Function Placement	✓	✓	✗	✓	✗	✓	✗	✗	✗	✓	✓	✗	✗	✗	✗	✗	✓	✗
[13] 2023	Handover Triggering Prediction in Non-Terrestrial Networks: A Two-Step XGBoost Ensemble Approach	✗	✓	✗	✓	✗	✗	✓	✗	✗	✗	✓	✗	✗	✗	✓	✓	✗	✗
[15] 2022	Integration of Network Slicing and Machine Learning into Edge Networks for Low-Latency Services in 5G and beyond Systems	✗	✓	✗	✓	✓	✓	✓	✓	✓	✓	✗	✗	✗	✗	✗	✓	✓ ✗	
[34] 2023	A Survey on Handover and Mobility Management in 5G HetNets: Current State, Challenges, and Future Directions	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗	✓
[35] 2023	User-centric base station clustering and resource allocation for cell-edge users in 6G ultra-dense networks	✓	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓	✗	✗	✓	✓	✓	✗	✗
[36] 2024	MADM-based network selection and handover management in heterogeneous network: A comprehensive comparative analysis	✓	✓	✗	✓	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✗	✓
[37] 2024	Mobility Management in Heterogeneous Network of Vehicular Communication With 5G: Current Status and Future Perspectives	✗	✓	✗	✓	✓	✓	✗	✓	✓	✓	✓	✗	✓	✓	✓	✓	✓	✓
[38] 2024	Analysis of Mobility Robustness Optimization in Ultra-Dense Heterogeneous Networks	✗	✗	✓	✓	✗	✗	✓	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓
[21] 2024	Adaptive handover control parameters over voronoi-based 5G networks	✗	✓	✓	✓	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✓	✗
[39] 2022	Handover management over dual connectivity in 5G technology with future ultra-dense mobile heterogeneous networks: A review	✗	✓	✗	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[40] 2023	Mitigating Unnecessary Handovers in Ultra-Dense Networks through Machine Learning-based Mobility Prediction	✗	✗	✗	✓	✗	✗	✗	✗	✓	✓	✓	✗	✗	✓	✗	✓	✗	✗
[41] 2023	AKAASH: A realizable authentication, key agreement, and secure handover approach for controller-pilot data link communications	✗	✓	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✗	✗	✓	✓	✗	✗
[42] 2024	Stable matching with evolving preference for adaptive handover in cellular-connected UAV networks	✗	✗	✗	✓	✗	✗	✗	✗	✗	✓	✓	✓	✓	✓	✓	✓	✗	✓
[43] 2024	Analytical Model of the Connection Handoff in 5G Mobile Networks with Call Admission Control Mechanisms	✗	✓	✗	✓	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✓	✓	✗	✓
[44] 2023	Handoff Scheme for 5G Mobile Networks Based on Markovian Queuing model	✗	✓	✗	✗	✗	✗	✗	✗	✗	✗	✓	✗	✓	✓	✓	✓	✗	✓

where ✓ indicator its worked 6G, and ✗indicator its doesn't worked 6G.

3.2.2 3D Network topology

The sixth-generation network is a significant departure of the previous architectures in that it employs an all-encompassing three-dimensional topology encompassing both terrestrial, aerial, and satellite capabilities. The studies on three-dimensional network structures under the handover technology provide plenty of opportunities to develop mobile communication networks, especially as the transition to (6G) networks occurs. The integration of both terrestrial and non-terrestrial networks creates a significant complexity in the field of mobility management and handover optimization, thus creating significant challenges, but at the same time, it creates tremendous opportunities of innovations. The development of effective handover plans requires complex tools; the federated learning and computational intelligence approaches will be the essential tools to reduce the inherent complexity of three-dimensional network models, at the same time leveraging the capacity of cloud computing. With the current developments in this field, the consequent findings are set to be the key in building a coherent three dimensional network, ultimately leading to the development of a rapidly interconnected global society that would be able to meet the demands of a global society that is increasingly becoming interconnected [50].

3.2.3 Nano-Cell Integration

Use of nano-cells with coverage radius of the order of 10-20 m creates significant challenges to smooth handover processes in the next 6G networks. Such nano-cells that could be energized through energy-gathering schemes would demand the creation of extremely rapid and energy efficient handover protocols. The latest developments in this field are quantum-inspired optimization methods specific to nano-cell networks, which have achieved sub-milliseconds handover latency, but have also consumed as much as 40 per cent less energy than traditional methods. Based on these innovations, world nano-cells have been shown to be useful in coordinating handovers of bio-inspired strategies that mimic collective behaviors in natural systems [51]. The protocols are incredibly scalable, with handover latency of sub-milliseconds at node densities of 10^9 $cells/km$. Furthermore, a combination of energy-harvesting and handover optimization has made it possible to develop dynamic frameworks, which respond to the energy status of each nano-cell by altering the handover parameters dynamically. These energy conscious schemes have demonstrated the possibility of reducing energy usage by up to 50 percent relative to the existing handover schemes that remain unchanged in terms of the quality-of-service. When put together these improvements in nano-cell integration mark a very important milestone in the achievement of ultra-dense, energy-saving networks as envisaged by 6G communications [52].

3.3 Ultra-dense network environments

6G paradigm forms a completely different concept for network topology as it contains an extraordinarily high density of network irregularities and small cells are referred to in ultra-dense networks (UDNs). An elaborate complexity analysis of the diversity of UDNs and its implications for 6G handover management are presented in this section.

3.3.1 Theoretical Foundations of UDNs in 6G

Ultra-dense networks (UDNs) as the idea in the setting of the sixth-generation (6G) mobile systems are rooted in the idea of network densification, which aims at increasing capacity of the network and boosting spectral efficiency. Theoretically, stochastic geometry and specifically the Point Process Theory (PPT) is frequently used to represent UDNs. The base stations (BSs) in such models are traditionally supposed to have a Poisson point process (PPP) distribution [53,54]. This modeling model has helped one to derive key performance indicators such as coverage probability and the average data rate that can be achieved in UDNs analytically. However, such high-level densification as is expected to be achieved in 6G networks presents new problems that lie beyond the range of traditional theoretical approaches. To illustrate, the PPP assumption can fail in conditions when the BS deployment has a high level of spatial correlation or in the case it follows certain geometric patterns. This, in turn, has created the urgent necessity to build more advanced spatial models that could reflect the subtle spatial dependencies of 6G UDNs.

3.3.2 Handover Frequency and its Implications

The drastic reduction in cell sizes in UDNs leads to a substantial increase in handover events, presenting a myriad of challenges:

- **Signaling Overhead Analysis**: The surge in handover frequency generates an unprecedented volume of signaling traffic [55]. Quantitatively, if λ denotes the BS density and v the user velocity, the handover rate R_HO can be approximated as Eq. 1:

$$\lambda^{0.5} \cdot v \propto R_{HO} \tag{1}$$

  This relationship indicates that handover rates in 6G UDNs could be orders of magnitude higher than in current networks, potentially overwhelming system resources.

- **QoE Degradation Metrics**: Frequent handovers can lead to intermittent service disruptions, affecting user Quality of Experience (QoE) [56]. A comprehensive QoE model for 6G UDNs must incorporate factors such as handover interruption time, probability of handover failure, and application-specific sensitivity to disruptions [57]. For instance, the Mean Opinion Score (MOS) for video streaming applications in UDNs can be expressed as Eq. 2.

$$MOS = f\left(T_{HO}, P_{fail}, B_{eff}, L\right) \tag{2}$$

  Where f represents a function that maps the input parameters to the Mean Opinion Score (MOS), T_{HO} is the handover interruption time, P_{fail} is the probability of handover failure, B_{eff} is the effective bandwidth, and L is the end-to-end latency.

