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Review

A Comprehensive Survey on Machine Learning Methods for Handover Optimization in 5G Networks

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Abstract: One of the key features of mobile networks in this age of mobile communication is seamless communication. Handover (HO) is a critical component of next-generation (NG) cellular communication networks, which requires careful management since it poses several risks to quality-of-service (QoS), including a decrease in average throughput and service disruptions. Due to the dramatic rise in base stations (BSs) and connections per unit area brought about by new fifth-generation (5G) network enablers, such as Internet of things (IoT), network densification, and mm-wave communications, HO management has become more challenging. The degree of difficulty is increased in light of the strict criteria that were recently published in the specifications of 5G networks. In order to address these issues more successfully and efficiently, this study has explored and examined intelligent HO optimization strategies using machine learning models. Furthermore, the significant goal of this review is to present the state of cellular networks as they are now, as well as to talk about mobility and home office administration in 5G alongside the overall features of 5G networks. This work presents an overview of machine learning methods in handover optimization and of the various data availability for evaluations. In the final section, the challenges and future research directions are also detailed.

Keywords: handover; 5G networks; HO management; HO optimization; machine learning; challenges; research directions

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1. Introduction

Wireless communication models have been evidencing unparalleled requirements on connectivity and bandwidth, in this age of network communications, processing big data [1]. This is stated in Ericsson's mobility report, who reported that the network traffic of mobile signals rose more than 50% in 2020 [2], witnessing the impending challenge that is required to be noticed and solved. High-definition video streaming, virtual reality, and the tactile internet are just a few of the new applications that are rapidly expanding along with the surge in global data traffic. For instance, according to the same report, more than half of all mobile data traffic is used for video streaming, and there is a tendency toward higher resolutions, which raises questions about the quantity of data needed. This made the fifth generation of cellular networks (5G) feasible, which offers a thousand-fold boost in capacity. However, this also poses serious issues for older networks [3,4]. Therefore, to serve the aforementioned bandwidth-hungry applications, improved mobile broadband has been included as one of the possibilities in 5G New Radio (NR), in conjunction with ultra-reliable low-latency communications (URLLC) and massive machine-type communications (mMTC) [5].

In contrast, Internet of Things (IoT) devices are present in many areas of life, such as smart cities, smart living, healthcare, and agriculture [6–8]. By placing IoT sensors in the right places, smart cities may use IoT technology to intelligently handle various challenges, such as municipal waste, building health monitoring, traffic, and other difficulties [9]. A prominent example of this phenomenon is found in the Mayor of London's presentation of the Agenda 2 Smart City Blueprint, which has the slogan "Smarter London Together" and calls for a significant use of IoT technology in London to enhance the quality of life for its residents and increase the efficiency of the city. The appeal of IoT technology may be attributed to its promises of improving industrial and daily life operations via continuous monitoring and prompt reactions [10,11]. Moreover, the confrontations in 5G communications for providing seamless communications are listed below:

i. The need for additional bandwidth as a result of more sophisticated smartphones with greater processing power and the growth of data-hungry apps, such as augmented reality and online gaming [12].
ii. The rapidly expanding number of cellular connections, mostly as a result of Internet of Things technologies. To address these problems, a number of solutions have already been put forward, and two of the most significant options for increasing network capacity are millimeter-wave (mm-wave) communications and network densification [13].

"Network densification" is the method of increasing the base station (BS) density in a certain region to increase the radio access network (RAN) capacity. The main idea underlying this concept is called frequency reuse, which states that other base stations (BSs) are allowed to utilize a base station's frequency spectrum for as long as there is no mutual interference. In order to restrict the overlapping zones, this avoidance is accomplished by lowering the transmitting power. More deployment options arise from a reduced footprint of BSs, which boosts the RAN capacity. However, mm-wave greatly improves the RAN performance of cellular networks by using the enormous amount of bandwidth that is available across the mm-wave frequency range. Additionally, as antenna diameters shrink with the increasing carrier frequency, millimeter-wave communication enables the adoption of Multiple-Input Multiple-Output (MIMO) technology, which boosts the network's capacity and dependability [14]. Stated differently, there are two primary reasons for the capacity improvement that millimeter-wave communications provide [15]:

i. MIMO technology
ii. Improved bandwidth availability.

These are reasonable and practical ways to increase the bandwidth available to cellular networks, but as soon as they are implemented, mobility management becomes a significant side effect. Network densification and millimeter-wave communication are combined with the concept of the more often occurring handovers (HOs), which are described as the user equipment's (UE) change of channel, resource, or cell 3 connection while maintaining a continuous conversation or session.

The primary cause of this outcome is the decrease in the footprint of base stations. First, small cells (SCs) are used to purposefully lower the footprint in the event of network densification, allowing for additional base station (BS) installations via frequency reuse. Additionally, considering mm-wave communications, the greater propagation losses (increased reliance on the line of sight (LOS)) at mm-wave frequencies result in a smaller footprint for base stations. Moreover, the mm-wave signals' range is shortened by the higher bandwidth [16].

Because there are more BSs in a given environment, mobile UEs must conduct more HOs, which increase the number of HOs as a result of BSs having smaller footprints. Because a user's average throughput is inversely related to the number of HOs [17], this problem negatively impacts the quality of communication and lowers the quality of service (QoS). Furthermore, user satisfaction percentages are adversely impacted by service outages during HOs, undercutting the lofty goals of 5G networks.

The main reasons for these unfavorable outcomes are the quantity of HOs encountered during a discussion or data transfer session, as well as the HO cost incurred for each HO encountered. Because of this, the bulk of research on HO management has focused on these two aspects: lowering the number of HOs and the cost of each HO. There are some positive impacts as well, despite the fact that the statistics about the growth of BSs and IoT devices, as well as the increasing demand for data-oriented services, have mostly been reported adversely so far. To enable more effective management, network operators may make use of the vast amounts of data created by cellular networks, which are also expanding significantly [18,19]. Put another way, even if networks are becoming larger and more complicated, the massive amount of data being generated becomes essential to reducing that complexity; in other words, this so-called issue presents a unique opportunity and solution. Because of this, machine learning (ML) methods have drawn a lot of interest in the area of wireless communications. This is because large amounts of data can be effectively used to train ML models, which might provide network experience and enable them to make more proactive and informed decisions.

