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Review

A Survey of Handover Management in Mobile HetNets: Current Challenges and Future Directions

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Abstract: With the rapid growth of data traffic and mobile devices, it is imperative to provide reliable and stable services during mobility. Heterogeneous Networks (HetNets) and dense networks have been identified as potential solutions to address the upcoming capacity crunch, but they also pose significant challenges related to handover optimization. This paper presents a comprehensive review of recent handover decision algorithms in HetNets, categorizing them based on their decision techniques and summarizing their input parameters, techniques, and performance evaluations. Our study highlights the technical challenges and opportunities related to handovers in HetNets and dense cellular networks and provides key findings from recent studies. The significance of this survey is to provide a comprehensive overview of handover decision algorithms in HetNets and dense cellular networks, which can aid in the development of more advanced handover optimization approaches.

Keywords: handover; self-optimization; heterogeneous networks; mobility management; handover control parameters; mobility robustness optimization; time-to-trigger; small cells; 5G networks; handover margin

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1. Introduction

With the introduction of new wireless technologies and applications, mobile communication networks have seen a huge surge in data traffic and the number of mobile connections. This increase in the number of mobile connections and data traffic is most visible in cities and other areas with high human activity. According to Ericsson, overall mobile data traffic will exceed 113 Exabytes per month, including Fixed Wireless Access (FWA) by the end of 2022 and 368 EB per month by the end of 2027 [1]. This significant increase in data traffic is due to a variety of mobile network-dependent applications, including mobile phone users, wireless augmented reality, gaming, high definition video streaming [2], voice and video calling, Intelligent Transportation Systems (ITS), Vehicle to Vehicle (V2V), Vehicle to Everything (V2X), Internet of Things (IoT), High-Speed Railway (HSR), Unmanned Air Vehicle (UAV), and Automated Driving Vehicles. All of these applications demonstrate a dynamic communications paradigm in which low latency, high reliability, and efficient spectrum usage are always required to provide optimum Quality of Service (QoS) and accommodate a greater number of connections. We can fulfill these high data-demanding requirements by expanding the system's bandwidth and capacity. This gives rise to the concept of high-frequency mmWave communications, which will provide a very wide bandwidth in high-frequency bands, whereas network densification and load sharing of larger networks into smaller and diverse HetNets, will increase capacity and QoS, especially at the dense and congested areas such as stadiums, shopping malls, city centers and dense cities by allowing load sharing between different types of cells [3–9]. Figure 1 showcases the progression of mobile cellular generations from 1G to the envisioned 6G, emphasizing the varying applications and the data rates available.

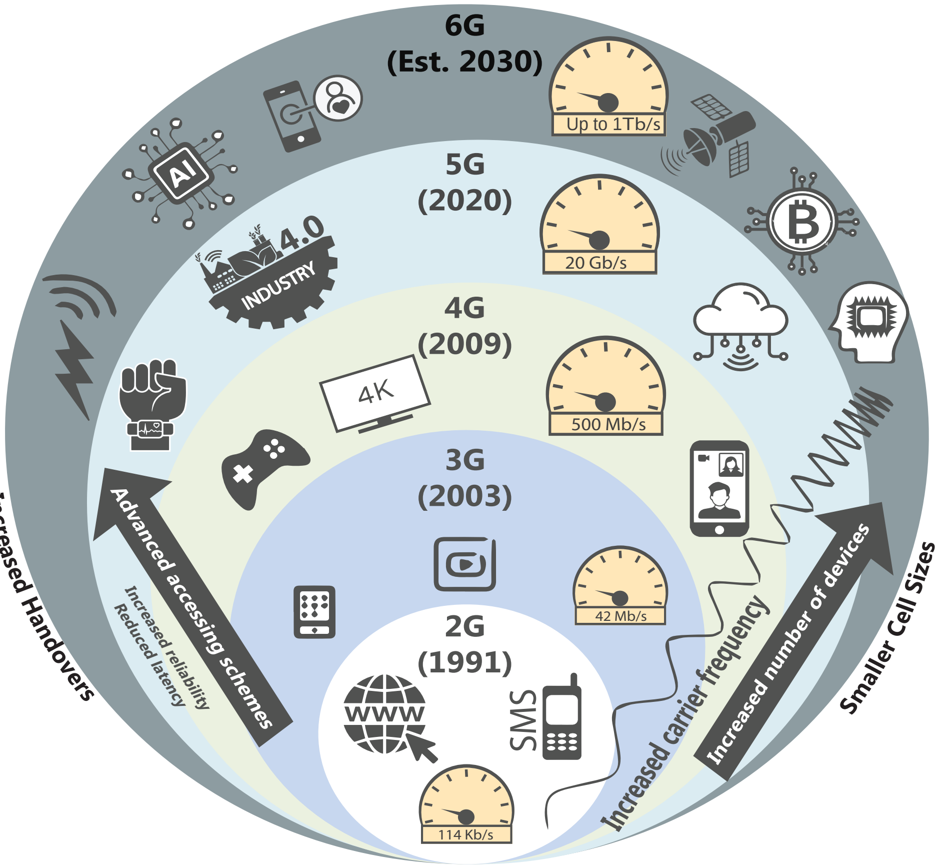

Figure 1. Mobile Cellular Generations with their Applications.

The small cell base stations (BS) are defined as low-power nodes that cover a limited range of up to a few hundred meters. These BSs can also operate independently or in conjunction with the macro cell [8,9]. mmWave communication and network densification have greatly enhanced bandwidth, capacity, and data rate, as well as QoS, but at the expense of mobility management and handovers (HO). Because both concepts rely on the idea of small cells with a relatively limited coverage footprint, resulting in more frequent HOs. In the case of network densification, the coverage area of small cells is reduced intentionally to accommodate more user equipment (UE) by deploying more BSs based on the principle of frequency reuse. In contrast, increased propagation losses limit the expansion of the coverage area for mmWave communications [10,11]. Due to the smaller cell coverage area, UE must perform a higher number of handovers in certain scenarios, leading to several handover-related issues that must be evaluated as key performance indicators (KPI), such as handover ping-pong (HOPP), unnecessary handovers (UHO), handover failures (HOF), handover latency (HOL), radio link failures (RLF), interruption time (IT), cell dropping ratio (CDR), and cell blocking ratio (CBR). This affects throughput, which is closely linked to the number of handovers, resulting in a decrease in QoS and user satisfaction.

The research community has focused primarily on improving mobility and HO management to reduce the number of HOs and enhance related metrics such as throughput, cost, and user satisfaction [12–14]. Proposed HO approaches were designed based on various scenarios and situations, with soft computing methods like fuzzy logic controllers widely used in these networks for traffic management, congestion control, decision-making, and network optimization. Additionally, deep learning (DL), machine learning (ML), and metaheuristic approaches were also applied, along with several self-optimization algorithms developed based on parameters such as UE velocity, reference signal received power (RSRP), and geographical information.

The Third Generation Partnership Project (3GPP) introduced the Mobility Robustness Optimization (MRO) and Load Balancing Optimization (LBO) functions as part of Self-Optimizing Networks (SON) techniques to adjust handover control parameters, including handover margin (HOM) and time-to-trigger (TTT) [15–17]. The main objective of MRO and LBO is to automatically optimize these parameters to maintain a high-quality connection between communicating UEs, evaluated using KPIs. These optimization methodologies have improved the overall performance of the system, although adjusting the HOM and TTT values affects multiple KPIs. For example, increasing TTT reduces HOPP, but increases RLF at high UE speeds. Thus, finding the optimal balance remains a challenge in managing and improving KPIs. Although several optimization methods are available in the literature, there is still a gap to be filled in finding the ideal solution for optimal triggering settings for HOM and TTT.

Mobility management is considered to be a crucial design challenge in current and future mobile communication systems, due to the rise in mobility-based users and applications. The use of high frequencies for larger bandwidths, smaller cells, and HetNets for increased user capacity and constant data demands have already emphasized the significance of handover management. In this survey, we concentrate on the current and future requirements related to mobility and handover management in mobile communication networks. To gain an understanding of the necessities and techniques for effective handovers, we scrutinized different handover approaches including RSRP, velocity-based, and advanced methods such as machine learning, deep learning, and soft computing. It is vital to comprehend these recent approaches as they will play a crucial role in the intelligence and management of 5G and beyond 5G mobile networks [18–20].

There are numerous methods for managing HO that have been suggested in the literature, but none of them is perfect enough to provide a solution. There is still a lot of research required to be done in this area to find an optimal solution for 5G and B5G networks, where the number of HOs will increase significantly. Therefore, continued research into handover management in 5G and HetNets is imperative in order to fully realize the capabilities of these networks. This survey's primary contribution can be summed up as follows:

- This research focuses on HO and mobility management procedures using self-optimization, soft computing, and ML/DL approaches. These approaches have been thoroughly discussed, highlighting the most cutting-edge methods available in various categories. As a result, this study will pave the way for future research on HOs in mobile networks.
- To better understand the impacts of different parameters on HO, available methods are classified into different categories.
- Highlight the available challenges for each grouped category and tabulate them in the form of a summary that includes the proposed scheme, flaws, and findings, as well as the KPIs and HCPs used.
- The "Open Issues and Future Directions" section highlights potential future research areas for handovers in 5G, Beyond 5G (B5G), and 6G communications.

This survey paper endeavors to furnish a comprehensive examination of handovers in HetNets. This paper starts with a review of related surveys. The background section provides an overview of handovers in HetNets, including handover control parameters, self-optimization network in HetNets, and handover challenges. The central focus of this paper is on handover decision techniques, which include velocity, RSRP, fuzzy logic, machine learning/deep learning, heuristic approaches, and spatial information. The paper also sheds light on open issues and potential future directions for handover decision techniques. The conclusion summarizes the key contributions of the survey paper, and provides recommendations for future research. The outline of this article is presented in Figure 2.

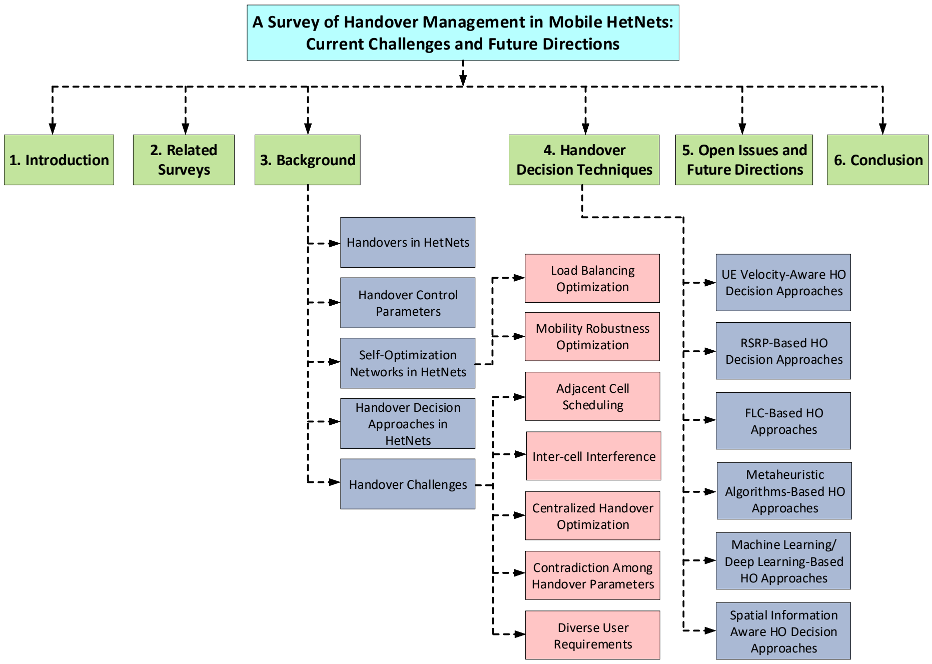

Figure 2. Outline of the Article.

2. Related Surveys

Several survey papers have been published on the topic of handover and mobility management in mobile HetNets. The authors provided a detailed overview of the handover and mobility issues in the burgeoning ultra-dense mobile networks in [21]. They discussed the key findings from recent studies, highlighted the technical difficulties and potential opportunities related to mobility from the perspective of developing ultra-dense cellular networks. They not only presented a thorough tutorial on 5G mobility approaches, but also highlighted the key mobility risks of legacy networks. An overview of the handovers and mobility management utilizing 5G enabling technologies is provided in [22]. They described the 5G wireless network layout and explored HO information gathering and decision management methods for ultra-dense small cell networks, with a particular emphasis on how machine learning approaches can assist in optimizing the HO process in 5G networks. Additionally, they addressed the HO information gathering techniques, radio resource control, HO metrics, and categorization of HO decision systems. In the survey by [23], the authors provided an overview of the current state of cellular communication networks. They then provided a comprehensive tutorial on mobility and handover management in 5G, emphasizing the unique challenges posed by its features such as mmWave communications, HetNets, IoT, vehicular communications, device-to-device communications (D2D), and high-speed train communications, which are more complex than in 4G. Additionally, they discussed the basics of handover management in B5G and 6G THz communications. They also discussed the main branches of ML, including supervised, unsupervised, and reinforcement learning (RL), and how each is applied to the handover management process. They provided a thorough analysis of recent research on ML-assisted handover management methods under a novel classification based on the two major categories of visual data-based and wireless network data-based handover management methods. In the survey paper [24], the authors provided an overview of SON functions and its various definitions. They discussed the major categories of SON and highlighted the most well-known applications of SON in 5G cellular networks. They also discussed the different SON architecture designs that aim to make the system more scalable, flexible, and open, and provide more intelligence to the 5G network. The authors emphasized the benefits of using ML and big data to overcome the constraints of SON implementation in 5G networks, while also highlighting the drawbacks and challenges of implementing

SON in 5G cellular networks. They grouped the SON functions based on how 5G mobile networks are managed, and explained the challenges that SON must overcome to be effectively used in 5G networks. The authors of [25] discussed recent research on various handover and mobility management strategies in 5G ultra-dense HetNets, with a focus on dual connectivity (DC). They first provided an overview of the fundamental principles of 5G networks and HO procedures in 5G HetNets. They then examined the use of DC in 5G, highlighting its benefits and drawbacks, as well as the significant challenges that may arise as a result of DC in future networks, such as mobility management, spectrum management, high data rate requirements, and security and privacy. They also explored opportunities and potential solutions to these challenges through the use of AI, ML, and DL techniques and optimization of load and mobility processes.