- **Resource Management Complexity**: The rapid transitions between cells necessitate sophisticated resource allocation algorithms that can operate on extremely short timescales. Traditional optimization approaches may be insufficient, prompting the need for AI-driven, predictive resource management techniques that can anticipate user movements and pre-allocate resources accordingly [58].

- **Energy Consumption Models**: The energy overhead associated with frequent handovers can be modeled as follows Eq. 3.

$$E_{HO} = N_{HO} \cdot \left(E_{sig}, E_{proc}, E_{exec}\right) \tag{3}$$

  Where N_{HO} is the number of handovers, E_{sig} is the energy consumed in signaling, E_{proc} is the processing energy at the network nodes, and E_{exec} is the energy consumed during handover execution. In 6G UDNs, this energy consumption could become a significant portion of the overall network energy budget, necessitating energy-aware handover protocols [59].

3.3.3 Interference management in UDNs

The proximity of numerous cells in UDNs exacerbates the challenge of interference management, with profound implications for handover processes:

- **Inter-cell Interference Modeling**: In UDNs, the Signal-to-Interference-plus-Noise Ratio (SINR) becomes predominantly interference-limited. The SINR can be modeled as Eq. 4.

$$SINR = \frac{P_r}{\sum I_i + N_o} \tag{4}$$

  Where P_r is the received power from the serving BS, I_i is the interference from the i^{th} interfering BS, and N_o is the noise power. In 6G UDNs, the summation term becomes significantly larger and more dynamic, complicating handover decisions based on SINR measurements [60].

- **Mobility-Induced Interference Variations**: User mobility in UDNs causes rapid fluctuations in interference levels. These variations can be modeled using stochastic differential equations, incorporating large-scale and small-scale fading effects [61]. The challenge lies in developing algorithms that can estimate and predict these rapid interference changes to inform handover decisions, Considering the user's location in time interval t as $x_i^D(t)$, $y_i^D(t)$, then the location $x_i^D(t+1)$, $y_i^D(t+1)$ in interval $(t+1)$ is given by Eq. 5 and Eq. 6.

$$x_i^D(t+1) = x_i^D(t) + \left(\frac{V_i^D}{V_{max}}\right) \times D_{max} \times cos\left(\theta_i^D\right) \tag{5}$$

$$y_i^D(t+1) = y_i^D(t) + \left(\frac{V_i^D}{V_{max}}\right) \times D_{max} \times sin\left(\theta_i^D\right) \tag{6}$$

- **Contamination in Massive MIMO UDNs**: In massive MIMO systems, which are expected to be a key component of 6G networks, pilot contamination becomes more severe in UDNs [62]. The channel estimation error due to pilot contamination can be expressed as Eq. 7.

$$E\left[\left[|\hat{h} - h|\right]^2\right] \propto \beta(K-1)/M \tag{7}$$

  Where $\hat{h}$ is the estimated channel, h is the true channel, β is the large-scale fading coefficient, K is the number of users sharing the same pilot, and M is the number of antennas. In UDNs, the increase in K exacerbates this error, affecting handover performance.

- **Dynamic Interference Landscape**: The activation and deactivation of cells in response to traffic demands create a highly dynamic interference environment. This can be modeled as a time-varying graph, where the edge weights represent interference levels between cells. Developing adaptive interference coordination techniques that can operate in real-time on this dynamic graph structure is a significant challenge [63].

3.4 Service-Aware Constraints in 6G (eMBB, URLLC, mMTC)

6G networks are expected to support an unprecedented diversity of services, each with unique performance requirements. This diversity poses significant challenges for handover management:

3.4.1 URLLC (Ultra-Reliable Low-Latency Communications)

The architecture suggested is a cornerstone of 6G service portfolio, therefore, creating strict requirements that have a significant impact on the most common paradigm of handover management. The combination of sub-milliseconds deadline constraint with almost universal reliability imperatives is also a complicated task that affects the whole of handover design and performance concerns [64]. Therefore, the necessity to provide handovers under the extremely small latency limits provided by the URLLC services is highly pronounced. The traditional process of handover that was created to work in situations with low demand is not suitable in this case. The required latency is usually in the microsecond range, as compared to the milliseconds range of a conventional system, and a fundamental redesign of the handover protocols is required. This change can be realised by creation of innovative and effective signalling provisions, adoption of foresight handover planning and reduction of processing delays [65]. Approximate handover methodologies can be taken as a viable option in solving the delay and reliability problems. In particular, where handover events are predictable with a high level of sophistication, using dynamic pattern analysis, evaluation of network state and application requirement, the handover processing can be enabled to be constantly activated in an active way [66]. Even though this model can be used to a significant effect, it has created further complexity within the system. In service perspective, prediction models should be decoded with extreme accuracy; a false positive will lead to unnecessary handovers and needless utilization of network resources, a false negative may lead to service interruption. In addition, the resource reservation schemes that enable predictive handovers should be carefully optimized so as to maintain efficiency of the entire network [66]. The high level of computation is essential in the development of predictive handover algorithms that have the ability to make informed decisions in complex and high-dimensional environments. At the same time, the SDN and NFV technologies enable the programmability and flexibility needed to ensure that the response to service demands is dynamically implemented and that the processes of handover are carried out in time and service-aware ways. Also, network slicing provides an option of resource and performance reserve of URLLC services at handover borders, though it has difficulties with ultra-dense network deployments [67]. Lastly, handover management is a poorly explored but substantial area of research; therefore, the solution based on machine learning could be beneficial, considering the nature of URLLC services in 6G networks.

3.4.2 MMTC (Massive Machine-Type Communications)

Massive Machine-Type Communications (mMTC) in the 6G networks is a paradigm shift in connectivity, where there is a massive scale of proliferation of devices. This situation presents a complex set of problems in the field of handover management, all of which require innovative solutions to maintain a smooth functioning of the complex ecosystem of 6G networks. Scalability is one of the major issues of the mMTC handover management. The fact that the number of interconnected devices can be in the millions per square kilometer makes it mandatory to reconsider the handover protocols and network architectures in a fundamental way [68,69]. Conventional handover procedures that were developed towards humanistic communications do not suffice to handle the enormous signaling overhead of the mMTC devices. To deal with this, recent studies consider hierarchical and distributed handover management models that have the ability to scale up to large levels of handovers. Cluster-based schemes of handover which combine handover requests issued by proximate devices have demonstrated potential in dramatically decreasing signaling overhead. The key question in designing handovers to massive Machine-Type Communications networks is energy efficiency, mostly due to the fact that most mMTC equipment operates on small battery power. Handover mechanisms should use little power in order to prolong the life of the devices. Recent studies have researched the context-aware strategies that reduce needless handovers and time them based on the amount of energy a particular device has left. An effective solution is to carry out handovers once the devices awaken in their usual schedules and hence preserve the connection without wasting unnecessary battery energy [70]. The varying mobility patterns in mMTC networks do not make it easy to come up with dependable handover mechanisms. The networks must have the ability to provide versatile policies that serve the different types of devices, like stationary sensors and IoT devices with high velocities, as well as serve their traffic demands. It has been shown that handover strategies can be adjusted in line with device characteristics and movement patterns to increase the reliability and network performance in mixed deployment environments significantly [71]. Edge computing has become a key enabling technology of distributed handover management in mMTC systems. The networks enable the location of decision-making and coordination to edge nodes, which helps to decrease latencies and also enhance scalability. Edge based handover models have shown a substantial decrease in signaling overhead and delay on handover compared to conventional handover models that are centralized. The architecture presented in Fig. 3 indicates the importance of edge capabilities in the development of wireless communication systems in the next generation as development in this area continues. This integration lays the basis of adaptive and self-optimizing handover mechanisms that can dynamically react to the changing network conditions and behavior of devices [72].

