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A B S T R A C T

The need for load balancing will be more significant in fifth generation mobile network and beyond due to the massive upsurge in the quantity of users and rising use of small cell sizes. The load balancing function must be efficiently designed to distribute loads between various cells by moving excess traffic from high-load cells to adjacent inactive cells. The load balancing self-optimization feature is an important function that optimises the handover control parameter by switching some loads in overloaded cells to adjacent cells with fewer loads. This paper has focused on analysing the performance of load balancing self-optimization within fifth generation cellular networks. Also, this paper provides a brief overview about load balancing in 5G and 6G mobile networks and highlighting the sources of issues, technical challenges, some of the suggested solutions and highlighting the research challenges that are needed to be addressed in the second phase of 5G and 6G mobile networks. At the same time highlighting the research that has been conducted in the literature to address these stranding issues. Study also, developing simulation model that can be utilized to study, investigate and analysing LBSO in 5G mobile network with a variety of mobile speed scenarios. The work developed a simulation model that is utilized to study, investigate, and analyse LBSO in 5G mobile networks with a variety of mobile speed scenarios. Optimization algorithms were selected from the literature and validated to ensure their efficiency and functionality with different mobility scenarios, based on the UE condition after each measurement report. The network evaluation and analysis have been conducted in terms of ping-pong handover probability, radio link failure and spectral efficiency. The simulation outcomes explain that the Optimization based on the Distance algorithm demonstrated a noticeable performance enhancement through significantly reduces the PPHP, RLF and SE for different mobile speed scenarios over the entire simulation as compared to the Cost Function and Fuzzy Logic algorithms. These obtained results indicate that the location of user is a significant factor that contributes effectively in optimizing handover control parameters in future mobile networks. Thus, considering the distance as a direct or not direct factor in designing handover Optimization algorithms will contribute effectively in estimating the suitable handover control parameters in mobile networks.

1. Introduction

The emergence of 5G networks is required global mobility management since a large number of spectrum-sharing schemes are adopted as an answer to users' ever-increasing demands for enhanced data traffic. This trend began with the deployment of Heterogeneous Networks (HetNets). Previous standards can give way to a multi-level network where various services coexist, such as vehicle-to-vehicle, device-to-device or large-machine communications [1–3]. Fifth generation (5G) mobile network became a main focus of interest in the last few years. These mobile networks are made up of various cell types (like; femto, pico and macro) to meet various user requests. The key role of 5G mobile network is to improve network performance by increasing data rate, capacity

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Nomenclature

3GPP	3rd Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
6G	Sixth Generation
RAT	radio access technology
AI	Artificial Intelligence
ASO	Automatic Self-Optimization
AWGN	Additive White Gaussian Noise
BS	Base Station
CDF	Cumulative Distribution Function
COR	Call Outage Rate
eMBB	enhanced Mobile Broadband
HCP	Handover Control Parameter
HetNets	Heterogeneous Networks
HO	Handover
SO	Self- Optimization
HOF	Handover Failure
HOM	Handover Margin
HOP	Handover Probability
HPSO	Handover Parameters Self Optimization
ICI	Inter-Cell Interference
IoTs	Internet of Things
LB	Load balancing
LBEF	LB Efficiency Factor
LBO	Load Balancing Optimization
LBSO	Load Balancing Self-Optimization
LTE-A	LTE-Advanced
LTE	Long Term Evolution
mBS	macro-cell BS
ML	Machine Learning
MLB	Mobility Load Balancing
MPCs	Major Performance Criteria's
MRO	mobility robustness optimization
NAS	Non-Access Layer
NCL	Neighboring Cell List
NSA	Non-Standalone
OP	Outage Probability
OT	Outage Time
PPHP	Ping-Pong Handover Probability
QoS	Quality of Service
RFA	Reverse Frequency Allocation
RLF	Radio Link Failure
RSRP	Reference Signal Received Power
RT	Residence Time
SA	Standalone
sBS	small cell BS
SE	Spectral Efficiency
SINR	Signal to Interference plus Noise Ratio
SISO	Single-Input Single-Output
ST	Stay Time
UE	User Equipment
UMLB	Utility-based MLB

and coverage, as shown in the third-generation partnership project (3GPP) [4–6]. A super-dense small cell that includes numerous small cells overlapping macro cells was introduced in the next generation of cellular networks to enhance coverage and user experiences [7–9]. Initially, 5G networks are deployed alongside the existing fourth generation (4G) networks. The first stage of 5G service introduction began as non-standalone (NSA). 5G standalone (SA) can be implemented once 5G coverage is fully established. 5G network implementation sometimes interferes with the 4G network, creating mobility problems when moving utilizers from one base station (BS) to another [10–13]. The small cell represents an essential part of the 5G mobile network since it supports the expected data demand and improves network capacity. The primary goal behind the design of small cells is to expand service coverage within macro-cells. Small cells can be deployed in various densities to greatly increase wireless network capacity [14–16]. Thus, future networks may take over small cells technology to support growing demands for more data. The deployment of small cells is introduced to support services that entail high data rates as well as to expand the coverage of macro cells for 5G networks [17–19].

