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AI-Driven Handover Management and Load Balancing Optimization in Ultra-Dense 5G/6G Cellular Networks

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Abstract

This paper presents a comprehensive review of handover management and load balancing optimization (LBO) in ultra-dense 5G and emerging 6G cellular networks. With the increasing deployment of small cells and the rapid growth of data traffic, these networks face significant challenges in ensuring seamless mobility and efficient resource allocation. Traditional handover and load balancing techniques, primarily designed for 4G systems, are no longer sufficient to address the complexity of heterogeneous network environments that incorporate millimeter-wave communication, Internet of Things (IoT) devices, and unmanned aerial vehicles (UAVs). The review focuses on how recent advances in artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), are being applied to improve predictive handover decisions and enable real-time, adaptive load distribution. AI-driven solutions can significantly reduce handover failures, latency, and network congestion, while improving overall user experience and quality of service (QoS). This paper surveys state-of-the-art research on these techniques, categorizing them according to their application domains and evaluating their performance benefits and limitations. Furthermore, the paper discusses the integration of intelligent handover and load balancing methods in smart city scenarios, where ultra-dense networks must support diverse services with high reliability and low latency. Key research gaps are also identified, including the need for standardized datasets, energy-efficient AI models, and context-aware mobility strategies. Overall, this review aims to guide future research and development in designing robust, AI-assisted mobility and resource management frameworks for next-generation wireless systems.

Keywords: 5G; 6G; ultra-dense networks; handover; mobility management; artificial intelligence; smart city

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Academic Editor: Arash Habibi Lashkari

Received: 18 April 2025
Revised: 11 June 2025
Accepted: 12 June 2025
Published: 01 July 2025

Citation: Chabira, C.; Shayea, I.; Nurzhaubayeva, G.; Aldasheva, L.; Yedilkhan, D.; Amanzholova, S. AI-Driven Handover Management and Load Balancing Optimization in Ultra-Dense 5G/6G Cellular Networks. *Technologies* **2025**, *13*, 276. https://doi.org/10.3390/technologies13070276

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1. Introduction

The development and deployment of 5G cellular networks, the fifth generation of wireless mobile communications, are expected to be catalysts for new paradigms in mobile network architecture. One such paradigm is the concept of ultra-dense networks

(UDNs) [1,2]. Modern users generate an unprecedented volume of data traffic, necessitating a fundamental shift in network design. Emerging services and applications, such as high-definition video streaming, augmented reality, cloud computing, and the IoT, impose stringent performance requirements. Compared to 4G, 5G cellular networks support up to 100 times higher throughput, primarily through aggressive cell densification using femtocells, picocells, and microcells. However, despite the maturity of the 5G standard, several critical challenges remain [3,4]. In parallel, global efforts are underway to define the 6G standard, which targets ultra-low latency, extreme data rates, and integration with AI-native services [5,6]. Sixth-generation cellular networks aim to support new services with extremely stringent requirements, including ultra-low latency, extreme data transfer rates, and enhanced AI-enabled applications. The sheer complexity of 6G has garnered global research interest, with major contributions from research teams in China, South Korea, the United States, and Europe. Despite the growing attention on 6G, significant research efforts continue within the 5G domain, particularly in relation to enhancing network performance, scalability, and efficiency. This paper reviews recent publications focused on mobility and resource management in ultra-dense 5G and 6G cellular networks. Special attention is given to handover management, which becomes increasingly complex in UDNs due to more frequent inter-cell transitions. Frequent handovers may result in ping-pong effects and degraded performance due to increased signaling overhead and handover failures. These issues are particularly critical for mobile devices, which are sensitive to energy consumption [7,8]. Additionally, interference management is a pressing concern, as dense cell deployments heighten co-channel interference. Traditional mitigation techniques, such as power control and frequency reuse, must be enhanced through AI-driven predictive modeling to ensure reliable connectivity. Load balancing mechanisms are equally vital, as they efficiently distribute user traffic to prevent congestion, which can affect the quality of service (QoS) [9,10]. Load balancing strategies in wireless networks aim to distribute traffic and user connections evenly across available base stations or network resources to prevent congestion [11], reduce latency, and enhance QoS. Traditional methods include cell range expansion, handover thresholds, and resource-aware scheduling. With the increasing complexity of heterogeneous and ultra-dense networks [12], AI-based approaches have emerged as effective solutions. These approaches utilize machine learning (ML) and deep learning (DL) techniques such as deep reinforcement learning (DRL), federated learning, and edge intelligence to make dynamic, real-time decisions for optimal resource allocation and traffic distribution. AI models can learn from historical and real-time network data to predict congestion patterns, anticipate user mobility, and proactively balance loads across the network [13].

UAVs are anticipated to play an integral role in future mobile networks, contributing to the vision of self-organizing networks. UAVs will be deployed both as mobile users and airborne base stations, offering remarkable versatility and adaptability. Their increasing popularity stems from their flexibility, low cost, and ease of deployment, making them promising candidates for enhancing 5G, 6G, and beyond. Despite their advantages, UAV-based networks also introduce unique challenges, particularly in data transmission management. Unlike traditional terrestrial networks, UAVs operate in three-dimensional space, significantly increasing mobility complexity [14,15]. Free-space orientation and antenna sidelobes impose constraints on transmission, making data transfer in UAV-based networks a critical issue in both 5G and 6G environments. Ensuring stable and reliable connectivity requires advanced mobility management and transmission techniques to overcome these limitations. A comprehensive survey of data transmission management for UAV-connected networks in next-generation mobile ecosystems is provided in [13]. This paper contributes to the ongoing discourse by presenting a structured survey of existing ap-

proaches to handover management and load balancing in ultra-dense 5G/6G environments. Unlike prior works that focus on narrow aspects, this review synthesizes methodologies across multiple domains, identifies limitations, and outlines future research directions. The goal is to inform the design of more resilient, AI-assisted network architectures in the context of increasingly dense and dynamic wireless ecosystems.

UDNs [16] refer to wireless network architectures characterized by the deployment of a very high number of small cells (femtocells, picocells) within a given geographical area, resulting in a cell density that far exceeds that of traditional network designs. The primary goal of UDNs is to significantly improve network capacity, spectral efficiency, and user experience by reducing the distance between users and access points, enabling higher frequency reuse and supporting massive device connectivity, which is essential for 5G and 6G cellular networks, as well as any future advancements.

The remainder of this paper is organized as follows: Section 2 provides essential background information on 5G and 6G cellular networks, their architectures, enabling technologies, and small-cell types. Section 3 presents a comprehensive review of recent research related to handover management, load balancing, and AI integration. Section 4 discusses current challenges and outlines future research directions for UDNs. Section 5 concludes the paper by summarizing the key insights and emphasizing the impact of AI-driven solutions in next-generation wireless systems.

