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Review

# Handover parameter for self-optimisation in 6G mobile networks: A survey

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ABSTRACT

One of the most crucial issues in mobile networks is ensuring reliable and stable connectivity during mobility. In recent years, numerous research has examined Fourth Generation (4G) and Fifth Generation (5G) mobile networks to address issues related to handover (HO) self-optimisation. Different approaches have been developed to identify the best Handover Control Parameters (HCPs) settings, including Time-To-Trigger (TTT) and Handover Margin (HOM), since managing HCP values is a key factor in determining the efficiency and accuracy of handover decisions. The purpose of this work is to address the challenges associated with HO management in Sixth Generation (6G) mobile networks, where a massive number of diverse devices, high mobility, and varying network conditions (e.g., Ultra Dense Network (UDN), Heterogeneous Network (HetNet) and Millimetre Waves (mmWaves)) are established. This, in turn, presents complex HO issues which require solutions that can adapt to different deployment settings. To provide a brief background of mobility management, the paper presents the basic HO concept, HO history, and HO procedure. Additionally, a comparison of HO in 4G to 6G is discussed to gain a better understanding of technology development and its effect on HO solutions. Furthermore, the basics of Mobility Robustness Optimisation (MRO) is explained, which involve HCP values. Previous MRO approaches have made significant advancements; however, they often lack adaptability and robustness to dynamic network conditions. By leveraging Artificial Intelligence (AI) algorithms with MRO techniques, this approach offers an improved solution to optimize handover decisions in a self-optimizing manner, thereby enhancing the overall network performance. To achieve this goal, it is necessary to analyze previous MRO and AI-integrated solutions and make comparisons between them. Additionally, the advantages and disadvantages of these solutions are considered. The contribution of this work lies in identifying the directions for HO self-optimization in 6G deployment. It demonstrates that deploying an AI-based solution would benefit future MRO deployments. This survey will aid in the analysis of mobility management challenges, particularly for the future mobile MRO self-optimization implementation in future technologies.

## 1. Introduction

The rapid increase in the number of wireless devices in recent years has increased need for high system capacity and data rates [1]. Subscriptions to the Fifth Generation (5G) are estimated to reach 580 million by the end of 2026 [2]. The Heterogeneous Network (HetNet) and Millimetre Wave (mmWave) have been introduced to cater to these demands. The HetNet consists of many Small Cell Base Stations (SCBS) deployed to overlap the Macro Cell Base Station (MCBS) [3]. Another key technology that makes use of large numbers of SCBS is the Ultra Dense Network (UDN). While the introduction of mmWaves and UDN may enhance both system capacity and network throughput, they also create critical challenges during handover (HO) for instance, a rise in the number of needed and unneeded HOs, Radio Link Failure (RLF) and Handover Ping Pong (HOPP) probability which negatively affect the network Quality of Services (QoS) [4] and Quality of Experience (QoE) [5]. The vision is to have ultra-high data rates and ultra-fast mobility in the Sixth Generation (6G) network, which will involve more HO challenges.

To address the HO issues, the Third Generation Partnership Project (3GPP) group proposed Mobility Robustness Optimisation (MRO) as part of the Self-Optimisation Network (SON) function [6]. It has made a substantial contribution to addressing HO and mobility management problems in 5G mobile networks [2]. MRO automatically modifies or

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auto-tunes the Handover Control Parameter (HCP) parameters to preserve the User Equipment's (UEs) connection quality. MRO's primary goal is to automatically optimise the settings of the HCP, such as Time-To-Trigger (TTT) and Handover Margin (HOM), with little human involvement [7], where the methods used, will be dependent on the algorithms which have been designed to keep the connection quality during communication between the UEs and the serving BS above a specific value [8].

The general issue in MRO is resolving the mobility management by finding the optimal HCP setting that would improve HO performance in different UE and network environments. An optimized HCP setting is crucial in order to reduce HO-related issues which can lead to network performance degradation, such as early HO, late HO, and wrong cell HO. Emerging technologies such as high frequency deployment have short coverage areas that would increase HO between cells. Likewise, UDN deployment, beamforming, New Radio (NR) access technologies and UAV deployment that would create multi-HO problems that reduces network performance.

The various research solutions developed to solve MRO issues can be broadly categorised as MRO non-AI and AI-based research. These helps to cater to the demand and evolution of 6G owing to the network diversity and multiple HO problems. The existing non-AI based research makes use of different HO decision algorithms, such as signal strength (Received Signal Strength (RSS), Reference Signal Reference Power (RSRP) and signal-to-interference-plus-noise ratio (SINR)) [9], UE speed [10], energy efficiency (EE) [11], dynamic programming [12], prediction [13], fuzzy [14], cost-function [9] and security [15]. Current research trends also focus on MRO AI-based approaches such as Machine Learning (ML), Deep Learning (DL) and Reinforcement Learning (RL). The AI-based solution provides a better multi-objective output compared to the non-AI based solution. The AI-based solution can adapt and self-learn different network conditions. The main focus is on SON and AI-based solutions since the combination of both will provide better HO results that can cater to multiple optimisation areas.

Although numerous MRO algorithms are available across all of the literature, to date, no algorithm can deliver an optimal solution [16]. The primary area of research that has to be addressed is finding the optimal triggering conditions for HOM and TTT. [7]. Advanced, dynamic and robust MRO algorithms are needed to determine the proper HCP settings based on a variety of parameters, such as different mobility and deployment scenarios. Providing an adaptive solution rather than a singular or partial optimisation solution is necessary [17]. These issues will become critical with the widespread deployment of UDN and mmWaves in 6G. The increase in UE mobility will make HO issues more complex in such an environment [18]. To keep up with developments and be able to automatically identify and solve mobility issues and HO failures, the SON MRO algorithm must be improved.

Several review papers have extensively focused on MRO deployments and solutions, providing comprehensive insights into the advancements and challenges in this field. In article [2], the authors studied the pros and cons of different algorithms and techniques of MRO, acquiring various outcomes. HO self-optimisation challenges, solutions and future directions were also discussed. In article [19], the authors reviewed different MRO approaches and determined the inefficient techniques. In article [20], MRO function and Load Balancing Optimisation (LBO) were examined, including their relationship with HO issues. As an alternative, ML can be used to identify and resolve any conflicts between HPO and LBO functions. The author in [21] provides a thorough analysis of current HO decision algorithms in HetNets, classifying them according to their decision procedures, summarising their input parameters, and providing performance evaluations. The following is a summary of this paper's significant contributions:

- HO problems for the current 5G and future 6G deployments are discussed. The review includes mobility management, mobility issues, the HO concept as well as the functions that can be used to solve HO issues.
- The basic concept of SON is covered, including the areas in which SON is used in wireless networks. The relationship of SON and MRO is also discussed.
- An overview of suggested and currently deployed solutions is provided, highlighting the importance of MRO and AI-based solutions.
- A systematic overview of integrated MRO AI-based solutions in 5G/6G mobile networks considering the HCP values, UE mobility and HO performance metrics.
- The survey paper references studies conducted between 2017 and 2023, a period during which advancements were made in 4G to 6G technologies.

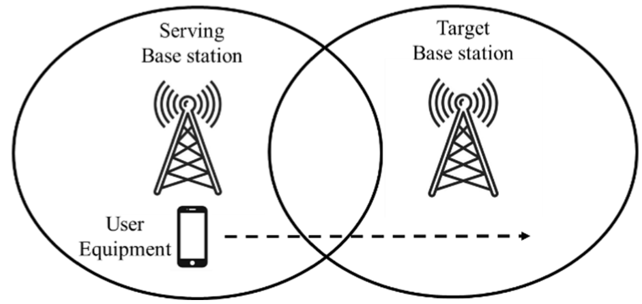


**Fig. 1.** UE moves from serving BS to target BS for handover to occur.

This paper is organised as follows. Section 2 provides an overview of mobility management in both the current 5G and future 6G networks, including the HO problems experienced in 5G. Section 3 introduces the MRO, which includes HCP function in the HO procedure. Section 4 briefly highlights AI in MRO and compares various ML methods for wireless networks. Section 5 discusses the challenges of mobility management in the 6G network deployments. Section 6 presents the related studies and solutions for MRO-based wireless network. Section 7 suggests future directions of AI-based MRO and Section 8 concludes the paper.

## 2. Mobility management

Mobility management is crucial for delivering continuous communication at various levels globally. In wireless networks, mobility management is the capacity to keep the UE's connection with the serving BS intact when it moves between cells (in the ideal case) [19]. By switching the UE from one cell to another, using a mechanism called HO process, it is crucial to maintain the radio link connection between the UE and BS inside the coverage region [7]. By switching from one channel to another, HO lets mobile devices to maintain their connection to the core network. A basic overview of HO and its related functions is provided in this section.

### 2.1. Handover concept

Handover is the process of establishing and shifting the connection of UE from the source BS to the targeted BS. Two types of HO are present: vertical handover (VHO) and horizontal handover (HHO) [22]. VHO is for inter-system HO where HO is performed in different link-layer technology, while HHO is known as intracellular HO where HO is conducted within the same link-layer. HO makes it feasible for mobile devices to maintain a connection to the core network when switching from one channel to another [23]. Fig. 1 displays the basic handover concept when the UE moves from the serving BS to the target BS.