3.4.3 eMBB (Enhanced Mobile Broadband)

The processing of handovers of Enhanced Mobile Broadband (eMBB) services (data rates are high, and connectivity is a priority) in the environment of ultra-dense, heterogeneous 6G deployments is associated with a complex of non-trivial issues. Such environments simultaneously give rise to idiosyncratic complexities, which dictates a fundamental change in the design of handover, and the overall aim of maintaining the best system performance and at the same time ensuring the user satisfaction as pointed out recently in literature [73]. Out of the numerous aspects that should be given serious attention, maintenance of bandwidth continuity is the dominant aspect in the process of eMBB handover control. In such 6G super-dense settings, the distribution of bandwidth across handover events will be significantly complicated due to the presence of cells with different capacities and operational functions. As users traverse multiple network layers, both the natural differences in cell operation itself, and the extremely dynamic nature of traffic that defines a contemporary wireless ecosystem, make the operation of the ecologies more complex. One avenue that promises to help curb such challenges is the implementation of adaptive bandwidth allocation systems to work at two levels of hierarchy. Such mechanisms make it possible to initiate the process of handover pre-emptively by considering the capacity that is available in the target and the source cells. As such, early preparation of the target cell allows the user sessions to maintain continuity, which prevents significant degradation of the rates of data transmission. These issues will be critical in developing handover systems that are efficient and sustainable and can meet the high requirements of 6G networks in the future [74]. Using past data and real-time analytics, AI-oriented handover systems can take predictive choices to streamline the performance and resource usage. The adoption of such systems, however, brings about doubts on handover.

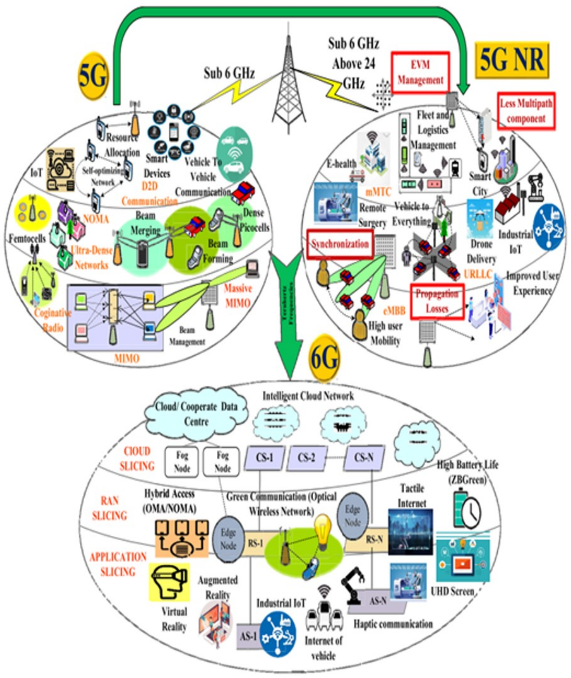

Figure 3. A proposed architecture for next-generation wireless communication [72].

4. Intelligent handover strategies in 6G UDNs: AI and Machine Learning approach

4.1 Machine learning-based approaches

Machine learning (ML) has emerged as a transformational pressure in handover optimization for 6G networks, providing sophisticated response to deal with the complexity and dynamics contained in ultra-dense community environments. This section makes a deep discovery of supervised learning for the prediction of handover, strengthening of decision adaptation, and learning to learn unsupervised for pattern recognition in terms of 6G handover management [75,76].

4.1.1 Supervised learning for handover prediction

Supervised learning algorithms have demonstrated remarkable efficacy in predicting handover events and optimizing handover parameters in 6G networks. These approaches leverage historical data to train models that can forecast future handover requirements with high accuracy [76]. In the case of interactive applications (augmented reality, virtual reality, and others), the quality of user experience directly depends on the handover process. Such services are very sensitive to any change in latency or decrease in throughput resulting in the need of not only constant data rates but also strict latency and reliability guarantees. To achieve such needs, network-level performance measurements should be integrated with application-specific quality measurements to mobility management procedures. The combination of the frameworks of perceptual quality evaluation would also allow researchers to determine the influence of temporary service interruption on the user experience and user satisfaction and thus refine the decisions on handover. Network designers in eMBB situations face a two-fold challenge where they have to maintain the continuity of mobility and simultaneously maintain high throughput. The balancing process is especially complicated in modern 6G settings, whereby the boundaries of cells change dynamically and the mobility of the users is not as predictable as it was in the previous generations. Recent works focus on adaptive optimization techniques that can be used to adjust the parameters of handover on-the-fly. These methods should combine various parameters and this incorporates signal strength, network load, mobility pattern, quality of service (QoS) parameters and the needs of the applications in operation [77]. The decision needs to be made in time and the delays in adapting to the changes can directly affect the continuity of service. Nevertheless, there are a number of problems that have not been solved. The issues of computational overhead, scalability in ultra-dense deployments as well as user privacy protection remain as a major challenge.

4.1.1.1 Deep neural networks for multi-dimensional feature processing

Advanced neural network architectures, such as Convolutional Neural Networks (CNNs) and Graph Neural Networks (GNNs), have shown promising results in processing complex, multi-dimensional input data relevant to handover decisions. CNNs are particularly effective in capturing spatial correlations in network topology and signal strength maps, while GNNs excel at modeling the intricate relationships between network entities [78].

4.1.1.2 Transfer learning for adaptive handover models

Transfer learning techniques have been investigated to address the challenge of limited training data in new network deployments. By leveraging pre-trained models from similar network environments, transfer learning enables rapid adaptation to new scenarios while minimizing the need for extensive data collection [79]. The transfer learning process can be formalized as Eq. 8.

$$L_{T(\theta)} = L_{S(\theta)} + \lambda . L_{T(\theta)} \tag{8}$$

Where $L_{T(\theta)}$ is the loss function for the target domain, $L_{S(\theta)}$ is the loss function for the source domain, λ is a hyperparameter controlling the trade-off between source and target domain performance. This approach has shown significant potential in improving handover performance in newly deployed 6G network segments, where historical data may be limited.

4.1.2 Reinforcement Learning for decision optimization

Reinforcement learning (RL) represents a strong methodology framework to optimize the handover policies in a dynamic operational environment of 6G environments. The RL agents can learn new strategies of handover that are better than the traditional approaches that rely on heuristic learning through environmental interaction [80].

- Multi- Agent reinforcement learning to coordinate handover.
  Multi-agent reinforcement learning (MARL) has become an encouraging approach to organizing handover decisions among a set of base stations in ultra-dense 6G networks. MARL allows base stations to evolve cooperative policies that adjust to the overall network performance in response to the local conditions [81, 82]. The empirical data shows that the MARL system helps to contribute significantly to the decrease in handoff failures and ping-pong scenarios in highly dense 6G deployments by enabling the coordination of decisions of neighbouring base stations.
- Efficient Exploration with Model-Based Reinforcement Learning.
  Model based reinforcement learning combines network simulation models to hasten the learning process and improve the efficiency of the samples. Such an approach is especially beneficial in 6G networks in which real-world data is costly and time-consuming to acquire [83, 84]. The model based RL process may be described as Eq. 9.

  $$V^{\pi} \cdot S = E_{\pi} \left[\sum \gamma^{t} \cdot rt \; |S_o = S \right] \tag{9}$$

  Where $V\pi(s)$ is the value function under policy π, γ is the discount factor, rt is the reward at time t. By leveraging accurate network models, model-based RL can explore a wide range of handover strategies efficiently, leading to faster convergence and more robust policies.