2. Contribution and Comparison with Related Surveys

This section aims to highlight the contributions of this survey in comparison to other related surveys in the field of handover management and load balancing in ultra-dense 5G/6G cellular networks. By reviewing previous surveys, we identify gaps and outline how our work addresses these gaps, providing comprehensive and up-to-date analysis, as shown in Table 1.

Table 1. Comparison of Related Surveys and Contributions of This Survey.

Reference	Focus	Challenges Addressed	Limitations
2022 [17]	Integration of 5G networks with IoT in UDNs.	Latency, scalability, interoperability, security vulnerabilities, computational costs, limited AI training data.	Primarily focuses on IoT integration and does not extensively cover handover management and load balancing.
2024 [5]	Role of UDNs in high-capacity and low-latency communication.	Interference management, resource allocation, energy efficiency.	Focuses on UDNs but does not provide a detailed analysis of AI-driven handover and load balancing techniques.
2024 [18]	Evolution of UDNs and small-cell integration.	Interference management, resource allocation, energy consumption.	Provides a broad overview but lacks in-depth analysis of specific AI techniques for handover and load balancing.
2020 [19]	Future research directions in UDNs.	Scalability, energy efficiency, security.	Focuses on future directions rather than current state-of-the-art techniques.
2025 [20]	Adaptive handover management in high-mobility networks for smart cities.	Service continuity, latency, network resource optimization.	Focuses on smart city applications but does not cover load balancing in detail.

Table 1. *Cont.*

Reference	Focus	Challenges Addressed	Limitations
2023 [21]	Handover and load balancing self-optimization in 5G mobile networks.	Seamless connectivity, congestion, latency.	Focuses on 5G but does not extensively cover 6G technologies and AI-driven solutions.
2022 [22]	ML-based load balancing algorithms in future heterogeneous networks.	Managing user traffic in dense networks, inefficiency of classical methods.	Focuses on load balancing but does not cover handover management.
2022 [23]	Roadmap for UAV cellular communications from 5G to 6G.	Cell selection, interference, coverage limitations in UAV networks.	Focuses on UAV communications but does not provide a comprehensive overview of handover and load balancing.
Contributions of This Survey	Comprehensive review of handover management and load balancing optimization in ultra-dense 5G/6G networks using AI-driven techniques.	Comprehensive review of handover management and load balancing optimization in ultra-dense 5G/6G cellular networks, analyzing the latest AI-driven techniques like deep learning and reinforcement learning. It also examines the integration of UAVs and IoT devices, identifies research gaps, and outlines future directions, with a focus on practical applications in smart cities.	This survey primarily focuses on the theoretical and research-oriented aspects of handover management and load balancing in ultra-dense 5G/6G cellular networks, providing a comprehensive review of AI-driven techniques. While it offers valuable insights into the latest advancements and future directions, it does not delve into detailed implementation examples or case studies. Additionally, the scope of this survey is limited to current research and does not cover all potential future developments in 6G technologies.

3. Network Background

In the near future, 5G and 6G cellular systems will be the most dominant networks, providing advanced and varied services. Both 5G and 6G networks aim to enhance user experience, optimize resource utilization, and support emerging applications such as smart cities, autonomous vehicles, and next-generation industrial automation.

3.1. Fifth-Generation Cellular Networks

Currently, 5G cellular networks have been launched in many countries. Deployment is still ongoing, with plans for further expansion. This network, 5G, now represents the latest advancement in wireless mobile broadband technology, offering key features such as higher data transmission speeds, reduced latency, support for a massive number of connected devices simultaneously, and improved energy efficiency [24]. In today's era, modern technological applications demand the robust capabilities of 5G in order to accommodate diverse services. The evolution of 5G technlogy is ongoing, shaping the development of a truly wireless network referred to as the WWWW. The 5G communication network is developed based on a combination of 4G and the WISDOM [25].

Due to the fundamental principles of communication, 5G achieves high-speed data transmission, leveraging short frequencies and large bandwidths to enhance network efficiency. The designated spectrum for 5G spans from 30 GHz to 300 GHz, which restricts communication to short distances but enables bandwidths exceeding 1 Gbps [26].

Mobile communications are becoming increasingly congested due to the rising user data demands and the need for new services [27]. To address this, 5G cellular networks are

designed to accommodate growing data requirements, particularly for industrial users and emerging technologies like machine communication [24]. The expansion of 5G cellular technology is driving a surge in internet-connected devices, including smartwatches, meters, industrial sensors, and IoT applications. The IoT extends mobile communication beyond people to smart systems, enabling mobile health, smart homes, industrial automation, and environmental monitoring. The big data generated will rely on cloud computing for storage and processing [28]. Fifth-generation technology will revolutionize industries, shaping the future of mobile broadband (MBB) and the IoT in everyday life, as illustrated in Figure 1.



Figure 1. Fifth-Generation connectivity and its applications across various sectors.

It can be stated that 5G cellular networks represent the fifth generation of mobile communication systems, being designed to address the growing demand for high-speed, low-latency, and reliable wireless connectivity. They introduce advancements such as

- eMBB for high-speed data transmission;
- URLLC to support mission-critical applications;
- mMTC to enable large-scale IoT deployments.

One of the key enablers of 5G is SDN, which enhances flexibility and programmability in network management, allowing dynamic resource allocation and the efficient control of traffic flows.

3.2. Sixth-Generation Cellular Networks

In 6G communication, emerging technologies such as terahertz communication, visible-light communication, and advanced access-backhaul integration are introduced to achieve ultra-high peak rates, massive connectivity, and exceptional reliability in communication networks [7], as illustrated in Figure 2. As shown in Table 2, 6G is expected to significantly outperform 5G in various aspects. However, merely introducing new technologies is insufficient, as the existing architecture cannot fully address these challenges. Therefore, the core network architecture must be restructured to create a more powerful, flexible, and intelligent system. The following section presents a brief vision of a 6G cellular network [1].

3.2.1. Diverse Mobile Communication Technologies

To enable global internet access, 6G cellular networks will seamlessly integrate satellite, UAV, and maritime communications. These technologies will complement terrestrial

networks, significantly extending 6G coverage [1]. However, despite being access network technologies, their expansion requires robust support from the core network.