The load balancing optimization (LBO) function adaptively adjusts the settings of handover control parameter (HCP) to achieve balance uneven loads between adjacent cells. The load balancing (LB) function is needed when the coverage of two cells overlaps, when the coverage of two hierarchical cells overlaps or when the coverage of adjacent cells overlaps. If the loads between two different cells are imbalanced, the LBO algorithm/technique enables the corresponding cell to adjust the HCP settings. This is achieved to handover (HO) the user equipment (UE) at the edge of cell to an available cell with more resources and less payload. The LBO algorithm initially monitors the cell loads and later exchanges of relevant information inside neighboring gNBs. It then indicates whether the load of each cell is low, medium, high or overburdened according to this information. The gNB serving the appropriate target cell is determined according to the load index. The LBO algorithm is enabled once the service cell is overloaded or when the specified target cell pregnancy is less than or equal to the mean pregnancy. The LBO algorithm can't be enabled when the service cell load does not arrive to the overload level. Although this functionality is generally provided to contribute for solving the issues of mobility, more efficiency LBO algorithms are still needed [1,2,20–22]. Thus, the main purpose of optimizing load balancing in the self-Optimization functions is to solve the congestion problem by distributing cell load equally among cells. This equal distribution can be done by adjusting the HCPs to take HO actions. The LBO with an adaptive cell can enhance the system capacity. Also, optimizing load balance helps the network management minimize human intervention and avoid cell congestion. Three optional support sub functions of LBO are controlled by the operation and maintenance (O&M) system; namely, load reporting, adapting HO, and load balancing action based on HOs. One more subfunctions can be implemented, depending on an operator strategy [23,24].

In 5G and six generation (6G) mobile networks there are several potential sources that can cause load imbalance between cells in 5G mobile networks. As some of these examples: (i) A massive growth of connected users can be a critical issue for rising the issues related to load balancing in 5G and 6G mobile networks. As the number of users increases, the demand on the network infrastructure and servers also increases, which can lead to performance issues, downtime, and other problems. (ii) Uneven user distribution: If users are not evenly distributed across cells, it can cause some cells to become overloaded while others remain underutilized. This can happen if users are concentrated in specific areas or if there are certain cells that have better coverage or signal quality. (iii) Resource allocation: In a 5G mobile network, resources such as bandwidth and processing power are shared among cells. If resources are not allocated efficiently, it can cause some cells to become overloaded while others remain underutilized. (iv) Mobility: As users move around within the network, their devices may switch between different cells. If the handover process between cells is not optimized, it can cause load imbalances and impact network performance. (v) Interference: Interference from other devices or networks can also impact the performance of individual cells and cause load imbalances. These sources of issues causing potential problems that can arises more in 5G and 6G mobile networks. For example, (i) *complexity*; (ii) *Single point of failure*; (iii) Overload: In some cases; and (iv) Security. Overall, load balancing can be an effective way to improve performance and reliability, but it requires careful planning, configuration, and management to avoid potential problems.

To address these sources of load imbalance, 5G mobile networks employ various load balancing techniques. These techniques include: (i) Cell range expansion: This involves adjusting the coverage area of cells to balance user distribution and avoid overloading. (ii) Load-based resource allocation: This involves dynamically adjusting resource allocation based on current traffic and usage patterns to avoid overloading. (iii) Mobility-aware handover: This involves optimizing the handover process between cells to ensure that users are connected to the best available cell based on their location and usage patterns. (iv) Interference management: This involves using advanced techniques such as beamforming and interference cancellation to reduce the impact of interference on network performance. Generally, load balancing is an important issue in 5G mobile networks, and it requires careful planning, configuration, and management to ensure that the network can handle the demands of a large and dynamic user base.

There are indeed several studies that have been conducted to address load balancing issues in 4G and 5G mobile networks [1,14,25–56]. This article discusses LB in various mobile networks, which is crucial for optimizing network performance and efficient resource utilization. LB can be achieved through software-defined networking (SDN) that separates the control plane from the data plane and dynamically controls network behavior through a centralized controller. The article highlights several LB algorithms that have been proposed to balance loads between cells more efficiently. These include mobility load balancing (MLB), utility-based MLB (UMLB), and HO LB method for HetNets. The article also suggests that reducing the number of handover target cells is a better strategy for reducing signal overload caused by user mobility in small cells. Furthermore, the article addresses the issue of load imbalance between small and macro cells, which is addressed by providing insights for the standardization of HetNets. The analysis and results suggest that a combination of signal strength, signal to interference plus noise ratio (SINR), and cell loads is needed to maximize cell coverage and system capacity while minimizing load imbalance between small and macro cells. Other proposed methods include using location information for LB mechanisms to temporarily reduce HO or contact blocking rates in overloaded serving cells by adjusting the coverage area. Although various studies have been conducted in the literature, the load balancing still a challenge that need to be studied and investigated further, especially with the major changes in 5G and 6G mobile networks specifications, emerging technologies, and characterizations. This requires ongoing research and development efforts by industry experts and academics to address emerging challenges and explore new approaches and solutions.

This study explores load balancing in 5G mobile networks and develops a simulation model to analyze the performance of load balancing handover control in different scenarios using various algorithms, including Distance, Cost Function, and Fuzzy Logic. The algorithms are evaluated and compared in terms of ping-pong handover probability (PPHP), radio link failure (RLF), and spectral efficiency (SE), and the Distance algorithm shows a noticeable performance enhancement compared to the other algorithms. However, the study has limitations in investigating more efficient algorithms and proposes the use of machine and deep learning for further enhancements. The future work will focus on developing more enhanced algorithms based on Machine/Deep learning technology and considering additional key performance indicators with various deployment and mobility speed scenarios to address handover self-optimization issues.

Thus, the main contributions can be sum up in this paper as follows:

Provide a brief overview about LB in 5G mobile networks and highlighting the sources of issues, technical challenges and some of the suggested solutions. At the same time highlighting the research that has been conducted in the literature to address these stranding issues.

Developing a simulation model that can be utilized to study, investigate, and analyze load balancing self-optimization (LBSO) in 5G mobile networks with a variety of mobile speed scenarios.

Optimization algorithms were selected from the literature and validated to ensure their efficiency and functionality with different mobility scenarios, based on the UE condition.