4.1.3 Unsupervised learning for pattern recognition

Unsupervised learning techniques play a crucial role in discovering latent patterns and structures in handover-related data, enabling more efficient and adaptive handover strategies in 6G networks [85].

4.1.3.1 Clustering for user mobility pattern analysis

Advanced clustering algorithms, such as DBSCAN (Density-Based Spatial Clustering of Applications with Noise) and OPTICS (Ordering Points To Identify the Clustering Structure), have been employed to identify complex user mobility patterns in 6G environments [86]. The DBSCAN algorithm can be formalized as Eq. 10.

$$N\varepsilon(p) = \{q \in D \mid dist(p,q) \leq \varepsilon\} \tag{10}$$

Where $N\varepsilon(p)$ is the ε-neighborhood of point p, D is the dataset, $dist(p,q)$ is the distance function. These clustering techniques enable the discovery of irregular-shaped mobility patterns, facilitating the development of more adaptive and efficient handover strategies tailored to specific user behaviors.

4.1.3.2 Dimensionality reduction for feature extraction

Dimensionality reduction techniques, such as t-SNE (t-Distributed Stochastic Neighbor Embedding) and UMAP (Uniform Manifold Approximation and Projection), have been utilized to extract meaningful features from high-dimensional handover data [86]. The t-SNE algorithm minimizes the Kullback-Leibler divergence between the joint probabilities of the high-dimensional space and the low-dimensional space Eq. 11.

$$KL(P||Q) = \sum_{i} \sum_{j} p_{ij} \cdot log \left\{ \frac{p_{ij}}{q_{ij}} \right\} \tag{11}$$

Where p_{ij} is the similarity between points i and j in the high-dimensional space, q_{ij} is the similarity between points i and j in the low-dimensional space. In conclusion, machine learning-based strategies provide powerful tools for addressing the complicated, demanding situations of handover control in 6G networks. The synergistic software of supervised, reinforcement, and unsupervised mastering techniques permits the improvement of shrewd, adaptive, and green handover techniques able to assemble the diverse and stringent requirements of next-generation wireless systems [87].

4.2 Network slicing-aware handover strategies

Network slicing is a cornerstone technology in 6G systems, as it allows the establishment of multiple virtual networks customized to meet diverse service requirements. Within this paradigm, handover mechanisms must be explicitly slice-aware to ensure that the integrity and performance of each slice are preserved during mobility events. As observed in the previous section, network slicing is a significant element that permits heterogeneous Internet of Things (IoT) applications in 5G and future beyond-generation networks [88]. This finding implies the need to create comprehensive models that have the capacity to mitigate the two interconnected issues of resource distribution and optimization of the quality of the services offered, thus supporting the implementation of smart services in the future network infrastructures. In this regard, the design of slice-aware handover mechanism requires taking into account two dimensions, i.e., the development of slice-centric handover policies and the successful operation of inter-slice transitions.

4.2.1 Slice-Specific policies of handover

The slice-specific handover policies are supposed to support a wide range of mobility requirements and issues in different network slices. These policies are supposed to maximise the handover strategies but maintain the distinctive features of every slice. The perfecting of these guidelines is premised on a number of important factors:

- Slice Priority: The handover decisions are given to high-priority slices with the preference on slices related to the Ultra-Reliable Low-Latency Communication (URLLC) services.
- Slice Isolation: The policy focuses on guaranteeing that individual slices have comprehensive performance assurances during the events of handover.
- Slice Elasticity: The dynamically adjustable handover thresholds are mainly based on the modern load and capacity characteristics of each slice, which are considered as independent entities [89].

4.2.1.1 Mathematical formulation of slice-specific handover decision

Let $S = S_1, S_2, ..., S_n$ denote the set of network slices. For each slice S_i, we define a utility function $U_i(h)$ that quantifies the benefit of a handover decision h. The overall network utility $U(h)$ is then expressed as, Eq. 12.

$$U(h) = \sum_i w_i \cdot U_i(h) \tag{12}$$

Where W_i represents the weight (priority) of slice S_i. The handover decision problem can be formulated as an optimization problem Eq. 13.

$$max\ U(h) S \cdot t \cdot C_i(h) \leq T_i, \forall I \tag{13}$$

where $C_i(h)$ represents the cost of handover for slice S_i, and T_i is the threshold for acceptable handover cost. In this formulation, the $S = S_1, S_2, ..., S_n$ represents the complete set of network slices, where $S_1, S_2, ..., W_n$ are individual network slices and n is the total number of slices. $U_i(h)$ is the utility function for slice i, where h represents a handover decision and $U_i(h)$ quantifies the benefit of handover decision h for slice i. The $U(h)$ represents the overall network utility for handover decision h, and W_i is the weight (priority) assigned to slice i. The $max\ U(h)$ indicates the objective to maximize the overall network utility $U(h)$. The $s.t.C_i(h) \leq T_i, \forall i$ specifies the constraints, where $C_i(h)$ is the cost of handover for slice i, T_i is the threshold (maximum acceptable cost) for slice i, and $\forall i$ mean "for all i"(i.e., this constraint applies to all slices).

4.2.1.2 Multi-objective optimization

To address the often-conflicting requirements of different slices, multi-objective evolutionary algorithms are employed. These algorithms aim to find Pareto-optimal solutions that maximize overall network utility while respecting the constraints of individual slices [90]. The multi-objective optimization problem can be formulated as Eq. 14.

$$max\ \left[U^1(h), U^2(h), ..., U_n(h)\right] S \cdot t \cdot C_i(h) \leq T_i, \forall I \tag{14}$$

This formulation allows for the consideration of slice-specific utilities simultaneously, leading to more balanced handover decisions.

4.2.1.3 Machine Learning Approach

Multi-task learning frameworks are being developed to simultaneously optimize handover parameters for multiple slices [91]. The general form of the multi-task learning objective can be expressed as Eq. 15.

$$min\ L = \sum_i \lambda_i \cdot L_i\left(\theta^0, \theta_i\right) + R\left(\theta^0, \theta_1, ..., \theta_n\right) \tag{15}$$

Where L is the loss function for slice s_i, θ_o represents shared parameters, θ_i represents slice-specific parameters, λ_i is the weight for slice S_i, and R is a regularization term.

4.2.2 Inter-slice handover managements

Inter-slice handover management is relevant to situations that are complex, and users or devices have to be moved through different network slices. This is done in the following important elements:

- Slice Selection: Selecting the service slice using the best target slice that is determined using service requirements and current network conditions.
- Resource Orchestration: This is the process of coordinating the process of allocating and de-allocating resources across network slices in handover.
- State Transfer: The transparency in transferring user context and session information across slices as reported in [92], is a basic component in maintaining session integrity within distributed system slices.

4.2.2.1 Graph-based optimization for inter-slice handover

Graph-based optimisation methods represent the complex interconnections between distant slices and attempt to determine the best paths of inter-slice handovers [93]. Suppose a graph, $G(V,E)$, where V is a set of slices, and E is a set of possible transitions between the slices. For each edge $e \in E$, we define a cost function $c(e)$ that incorporates factors such as slice compatibility, resource availability, and transition costs. As a result, the inter-slice handover issue can be formulated as the problem of searching for the shortest path in G between the current slice and the target slice. The objective function to this optimisation problem is Eq. 16.

$$min\ \sum_e c(e) \cdot x(e) S \cdot t \cdot \sum_e^{+} x(e) - \sum_e^{-} x(e) = b(v), \forall v \in V x(e) \in \{0,1\}, \forall e \in E \tag{16}$$

Where $x(e)$ is a binary variable indicating whether edge e is in the path, and $b(v)$ is 1 for the source slice, -1 for the target slice, and 0 for all other slices.