**Table 1**
Handover technique across different mobile generations from 3G to 6G networks.

| Reference | Network Generation | Handover Type | Description |
|---|---|---|---|
| [24] | Third Generation (3G) | Hard handover and soft handover | • In hard handover, the old connection is broken first before a new connection is active. Short communication breaks occur. Hard handover is applied by systems that use frequency division multiple access (FDMA) and time division multiple access (TDMA), such as GSM and General Packet Radio Service (GPRS).<br>• In soft handover, a new connection is active before an old connection is broken, leading to more consistent communication. Soft handover is employed by code division multiple access (CDMA) systems where cells use the same frequency band. |
| [25,26] | Fourth Generation (4G) | X1, S1, MDHO and FBSS | • The Orthogonal Frequency Division Multiple Access (OFDMA), which is a frequency division method, is also used.<br>• HO and the information process are accomplished using the X2 and S1 interface. X2 directly permits HO between BSs, while S1 permits HO connected to the Evolved Packet Core (EPC).<br>• Wireless Metropolitan Area Networks (WIMAX) uses Fast Base Station Switching (FBSS) and Macro Diversity Handover (MDHO) methods, which are two types of optional soft handover. |
| [27] | Fifth Generation (5G) | Xn and N2 | • The 5G system utilises the network function (NF) as the CN. Xn handover and N2 handover similarly function as the X2 and S1 in 4G.<br>• HO occurs when the Source BS and Target BS are connected to two different User Plane Functions (UPFs) or Core Network (CN). Re-registration is required after successful handover if the Source BS and Target BS belong to different Tracking Areas (TAC).<br>• The difference is that Xn, it only connects to the same Access and Mobility Management Function (AMF), while N2 can connect to both. |
| [27] | Six Generation (6G) | Not establish | • At present, no optimal HO technique for the 6G system is present, remaining as an open for research. The HO problem requires faster processing. Increasingly intelligent mobile terminals can play a crucial role in the handover process. |

## 2.2. Handover history

The first generation (1G) of mobile wireless communication was introduced several decades ago. Technology and network requirements have significantly evolved with time. Similarly, the handover procedure has changed to adapt to different systems. The handover procedure has transformed throughout various network generations, from 3G to 5G. Table 1 summarizes the evolution and advancements in HO techniques and protocols across different generations of wireless communication.

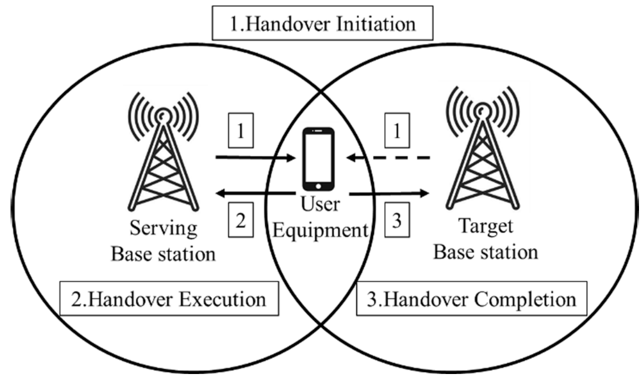


**Fig. 2.** Basic handover procedure with three steps for a success handover.

**Table 2**
Handover decision algorithm in phase one on the handover initiation.

| Reference | Handover Decision Algorithm | Advantages | Disadvantages/ Drawbacks |
|---|---|---|---|
| [9] | RSS/SNR/RSSI/ interference-based | • Less HO failure, more accurate HO. | • HO failure delays. |
| [9] | Cost-function-based | • Weighted summations and multi-parameter functions. | • Low speed, increased HO delay. |
| [11] | Energy efficient-based/ power-based | • UE may stay longer in network with less power consumed.<br>• Battery life of UE increases. | • HO does not occur due to high speed. |
| [12] | Dynamic programming | • Several parameters involved.<br>• HO speed and reduced delay. | • No general formation.<br>• Complexity of design. |
| [13] | Prediction-based | • Less HO delays. | • Additional complications.<br>• Increased signalling involved for collecting parameters and predictions. |
| [14] | Fuzzy handover | • Algorithm more reliable and accurate.<br>• Low power consumed. | • Low speed, increased HO delay.<br>• More complex deployment. |
| [15] | Security-based | • High security, authentication. | • Delayed HO due to encryption process. |
| [27] | Speed/velocity-based | • HO predicted depending on UE speed. | • Increased HO failures.<br>• Overhead when calculating HO.<br>• Velocity not constant due to high HO. |
| [29] | Location-based | • Reduced HO in dense network. | • Higher signalling overheads and RLF. |

## 2.3. Handover procedure

Handover was designed to preserve the connection of the UE as it moves across the network due to UE mobility. The handover procedure is a critical aspect of MRO where the process of handover occurs. Fig. 2 presents the basic handover procedure between cells. The handover procedure is divided into three phases [28]:

**Table 3**
Comparison of 6G with 4G and 5G mobile networks with a focus on the relationship between mobility and handover.

| Reference | Deployment Parameter | 4G | 5G | 6G | Argument on Mobility and HO |
|---|---|---|---|---|---|
| [31] | Operating Frequency | 700 MHz (low band) 2 and Sub-6 GHz (mid band) | 700 MHz (low band) and Sub-6 GHz (mid band) | 26 and 28 GHz mmWaves (high band) Above 10–100 GHz (Terahertz (THz) bands) | High frequency and multi frequency coordination will increase HO issues. |
| [32] | Bandwidth (MHz) | 100 | 400 | >1000 | Increase of HO issues will lead to depletion of bandwidth resources. |
| | Latency (ms) | 50 ms | 1 ms | <1ms | HO issues require fast response time. |
| [33] | Connection Density (devices/km$^2$) | $10^5$ | $10^6$ | $10^7$ | Multiple devices and coverage areas will increase HO issues. |
| [34] | Mobility (km/h) | 350 | 500 | >1000 | Faster mobile movement will increase HO issues. |
| [33] | Architecture | SCBS umbrella MCBS | Dense SCBS umbrella MSBS | Small THz cell, SCBS umbrella MSBS, drones | Denser BS deployment will increase HO issues. |

#### 2.3.1. Handover initiation

In the first phase, UE sends the measurement report of neighbouring cells to the serving cells. The serving cells will determine and send requests to target cells. The target cells will evaluate the requests based on available resources. If the UE is admitted, the target cells will send a HO response. An uplink path is then established, and the HO request is based on the selected HO decision, which consists of parameter selection and processing. In the parameter selection step, which is a crucial part of HO, parameters that the algorithm requires are chosen to evaluate and weigh a candidate's association [24]. Different techniques and algorithms have been applied to ensure HO, and each demonstrates various performance capabilities and accuracy. Handover between cells can be divided into various categories such as received cost-function-based, RSS based, speed-based, interference-aware and energy-efficient-based. Other types of general handover algorithms are throughput-based, RSSI-based, SNR-based, network cost-based and security-based handover [30]. There are advantages and disadvantages in using this general method, as listed in Table 2. The handover decision will later evolve to accomplish better optimisation with the use of the SON MRO function.

#### 2.3.2. Handover execution

A handover command will be sent to the UE by the serving cell for handover execution. After that, the UE will start establishing a radio connection.

#### 2.3.3. Handover completion

Handover completion is accomplished when the UE sends a handover confirmation message to the target cell, which in turn, will send a path switch request message to the core network. An acknowledgement is sent to the target cell once the downlink path setup is complete.

### 2.4. Comparison of handover in 4G to 6G

Although the 5G system has made significant advancements, numerous difficulties relating to mobility management have become more challenging in HetNets. HO issues have become more complicated with the introduction of UDN and mmWaves. These challenges must be quickly resolved to deliver a seamless and consistent connection during user mobility. One of the primary issues in implementing 5G and future systems is that HCPs has to be modified in response to dynamic occurrences. New studies and plans for the 6G network have begun, with the primary goal of providing greater capacity, faster data speeds, decreased latency, lower battery usage and reduced cost compared to 4G/5G systems [32]. Table 3 offers a comparison of 4G to 6G deployment requirements which significantly affect HO performance [35,36].