In 5G, SON algorithms can analyze network performance data, identify areas that require improvement, and make automatic adjustments to optimize network parameters.

SON also allows the network to adapt to changing network conditions and traffic patterns, improving service quality and reducing the need for manual intervention. This helps network operators to reduce operational costs, improve network efficiency, and provide better user experiences.

SON can optimize various network parameters such as signal strength, bandwidth allocation, interference management, and handover procedures. For example:

Coverage and Capacity Optimization: SON algorithms continuously monitor the network performance and adjust parameters to optimize coverage and capacity, providing better service to users.

Interference Management Self-Optimization: SON can mitigate interference between network elements by adjusting transmission power, resource allocation, and other parameters. This function ensures that users receive a stable and reliable connection, reducing dropped calls and improving the user experience.

Energy Saving: SON algorithms optimize energy consumption by adjusting the power levels of network elements based on network traffic and usage patterns, reducing operational costs.

Mobility Robustness Optimization: SON algorithms optimize the handover procedures between cells to minimize dropped calls and improve the quality of service for users on the move.

Load Balancing Self-Optimization: Under SON there is one algorithm known as LBSO function, which is a function that balance the load between cells to avoid network congestion and ensure optimal user experience.

In summary, SON in 5G is a technology that enables automated network optimization using AI and ML techniques, resulting in improved network performance, QoS, and user experience. For that, SON in 5G enables a more efficient and intelligent network that can adapt to changing network conditions and user behavior.

2. Concept of load balancing optimization (LBO) function

The LBO function adaptively adjusts the settings of HCP to achieve balance uneven loads between adjacent cells. The LB function is needed when the coverage of two cells overlaps, when the coverage of two hierarchical cells overlaps or when the coverage of adjacent cells overlaps. If the loads between two different cells are imbalanced, the LBO algorithm/technique enables the corresponding cell to adjust the HCP settings. This is achieved to hand over the UE at the edge of cell to an available cell with more resources and less payload. The LBO algorithm initially monitors the cell loads and later exchanges of relevant information inside neighboring gNBs. It then indicates whether the load of each cell is low, medium, high or overburdened according to this information. The gNB serving the appropriate target cell is determined according to the load index. The LBO algorithm is enabled once the service cell is overloaded or when the specified target cell pregnancy is less than or equal to the mean pregnancy. The LBO algorithm can't be enabled when the service cell load does not arrive to the overload level. Although this functionality is mostly provided to contribute for solving the issues of mobility, more efficient LBO algorithms are still needed [1,2,20–22].

Thus, the main purpose of optimizing load balancing in the self-Optimization functions is to solve the congestion problem by distributing cell load equally among cells. This equal distribution can be done by adjusting the HCPs to take HO actions. The LBO with an adaptive cell can enhance the system capacity. Also, optimizing load balance helps the network management minimize human intervention and avoid cell congestion. Three optional support sub functions of LBO are controlled by the operation and maintenance (O&M) system; namely, load reporting, adapting HO, and load balancing action based on HOs. One more sub-functions can be implemented, depending on an operator strategy. Fig. 1 displays the functional architecture of LBO [23,24].

LBO consists of a series of related functions, which can be explained as follows:

(a) Load Reporting

This function aims to exchange the cell load information among neighbor cells. Such exchange can be executed over the X2 and S2 interfaces for intra-long-term evolution (intra-LTE) and inter-radio access technology (inter-RAT) scenarios, respectively. For the former, the load information consists of three main categories:

- Use of radio resource;
- Load indicator that specifies the cell weight (i.e., low, medium, high, or overload); and.
- Capacity value refers to the available cell capacity for LB.

The value of cell capacity class is set by the O&M system that is used to weigh and compare the capacities of different radio access technologies (RATs). However, the latter only implements the capacity value, which refers to the available cell capacity for LB.

(b) Load Balancing

Working on the basis of HO, the load balancing action based on HO occurs when a serving cell initiates HO due to cell load. Admission control for the load balancing HO is performed by the target cell. The admission control for HO action is different from other HO cases aforementioned in mobility robustness optimization (MRO).

(c) Adapting Handover Configuration

One of the important functions, as part of the LB execution, is to adapt the HO configuration function to allow the request to change and/or redefine HO parameters in the target cell. The target cell is informed of the new mobility settings by the source cell, which provides a reason for that change (such as a demand for LB) and the proposed change is expressed through various current and new values of the HO operator. However, the change of HO parameters or mobility configuration for the serving/target cell is done by the serving cell that initialized the LB estimation. The serving cell initializes the HO procedure toward the target cell if HO parameters are required to be adjusted. Consequently, it notifies the target cell of the new setting of the HO configuration and then prepares for the change of radio link. The serving cell must consider the responses before implementing the strategic change in the setting of mobility [51,57,58].