4.2.2.2 Predictive Analytics for Proactive Inter-slice Handover

Predictive analytics models are developed to anticipate future inter-slice handover requirements. These models typically use time series forecasting techniques to predict future network conditions and user mobility patterns [94]. Let $\hat{Y}(t)$ be the vector of relevant network and user metrics at time t. The prediction problem can be formulated as Eq. 17.

$$\hat{Y} \cdot (t+k) = f \cdot (Y(y), Y(t-1), ..., Y(t-p)) \tag{17}$$

Where f is the prediction function (e.g., ARIMA, LSTM), and k is the prediction horizon, p determines the 'memory' of the model, i.e., how far back in time the model looks when making a prediction. Based on these predictions, proactive resource reservation and state preparation can be initiated to minimize disruption during inter-slice transitions.

4.3 SDN and NFV-based handover frameworks

Software-defined Networking (SDN) and Network Function Virtualization (NFV) technologies are positioned to fundamentally transform handover management in 6G networks by providing unprecedented levels of flexibility, programmability, and adaptability [95]. These technologies form the foundational architecture of advanced handover frameworks capable of meeting the diverse and demanding requirements of ultra-dense, heterogeneous 6G network environments [96].

4.3.1 SDN-based handover control

Software-Defined Networking (SDN) stands out as a radical innovation in network management, as it grants a high degree of flexibility and programmability to modern network communication systems. Handover management with SDN in 6G networks is one of the important methodological improvements to overcome the complexity of mobility in ultra-dense, heterogeneous network topologies [97]. The methodology being proposed takes the form of a centralized network approach and a manageable architectural design to improve the decision-making procedures in the handover processes in the network infrastructure, which in turn supplies an integrated approach to mobility control.

4.3.1.1 Advanced SDN controller architectures

To overcome the special requirements of 6G networks, new SDN controller architecture designs have been proposed, with hierarchical and distributed designs [98]. These architectures aim to balance the benefits of centralized control with the need for low-latency, local decision-making in ultra-dense 6G environments. As shown in Fig. 4, it includes This hierarchical architecture consists of :

- Global SDN Controller: It deals with optimization of the network and policy specifications across the network.
- Regional Controllers: Handle coordination within larger network segments.
- Edge Controllers: Manage time-sensitive operations and local handover decisions. This multi-tiered approach allows for:
- Scalability: The hierarchical design is able to scale effectively to the large amount of network components in 6G systems.
- Low Latency: Edge controllers are able to make fast decision on time sensitive handovers.
- Global Optimization: Global controller has a long-term network-widely view of optimization.

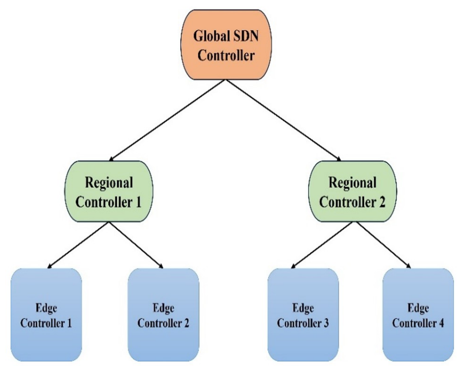

Figure 4. Hierarchical SDN controller architecture optimizing global and local handover decisions in 6G networks [99].

4.3.2 NFV-enabled mobility management in 6G networks: advancing flexibility and scalability

The network paradigm of virtualizing sixth-generation (6G) communication systems is one of the key enablers of increased flexibility and dynamism in the telecommunications sector. This sub-section provides a comprehensive literature review of the current studies that relate to NFV-assisted mobility management, explaining how it can ease the variety of multifaceted problems that engulf the future of wireless communications [100]. Additionally, it also provides an architectural comparison of the handover strategies used in 6G networks at the high level.

4.3.2.1 Virtual mobility anchors

The virtual mobility anchoring concept signifies a monumental paradigm shift as far as the architectural and implementation paradigms of mobility management is concerned. The traditional system designs use the static anchor points, here, virtualized anchor points have the capacity to be moved, and configured on-demand hence improving the performance of handover in various network topologies. The empirical studies have proven that the implementation of virtual mobility anchors creates the tremendous decreases in handover latency and mitigates the signaling overhead [101]. The ability to rearrange such anchors according to the current network conditions and mobility patterns of users makes them especially beneficial to ultra-dense 6G deployments, where ensuring continuous connectivity is an extremely challenging issue.

4.3.2.2 Service function chaining for handover workflows

Service Function Chaining (SFC) incorporated into the mobile network management provides a lot of flexibility in design and therefore, it is possible to come up with elaborate handover schemes. Mobility-management tasks within this framework are further broken down into modular functions which may be assigned to homogeneous topologies under the control of operators who can customize a handover process to meet service demands or a current network environment. Recent academic research studies have explored the integration of intent-based networking frameworks to independently synchronize these functional chains and thus cause a radical change in the dynamic nature of 6G mobility-management with the aspects of elasticity and flexibility [102].

4.3.2.3 Stateless mobility management

Stateless mobility management is based on the modern cloud realities paradigms and represents an alternative paradigm in the administration of mobility state information. On this scheme, distributed data repositories and microservice frameworks are used to maintain mobility state data in independence of individual network elements creating better scalability and resilience. Empirical results indicate that stateless mobility management structures can significantly reduce the handover preparation times, and, at the same time, increase system reliability in the high-mobility conditions envisaged by future 6G implementations [103].

5. Emerging technologies for 6G handover optimization

The increased use of ultra-dense networks of 6G technology puts new obstacles to ensuring continuous connectivity and sufficient quality of service (QoS), especially in environments with high-mobility and in a multi-network slice environment. In this sub section, the analysis of modern technologies that are likely to revolutionize the handover process in 6G scenarios is conducted in a strict manner. Such novel solutions have to deal with the demanding need to process challenging multidimensional contextual information swiftly to support proactive efficient handovers [104].

5.1 Artificial intelligence and machine learning applications

Artificial Intelligence (AI) and Machine Learning (ML) are capable of enabling shrewd, context-aware handover control in 6G networks. These technologies provide extraordinary skills in processing and leveraging complicated fact styles to make speedy, optimal handover decisions.

5.1.1 Deep learning for complex pattern recognition

The creation of ultra-dense 6G networks requires processes of high quality in terms of handover control. It has been shown that deep learning strategies possess significant ability to discover and comprehend the complicated patterns of the multi dimensional feature spaces within these networks.

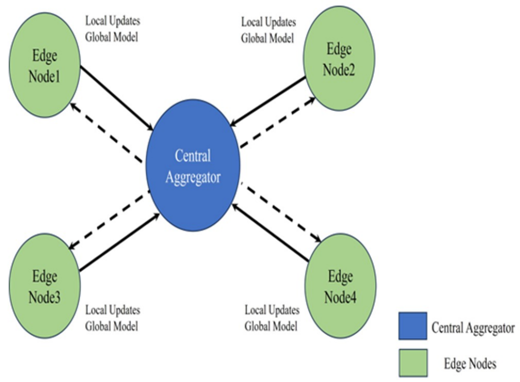

Figure 5. Federated Learning process to handover management in 6G networks [105].