### 2.5. 6G infrastructure and handover effect

6G is still in the research and development phase, and there is multiple infrastructure suggested. To meet the future requirements of high data rates to support multiple connection such as UE, High Speed Train (HST), and Internet of Things (IoT) devices, the infrastructure of 6G is designed to provide robust support for these demanding

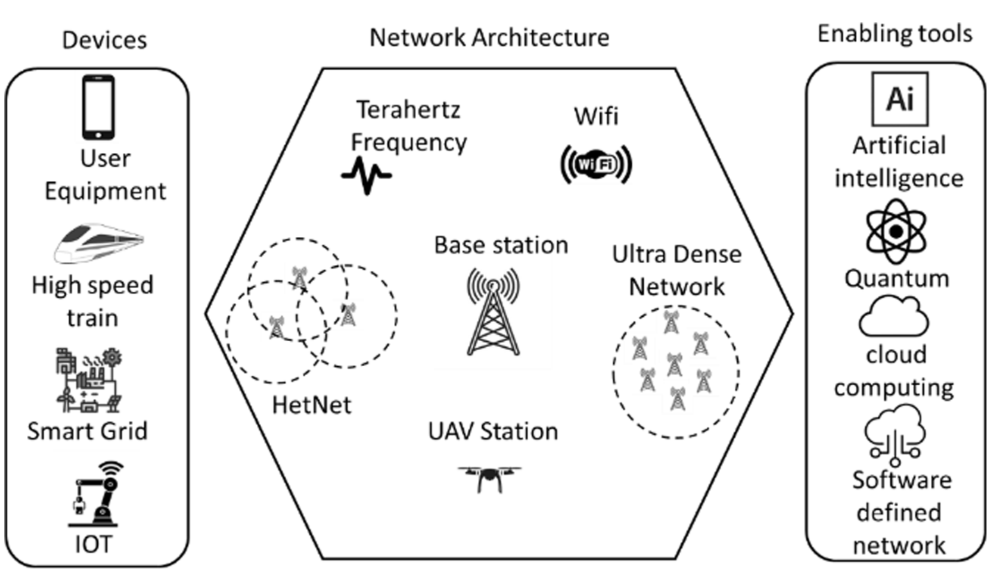


**Fig. 3.** The infrastructure of 6G and the impact to future handover for devices in the network.

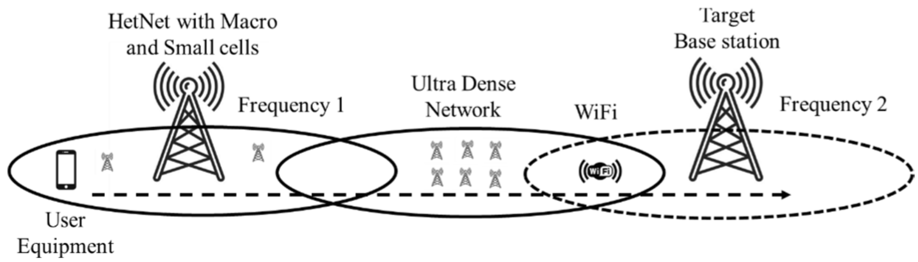


**Fig. 4.** Handover scenario that could occur for devices during mobility in a network with different technologies.

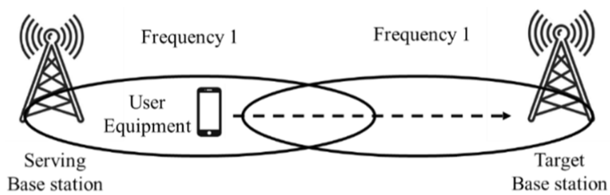


**Fig. 5.** Intra-frequency handover occurs between serving BS to target BS with the same frequency.

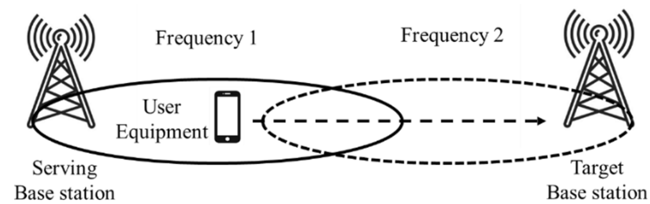


**Fig. 6.** Inter-frequency handover occurs between serving BS to target BS with different frequency.

connectivity needs [37]. The network architecture incorporates features such as HetNets, UAV stations, UDN, THz frequency, and WiFi capabilities [35]. To effectively optimize these technologies, essential tools such as AI, quantum computing, cloud computing, and Software Defined Network (SDN) are deployed. These enabling tools play a vital role in enhancing the HO process across different types of devices by providing intelligent decision-making capabilities. Fig. 3 shows the 6G infrastructure that is expected to be deployed in future. In terms of HO, 6G is expected to rely on more advanced and efficient solutions. To meet the challenges posed by fast-moving devices and the involvement of multiple networks, the HO techniques in 6G and beyond must present reliability, adaptability, and the ability to function seamlessly under different technologies. The increasing complexity of mobility management, coupled with the need for efficient HO, demands advancements in HO techniques to minimize delay and ensure uninterrupted connectivity as users transit between networks. Fig. 4 shows multiple networks with different technologies in 6G infrastructure that need to be cater in HO procedure during mobility. The complexity of the procedure increases with the increase of number of network, hence enabling tools in 6G deployments is critical [34].

## 2.6. Handover scenarios

In a network that has different cell types that operate at different radio access technology (RAT) and frequency, the handover will be more complex. Since each cell has different parameters, including interference management, cell radius setting, transmission power, and path loss model, HO will need efficient algorithms. The different available HO scenarios are briefly discussed, as follows [38,39].

### 2.6.1. Inter and intra-RAT handover

Intra-RAT handover occurs between the serving BS and the target BS of the same RAT; e.g., Long-Term Evolution (LTE) and LTE or 3G and 3G are the same RAT. Inter-RAT handover occurs between different RATs that are operating at two different carrier frequencies; e.g., LTE-3G, 3G-2G GSM or 3G-GSM. Intra-RAT HO is commonly referred to as horizontal HO. RAT handover is further characterized between intra-frequency and inter-frequency.

### 2.6.2. Inter and intra-frequency handover

The HO types where the carrier frequency is involved are intra-frequency and inter-frequency. It is commonly referred to as intra-frequency HO if the UE is to travel to the target cell at the same frequency as the serving cell. On the other hand, inter-frequency HO happens when the UE utilises a different carrier frequency in the target cell. The interference that the UE encounters during handover is the main difference between intra-frequency and inter-frequency HO. In intra-frequency handover, the handed over UE suffers from interference between the serving and target BSs. Figs. 5 and 6 display the types of HO.

### 2.6.3. Inter and intra-layer handover

HetNets offer a range of cellular layers such as MCBS, SCBS and Pico Cell Base Station (PCBS). Intra-frequency MCBS-MCBS and PCBS-PCBS HO is called intra-layer HO, where HO occurs from cells belonging to the same layer. Offloading UE to a smaller cell layer (e.g., MCBS to PCBS or PCBS to SCBS) is called inter-layer HO [40].

### 2.6.4. Inter and intra-operator handover

Users have the option to choose from multiple systems and technologies offered by various operators. Intra-operator HOs refer to events that happen within the same operator’s systems, networks, and technologies. Inter-operator HOs, in contrast, are those that occur between networks, technologies and systems that are operated by different operators. Roaming is a typical model of inter-operator HO, which describes the potential for a user to connect to another available network when they are outside the range of their home network. However, an arrangement must be made between operators for the inter-operator process to work.

## 2.7. Basic issue in mobility management

The main key challenges in mobility and handover for evaluating and validating the performance of the system are as follows [41,42].

### 2.7.1. Early handover

Early HO occurs when the UE connects to the target BS too early and then re-establishes connection with the serving BS, resulting in RLF from the serving BS and low SINR level at the target BS [43]. Early HOs are normally caused when the coverage area of the target BS is within the coverage area of the serving BS.

### 2.7.2. Late handover

Late HO occurs when UE loses its connection from the serving BS due to HO occurring very late, resulting in RLF. Later UE re-connects to the target BS [41]. UEs with high mobility frequently triggers late handovers.

### 2.7.3. Handover to wrong cell

When a third BS coverage area sits in between the serving and target BS respective coverage areas, it will result in HO to wrong cell. The UE briefly establishes a connection to the incorrect BS when it disconnects from the serving BS, resulting in RLF. The UE then re-establishes connection with the target BS [41].

## 2.8. Key performance indicators

Key Performance Indicators (KPI) in mobility management are used to evaluate the effectiveness and quality of the handover solutions used. The common KPIs used in mobility management include.

### 2.8.1. Handover probability (HOP)

HOP is the probability that HO will happen when the UE switches from one BS to another. It represents the percentage of HO occurrence during a period. Increased HOP will affect the network's performance [5].

### 2.8.2. Handover ping pong (HOPP)

The frequent connections and disconnections of UE between two close-by BSs are what causes the ping-pong effect due to signal fluctuations. The more often this happens, the more HOs will require processing, which will cause network delays [7]. Ping-pong effect is regarded as a crucial metric for evaluating the effectiveness of any suggested HO solution.

### 2.8.3. Radio link failure (RLF)

RLF occurs when the moving UE encounters a bad connection, a lot of interference, or both at once [44]. The communication session is broken due to the condition. Steps must be taken to sustain communication and dependability. RLF should therefore be minimised to decrease latency and resource use.

### 2.8.4. Handover failure (HOF)

HOF occurs when user attempts to handover from one BS to another's BS but fails and result in the connection broken [45]. This is due to poor signal quality and network congestion.

### 2.8.5. Throughput

Throughput provides a measure of the actual data transition from the BS to the UE. The network throughput is the sum of data rates delivered to the BS in the network or the measurement of data that can be transferred. These KPIs are important measures that need to be taken into account [46,47].

### 2.8.6. Delay

Network deployment of UDN can cause delays such as HO delay, time delay and transition delay. This will cause resource depletion and impact network performance [48].

# 3. Mobility robustness optimisation

This section provides a brief description of SON, the types of SONs where MRO is included, how MRO is conducted and the relationship of MRO and HCP.

