AI-Based Approaches for Handover Optimization in 5G New Radio and 6G Wireless Networks

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***Abstract*—In the future, communication networks such as fifth-generation new radio (5G NR) and sixth-generation (6G) will require large data rates and capacities. As a result, mmWave and terahertz (THz) bands are being employed to meet these demands. Unfortunately, these high-frequency bands are susceptible to high path loss, necessitating the deployment of small cells. This, in turn, calls for the installation of a massive number of base stations to cover the whole area. The sheer number of cells and users in such a setup can lead to interruptions in calls when users switch cells, a process known as handover (HO). This has a negative effect on the quality of service (QoS) and the quality of experience (QoE). Therefore, this survey focuses on exploring and comparing artificial intelligence (AI)-based intelligent HO solutions that can optimize HO in 5G NR and 6G networks.**

***Index Terms*—5G new radio, 6G wireless communications, artificial intelligence, handover optimization, mmWave, quality of service, quality of experience, terahertz**

I. Introduction

Over the past decade, the use of mobile data has risen significantly, and it is expected to grow even more over the coming years. Implementing ultra-density cells to meet the heightened data traffic requirements in future mobile networks is a challenging approach. By reducing cell coverage, system capacity and spectral efficiency can be increased, enabling more efficient frequency reuse and reducing the amount of users served, thereby assuring high service quality. Nevertheless, shrinking the cell area and increasing the number of base stations also leads to more handovers and thus, higher signaling overhead which decreases the user throughput [1].

Future networks must be able to support a high data rate in order to meet the demands of current and upcoming applications such as the internet of things (IoT), vehicle-to-everything (V2X), machine-to-machine (M2M), and device-to-device (D2D). Trustworthy handover (HO) procedures must be implemented in order to enhance the quality of service (QoS) and the quality of experience (QoE) for the end user. Previous studies have mainly focused on the capacity and throughput evaluation of small cells; however, the real challenges for future networks will be making HO reliable and providing high data rates in dense urban areas [2]. There have been numerous studies conducted for the 6G network, aiming to achieve higher data rates, lower latency, reduced delays, and minimized battery power consumption when compared with 5G networks [2]. HO is a key element of mobility management [3], which involves transferring an active user connection from one cell to another. In forthcoming heterogeneous networks (HetNet), such as those used in 5G, Beyond 5G, and 6G, there will be an increase in the number of HOs due to the presence of small cells. Consequently, the main goals of HO schemes are to reduce the number of frequent HOs and HO delays and increase the HO success rate [4]. Although increasing network size increases complexity, the large volume of data generated can be used to reduce complexity. By applying machine learning (ML) algorithms, this data can be effectively employed to train ML models that can help networks gain more knowledge about the network and make proactive, better-informed decisions [5]. Therefore, this review will concentrate on the ML algorithms used for HO optimization in the current and future 5G networks, primarily HetNets.

II. Smart Future (5G NR and 6G Networks)

The 3rd generation partnership project (3GPP) finalized the first phase of the fifth-generation (5G) of mobile communications with Release 15 in June 2018, which set the stage for global commercial 5G rollouts [6]. Since then, 3GPP has been advancing the 5G technology through releases 16 and 17 to increase performance and accommodate novel applications [7]. Recently, 3GPP approved the work package for Release 18, beginning the 5G Advanced evolution. Fig. 1 [8] shows a 5G road map of 3GPP releases 15 to 18. 5G NR Release 15 is the first official release of 5G new radio (NR) from 3GPP. It is an important milestone in the development of 5G and is the basis of the initial commercial deployments of 5G networks. Release 15 includes the core network and radio access network specifications for non-standalone 5G NR and provides enhancements over the initial release 14. This includes features such as new radio channel bandwidths, enabling of massive multiple-input multiple-output (MIMO), and support for different frequency bands [7].

5G NR release 16 offers enhanced existing features such as MIMO, dynamic spectrum sharing (DSS), dual connectivity/carrier aggregation (DC/CA), and improved user equipment (UE) power saving. Additionally, Release 16 introduces new features such as industrial internet of things (IIoT), ultra-reliable and low latency communication (URLLC), unlicensed spectrum, V2X, enhanced positioning, and integrated access and backhaul (IAB) [9]. Release 17 of 5G NR provides improved performance and new features to help meet the ever-growing demands of 5G networks. Enhanced existing features such as MIMO, DSS, UE power saving, improved coverage, improved positioning, and URLLC. Added new features such as reduced capability (RedCap), support for frequencies beyond 52 GHz, massive broadcast system (MBS), and network topology notification (NTN). Release 17 also includes enhancements to the 5G core network, such as improved support for non-standalone