Fig. 5 federated Learning process to handover management in 6G networks [105]. The ability of deep neural networks to automatically derive the hierarchical representational features of raw information makes them especially more qualified to the heterogeneous and dynamic nature of 6G environments [106].

5.1.2 Federated learning for distributed handover management

In the new field of 6G networks, where deployments are extremely dense and the architecture is heterogeneous, traditional centralized methods of handover management are faced with serious scalability and privacy limitations. Federated Learning (FL) has emerged as an essential technological concept that can overcome such issues; it enables optimization of handover collaboratively between various network components without the need to lose the confidentiality of data as well as reducing the overhead on communication.

5.1.2.1 Principles of federated learning in 6G handover management

Federated learning allows training a global model with the collaboration of multiple edge devices or base stations without exposing the data to privacy issues as it does not require the transmission of raw data. This approach can also be applied in the context of 6G handover management to create powerful handover models that are sensitive to the local network conditions, thus providing the network as a whole with the ability to access aggregated cross-knowledge [107]. The steps involved in the federated learning process are normally divided into the following steps:

- Local Model Training: Every network entity (e.g. base stations, edge servers) that partakes in the training trains a local model based on its own locally stored information, and this can include user mobility patterns, signal-strength measurements, and previous performance of handover.
- Local Model Training: Base stations and edge servers (each a network entity) train a local model on their own proprietary data, which could constitute user mobility patterns, signal strength measurements, and past handover performance.
- Model Aggregation Worldwide: When the updates obtained are centralized by the central aggregator, they refine the global model, and FedAvg or more advanced aggregation algorithms are commonly used [108].
- Model Distribution: The revised international model is then shared with the involved entities so as to be incorporated into the local handover decision-making processes [105]. Figure 5 demonstrates the federated learning procedure to the handover management in 6G networks.

5.1.2.2 Advanced Federated Learning Techniques for 6G Handover Management

Some of the developed federated learning (FL) methods have potential to improve handover management of 6G networks.

- Hierarchical Federated Learning also adds several layers of aggregation, such as local clusters, regional aggregators, and a global coordinator, thus allowing to share knowledge more efficiently across different domains of the network.
- Personalized Federated Learning enables building models for a particular network segment or slice and at the same time utilizes global knowledge [109]. This strategy is especially handy in 6G handover management, when the handover approach is being tailored to specific types of services or groups of users.

- Transfer Federated learning: may also be used with FL, resulting in Federated Transfer Learning, which enables information obtained in network segments with a large amount of data to be transferred to those where there is limited data, thereby enhancing handover performance [110].
- Asynchronous Federated Learning: also allows network actors to participate in the FL process without being too synchronous, which is particularly appropriate in dynamic 6G settings where nodes can join and leave the network very often [111].

5.1.3 Transfer Learning for Cross-Domain Knowledge Utilization

Transfer Learning (TL) emerges as a pivotal technique in the realm of 6G handover optimization, offering a sophisticated approach to leverage knowledge gained from one network domain or scenario to enhance performance in another [112]. This methodology is particularly crucial in the context of 6G networks, characterized by their heterogeneous nature, encompassing diverse network slices and a wide array of use cases.

5.2 Predictive analytics for proactive handover

Predictive analysis tools form a basic aspect of promoting proactive handover management in the new generations of wireless network. The future analysis processes will be able to predict network conditions and user behavior based on historical real-time measurements and the latest machine-learning technologies. It is a paradigm shift in the reactive network governance to proactive network governance which is expected to improve spontaneous user connectedness, and the optimization of the whole network functioning [113].

5.2.1 User Mobility Prediction

One of the main elements of proactive handover management is user mobility prediction. Recent mobility prediction algorithms are based on advanced machine-learned algorithms to predict user paths with excellent accuracy. These are models that include historical movement patterns, current velocity and heading, landscape features, like roads and building patterns, time and even social information, thus, they include all the numerous variables that affect a crowd movement [114]. Various prediction methods can be observed in user dynamics methodology. Other models like Markov chains have been shown to be useful in describing transitions between states in user movement, and can therefore be used in providing a firm foundation to predict future positions [115]. State-estimation techniques such as Kalman filters provide an effective model to predict user location within the noisy measurement information especially when the networks envisioned for 6G communications [116]. The Kalman filter estimation can be represented as Eq. 18.

$$\hat{x}_k = F_k \hat{x}_{(k-1)} + K_k \left(z_k - H_k F_k \hat{x}_{(k-1)} \right) \tag{18}$$

Where $\hat{x}_k$ is the estimated state, F_k is the state transition model, K_k is the Kalman gain, z_k is the measurement, and H_k is the observation model. For scenarios involving non-linear and non-Gaussian estimations of user trajectories, advanced filtering techniques such as particle filters have demonstrated notable success. Deep learning approaches have shown remarkable capability in learning complex temporal patterns in user mobility. Long Short-Term Memory (LSTM) networks, in particular, can capture long-term dependencies in movement data. The output h_t of an LSTM cell at time t can be computed as Eq. 19.

$$h_t = O_t \odot \tanh(C_t) \tag{19}$$

Where O_t is the output gate, and C_t is the cell state, and $\odot$ is the Hadamard product used to element-wise multiply the output gate (O_t) with the hyperbolic tangent of the cell state ($tanh(ct)$). In addition, graph-based neural network models have also become a powerful tool to implement spatial relationships and network structure in mobility prediction networks, therefore, offering a more holistic viewpoint to user paths in the context of the structural map of the network [117].

5.2.2 QoS/QoE prediction models

The third pillar for future research on active handover management is the prediction of Quality of Service (QoS) and Quality of Experience (QoE). The main purpose of such predictive models is to forecast the quality of service that is required after the handover implementation. This expectation is linked to a set of factors, and they are expected network conditions after handover, the peculiarities of the applications, preferences of individuals, and the technical capacity of user equipment [118]. The advent of 6G networks has made Quality of Service (QoS) and Quality of Experience (QoE) even more difficult to predict. The complexity of such networks is due to two main aspects: the high level of heterogeneity of services that these networks need to support, and the dynamic nature of network conditions. It is important to note that, recognizing the limitations of conventional approaches to measurement, the academic community has resorted to the use of data-driven approaches. These modern methods have a higher capabilities of modelling the subtle and multidimensional interdependences between objective measures of performance and subjective experience of the users. One of the largest groups of modern literature focuses on the study of neural network structures to predict Quality of Service (QoS) and Quality of Experience (QoE). These models have demonstrated a strong potential, and in particular in dealing with the nonlinear properties, which dominates the relationship between network-level parameters and the perceived quality by the user. Empirical studies have confirmed that multilayer neural structures can accurately model the complex interdependences between physical network measures with consumer quality indicators [119]. Convolutional neural networks (CNNs) have been found to be quite useful in this area, identifying spatial patterns in the quality of services that are often lost in aggregate measures. These spatial relationships allow the CNN-based procedure to have a deeper insight into the quality difference in different network locations. [120, 121]. A deep neural network for QoE prediction can be represented as Eq. 20.

$$QoE = \sigma\left(W_h \sigma\left(\ldots \sigma\left(W_2 \sigma\left(W_1 x + b_1\right) + b_2\right) \ldots\right) + b_n\right) \tag{20}$$

Where σ is the activation function, W_i are weight matrices, b_i are bias vectors, and x is the input feature vector. As a complement to these methods, reinforcement learning (RL) methods have acquired growing academic interest. Unlike the very traditional prediction systems, the RL systems can also be modified with time, incorporating real user feedback, thus increasing their accuracy as the network conditions and the expectations of the users change [122]. This flexibility presupposes special importance in 6G cases when service needs and network conditions demonstrate high dynamism. It is a style that makes use of probabilistic graphical models that furnish an organized display of conditional connections between network performance indicators, application behaviour, and the level of user satisfaction [123]. The fact that these models conceptualize QoE as a probabilistic interaction as opposed to a fixed metric provides researchers and operators with an opportunity to look at performance through many different lenses. QoE can be measured simultaneously using perspectives of end users, service providers and network operators as depicted in Fig. 6. Another significant implication of the accurate prediction of QoS/QoE is the possibility to implement individualized mobility and handover plans. User-preferred network overlay and historical QoE information can be used to adapt mobility decisions in accordance with the individual usage patterns to recognize the fact that to different users and applications, the subjective experience is significantly different. This customization is an essential move towards user-centric mobility management in the future intelligent network systems [124, 125].