## 3.1. Handover self-optimisation

Self-Organisation Networking (SON) was introduced approximately 10 years ago by 3GPP [19]. The aim is to assist network management by automatically configuring, planning and reliably optimising mobile networks [49]. With SON, human error in network operation and human involvement in network design are essentially eliminated. Effective self-organisation improves the level of key performance indicators by selecting the ideal network configuration and continually seeking out effective solutions [50]. Three types of SON functions are present: self-configuration, self-optimisation and self-healing. Table 4 summarises the three SON functions Self-configuration can automatically adjust its condition when changes occur to the network. Self-optimisation dynamically tunes network parameters (quality, coverage, capacity bandwidth, interference and handoff) for optimal performance in changing network conditions. Finally, self-healing is used in automatic compensation of network node failures to restore service and maintenance.

**Table 4**
Three types of SON functions and the usage in mobile network.

| Self-Configuration | Self-Optimisation | Self-Healing |
|---|---|---|
| • Parameter adjustment<br>• Neighbour cell list<br>• Radio access parameter<br>• System update<br>• Authentication<br>• Cell coverage estimation<br>• Cell deployment | • Interference control<br>• Load balancing optimisation<br>• Handover<br>• Mobility robustness optimisation<br>• Resource optimisation<br>• Monitoring signal quality and traffic | • Cell Outage<br>• Self-recovery of network<br>• Power<br>• Outage<br>• Network localisation |

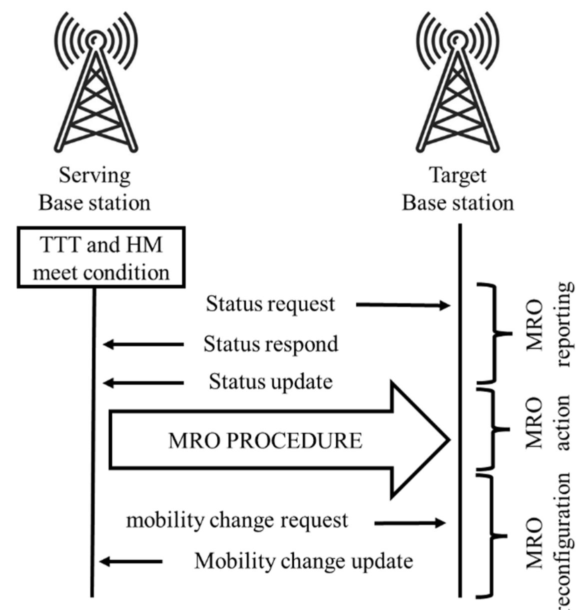


**Fig. 7.** Basic MRO procedure for handover deployments.

## 3.2. What is mobility robustness optimisation?

MRO was introduced to detect, correct and solve handover issues due to mobility in 4G and 5G networks [8]. The MRO algorithm adaptively adjusts HCP settings to instantaneous network conditions when a handover issue is detected [50]. This is to maintain network quality. The handover problem covers several handover failures (HOFs) such as too late HO, too early HO, handover to the wrong cell, unwanted handover and ping-pong handover between the source and target cells. Other handover issues that affect network continuity include dropped calls and RLFs. MRO is used to minimise these handover problems.

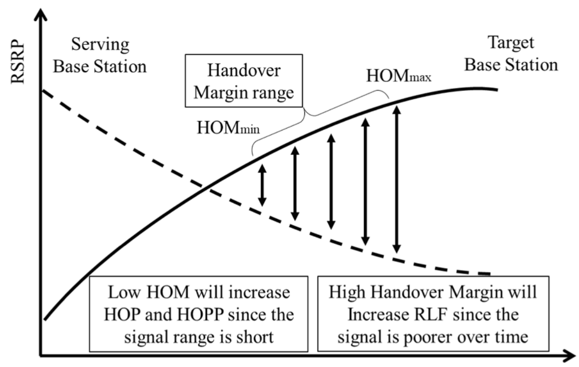


**Fig. 8.** Concept of HOM in mobile network with different HOM margin range settings.

### 3.3. MRO procedure

MRO algorithms estimate appropriate HCP settings as a threshold (such as signal strength and signal quality) to maintain network quality that is affected by multiple parameters, such as mobility. Previously, HCP settings were adjusted to fixed settings to adapt to different mobility situations. However, this has a negative effect on network performance, particularly when the UE speed is relatively high. The current research effort is to suitably adjust HCP settings to address this dynamic network condition. However, manually performing the HCP setting will increase the cost of management and maintenance complexity. Fig. 7 presents the basic HO concept in the MRO procedure [51]. A handover decision will be made if the following conditions are satisfied:

- The minimum and maximum values of the entry condition for the A3 event must be recorded by the MRO functions of BSs, where the RSRP value recorded from the target BS is greater than the serving BS, thereby not causing RLFs.
- BSs identify their own individual BS load and that of nearby BS to exchange load data. If necessary, the LBO function in BS A will be activated if some BSs, like BS A, are overloaded. Each BS's load is managed via the LBO function. Several solutions do not include LBO function, meaning they only depend on the MRO function for mobility management.
- The selected HCPs used to confirm the HO triggering condition determine the MRO transmission time. Due to the dynamic channel characteristics, the parameter known as TTT is employed to reduce the frequency of MRO initiation.
- The target BS signal strength or RSRP must be larger than the sum of HOM and serving BS signal strength.
- HO will take place if the above scenario remains true for TTT, the period during which the handover criterion is satisfied.

### 3.4. Handover control parameters (HCPS)

The HCP has two parameters that is the HOM and TTT. The UE performs handover between the serving and targeted BS depending on the system's allocated HCPs. When the HCP requirements are satisfied, the handover decision algorithm initiates the request for handover. The MRO function dynamically optimises HCP values to handle different HO problems. Adjusting HCPs is a major challenge since it must be adjusted according to the dynamics of network events [23]. The two types of HCPs are described as follows.

#### 3.4.1. Handover margin (HOM)

The HOM parameter, also identified as hysteresis margin, is a constant variable that represents the threshold of the received signal strength differential between the serving and target BSs. These variables can be represent by RSRP or SINR depending by the configuration [5]. The actual values often range from 0 to 12 dB, with a 0.5 dB difference between each value [7]. The HOM can either provide advantages or disadvantages to improve or reduce the HO performance. HOP, HOPP, and RLF can all be avoided or minimized by adjusting the HOM setting. Lowering the HOM values will reduce RLF, however, it will increase the HOP and HOPP. Increasing HOM will reverse the effect [5]. Thus, the HOM setting must be carefully defined. Fig. 8 presents the HOM concept used in mobile network in different HOM margin ranges.

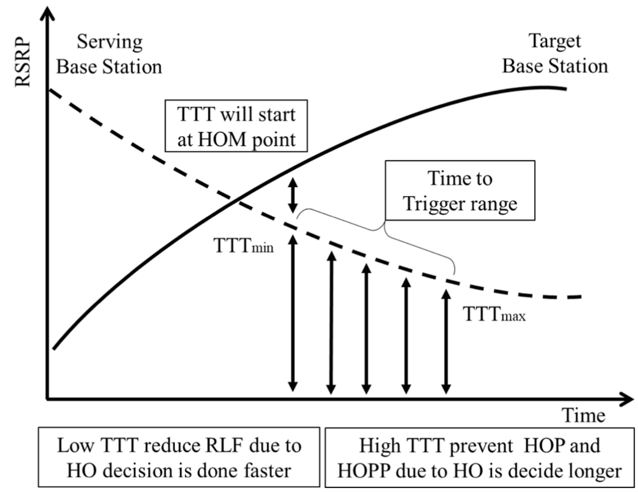


**Fig. 9.** Concept of TTT in mobile network with different TTT ranges settings.

#### 3.4.2. Time-to-trigger (TTT)

Another parameter that controls the HO process in MRO is called TTT. The TTT is the length of time or interval time used to calculate the received signal power. The RSP is required to satisfy the HOM condition for handover to occur from the serving BS to the targeted BS for the UE [5]. The TTT values fall in the range of 0, 40, 64, 80, 100, 128, 160, 256, 320, 480, 512, 640, 1024, 1280, 2560 and 5120 ms. The different interval values can affect the HO performance similarly to the HOM values. High TTT settings can reduce the likelihood of HOP and HOPP, but it could increase RLF rates. Similar to how reduced TTT settings value can lower RLF rates, but it may also result in higher HOP and HOPP rates. Additionally, the TTT setting must be precisely set. Determining the right self-optimising algorithm for HCP settings is crucial to enhance the performance of the 5G network [52]. Finding the ideal balance between HOM and TTT values while simultaneously guaranteeing that the network is in a stable operating position are the key issues facing the MRO algorithm for SON for an extensive amount of time with as few handover issues as possible [44]. Fig. 9 presents the TTT concepts in mobile network with different TTT ranges.

## 4. Artificial intelligence (AI) in MRO

This section briefly explains the background of AI and AI comparison in mobility management deployments. AI was first introduced in the 1950s where a decision-making machine was used to interact with humans [53]. Today, AI has become a widely used tool in daily life. AI applications are called ML which is a statistical instrument used to determine patterns and perform predictions based on the input and output of data provided [56]. 3GPP release 16 has initialised network automation. Release 17 will discuss the framework of AI/ML [54]. The AI will become a crucial part of MRO deployment.