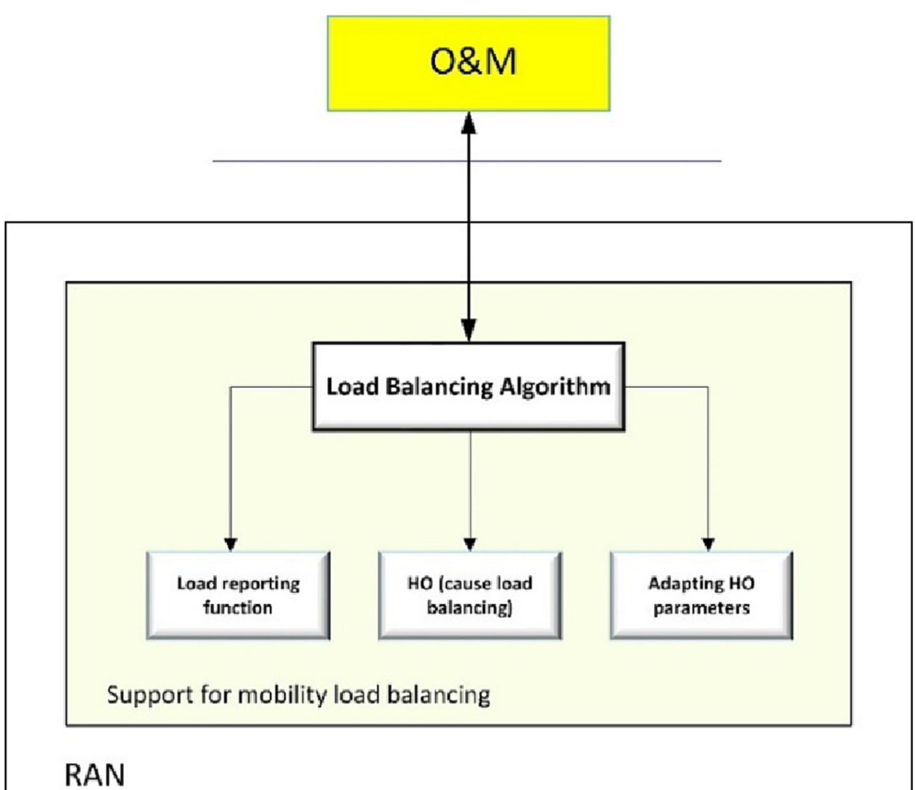


Fig. 1. Load Balancing Optimization.

Due to the large variation in cell sizes with different transmission powers, the classical HO process (which only depends on measurements) will cause an unbearable increase of excessive HOs in the network. One significant challenge concerning the future ultra-dense networks is the load imbalance between small and macro cells, mainly produced from the discrepancy in received power between small and macro cells. This leads to the poor utilisation of system capacity [50,59–61].

The HO process and related issues will degrade mobile connection, stability and reliability of connection throughout UE mobility. To address these problems, there is a need for mobility protocols with highly efficient and robust. Fig. 2 provides an example of the HO scenario in 5G mobile network which contains horizontal and vertical HOs where the active UE is delivered from one BS to another by many of gNBs. The multiple radio access technology is suitable for 5G mobile network since it requires smart technology to establish a seamless connection. An effective HO algorithm can support the continuity of the service and improve QoS without any service interruptions. HO decision algorithm, which is part of HO procedures, is essential process to design effective LBSO techniques. HO decision algorithm is taken based on some specific HCPs setting, which are significant for speeding or delaying the initiation of handover procedure. These HCPs settings are the main work in this research. They are optimized in order to balance the loads between adjacent cells. There are various algorithms have been developed in the literature based on different methods to optimize HCPs settings in order to balancing loads between cells.

The key issue with the deployment of future 5G mobile network is use of millimeter waves (mm-wave) bands as this leaded to decrease the provided coverage. That in turn leads to raise the handover probability (HOP), in which leads to impact the system performance through the mobility of UEs. Moreover, most of the current solutions had been developed for 4G networks, which are totally different in terms of provided coverage, system specification and technology requirements. This is why the current solutions proposed for 4G are not that efficient to tackle them. Moreover, one of key requirement for 5G system is to support high mobility speed scenario, which can reach up to 500 km/h, this is also an addition issue that causes a high rate of HOP, PPHP and RLF. Also, the system performance is consequently degraded due to the use of high frequency bands in 5G mobile networks, this will also lead to rise the call outage rate (COR) and long outage time (OT). These problems must be resolved to ensure that next generation networks provide seamless connection through user mobility in various deployment scenarios [62–64]. Previous studies have specified causes that may cause handover failure (HOF) as well as the restrictions of available HOF solutions. LB solutions are proposed for 4G, third generation (3G), and even second generation (2G) of mobile systems; however, they will not be completely effective in 5G and 6G networks. The LBSO problem in 5G mobile network must be extensively addressed and resolved. New solutions are needed to effectively design future systems that feature the specifications and requirements of more advanced networks.

2.1. Key factors rising challenges in load balancing

LBSO techniques in 5G mobile networks are a relatively hot area of research, and there is still much that is not fully understood. LBSO techniques play a critical role in ensuring the efficient operation of 5G mobile networks. However, the existing challenges can have a significant impact on the performance of LBSO techniques. LBSO techniques in 5G mobile networks face several challenges that can impact their performance. Some of these challenges include:

Heterogeneity of devices: With the proliferation of various devices, such as smartphones, tablets, laptops, and internet of things (IoT) devices, the number of heterogeneous devices accessing the network increases, making it difficult to balance the load across the network.

Network densification: 5G networks require a high density of small cells, leading to an increase in network complexity, which may affect the effectiveness of load balancing algorithms.

Scalability: With the increase in the number of users and devices, the load balancing algorithm must be scalable to handle the increased traffic demand.

Mobility management: 5G networks need to manage the mobility of users seamlessly, which can pose a challenge to load balancing algorithms as they need to take into account the user's location and movement patterns.

Energy Efficiency: Load balancing algorithms should be energy-efficient, considering the power consumption of the network elements, especially in the case of small cells that may have limited power resources.