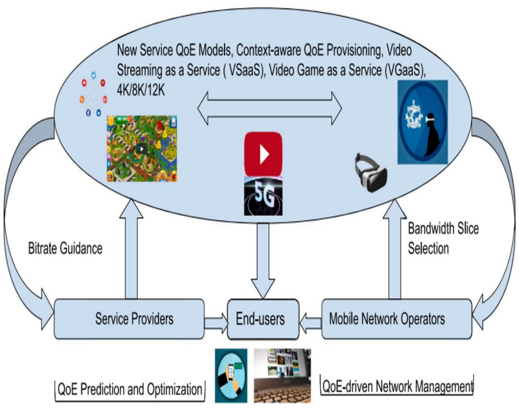

Figure 6. QoE management from three perspectives: end-user, service provider, and network operator [123].

6. Performance metrics and evaluation methodologies for 6G handover management

The emergence of the ultra-dense 6G network introduces unprecedented challenges in handover management evaluation, requiring a paradigm change in performance evaluation methods. This section presents a systematic structure incorporating state-of-the-art experimental platforms to validate advanced matrix, quantum-comprehensive simulation environments, and the next-generation handover system.

6.1 Key Performance Indicators (KPIs) for 6G handovers

The multifaceted nature of 6G handover processes necessitates a sophisticated framework of Key Performance Indicators (KPIs) that transcends traditional evaluation metrics. This section presents a comprehensive analysis of interconnected performance metrics, establishing theoretical foundations and examining their collective impact on system performance in ultra-dense 6G deployments [126]. The fundamental performance metrics in 6G handover scenarios can be expressed through a unified theoretical framework Eq. 21.

$$P(H) = f(L, R, S, E) \tag{21}$$

Where $P(H)$ represents overall handover performance, L denotes latency components, R encompasses reliability measures, S represents scalability factors, and E captures energy efficiency metrics. This interdependent relationship establishes the basis for comprehensive handover evaluation in ultra-dense networks.

6.1.1 Multi-Dimensional Latency Metrics

The handover delays are considered the crucial component of the 6G networks that have a direct effect on the user experience and continuity of the session; therefore, they affect a wide range of applications, such as holographic communications and autonomous systems [127].

- Total Holistic Handover Execution Time (HHET): According to the definition, HHET shows the total time frame of the entire process of handover including the initialisation and any changes that might take place during the network state [128]. The measure has a complete time profile that is required in ultra-latency applications of 6G. It also includes factors of signalling overhead, resource-allocation delay, and certification procedures, hence allowing the determination of the exact source of delays in handover process Eq. 22.

$$HHET = \int \left[t_o tot_f\right] f(t, \omega) dt \tag{22}$$

  Where $f(t, \omega)$ represents the time-varying handover process, incorporating network state ω, from initiation (t_0) to completion (t_f).
- Predictive Latency Optimization Factor (PLOF) is a metric of artificial intelligence that measures the effectiveness of future handover plans. PLOF makes clear the benefits of having complex predictive algorithms by comparing the delay that is expected in handovers to the baseline reactive strategies [129]. The measure is especially relevant in the evaluation of learning-based handover programs that have the capacity to predict both user and network behavior so as to facilitate proactive handovers Eq. 23.

$$PLOF = \frac{T_{baseline} - T_{predictive}}{T_{baseline}} \tag{23}$$

  This metric quantifies the efficacy of AI-driven predictive handover mechanisms, where Tbaseline and Tpredictive denote conventional and predictive handover durations, respectively.
- Cross- layer Handover Latency (CHL): This model of generalized analysis is used to measure the latency of a network along with multiple abstraction layers. This measure is needed in 6G networks, in which cross-layer optimization is critical in realizing ultra-low latency. The Cross-layer Handover (CHL) model defines delays at the physical layer, e.g. beam-alignment in millimetre-wave systems, at the MAC layer, e.g. contention-resolution protocols, at the network layer, e.g. IP address re-assignment, and at the application layer, e.g. session initiation [129]. Additionally, it explicates the latency and reliability demand of various URLLC services Eq. 24.

$$CHL = \sum_{i=1}^{n} \alpha_i \cdot L_i \tag{24}$$

  Where L_i represents latency components across n network layers, and α_i are corresponding weighting factors.
- Contextual Handover Latency Variation (CHLV): is used to measure the variation of handover delay with change of different network contexts such as user mobility patterns, spatial changes in cellular density and traffic-load conditions (see references [130, 131]). This measure helps to evaluate the consistency and predictability of handover performance within an array of likely 6G conditions and in this way secure the continuation of the quality of service at a consistent level.

Figure 7. Small Cell deployment [132].

7. Open Research Challenges and Future Directions

The shift towards 6G networks introduces new issues in handover management, requiring a complete overhaul of current systems and novel approaches to solutions. This section provides of the major obstacles in performing appropriate research on ultra-dense 6G networks while simultaneously addressing the profound gap in the literature around intelligently automated handover management systems.

7.1 Advancing AI-Driven Handover Optimization: Challenges and Next Steps

The extreme congestion of the wireless networks during the 6G era brings with it some inherent challenges, which demand a paradigm shift in the handover management approaches. The traditional handover mechanisms are becoming ineffective as the density of the network becomes closer to 1000 cells per square kilometer in an urban setting [133]. Figure 7 shows the deployment of small cells, which are applicable in 6G handover. This part evaluates major issues and possible remedies to the attainment of scalable handover management in ultra-dense networks (UDNs), specifically, the distributed algorithms and hierarchical structures. Network density can be measured by the density complexity relationship whose strengths can be used to measure the effect of network density on handover management Eq. 25.

$$C_{total} = \alpha Nd \cdot log(Nc) + \beta_i \sum_{i=1}^{Nd} \sum_{j=1}^{Nc} Hij + Y \sum_{k=1}^{R} Ik \tag{25}$$

Where Ctotal represents total system complexity, Nd is the number of user devices, Nc is the number of cells, Hij represents individual handover complexity, Ik represents inter-RAT complexity factors, R is the number of different RATs, alpha, beta, gamma (α, β, γ) are scaling factors reflecting the relative impact of each component. These difficulties require the creation of adaptive resource management measures which are able to adjust the use of resources on the various dimensions whilst maintaining the aim of handover performance. It is necessary to implement advanced technologies, including edge computing and artificial intelligence. should be carefully considered in terms of these resource obstacles to ensure practical and efficient implementation of handover management solutions in the 6G network [134]. Table 3 provides a comprehensive comparative evaluation of the 6G handover methods proposed against existing approaches in five key performance parameters. The LSTM and GRU-based forecasting structure achieves the accuracy of the best handover decision, while effectively reducing the ping-pong effect, compared to the implementation of traditional conventional fuzzy logic and Markov chain implementations [132], as well as the Markov chain. The reinforcement learning approach shows the best performance in the dynamic environment through autonomous decision-making capabilities [135], while the Split Federated Learning Methodology provides scalability benefits distributed across a scalability advantage for heterogeneous multi-RAT. This comparative analysis establishes the competitive advantages of the proposed framework in terms of calculation efficiency, adaptability, and next-generation 6G ultra-dense network architectures.