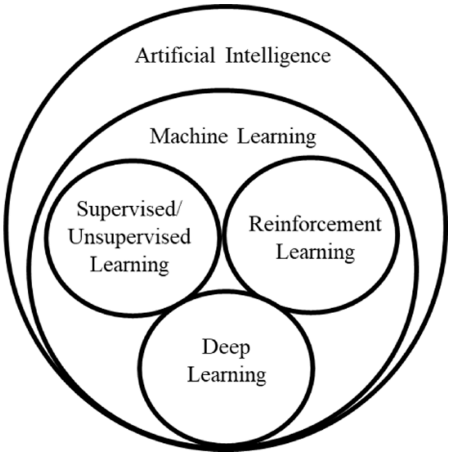


**Fig. 10.** Relationship between AI and ML with different types of learning algorithms.

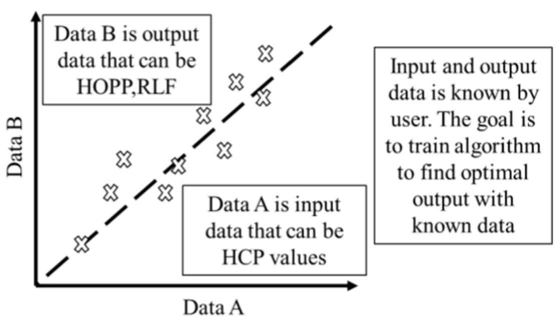


**Fig. 11.** An example of Supervised Learning usage for MRO 6G deployment.

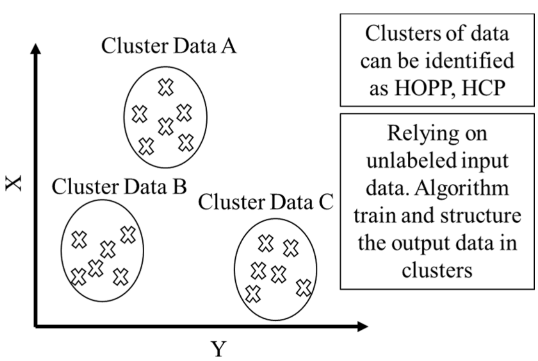


**Fig. 12.** An example of Unsupervised Learning diagram for MRO 6G deployment.

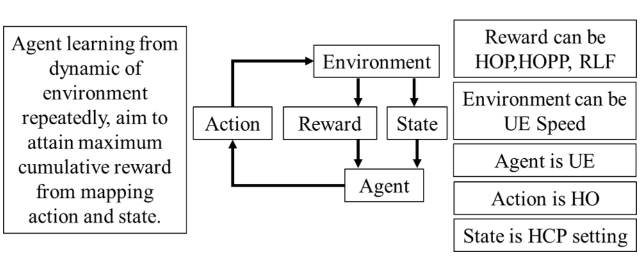


**Fig. 13.** An example of Reinforcement Learning diagram application for MRO 6G deployments.

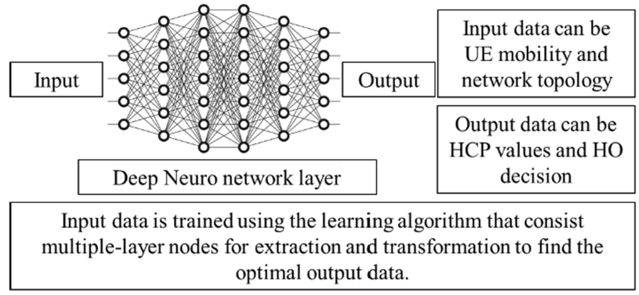


**Fig.14.** An example of Deep Learning diagram application for MRO 6G deployments.

### 4.1. AI in mobility management

The wireless network has rapidly expanded with rising demands. The communication industry developed multiple technologies to cater to these demands [55]. To support such large-scale networks, resource management plays a key role in handling problems such as computation offloading, user association, beamforming, subcarrier allocation and power management. ML optimisation techniques that are part of AI have become successful in managing issues throughout several years. They are expected to further grow in the near future [56]. The aim of 3GPP Release 18 is to study AL/ML and focus on network energy saving, MRO and load balancing. Adapting ML-based optimisation strategies to solve HO issues is vital for wireless networks [54]. Fig. 10 presents a diagram of AI and ML with all types of learning algorithms.

### 4.2. Comparison of ML wireless networks

This section provides a comprehensive review and comparison of various ML methods [57,58]. Firstly, the fundamental applications of Supervised Learning, Unsupervised Learning, Deep Learning, and Reinforcement Learning are discussed [59]. Then, the advantages offered by each type of ML and delve into the specific algorithms available for implementation are presented. Finally, the exploration on how these algorithms is effectively utilized in optimizing mobility management, particularly in addressing handover issues is done. By examining the relationship between optimization parameters and the usage of these algorithms, a deeper understanding of how ML can be leveraged to enhance handover performance can be achieved. Table 5 defines each ML type, the advantages, the types of algorithms available and their usage in the mobility management to resolve HO challenges.

## 5. Mobility management challenges

Future networks will deploy different types of small coverage BSs, drones (serving as either BS or UE), ultra-dense networks, combined with the massive usage of mobile devices [19]. The deployment of new technologies has created new network challenges, especially for handover and mobility. Addressing these problems is crucial since future consequences could impair the performance and dependability of the network. This part gives a helpful summary of what is missing from the literature on the challenges that MRO faces. The challenges are categorised into 7 parts.

### 5.1. Multi frequency challenge

The extensive increase of mobile traffic demands on frequency poses a significant challenge since the spectrum has very limited resources that must be efficiently managed [10]. Currently, three types of frequency bands are used: low band (0.7–3 GHz), mid band (3–6 GHz) and high band (24–52 GHz).

Co-channel involves frequency that uses the same band that causes

**Table 5**
Machine learning application comparison between different learning algorithms.

| Type of ML | Supervised Learning (SL) | Unsupervised Learning (USL) | Deep Learning (DL) | Reinforcement Learning (RL) |
|---|---|---|---|---|
| Definition | An amount of labelled data is used to train SL algorithms. A data-label pair solution is produced when the input data and the intended labels are both known. The objective is to use trained sample data-labels to map the input data to the output label. | USL algorithms rely on unlabelled input data and attempt to explore hidden features or structures of data. Since there are no sample data-label pairs, the output's accuracy cannot be evaluated consistently, which is the main difference from SL. | For feature extraction and transformation, DL algorithms rely on an interconnected "network" made up of multiple layers. The biological nerve system served as inspiration for this neural network (NN) algorithm for decision-making. It attains the maximum value by the process of trial and error learning with given datasets. | RL algorithms, which are trained by the data based on trial and error, are thought of as decision-making through learning from interaction with the environment (E). To achieve the highest cumulative weighted reward in the environment (E), RL learns how to map situations (S) into actions (A). |
| Advantage of using the algorithm | Classification and regression | Clustering and dimension reduction | Multi-layer and hierarchy | Decision making and prediction |
| Type of algorithm | Random forest, decision tree, k-nearest neighbour, and linear/logistic regression | K-mean clustering, isometric mapping | Deep neural network (DNN), auto-encoder, recurrent Neural Network (RNN) and Convolution neural network (CNN) | Multi-arm bandit, Markov Decision Process (MDP), Q-learning, Monto-Carlo Method. |
| Usage in mobility management | Data such as HCP values, UE mobility and HO feedback available. Next step is to develop a suitable classification and regression model that connects these values. | HCP clustering, UE mobility clustering, and analysis of UE behaviour in different environments can be useful in finding the optimal values that reduce HO problems | HO issues classification and prediction based on HCP detection, Interference classification and handover. Multi-level condition scenario | Suitable to solve HO issued as a decision-making tool. Environment is the network modelling scenario or HCP values. The situation would be the UE mobility and cell size. While the action can be the decision to HO or Not. Finally, we would map with the HO performance. |
| Diagram | Fig. 11 | Fig. 12 | Fig. 13 | Fig. 14 |

interference. This can also create problems if the service provider decides to optimise the same frequency for new technology usage [60]. Multichannel problems occur when each frequency band has its characteristics and usage, creating interference and propagation that require different solutions [35].

### 5.2. High frequency challenge

High frequency challenges involve the usage of mmWave and Terahertz (THz) frequencies. The high frequency bands create a high capacity network [19]. The high-band frequency, however, exhibits significant strong pathloss, increased atmospheric and rain absorption, as well as low diffraction close to obstructions. Therefore, it is only useful within a small range. With sharp fading, the measurement signal will have certain errors, resulting in lower successful switching rate and unnecessary switching. This will dramatically affect the user's communication experience. THz is a new frequency band scheduled to be introduced in 6G. THz may utilize the enormously large spectrum to substantially boost communication capacity. It offers a crucial chance to resolve the issue between capacity requirements and the lack of spectrum. Additionally, THz creates numerous challenges in terms of propagation loss, mobile cross cell, shorter wavelength and HO issues [61].