This review provides a limited perspective on the use of machine learning (ML)-developed algorithms to HO management in cellular networking, with a special emphasis on 5G and 5G networks, in order to keep the conversation relevant [20,21]. This is due to the fact that 5G is already a reality and that imaginative writing about 6G is beginning to surface in the literary canon. One of the constants across numerous studies that seek to map out the architecture of 6G is that artificial intelligence (AI) and machine learning (ML) will be essential components of 6G networks. This is due to the fact that 6G networks are expected to be powered by intelligence. Furthermore, because of the availability of bandwidth at these frequencies, it has been predicted that terahertz (THz) frequencies will be employed in 6G [22]. The lesser footprint will, however, be considerably more relevant since the THz spectrum encompasses far higher frequencies than the mm-wave band. This makes the HO management idea much more important. With this objective in mind, the latest advances in machine learning (ML)-based handoff management in cellular networks (specifically with regard to 5G and 6G) is investigated by taking into account the data used in the implementation of these algorithms. A high-level taxonomy of the data source is provided, consisting of two primary categories: visual data- and wireless network data-assisted handoff optimization.

Another important factor pertaining to the mobile networks in this mobile communication age is continuity of communication. Handover (HO) forms an integral part of NG cellular communication networks, which inevitably presents a quality of service (QoS) issue, explaining tendencies such as lowered average throughput rates and disrupted services. The emergence of new 5G network enablers, such as IoT, network densification, and mm-wave communications, has enhanced the number of BSs and connection density per unit area, adding difficulties in HO management. This is compounded by the fact that there are new, stricter requirement for 5G networks that are being developed.

Therefore, this research focuses on intelligent HO optimization techniques with ML models for the improved HO management in 5G networks. The significant contributions of this review are as follows:

- Current state of cellular networks
- Mobility and handover management in 5G
- Machine learning methods for handover optimization
- Data availability for evaluations
- Challenges and future research directions.

In this connection, this review has endeavored to discuss the aforementioned areas in order to achieve a better understanding of the current state of HO management in 5G networks, and to present the possibility of deploying machine learning in the improvement of these processes.

The HO process is then helped by the data in visual format, which may be utilized to identify obstructions or items that impact signal transmission [23]. Conversely, wireless network data refers to almost any kind of data that the wireless network is able to collect, including received signal strength, channel status data, BS traffic load, neighbor information, user locations, etc. Therefore, to the best of our knowledge, this is the first attempt to both analyze the most recent studies and investigate the use of visual data support in HO management. Additionally, this article does not address HO management of earlier networks, particularly 3G and 4G, since there is already a ton of research analyzing such networks available in the literature [24–26].

The remainder of this work is organized as follows: Section 2 describes various techniques involved in handover classifications. The works using machine learning models for HO management are deliberated in Section 3. The 5G network's HO management is discussed in Section 4. Section 5 provides inclusive discussions on HO optimization and challenges. The limitations and future research works are analyzed in Section 6, and the conclusions are presented in Section 7 at the end.

2. Handover Classifications

2.1. HO Classification Based on Techniques

There are two varieties of HOs: soft and hard. They are sometimes referred to as Connect Before Break (CBB) and Break Before Connect (BBC). The specifics are covered in [27] and are elaborated upon below.

2.1.1. Connect Before Break (CBB) or Soft HO

As a kind of HO approach, CBB involves including and relinquishing radio connections; hence, the user continuously maintains one link, linked to the entire structure [28]. Code Division Multiple Access (CDMA) models were introduced with softer and softer HOs [29]. When an electronic gadget is connected to cells in the same BS, a softer HO occurs [30]. It makes sense to use soft HOs when expecting phone calls to end, keeping sessions operational, and restarting parcel sessions. This makes switching between BSs seamless. Soft HO, however, is limited to operating between BSs that share the same frequency. It also uses many channels simultaneously for a single mobile user, increasing network resources and decreasing network capacity.

2.1.2. Break Before Connect (BBC) or Hard HO

Hard HO, also known as BBC, describes a procedure whereby the mobile device disconnects from the serving BS and then reconnects to the target base station [31]. In contrast to soft HO, hard HO requires the mobile device to disconnect from its existing radio connection and then rejoin a new base station. Interruptions in communication result from this. On the other hand, by transferring the resources of one user to the other end, a hard HO may enhance the network load resources. Hard and soft HOs are contrasted in Table 1 based on many crucial attributes.

Table 1. Feature comparison between hard handover and soft handover.

Features	Soft HO	Hard HO
Speed	Slow	Fast
Reliability	Moderate	High
Energy Consumption	Minimum	High
Service Interruption	Minimum	High
Complexity	More	Less
Packet Loss	Minimum	High

2.2. HO Classification Based on Networks

Regarding network and access technologies, there are two kinds of HOs: vertical and horizontal. Based on the network, the two HO types are shown in the image in Figure 1. Horizontal HO is a kind of HO in 5G networks that occurs between the same types of access technologies as HO. This kind of HO, sometimes referred to as horizontal HO, happens when a UE transfers and changes BSs inside the same network. Vertical HO is one type of HO that occurs between the two access techniques. Furthermore, there is a vertical HO when the UE connection switches between the wireless local area network (WLAN) and mobile cellular networks. Figure 2 displays the handover decision methods.