Table 3. Comparison of previous works with our Work in 6G Handovers.

Feature	Fuzzy Logic Controllers	Markov Chain Models	The proposal works in 6G		
			LSTM & GRU Based-Prediction	Reinforcement Learning (RL)	Split Federated Learning (SFL)
Adaptability	Dynamically adjusts parameters based on real-time input variables (e.g., RSRP, RSRQ, velocity).	Predetermined transition probabilities require frequent updates for dynamic environments.	Learns temporal dependencies in mobility patterns, enabling adaptive handover prediction.	The methodology obtains the best handover strategies independently based on the network rewards and penalties.	It enhances the flexibility of the network by implementing privacy preserving and collaborative artificial intelligence.
Computational Complexity	Higher computational load due to real-time fuzzy rule evaluations.	Lower complexity: Markov transitions require matrix computations.	Moderate complexity due to sequential learning computations.	Even though, the performance is high at the start due to the large training requirements, the system is efficient after training.	The method can be scaled by use of distributed learning that is deployed on edge devices, which alleviates the computational load per device.
Accuracy in Handover Decision	Higher accuracy in heterogeneous and ultra-dense networks.	Effective in uniform mobility environments but struggles with non-stationary user behaviors.	Highly accurate in predicting user mobility patterns, reducing unnecessary handovers.	The system also outperforms in a dynamic environment through time and handover selection optimization which is autonomous.	Strong handover decisions are achieved by using multi-device collaboration thus protecting privacy and providing opportunities to learn in a real-time.
Robustness Against Ping-Pong Effect	Minimizes ping-pong handovers by adaptively tuning HOM and TTT.	Can predict and mitigate unnecessary handovers but lacks real-time adaptability.	Effectively reduces handover oscillations through deep sequence learning.	This is a method of reducing ping-pong effects by maximizing mobility decisions in the long-term.	Optimization at long term is enabled by decentralized and safe model training that reduces the frequency of the handover.
Scalability	Well-suited for large-scale ultra-dense networks with varying mobility patterns.	More efficient in macrocell-based environments with lower cell density.	Scalable across multi-RAT heterogeneous networks, including terrestrial and non-terrestrial paradigms.	The framework can be scaled to changing 6G dynamic environments and adjust to the patterns of mobility.	It is perfectly adaptable to federated learning in edge-based 6G design, comprising terrestrial, aerial and satellite networks.

7.1.1 Distributed Handover Management Algorithms

The implementation of distributed handover management algorithms in ultra-dense 6G networks represents a critical research challenge that demands innovative solutions beyond conventional approaches. The existing centralized systems of handover management currently have severe weaknesses in ultra-dense systems, especially in the processing load, signaling overload, and the latency of decision-making. It makes distributed decision-making even more complicated is the fact that continuity of the service is required, at the same time, with the resources being optimally used in the thousands of cells [136]. The basic issue of distributed handover management is the establishment of effective information-sharing systems between network nodes. The ultra-dense networks require an advanced strategy to decide on local choices about the potential handover candidates, with the partial or even unavailable information sometimes available [137]. This difficulty in particular is amplified when the mobile users are considered as very mobile, where the change in network conditions is very quick and thus causes a great burden to the overhead of information exchange among distributed decision-making organizations. Organization of the distributed handover decision is a critical issue especially in maintaining stability in the network, failure to which causes instability. The existing solutions are often unable to strike the trade-off between local control and global adjustment particularly in situations where numerous user equipment (UE) devices would require joint handover choices [138]. The implementation of a distributed algorithm should address the challenge of resource adaptation in several dimensions, including spectrum efficiency, energy consumption, and computational resources. The interdependence of these factors in the ultra-defense network makes a complex adaptation challenge that should be navigated in real-time while maintaining acceptable levels of service quality and reliability [139].

7.1.2 Hierarchical Decision-Making Frameworks

The development of strong hierarchical decision-making structures is a valid strategy towards the challenge of dealing with the complexity that is inherent with handover processes in ultra dense 6G environments. These structures need to balance between two competing requirements: the need to have fast, localized decision-making and the general need to have the optimisation of the network comprehensively. At the same time, these systems should be capable of being used in a network of different densities and architectural designs. The recent studies have explored hierarchical deep reinforcement techniques that jointly optimise the radio access technology choice and power allocation within heterogeneous networks and have shown objectively quantifiable gains in network utility as well as addressing responsiveness to dynamic conditions [140]. The given approach unites Deep Q-network and Deep Deterministic Policy Gradient methods to address the hidden mixed integer non-linear programming problem, especially solving it with partial channel state information known as shown in Fig. 8. However, such hierarchical architecture design presents a number of basic research problems that require technical innovations.

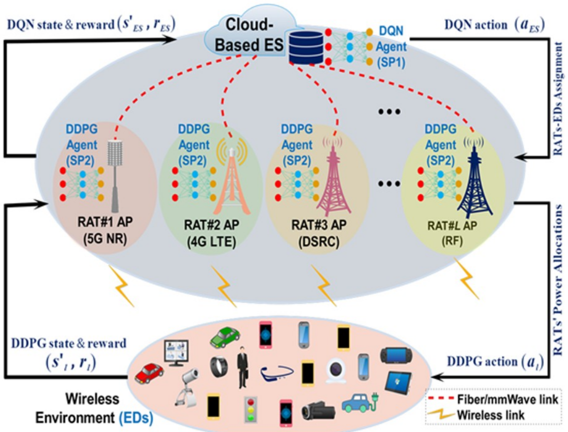

Figure 8. System model proposed Deep RAT framework for next-generation HetNets [141].

8. Conclusion

Handover management in ultra-dense 6G networks represents a critical challenge due to the combined effects of extreme network densification, heterogeneous access technologies, and increasingly stringent service requirements. As mobility events become more frequent and decision windows narrower, conventional handover mechanisms struggle to ensure seamless connectivity, low latency, and reliable service continuity. This review has provided a comprehensive and structured analysis of recent advances in intelligent handover management, emphasizing the growing role of artificial intelligence in enabling proactive and context-aware mobility support. In particular, learning-based mobility prediction, adaptive handover optimization, and emerging architectural enablers such as edge-assisted intelligence and network slicing were examined as key components for addressing the complexity of next-generation mobility management. The analysis also highlighted the importance of privacy-preserving learning paradigms in supporting scalable and trustworthy intelligence in future 6G infrastructures. Despite notable progress, the findings indicate that existing research efforts remain largely fragmented, often addressing individual techniques or architectural elements in isolation. Limited cross-layer integration, narrow performance evaluation perspectives, and insufficient consideration of security and ethical aspects continue to constrain the effectiveness of current handover solutions in ultra-dense environments. In this context, the present review contributes a holistic and system-level perspective that conceptually links intelligent learning mechanisms, privacy-aware architectures, and multi-dimensional performance considerations for handover management in ultra-dense 6G networks. By synthesizing these dimensions within a unified analytical framework, the study offers a coherent foundation for the development of adaptive, reliable, and scalable mobility solutions capable of meeting the demands of future wireless systems.

Authors' contribution

All authors contributed equally to the preparation of this article.

Declaration of competing interest

The authors declare no conflicts of interest.

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Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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