### 5.3. Massive connected devices challenge

As reported by Ericsson, there can be a potential global growth of 4.4 billion 5G wireless subscriptions, accounting for 48 percent of all mobile subscriptions by 2027 [62]. The internet serves as a platform for a wide range of applications that are made available to billions of users every day, making it a crucial tool for connecting applications. This is a massive growth of mobile devices. Smart phones and IoT components like wearables and sensors are examples of interconnected devices. With little to no human intervention, these IoT devices may connect with one another and share information. There has also been studies on smart hospital where devices are connected to the internet [63]. Beside the implementation of IoT over satellite has become another emerging technologies for deployment [64]. The amount of traffic increases, proportionally with the usage of IoT devices number steadily rises. This leads to HO issues between devices that support multiple bands, such as WiFi and 4G/5G networks. Despite various studies examining the impact of devices with different speed scenarios on network performance, additional testing is still needed to develop an ideal solution that can effectively handle high-speed scenarios and improve overall network performance. Previous studies have shown that implementation challenges with high-speed algorithms hinder their ability to perform optimally [65].

### 5.4. Network diversity challenge

UDN deployment, intensive deployment and placement of SCBSs collectively cause HO problems [66]. Network diversity in the form of several types of BSs with small coverage and the growing number of connected drones as BSs or UEs, random mobile positioning, mobility and unplanned deployment will further cause HO issues. Connectivity management in 5G networks is still a problem due to the complexity of radio access technologies, increasing network densification, and the unplanned network architecture [32]. The 6G architecture is more sophisticated than the 5G architecture in terms of network complexity. In the 6G network, it will be ineffective to analyse the difference between the use of autonomous coordination techniques and SON functions in the 5G framework. To reduce potential conflicts in 5G MRO functions, new self-coordination techniques that are compatible with 6G must be introduced. To acquire all spatiotemporal data concerning network issues, such as congestion and coverage gap locations, more intelligent SON for 6G end-to-end visibility must be developed [67].

#### 5.4.1. UDN architecture

For the UDN architecture, mobile UE experiences frequent and unnecessary handovers because the cell's radius is substantially smaller than its current size. Therefore, UEs are located in multiple cells [68]. One occurring issue would be the ping pong handover effect since the user's connection moves back and forth from one cell to another. This will create RLF, network disconnection and reduced network performance. Energy and network resources are used up faster than usual. [69].

#### 5.4.2. Different network layers

The handover process in traditional mobile communication systems takes place between two identical network levels. For the 5G network, handover is conducted between different network technologies such as

WCDMA, 3G and LTE. Handover will occur between the same network layers (horizontal handover) and between different network layers (vertical handover). The splitting of the control plane and user plane in the 5G system also creates additional handover problems [66].

### 5.5. Inefficient algorithm challenge

Various techniques and functions have been presented to resolve HO issues. Several HO methods were introduced, however, they usually focus on one aspect and disregard the rest. The performance of the HO will be impacted if the HCP parameter values are fixed. Too low or too high HCP values will lead to HOPP and RLF [7]. For future deployments, applying a flexible algorithm is crucial to adapt different network scenarios and UE speeds. Using effective mobility strategies will enable continuous cell connections during UE movement. However, currently there is no ideal mobility method that can totally resolve every mobility issues. For emerging systems like 5G or 6G technologies, these issues are still a research gap. Making proper selections according to different objectives remains to be a significant problem. Massive volumes of data are required for training and verification in all ML-based algorithm. But where can one find such accurate data? Operators are apprehensive about disclosing such information. Not all physical data are accessible, even if they were willing to share. The QoS or QoE will be compromised if any exploited ML-based algorithms cannot converge in a suitable amount of time [70].

### 5.6. Energy efficiency challenge

Increased power consumption will result from deploying such a complex and extensive network design. Therefore, EE will be a critical challenge for communication industries [71]. Significant energy is consumed due to frequent HO procedures that already waste resources. Therefore, it is crucial to perform EE calculations during the HO procedures decision step [10,69].

### 5.7. Large dataset challenges

Big data is key for ML MRO optimisation to further empower the 6G network. Big data provides information for the 6G network such as UE behaviour, prediction, dynamic association between the network, response time and network parameters to implement a fully intelligent ML network [72]. Improving all areas will require significant datasets for training. Increased overheads will reduce the accuracy and behaviour of AI tools [73]. Data cleansing or data filtering is needed by selecting the right data from the start of training. Uncertainty in data generalisation will increase complexity and create redundancy when learning is accomplished.

### 5.8. Security challenge

Data is important for running accurate AI and ML algorithms. Its exploitation may result in severe changes in the decisions made by these models. The significance of protecting data integrity is a security challenge. Different enablers can be used to enforce data reliability [74]. This will cause security issues between the UE and BS due to the authentication procedure that detects malicious users [75]. This procedure will cause latency issues that will affect network performance [73].

## 6. Related studies and solutions

This section provides a summary of related research and previous solutions in mobility management accomplished in the past 5 years. These studies which focuses on MRO for conventional-based and ML-based methods that were summarised on solving HO issues. For conventional studies we examine methods such as signal-based (SINR and RSRP), UE-based, EE and Fuzzy Logic (FL) optimisation on the HCP values. While AI-based highlights the best approaches for solving HO issues conducted with AI, with particular focus on both ML, DL and RL solutions.

### 6.1. MRO conventional-based approach

The conventional based approaches have influenced the usage of ML for future work. Conventional-based solution for MRO involves optimization with the network condition such as RSRP values, UE speeds and EE values. There is also cognitive optimization solution such as Geometry-Based and Fuzzy logic. In [23], the author uses the HO Self-optimizing method called Dynamic HCPs (D-HCPs) where HCPs are adjust based on UE experience in a HetNet deployments. This method manages to lower the number of HOs, RLF and HOPP ratio compared to other algorithms with different mobile speeds. The deployment of a large number of SCBSs can lead to increased interference and HO issues. To address this, the author in reference [76] suggests the use of a Self-Optimization Autotuning Optimization (ATO) algorithm that leverages both the UE speed and the RSRP in adapting to the HCP values. Results show that the average rates of HOPP and HOF are significantly reduced compared to other algorithms. The author in reference [77]suggests the use of a velocity-based self-optimization algorithm to optimize HCP in 4G/5G networks, aimed at reducing the rate of HOPP and RLF. By modifying the HCP values as the UEs are moving in the network, the proposed algorithm makes use of UE speed and power received. In reference [66], the author conducted a study on the HO problem in LTE ultra-small cell deployments. The HO issues were analyzed by considering various factors such as cell sizes, user speeds, and optimization parameters which are HO-related. The results showed that using a low TTT value in 5G ultra-small cell deployments can lead to improved HO performance. The author in reference [44] proposed a solution to minimize HOPP, too-early HOs, and too-late HOs by adjusting the HCPs based on the moving state of the UE. The results of this approach showed an improvement in KPIs, such as throughput, call drop rate (CDR), long interruption time (IT), and HO delay Another solution in MRO involves EE. The authors in reference [78] proposed a self-optimization algorithm that dynamically determines the HCP based on the current network EE states, Energy Reduction Gain (ERG), SINR and HOPP ratio for HetNet deployments. This solution resulted in a nearly 5 % reduction in HOPP and a 4 % increase in system energy efficiency. In reference [5], the author used a weight function solution to optimize individualistic HCP in 5G networks. The proposed algorithm resulted in noticeable improvements compared to distance-based, Fuzzy Logic Controller (FLC), and Handover Performance Indicator (HPI) algorithms. In addition, the author in reference [16] utilized a geometry-based algorithm to determine the optimal HCP values in order to reduce RLFs and the ping-pong effect. The optimal HCP value is subject to limitations imposed by factors such as fading, interference, and UE speed, which are dependent on the specific environment. The author in reference [79] proposed a dynamic approach to setting HCPs values in HetNets with dense SCBSs by addressing MRO based on handover types (too early, too late, and wrong cell handovers). The proposed algorithm aims to solve HO issues in these networks. The simulation results showed that the suggested algorithm considerably reduces the frequency of HOPP and RLF, leading to improved network performance. Additionally, the author in reference [80] proposed a UE–assisted and network-controlled hard HO procedure that results in a reduction of handovers and improves network performance. The HCP setting was analyzed in three different environments, including Inter Site Distance (ISD), the angle of UE movement, and UE mobility. The solution involves the use of a Markov chain. In reference [51], the author proposed a cell range expansion (CRE) solution for HCP to utilize SCBSs by using a Markov chain-based process for modeling. The study found an optimal relationship between the CRE and HCP setting. In reference [81], the author proposed an algorithm that uses a Markov Decision Process (MDP) to improve handover performance. The algorithm consists of two parts: an assisted HO detection mechanism to prevent false handovers, and the execution of effective HO. The handover decision is solved using the Q-Learning method. The author of [82] presented a novel MRO algorithm that focuses on enhancing the QoE for users at the cell edge and improving successful HO rates in a multi-service environment. The proposed algorithm was shown to improve cell edge QoE across the network and increase successful handover rates compared to traditional methods. Author [83] proposed using Dual Connectivity (DC) and Coordinated Multipoint (CoMP) to optimize the HCP in HetNet deployment. Simulation results showed improvement in network performance and reduction in HO failure, leading to a better user experience. Author [41] introduced a data-driven, centralized SON based MRO approach that makes use of information about network design and performance data. The results indicated a reduction in rates of late HO, early HO, and RLF. The study also analyzed the trade-off between optimizing late HOs and early HOs and between late HOs and HOPP. Author [50] studied the impact of various HCP settings on the performance of 5G networks. The research considered several factors such as UE speed, interference, distance, resource availability, and channel state.