The authors in [26,27] conducted a comprehensive survey on handover decision making in 4G and 4G/5G networks. They first provided a technical overview of admission control and handover procedures, as well as challenges in handover management in the latest LTE-A architecture. They then analyzed various handover methods and algorithms, focusing on the main approaches and factors used in making handover decisions. They highlighted the key mechanisms, inputs, advantages, and limitations of each method, and explained how they were utilized in the decision-making process. In [28], the authors delve into the intricacies of SON operations. They trace its evolution through various mobile communication generations and present design approaches proposed for SON in B5G contexts. The authors also provide a comprehensive overview of SON applications such as MLB, CCO, MRB and Automatic Neighbor Relations (ANR). They highlight the potential of AI and ML algorithms in the successful implementation of SON in 5G and B5G scenarios and discuss recent advancements in the field of research. The authors conclude by identifying key areas of focus for future SON research in order to ensure its success in upcoming networks like B5G. In the article [29], the authors delved into the topic of load balancing in HetNets. They began by providing an overview of what load balancing is and its objectives. Next, they explored various options for managing the load balancing problem in HetNets such as data analysis-based solutions, Cell Range Expansion (CRE), fuzzy logic solutions, cell breathing, and channel borrowing. They also discussed various key performance indicators (KPIs) that can be used to evaluate performance in HetNets, such as SINR, resource utilization (Physical Resource Balancing-PRB), user satisfaction, throughput, CBR, CDR, outage ratio (OR) and PLR. The authors also highlighted the importance of coordination between MRO and MLB, as well as strategies for conflict resolution. Finally, they looked at how different researchers have used various ML methods to solve the load balancing problem in HetNets. They discussed the basic implementation details, technical challenges, performance analyses, and model inadequacies of these ML methods. In [30], the authors conducted a detailed examination of the handover process in 5G networks, highlighting key parameters such as MRO and LBO optimization and exploring different decision-making functions for initiating a handover. The study also included a thorough examination of the literature pertaining to different optimization methodologies such as velocity aware-based, RSRP-based, and FLC-based. The authors also discussed the various scenarios, methodologies, key performance indicators, and simulator types, highlighting both the successes and challenges of the handover process and potential solutions.

Table 1 provides a comprehensive overview of various survey papers related to mobility and handover management. As far as our research is concerned, it is noteworthy that we only considered the most recent survey articles related to handover and mobility management. The analyzed works in the table focus on different aspects such as 4G and 5G network scenarios, handover and mobility, load balancing, machine learning applications to handover management, utilization of heuristic approaches, spatial information-based handover approaches, and conventional RSRP and UE velocity. These in-depth studies aim to provide a comprehensive understanding of the current state of the art in the field of mobility and handover management.

Table 1. Summary of Related Surveys.

Ref. No Year	Scenario		Mobility/HO	Load Balancing	AI/ML	Metaheuristic	Spatial Information	Measurement Based	
	4G	5G						RSRP	UE Velocity
2020 [21]		✓	✓		✓			✓	✓
2022 [22]		✓	✓		✓				
2021 [23]		✓	✓		✓				
2021 [24]		✓	✓	✓	✓				
2022 [25]		✓	✓	✓	✓				
2020 [26]	✓		✓				✓	✓	✓
2020 [27]	✓	✓	✓			✓	✓	✓	✓
2022 [28]	✓	✓	✓	✓	✓				
2022 [29]	✓	✓	✓	✓	✓				
2022 [30]	✓	✓	✓			✓		✓	✓
Our survey	✓	✓	✓	✓	✓	✓	✓	✓	✓

3. Background

Mobile communication technologies have evolved into an essential aspect of modern life. The growing number of communication devices, services, diverse applications and user behaviors necessitates fast data speeds, large capacity, and continuous connectivity. As the most recent mobile communication systems are capable of providing high data rates and lower latency with higher bandwidths, the increase in the number of connections necessarily requires an increase in network capacity, which can be substantially increased up to 100 times by using small cells and HetNets along with other benefits like offloading of congested macro cells, extend cell coverages, and better-received signal quality at the edges of macro cells [31,32].

HetNets are wireless networks that make use of multiple types of access networks. A broadband network may offer wireless services in places with various traffic densities, such as outdoor areas, within buildings, residences, and even underground sites such as tunnels, by employing macro cells, micro cells, and femtocells. These types of deployments always need better network capability in terms of network coverage, capacity, and data rates. High data rates, spectrum efficiency, energy efficiency, and lower congestion are among the benefits of HetNets. However, mobile communication systems provide a more complex scenario. As a result of dense deployments of access points and base stations, mobility and HO issues, as well as higher path losses, smaller coverage regions, and rapid signal fading, will occur, resulting in more errors and a drop in QoE. To maximize overall network performance, HO and mobility problems must be addressed effectively [33].

This section's goal is to provide an overview of the handover mechanism and its numerous related functions.

3.1. Handovers in HetNets

For next-generation mobile communication networks, HetNets will be a key solution since they will deliver better data rates, more user capacity, and wider coverage. Low-power small cells such as microcells, picocells, and femtocells are incorporated inside the high-power macro cell positioned within the same geographical coverage region to form HetNets which resultantly achieve cost-effective and energy-efficient solutions for users QoE [34–36]. However, the massive and ultra-dense deployment of these small cells increases the number of HO. This spike in the number of HO is exacerbated in a high-speed mobility environment. When compared to a pedestrian-moving UE, a high-speed UE requires a more smooth and more effective HO transfer to the next cell to ensure connectivity and quality. The incorrect or inefficient HO strategy does have quite a severe impact on communication quality in the form of longer interruption times, higher call dropouts, and throughput deterioration. As a result, in order to offer seamless connectivity and services to mobile customers, HOs must be maintained properly and optimally [30,37].

The HO phenomenon refers to a user's radio link process switching from a source cell to a target cell in order to retain connectivity while traversing from one cell to the next [38,39]. Figure 3 illustrates the basic concept of HOs in mobile communication systems with a number of scenarios. HOs ensure that users receive better QoS and uninterrupted connectivity, as well as maintain good network performance overall. The number of successful/failed HOs, interruption times, and radio link failures all affect QoS and performance. Although HO techniques vary by technology, we may model them in three or four steps [26,40–42]:

- Measurement Phase: The UE constantly collects RSRP values from surrounding cells during the measurement or information collecting phase in order to look for improved signal conditions for HO. This method of continual scanning or information collection assures QoS and network availability. Other parameters, such as RSRQ, SINR, and RSSI, can also influence this measuring and scanning procedure for HO decisions.
- Decision Phase: The HO decision step will proceed after the information acquisition and measurement phase at the serving cell. A list of adjacent cells will be examined

during this process to determine the target cell that best meets the requirements. Following analysis, the target cell with the highest RSRP value receives the HO request message. The target cell has the option to accept or reject the HO request after it is received. Requests that are not accepted set off the HOF, which eventually results in RLF. As an alternative, the target cell will begin preparing for the UE's arrival.

- Execution and Completion Phase: The execution and completion phase is about the signaling and radio link transfer process for UE mobility to the target cell from the serving cell. In addition, the data transfer process, synchronization, network reconfiguration and authentication have all been completed in the execution phase. Lastly, the UE initiates the completion message to indicate the HO completion process.

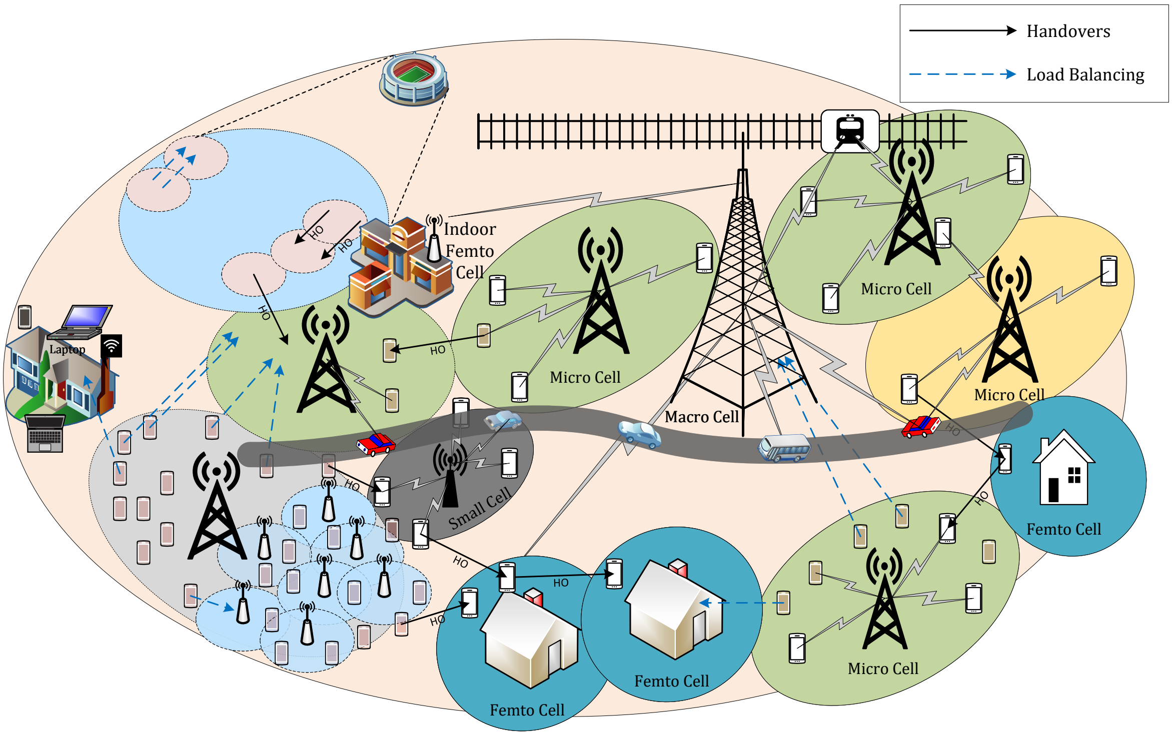

Figure 3. A simple HetNets scenario.

3.2. Handover Control Parameters

The HCPs are the key decision-making parameters in HO management. The decision of when to initiate a HO from the serving cell to the target cell is based on the values of the HOM and the TTT. As a result, these can significantly help in keeping the connection stable and the quality high among the UEs in communication. Previously, fixed TTT and HOM values worked effectively for traditional mobile communication scenarios where there was no coverage overlapping and HOs typically occurred at cell boundaries following frequent away movement from the cell center. However, in the situation of dense deployments and small cells, this static approach is no longer viable, as a UE with changing requirements may regularly relocate into an area where the cell coverage of several BSs overlaps. Furthermore, rather than having generic HO parameters for the entire scenario, HetNets and dense networks required more diverse and customized HO parameter settings for each UE based on their specific requirements [43–47]. If a user is moving at a high speed, for instance, they may cross through multiple cells, leading to a too late HO. For this reason, HCPs should be kept relatively low so as to prevent RLF. A low-speed scenario, on the other hand, results in a shorter distance and a higher-quality signal for the user. Low HCP values may cause too early HO, which then necessitates adjustments at higher HCP levels. Therefore, avoiding HOPP and RLF demands for high HCP levels. Figure 4 depicts numerous scenarios of HO issues that are commonly caused by incorrect HCP parameters. Similarly, Table 2 displays the various combinations of HOM and TTT and their respective dependencies.

Figure 5 summarizes the HCP parameters relevant to the handover decision. The handover process is triggered when the RSRP from the target cell exceeds the RSRP of the serving cell at the HOM level. The received power should be measured repeatedly at the UE based on the TTT interval. This shows the impact of HCP settings on the handover decision-making process.

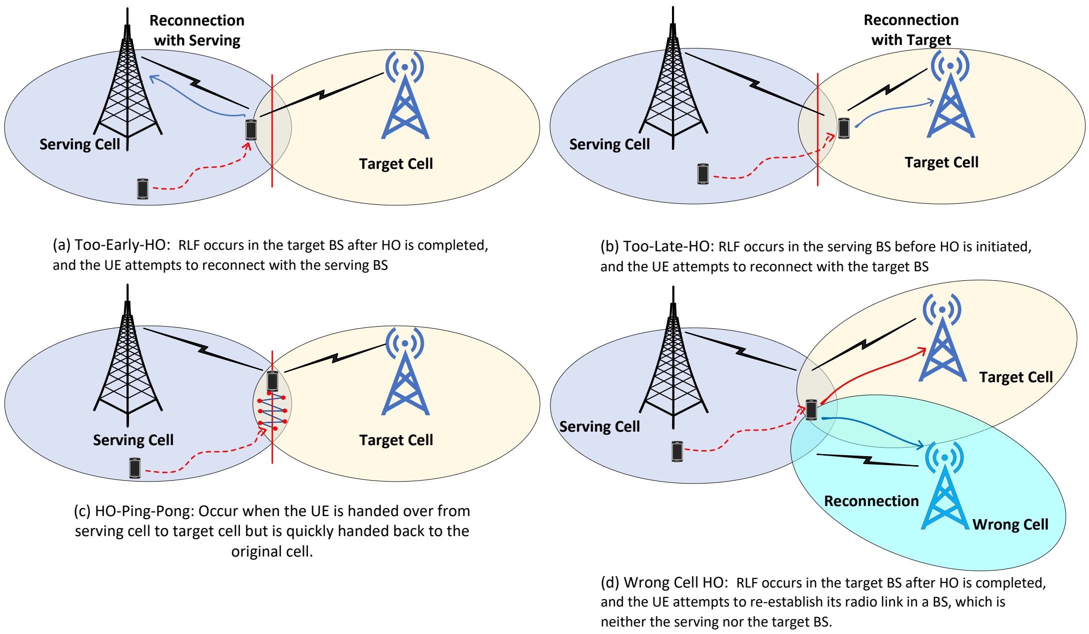

Figure 4. HOs scenario in HetNets.

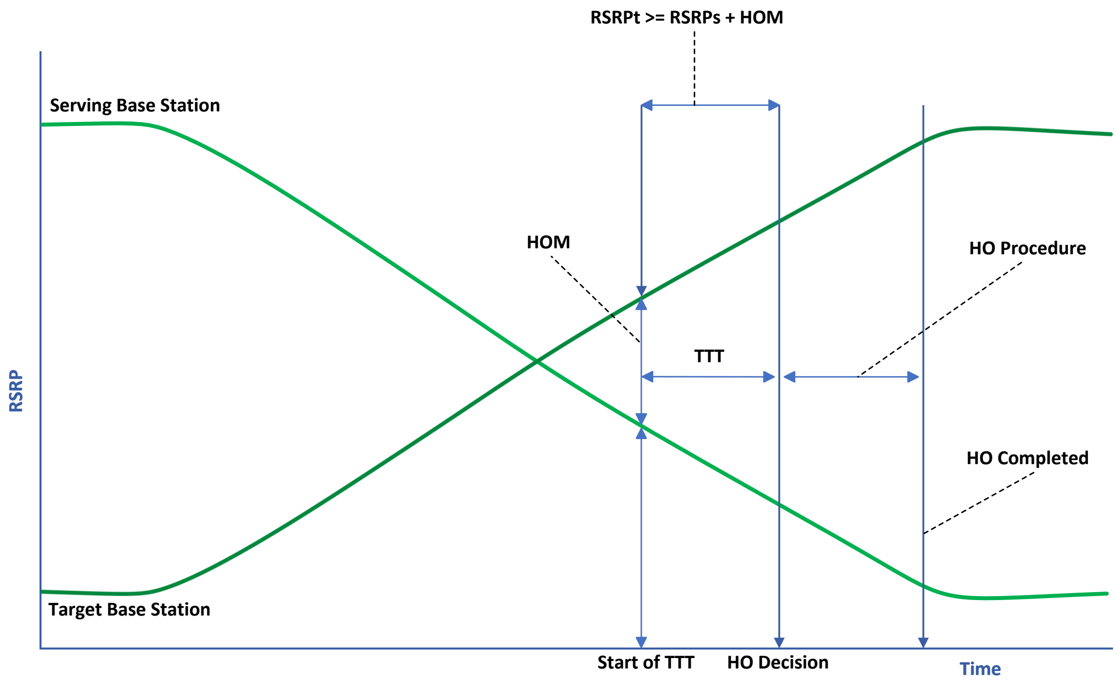

Figure 5. Handover decision and description of Handover Control Parameters.