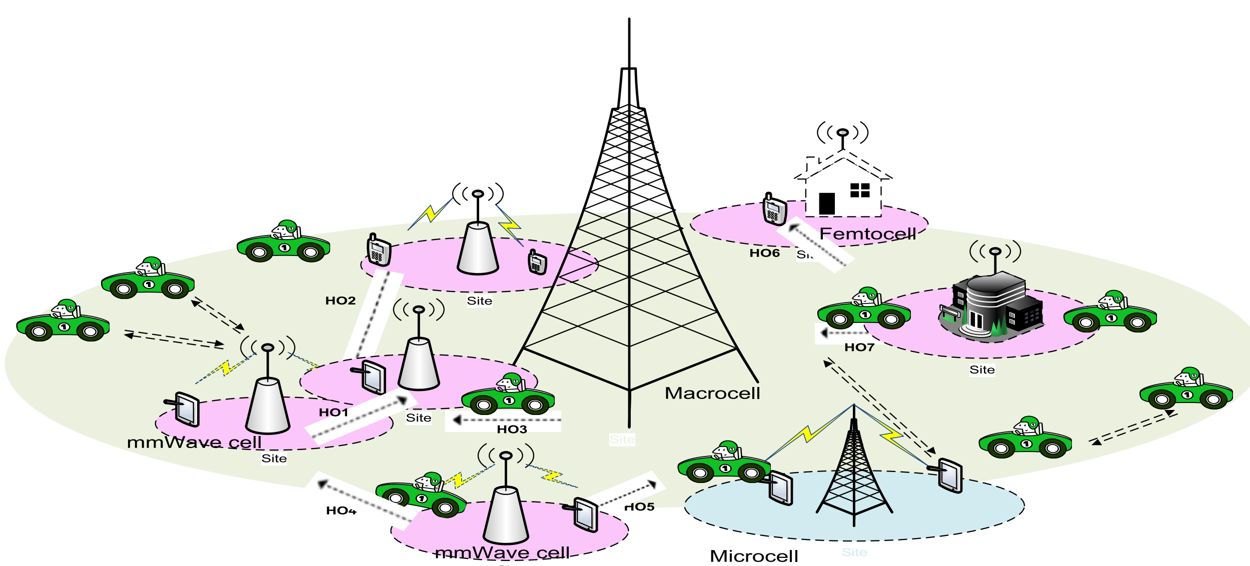


Fig. 2. The handover concept and some handover scenarios in future HetNets with the existing of 5G networks.

Quality of Service (QoS) Requirements: Different applications and services have varying QoS requirements, such as throughput, latency, and packet loss. LBSO techniques need to take these requirements into account when balancing the network load to ensure that the QoS requirements of all users are met.

Dynamic Network Conditions: 5G networks are subject to various dynamic network conditions, such as channel fading, interference, and congestion. LBSO techniques must be able to adapt to these changing conditions in real-time to maintain optimal network performance.

Security and privacy concerns: With the increasing number of devices and users accessing the network, security and privacy concerns are becoming more critical. LBSO techniques must ensure that user data and communications are protected while balancing the network load.

Resource Constraints: 5G networks have limited resources, such as bandwidth, processing power, and memory. LBSO techniques must be able to balance the network load while optimizing the use of these resources to ensure efficient network operation.

Overall, addressing these challenges is crucial to developing effective LBSO techniques that can optimize network performance and meet the diverse requirements of 5G networks.

3. Relevant studies

A major challenge in wireless networks is user mobility in small cells due to the presence of thousands of target cells [25]. Reducing the HO target cells number is therefore a better strategy for decreasing signal overload. LB in 5G networks is particularly important due to the high-speed and low-latency requirements of applications such as streaming video, virtual reality, and cloud computing. It is a significant function in mobile networks, as it can help to optimize network performance and ensure that resources are used more efficiently.

SDN can be used to balance loads between cells in 5G networks. SDN is a networking method that can separates the control plane from the data plane. Control plane manages network traffic, while data plane carries the traffic. The control plane is managed by software, which allows network administrators to dynamically and programmatically control network behavior through a centralized controller. But to the best of our knowledge, the SDN also need to have more advanced algorithm that can perform the Optimization. Furthermore, mobility robustness and balancing load self-Optimization functions have been introduced in 4G and 5G networks to deal with balancing loads by optimizing the handover control parameters. There are several research works have been conducted in the literature to balancing the loads between cells more efficiently.

The authors in [26] were the first to show the efficacy of simple LB algorithms using simulations. The rate of call blocking decreased, and the throughput at the cell edge increased according to the automatic tuning of delivery parameters.

LB is implemented in 5G mobile network and various new mobile networks by the dynamic optimization of the data splitting ratio's utility function among multiple access networks, regardless of application type or the QoS required [27,28].

The authors in [29] suggested self-optimization which uses the mobility load balancing (MLB) status by 3GPP to switch UEs connections from cells that have overload to adjacent cells that have lower load to improve the overall QoS and network gain capacity. Both researchers and industry players have suggested several technologies for MLB application [30–32]. These technologies adjust network parameters to achieve the best configuration for reducing congestion in open air [33,34].

The authors in [35] provided location information for LB mechanisms to temporarily reduce HOs or contact blocking rates in overloaded serving cells through adjusting the coverage area. Other studies [36–39] have applied user location to enhance the self-optimization mechanism and reduce costs without using the MLB case.

Reference [40] suggested the Utility-based MLB (UMLB) and LB efficiency factor (LBEF). The UMLB algorithm takes into account the utility of the operator and utilizer tool for the MLB-based HO process, while LBEF proposes to correctly arrange the loaded cells for the MLB algorithm process. The simulation outcomes show that UMLB decreases the standard deviation at a higher rate for the UE data rate comparison with the current LB algorithms, thus achieving a balanced network.