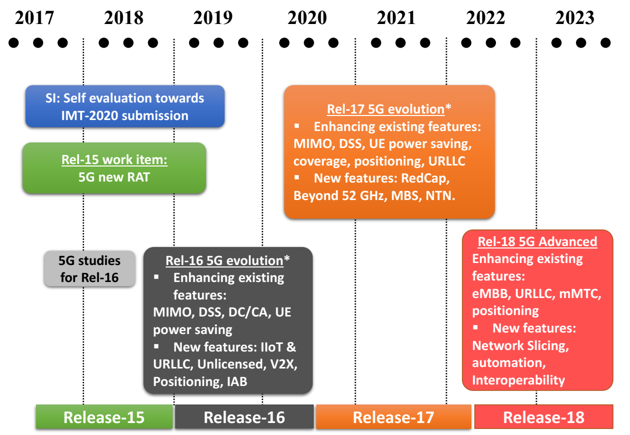

Fig. 1. The road map of 3GPP releases of 5G networks.

(NSA) and standalone (SA) modes, as well as improved support for multi-access edge computing (MEC) [10]. 5G NR Release 18 is the latest 5G technology release from the 3GPP. It provides enhanced existing features such as enhanced mobile broadband (eMBB), URLLC, massive machine type communication (mMTC) and positioning, as well as adding new features such as network slicing, automation and interoperability [8], [10].

Future 6G communication networks need additional requirements and system capacity when compared to current 5G networks. In the future, the connection channel between the users and the machines will be wireless [11]. It is expected that everything in the next era will be connected, automated, and shared. According to the requirements of modern applications, the future network should satisfy and guarantee an excellent QoS, very high data rates, very small latency and delay, very high reliability, and very wide cell coverage, as shown in Fig. 2 [12], [13].

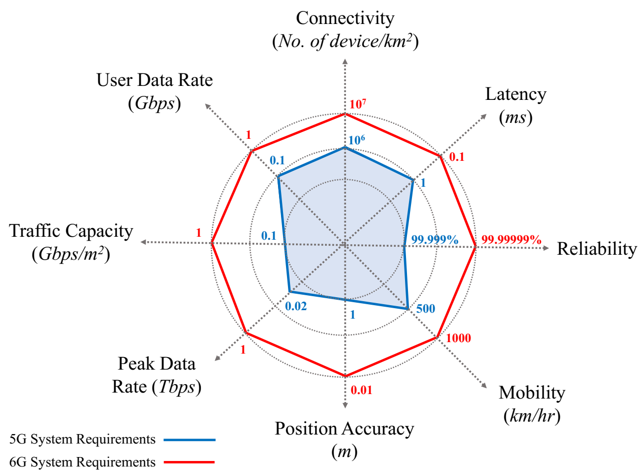

Fig. 2. 5G vs. future 6G system requirements.

III. Enabling Technologies

This section gives a thorough overview of the categories of prospective 5G NR and 6G technical enablers.

A. New Spectrum

1) Millimeter wave (mmWave): The use of mmWave (up to 300 GHz) began with the 5G New Radio (5G NR) and will continue into future 6G networks. Working with more frequency bands (>6 GHz, which is used in RF technologies) will give us a chance to increase the bandwidth, thus maintaining high data rates and smaller antenna sizes, leading to higher dimensions of antenna arrays and narrower beams [14]. The channel characteristics depend on the frequency band used. For example, some bands like 35 GHz, 94 GHz, 140 GHz, and 220 GHz are exposed to low attenuation loss, so they are used in high-distance communications. Other frequency bands, such as 60 GHz, 120 GHz, and 180 GHz are exposed to higher attenuation, so they are used in short-distance communications [15]. Most of the current research uses the 60 GHz band for indoor usage.

The propagation of mmWave is affected by obstacles in indoor and outdoor scenarios, such as people, vehicles, walls, atmospheric conditions [16]–[18]. When working with small cell coverage (200 m), such as picocells, these effects are reduced [19]. Even if they are propagated in urban areas with extreme rainfall, the attenuation loss will not be significant [20]. Using mmWave requires short-range communications, where frequency reuse will be highly used, thus increasing the system's capacity, but it also needs more small cells (SCs) to be deployed with more frequent HOs. The frequency of the mmWave is high, causing it to be very sensitive to blockage, but with different behaviors depending on the frequency [21]. The transmitter and receiver in mmWave communications need to focus the beam toward the users or toward each other, as the mmWaves are directed waves. This can be advantageous because the beam has a high gain. The UE must train or track the beam to which it wishes to connect.