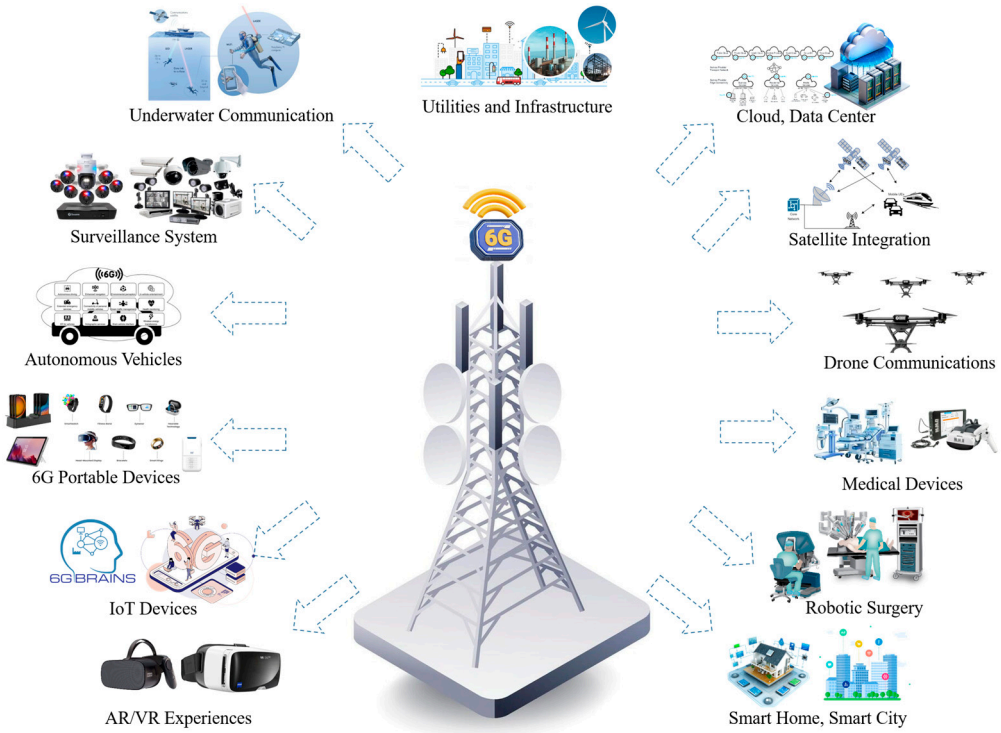


Figure 2. Potential applications and use cases of the 6G mobile technology.

Table 2. Comparison of key performance metrics between 6G and 5G cellular networks.

	5G	6G
Mobility	350 km/h	>1000 km/h
Delay	Tens ms	<0.1 ms
Reliability	99.99%	>99.99999%
Peak data rate	10 Gbps	>1000 Gbps
Connection density	1 million/km^2	>10 million/km^2

3.2.2. Reliable Low-Latency Mobile Broadband

Multi-sensory XR applications will be a key feature of 6G, requiring high bandwidth and ultra-low latency to prevent performance issues [9]. Because XR devices are wearable, user movement can trigger frequent handovers and service migrations, adding system uncertainties. These applications demand significant computing power and real-time responsiveness, with network congestion potentially causing latency violations. To ensure seamless performance, the 6G cellular network must dynamically detect changes and efficiently reallocate resources.

3.2.3. AI-Integrated Communication

Sixth-generation cellular networks aim to achieve the Internet of Everything by connecting numerous heterogeneous devices while leveraging AI. However, AI applications require significant computational power, creating challenges in resource allocation. Traditional cloud-driven AI increases the network load and latency, while edge computing faces resource constraints [1]. Unlike previous networks that separated communication and computation, 6G introduces network-empowered AI, where AI and computational resources are fully integrated. The network manages and optimizes the connected devices,

creating an intelligent infrastructure. Additionally, AI-empowered networks will enable 6G to dynamically adapt to changing environments, using AI-driven controllers to enhance both network efficiency and real-time performance.

Sixth-generation cellular networks are envisioned as the successor to fifth-generation variants, being expected to revolutionize wireless communication by integrating AI, THz communication, and satellite–terrestrial networks. The key features of 6G include

- Extreme data rates, potentially reaching terabits per second;
- AI-driven network automation for self-optimizing connectivity;
- Satellite integration for global coverage and seamless connectivity.

Sixth-generation cellular networks will build upon SDN principles, further improving network flexibility and enabling adaptive control based on AI and real-time data analytics.

3.3. Ultra-Dense 5G/6G Cellular Networks

UDNs are characterized by having a higher number of cells than active users [10,29,30]. Specifically, a UDN is defined as when the density of the base stations (λb) significantly exceeds the density of users (λu). Another definition of a UDN is based solely on cell density, independent of user density, where a network is considered ultra-dense when it reaches a density of $\geq 10^3$ cells/km^2 [11]. In a UDN, high-power macrocells coexist with numerous low-power small cells, which may include picocells, femtocells, RRHs, and relay nodes [15]. Small cells in UDNs are generally categorized into fully functional BSs, such as femtocells and picocells, and macro-extension access points, including RRHs and relays [31]. A fully functional BS operates at lower power over a smaller coverage area while retaining all macrocell capabilities and executing the full protocol stack [32]. Conversely, a macro-extension access node enhances the macrocell coverage while performing some or all of the physical (PHY) layer functions [33,34]. UDNs play a critical role in future network evolution, enabling wireless backhaul deployment, fostering a new industry ecosystem for 6G services, and supporting both licensed and unlicensed spectrum usage. Their adaptability makes them an optimal solution for enhancing spectrum efficiency and improving the user experience in high-density environments [35].

3.3.1. Type of Cell Coverage/Base Stations

There are different types of cell sizes with different characterizations. For example, small cells are characterized by low-power, short-range wireless access points that enhance the network capacity and coverage in dense environments. They include femtocells, picocells, microcells, relay nodes, and RRHs, each designed for specific applications, as presented in Figure 3. These cells play a crucial role in 6G ultra-dense networks, enabling high-speed data, low latency, and seamless connectivity in smart cities and IoT ecosystems, as shown in Table 3.

Table 3. Characteristics of various types of small cells.