Table 2. Summary of HCP parameters for HOF and HOPP.

Serial. No	UE Speed	HOM	TTT	HOF	HOPP
1	Increase	Low	Low	Lower	Lower
2	Increase	Low	High	Higher	Lower
3	Increase	High	High	Higher	Lower
4	Increase	High	Low	Higher	Lower
5	Decrease	Low	Low	Higher	Higher
6	Decrease	Low	High	Higher	Lower
7	Decrease	High	Low	Lower	Higher
8	Decrease	High	High	Lower	Lower

3.3. Self Optimization Network in HetNets

The extensive use of SON in numerous domains makes it difficult to define precisely. However, somehow we can demonstrate it as an efficient way to manage the dynamic requirements in a distributed environment. Similarly, it can be described as a method or technique that allows a system to modify its organization without explicit command during execution [48].

In 2008, Self-configuration and Self-optimization networks were introduced as a part of LTE networks [49] and been standardized in 2009 starting from release 9 [50]. The aim of this deployment for LTE was to achieve the expected network performance indicators named KPIs. Such as capacity, coverage, QoS, user satisfaction, CAPEX/OPEX, etc. Later on, this SON concept was extensively adopted in telecom sectors for performance optimization techniques and worked as a fundamental part for 4G mobile networks, as well as 5G networks [51–56]. Three categories are designated for SONs: Self-configuration, Self-optimization, and Self-healing. Self-configuration autonomously adjusts the parameters according to the condition without human intervention. Whereas, Self-optimization is the procedure that automatically optimizes the parameters after the configuration proposed by the network or system. Lastly, Self-healing works to recede errors and faults from the network by adopting suitable actions suggested after optimization [24]. Several autonomous functions for self-optimization have been introduced for 4G and 5G systems. The functions defined under this are mostly related to the optimization of [24,53,54]:

- Coverage and Capacity
- Handovers
- Interference

This article focuses on HO-based matters, so here we will discuss the SON parameters that only relate to HO and mobility management. LBO and MRO work as HCP controlling functions that automatically optimize the values for HOM and TTT. As HOs have a time constraint set by the 3GPP, these SONs have to provide optimized results in a real-time scenario to reduce the latency as well as to maintain connectivity and quality according to the user requirements. Due to certain requirements and conditions, MRO and LBO parameter settings may conflict or be compromised. Both functions seek to optimize the HCPs in order to increase HO performance. For example, the MRO function adjusts HCPs based on user mobility, whereas the LBO function adjusts HCP values to balance load among cells, resulting in a conflict. Many authors have tried to resolve the issue [38,57–60], but it still requires attention to produce an optimal value for HCPs.

3.3.1. Load Balancing Optimization

Mobile communication systems employ an RSRP-based user affiliation process, with the cell that has the highest RSRP working as the serving cell. The same RSRP-based user affiliation approach is used in most research on HetNets. The issue with this strategy is that it needs to consider the various aspects that affect network performance. These aspects include the SINR, the candidate cell's load, the future load required by the user, the free resources of the destination cell, and overall system capacity. These issues become more prominent in HetNets, where the transmission power and coverage area are limited. Resultantly, fewer users will be attracted by small cells compared to macro cells, leading to non-uniform user distribution in cells. That will create severe problems concerning resource utilization, QoS, QoE and load balancing [61].

Load balancing refers to the equitable distribution of cell loads across neighboring cells or the shifting of traffic from crowded cells to more vacant cells such that radio resources are highly optimized. The bandwidth of a cell is shared by all users affiliated with that cell. An overloaded state arises when the cell load surpasses or approaches the limit as a result of the maximum number of users per cell being reached. At this stage, the load balancing system begins to deliberately shift users to other less crowded cells in order to avoid overloading or congestion, which would result in performance degradation. From 2009, 3GPP [50,62] standardized the CIO and CRE process through LBO that can address the load balancing problem. However, non-optimal use of this value can result in even more severe load-balancing issues. Thus, the SON function is designed to optimize and automate HO-related problems as well as for load balancing to overcome from issues related to cell capacity and coverage. To improve load balancing performance, all of these studies [29,46,58,63–72] employed various combinations of HCPs and optimization techniques such as PSO, clustering and utility-based clustering techniques, auto-tuning hybrid approaches for MLB and LBO, CRE-based approaches, game theory, markov decision processes, fuzzy logic approaches and recent ML and DL-based approaches.

3.3.2. Mobility Robustness Optimization

Inefficient HCP settings in traditional schemes become even more challenging in HetNets and dynamic scenarios when networks become dense and conditions change dynamically and often. These suboptimal settings result in more RLF and a higher number of HOs. MRO, also known as handover optimization, is a Self-ptimization function that improves the condition of handovers in the network to enable continual mobility for UEs. It focuses on minimizing RLFs, unnecessary handovers, ping-pongs, and call dropouts resulting from poor handover parameter settings. The serving and target cells' RSRPs are continually monitored, and handovers are initiated based on the triggering point defined by the handover parameters. There are several mobility characteristics such as HOM, TTT, CIO, and so on, and a lot of the research has focused on optimizing a triggering point specified by HOM and TTT.

To maximize the HOM and TTT for both MRO and LBO, a variety of algorithms have previously been suggested and implemented. The research community is very interested in MRO. The multiple HO optimization strategies used for various radio access technologies reported in the literature illustrate this. To improve HO performance, all of these studies [34,73–83] employed various combinations of HCPs and optimization techniques. And the algorithms' performance has been mainly evaluated using KPIs such as HOF, HOR, HOPP, UHO, CDR, RLF, CBR, IT, and throughput. Table 3 lists the various key performance indicators and the articles in which they were used for performance evaluation.

Table 3. Research Articles based on Performance Parameters.

Serial. No.	Performance Parameter	Research Articles
1	Handover Ping Pong (HOPP)	[37,38,44,77,79,83–100]
2	Radio Link Failure (RLF)	[37,77,83–86,91–93,95,96,98,101]
3	Handover Latency (HOL)	[37,44,84,102,103]
4	Handover Failure (HOF)	[37,38,44,77,79,86,87,89,90,93,97,103,104]
5	Handover Probability (HOP)	[37,38,44,76,85,87–92,94,98,101,105–107]
6	Handover Interupption Time (HIT)	[37,38,44]
7	Throughput	[68,102–105,108–117]
8	No. of Handovers	[100,104,108,109,112,115–119]
9	Signal to Interference and Noise Ratio (SINR)	[83,106,120]
10	Packet Loss Ratio (PLR)	[103,109,116,117,121]

3.4. Handover Decision Approaches in HetNets

In HetNets, the HO processes are getting more complex, mainly when it is only based on traditional techniques like RSRP along with some HOM value. Macro cells transmit signals at high power and in the HetNet scenario, UEs receive these strong signals at every point in the cell compared to small or micro cells with low transmission power and coverage area. Resultantly, most of the HOs will be performed with macro cell, which will create several issues, including HOs and load balancing. Therefore, in HetNet scenarios, the HO decision must require coordination or updates from various collaborating parameters that can be used along with RSRP to enhance this decision-making process. These parameters and updates can be in the form of some threshold value, SINR, bandwidth, cell load, cost function, weight function, the velocity of the UE, or some optimized values. And these HO decision approaches perform evaluation on the basis of number of HOs, PLR, HOL, throughput, HOPP, HOF and CDR etc. Details about these HO decision categories will be discussed in the coming section below. Tabular categorizations are shown in Table 4, where we collected the data according to the information collection and decision-making point of view.

Table 4. HO Information collection and Decision making.

HO Information Collection		HO Decision Making	
Network Related	**UE Related**	**Strategy Related**	**Criteria Based**
Coverage area	Velocity	ML/AI	Velocity based
Link quality	Location	Weight function	RSRP based
Cell load	User preference	Cost function	RSRQ based
Cost	RSRP	Fuzzy logic	SINR based
		Metaheuristic approaches	Bandwidth based
		Multi attribute decisions	Location based

Table 4. *Cont.*

HO Information Collection		HO Decision Making	
Network Related	**UE Related**	**Strategy Related**	**Criteria Based**
			Direction based
			History based
			User preference
			Operator preference

3.5. Handover Challenges

HetNets has significantly enhanced the network throughput, spectral efficiency and QoS, but they also lead to several technical challenges. Due to the dense deployment of cells and overlapping coverage areas, a UE will observe frequent HO. That will create challenges related to interference from adjacent cells and Inter-Cells, scheduling of neighbour cells available for target cells, load management between cells and mobility management.

3.5.1. Adjacent Cell Scheduling

Handover enables seamless connectivity between UEs and BSs during movement. To improve the quality of HOs, a process enlists and schedules all the adjacent cells available based on the UEs measurement report. This scheduling process may become time-consuming, affecting the HO decision process and quality. Therefore, scheduling and minimizing adjacent cells is mandatory to improve the HO decision process and quality. 3GPP introduced and standardized Neighbor Cell List (NCL) and Automatic Neighbor Relation (ANR) procedures in [122] to improve the operation and maintenance of HOs in wireless networks. The target BSs can now be constrained to specific neighbour cells with only specific quality parameters to avoid handover failure, which NCL provides. However, due to small cells and HetNets, adjacent cell scheduling list size may become large, affecting the handover decision as the searching time will be increased to select the suitable target cell. Several studies have been done by the authors [123–128] to enhance this scheduling and minimization process of neighbour lists to improve HO performance as well as to lower signal overhead, and energy consumption.

3.5.2. Inter-Cell Interference

With the increasing data traffic and capacity requirements, HetNets are considered an effective and efficient way to enhance user capacity and utilization of the spectrum resources. The overlapping signal coverages at a single point and splitting cells into smaller cells make optimization and network design even more complex due to several issues, especially Inter-Cell Interference (ICI) at the cell edges. The handover decision in mobile networks is mainly based on the RSRP, along with other decision-making parameters. Thus, dense deployment of small cells inside the macro cell will decrease the signal quality with the increase in the interference, which results in the degradation in HO performance. To ensure a satisfying QoS in severely affected areas, 3GPP introduced Inter-Cell Interference Coordination (ICIC) in Release 8, later on, introduced as enhanced Inter-Cell Interference Coordination (eICIC) in Release 10. Similarly, in Release 11, 3GPP formalized Coordinated Multipoint (CoMP) Transmission procedure for interference mitigation. To improve from interference challenges, the authors have conducted several studies on various interference reduction measures [129–139]. However, adapting the majority of these methods to 5G standards with massive network sizes and capacities will be a considerable problem for future HetNets.

3.5.3. Centralized Handover Optimization

Many studies have focused on analyzing handover self-optimization at the base station level without considering individual user behaviour. This is because handover decisions are typically based on the overall network state and the signal strength of neighbouring cells rather than on individual user characteristics such as traffic patterns or mobility behaviour. However, it is becoming increasingly clear that individual user behaviour can play a significant role in handover performance. Factors such as user mobility, traffic patterns, and service requirements can all have an impact on the handover process. This implies that the centralized handovers are causing a significant challenge to the communication system's performance. As they impose higher complexity and higher signalling overhead that can cause a bottleneck or a single point of failure in the network [95,140–142].

In recent years, there have been some studies that have looked at optimizing handovers on a per-user basis. These studies have found that by considering individual user behaviour, it is possible to improve handover performance by reducing call drops, increasing handover success rates, and reducing call setup times. Such approaches can include techniques like analyzing the user's traffic pattern, Mobility prediction and using machine learning algorithms to learn the user behaviour and proactively trigger handover. However, these studies are still in the investigative stages, and more research is needed to fully understand the impact of user-centric handover optimization on network performance [143–146]. It's also important to note that the implementation of user-centric handover optimization may come with some complexity, such as the need for more information from the mobile devices and more computation and decision-making on the network side.

3.5.4. Contradiction among Handover Parameters

In 4G/5G Hetnets, MRO and LBO are the key handover optimization functions that aim to improve handover performance and network capacity. However, there can be a situation when the objectives of MRO and LBO may conflict with each other during the handover process, leading to trade-offs and potential issues. For example, in some situations, LBO may want to perform a handover to a cell that is farther away but has less load, while MRO may want to perform a handover to a cell that is closer but has more load in order to minimize the RLFs. Similarly, MRO and LBO can have different handover parameters and decision algorithms, leading to different handover decisions and potential inconsistencies. To mitigate these issues, coordination and standardization of handover parameters across different networks and network elements are necessary [38,84,91].

3.5.5. Diverse User Requirements

In HetNets, handovers can be challenging due to diverse user requirements. As, HetNets consists of a combination of different networks, which have different coverage areas and capacities so they may have different requirements for handovers, such as high throughput, low latency and minimal interruption time, etc. Additionally, the varying characteristics of the different network types can make it difficult to ensure that handovers are performed seamlessly and efficiently. Therefore, it is important to design and optimize handover algorithms to meet the diverse user requirements in HetNets. For example, some advanced handover techniques such as proactive handover, conditional handovers, multi-attribute decision-based handovers and hybrid handover, etc, can be used to improve handover performance in HetNets [100,147].

4. Handover Decision Techniques

In this survey, we categorized the HO decision approaches based on:

- UE Velocity
- RSRP
- FLC approach
- Metaheuristic Approach
- ML/AI

- Spatial Information

4.1. UE Velocity-Aware HO Decision Approaches

In velocity or speed-based HOs, UEs velocity acts as an input parameter for HO decisions. Numerous techniques added UE speed as an input parameter for the HO procedure to reduce the number of HOPPs. The velocity-aware HO approaches work by modifying the HCP parameters in accordance with speed depending on specified threshold values as shown in Figure 6. In [148], they performed an experimental study on the impact of high-speed mobilities on the HOs. The results show that UE speed has a direct impact on HOF and overall handover timing. As the HO phenomena in HetNets is more complex compared to base networks, we can predict and perform more accurate HOs in these networks by using UEs speed as a HO decision parameter. This results in significant improvement in network performance in terms of HOPP and RLFs. Numerous studies based on UE speed have been conducted; a few of them are listed here.