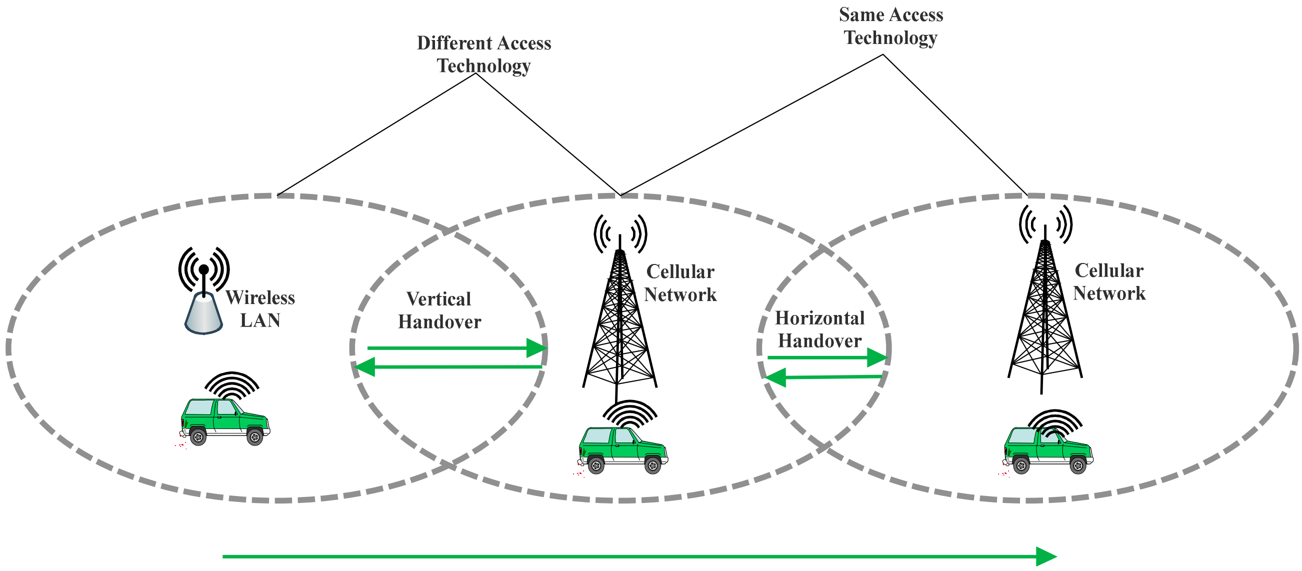

Figure 1. Vertical handover and horizontal handover with different technologies.

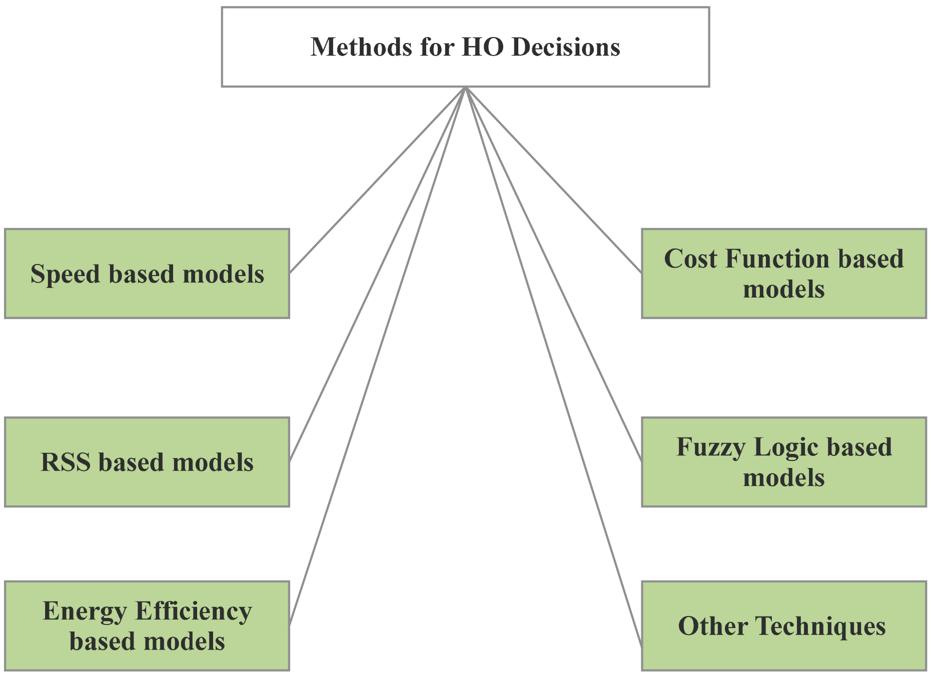

Figure 2. Classification of HO decision methods.

3. Contributions of Machine Learning Models in HO Management

Self-organizing cellular networks and machine learning applications were reviewed in [32], where the authors covered the features of self-organizing networks and the ML methods in detail. Under the headings of the three main functions of self-organizing networks—self-configuration, self-optimization, and self-healing—the authors introduced ML applications to cellular networks. Several use cases were shown for every previously described feature, resulting in an all-encompassing image of machine learning applications in cellular networks. Consequently, rather than focusing on HO management in 5G networks, the main goal of this work was to create a comprehensive form for ML applications to multi-domain mobile networks, including anomaly detection, backhauling, radio resource management, and so forth, even though it focused on ML applications and included a brief section on HO management. The study in [33] concentrated on the use cases for mobility predictions and offered a thorough analysis of the features and techniques of mobility estimate, including user location, mobility predictability, prediction output, and efficiency metrics. The study mostly focused on machine learning (ML), even though it was not intended to be limited to ML. This is because the techniques described are primarily ML algorithms.

Although one of the use cases is HO management, the work's scope is not limited to it. The authors presented a brief evaluation of HO management in 5G and 5G networks in [34]. They provided an overview of 5G networks and some of the supporting technologies, including software-defined networking, mm-wave communications, heterogeneous networks (HetNets), and machine learning. Even though the main focus of the authors' research was HO management in the next generation of cellular networks, they did not go further into any specific issues; rather, they carefully reviewed the literature. Despite the wide range of ML implementations, the researchers did not fully explore the potential applications of ML for 5G HO management. Additionally, they completely ignored the visual data in their work that helped HO management and HO in emergency situations. A thorough analysis was presented in [35], wherein HO management was created and comparisons between long-term evaluation (LTE) and 5G networks were discussed. A detailed explanation of HO categories came after the step-by-step demonstration of HO techniques in LTE and 5G. Even though several ML applications were emphasized, the study's scope was restricted to HO management and not the applications of machine learning to HO management since the state-of-the-art methodologies were assessed without a specific emphasis on machine learning algorithms. Similarly, the authors of [36] offered a comprehensive review of ultra-dense network mobility management.

Specifically, the writers included a comprehensive guide on mobile network administration. Talks on proactive mobility administration in the next mobile network generations, which included an overview of several machine learning techniques, were next. The authors also examined AI assistance for mobility management, identifying the AI methodologies and use cases that were implemented and examining the literature. In [37], a second comprehensive investigation on mobility management in 5G HetNets was conducted. To be more precise, the authors offered a comprehensive tutorial on the radio resource control (RRC) modes contained in 5G NR in addition to the initial access and reachability. Cellular communication networks depend on the RRC protocol to carry out several critical tasks, such as connection establishment and release, radio beacon (RB) setup, establishment, and release, broadcasting of system data, etc. After that, problems with beam-level mobility management were discussed regarding connected mode mobility, or HO, with different kinds of HOs. Mobility management remained the primary emphasis of their work, with ML implementations not being their primary area of interest.