**Table 6**
General comparison of conventional and AI-based solutions.

| Conventional based | AI-based |
|---|---|
| The optimization algorithm is based on Model-driven optimization, taking into account various factors such as UE speed, channel condition, and EE. However, it operates under restrictive assumptions and starts with certain HCP parameters, making changes only when simulation scenarios change. | An AI-based model is more adaptable as it can adjust to different conditions based on data collected or available during the learning process. The longer the learning period, the more accurate the model's output estimation becomes. Additionally, AI has the ability to provide regression equations that can estimate various parameter relationships. |
| Optimization results may not hold in changing network and UE environments due to restrictive assumptions. Lack of adaptation limits accuracy over time. | The learning process in AI-based models becomes more accurate as it is based on near real-time scenarios. |
| When faced with a scenario where multiple HCP values and network conditions exist, traditional algorithms may struggle to fully understand the interactions between these variables. To enhance the accuracy of predictions and outputs, it becomes necessary to make modifications to these algorithms. | An AI system that has access to a sufficient amount of data and is continuously learning can become highly intelligent in adapting to multiple objectives and making decisions that optimize its performance. This makes it possible to consider a combination of different HCP values and mobility environments to optimize specific HO issues. |
| The simplicity and ease of implementation of model-driven simulations is due to the fact that they are not required to adapt to multiple conditions. | The implementation of AI-based models can be more complex due to the requirements of data collection, storage, and cleansing. For SL solutions, labeled data is necessary. USL solutions require sets of data to be collected. RL requires an understanding of the environment, actions, and rewards. In DL, each layer must be adjusted for optimization purposes. |
| The solution may only be able to adapt to certain short-term KPIs, and its effectiveness in a changing environment may be dependent on the performance of the algorithm. | An AI-based solution is well suited for long-term applications as it operates based on real-time scenarios and can adapt to changes in real-time. |
| The conventional solution typically relies on independent optimization, making it difficult to integrate with other solutions without significant modifications to the algorithm. | An AI-based solution has the capability to perform cooperative optimization with other optimization solutions, allowing for adaptation to different types of networks built around the system. |

### *6.2. MRO machine learning-based approach*

ML solutions have been extensively used over the last 10 years to solve HO related issues. In [45], the authors proposed the ML method for learning the optimal time and handover prediction during mobility. The result revealed a reduction in RLF, HOPP and unnecessary HO. In [84], the authors proposed a cloud-oriented ML-based approach to optimise the number of handoffs due to ping-pong effect, thus improving the overall QoS delivered by the network to the node. The results revealed a reduction of ping-pong probability by more than 32% and handoffs by 10% when compared to standard handoff algorithms. In [85], the authors proposed the ML-based Genetic Algorithm (GA) combined with a heuristic technique to discover the optimal combination of Cell Individual Offset (CIO) and HOM used in mobility. This maximises the mean value of SINR for all connected users. The outcomes predicted the optimal mean SINR over different CIO and HOM settings. In [86], the authors proposed a centralised solution that learns the self-organised network functions model based on network history using supervised learning, semi-supervised learning and DL. They presented a higher degree of automation using the regression method and long-term reward, leading to less errors in HO calculations.

### *6.3. MRO deep learning-based approach*

This section highlights the proposed solutions of DL. In [28], the authors proposed DL using the DNN algorithm for highly accurate classification of handover problems. The results presented satisfactory performance in terms of the radio link failure rate and the ping-pong rate in 5G networks. In [46], the authors proposed an offline scheme based on double deep reinforcement learning (DDRL) to minimise the frequency of HOs in mmWave networks. The obtained results reveal that the proposed method largely outperforms conventional and other AI-based models by reducing HO and average reward. In [87], the authors examined an off-policy deep reinforcement learning (DRL) based Mobility Load Balancing (MLB) framework to balance the load evenly across all cells. This can be accomplished by tuning the CIO of each neighbouring cell pair to control logical cell limits. In terms of average rewards and HO failure rate, the suggested DRL-based MLB model can outperform current methods. In [88], the authors proposed the HCP and power allocation-based optimisation using multi-agent DRL to maximise the overall throughput while minimising HO frequency. This led to better performance when compared to other existing methods for the HetNet system. In [89], the Deep Neural Network (DNN) was proposed as the HO controller learned by each UE via RL by using supervised learning for initialising the DNN controller to lower the HO rate. The outcomes show that lowering the HO rates can ensure better system throughput performance. In [90], the authors proposed a two-model based algorithm using multi-layer many-to-one Long Short-Term Memory (LSTM) architecture, a multi-layer LSTM Auto Encoder (AE) in combination with a Multi-Layer Perceptron (MLP) Recurrent Neural Network (RNN). The results indicate that using available handover decision data does improve the QoE performance. In [91], the authors proposed a DL-based MRO (DRL-MRO) solution that learns the appropriate values for the required parameters of each mobility pattern in individual cells. The outcomes show that the function learns to optimise HO performance and distribute excess load throughout the network. In [92], the authors offered a DL-based adaptive handover optimisation using RNNs according to the Gated Recurrent Unit (GRU) and LSTM cells for ultra-dense 5G mobile networks. The obtained results indicate an improvement in traffic performance accuracy. Similarly, in [93], the DL mobility model manages network mobility by utilising the DL network and prediction. To train the model to analyse network traffic and handover needs, the network KPIs are used. A fundamental model was built, yet further developments are required. Author in [94], proposed a novel HO decision scheme utilizing DRL to optimize HO decisions for UAVs while ensuring stable connectivity. For online learning of UAV HO

**Table 7**
Summary of related studies involving MRO AI-based handover.

| Reference | SON AI Type Algorithm | 6G UDN and mmWaves | HCP | Mobility | Handover Metrics | Other Metrics |
|---|---|---|---|---|---|---|
| [17] | ML-based mobility Transfer Learning (TL) and geometry-based computation | Yes | Yes | Yes | Yes | No |
| [18] | Intelligent handover triggering mechanism in 5G ultra-dense networks via clustering-based RL | Yes | Yes | Yes | Yes | No |
| [28] | DNN to reduce HO problems using a classification problem | Yes | Yes | Yes | Yes | Yes |
| [45] | ML method for learning the optimal time and destination | No | Yes | Yes | Yes | No |
| [46] | Scheme using double DRL with double deep Q-learning | No | Yes | Yes | Yes | No |
| [82] | Self-optimise Q-learning algorithm for mobility, combining well-known RL and ANN techniques | No | Yes | Yes | Yes | No |
| [84] | ML over QoS optimisation | No | No | Yes | Yes | No |
| [85] | ML-based Genetic Algorithm (GA) to predict optimal mean SINR | No | Yes | Yes | Yes | SINR predict |
| [86] | ML-based Self-Organised network functions (SF) to balance MRO and LBO | Yes | Yes | Yes | Yes | Unsatisfied user |
| [87] | DRL using Markov MDP and DNN | No | Yes | Yes | Yes | No |
| [88] | Multi-agent reinforcement learning (MARL) algorithm based on the proximal policy optimisation (PPO) and multi-agent deep deterministic policy gradient (MADDPG) algorithm | No | Yes | Yes | Yes | Power throughput |
| [89] | Asynchronous Multi-DRL | No | Yes | Yes | Yes | Throughput |
| [90] | Long Short-Term Memory (LSTM) architecture and a multi-layer LSTM Auto Encoder (AE) in conjunction with a Multi-Layer Perceptron (MLP) RNN | Yes | No | Yes | Yes | No |
| [91] | DL-based MRO solution (DRL-MRO), which learns the required parameter's appropriate | No | Yes | Yes | Yes | Subscribers |
| [92] | DL-based adaptive handover optimisation using RNN | No | Yes | Yes | Yes | Traffic accuracy |
| [93] | DL approach using LSTM RNN | No | Yes | Yes | Yes | RSRP Throughput |
| [95] | DRL learning-based approach for the phasor measurement units (PMUs) | No | No | No | No | Delay and power consumption |
| [96] | Reinforcement Learning (RL) based joint self-optimisation method for the fuzzy logic handover algorithm | Yes | Yes | Yes | Yes | Throughput |
| [97] | RL with tile coding function approximation in 5G UDN | Yes | Yes | Yes | Yes | No |

decisions, the DRL system includes a proximal policy optimization algorithm and a Received Signal Strength Indicator (RSSI)-based reward function. The HO scheme is put to the test in a 3D-simulated UAV mobility environment, where it significantly reduces unnecessary HO compared to Q-learning-based handover and greedy scheme.