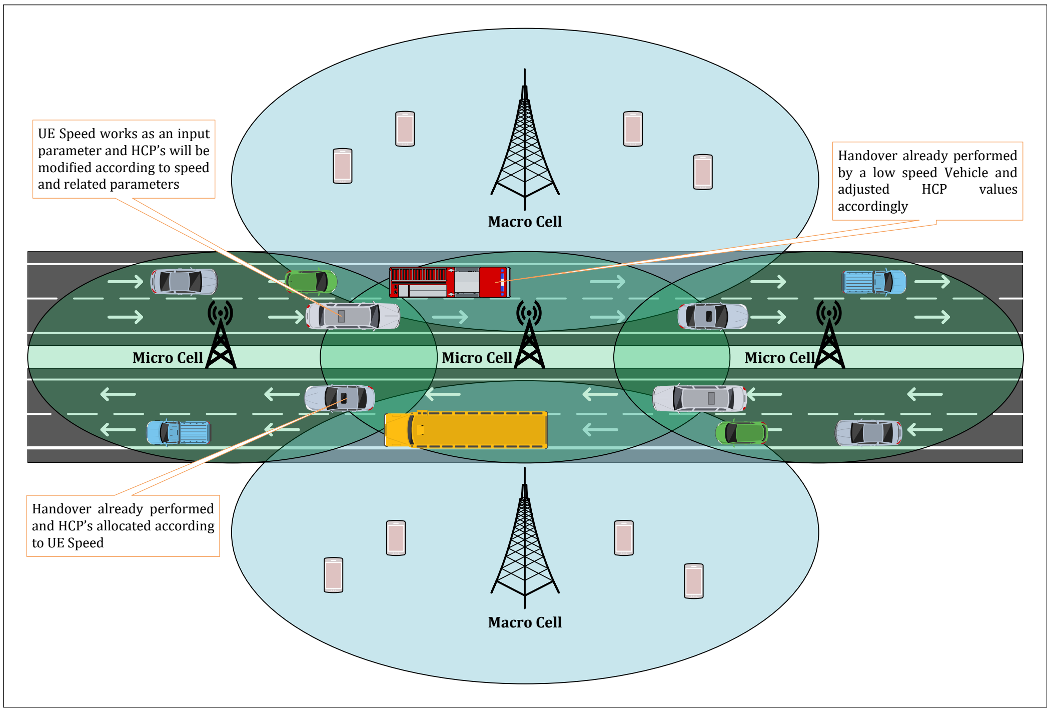

Figure 6. Illustration of Velocity Aware Handovers in HetNets.

In [38] the authors proposed a conflict resolution approach to solve the optimization conflict between MRO and LBO. This conflict is caused by the non-optimal HCP values after optimization which leads to network performance degradation. To overcome the said issue they used UE Velocity, Cell Load, and RSRP values of the serving and targeting BS to get optimal values of HCP. This Optimization of HCP parameters is based on weight functions for each user for each parameter. After optimization in the second stage they adjust the HCP values according to the handover failure type. According to the results presented in the paper, the proposed scheme is compared with MRO, LBO, and a Hybrid of MRO and LBO. Results show that the proposed scheme outperforms the previous schemes by a significant margin. In [85], authors proposed a Velocity Aware Handover Self Optimization algorithm for 4G and 5G dense networks to optimize HOM and TTT values according to the UE Velocity. Moreover, HOP, HOPP, and RLF were used to evaluate the performance. They developed a distributed UE velocity-aware HO optimization algorithm that works in a hybrid way. Initially, the system monitor and get the values of RSRP and Velocity of the UE. HOM and TTT values will be adjusted based on these threshold values (conditions) in the second phase with respect to UE speed states. These conditions or values were categorized on the basis of UE Velocity; however, the velocity range is only from 40 to 160 km/h. Fixed mobility patterns, absence of LB information and use of fixed pattern or jumping values for HCP adjustments can degrade the algorithm's performance. Similarly, some optimization approaches can predict more accurate HCP values instead of manual adjustments in a jumping manner. The paper's [86] authors proposed a robust algorithm for the optimization of HCP parameters in an LTE-A HetNets environment by introducing a new relationship between HOM and TTT values. By doing this, they achieved excellent results compared to the previous literature by comparing RLF, HOPP, and HOFs. Their proposed scheme adaptively selects the HOM and TTT values according to the UE Velocity for each user. They assumed the locations of UE and BS to estimate the velocity and UE's distance from the BS. Using this location and Velocity information, they adaptively predict the HOM Values. They also considered the RSRP and SINR from both serving and targeting cells for predicting HOM according to UE Velocity. TTT is purely a time-dependent phenomenon, but this article has shown a direct relationship between TTT and HOM. It means the TTT values are dependent upon HOM as well as the velocity of the UE, and they derived this relationship with the help of a geometric function to create a base against fixed or unjustified steps [85] for tuning the HCPs. Similarly, the authours in [149,150] investigates the downlink coverage and handovers by employing stochastic geometry and SINR to enhance coverage and handover performance in 5G HetNets.

The partial optimization of HCP parameters results in inefficient HO triggering, lowering overall system efficiency. Similarly, Manual optimization, non-optimal analysis of HCPs, and central optimizations are the obstacles to optimal HO triggering. This necessitates the use of distributed optimization approaches because each UE needs specific HCP values. In this research [91], the authors developed a distributed optimization strategy for 5G networks based on weight functions. According to UE requirements, the system automatically predicts the weight values for each unique user. The weight values for SINR, UE load, and UE speed are first evaluated by the weighting mechanism. Following the initial evaluation of input parameters, the outputs are transmitted to the second weight function to produce the final output weight value, which will be utilized as an indicator for the optimization of HCP for a particular user. The proposed weight algorithm's results were compared against HOPP, HOP, RSRP, and RLF. The benefit of this proposed strategy is that it does not interfere with other participating UE's HCP values, resulting in an improvement in RSRP and a reduction in HOPP and RLF overall. Similarly, in [44], they used a fuzzy logic approach based on UE's velocity along with RSRP and RSRQ as input parameters. The optimisation approach aims to introduce a robust HCP combination for 5G and next-generation networks. They evaluated the algorithm with different mobility speed scenarios in 5G networks for HOP, HOPP, HOF, HOL, and HIT as compared to HOPP, HOP and RLF of their previous work [85].

HCP values for some grouped velocities cannot be fixed because these can change rapidly with the change in velocity and other parameters. To establish these groups for fuzzy systems, an impact of change in velocity must be measured on HCP values. In mobile communications, HetNets and network densification are perceived as an essential approach for handling the ever-increasing capacity and data rate demand, its impact on the handover (HO) rate is often ignored. The benefits offered by HetNets directly affects by the number of HO's and delays caused by moving users. The authors in [151] developed a velocity-aware HO skipping algorithm via stochastic geometry method, for cellular HetNets to overcome the HO effects and to improve the data rates. The HO skipping or bypassing scheme skips the cell that have highest SINR value along the user trajectory to prolong the service or connection duration with the serving cell. This process resultantly reduces the number of HOs and its related effects on the performance. Specifically, the simulation results indicate that the velocity-aware HO skipping methods can generate up to 77% higher data rate gains than the typical HO strategy that always maintains the optimal RSRP based relationship. In [152], a velocity-aware HO triggering method for cellular HetNets was developed that relied on the coordination of MIH (Media-Independent Handover) and PMIPv6 (Proxy Mobile IPV6) to facilitate user mobility while reducing packet loss and HOL. They segmented the procedure into several parts, such as velocity tracking to obtain stabilized values, updating the velocity values based on GPS tracking to obtain UE lifespan for better decision making, and finally performing triggering choice. They effectively improved packet loss and HOL issues but ignored HOP and HOPP.

In article [76], the authors intended to show the effect of different HCP values on the performance of 5G network by analyzing fixed HCP settings. They used various scenarios to explain the necessity for applying more advanced approaches in 5G networks. They have used HOM's and TTT's predefined values with the predefined velocity of UE to check the behavior of UE based on HOP, HOPP, and RLF. According to the simulation results, lower HCP values can minimize the number of HOF while increasing the HOPP. These results can further highlight that the medium HCP values may be the best solution when using some fixed HCP environment for specific velocities. But for HetNets and dense networks, the network conditions are highly dynamic, where these fixed HCP settings will not work, resultantly requiring an adaptive solution. Similarly, in [83] same authors investigated the performance of different MRO algorithms for 5G networks by considering different mobile velocities. The purpose was to suggest the best MRO approach in dynamic scenarios on the basis of HOPP, SINR and RLF. Table 5 lists the studies discussed in this section, including their parameter selection criteria, HCPs considered for optimization, KPI's used for evaluation, the simulator used, the achievements and drawbacks, and the velocity of the UE.

Table 5. Summary of Velocity-based Handover Approaches.

Ref. No Year	Criteria of Parameter Selection	HCP's	KPI's	Simulator	Achievement	Drawbacks	Velocity
2021 [76]	Cell Load, UE Velocity, RSRP, SINR	HOM, TTT	HOP, OP, PPHP	MATLAB	Studied the impact of different predefined HCP settings to check the 5G system performance	Compared different predefined UE velocities, HOM, and TTT values	Up to 140 Km/h
2022 [38]	UE Velocity, Cell Load, and RSRP	HOM, TTT	HOP, HOPP, HOF, HIT	MATLAB	Reduced average HOPP, HOF, and interruption time by over 90%, 46%, and 58%, respectively	Jumping values may not work well when network conditions change dynamically	Up to 140 Km/h
2019 [85]	RSRP, UE Velocity	HOM, TTT	HOPP, RLF, HOP	MATLAB	Remarkable reduction in HOPP and RLF by an average of more than 70%	They used jumped values of HOM and TTT against some predefined conditions that are showing some sort of fixed behavior	Up to 160 Km/h
2022 [83]	Load Balance, Velocity, RSRP	HOM, TTT	RLF, SINR, HOPP	MATLAB	Weight function-based optimization and distance-based approaches work best		40 Km to 200 Km/h
2022 [44]	RSRP, RSRQ, Velocity	HOM, TTT	HOP, HOF, HOPP, HOL, HIT	MATLAB	FLC based approach compared with [51,87] and improved by 86.78% and 95.5% respectivily	Adjustment of Output values against FLC seems to be fixed for fixed velocity ranges, also UE mobility is limited in specific directions	20 Km to 160 Km/h
2020 [89]	RSRP, RSRQ, SINR, UE Velocity	HOM	HOP, HOPP, HOF, Data Rate	MATLAB	The proposed model enables to define the best time and the best antenna to perform the HO. The results demonstrate a decrease of up to 43% in HOPP	HOM is the only HCP and use of other decision parameters can enhance the performance further	0 to 80 Km/h
2022 [90]	RSRP, RSRQ, SINR, UE Velocity	TTT	HOP, HOPP, HOF		Compared to the previous [87,89], this algorithm reduced the HOP and HOPP without increasing HOF	RLF and HOF are relatively on the higher sides as compared to basic FLC models	0 to 80 Km/h
2020 [91]	SINR, UE Velocity, Cell Load	TTT, HOM	HOP, HOPP, RLF, RSRP	MATLAB	Weight function estimates the HCP values individually for every user according to the input parameters		0 to 140 Km/h

Several velocity-aware HO techniques have been proposed in recent years to improve handover performance in HetNets. UE speed has been used as a decision parameter to modify the HCP values, resulting in reduced HOPPs and improved network performance. The proposed techniques use weight functions, fuzzy logic, and other optimization approaches to adapt HCP values to UE velocity. The results of these studies have shown improved performance in terms of HOPP, RLF, and HOF compared to traditional handover techniques. Distributed optimization strategies have been developed to overcome the limitations of manual optimization and central optimization, resulting in efficient handover triggering and improvement in overall system performance.

4.2. RSRP-Based HO Decision Approaches

UE performs periodic or event-triggered measurements and reporting for handovers to get signal quality and power level. 3GPP defined a few measurement parameters, and RSRP is one of them. RSRP-based handover procedures are more practical and can perform better in conjunction with other measurements or decision parameters to adjust user requirements. RSRP is the average received power of a single reference signals resource element. An illustration of the RSRP-based handover process is shown in Figure 7. In this section, we included some literature related to RSRP-based HO decisions.

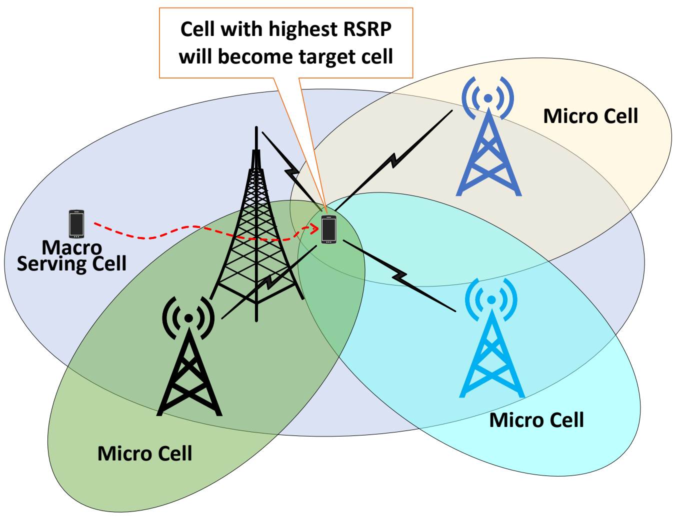

Figure 7. Basic illustration of RSRP based Handovers in HetNets.