2) Terahertz (THz) communications: Working with the THz frequency band, which plays an important role in the radio access network (RAN) in next-generation 6G communications, allows for very high bandwidth and data rates. But, the THz bands are also opposed to high path loss and need a very limited coverage area using very small cells. The THz band facilitates the processes of beamforming and tracking and will be very applicable in indoor communications [14]. The higher frequencies of the THz band allow for smaller antenna sizes. It is expected to embed up to 10,000 antennas per base station (BS) [22], thus overcoming the propagation loss by making narrower beams than in the mmWave band. As a result, it can support an increasing number of users per cell while increasing traffic capacity, which is one of the most important goals of future 6G communications to support the internet-of-everything (IoE) technology [14]. The technical issues with THz communication are implementing the electronics (hardware) circuits of antennas, modulators, and amplifiers [23], [24], especially when modulating the baseband signals to higher THz frequencies. This will need a more special modulation system without using the intermediate frequency stage [25].

B. Heterogeneous networks

For next-generation 6G mobile networks, HetNet is a very promising solution. It will effectively provide greater coverage, higher data speeds, and higher capacity. HetNets include many types of cell sizes, such as macrocells, microcells, picocells, and femtocells, to satisfy the requirements of next generation networks. The coverage area and capacity of different cell types are listed in Table I. Because macro cells have a large coverage area, they must send signals with high power to cover their area, which interferes with neighboring cells. By using the HetNets in future communications, we can integrate the low-power small cells under the coverage of high-power macro cells, leading to optimized energy solutions for 5G standards and satisfying the QoE [25].

TABLE I
COVERAGE AND CAPACITY OF DIFFERENT CELL TYPES IN WIRELESS COMMUNICATIONS.

Cell Type	Range (m)	Capacity (UEs)
Femtocell	10-20	<20
Picocell	200	20-40
Microcell	2000	>100
Macrocell	30,000-35,000	Many

IV. MOBILITY AND HO MANAGEMENT IN B5G AND 6G NETWORKS

B5G and 6G communications have numerous use cases that set them apart from 5G communications. Some of the applications that can be applied in future communications are the integration of unmanned aerial vehicles (UAVs) [26], holographic projection, high-speed vehicles and devices (above 500 km/h), etc. [27]. High-mobility devices in B5G communication networks that will use mmWave and THz spectrum will present big challenges in future communications as a result of their huge density and high speed. Mobility and HO management are expected to be the most common issues that should be taken into account in the B5G networks, as these networks will be highly dynamic and contain many layers (such as HetNets), causing more frequent HOs. The high mobility of these devices in B5G networks will make the BS uncertain about the location of these devices, causing high blockage by many obstacles such as people, buildings, etc. [5].

The known conventional schemes of HO management cannot quickly react. Adopting artificial intelligence (AI) to solve the problems of mobility and HO management is one of the best solutions that can minimize the number of occurrences of HO and predict the mobility of moving devices inside the network, thus making the system intelligent and optimizing the beam or the BS selection, causing a reduction in signaling, achieving high reliability and data rates, and minimizing the latency of the whole system [27].

There are many classifications and types of HO, such as inter- and intra-frequency HO, inter- and intra-cell layer handover, inter- and intra- radio access technology (RAT) HO, and inter- and intra-operator HO [2]. The performance of HO can be measured using many parameters, such as the HO failure rate (HOF), HO frequency (HO rate), ping pong (PP) rate, HO delay, HO energy consumption, HO success rate, data latency, HO interruption time, HO signaling overhead, and HO cost [5]. The handover control parameters (HCPs) are essential to controlling and managing the procedures of HO. As far as controlling the HO technique goes, time-to-trigger (TTT) and handover margin (HOM) are generally regarded as the two key control parameters of HO. They make a big difference in keeping UEs' connections stable.

A. HO Control Parameters

HCP settings in previous mobile generations, e.g., fourth-generation (4G), were changed and adjusted manually; these changes affected the operational costs and caused the system to be ineffective. Numerous problems could be due to different settings. More HCP settings result in a lower HO ping pong probability (HPPP). Too late HO, as shown in Fig. 3(a), increases radio link failure (RLF). As shown in Fig. 3(b), lower assigned HCP settings cause a reduction in RLF and an increase in HPPP. Inappropriate settings could produce unnecessary HO or send it to the wrong cell, as shown in Fig. 3(c) and (d). A novel HO algorithm that can automatically self-optimize for HCP scenarios while requiring the least amount of human interaction has been made available by fourth-generation (4G) technology [28].