Cell Types	Placement	Coverage	Served Users	Power Consumption	Backhaul	Access
Macrocells	Outdoor	1–50 km	Up to 200 users	60 w	Fiber/microwave	Open access
Microcell	Outdoor	200–2000 m		10 w		
Femtocell	Indoor (unplanned)	10–30 m		≤100 mW	Non-ideal (broadband/DSL)	Open/closed/ hybrid access
Picocells	Outdoor/indoor (planned)	4–200 m	Up to 64 users	Outdoor (0.25–2.00 W) Indoor (≤100 mW);	Ideal (fiber/microwave)	Open access
RRH	Outdoor (planned)	Up to 100 m	Varies	Outdoor (0.25–2.00 W) Indoor (≤100 mW);	Ideal (fiber/microwave)	
Relay	Outdoor/indoor	Up to 100 m		Outdoor (0.25–2.00 W)	Wireless (out-of-band/in-band)	

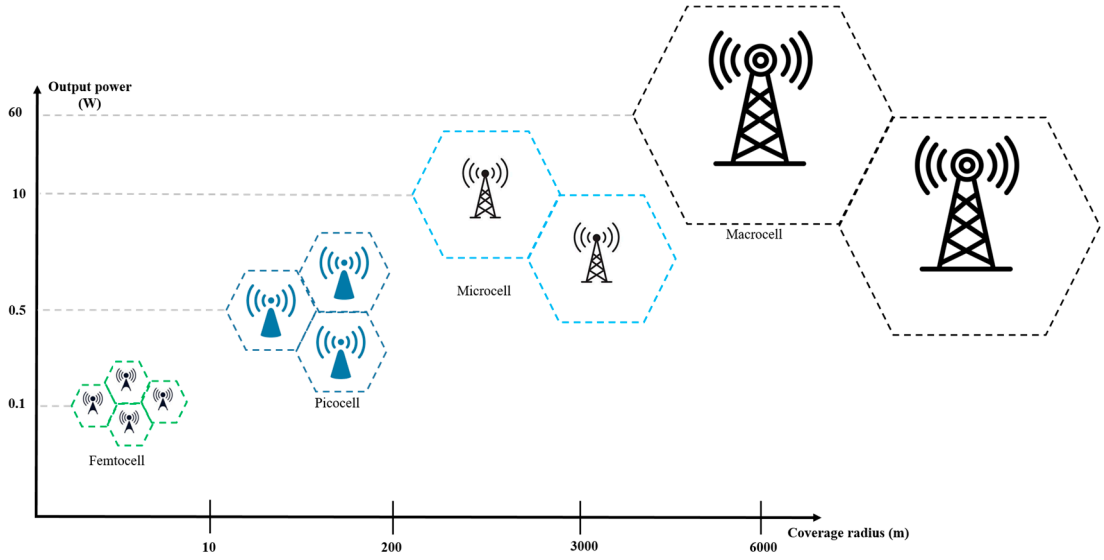


Figure 3. Comparison of small-cell and macrocell coverage and output power.

- Macrocells

Macrocells are large BSs designed to provide broad coverage in both urban and rural areas. Their antennas are typically mounted on towers, rooftops, or other elevated structures to ensure optimal signal propagation. Macrocell BSs operate at high transmission power, typically in the range of tens of watts, enabling them to cover long distances. In rural areas and highways, macrocells play a crucial role in providing widespread connectivity, although operators often limit coverage to essential voice services due to the high cost of deployment and the lower number of users. Network planning tools, combined with real-world measurements, are used to optimize macrocell deployment and ensure efficient coverage [36].

- Microcell

Microcells are small cellular base stations with a typical coverage range of less than 2 km, deployed to enhance the network capacity in densely populated areas such as urban buildings and highways. They offer a cost-effective alternative to picocells for creating high-density mobile networks while using power control mechanisms to limit their coverage area. Although microcells improve channel capacity, they introduce challenges in radio resource management and are more susceptible to short-term fluctuations in traffic and environmental changes, such as new buildings, compared to macrocells [37].

- Picocells

Picocells are small BSs installed by network operators to provide coverage within a 100 m range, primarily in hotspots (indoor and outdoor), to offload traffic from macrocells and enhance network capacity [4,5]. They typically support tens of active users and operate with a transmission power of up to 33 dBm. Picocells use fiber or microwave links for backhauling, similar to macrocells, ensuring low latency and high-bandwidth connectivity [4].

- Femtocell

Femtocells are user-installed indoor BSs designed to provide coverage in homes, offices, and meeting rooms, serving a limited number of users. They operate at a transmission power of less than 20 dBm and cover a range of tens of meters, significantly improving the indoor signal strength [4]. Femtocells connect to the network via consumer broadband

services, such as DSL, cable, or fiber, making them an effective solution for enhancing indoor connectivity where most data traffic is generated.

- RRH

RRHs are RF units that extend macrocell coverage to remote areas by connecting to a central BS through fiber optics or microwave links [28]. They serve as a centralized densification alternative, differing from the distributed densification provided by picocells and femtocells. By expanding macrocell coverage, RRHs enhance network capacity and improve connectivity in areas where deploying traditional base stations is impractical [38].

- Relay

Relays are operator-installed access points designed to enhance the macrocell edge performance and provide coverage in dead zones [39]. They function by transmitting and receiving user data between macrocells and end-users using wireless backhaul [5].

While relays and picocells share similar coverage areas and transmission power, they differ in three key aspects: (1) relays act as extensions of macrocells, whereas picocells function as independent base stations; (2) picocells are deployed primarily for capacity enhancement, whereas relays are used for coverage expansion; (3) picocells use an ideal fiber or microwave backhaul, whereas relays rely on wireless in-band or out-of-band backhaul.

3.3.2. Fundamental Feature of the UDN

To understand the distinct characteristics of UDNs compared to traditional networks, several key aspects must be highlighted.

- High Density of Small Cells: UDNs consist of many small cells with low power and small coverage areas, often located within meters or tens of meters from users [38]. This creates a unique wireless coverage environment where users are in close proximity to multiple small cells [40].
- Idle-Mode Capability: Due to the high concentration of small cells, many remain inactive at a given time. To mitigate interference and improve energy efficiency, idle-mode mechanisms are implemented, allowing inactive small cells to be turned off [41,42].
- Severe Interference Challenges: The close proximity of small cells in the UDN environment results in significant interference between neighboring cells. Thus, strict interference management techniques are required to minimize disruptions and maintain network performance [43,44].
- Advanced Frequency Reuse Techniques: Unlike traditional networks where frequency reuse occurs at the cell cluster level, UDNs require a paradigm shift in spectrum reuse strategies. In CDMA and OFDMA systems, the frequency reuse factor is one, but UDNs demand more innovative frequency reuse approaches [40].
- Complex Backhauling Requirements: Providing low-latency, high-speed backhaul for each small cell in a UDN is challenging. The backhaul capacity may become a bottleneck, limiting the air interface capacity of small cells [26,30,44].
- High Probability of Line-of-Sight (LOS) Transmission: Due to the short distances between base stations (BSs) and users in UDNs, LOS transmission is more common. Consequently, new propagation models are required, incorporating Rican fading models to account for the dominant LOS component in the received signals [11,28].

These characteristics highlight the unique design and operational challenges of UDNs, necessitating advanced interference management, frequency reuse, and backhauling solutions to ensure efficient and scalable network performance.