For the 4G and 5G HetNets scenario, the authors of article [92] developed a dynamic HO control technique to optimize the HCP values and decrease HOPP and RLF. The proposed algorithm was based on the type of HOF. They employed three types of HOFs named too-early-HO, too-late-HO and wrong-cell-HO and justified that these HOFs occur due to different speed scenarios. However, one criterion for these failures is the UE's speed, and other factors that contribute to HOFs include RSRP, SINR, and aberrant HCP changes. These need to be adjusted dynamically to efficiently cover different speed scenarios and RSRP levels. According to the proposed algorithm, the system will initially monitor input parameters like RSRP, SINR, UE speed, etc. Following HOF occurrence, they classified HOFs into three types and adjusted HCP parameters based on HOF type. Without taking HOF into account, the results showed improvements in HOP, HOPP, RLF, and IT when compared to earlier papers. Similarly, in [37] , the same authors proposed an auto-tuning optimization algorithm with the similar approach based on RSRP and UE speed to tune HCP values. The objective of the algorithm was to reduce HOF and HOPP, and its performance was measured using HOPP, RLF, CDR, HOF, HOD, and IT. In article [68], a penalized HO load balancing algorithm was proposed for cell edge users in LTE HetNets. The technique was based on the optimization of the MLB algorithm by cooperative UE selection and target cell selection along with Handover parameter optimization to achieve the objective of efficient load balancing along with better QoS. They used RSRP, cell load and SINR to optimize HCPs and the comparison of the results shows a reduction in the number of unwanted switching between UE and BS, thus increasing the throughput and QoS of the system. In [153], the authors developed an efficient HO algorithm for load balancing in the LTE HetNets scenario. They created a list of possible femtocells using RSRP from neighboring cells and SINR. This possible femtocell list is divided into three categories of neighbor cells based on the RSRP, expected RSRP, and number of free resource blocks (RB), respectivily. To begin, the algorithm will select the femtocell with the highest number of available resources in order to achieve the maximum possible throughput. In the event that a candidate femtocell is unavailable, the algorithm forces users to connect to a macro cell with adequate resource blocks. They tested the algorithm in a variety of scenarios with varying numbers of users and UE velocity for throughput and HOPP. To address HOPP and HOF, [154] proposed a method for adjusting the start of the handover process using the TTT value based on the prediction of SINR in LTE HetNets. A predictive method based on the recursive least squares algorithm was used to forecast SINR value. The handover process selects the most appropriate triggering time with the help of the monitoring of decay in SINR value. The results showed an improvement in the quantity of HOF and HOPPs.

Frequent HOs degrade system performance and can be brought on by factors including channel fading, static users, and slow-moving users. Within a small cell network, high-speed UE are more likely to encounter HOs than low-speed users. These recurrent HOs require adequate detection and prevention measures. In order to reduce unnecessary HOs in HetNets, the authors suggested a frequent HO mitigation technique based on a threshold control parameter. This is achieved by identifying users as fast-movers or HOPP based on the frequency with which they encounter HOs. The suggested system tracks users' dwelling times and their serving cell histories to identify intrusive HOs. The algorithm labels a situation as "ping-pong" if the HO history data shows a pattern of repetition within a relatively small amount of time spent at each location. It is assumed that users are always on the move if there is no discernible trend in the HO history data over a very short dwelling time. The problem of superfluous HOs has been effectively addressed by the suggested approach [108]. A distributed optimization algorithm for MRO was proposed in [95] to minimize the number of RLFs in LTE small cell scenarios. They employed RSRP for HO decisions and adjusted the TTT, HO offset and CIO value for HCP tunings. Here TTT and CIO act as temporal and spatial parameters for joint optimization. The simulation results are compared on the basis of the number of RLFs, and HOPPs. They also highlighted the impact of UE speed on RLFs. The inclusion of HOM value along with included parameters can further enhance the efficiency of the algorithm. Table 6 presents the studies discussed in this section, along with their selection parameters, HCPs considered for optimization, key performance indicators, the simulator utilized, and the achievements and limitations of each.

4.3. FLC-Based HO Decision Approaches

Fuzzy logic is a technique that attempts to find accurate solutions for problems with imprecise data. In simple words, it allows situations, problems, or actions to be described and processed in linguistic terms such as "low", "medium" and "high" instead of values like "30 kmph", "70 kmph" and "120 kmph" [155]. It has been employed in a variety of engineering applications. FL approaches can be used in mobile communications to determine when and which cell to handover. These decisions can be based on multiple criteria and attributes as shown in Figure 8 for an enhanced decision-making procedure. In this subsection, we highlighted the recent literature that employed the FL-based approaches for handovers in the HetNets environment.

Due to HetNets and dense cell deployment in 4G LTE and 5G networks, the probability of HOPP, HOF and RLF on high-speed UE has increased tremendously. That is why managing and optimizing the HCP values is required by adjusting the conflicts between

MRO and LBO. In this article [84], the authors proposed a coordinated self-optimization technique based on fuzzy logic to perform seamless handovers in HetNets. To manage the HO parameters along with adjustment of MRO and LBO conflict, authors used Cell Load instead of LBO and Weighted FLC for MRO to get optimized values of HCP according to the input parameters. Simulation results were compared based on HOPP, RLF and HOL.

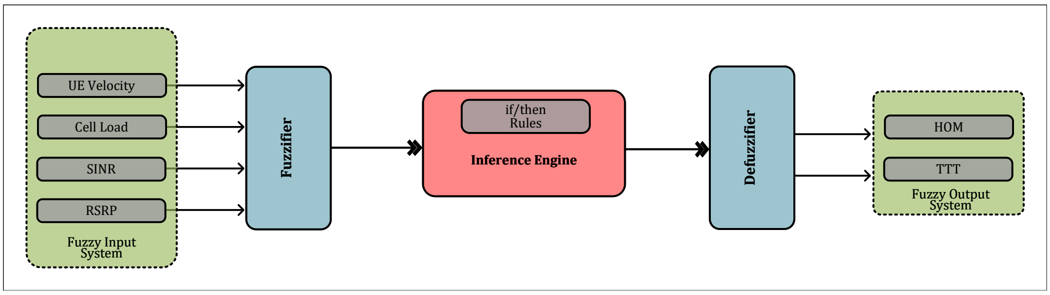

Figure 8. Schemetic Diagram of Fuzzy Logic-based Handovers in HetNets.

Table 6. Summary of RSRP-based Handover Schemes.

Ref. No Year	Criteria of Parameter Selection	HCP's	KPI's	Simulator	Achievement	Drawbacks
2019 [92]	RSRP	HOM, TTT	HOPP, RLF, HOP	MATLAB	Velocity aware technique HOPP, RLF and IT by 78.31%, 49.86% and 44.94% respectively as compared to static HCP approach	According to the Handover types, TTT and HOM values are adjusted, but these step based jumping adjustments in HCP shows fixed behavior
2019 [37]	RSRP, UE Velocity	HOM, TTT	HOPP, RLF, HOF, HOP, HOD, HIT	MATLAB	Proposed Auto-Tunning Algorithm reduced HOP by 92% and 73%, RLF by 65% and 87%, HOPP by 98.14% and 93.21% and HIT by 90% against [156,157] respectively	Manual definition of rules may not be appropriate in practical scenarios
2021 [68]	Cell Load, SINR, RSRP	HOM	Throughput		A cooperative distributed load balancing approach reduced call drop to 0% as compared to 8.42% and 2.78% against [158,159] similarly, reduced overloaded cells to 3% and RB utilization to 99%	Must compare the results for HOPP to show the effectiveness of the algorithm against HOPP
2021 [93]	RSRP, SINR	HOM, TTT, and CIO	RLF, HOPP	NS-3	Adaption time and user satisfaction rates are only 4.17% and 416.7% at 5 Km/h, and 33.33% and 187.8% at 30 Km/h respectively as compared to baseline algorithm	For the real-time scenarios this may lead to higher RLF in case of an increase in the number of UEs and speed
2019 [101]	RSS, Velocity, Path Prediction	HOM	HOP, RLF	MATLAB	HOPP mitigation success rate increased to 74% as compared to conventional RSRP scheme from 56% and handover success rate of 60% to 30% of Monte Carlo method	High speed scenarios were not considered
2019 [108]	RSRP	Threshold	No. of HO, Throughput	NS-3	FHM reduced 79.56% of the total number of HOs and network throughput increased by 10.82%	By offloading UEs towards the Macro cell, may overload the cell and reduce the overall performance also an increase in number of users at higher speeds specifically degrades the throughtput
2018 [95]	RSRP	CIO, TTT, HO offset	HOPP, TTT, RLF	NS-3	Categorized handover failures by rationale and adaptively optimized HCPs according to the dominant handover failure reason	The authors used simulation to minimize the RLFs and HOPPs, but no analytical justification was provided

Previously the same author in [77] employed FL by proposing a weighted fuzzy self-optimization approach to optimize HCP parameters in HetNets. They optimize the HOM and TTT by taking SINR, UE speed, and BS traffic load into account as input parameters. The weighted fuzzy algorithm automatically optimizes the HCP values according to the input parameters. They compared the simulation results on the basis of RLF, HOPP and HOF. In [102], authors proposed a fuzzy logic-based vertical handover decision-making scheme for HetNets using only throughput and end-to-end delay as input parameters. Simulation results compared on the basis of throughput, end-to-end delays, jitter and handover decision time. The authors extended their previous work [79] in this [87] article by employing fuzzy logic to optimize only the HOM value by using RSRP, RSRQ and UE velocity as inputs to fuzzification system. They achieved the dynamic HOM values by enhancing the fuzzy rules from the previous work according to the quality and velocity of the UE. The simulation results were compared to numerous approaches based on HOF, HOPP, number of HOs, and average connection time. A three-stage fuzzy logic handover approach was proposed in [109] for the D2D scenario. They used RSRP, PLR and throughput as input criteria to the fuzzification system and developed a minimum quality function to estimate the handover necessity; the purpose was to reduce the unwanted handovers. In the second stage, they designed a fuzzy logic-based target cell selection scheme to process the UEs requiring handovers. Whereas in stage three, the selected target cell will be checked for the radio resources availability. The simulation results were compared with several TOPSIS and simple fuzzy schemes on the basis of PLR, average throughput and number of handovers. However, in the article [88], the authors used RSRP, RSRQ and UE velocity as inputs to a fuzzy logic system to optimize HOM as well as TTT values. But the results were only compared on the basis of HOPP and HOP for different UE velocities. The majority of the available literature for fuzzy logic-based handovers has used numerous input parameters to obtain more appropriate optimization values. However, the authors of this article [96] only used SINR as an input parameter, together with changes in SINR value, to forecast the HOM. They defended this technique by claiming that when a UE's SINR value drops, the UE is likely to move away from the BS and disconnect soon. As a result, they proposed that when the SINR is low, the HOM value be set low to initiate the handover process early. They simply employed nine fuzzy rules to calculate HOM and compared simulation results using RLF and HOPP.

Basic FL approaches employed in mobile communications performed well. They act as a reliable and robust approach for optimizing HCPs based on uncertain data however, these basic approaches have some flaws. For example, they cannot produce a reliable and robust decision if the number of input decision criterion increases. Similarly, designing of membership function also needs some automation instead of human experiences as, due to dynamically changing environments these approaches may not work in all scenarios. A fuzzy logic TOPSIS approach was presented in [89] that used RSRP, RSRQ, SINR and UE velocity as input parameters. From these input parameters, fuzzy logic utilized three inputs named RSRP, RSRQ and UE velocity for the fuzzification process that will help in the handover decision process. The basic purpose was to optimize the HOM by considering multiple input parameters. They used TOPSIS to prioritize the selected target cells from the available list and compared the results based on the number of HOs, HOF, HOPP and data rate. Using SINR and UE velocity helps to improve HOM optimization according to the user requirements. Similarly, the article [94] proposed a fuzzy logic and TOPSIS-based approach. They utilized fuzzy logic to manage dynamic input control parameters and TOPSIS to select the best BS. In order to improve the decision criteria, they used the concept of subtracting cluster scheme to generate membership functions based on historical data. They utilized SINR, RSRP, jitter, and packet loss as input parameters and compared simulation results using HOPP, the number of HOs, and the mean option score, which is a performance indicator for algorithms. Instead of using TOPSIS, the authors in [90] used a deep-Takagi-Sugeno-Kang fuzzy classifier (DTSK-C) for HetNets scenarios. They named it H2RDC (heuristic handover based on RCC-DTSK-C) with the purpose to reduce the number of HOPP. The DTSK-C classifier used a deep stack structure between different subsystems to classify and prioritize the target cell for handovers. They considered SINR, RSRP, RSRQ and UE velocity as input parameters for the fuzzification process to construct the input dataset for handovers. The simulation results were compared with the state-of-the-art approach [89] along with two other basic approaches by considering HOPP, HOF, number of HOs, CDR and time required for handovers. Table 7 presents the studies discussed in this section based on FLC.

Table 7. Summary of FLC-based Handover Decision Approaches.

Ref. No Year	Criteria of Parameter Selection	HCP's	KPI's	Simulator	Achievement	Drawbacks	Fuzzy Rules
2022 [84]	SINR, Cell Load, UE Velocity	HOM, TTT	HOPP, RLF, HOL	MATLAB	Eliminated LBO-MRO conflict by employing Cell Load instead of LBO and simulation results are relatively better than the [89] model in terms of HOPP, HOL and RLF	Complexity of the fuzzy model is greater than that of the original model	FLC 3 × 3 × 6
2019 [77]	SINR, Cell Load, UE Velocity	HOM, TTT	HOPP, RLF, HOF	MATLAB	WFSO scheme calculates the weights against input parameters, and results reduce HOF rate by 95.9 %	HCP adjustment according to UE requirements can further enhance the HO performance.	Weighted Fuzzy System 3 × 3 × 3
2022 [94]	RSRP, SINR, Jitter, PLR	TTT	HOPP, HOP	MATLAB	Fuzzy-TOPSIS reduced the number of handovers by 90% and HOPP by 10% as compared to RSRP method whereas, historical information based Clustering Fuzzy-TOPSIS further reduce the number of handover by 10% and RLF by 3%		Clustering Fuzzy-TOPSIS 5 × 5 × 5
2020 [102]	Throughput, End-to-End Delay	Q-Parameter	HOD, Throughput, Latency	NS-3	FL approach used E2ED and throughput as input to HO decision maker, which gives 97% better performance in terms of handover delay than compared technique.	They only considered throughput and E2ED as handover input parameters, which may eliminate a lot of handover decision-making useful information	FLC 3 × 3
2018 [87]	RSRP, RSRQ, UE Velocity	HOM	HOP, HOF, HOPP, Connection Time	MATLAB	Proposed scheme reduced the HOPP and shows prominent results for HOF and HOP	Only considered HOM as an HCP, however, HOM along with TTT can produce better results	FLC 3 × 3 × 4
2021 [88]	RSRP, UE Velocity, RSRQ	HOM, TTT	HOPP, HOP	MATLAB	The proposed approach reduces HOPP probability by 0.5% compared to 50% and 10% in [51,87]	The performance evaluation can be extended for RLF, and user velocity support is also limited	FLC 3 × 4 × 4
2021 [96]	SINR, Delta SINR	HOM	HOPP, RLF	MATLAB	This algorithm dynamically determines HOM according to the SINR and the change in SINR of a UE and related this decay with the possible handover in near future	Use of SINR and change in SINR can work better if RSRP, RSRQ, location and trajectory information is also considered for possible handovers	FLC 3 × 3
2020 [89]	RSRP, RSRQ, SINR, UE Velocity	HOM	HOP, HOPP, HOF, Data Rate	MATLAB	This model outperforms the previous models in terms of average number of handovers by 42% and average HOPP by 43% due to the inclusion of SINR and Velocity	Higher link failures as compared to the other considered approaches	FLC (AHP) and TOPSIS 3 × 4 × 3
2022 [90]	RSRP, RSRQ, SINR, UE Velocity	TTT	HOP, HOPP, HOF	MATLAB	Reduced the handover rate by 83% and HOPP by 76%.	RLF and HOF are relatively on the higher sides as compared to basic FLC models compared in this paper	Statistical Fuzzy System 3 × 4 × 4 × 3
2018 [79]	RSRP, RSRQ, UE Velocity	HOM	HOF, HOPP	MATLAB	Effectively enhances the handover decisions by reducing HOF and HOPP	The inclusion of the TTT can further enhance the effectiveness against handover decision process	FLC 3× 3 × 4
2020 [109]	RSS, Throughput, PLR	NSF	Number of HOs, PLR, Throughput	MATLAB	This approach surpasses traditional and MADM-based fuzzy schemes in terms of the number of handovers and throughput performance		FLC 3 × 3 × 3

Fuzzy logic has been widely used in mobile communication applications as a reliable and robust approach for optimizing handover control parameters based on uncertain data. Despite its advantages, it still has some limitations, such as its inability to produce a reliable decision when the number of input decision criteria increases. Therefore, more research is needed to automate the membership function design and to improve its performance in dynamically changing environments.