Reference [41] introduced a traceable analytical network model that mitigates Inter-Cell Interference (ICI) by using a reverse frequency assignment scheme alongside user correlation based on cell scale expansion. In this suggested model, researchers analysed the coverage probability and rate user for the combined impact of reverse frequency allocation (RFA) and LB in 5G mobile network, with and without the deployment of selective small cell BSs (sBS). From the numerical results, it is evident that improvement in coverage and user rate, with the use of RFA, attenuates the ICI of the conventional macro-cell BS (mBS) for discharged utilizers. It was further noticed that if CRE is enhanced through the RFA scheme, it can efficiently improve the modifier execution. Selective sBS diffusion can greatly enhance the coverage and user rate without any additional resource cost.

The issues of load imbalance between small and macro cells as well as poor resource management due to super-dense HetNets have been addressed in [42]. An unavoidable approach is to address the capacity crisis in cellular networks by providing a solution to maximize cell coverage and system capacity while minimize load imbalance between small and macro cells. In this work, the analysis and results provided design insights for the standardization of HetNets, like the need to switch from the central signal strength of a conventional macro cell's, or SINR which focuses on user association and cellular network optimization, to a combination of SINR, signal strength and cell loads.

Reference [43] proposed a new method of internal HO for the purpose of LB to improve the throughput of HetNets. The interference effect of both macro and small cell BSs was considered. The load used from the crowded cell is unloaded and forced to HO to the small cell to provide good data rate. This is accomplished by selecting the best small cell that has the maximum SINR from the low Neighboring Cell List (NCL). NCL is optimized with the SINR threshold and Residence Time (RT), however, the suggested method uses HO initiation event adjustment while considering interference and cell load. The simulation outcomes indicate that the suggested method can perform HO while keep good throughput levels. It also greatly reduces HOs of inter-small cells and radio link failures compared to current methods. The outcomes of load factors and call access rates explain that the suggested method can dramatically provide enhanced performance under various network conditions, thus producing higher user and network throughput.

In [44], the authors suggested the HO LB method for HetNets, forcing UEs to perform HO for small cells when their velocity is low and small cell capacity is available. These UEs equipment are generally allowed to temporarily connect to macro cells if small cell capacity is insufficient for reducing the HO failure. Fast-moving UEs are also related to the macro cell. This method is ineffective if propagated into dense, small cell networks, which may lead to deploy a huge number of small cells in NCL, excessive amounts of unnecessary HOs and signal overheads.

Reference [45] presented the HO method for LB where the predicted stay time (ST) effect and interference are used to investigate the discharge from micro-cells to small-cells. The HOM is derived based on the source cell load for performing the traffic dump. The outcomes detected that this technique decreased unnecessary repeated HO and the probability of failure, as well as improved throughput.

LB has been analyzed in [46–48] for systems with distributed BSs using random simulation, in accordance with 3GPP specifications. Several criteria based on biased received energy have been suggested to control the number of utilizers connected to low-power BS operations [14,49]. These works compared various BS correlation rules using tools of random geometry (such as maximum SINR, the highest received power, biased SINR-based cell selection, and the closest BS) that impact the distribution of downlink SINR and the achieved average rate [1,46,48]. Shadowing also has an important outcome on the system performance of HetNets, however, it was not considered in [27,28,50]. This may be due to the complexity of the mathematical solution.

The authors in [51] examine the influence of various HCPs settings on 5G mobile network execution through suggesting and investigating several system scenarios based on various mobile speed scenarios. The simulation outcomes show that there is a trade-off in the outcomes gained from different systems, where using lower HCP settings gives a significant disadvantage by rising the PPHP rate more as compared with the higher HCP settings. At the same time, using lesser HCP settings delivers notable improvements compared to higher HCP settings regarding of RLF for all mobile speed scenarios. Consequently, this study confirms that implementing automatic self-optimization (ASO) functions as the better solution that takes into account the user experience in the case of implementing one of these systems.

In [52], the authors propose a fuzzy logic (FL)-based HO scheme for adjusting two HO parameters values dynamically in relation to every UE unit, which includes handover margin (HOM) and time to trigger (TTT). This proposed algorithm which has dynamic adjustment of both TTT and HOM will use two inputs for the FL controller, namely; SINR and the horizontal movement speed of the UE. Simulation outcomes show that the propose algorithm improves the performance of HO for 5G ultra-dense networks (UDNs) based on number of HOs, total system throughput, and the PPHP ratio when comparison with the conventional HO system and the FL-based HO scheme with only dynamic HOM adjustment.

The authors in [53] propose a self-optimizing fuzzy-coordinated H0 scheme for the HetNets networks (4G/5G) for achieving the seamless HO through transition the users in multiple wireless access networks. The proposed scheme solves the conflict between MRO and LBO functions through using three input parameters of fuzzy system considering, which includes; load of cell, SINR, and UE speed, to estimate independently the HCPs for every utilizer. The simulation outcomes exhibit that the proposed scheme reduces the complex relationship between the LBO and MRO functions, which provides a smooth HO in the internal RAT networks. Furthermore, it shows best performance evaluation with respect of spectral efficiency for cell edge, outage probability, and HO latency. These results indicates that the input parameters considered and approach of coordination are necessary to design smart HO schemes for dense urban HetNets to enhance the performance of overall network during move the utilizers amongst cells.

In [54], the authors propose algorithm for optimized HO decision through use a Machine Learning (ML) technique to enhance the procedures of HO and improve QoS in 5G HetNets. The ML technique proposed will monitor the reference signal received power (RSRP), active time, UE velocity, and available radio resources to ensure effective HO decisions. Therefore, the proposed algorithm reduces the recurrent effects of HOs and PPHP through improving the HO actions. The simulation results explain that the proposed algorithm achieves best outcomes through applying a supervised ML approach with respect to efficiency and throughput compared to the existing methods.