As a result, because machine learning was not the goal, neither was the source of the data creation. The authors of [38] examined femtocell HOs in HetNets and presented a thorough overview of the LTE HO process, paying special attention to femtocell HOs. A comprehensive assessment of the current HO decision procedures was carried out after the identification of some issues with the HO selection procedure in two-tier networks.

Despite the paper's intended audience being 5G networks, the primary narrative began with LTE networks, since 5G networks' mobility management was not specifically covered. Additionally, since only HO decision techniques were discussed, the breadth was quite limited. While some of the referred literature included ML applications, ML did not represent the main emphasis. The authors of [39] provided very basic descriptions of mobility and HO processes in HetNets, along with a quick evaluation of HO-oriented mobility management.

Specifically, location management and HO management were divided into two divisions under mobility management. Then, each category was given further explanation. However, no 5G nor 5G cellular networks for communication were discussed, nor was any particular HO management solution, such as machine learning (ML) HO management, provided. Another brief summary of mobility management in 5G networks can be found in [40]. A summary of the development of cellular networks from 1G to 5G was followed by discussions on 5G network architectures and mobility management.

With the introduction of several HO types and parameters, HO management was also evaluated. Nevertheless, the talks were somewhat brief, and neither mobility management nor 5G networks received a thorough explanation. Moreover, the survey on artificial intelligence applications to HO administration was not the author's intention. A study also conducted on a thorough analysis of mobility management by raising concerns about the state-of-the-art solutions' suitability for the next 5G and 5G cellular network generations.

4. Handover Management in 5G Networks

Handover management may be divided into two main groups, notably:

i. Inter–intra-frequency-based HO management
ii. Inter–intra-radio access technology (RAT)-based HO management.

4.1. Inter–Intra-Frequency-Based HO Management

The different forms of HO are discussed in this section, along with the detailed procedure for HO in 5G NR and the criterion for HO and its relationship to radio resource management. Handover between frequencies takes into account both intra- and inter-frequency information. When the UE travels to the destination cell utilizing the same frequency as the serving cell, this is referred to as intra-frequency HO, as shown in Figure 3, Scenario 1. On the other hand, when the UE utilizes a different carrier frequency in the target cell, as seen in Scenario 2 of Figure 3, inter-frequency HO takes place. The events A3 and A6 initiate the intra-frequency HO. Events A3 and A6 are triggered when the serving BS's RF condition is lower compared to that of the adjacent BS. Additionally, the UE camps on the secondary frequency's intra-frequency HO, which uses Event A6. Inter-frequency HO usually uses Events A4 and A5. When one of the neighboring BSs' RF conditions exceeds the threshold in comparison to the other BSs', Event A4 is set off. However, when one of the neighboring BS's RF conditions exceeds the higher threshold, Event A5 is set off when the serving BS's RF condition falls below the lower threshold [41].

For inter-frequency instances, the UE simply analyzes the measurement gap at various frequencies [42,43]. For the UE to send and receive data to and from the cell that provides service concurrently, and to measure the desired carrier frequency, there must be a measurement gap. The time period during which no downlink (DL) or uplink (UP) signal is sent is specified by the measurement gap. The term "measurement gap" exclusively refers to certain instances of intra-frequency HO, in which the expanded UE coverage may not always line up with the center frequency of the serving gNB. However, according to 3GPP, the measurement gap is necessary in every instance of the inter-frequency HO. Fundamental questions about how to minimize measuring gaps are the focus of research, since a big measuring gap leads to decreased throughput and increased energy consumption for user equipment.

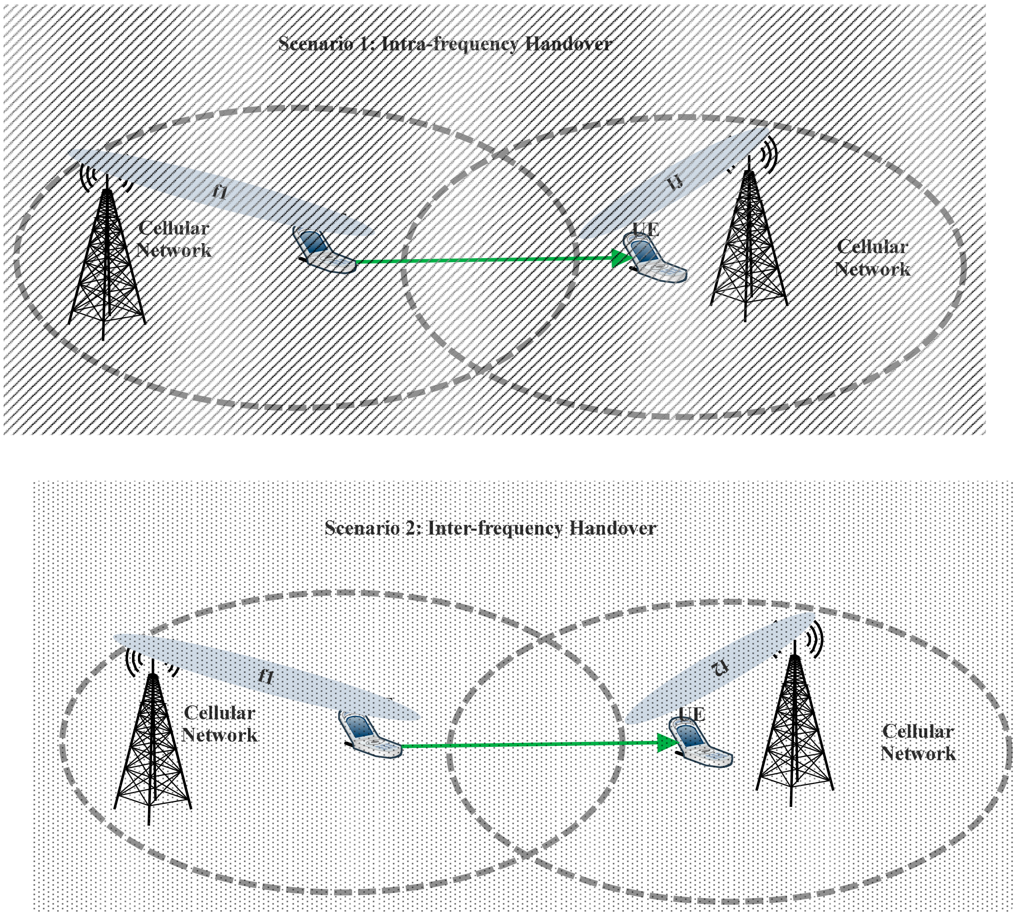

Figure 3. Illustration of HO in intra- and inter-frequency ranges.