4.4. Metaheuristic Algorithms-Based HO Decision Approaches

In telecommunication, the design problem can be of large scale and complex that requires more computational power and time. These issues become severe and more challenging with the increase in different user requirements like data rate, speed, capacity etc. The complexity of these real-world challenges and requirements constrains the use of conventional methods. Metaheuristic algorithm highlights a process that is meant to discover a satisfactory solution to a complicated and difficult-to-solve optimization issue. For real-world problems with limited resources (e.g., processing power and time), it is crucial to find a near-to-optimal solution based on imperfect or partial knowledge. Metaheuristic algorithms can be classified into multiple categories: evolutionary, trajectory, and nature-inspired approaches. We added several papers in this subsection that use nature-inspired and evolutionary methods to address handover problems. Figure 9 illustrates the fundamental principle of utilizing Nature-Inspired and Evolutionary algorithms in optimizing handover procedures.

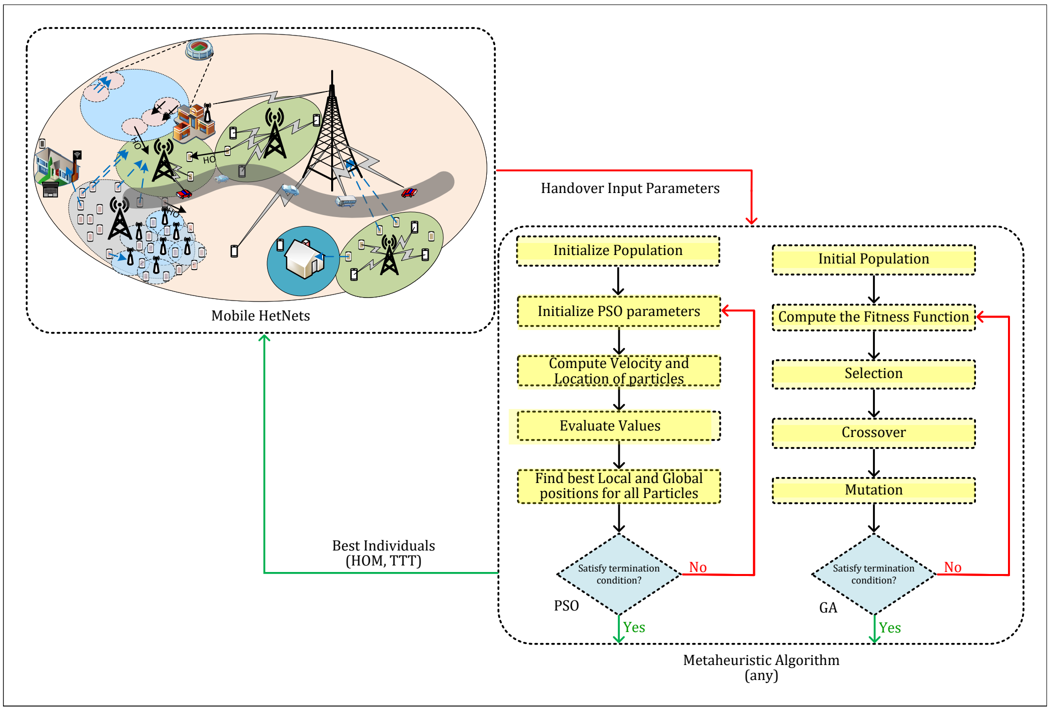

Figure 9. Schemetic Diagram of Metaheuristic-based Handovers in HetNets.

Due to multiple user requirements and dynamic behaviors, HCP values cannot be fixed to perform handovers. In article [97], the authors proposed a PSO algorithm along with mobility load balancing to get optimized HCP values for dynamic behaviors and requirements by using RSRP, UE velocity and load information. The performance evaluation was done based on HOPP and HOF. They compared fixed HCP values, optimized TTT, optimized HOM, and proposed scheme that utilizes TTT, HOM and offset. The simulation results showed that the HOPP and HOF have greatly improved compared to fixed or partial HCP optimization schemes. Using other KPIs can further validate the effectiveness of the proposed approach. Similarly, [105] devised a hybrid technique that combined the principles of PSO and SFO for 5G HetNets. The proposed adaptive particle-based sailfish optimizer (APBSO) determines weights depending on input parameters such as SINR, E2E Delay, HOP, Jitter, and Packet Loss in order to select the optimal network from a list of potential networks. These weights are then supplied to a Deep Auto Encoder section, which optimizes these weight values to perform handover decisions. The proposed technique performs well in terms of delay, HOP, stay time, and throughput when compared to earlier studies. The authors in [118] presented the PSO and PSO passive congregation (PSOPC) optimization algorithms to decrease handovers by relocating UEs between Macro and Femto cells based on their speed and data requirements. When compared to the PSO optimization approach, the PSOPC optimization technique reduces handovers by 20%.

The basic purpose of handover optimization approaches is to provide users with seamless services during mobility such that an up-to-mark QoS is available to every user in the network. The authors in [111] proposed an integrated optimization approach based on grey wolf optimization (GWO) and mayfly optimization (MFO). They employed the characteristics of GWO for network initialization and MFO for handover decisions. For the initialization phase, they considered security level, battery level, RSRP and QoS as input parameters for handover triggering. The Simulation results showed on the basis of delay, call drop, energy consumption and throughput. The authors of [104] also developed a hybrid approach to manage the frequent handovers and power consumption issues in HetNets. They employed cuckoo search (CS) and genetic algorithm (GA) for handover optimizations. Resultantly, they achieved better results with proper resource utilization and mobility in terms of throughput, delay, number of HOs and HO Failure Probability. They used the location and velocity information of the UEs to get the effective solution population from the cuckoo search algorithm, and passed these population values to a GA to get an optimal handover triggering value. Instead of using a hybrid approach the authors in [112] used the basic GA for handover optimization process on the basis of data rate, bit error rate, RSRP and delay for HetNets scenario.

The development of dense networks and HetNets has greatly increased the functional complexity by many folds. This rise in functional and optimization complexity directly affected the network performance in the form of KPIs degradation. Coverage and handover-related parameters are mainly affected in HetNets, which needs to be optimized in an efficient way such that the KPIs and QoE can be maximized. Heuristic algorithms and ML techniques allow you to model and map out functions in the form of data that cannot be evaluated directly or mathematically. Instead of using simple heuristic approaches, now, most authors prefer to use these approaches with ML or DL techniques [110]. Similarly, in [120], the author's used ML techniques with GA to get the optimal values for HOM and CIO that can resultantly enhance the SINR for users in the network. Firstly, they generated the synthetic data values for possible combinations of HOM and CIO. These generated values are forwarded to the ML model to predict the most optimal KPIs that can enhance the system's performance. Lastly, they used GA on the outputs of ML model for faster convergence. The performance analysis result shows that CatBoost performs best amongst ML techniques and GA can find the optimal convergence point more efficiently. To obtain optimal values for HCPs, the authors [107] used a data-driven multi-objective optimization approach. Firstly, they generated synthetic data for XGBoost, an ML model, to generate reliable KPI values, and then they used GA to maximize the RSRP and HOSR jointly. Later this work was extended by the same authors in [106]. The authors proposed a synthetic data-driven self-optimization approach for inter-frequency handovers by employing XGBoost and modified GA. They asserted that this is the first method of its kind that optimizes handover parameters with severely time-bounded constraints using synthetic data rather than real-time operator data. TTT, threshold1, and threshold2 are the three handover parameters that they optimized. The performance of these parameters was justified based on the handover success rate, RSRP, and SINR. The multi-Objective Optimization function determined the optimal values of TTT, Th1, and Th2. This designed objective function jointly maximizes the three KPI indicators: HOSR, RSRP, and SINR, and also maintains the fairness among KPI defined by the operators. This Optimization process was based on the training of Synthetic data designed with the help of SHAP implemented in the newly developed Simulator "SyntheticNet" [160] and produced with the help of the XGBoost gradient model. In the end, they used a Modified GA named Intelligent Mutation GA (IMGA) on the output values of XGBoost model for faster convergence to get optimal values. List of some of these studies have shown in Table 8 by considering different metahueristic algorithms.

Table 8. Summary of Metaheuristic-based Handover Schemes.

Ref. No Year	Criteria of Parameter Selection	HCP's	KPI's	Simulator	Achievement	Drawbacks	Algorithm
2020 [105]	SINR, E2E Delay, HOP, Jitter, Packet Loss	Output (Yes/No)	Delay, HOP, Stay Time, Throughput	Python	Reduced handover delay to 11.37 ms, increased connection/stay time to 7.79 s and throughput to 12.72 mbps	Shows poor performance for the seamless connectivity because of neglected handover input parameters	APBSO based Autoencoder
2021 [110]	UE Velocity, Location		Throughput		PSO-NN hybrid approach improved throughput upto 34.34% as compared to previous works		Hybrid of PSO-NN
2022 [106]		TTT, threshold1, threshold2	RSRP, SINR, HOSR (HOP)	Synthetic-NET	Data driven approach having root mean square error of 0.0635 dBm, 0.1995 dB and 2.99% for RSRP, SINR and handover success rate respectively, modified GA further improves performance by 21 times faster	Synthetically generated data may not exhibit much better performance when it is applied to real-time scenario	XGBoost with modified GA
2020 [120]		CIO, HOM	SINR		With limited data availability CatBoost achieved RMSE of 1.144 dB for SINR, GA further enhance the performance by finding optimal values	May require a large dataset to reach a sufficient accuracy also the optimization of TTT predicts more optimal results	CATBoost with GA
2022 [118]	RSRP, UE Speed, UE Data Type		No. of Hos, Energy Consumption	MATLAB	Compared to the PSO, the PSOPC reduced handovers by 20%.		PSO and PSOPC
2022 [111]	Security information, Battery level, QoS, RSRP	QoS	HOD, CDP, Throughput, Energy Consumption	NS-2	Improved energy consumption, delay, call drop, and throughput with the values of 0.05359J, 0.0142sec, 0.0628sec, and 104.58 kbps respectively		GWO and MFO
2022 [104]	Location, Distance, Velocity of UE, Position of UE	Cost function	Delay, No. of HOs, Throughput, HOF	MATLAB	Novel scheme based on CS and GA achieved better results in terms of Throughput, Delay, No. of HOs and HO Failure Probability	further investigation about the scheme may be required with other handover related parameters	Hybrid of CS and GA
2020 [107]		TTT, th1, th2	RSRP, HOSR	Synthetic-NET	An optimization approach used XGBoost that predict HOSR and RSRP with RMSE of 2.5% and 0.074dBm respectively, GA further enhanced the results by 48 times against brute force		XGBoost with GA
2021 [97]	RSRP, UE, Velocity, Load	TTT, HOM	HOF, HOPP		TTT, HOM, and MLB should be adjusted based on UE speeds and traffic loads		PSO

The development of metaheuristics and nature-inspired algorithms has proven to be a crucial method in optimizing handover procedures in HetNets. A multitude of studies have shown the effectiveness of such algorithms in reducing handovers and improving KPI's such as HOPP, HOF, delay, call drops, energy consumption, and throughput. The integration of machine learning and deep learning techniques has further enhanced the performance of these optimization algorithms.

4.5. Machine Learning/Deep Learning Based HO Approaches

In 4G and 5G network paradigms, handover management is a critical challenge in small-cell HetNets and can negatively impact the QoS and QoE with an increase in handovers. To address this challenge, deep learning and machine learning have been adopted as effective solutions for managing mobility and handovers by optimizing HCP parameters. These techniques have gained popularity over traditional optimization procedures due to their robust optimization and convergence properties. As demonstrated in Figure 10, advanced Machine/Deep/Reinforcement Learning strategies can be utilized to optimize handover procedures in HetNets. Several articles that have utilized ML and DL methods to tackle handover issues are highlighted in this subsection and summarized in Table 9.

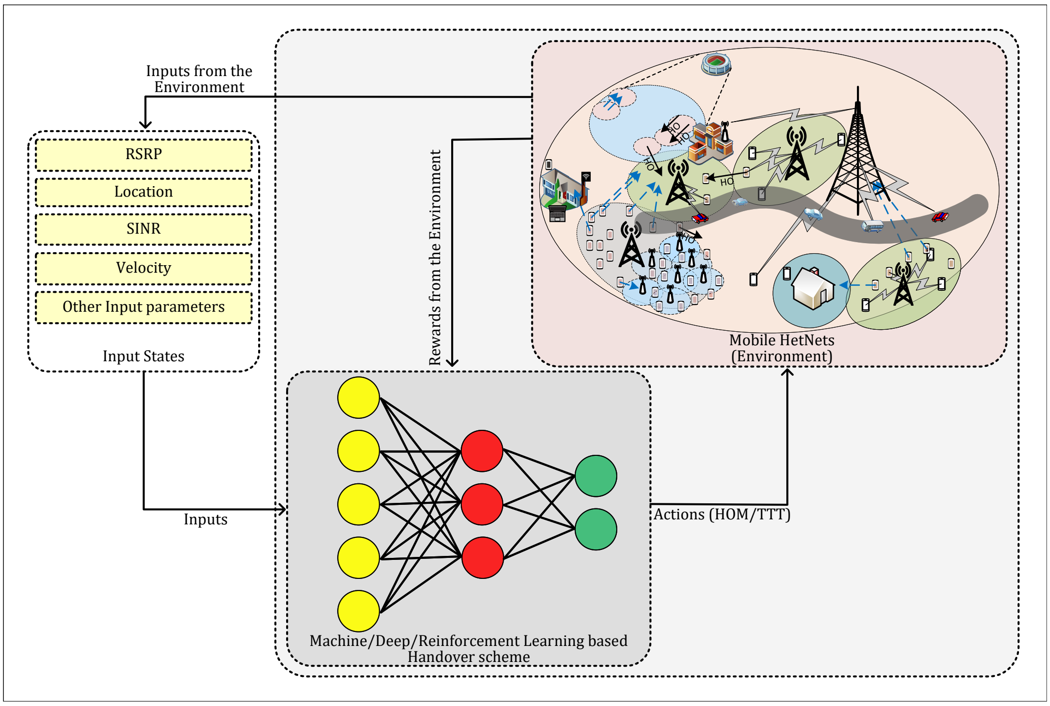

Figure 10. Schemetic Diagram of Machine Learning/Deep Learning-based Handovers in HetNets.