The accuracy of the system depends heavily on this automatic self-optimization technique, especially when using HetNets in future networks. The 3GPP has introduced key functions for automatic HCP setting adjustment. Various self-optimized HO schemes for future HetNets include mobility robustness optimization (MRO) and load balancing optimization (LBO). The main aim of the MRO is to reduce the HO problem, especially too late or early HOs and HO in the wrong cell, which are shown in Fig. 3. When the cell traffic is very high and congested with users, the LBO can reduce the load in the serving cell and achieve a good QoS by offloading some users to other, non-loaded, cells [28].

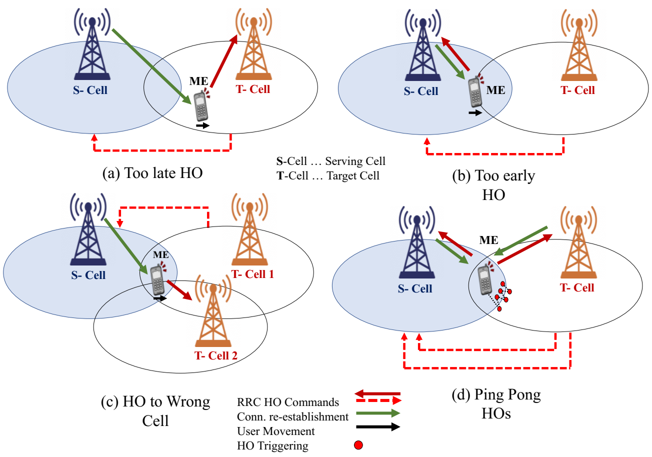

Fig. 3. Issues and decisions of HO in HetNets.

V. MACHINE LEARNING BASED HO OPTIMIZATION

Due to the high frequency bands of 5G and B5G communications, the footprint of BSs is very small, resulting in more occurrences of HO. So, optimizing the HO is very essential in those networks when the UE decides which BS or beam it should connect to in order to minimize the recurrent HO. This is due to the fact that recurrent HOs

TABLE II
AI-BASED HO TECHNIQUES.

Paper Ref.	**Year**	**Focus**	**Visual Data (Image/Video)**	**Wireless Data**	**Strategy**		**AI Algorithm**
					Beam Selection	***BS (AP) Selection***	
[24]	2020	5G	✓	×	×	×	DRL / I2D-PH[1]
[25]	2019	5G	✓	×	✓	×	CNN[2]
[21]	2020	5G/B5G	✓	×	×	×	DNN[3]
[29]	2022	B5G/6G	✓	×	×	×	NN using multivariate regression
[27]	2022	6G (THz)	✓	×	×	✓	Q-learning
[30]	2018	5G (mmWave)	✓	✓	✓	×	SVM[4]
[31]	2019	B5G/6G (THz)	×	✓	✓	×	RFC[5]
[32]	2019	6G (THz)	×	✓	✓	×	RBF-NN[6]
[33]	2020	5G (mmWave)	×	✓	✓	✓	DNN
[34]	2020	5G NR/6G (mmWave)	×	✓	✓	×	DNN
[35]	2020	5G (mmWave)	×	✓	✓	×	MARL[7]
[36]	2022	5G/B5G (mmWave)	×	✓	✓	×	DNN-ST[8], DNN-MT[9], and DNN-EMT[10]
[37]	2021	5G/B5G (mmWave)	×	✓	✓	×	Q-learning
[38]	2018	mmWave	×	✓	×	✓	DNN
[39], [40]	2019, 2020	mmWave	×	✓	×	✓	MAB
[41]	2020	mmWave	×	✓	×	✓	DDRL
[42]	2020	5G (mmWave)	×	✓	×	✓	Q-learning
[43]	2021	5G (mmWave)	×	✓	×	✓	ADA-CS[11]
[44]	2021	mmWave	×	✓	×	✓	ADA-CS
[45]	2022	5G	×	✓	×	✓	DRL/ A2T-KNN[12]

[1]Image-To-Decision Proactive Handover, [2]Convolutional Neural Network, [3]Deep Neural Network, [4]Support Vector Machine, [5]Random Forest Classification, [6]Radial Basis Function Neural Network, [7]Multi-Agent RL, [8]DNN Single Task, [9]DNN Multi-Task, [10]DNN Extended Muti-Task, [11]Adaptive Cell Selection, [12]Adaptive to Target K-Nearest Neighbor.

raise the cost of doing so, which lowers system throughput. Thus, by optimizing the HO process, the system can choose which target base station (T-BS) can guarantee and support the maximum throughput for the user. Many AI-based techniques can be used to optimize the HO and help in the beam/BS selection. They aid in T-BS prediction and ensure that sufficient resources are available at the T-BS prior to the occurrence of HO to ensure a smooth HO. Table II summarizes the AI algorithms used for HO optimization in B5G and 6G networks.