3.3.3. UDN in 5G Cellular Networks

According to ITU-R Report M.2320 [39], UDNs are recognized as a key technological trend to meet the high-throughput demands of 5G cellular networks. The report highlights several critical aspects of UDN development. First, enhancements in the network architecture and protocol procedures are necessary to optimize data and control paths, mobility management, and signaling processes, ultimately reducing the end-to-end latency and overhead. Second, effective interference avoidance and inter-cell coordination will improve interference management, enhancing overall system throughput and ensuring a seamless user experience. Additionally, energy efficiency plays a crucial role, encompassing both network energy conservation and user equipment (UE) power savings. Lastly, the concept of an SON is introduced to ease network optimization for operators while increasing the flexibility of deployments. These advancements collectively contribute to the efficient and scalable implementation of UDNs in future 5G networks and beyond.

3.3.4. UND in 6G Cellular Networks

The 6G ultra-dense cellular networks leverage large-scale MIMO antennas and mmWave communication technologies to enable gigabit-level wireless traffic. Massive MIMO uses hundreds of antennas per BS, enhancing the network capacity while requiring a reduction in the transmit power, which in turn reduces the coverage radius of each BS [45]. mmWave technology further enhances the wireless transmission capacity, operating in the range of hundreds of megahertz. However, due to propagation losses and physical obstructions, its effective transmission range is limited to 100–200 m. As a result, many small cells will be deployed to support ultra-dense network architectures, ensuring seamless connectivity [45,46]. To achieve extensive coverage, the 6G base station density is required to increase significantly, reaching 40–50 BS/km^2, making 6G cellular networks ultra-high-density systems. This densification introduces architectural challenges, necessitating the exploration of distributed network designs incorporating single- and multiple-gateway models to optimize performance and scalability [5].

3.4. Smart Cities and Ultra-Dense Networks

UDNs are a critical enabler of smart cities, supporting the ever-growing demand for seamless connectivity across IoT devices, autonomous systems, and smart infrastructure. These networks are characterized by a high density of wireless APs, often exceeding the density of user terminals, with inter-AP distances reduced to just a few meters. In smart cities, UDNs facilitate high-speed data transmission and ultra-low latency, features which are essential for applications such as intelligent transportation, environmental monitoring, and public safety systems [47]. By minimizing the distance between APs and users, UDNs reduce path loss, enhance signal quality, and improve overall network performance [48]. This makes them a fundamental component of modern urban ecosystems, providing a robust, scalable, and energy-efficient communication infrastructure that enhances connectivity, efficiency, and sustainability in smart cities [47].

3.5. Handover Management in Ultra-Dense 5G/6G Cellular Networks

HO management is a crucial process in wireless mobile networks, ensuring that a user's connection remains uninterrupted while moving between different coverage areas. This process involves dynamically transferring the connection from one BS to another that provides a stronger and more stable signal. Effective handover management is essential for maintaining mobility, reducing RLF, minimizing interruption times, and ultimately enhancing network reliability and user experience. By optimizing HO strategies, wireless networks can significantly improve throughput, decrease connection disruptions, and support seam-

less connectivity for users in motion [49,50]. Handover management in ultra-dense 5G and 6G cellular networks refers to the process of maintaining seamless connectivity for mobile users as they move between overlapping small cells in densely deployed network environments. This process ensures continuous service delivery by efficiently transferring active connections from one base station to another, thereby minimizing interruptions and maintaining high-quality communication [6]. In UDN scenarios, where many small cells are deployed to meet the increasing demand for high data rates and low latency, handover management becomes particularly challenging. The proximity of numerous base stations can lead to frequent and unnecessary handovers, increased signaling overhead, and the potential degradation of user experience [8]. Effective handover management strategies in such environments involve optimizing handover parameters, employing predictive algorithms, and using ML techniques to anticipate user movement and network conditions. These approaches aim to reduce handover failures, minimize latency, and enhance overall network performance, thereby ensuring reliable and efficient connectivity in ultra-dense 5G and 6G networks [51].

3.6. Load Balancing Optimization in Ultra-Dense Networks

Load balancing optimization in UDNs refers to the strategic distribution of network traffic across several densely deployed small cells to prevent congestion, enhance user experience, and improve overall network performance. In UDNs, the asymmetric data loads handled by different types of APs necessitate the development of effective load balancing algorithms to manage these disparities [52]. Traditional load balancing methods, which adjust parameters like CIO to distribute load among neighboring cells, may not suffice in ultra-dense environments due to the complex and dynamic nature of traffic patterns. To address these challenges, advanced techniques such as DRL have been proposed. For instance, a DRL-based mobility load balancing algorithm uses a two-layer architecture to autonomously learn optimal policies, effectively handling large-scale load balancing problems in UDNs [18,53]. Moreover, D2D communications have been explored as a means to facilitate load balancing without requiring additional spectrum resources. In this approach, data traffic is offloaded from congested small cells to underutilized neighboring cells via D2D links, thereby maximizing the system's sum rate and alleviating congestion [54]. Effective load balancing optimization is crucial in UDNs to manage spatial–temporal fluctuations in mobile data traffic, ensuring efficient resource utilization and maintaining the quality of service in next-generation wireless networks [31].

3.7. AI-Driven Solutions for Handover and Load Balancing

AI-driven solutions play a critical role in optimizing handover management and load balancing in modern wireless networks by leveraging advanced ML techniques. These solutions utilize neural networks, including LSTM and GRU, to analyze complex traffic patterns, predict fluctuations, and dynamically adjust network operations [18]. In handover management, AI enables systems to learn from real-time data and ongoing operations, allowing for adaptive decision-making that enhances connection stability and reduces service interruptions [54]. AI-based reinforcement learning models further optimize handover processes by predicting user mobility and proactively adjusting network parameters. For load balancing, AI-driven approaches improve traffic prediction accuracy and optimize data distribution, ensuring efficient resource allocation across densely deployed networks. By integrating AI with real-time sensor data and traffic management systems, networks can dynamically adjust signal timings, reduce congestion, and enhance overall efficiency in smart city environments [18]. These AI-powered techniques significantly enhance net-

work reliability, user experience, and operational efficiency, making them essential for next-generation 5G and 6G ultra-dense networks.

3.8. Integration of Handover and Load Balancing for Future Networks

The integration of handover and load balancing in future wireless networks refers to the coordinated approach of managing user transitions between cells (handover) and distributing network traffic across multiple cells (load balancing) to enhance overall network performance and user experience. This integration aims to ensure seamless connectivity, reduce latency, and optimize resource utilization in complex network environments [55]. In HetNets, where multiple radio access technologies coexist, integrating handover and load balancing is crucial for maintaining the QoS. Advanced algorithms dynamically adjust handover parameters based on real-time network conditions, facilitating efficient traffic distribution and minimizing handover failures [56]. Emerging technologies, such as AI and ML, are being employed to enhance this integration. Predictive handover strategies using DL algorithms can anticipate user movements, enabling proactive load balancing and reducing unnecessary handovers. These AI-driven approaches contribute to the development of self-optimizing networks capable of adapting to dynamic environments. Overall, the integration of handover and load balancing is pivotal for the evolution of future networks, ensuring the efficient management of network resources and delivering a seamless user experience [57,58].