The authors of [161] suggest using AI-assisted mobility predictors to manage a dense 5G network, aiding in resource allocation, load prediction, and energy saving. XGBoost was found to be more accurate in predicting mobility, achieving up to 95% accuracy with new input features, a realistic mobility model, and HetNet with shadowing. Similarly, [162] proposes an XGBoost algorithm to improve handover success rates in a sub-6 GHz LTE and mmWave HetNets, improving session maintenance and meeting the demands of 5G. To address the challenges of HetNets, the authors of [163] proposed a fuzzy logic-based vertical handover decision algorithm. This algorithm takes into account multiple input parameters to determine the most desirable network preference between LTE and WLAN for handover. By using this algorithm, it's possible to maintain QoS during the handover process. Additionally, the authors proposed an intelligent interface activation technique that uses an RNN model to predict network conditions and reduce unnecessary network measurements during excellent network conditions. This technique optimizes power consumption in mobile terminals, further enhancing the user experience in HetNets.

The authors in [164] proposed a handover algorithm for next-generation multi-tier cellular networks. The proposed algorithm utilizes a look-up table, DL, and LSTM approaches to improve user QoE and QoS requirements while reducing HOF and ping-pong rates. Simulation results show that the proposed algorithm outperforms the current 3GPP scheme, with a significant increase in overall network throughput 40 to 60% and a reduction in HOF and ping-pong rates by 30% and 86%, respectively. These promising results suggest that the proposed solution could effectively enhance handover in next-generation multi-tier cellular networks. The authors of the article [165] proposed an adaptive approach for cell selection in two-tier HetNets using SDN and ML. The proposed adaptive algorithm, called adaptive two-tier based on the K-Nearest Neighbor (A2T-KNN) algorithm, intelligently selects the best BS from the two-tier BSs based on vehicle information and the features of the HetNet. The results demonstrate that the proposed algorithm outperforms other related schemes in terms of the average number of handovers, achieving up to 45.83% improvement. Additionally, the proposed algorithm improves the average achievable downlink data rate and network energy efficiency achieved by up to 17.18% and 16.86%, respectively.

In [93], a transfer learning (TL) and RL based robust optimization approach was proposed for small cell networks. The TL-based first part of the approach was used for network topology adoption in a centralized environment. Whereas the RL-based second part was used for HCP parameter optimization. In the topology adaption phase, they check the topology for any change in previously available information (Similarity detection). If there is no change, the previously selected HCP values will be forwarded to the topology. And in case of any change, the newly estimated HCP values will be forwarded and new topology information will be stored in the database for the next iteration. Geometry-based computation for CIO's upper and lower bound values was also established, representing a maximization function of Too-Early HO (TEHO) and HOPP and a minimization function of Too-Late HO (TLHO). Lastly, RL based HCP adaption algorithm uses prior knowledge of the parameters and fine-tunes them to an optimal value. They optimized the HOM, TTT and CIO values and compared the results on the basis of RLF and HOPP. In [98], the authors developed an approach based on Q-learning (QL) algorithm to perform self-optimization in LTE networks. The basic purpose of this approach was to perform optimal handover configurations independently. For this, the author has used an epsilon-first learning algorithm for cell selection. However, for distributed self-optimization, this single learning agent has to be used on a shared learning policy in which different actions are collected separately from these single agents and forwarded into a central Q-Table. They created TTT and HOM tuples according to UE velocity and divided velocities into thirteen groups. The change in velocity will be observed and depending on this change, the suitable action or values will be selected from the centralized Q-Table. After this, the behaviour against performed action will be monitored, and accordingly, the reward will be updated. The simulation results were compared for cell load, user satisfaction, HOPP, HOP and RLFs. In [103], an online reinforcement learning technique was developed that uses Kalman filter to compute the best of the serving and target cells' RSRP values. Based on the projected signal quality, a state-action-reward-state-action (SARSA) based reinforcement scheme was employed for target cell selection which results in a dynamic handover decision that considers future network conditions. They also used an epsilon greedy method to dynamically change the TTT and HOM levels based on the user's requirement. They considered different UE speed scenarios for simulation and checked the scheme for throughput, PLR, packet delay, HOL, HOF and error rate.

In [166], the authors proposed a recurrent neural network-based trajectory prediction mobility model. The fundamental concept is to reduce complexity by eliminating raw data and improving the accuracy of trajectory prediction to learn the user's mobility behavior. The authors of [167] proposed a user mobility prediction scheme for HO management in Cellular networks by acquiring user mobility data. After acquiring mobility data, they utilized a hybrid deep learning algorithm known as vector autoregression and gated recurrent unit (VAR-GRU) to estimate the UE's future trajectory. The proposed method is subsequently evaluated in terms of future mobile location error, HO cost, and HO processing cost. In [168], they proposed an LSTM-based framework for single and multi-user UE trajectory prediction. They employed a fundamental framework for single-user trajectory predictions and a sequence-to-sequence framework for cluster-based multi-user trajectory predictions. The simulation outcomes compared single-user and multi-user prediction strategies. Prediction of UE's future location can result in improved estimation and performance in handover procedures, thereby improving HO-related issues.

The authors developed a deep neural network-based proactive conditional handover scheme for 5G dense networks in [147]. As 5G networks are more prone to blockages and obstacles, a robust approach that can bear the sudden signal changes is required. With conditional handovers, multiple target BSs prepared in advance for handovers even when the connection between the UE and its serving BS is still reliable. The proposed proactive deep learning approach compared, different blockage densities; however, during the preparation phase, the target BSs have to reserve radio resources for the UE, which will cause inefficient resource utilization. The authors of [113] employed RL algorithms to predict the proactive handover decision-making based on pedestrian movement data. They used the location and mobility rate of pedestrians to determine the appropriate handover policy for maximizing the system's throughput. They collected the position and velocity of the users using an RGB camera. On the basis of the obtained data, a Q-learning algorithm was implemented and a handover decision was made. The simulation results demonstrate that the Q-learning-based handover prediction is superior to the current heuristic handover decision-making in terms of obtaining higher throughput against service disruption times.

The authors of [114] proposed a cognitive self-optimization approach by using a fuzzy-based Q-learning algorithm along with a load difference method to optimize the load balancing issues. According to the authors, these cognitive approaches can perform better for unknown parameter relationships as compared to traditional rule-based or command-based systems in which each rule has to be defined separately for every possible scenario. They compared the Q-learning framework with traditional approaches at different speed scenarios for throughput, the number of unsatisfied users, and energy efficiency. Similarly, this research [169] also emphasized that proactive and cognitive approaches based on deep learning can assist mobile networks to provide optimal services to end customers without sacrificing quality. They used two distinct approaches for predictive and non-predictive handover scenarios. They developed a mathematical model to evaluate the HO cost, which incorporates latency, signaling overhead, call dropping, etc. In addition to this analytical method, they also proposed data-driven deep learning-based HO prediction algorithms to further enhance the HO cost parameters. Simulation results of MLP and deep-stacked LSTM frameworks show the dominance of LSTM over MLP for handover prediction. The enhanced performance can be due to LSTM's inherent recurring nature, which facilitates a more accurate representation of time series data. The authors in [115] proposed a two-layer approach for HO optimization in an ultra-dense network. Initially, they performed a two-tier operation to form clusters of similar mobility types and get the optimal controller for each cluster by using k-means clustering algorithm. Then they used a model-free asynchronous advantage actor-critic (A3C) reinforcement learning technique to get HO information for each cluster. Lastly, they generate the generalized weights for every cluster on the basis of available information about clusters. In terms of handover rate and throughput, simulated results revealed that the proposed method outperforms the existing techniques.

Various studies have been carried out in recent years to improve handover performance in cellular networks through the use of transfer learning, reinforcement learning, deep neural networks, and other techniques. The approaches summarized in Table 9 demonstrate the effectiveness of using machine learning algorithms in improving handover performance by predicting user mobility, optimizing network parameters, and balancing network load. However, more research is needed to further optimize these techniques and find new ways to improve handover performance in 5G HetNets.

4.6. Spatial Information Aware HO Decision Approaches

As mobile networks are proliferating, fewer communication delays, higher data rates and higher capacities are expected in these networks. However, these factors can be compromised for high-speed scenarios in HetNets and small cells as they will observe frequent handovers and high signalling overheads. Most of these handovers are unwanted or can be avoided if the UE performs better handover decisions. Basic and conventional handover approaches only required signal strength information to perform handovers; however, these approaches can severely affect the handover performance in HetNet scenarios. For example, the conventional systems choose a cell with the highest signal strength as the handover target cell even if its link would be lost within a second after the handover process. Instead, another cell with a lower signal strength but a longer stable link could have prevented the system from frequent handovers. So the use of proactive and conditional handover schemes as shown in Figure 11 can be combined with location-based decision-making procedures to predict more accurate estimation for handovers. In this section, we present a summary of studies that utilize location and trajectory information for handover decision-making. The findings from these studies are presented in tabular form in Table 10.

Table 9. Summary of Handover Decision Approaches based on ML/DL.

Ref. No Year	Criteria of Parameter Selection	HCP's	KPI's	Simulator	Achievement	Algorithm
2022 [170]	RSRP, RSRQ, Cell information, Channel Conditions, Channel Bandwidth				Based on a real-time collection of data, but more information about dataset will be beneficial for understanding	Deep-Mobility an LSTM based approach
2021 [93]	RSRP, SINR	HOM, TTT, CIO	RLF, HOPP	NS-3	Adaption time and user satisfaction rates are only 4.17 % and 416.7% at 5Km/hr, and 33.33% and 187.8% at 30Km/hr respectively as compared to baseline algorithm	TL, RL
2016 [98]	SINR, Cell Load	HOM, TTT, CIO	Cell Load, User Satisfaction, HOPP, HOP, RLF	C++ based LTE Simulator	Adjust the HO configurations autonomously using reinforcement learning for MRO and MLB	Q-Learning, RL
2020 [166]				Python (Keras)	LSTM (RNN) based deep learning model to predict Mobile User trajectory, also used line simplification method to clean data to reduce execution time	LSTM
2021 [167]	UE trajectory data		Location, HO and Processing Cost	Python (Keras)	Based on a real-time dataset for user trajectory prediction and improved the processing cost and transmission cost by 57.14% and 28.01% respectively	VAR-GRU
2019 [168]					Proposed a single-user and multi-user trajectory prediction scheme for future mobile HO management by using LSTM approach	LSTM
2020 [147]	RSRP	TTT, HOM	HO Success rate	Python, MATLAB	Conditional HO (CHO), a deep learning-based scheme that forecast the future target cell with an accuracy of 97.8% for upcoming HO in mmWave scenario	DL
2018 [113]	RSSI, Velocity, Location		Throughput		A Q-Learning model for the prediction of HO in mmWave network by utilizing the RSSI and, Velocity and Location of pedestrian and perform better as compared to existing heuristic handover decision approaches	Q-Learning
2020 [114]			Throughput, No. of Unsatisfied UE	LTE-Sim	A Fuzzy-logic based Q-Learning approach with a load difference algorithm that optimize the load balancing and mobility related issues	Fuzzy Q-Learning
2019 [169]	User Location based on RSSI		Signaling Overhead, Latency, Call Dropping, and Radio Resource Wastage, User dissatisfaction		An analytical model that evaluates the HO cost which includes latency, signaling overhead, call dropping, etc. secondly, a data-driven deep learning-based HO prediction approach that further enhance the HO cost parameters	LSTM
2018 [115]			Throughput, HO rate		Formed two-tier clusters of similar mobility types and get the optimal values for each cluster by using asynchronous advantage actor-critic reinforcement learning technique and lastly, by using available clustering information, the generalized weights produced for every cluster	RL, DL
2022 [103]	RSRP, RSRQ	TTT, HOM	Throughput, PLR, Packet Delay, HOL, HOF, Error Rate	NS-3	Used Kalman filter to compute the best RSRP of serving and neighbor cells and applied SARSA-RL technique to best target cell according to environment characteristics	Kalman filter with SARSA based RL

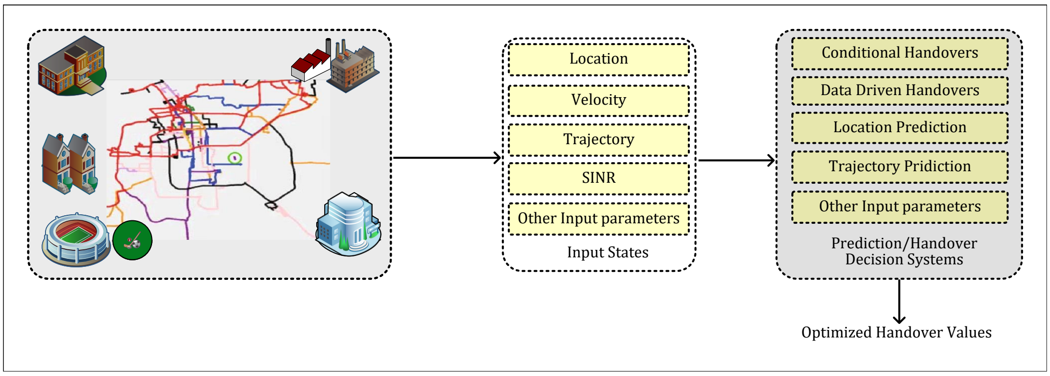

Figure 11. A Basic Illustration of Spatial Information-based Handovers in HetNets.

Table 10. Spatial Information based Handover Decision Approaches.