Ref. [55] suggests algorithm of individual dynamic HO parameter Optimization depends on automatic weighing function (AWF) for the 5G network. The proposed algorithm estimates HCPs settings dynamically for every individual UE depends on UE trials, where it is based on three finite functions and their levels of automatic weights. The algorithm is validated across different 5G network mobility conditions, and performance evaluation comparisons are made with respect of HOP, RLF, PPHP, and RSRP. The simulation outcomes demonstrate that the suggested algorithm provides remarkable improvements for different scenarios of mobile phone velocity when comparison with the existing HPSO algorithms.

In Ref. [56] the authors suggest learning-based intelligent mobility management (MM) which bases on online learning mechanism to MM in 5G and beyond, with smart adaptation of the values of TTT and hysteresis. Learning-based intelligence (MM) utilizes a Kalman filter for prediction the quality of future signal for the cells which subjects to the serving and neighborhood. In this method the target cell for the HO is selected by utilizing the reinforcement learning based on state-action-reward-state-action, and it adapts with the TTT and hysteresis. The proposed algorithm has been extensively analyzed, where it has been observed that this algorithm can significantly enhance the HO process in high-speed mobility scenarios.

Although various Load Balancing algorithms have been proposed, but no optimal algorithms exist that can solve the issues optimally. Therefore, this paper aims to study the load balancing function and investigating various models from the literature over 5G mobile network. LBSO performance is examined and verified using different system setting and mobile speed scenarios.

4. System and simulation model

The considered 5G mobile network framework is utilized to evaluate the investigated algorithm with various mobility speed scenarios. In this work, the considered network architecture consists of multiple 5G small cells based on 3GPP Rel.16. The small cells are unilaterally distributed in a uniform hexagonal deployment. Furthermore, in this simulation model all the deployed small cells in our simulation are assumed to be active. This simulation is system level model developed to study mobility management in 5G mobile networks with high frequency bands. This network has been designed according to the Long Term Evolution (LTE)-Advanced Pro 3GPP Rel. 16 specifications, as demonstrated in [10,25,65–70].

4.1. Network deployment scenario

The simulation model has been developed with the assuming that the network environment will be micro small cells deployed in urban areas. The planned cellular network is a hexagonal grid. Fig. 3 illustrates an example of the hexagonal cells' deployment scenario utilized in this paper. The single hexagonal cell represents one micro small cell with cell radius (R). Each single hexagonal cell has one 5G gNB allocated at the centre of the cell with three sectors antenna design. The hexagonal cell number can also be incremented automatically on the basis of time interval determinant in the simulation. As illustrated in Fig. 4 the measured mobile users will move in one direction. This is useful to avoid the west of time of considering random mobility model. Thus, when the simulation time is increased, mobile user will move to a far distance. In this

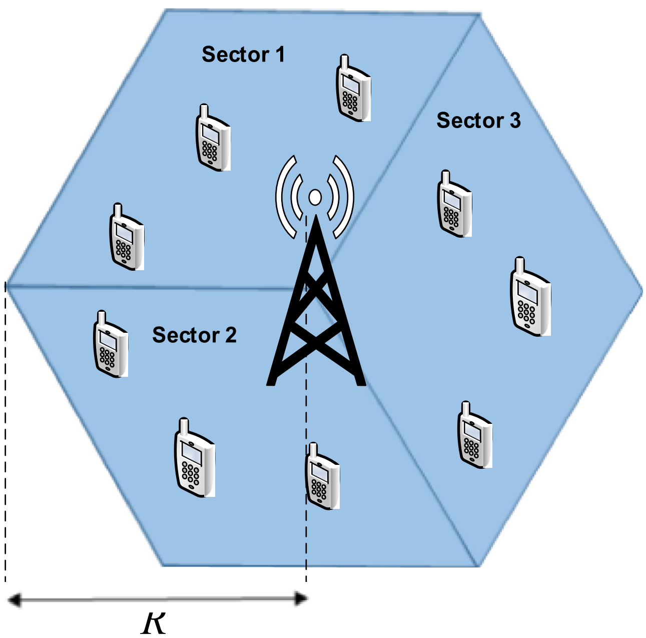


Fig. 3. The deployed hexagonal cell in 5G mobile network model.

case we enable the simulation to extend the simulation area by adding more hexagonal cell in the side of where mobile users are heading to it. This consideration will ensure that the mobile users are moving in area that covered by 5G mobile networks during all simulation time.

4.2. Mobile users

A number of mobile users have been generated with random distribution inside each hexagonal cell boundaries. In the beginning, 200 users were generated and distributed randomly within every hexagonal cell during the simulation periods. Users are generated randomly around the center of each cell with random distribution inside the cell. In other words, the random locations of each UEs are determined randomly around the center of each cell. The distribution is restricted to be inside the cell boundary. This controlled by using the cell radius as maximum range for the distribution. The mobile number is changed randomly and frequently in every cell. This means that the traffic for every gNB automatically

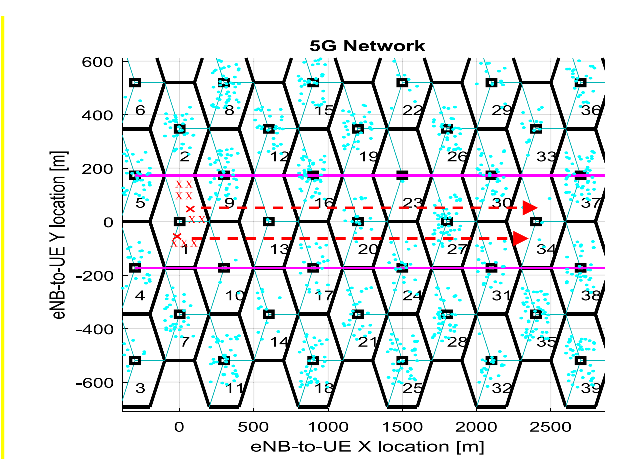


Fig. 4. Mobility model in the deployed mobile network.

and regularly changes from time to time to characterize the environment of actual network. This was taken into consideration in the development of the simulation model to imitate the load traffic random generation and to enable the full acceptance of control function in the target cell while the user is on the mobility. The number of UEs in each cell will be change from time to time randomly. This chance will not impact the number of 15 users that are generated to be utilized for measuring the performance of the networks. It is only for the users that are generated in each cell to simulate the change of traffic in the recall networks. This is considered to simulate the change of connected mobile users in real networks.