4.2. Inter–Intra-Radio Access Technology (RAT)-Based HO Management

The target BS (T-BS) and the serving BS (S-BS) share the same RAT during an intra-RAT handoff. What is often referred to as intra-RAT HO, or horizontal HO, is seen in Figure 4. In intra-RAT HO, both intra- and inter-frequency HO are conceivable. The primary source of load balancing or measurement trigger conditions is intra-RAT HO, which aims to keep the UE connected to the present network [44]. When UE HO occurs, it seeks to locate itself on the cell that receives the strongest signal. Unlike intra-RAT HO, inter-RAT (or vertical) HO occurs when the UE hands over control to a T-BS that uses a different RAT than the S-BS. When selecting the target cell in inter-RAT HO, other factors are taken into account than in intra-RAT HO, which selects the cell with the strongest received signal. These factors include user accessibility, service type, and network property and condition. It also involves switching the logical interfaces of the two RATs [45].

For many applications and services, the latency experienced during inter-RAT HO remains prohibitive, which presents a serious issue for NexGen mobile systems. Centralized architecture for inter-RAT HO, which combines legacy and NR network protocols, was suggested as a way to enhance the user experience [46]. It is evident from the graphic that centralized and distributed CN architectures for multi-RATs are both feasible. One benefit of the centralized design is that it may result in a significant decrease in interruption time and HO signaling. The baseband unit (BBU), remote radio head (RRH), and unified CN are all parts of the centralized architecture, and they are all separated by a transport method, such as optical fiber. The RRHs and the BBU pool are linked in a C-RAN design via fronthaul or high-bandwidth transport lines.

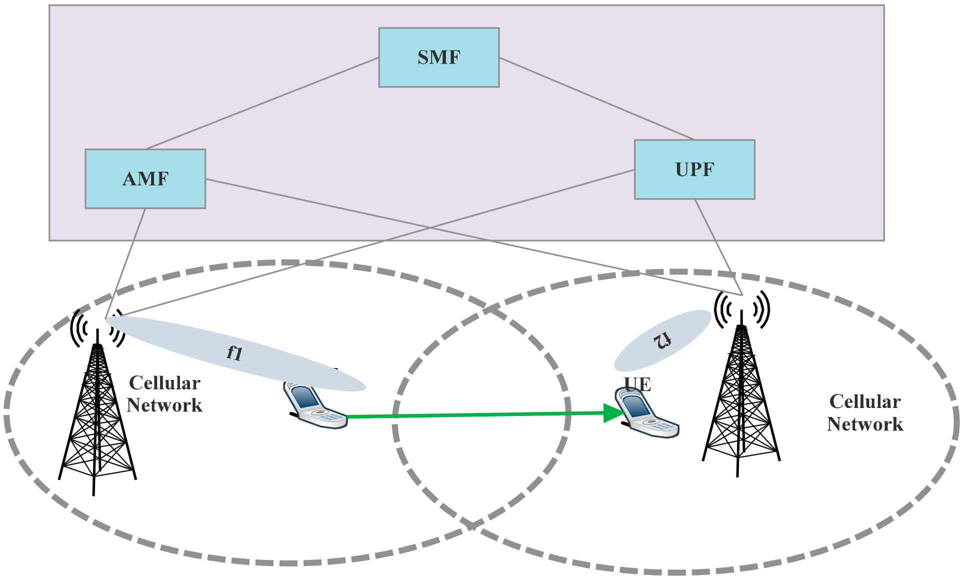

Figure 4. Illustration of HO from one cell to another.

5. HO Optimization and Challenges with Machine Learning Models

Conventional solutions would not be able to tackle the increased issues and complexity that the usage of millimeter-wave and greater frequency bands in 5G networks would bring to the HO management. First of all, the transmission distance of these frequency ranges will be limited due to their extreme attenuation (higher penetration losses, for example). Consequently, to cover the same area as those who would have used the microwave frequencies, additional base stations (BSs) must be erected [47]. This suggests that the network will grow significantly in size and complexity and that consumers will experience more frequent HOs, which will hurt their quality of service (QoS), especially for highly mobile users and apps. The work in [48] presents HO optimization issues and solutions in B5G in detail. It begins by outlining the history of research and explaining HO in legacy. The HO optimization problems in B5G are then examined, along with potential future research avenues. The most well-known and cutting-edge methods and technical advancements for HO optimization handling in B5G are then covered in the study. The following study is offered by El-Gayar [49], where NOMA and OMA systems were employed in a single cell to enhance the energy efficiency of the system, distribution of contents, and latency and transmission rates in the communication systems. It especially revolves around a model that transforms UAVs into aerial infrastructures for the ground users or users at the base, and it also proposes a caching mechanism for reducing the latency and organizing the cached contents. The paper quantifies the extent to which NOMA and OMA achieve higher rates and energy in the cache capacity scenarios, user numbers, and power configurations.

Second, since mm-wave networks use directed beams for transmission, obstructions in the transmitted beam's path might either totally prevent a user from connecting to the network or have a detrimental effect on the signal's quality. Therefore, users in mm-wave communication networks need to choose not only the best base station (BS) but also the best beam to connect to at any particular time in order to maximize their quality of service (QoS). Optimal beam selection has thus evolved into another factor to consider in the HO management process due to the massive number of beams that the user must pick from during each HO instance, which would further add complexity to the HO process [50,51]. At the end, it is essential to provide some critical services that need high mobility in emergencies. For example, patients in ambulances on the way to a hospital may receive medical attention via real-time consultations with physicians located at a distant hospital. These services may be necessary, particularly in the current pandemic scenario, to keep patients alive under severe situations until they can be transported to a hospital for appropriate medical care [52,53]. Cognitive HO optimization would assist in estimating the ambulance's path, choosing the best base stations to connect to, and pre-allocating the resources required at the base stations. This measure is expected to mitigate the risk of sporadic service disruptions and ensure the quality of service required to facilitate communication between ambulance paramedics and distant medical professionals [54].