4. Related Works

This section provides a detailed analysis of recent the state of the art (SOTA), as presented in Table 4.

Table 4. Summary and comparative analysis of related work.

Reference	Key Focus	Challenges Addressed	Future Research Directions
Long, Q et al. [17]	Integration of 5G networks with IoT in UDNs	Latency, scalability, interoperability, security vulnerabilities, computational costs, limited AI training data	AI-driven optimization, big data analytics, wireless power transfer, and cooperative energy-sharing methods.
Attar H et al. [5]	Role of UDNs in high-capacity and low-latency communication	Interference management, resource allocation, energy efficiency	Hybrid network architectures, self-organizing capabilities, and ML-based optimization.
Konatam S et al. [18]	Evolution of UDNs and small-cell integration	Interference management, resource allocation, and energy consumption	Advanced beamforming, ML-driven optimization, and self-organizing networks.
Arjoune Y. & Faruque S. [19]	Future research directions in UDNs	Scalability, energy efficiency, and security	AI-driven resource allocation, integration with 6G, edge computing, and blockchain.
Yahya S. Junejo et al. [20]	Handover management in smart city UDNs	Service continuity, latency, and network resource optimization	Edge computing, blockchain-based authentication, and self-organizing networks.
Wasan Kadhim Saad et al. [21]	Handover management and load balancing in the UDNs	Seamless connectivity, congestion, and latency	Predictive AI-driven handover, SDN-based load balancing, and integration with edge computing.

Table 4. *Cont.*

Reference	Key Focus	Challenges Addressed	Future Research Directions
Gures et al. [22]	Survey of ML-based load balancing strategies in HetNets	Managing user traffic in dense networks, inefficiency of classical methods, benchmarking RL/DRL against KPIs (SINR, throughput)	Development of scalable RL/DRL frameworks, integration of real-time analytics, and federated learning for load distribution
Luo and Fu [59]	AI-driven UAV-based D2D communication model for 5G/6G	UAV placement optimization, SINR/bandwidth/backhaul constraints, scalable clustering	Swarm intelligence and DL integration for adaptive clustering; hybrid UAV–ground coordination under dynamic network loads.
Wasan Kadhim Saad et al. [60]	Load balancing self-optimization using HCP tuning in 5G	PPHP, RLF, spectral inefficiency at varying speeds; ineffective static HCP	Context-aware HCP optimization; fuzzy and distance-based models for adaptive mobility-aware load balancing.
Giovanni Geraci et al. [23]	Roadmap for UAV cellular communications from 5G to 6G	Cell selection, interference, coverage limitations in UAV networks	Non-terrestrial networks, cell-free and THz systems, and AI-driven UAV networking architectures.

The work of Long, Q et al. [17] explores key challenges and advancements in integrating 5G cellular networks with the IoT, particularly in the context of UDNs. It highlights the role of AI-driven optimization techniques, ML models, and big data analytics in enhancing network efficiency, resource allocation, and security. This study reviews existing approaches to energy-efficient communication, intelligent traffic management, and real-time data processing while addressing critical concerns such as latency, scalability, and interoperability. In addition, it examines the impact of wireless power transfer and cooperative energy-sharing methods in terms of sustaining network operations. Despite significant progress, unresolved issues such as security vulnerabilities, high computational costs, and limited training data for AI models remain. This paper contributes to this evolving field by proposing a framework that balances network performance, energy efficiency, and security, paving the way for more resilient and adaptive UDN architectures in future wireless communication systems.

Attar H et al. [5] analyzed the role of UDNs in addressing the growing demand for high-capacity and low-latency wireless communication. Their work highlights the significance of small-cell types, including femtocells, picocells, and microcells, in enhancing network coverage, spectral efficiency, and user experience. By deploying a dense network of small cells, UDNs effectively mitigate congestion but introduce challenges such as interference management, resource allocation, and energy efficiency. This paper reviews various techniques, including coordinated multipoint transmission, interference cancelation, and ML-based optimization, to overcome these challenges. Furthermore, it discusses the distinct advantages of different small-cell types in network densification, considering factors such as coverage area, power consumption, and user capacity. Recent advancements in hybrid network architectures and self-organizing capabilities have also been explored to improve the scalability and adaptability of UDNs. The findings contribute to ongoing research on optimizing small-cell deployments for future wireless networks.

Konatam S et al. [18] examined the evolution of UDNs as a pivotal solution for enhancing wireless communication efficiency. It explores the integration of small-cell types, such as femtocells, picocells, and microcells, to improve the network capacity, coverage, and spectral efficiency. This study highlights the primary challenges associated with UDNs,

including interference management, resource allocation, and energy consumption. Various methodologies, such as advanced beamforming techniques, ML-driven optimization, and interference coordination strategies, are analyzed to mitigate these challenges. In addition, the paper discusses the role of small-cell networks in enabling seamless connectivity and network densification, emphasizing their adaptability to diverse deployment scenarios. Emerging technologies, including self-organizing networks and hybrid architectures, are also explored to enhance the scalability and flexibility of UDNs. The findings contribute to the ongoing research on optimizing ultra-dense small-cell deployments for next-generation wireless communication systems.

The work of Arjoune. Y Faruque S. [19] outlines key future research directions in the evolution of UDNs and small-cell deployments. This research emphasizes the need for advanced interference management techniques to enhance network performance in increasingly congested environments. Future studies should explore intelligent resource allocation strategies, leveraging artificial intelligence and ML to optimize spectrum efficiency. Additionally, energy-efficient small-cell architectures are highlighted as a critical research area in relation to efforts to minimize power consumption while maintaining high network capacity. The paper also discusses the potential integration of UDNs with emerging technologies such as 6G, edge computing, and block chain for enhanced security and connectivity. Moreover, self-organizing networks and dynamic reconfiguration mechanisms are proposed to improve network adaptability. These future directions aim to address the scalability, efficiency, and sustainability challenges of next-generation wireless networks, paving the way for more robust and intelligent small-cell deployment.