A. Visual data

In 5G and B5G networks, the BSs include multiple antennas, and there will be many line-of-sight (LOS) beams between the users and the BSs. The received signals at the end users' devices would be vulnerable to various types of interference. When choosing the best beam for connecting the user to the networks, a significant amount of overhead signaling would be necessary if solely wireless sensory data were used. This is because there would be a large number of beams involved [46].

The large scale of mmWave and THz wireless networks make it difficult to capture all of the external factors, including obstacles and buildings, with wireless sensor data. To solve this problem, it may be necessary to use visual-assisted handover optimization. As a result, detecting or predicting the presence of obstructions that may hinder or prevent the received beam and reduce throughput at the user end using only wireless sensory data is extremely difficult. However, vision-supported HO optimization, on the other hand, integrates wireless sensory data with visual data, such as pictures and videos, to give proactive obstacle identification, optimal beam, and BS selection, which would help to improve the user's QoS [47]. Additionally, by developing computer vision, the training overhead commonly associated with training ML models for the best beam selection can be significantly reduced by using network images to create deep learning (DL) algorithms for effective HO operation [48].

B. Wireless data

The majority of HO optimization-based wireless data requires traditional information instead of sensory vision (image or video) information for the optimization process, such as channel status, received signal power, and any other information related to the user's position, in order to optimize the user's switching between BSs or beams. In wireless systems, this is the most widely used scheme.

1) Beam selection: To overcome route loss and the fact that the mmWaves are vulnerable to obstruction due to their high frequencies, a significant number of BSs with directive antenna arrays and narrow (high-gain) directed beams for each user in the cell should be deployed in mmWave communications. This method, known as beamforming [49], is suggested for use in 5G and B5G communications. This technique can be used to establish a direct connection between the BSs and UEs. It becomes increasingly difficult for the UE to choose the best beam out of hundreds of beams for connection and QoS fulfillment as the number of BSs and beams in a single cell increases.

In [50], the author proposed a data-driven algorithm based on ML for analog beam selection in hybrid MIMO systems in mmWave channels. This scheme is a multi-classification problem that is solved by using the support vector machine (SVM) algorithm to select the optimal beam for each network user. This scheme showed good data rate performance when compared to other conventional schemes, but with less complexity. The authors in [51] proposed a beam selection method that may be applied to THz communications to combat the system's computational complexity in hybrid beamforming that is presented in current schemes. The proposed beam selection scheme is based on the random forest classification (RFC) algorithm, which is used to obtain the optimal beam that the user needs to connect to.

2) Base station selection: AI-based BS selection is a technique used to ensure seamless handover. It uses AI to analyze the signal strength, latency and other characteristics of the base station and the surrounding environment to determine the most suitable base station to connect to. AI-based base station selection in handover can provide better overall user experience by providing more reliable connections, faster speeds, and lower latency. Additionally, it can also be used to increase network capacity and reduce power consumption. Base stations can be selected to optimize network performance and reduce congestion.

In [52], the authors proposed a DL-based HO scheme for learning how to predict the blockage of signals that the UE may face in mmWave systems. The scheme can make the serving BS switch to another BS without disconnection. As a result, the system will be highly reliable and have low latency. An effective BS selection with speeding technique based on multi-armed bandit (MAB) approach in ultra-dense mmWave network to guarantee a long-time connection with the BS after the HO process is proposed in [53]. Another intelligent BS selection scheme based on offline double deep reinforcement learning (DDRL) for ultra dense network (UDN) in mmWave communications is proposed in [54]. In many scenarios, the scheme can reduce the number of HO occurrences while enhancing the users' QoS when compared to other conventional AI-based schemes. The authors in [55] proposed a BS selection for HO optimization based on a centralized RL agent among the BSs in 5G networks. They created a Q-learning strategy by modeling the HO issue as a contextual MAB (CMAB). The scheme showed an improvement in link-beam gain efficiency in practical environments.

VI. Conclusion

To meet the future B5G and 6G communication network requirements of higher data rates, low latency, high throughput, etc., higher frequency bands should be used, such as mmWave and THz bands. These bands suffer from high path loss, so small BS coverage areas should be used with a higher number of cells. The massive number of cells causes more frequent HOs that should be considered when we need to design reliable communication systems. In this paper, we summarized and reviewed many of the HO management and optimization techniques that are based on ML in order to minimize the number of HO occurrences and thus enhance the system's efficiency.

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