Ref. No Year	Criteria of Parameter Selection	HCP's	KPI's	Simulator	Achievement	Drawbacks
2017 [121]	UE speed, UE trajectory, UE Location, Cell Location, RSRP	Weight Value	Packet Delay Ratio, Packet Loss Ratio	LTE-Sim	Evaluation of movement direction distance (MDD) algorithm in different dense network scenarios that achieved better results in the form of PDR and PLR by 85% and 60% respectively	For comparison purposes, consideration of HOPP, HOP, RLF, etc. can justify the performance in a much better way
2016 [99]	HOPP, Frequent HO, CDR, CBR, PLR	Quality Indicator Weight	HOPP, CDR, CBR, Unnecessary HO	MATLAB	A Spatio-Temporal Weight estimation approach that reduced the unnecessary HO, HOP and HOPP by 35%, 37% and 17% respectively	
2018 [100]	RSRP, SINR, OP, UE Location	RSRP, SINR, OP	HOPP, No. of HOs, PP Rate		MADM based multi-attribute scheme that considered UE location in a cell which is divided into non-overlapping regions, results in an improvement in the overall throughput	Fixed mobility speed of UE seems impractical for dynamically changing networks also the results show an increase in the average number of HOPP and HOs
2018 [116]	Distance, RSRP, UE Speed, UE Location, Cell Location		PDR, PLR, Throughput, No. of HOs	LTE-Sim	movement direction distance vertical handover (MDD-VHD) scheme reduced the average number of HOs, PDR, PLR, signaling cost by 48%, 91%, 86.2% and 99% respectively in comparison with [171]	For comparison purposes, consideration of HOPP, RLF, etc. can justify the performance in a much better way
2018 [117]	RSRP, UE Location, Cell Location, Cell Load	past values, thresh values for HO	PDR, PLR, Throughput, No. of HOs	LTE-Sim	A new handover procedure that was based on two policies, the moving direction prediction and the historical information of UEs and reduced the average number of HOs, PDR, PLR and signaling cost by 19.5%, 15.6%, 42% and 99% respectively as compared to [172]	
2019 [119]	RSRP, UE Speed, UE Location, Cell Location	distance, trajectory angle	No. of HOs	MATLAB	Use of Lagrange interpolation to calculate the probability of UE transition to its neighbor cell on the basis of the velocity and the slope of the trajectory that reduced the number of HOs upto 30% as compared to the LTE HO approach	Only considered the number of HOs for comparison, must be checked for other parameters

In the article [116,121], a movement, direction and distance-based multi-criteria handover decision algorithm was proposed for femto cells and dense macro cells. The proposed algorithm employed UE speed, distance, UE trajectory, UE location, Cell location and RSRP as input parameters for different handover scenarios. The simulation results were evaluated for packet delay and packet loss in [121] and packet delay, packet loss, throughput and number of HOs in [116] on different cell radius proximities. Too close and too distant from the BS induce HOPP and HOF, respectively, and they related this in the form of packet loss rate. Similarly, in [99], the authors used spatio-temporal information for the handover decision process. For target small cell selection, they considered a number of quality indicators such as packet loss rate, HOPP, call drop and block rate, etc. This approach was intended to reduce unnecessary handovers and HOPP in 5G macro and small Cell mobile networks. They employed Kringing Interpolator with Semivariogram analysis for spatial estimation of the collected values at the first stage. They used a k-order autoregressive model for temporal estimation to get temporal values against each target cell. This temporal estimation aimed to get more stable target cells for the mobility management process. The simulation results were compared with the traditional handover process by considering HOPP, HOF, CDR, CBR and PLR. The authors of [100] proposed a multi-attribute decision making QoS aware handover technique for HetNets. They considered RSRP, co-channel interference and outage probability on the basis of UE location for better target cell selection. They divided the cell coverage area into three regions. On the basis of available values of input parameters, they calculated the weight values by using the analytical hierarchy process (AHP) to acquire handover utility of all the target cells. For analysis, they developed an analytical model as well as a simulation model and performed the comparison based on the number of ping pongs, number of handovers, HOPP and throughput.

In general, humans perform geographically limited periodic movements most of the time, which can be used to extract many useful aspects of movement behaviors. A very basic illustration of the scheme is shown in Figure 11, which shows that by utilizing the periodic and time-oriented movement information, the trajectory of a user can be predicted. Which can enhance the performance of the handover approaches greatly. The authors of [116,121] proposed a movement direction information history handover (MDIH-HD) method in [117] that utilized the concept of historical UE trajectory information and future location prediction for the handover process in LTE-A networks. The basic purpose of this MDIH-HD approach was to enhance the throughput and reduce the cell searching time, number of handovers, packet loss and delay at high speeds. Along with basic signal measurement parameters, they used UE direction, mobility pattern history and target cell load for this scheme. For an expected path, the UE's historical data was utilized, while the moving direction prediction was employed for the random route. They updated the user historical data table based on the moving direction method, whereas the moving direction prediction technique relies on the UE trajectory to estimate the target cell. The selection of the target cell is based on its location, angle, and load capacity. When the UE is close to the handover point, it will choose the target cell by looking at its past. If the UE trajectory does not exist in the history or the target cell's load is full, the user will begin searching for the target cell using the distance and cosine weight function. The simulation results show the improvement in considered parameters as compared to standard approaches. Similarly, in [119], they proposed a UE mobility prediction method for dense networks by using lagrange interpolation approach and calculated the probability of UE transition to its neighbour cell on the basis of the velocity and the slope of the trajectory. They divided the cell coverage into two tiers. No mobility prediction is required in the first tier or closed proximities of BS. However, in the second tier, the mobility or trajectory prediction process will be employed if a user moves away from the BS. They used random way point (RWP) model for random topology generation with the speed and position of the users and applied larange interpolation for the trajectory prediction. Their simulation model checked the accuracy of the trajectory prediction and compared results for the number of unnecessary handovers.

The findings from these studies suggest that the integration of proactive and conditional handover schemes with location-based decision-making procedures can improve the handover performance in high-speed scenarios. The use of UE speed, distance, UE trajectory, UE location, Cell location, RSRP and interference information can greatly enhance the accuracy of handover estimation and reduce unwanted handovers, packet loss, and delay. The concept of historical UE trajectory information and future location prediction, as well as the utilization of mobility prediction methods and spatiotemporal analysis, can further improve the performance of handover approaches in 5G macro and small cell mobile networks. In general, the integration of location and trajectory information in handover decision-making can greatly enhance the performance of handover approaches in HetNets.

5. Open Issues and Future Directions

A lot of work has already been done to address the HO and mobility issues in future mobile networks, but significant work still needs to be done in this area. Handover management is a critical aspect of wireless networks, particularly in 5G dense networks where there is a high density of cells and a large number of devices connecting to the network with dynamic requirements like high-speed mobility, low latency, high reliability and high data rates, etc. Similarly, a lot of emerging technologies such as; wireless augmented reality, gaming, high-definition video streaming, voice and video calling, ITS, V2V, V2X, IoT, HSR, UAV, automated driving vehicles, etc. introduced new challenges in these networks. Research in this area is already focusing on various techniques such as machine learning, deep learning, network slicing, and network virtualization to improve handover management and to make it more efficient and flexible. There are still many open areas to be addressed, such as the need for better prediction algorithms, the need for new protocols to reduce

HOL, HOPP, RLF, the number of handovers, and the need for solutions that can scale to handle the large number of handovers that will be required in 5G small cell dense networks. In this section, we will briefly highlight a few of the key points related to the future research directions.

1. Software Defined Networking (SDN): The implementation of SDN in 5G HetNets aims to address the dynamic and complex nature of various network architectures by centralizing control and management. One of the key focus areas in this context is optimizing the handover process, which is transferring a connection from one network to another, to improve the overall performance and user experience in 5G HetNets. Here are some of the research challenges in the context of SDN-based handover optimization in 5G HetNets:
    - Developing accurate and efficient handover decision algorithms
    - Minimizing handover interruption time
    - Managing network resources during handover
    - Managing the load balance

    SDN can play a key role in addressing the above-mentioned research challenges by providing centralized control and management, which can be used to optimize the handover process and improve the overall performance and reliability of 5G HetNets [165,173–177].
2. Machine Learning: ML-based handovers in 4G/5G HetNets can improve wireless networks' overall performance and efficiency by making more accurate and efficient handover decisions. However, several key research challenges need to be addressed to fully realize the potential of machine learning in this area. These challenges include dataset availability and quality issues, privacy and security, online and offline learning, centralized and distributed learning, frequent handovers, signaling overhead, energy efficiency, and load balancing. These challenges need to be addressed in order to develop accurate and efficient machine learning algorithms for handovers in HetNets and to ensure that these algorithms can handle the complexity and uncertainty of real-world wireless networks [178–182].
3. Deep Learning: DL has been proposed as a solution for handover management in 4G/5G HetNets due to its ability to learn and make predictions from large amounts of data. This can be useful in HetNet environments, where the number of possible network states and configurations is high. Deep learning can be used to predict the likelihood of a handover event, optimize the allocation of resources, improve QoS and QoE, enhance security and privacy, reduce HOL and improve the real-time performance, and make the decision-making process of the handover more transparent and interpretable. Overall, the use of deep learning in handover management in HetNets can enable more intelligent and efficient handover decisions, which can improve the system's performance and enhance the user experience.
4. Dual Connectivity (DC): DC is a technique used in HetNets to improve handover performance. It allows a UE to simultaneously connect to multiple BS's, typically a macro cell and a small cell, and use both connections to transmit data. This improves handover reliability and reduces interruption time during handover, as the device can seamlessly switch between the two connections without losing data. Additionally, it can also increase the overall network capacity, throughput and improve coverage in areas with high user density. However, there are several challenges that need to be considered, such as coordination between different base stations for fast switching during handovers, interference management, mobility, load balancing, security, energy efficiency, and QoS management between different macro cell and small cell users [25].

5. Data-Driven Handovers: In 4G/5G HetNets, data-driven handover approaches are crucial to ensure optimal performance and user experience. Future research will focus on developing new techniques and methods to handle the complexity of these networks, such as dealing with large amounts of data, accommodating high mobility, supporting multiple radio access technologies, adapting to dynamic environments, ensuring security, privacy and interoperability with other technologies. Overall, data-driven handover approaches are an essential aspect of 5G and B5G HetNets research and will have a significant impact on the overall performance and efficiency of these networks.
6. Digital Twins (DT): A digital twin in mobile networks refers to a virtual representation of a physical network infrastructure, such as a mobile device or a cellular network that can be used to simulate and optimize the performance of handovers. By creating a digital twin of a mobile device and the network infrastructure, network operators can test and optimize handover procedures in a simulated environment before deploying them in the actual network. This can help to identify and address potential issues with handovers, such as dropped connections or delays in the transfer process, bottlenecks and plan for capacity upgrades, and can lead to improved network performance and a better user experience. Digital twins can also be used in real-time monitoring, this way it can help to identify when and where handover issues are occurring in the network and take appropriate action to resolve them [183–187]

6. Conclusions

The management of handovers in mobile networks has been recognized as a crucial concern, particularly with the implementation of 5G dense networks and technologies that increase capacity. In this paper, we presented a comprehensive survey of handover mechanisms in mobile HetNets, with a focus on providing a detailed and up-to-date analysis of the current state of handover management. Our survey covers the basic procedures for handovers, the impact of handover control procedures on key performance indicators, self-optimization techniques, and the major challenges faced in handover management. We also categorized current handover algorithms and reviewed evaluation methods for performance.

The goal of this paper was to provide a comprehensive and updated overview of handover management in mobile HetNets, highlighting the current research direction and open problems in the field. Our survey presents a valuable resource for researchers in the area of handover management, offering insights into the state of the art and future directions for research.

In conclusion, this paper provides a valuable resource for researchers working in the field, offering an up-to-date overview of the current state of the art and future directions for research.

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Abbreviations

The following abbreviations are used in this manuscript:

3GPP	Third Generation Partnership Project
A3C	Asynchronous Advantage Actor-Critic
AHP	Analytic Hierarchy Process
AI	Artificial Interlligence
ANR	Automatic Neighbor Relations
APBSO	Adaptive Particle-based Sailfish Optimizer
B5G	Beyond 5G
BS	Base Station
CAPEX/OPEX	Capital expenditures/Operating expenses
CATBoost	Categorical Boosting
CBR	Cell Blocking Ratio
CCO	Coverage and Capacity Optimization
CDR	Cell Dropping Ratio
CIO	Cell Individual Offset
CoMP	Coordinated Multipoint
CRE	Cell Range Expension
CS	Cuckoo Search
D2D	Device-to-Device
DC	Dual Connectivity
DL	Deep Learning
DT	Digital Twins
DTSK-C	deep-Takagi-Sugeno-Kang fuzzy classifier
eICIC	enhanced Inter-Cell Interference Coordination
FLC	Fuzzy Logic Controler
FWA	Fixed Wireless Access
GA	Genetic Algorithm
GWO	Grey Wolf Optimization
H2RDC	Heuristic Handover based on RCC-DTSK-C
HCP	Handover Control Parameters
HetNets	Heterogeneous Networks
HIT	Handover Intrupption Time
HO	Handover
HOF	Handover Failures
HOL	Handover Latency
HOM	Handover Margin
HOPP	Handover Ping Pong
HOR	Handover Rate
HOSR	Handover Success Ratio
HSR	High Speed Railway
ICI	Inter-Cell Interference
ICIC	Inter-Cell Interference Coordination
IMGA	Intelligent Mutation GA
IoT	Internet of Things
IT	Intrupption Time
ITS	Intelligent Transportation Systems
KPI	key performance indicators
LBO	Load Balancing Optimization
LSTM	Long Short-Term Memory
MDIH-HD	Movement Direction Information History Handover
MFO	May-Fly optimization
MIH	Media-Independent Handover
ML	Machine Learning
MLP	Multilayer Perceptron
mmWave	millimeter wave

MRO	Mobility Robustness Optimization
NCL	Neighbor Cell List
OR	Outage Ratio
PLR	Packet Loss Ratio
PMIPv6	Proxy Mobile IPV6
PRB	Physical Resource Balancing
PSO	Particle Swarm Optimization
PSOPC	PSO Passive Congregation
QL	Q-Learning
QoE	Quality of Experience
QoS	Quality of Service
RB	Resource Block
RL	Reinforcement Learning
RLF	Radio Link Failures
RNN	Recurrent Neural Network
RSRP	Reference Signal Received Power
RSRQ	Reference Signal Received Quality
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
RWP	Random Way Point
SARSA	State Action Reward State Action
SDN	Software Defined Networking
SFO	Sail-Fish Optimization
SINR	Signal-to-Interference and Noise Ratio
SON	Self-Optimization Networks
TEHO	Too-Early Handover
TLHO	Too-Late Handover
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TTT	Time-to-Trigger
UAV	Unmanned Air Vehicle
UE	User Equipment
UHO	Unnecessary Handovers
V2V	Vehicle to Vehicle
V2X	Vehicle to Everything
VAR-GRU	Vector Autoregression and Gated Recurrent Unit
XGBoost	eXtreme Gradient Boosting

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