Consequently, efficient HO optimization would make it possible to identify the best beam and base station for user connection, maximizing user connection while minimizing superfluous or needless HOs and facilitating obstacle identification and avoidance. Comparing mm-wave communication networks to earlier cellular network generations, these are some of the problems that make handling HO optimization more difficult. Moreover, most traditional approaches would find it very difficult to manage the HO process since it requires several network factors that need to be taken into account and tuned in real time to enable flawless HO. The problem with traditional HO management techniques is that they need a lot of processing power to execute, especially as the network dimension grows. The user must have left that place for them to choose which target BS to link them with. User QoS would suffer as a consequence, and a HO choice that is not ideal would be made. Furthermore, these algorithms are not able to precisely capture some network characteristics, such as the existence of barriers of varying sizes and kinds and the dynamic traffic demand patterns characteristic of 5G and 5G networks, both of which are crucial for determining the best possible house ordering [55]. Nevertheless, machine learning approaches may help introduce intelligence and support the network's self-optimization.

Machine learning techniques may be utilized to learn various network characteristics from network-generated data in order to optimize various network aspects. They can uncover patterns and concealed details from the network that analytical methods are unable to capture by using network data [56]. They may also foresee future demands from users or the network and react to such requests in advance, enabling the network to be prepared to handle them when they happen, since they are able to autonomously adjust to changes in the network environment [57]. They can be efficiently constructed computationally, enabling the training portion of the algorithm—which is often computationally intensive—to be finished offline. After that, the trained model may be used online for real-time optimization and updated often as it comes across fresh data [58].

Two main categories of HO management techniques are considered: those based on optical data and those based on wireless data. The major purpose of this unique taxonomy is to provide the outdated wireless data-driven HO schemes, which have long been ignored in the literature, a defined place alongside the visual data-aided HO management schemes. In the developing field of visual-aided wireless communications, visual information—pictures and videos—captured by cameras, light detection and ranging (LIDAR), and other wireless sensors are combined with wireless sensory data to enable wireless network optimization—channel prediction, HO optimization, and other related tasks. [59,60]. This is necessary because mm-wave communication networks have unique challenges that are difficult to address with wireless sensory data alone, while some of these challenges may be addressed with the use of visual data. Nonetheless, the two use cases of beam selection and BS selection provide a complete analysis of the most recent research on wireless data-based HO control.

6. HO Optimization and Challenges

When selecting the BS/beam to which a user should connect, frequent HO must be reduced because of the small footprint of the mm-wave and THz-wave BSs designed for usage in 5G. This occurs as a result of frequent HOs increasing HO expenses and decreasing network performance. The definition of HO given in [61], which introduces the term HO cost, will be used throughout this study. The network may choose the optimal T-BS to provide UE with a greater throughput by optimizing HO efficiently. Before the advent of machine learning, traditional techniques for choosing the best BS relied on measuring certain parameters. These tactics include selecting the T-BS based on distance or the BS that provides a higher KPI, such as signal-to-noise ratio, received signal strength indicator, and reference signal received power. Using measurement-based methodologies, the channel state information (CSI) from each surrounding BS's MR is evaluated, and the BS with the best CSI is selected as a potential T-BS. These techniques are viable at sub-6 GHz frequencies, but they are not successful in the mm-wave and THz application bands due to their high path loss and susceptibility to LOS occlusion [62].

Because ML approaches minimize computational overhead, delays, and frequent HOs, they may be very helpful in BS station selection and HO optimization. To guarantee a smooth HO, they assist in anticipating the TBS and ensure sufficient resources are accessible at the T-BS before HO. This section examines wireless data-assisted HO optimization and ML-based HO control for 5G networks from a visual standpoint. An overview of the most recent ML-based HO optimization in 5G mm-wave communication systems is presented in Table 2. The complexity of HO management in 5G systems is growing, as novel innovations are being developed or will be developed to fulfill their needs. By presenting novel network-supporting technologies, this section addresses the most important HO optimization issues in 5G networks.

Table 2. ML-based HO optimization in 5G mm-wave communication models.

References	Year of Publication	ML Algorithm	Application Scenario
[63]	2017	Deep Reinforcement Learning	Massive MIMO networks
[64]	2016	Deep Reinforcement Learning	Camera-based networks with proactive performance prediction in mm-wave environment
[65]	2019	Convolutional Neural Networks	mm-wave beam selection
[66]	2019	Deep Neural Networks	Location and mm-wave LIDAR help to select the proper beam.
[67]	2018	Support Vector Machine	Data-driven-based analog beam selection
[68]	2019	Random Forest	A Terahertz system has been described and a beam selection scheme is proposed for use with the system
[69]	2019	Artificial Neural Networks	Analog beam selection scheme for Terahertz systems
[70]	2019	Multi-Armed Bandit (MAB)	Mobile millimeter-wave communications
[71]	2020	Multi-Agent Reinforcement Learning	Joint user scheduling and beam selection in mm-wave networks
[72]	2020	Q-Learning	mm-wave vehicular networks
[73]	2020	Reinforcement Learning (RL)	Mobile millimeter-wave networks
[74]	2020	Deep Deterministic Policy Gradient RL	Ultra-dense cellular networks

It is important to note that the automation used in 5G networks is achieved through the help of machine learning algorithms, and they effectively improve the basic parameters of the networks while at the same time addressing the increasing complexity. DRL decides a number of parameters of resource control in Massive MIMO and mm-wave networks based on state representation, action space, and reward systems to obtain an optimal policy. Based on the kernel-based functions and regularization factors, Support Vector Machines (SVMs) are effective for selection of analog beams in a data-driven manner. Random Forest algorithms adapt schemes for the selection of the beams in a Terahertz system with the help of ensemble learning strategies [75,76]. Convolutional Neural Networks (CNNs) apply spatial features and convolutional layers for mm-wave beam selection, and these networks incorporate the spatial dependencies [77]. Newer Deep Neural Networks (DNNs) enhance the position and beam selection by utilizing the layered configurations and activation functions with the help of LIDAR [78]. Combined, these ML techniques improve the seven attributes of the 5G networks, covering efficiency, accuracy, and adaptability in the network management.