### 6.4. MRO reinforcement learning

The RL algorithm used as part of the MRO solution is reviewed in this section. In article [17], the authors proposed RL-based MRO algorithm that involves Transfer Learning (TL) and geometry-based computation to minimise RLF and ping-pong HOs in the context of user mobility and a dynamic network topology. The outcomes reveal an improvement in network performance. In [18], the authors proposed a clustering-based RL by using Q-learning frameworks and subtractive clustering techniques to control handover triggering. The results indicate a higher mobility robustness of the UE, an improvement between 60 % and 90 %, when measured against the conventional approach in terms of number of handovers, HOPP rate and HOF rate. For phasor measurement units (PMUs) to properly transmit data, the authors in [95] developed a DRL-based method that took SINR limitations into account. This led to maximised EE in HetNets, further satisfying delay constraints. In article [96], the authors proposed RL-based joint self-optimisation in 5G HetNets by applying Q-learning and clustering frameworks in conventional fuzzy logic-based HO algorithm (FLHA). The findings show a significantly decreasing in HO that reduces the HO failure and HOPP ratios while maintaining high network throughput and latency KPIs, the proposed self-optimised FLHA can improve UE mobility robustness. In addition, the authors in [97] proposed RL with tile coding function approximation to learn the optimal handover control policy by interacting with the environment. The suggested approach can efficiently improve the mobility robustness of UEs at various speeds, reducing the number of needless handovers and the HO failure rate while maintaining high throughput and low latency.

### 6.5. Conventional vs AI-based solutions

This section provides a comparison between conventional solutions and AI-based solutions for mobility management. Historically, conventional solutions have been widely employed to address HO issues. However, with the advent of AI-based solutions, their influence has grown significantly, and researchers are increasingly adopting them as part of their optimization solution. It is expected that the availability of AI-based solutions will continue to expand. To facilitate a comprehensive understanding, Table 6 presents a detailed comparison of both conventional and AI-based solutions in the context of mobility management.

### 6.6. Summary of related studies and solutions

Table 7 provides a comprehensive summary of prior research that explores the interplay between handover, mobility, and self-organization in the context of AI. The focus of this research lies in the deployment of AI-based algorithms for MRO within the 6G network, utilizing advanced technologies like UDN and mmWave. Additionally, this investigation encompasses the optimization of HCP in accordance with handover performance metrics. Furthermore, this section investigates into other critical network performance metrics, including throughput calculation, power consumption, RSRP and delay, as they bear significant importance and possess a direct relationship with overall network performance.

## 7. Future directions

The future of wireless networks is stimulating with the early stages of AI-based deployment found in multiple sectors. The future direction of MRO-based handover, the impact of these deployments and the areas in which the MRO algorithm can be used in future are further examined. Deploying wireless technologies is necessary to cater to network demands. The following is future direction of 6G deployments for mobility management:

### 7.1. AI-based method

The recent success of AI techniques, particularly in industrial deployments, has inspired the development of AI-based approaches to address the challenges associated with resource management [98]. The major goal is to obtain near-optimal performance for numerous applications, including beamforming, power control, computation offloading, and intelligent reflection surfaces, in a real-time approach [99].

### 7.2. Hybrid architecture and diverse technologies

Different types of technologies have been merged in 6G network. These technologies need to be adapt with each other [100]. Massive Multiple-input Multiple-output (MIMO) is one of the technologies impacting MRO deployment. Massive MIMO is effective in less crowded locations, whereas SCBSs are appropriate for denser environments. Depending on how dense the target area is, different massive MIMO techniques are used. Both are thought of as different categories of technology. Massive MIMO is typically less EE than SCBS networks. Due to its partially connected nature, massive MIMO and mmWaves can be coupled to create a hybrid architecture that uses less power. However, additional study must concentrate on the architecture's dynamic installation. Performance of the HO and network will be impacted by the hybrid deployment and various technologies [10,71].

One of the capabilities of mmWaves is beamforming where the antenna can densely cover narrow areas with a high-quality signal [101]. Deploying beamforming will further increase HO issues since the network becomes denser and leads to more signal interference. Employing MRO for HO optimisation will enhance the application of beamforming in future deployments.

Unmanned aerial vehicles (UAVs), or drones, will be considered as a potential future technology for network deployment by using it as mobile or moving BS [32]. More experimental studies will help us better understand how drones affect the environment. This will make it possible to improve UAV systems even more [10,42]. More mobile BSs will be involved in using UAVs which will benefit areas that are hard to access or need temporary usage of the network, however, it will introduce further HO problems due to UAV mobility.

6G networks will support HST connectivity to provide users with network access. High-speed train passengers will benefit from improved mobile broadband services thanks to the wide range of the mmWave frequency bands. HST includes both crucial and non-critical forms of communication. Speed control, dependability, and the efficient operation of HST require communication between HST and its supporting infrastructures. This kind of communication is regarded as crucial [102]. The introduction of MRO will assist HST in resolving HO issues during high mobility circumstances.

### 7.3. Dynamic spectrum management

Orthogonal Frequency Division Multiple Access (OFDMA), by far, has emerged as the most prevalent modulation standard over the previous ten years. Both 4G and 5G networks use it in the downlink. Particularly for multi-user interface services like device-to-device (D2D), machine-type communication, IoT, etc., multicarrier transmission is well suited to enabling 6G networks [32,103]. Dynamic spectrum management (DSM) plays a vital role in wireless communication networks since it improves spectral efficiency. 3GPP NR is specified as a flexible technology framework that can be tuned to support a variety of 5G scenarios [104]. The different types of future spectrum usage will experience HO issues since they involve multiple spectrum scenarios. Licensed, unlicensed and spectrum slicing are also present. Using MRO for HO optimisation will benefit spectrum usage [105]. While the benefit of a multicarrier technique includes optimisation of spectrum usage, it can also lead to multiple HO issues that will later require a solution. There will be issues on MRO for primary spectrum

**Table 8**
List of abbreviations.

| Item | Description |
|---|---|
| 1G | First Generation |
| 2G | Second Generation |
| 3G | Third Generation |
| 3GPP | Third Generation Partnership Project |
| 4G | Fourth Generation |
| 5G | Fifth Generation |
| 6G | Six Generation |
| AI | Artificial Intelligence |
| BS | Base Station |
| CIO | Cell Individual Offset |
| DL | Deep Learning |
| DRL | Deep Reinforcement Learning |
| DNN | Deep Neural Network |
| DSM | Dynamic Spectrum Management |
| D2D | Device to Device |
| FL | Fuzzy Logic |
| HCP | Handover Control Parameters |
| HO | Handover |
| HOF | Handover Failure |
| HetNet | Heterogeneous Network |
| HOM | Handover Margin |
| HOPP | Handover Ping Pong |
| HOP | Handover Probability |
| HST | High Speed Train |
| IoT | Internet of Things |
| KPI | Key Performance Indicators |
| LBO | Load Balancing Optimisation |
| LTE | Long-Term Evolution |
| LSTM | Long Short-Term Memory |
| MCBS | Macro Cell Base Station |
| MDP | Markov Decision Process |
| MIMO | Multiple-Input Multiple-Output |
| ML | Machine Learning |
| mmWave | Millimetre Wave |
| MRO | Mobility Robustness Optimisation |
| NR | New Radio |
| OFDMA | Orthogonal Frequency Division Multiple Access |
| PCBS | Pico Cell Base Station |
| QoE | Quality of Experience |
| QoS | Quality of Service |
| RAT | Radio Access Technology |
| RL | Reinforcement Learning |
| RLF | Radio Link Failure |
| RNN | Recurrent Neural Network |
| RSRP | Reference Signal Reference Power |
| RSS | Received Signal Strength |
| SCBS | Small Cell Base Station |
| SDN | Software Defined Network |
| SINR | Signal-to-Interference-plus-Noise Ratio |
| SON | Self-Optimisation Network |
| THz | TeraHertz |
| TL | Transfer Learning |
| TTT | Time-To-Trigger |
| UAV | Unmanned Aerial Vehicle |
| UDN | Ultra Dense Network |
| UE | User Equipment |

and secondary spectrum used by users.

### 7.4. Significant MRO implementation

Research has shown significant improvement to different network areas when implementing MRO solutions to solve HO issues for network deployment. These approaches will assist the mobile operator in lowering maintenance and administrative costs, shifting focus to performance improvement, and minimising energy consumption and delay costs. By reducing HO issues, the network and EE performance will improve. A reasonable setting of the parameter threshold of HOM and TTT can increase the handover performance of the LTE network system and improve the QoS. Multiple studies (as listed in Table 7) have demonstrated how parameter settings can significantly enhance handover performance. When HCP values are optimised, HO issues reduce, and HO performance improves in the aspect of network EE is closely related to network performance. Optimising the power consumption parameters will assist in achieving a better handover decision model [78].

## 8. Conclusion

This research paper presented a comprehensive and extensive overview of present and future MRO AI-based implementations. This survey illustrated the challenges that MRO will face during application in 6G cellular networks. The necessity of employing ML techniques to intelligently make HO decisions were discussed. The MRO algorithm must be enhanced to efficiently meet 6G requirements. This analysis is valuable for determining the ML techniques to apply, the HO parameters to optimise and the network model to implement.

## Declaration of Competing Interest

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

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## Appendix

See Table 8.

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