Yahya S. Junejo et al. [20] explore the critical role of handover management in ensuring seamless connectivity within UDNs, particularly in smart city environments. Efficient handover mechanisms are essential to maintain service continuity, minimize latency, and optimize network resources. The study highlights various handover strategies, including predictive and AI-driven models, to enhance mobility management and reduce handover failures. In addition, it discusses the integration of small cells in smart cities, enabling improved coverage, energy efficiency, and scalability. This paper emphasizes how intelligent transportation systems, IoT devices, and urban automation rely on robust handover protocols to support real-time applications. Future advancements in handover management are expected to leverage edge computing, blockchain-based authentication, and self-organizing networks to further enhance the efficiency of smart city infrastructures. These insights contribute to the ongoing development of next-generation wireless networks, ensuring high reliability and seamless connectivity in urban environments.

Wasan Kadhim Saad et al. [21] investigate the interplay between handover management and load balancing in UDNs, emphasizing their significance in enhancing network performance and user experience. Handover mechanisms are crucial in maintaining seamless connectivity, especially in high-mobility environments, where frequent transitions between small cells can lead to increased latency and connection failures. This study explores predictive, AI-driven, and context-aware handover techniques to minimize disruptions and optimize resource allocation. In addition, load balancing is examined as a key factor in ensuring a fair distribution of traffic across network nodes, preventing congestion, and improving overall system efficiency. This paper highlights dynamic load balancing approaches, including ML algorithms and SDN, to adaptively allocate resources in real time. Future research directions emphasize the integration of these strategies with edge computing and blockchain-based authentication to enhance network resilience and scalability. These insights contribute to the development of next-generation wireless systems with improved reliability and efficiency.

Gures et al. [22] present a comprehensive survey of ML-based load balancing algorithms designed for next-generation heterogeneous networks (HetNets), emphasizing their role in managing user traffic across densely deployed macro- and small cells. The paper categorizes classical and AI-driven strategies such as cell range expansion, cell breathing, and interference mitigation and evaluates supervised, unsupervised, and reinforcement learning techniques for dynamic traffic redistribution. Notably, reinforcement learning and deep reinforcement learning emerge as promising tools due to their adaptability and scalability in complex network environments. The authors analyze over 30 models, benchmarking them against key performance indicators like SINR, throughput, and call drop rate. This work provides valuable insight into the design and deployment of intelligent, self-optimizing load balancing frameworks essential for sustaining service quality in future 5G and 6G cellular networks.

Luo and Fu [59] propose an intelligent UAV-based device-to-device communication model tailored for future 5G/6G cellular networks, combining deep learning optimization techniques with swarm intelligence and clustering algorithms. Their framework integrates Improved Hybrid Particle Swarm Optimization with K-means (IHPSO-K), Hybrid Fuzzy C-Means (HFCM), and a greedy selection mechanism to enhance UAV placement and cluster formation under varying network demands. By adopting both device-centric- and network-centric strategies, the model maximizes either throughput or the number of served devices while addressing constraints such as backhaul capacity, bandwidth, and SINR. Simulation results using MATLAB (v25.1.0.2943329) and a multi-UAV testbed validate the system's superior performance in energy efficiency, scalability, and link reliability. This work demonstrates the effectiveness of AI-optimized UAV deployments for robust and adaptive D2D communication in ultra-dense 5G/6G environments.

Wasan Kadhim Saad et al. [60] provides an in-depth analysis of load balancing self-optimization (LBSO) within 5G mobile networks. This study highlights the significance of load balancing due to the increasing number of users and the growing use of small cell sizes in 5G cellular networks. The authors develop a simulation model to investigate the performance of LBSO under various mobile speed scenarios, focusing on optimizing handover control parameters (HCPs) to balance loads between cells. The paper evaluates different optimization algorithms, including distance, Cost Function, and Fuzzy Logic, in terms of ping-pong handover probability (PPHP), radio link failure (RLF), and spectral efficiency (SE). The results indicate that the distance algorithm demonstrates superior performance, significantly reducing PPHP, RLF, and SE across different mobile speeds. This study underscores the importance of optimizing HCPs based on user location and mobility, providing valuable insights for improving load balancing and handover management in 5G and future mobile networks.

Giovanni Geraci et al. [23] comprehensively explored the future of UAV cellular communications, spanning from current 5G capabilities to anticipated 6G advancements. The authors start by reviewing the current state of UAV communications from an industrial standpoint, highlighting new 5G NR features that support aerial devices. They analyze the potential and limitations of these features, demonstrating how sub-6 GHz massive MIMO can address cell selection and interference challenges, and showcase encouraging mmWave coverage evaluations in urban and suburban/rural settings. The paper also examines direct device-to-device communications in the sky and previews next-generation UAV communications, listing use cases envisioned for the 2030s. The authors identify the most promising 6G enablers for UAV communication, such as non-terrestrial networks, cell-free architectures, artificial intelligence, reconfigurable intelligent surfaces, and THz communications, discussing their benefits and technological hurdles. The paper concludes with a series of original results and key takeaways, emphasizing the need for further research to

address open problems in UAV-specific opportunities and challenges. This work serves as a valuable resource for understanding the trajectory of UAV cellular communications and the technological advancements required to support their integration into future networks.

5. Challenges and Future Research Directions

As UDNs continue to evolve to support 5G and 6G technologies, several key challenges must be addressed to enhance network performance, energy efficiency, and security, as presented in Figure 4. The following areas require further research and innovation.

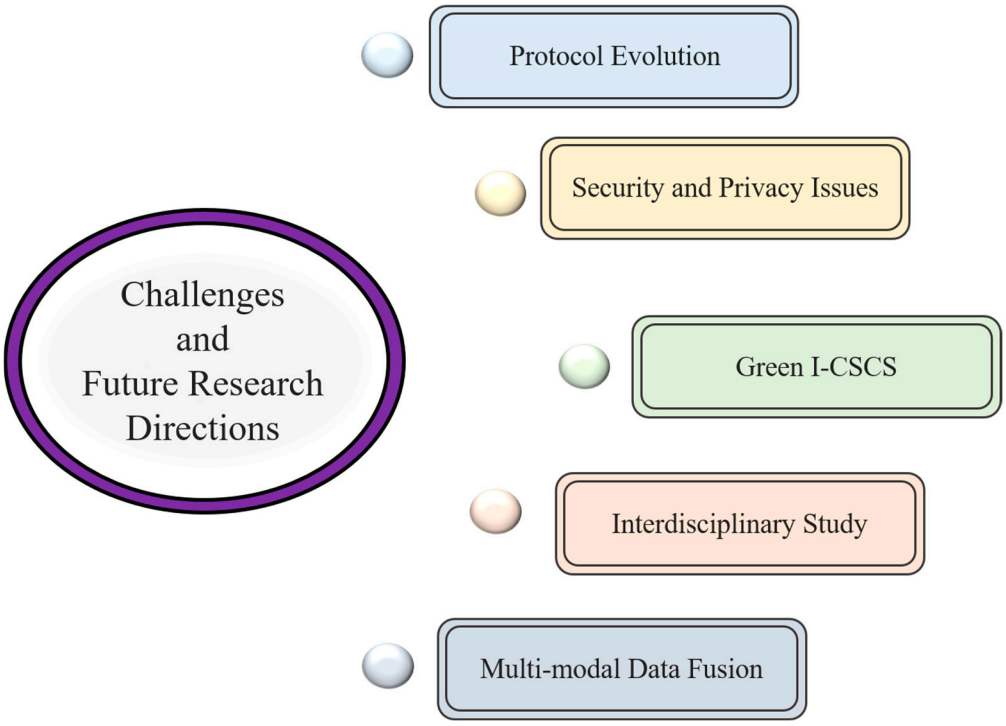


Figure 4. Key challenges and future research directions.