6.1. Ultra-Dense Network

In the ultra-dense network (UDN) design, the beginning radius is greater than the cell radius [79]. A recurring HO could be brought on by cutting down on the amount of time the mobile terminal spends within the cell. The mobile terminal initiated the HO in 12 s with the following parameters: 10 km/h moving speed, 25 m cell radius, and 5 m overlap length. The overlapped area persisted for four seconds. Many issues remain about the growth of UDNs, including how micro-cells and the expansion of mobile node applications on the connection contribute to the increase in HOs. New recurring HOs were the outcome of this. Furthermore, when a UE repeatedly changes between two or more cells in a short amount of time, the HOPP impact may be amplified by UDNs [80]. The control traffic spike causes a greater rate of energy and network resource consumption, which raises the possibility of HO failure (HOF). Put another way, as the number of cells grows, so does the number of HOs; hence, the target eNB, serving eNB, and mobile node experience an increase in signaling overhead [81]. Recurrent and alternating HOs may result from UDNs, and this can lead to other problems, including longer processing times and generalized errors in the HO process. In [82], the current resource-estimation methodology and SDN-based mobility management were proposed as solutions to the HO latency (HOL) problem. Additionally shown was a Markov chain-based HO management system for software-defined, ultra-dense 5G networks. Its functions included determining the best eNBs and virtually assigning them to the mobile node. The suggested approach decreased latency and HO mistakes by 52% and 21%, respectively, in comparison to the traditional method. A technique for state-dependent HO selection was presented in a different study [83], which has the potential to significantly lower the mistake rate in HO while maintaining the throughput user experience and the use of tiny cells.

6.2. Interoperability

The capacity of various networks, devices, access methods, or systems to interact and function as a cohesive one is referred to as interoperability [84]. Additionally, to guarantee connection and availability and allow mobile users to freely move between various mobile wireless networks and access technologies with ease, 5G will link users to a variety of mobile wireless networks. Doing so for HOs across different wireless technologies makes HO administration more difficult [85]. Thus, to assist the mobile user as it sweeps among many wireless network access points, sophisticated HO methods are needed.

6.3. Ultra-High Mobility

One major obstacle to the development of 5G systems is ensuring a reliable broadband wireless connection in high-speed mobility scenarios, such as HSR systems. Furthermore, a maximum mobility speed of 1000 km/h is anticipated to be enabled by the 5G system, including 6G. The main issues with high-mobility systems for HO were outlined in [86]. During periods of increased mobility, UEs often exhibit a greater HO rate. The system can also run out of time to finish the HO operation since UEs can move fast within the two BSs' overlapping coverage areas. Thus, in high-mobility systems, more delay control is needed for HO. Furthermore, swift UEs may fail to notice the ideal HO location, raising the possibility of HOF. Moreover, HO may be needed for several people to board at once in HSR systems, creating a group issue that uses a lot of network resources.

6.4. Fast and Seamless Handover

An ideal HO is the one that can switch the UE from one BS to the other with as little interruption as possible to the communication process. A "smooth" HO can also be described as a HO method that does not distort the data and does not interrupt the UE connection to the network during HO [87]. In addition, it is necessary to note that seamless HO aims at providing continuous data transfer in the event of the failure of the connection or in the case of an HO event [88]. Indeed, due to the nature of 5G that calls for ultra-low latency and continuous connectivity, which many service instances require, it makes hand-offs a big challenge to the system [89,90]. Therefore, fast and efficient HO methods are necessary for 5G mobile networks.

6.5. Huge Number of Devices

The amount of data has also risen annually due to the sharp rise in the number of devices linked to the Internet. The primary obstacle to 5G is the anticipated billions of gadgets and sensors that will be online. According to prediction assessments by Huawei and Information Handling Services (IHS) [91,92], there will be between 75.4 and 100 billion linked devices by 2025. Therefore, 5G/5G has to be able to handle enormous volumes of data coming from a seemingly endless number of sensors and linked devices and analyze them quickly. All things considered, the number of devices rose along with the frequency of HO, which in turn raised the HO problem. Therefore, in order to achieve the 5G standards, it is crucial to ensure HO approaches that can solve the issue of increasing the quantity of HO.

6.6. High Accuracy of Packet Transmission

The 5G network has to transfer data with extreme accuracy and zero faults in order to achieve its goals and fulfill its vision [93]. This is a major obstacle, particularly with regard to user mobility and HO management. Excessive data accuracy complicates HO management and necessitates prompt and accurate HO choices to guarantee the accuracy of data transmission. Moreover, when the data are extremely accurate, the UE is connected to the serving BS, regardless of the cell's edge. When the UE enters and quits the cell, there may be an increase in the HO frequency as a consequence, increasing signaling overhead and reducing system capacity. Therefore, in order to satisfy the needs and accomplish the goals of the 5G system, this problem has to be resolved quickly. Table 3 presents the contributions of existing models in HO management.

Table 3. Contributions of existing models in HO management and mobile communications.

Ref.	Year	Network	Motive	Contributions
[94]	2020	UDN	Mobility management (MM) challenges	Providing a valuable survey on mobility management in UDN
[95]	2020	5G or HetNets	Providing high coverage and mobility management	Survey work on MM with beam management and mobility
[96]	2020	5G or HetNets	HO management challenges and decisions	Providing a comprehensive survey on HO management
[97]	2020	5G	Provide data traffic demands and ensure QoS	Discussions about mobility management and solutions
[98]	2021	5G	HO management	Discussions about HO management using ML
[99]	2022	5G	ML techniques in 5G networks	Discussions about the impacts of ML in HO
[100]	2022	5G	HO management	Comparing many HO and mobility management methods using ML
[101]	2022	5G	Solving unaided issues in mobility management	Discussions on challenges, issues, and solutions for MM in 5G
[102]	2023	5G	HO management on 5G-NR networks	Analyzing the HO procedure for better QoS and reducing HO failure

Table 3. *Cont.*

Ref.	Year	Network	Motive	Contributions
[103]	2020	Wireless Network	Comprehensive overview of the current state of research and development in indoor localization for the Internet of Things	Provides a guideline and an excellent platform to further their research in indoor localization
[104]	2011	Ground-Penetrating Radar (GPR)	Outlines the design and application of a bowtie antenna specifically for ground-penetrating radar (GPR) applications	The design is constructed and the operating frequency range is established for use in measuring materials, such as concrete and soil
[105]	2023	Non-Terrestrial Networks (NTN)	A comprehensive exploration of AI applications in Satellite Communication (SatCom) and Non-Terrestrial Networks (NTN), emphasizing opportunities to enhance performance and efficiency through AI-driven solutions	Offers input and recommendations for using AI to advance the effectiveness, efficiency, and creative possibilities of Non-Terrestrial Networks
[106]	2021	Impedance-Matching Network (IMN)	Presents a quad-band rectenna design for highly efficient ambient wireless RF energy-harvesting in low-power applications sensors and wireless devices	Efficient quad-band rectenna design for RF energy-harvesting applications

Also, the design of a highly efficient, wideband multi-frequency [107] ambient RF energy harvester, optimized for capturing and converting ambient RF energy from various sources into usable electrical power. Key design aspects include a wideband antenna, adaptive matching network, and advanced rectification circuitry to achieve high conversion efficiency.

7. Challenges and Directions for Future Enhancements

Even though the problem of HO management in 5G [108], especially for mm-wave applications, has been the subject of several studies, there are still a number of important issues that need to be resolved. This section outlines future research goals and briefly highlights some of the difficulties in using ML approaches for HO control in 5G.

7.1. Dataset Availability

The availability of adequate and high-quality data for model development is a prerequisite for ML-based solutions. However, because of different data security restrictions, obtaining the datasets comprising user mobility history required for ML-based mobility and HO optimization is typically quite challenging [109]. Therefore, network simulations using synthetic data are often utilized for ML training. Additionally, there is the problem of data consistency, which arises when the resulting dataset is not compatible with other systems. Therefore, in order to confirm the legitimacy of various ML models that are being presented for mobility predictions and HO optimization, high-quality datasets must be created that can be used as benchmarks to evaluate the correctness of such models.

7.2. Privacy and Security

Customers' privacy is normally the responsibility of mobile service providers. Release of entire and high-quality datasets from mobile networks is thus very challenging without disclosing users' identification and violating their privacy. Furthermore, because deep learning models are vulnerable to adversarial attacks, ML model privacy is an additional concern that has to be taken into account. These assaults often include fictitious datasets in the training set, which lowers model accuracy and leads to less-than-ideal network performance [110]. Further studies are required to determine the best way to anonymize mobile operator datasets such that the relevant elements of the data collection are preserved, and no sensitive user information is disclosed. Further research is also needed to protect deep learning models against adversarial attacks that aim to compromise their accuracy. Furthermore, to ensure the security and confidentiality of user data, new privacy-preserving machine learning methods, such as federated learning, must be created and used for mobility management and house occupancy optimization.

7.3. Generalization of the Machine Learning (ML) Model

A machine learning model's capacity to predict unknown data by learning from seen data is known as generalization. It is not always clear if the trained model is really generalized since it may be difficult to determine whether the dataset used for model training contains all of the environmental factors and parameters required for the model to have been exposed to all of these aspects during training. Ensuring that all environmental parameters are adequately represented in the dataset—either by producing synthetic datasets or gathering real datasets for accessibility forecasts and HO optimization—is essential to improving the universality of the ML models.

7.4. Centralized vs. Distributed Deployment

ML models may be implemented in a distributed or central fashion, with both having advantages and disadvantages according to the network design. Decentralized implementation has the benefit of reduced processing and minimal signaling costs, on the one hand. It also has to contend with the problem of erroneous network optimization brought on by localized or incomplete global network data. Conversely, the centralized learning scenario has worldwide environmental knowledge and may carry out a coordinated and cooperative learning process on those results in worldwide network optimization. However, because of the end-to-end delays and frequent data gathering, it results in enormous signaling and computing overhead. Therefore, trade-offs between enormous overhead and worldwide accuracy must be taken into account [111].

Decentralized machine learning techniques for mobility management and home OB optimization would be more appropriate in 5G and 5G networks due to their larger network dimensions, increased complexity, and heterogeneous user equipment (UEs). These techniques can protect user privacy, minimize UE energy consumption, and minimize latency and communication overhead [112]. However, because of the coordination challenge for decentralized learning, further study and research are required to identify how to properly deploy decentralized machine learning algorithms for mobility management and HO optimization in 5G and 5G networks [113].

7.5. Frequent Handover

Due to the limited distance for transmission of mm-wave signals, deploying a high number of mm-wave small cells to meet the traffic needs of an increasing number of UEs will lead to a rise in needless HOs as well as HO failures. Increased signal overhead, worse UE QoS, and higher device power consumption are the outcomes of more frequent HO events [114]. Thus, more sophisticated models must be created in order to lower the frequency of HO incidents and enhance the HO decision-making process's workflow.

7.6. Load Balancing

Because of UE mobility and random cell locations, the network has an uneven distribution of UEs, which causes certain cells to be more loaded than others owing to more UEs connecting with those cells. Frequent HO and a decline in the UEs' QoS are brought on by this load imbalance between the cells [115]. Additionally, the majority of HO optimization techniques suggested in the literature advise HO skipping or an extended user link to a BS to minimize frequent HO [116], which might cause an imbalance in the network's load. Thus, to protect UE QoS and reduce network congestion, further investigation is required into how the suggested HO optimization strategies affect the network's load balancing.

8. Conclusions and Future Research Scope

One of the primary problems with cellular networks has always been HO management, and with the advent of 5G networks, this problem is expected to worsen because of potential capacity augmentation technology. Machine learning (ML) is becoming commonplace in many fields, such as healthcare, agriculture, disaster relief, etc., and it is integrated into 5G networks with demonstrated efficacy and efficiency. In addition, almost every forward-thinking initiative that aims to create a foundation for a 6G network predicts that machine learning would be central to 6G. In this study, it was attempted to obtain a picture of the present state of cellular communication networks. After outlining some of the unique features of 5G networks, a thorough instruction on both mobility and HO management was provided. Subsequently, the three main disciplines of machine learning (ML)—supervised, unsupervised, and RL (RL)—and their applicability to the HO management process were discussed. The most current research on ML-assisted HO management methods was reviewed in-depth under a new categorization depending on where the data for ML applications came from. Finally, the difficulties of integrating machine learning into home office procedures were noted and extensively examined.

Following this was a discussion of potential future study topics. Notwithstanding the abundance of survey studies examining HO management in 5G networks accessible in the literature, this is a novel attempt to concentrate solely on machine learning applications to HO management. Furthermore, the focus of the study was on HO management to provide a concise and clear analysis of the problem. The state-of-the-art, including the most recent studies, was examined to show readers the community's current focus of research and provide them with the most recent, timely, and relevant facts. In addition to the typical wireless data-driven applications, a special taxonomy that links the data source and visual data-assisted HO management strategies—disregarded in earlier survey publications—was included. The emphasis of studies is shifting away from traditional methodologies and toward visual data sources because of their intriguing possibilities in HO management. There was also a discussion on the usefulness of intelligent HO management in crises, which may include ambulances, mobile clinics, distant hospitals, etc.

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