5.1. Big Data and UDN Integration

The integration of big data analytics with UDNs brings both advantages and challenges. While big data-driven optimization can improve resource allocation and energy efficiency, the large number of IoT devices generating extensive datasets leads to increased computational complexity and power consumption. Future research should focus on AI-powered data processing techniques that enable real-time network resource management and adaptation to traffic fluctuations [54].

5.2. Network Analysis in the UDN

The deployment of dense small-cell networks increases network complexity, making real-time analysis crucial for identifying bottlenecks and inefficiencies. However, issues such as shadow fading and interference complicate performance monitoring. Future studies should explore AI-driven analytics and simulation-based methodologies to enhance network evaluation and autonomous optimization [7].

5.3. Traffic Patterns and Energy Harvesting

WPT is a promising approach for improving the energy efficiency of UDNs. However, adapting the power distribution based on traffic variations remains a challenge. Research should focus on developing intelligent energy-harvesting techniques that dynamically

adjust to network load and traffic demands. Additionally, collaborative energy-sharing mechanisms could be explored to optimize power use across small cells [61].

5.4. Overhead Information Exchange

As connected devices and data traffic grow, the exchange of control and signaling information between small cells increases energy consumption and network congestion. Current signaling protocols struggle with inefficiencies, affecting both latency and power usage. Future research should aim to develop optimized communication algorithms, energy-efficient protocols, and lightweight signaling techniques to enhance network scalability and efficiency [61].

5.5. Vertical Densification

Deploying small cells at different elevation levels (vertical densification) can enhance network coverage, but it also introduces deployment challenges, including signal interference, complexity in infrastructure management, and spectrum reuse issues. Further research is required to develop optimized deployment models, interference mitigation strategies, and performance evaluation techniques to improve the effectiveness of vertically layered networks [61].

5.6. Lack of Training Data for the AI Models

The adoption of ML in UDNs requires large-scale datasets for training. However, there is a shortage of publicly available datasets for developing AI-based network optimization models. Future research should focus on data augmentation techniques, synthetic dataset generation, and federated learning methods to bridge this gap [46].

5.7. Energy Efficiency in ML

ML models used in UDN management require substantial computing power, leading to high levels of energy consumption. The strong correlation between model complexity and energy use highlights the need for efficient AI models. Research should explore DL optimization techniques such as layer decomposition, pruning, knowledge distillation, and hardware acceleration using GPUs and FPGAs. These approaches can enhance computational efficiency while minimizing the power consumption in AI-driven network operations [4,47].

5.8. Security Challenges in UDNs

The high density of small cells makes UDNs vulnerable to security threats such as handover manipulation, cell interference, and encryption breaches. While encryption techniques provide protection, they often require significant computational power, increasing energy consumption. Future research should focus on developing lightweight security solutions, AI-powered intrusion detection systems, and adaptive attack–defense mechanisms to enhance security without compromising efficiency [25].

6. Conclusions

This paper presented a comprehensive review of AI-driven approaches to handover management and load balancing in ultra-dense 5G/6G cellular networks. The evolution of network architecture toward dense deployments, heterogeneous technologies, and high-mobility scenarios has created complex challenges in terms of maintaining seamless connectivity and efficient resource utilization. Traditional solutions fall short when addressing these dynamic environments, particularly in terms of the inclusion of UAVs and the increasing reliance on IoT and edge devices. By synthesizing recent research, this review highlights the potential of machine learning and deep learning in addressing

these challenges through predictive, context-aware, and adaptive mobility and load control mechanisms. Although significant progress has been made, several open issues remain, including the lack of standardized datasets, the need for energy-efficient AI models, and the integration of context-aware and real-time decision systems. This paper does not propose a novel framework or present original empirical results but instead provides a critical analysis of the state of the art, offering a roadmap for future research. Emphasis is placed on the importance of developing scalable, interoperable, and AI-augmented network management strategies suitable for smart city deployments and next-generation mobile ecosystems.

Author Contributions: Conceptualization, C.C., I.S. and L.A.; data curation, D.Y.; formal analysis, L.A., D.Y. and S.A.; funding acquisition, L.A.; investigation, C.C. and I.S.; methodology, C.C., I.S. and G.N.; project administration, L.A.; resources, I.S. and L.A.; software, C.C. and I.S.; supervision, L.A. and I.S.; validation, L.A., D.Y. and S.A.; visualization, C.C. and I.S.; writing—original draft, C.C. and I.S.; writing—review and editing, L.A., D.Y. and S.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research has been funded by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant No. BR24992852 "Intelligent models and methods of Smart City digital ecosystem for sustainable development and the citizens' quality of life improvement").

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created or analyzed in this study. Data sharing is not applicable to this article.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
IoT	Internet of Things
5G	Fifth Generation Mobile Network
6G	Sixth Generation Mobile Network
UDNs	Ultra-Dense Networks
LBO	Load Balancing Optimization
HetNets	Heterogeneous Networks
QoS	Quality of Service
PPHO	Ping-Pong Handover
UAVs	Unmanned Aerial Vehicles
WWWW	World Wide Wireless Web
WISDOM	Wireless System for Dynamic Operating Mega Communication
MBB	Mobile Broadband
eMBB	Enhanced Mobile Broadband
URLLC	Ultra-Reliable Low-Latency Communications
mMTC	Massive Machine-Type Communications
SDN	Software-Defined Networking
RRHs	Remote Radio Heads
BSs	Base Stations
RF	Radio Frequency
SON	Super Self-Organizing Network
mmWave	Millimeter-Wave

MIMO	Multiple Input Multiple Output
LOS	Line-of-Sight
APs	Access Points
HO	Handover
RLF	Radio Link Failures
CIO	Cell Individual Offset
DRL	Deep Reinforcement Learning
D2D	Device-To-Device
LSTM	Long Short-Term Memory
GRU	Gated Recurrent Units
WPT	Wireless Power Transfer
CDMA	Code Division Multiple Access
OFDMA	Orthogonal Frequency Division Multiple Access

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