4.3. Antenna gain

Every mobile user was equipped with a multi-directional antenna to enable communication with the service network. For each antenna, the radiation pattern corresponds to that explained in 3GPP, and mathematically represented as follows [44,71–73]:

$$\Re(\phi) = -\min\left[12\left(\frac{\phi}{\phi_{3dB}}\right)^2, \Re_n\right] \tag{1}$$

where $-180 \leq \phi \leq 180$ and $\Re(\phi)$ is the antenna gain (dBi) in the direction of $\phi\theta$, which signifying the angle between the antenna steering direction and the interest direction. ϕ_{3dB} refers to 3 dB beam width which coincides to 65 degrees and $\Re_n$ indicates the maximum loss of attenuation (20 dB) that can be resulted, with three sectors in every cell.

4.4. Path loss model

In regard to the path loss model, it is considered on the basis of 3GPP specification for Rel.16. Accordingly, the path loss model is represented by the following Eq. [74]:

$$L = 58.8 + 37.6\log_{10}(R) + 21\log_{10}(f_c) \tag{2}$$

where L indicates the path loss model, R is the cell radius in (m), f_c is the operating frequency band in (GHz). Also, in regard to the thermal noise power, it is considered based on the 3GPP specification for Rel.16. Accordingly, the thermal noise power is expressed as follows [74]:

$$\aleph_t = \aleph_w + 10\log\left(10^6 \times B\right) \tag{3}$$

where, $\aleph_t$ is the thermal noise power in (dB),$\aleph_w$ is the white noise power density in (dBm/Hz) and B is the system bandwidth in (MHz).

4.5. Mobility speed scenarios

In regard to the mobility speed, six different UE speeds were considered and examined in this simulation study. The speeds ranged between 40 km/h to 140 km/h, with 20 km/h increases. They represent the vehicle velocity characteristics of urban and suburban areas and thus acceptable for theoretical inquests. The velocities of all measured UEs have been assigned deterministically at the biggening of simulation to ensure that all UEs are utilizing the same velocities. This is very significant to make sure all systems are investigated under the same conditions with the same mobility scenarios. This will lead to have fair comparison in the system performance of these investigated systems.

4.6. Mobility model scenario

A directional mobility model has been proposed for all mobile phone UEs measured over the network. This represents the mobility model used in the simulation system. It allows mobile phone users to move in one direction range only, as illustrated in Fig. 4. All the measured mobile users will move in one direction only. This is considered as an advantage as compared to the random mobility model. This is because the random mobility model allows the users to move in eight directions at each iteration in the simulation. This may lead to keep the users move in the same locations, which is not recommended. Therefore, we consider a directional mobility model in this simulation.

4.7. Handover decision technique

HOM is generally involved to the RSRP level to initiate the HO decision algorithm, representing the further applied algorithms utilized for the HO decision [74,75]. Therefore, the HO decision algorithm is introduced when the service RSRP (RSRPs) is bigger than the summation of HOM and the target RSRP (RSRPt), mathematically provided as:

$$RSRP_s > (HOM + RSRP_t) \tag{4}$$

This is the HO decision process, which is taken based on the RSRP of the serving and target cell with a marginal level defined automatically or manually. This is the most usable and traditional HO decision process employed in LTE and LTE-Advanced (LTE-A) systems, respectively [76,77]. The average rates of PPHP, RSRP, HOP and RLF are computed for every simulation cycle, and the outcomes are the mean values of all 15 UEs.

4.8. System simulation parameters

Table 1 presents the presumptions of all parameter settings defined in the 3GPP specification (Rel. 16) that have been considered in the system simulations.

The signal's path losses have been estimated from this matrix distance, as well as the Rayleigh fading (model of fast fading) and log-normal shadowing (model of shadow fading). The assumed Gaussian-distributed random variable of zero mean and σ standard deviation is equal to 8 dB in multipath scenarios. We then compute the RSRP and SINR recognized by all UEs on each received carrier signal. Through simulation, every gNB in the network updates the rate report of Ping-Pong and RLF. The gNB further updates the load report and then sends the information of load to another gNB in the network. From the aspect of UE, the average BSRP and SINR are measured across the carrier by each UE and sent to a competent gNB for the optimization process. The gNB selects the modulation and coding scheme based on the received RSRP and SINR measurement reports [79], and the self-improvement process is then implemented. After completing the Self- optimization (SO) process, the gNB providing the service implements the HO decision based on the measurement report and the estimated HCPs by applying the sequence of the HO procedure in 3GPP [80,81]. If the gNB service provides satisfying signal quality, the connection with the UE will be preserved.

Table 1
System simulation parameters [74–78].

Network Parameters	Presumptions
Environment	Small micro cells, gNB Urban Area Small cells based on 5G Rel.16 System
No. of small micro cells	65
No. of sectors in each Cell	3
Height of gNBs antenna	15 m
Small Cell Radius R	200 m
f_c for 5G Cell	28 GHz
Noise,$\aleph_w$	−174 dBm/Hz
5G System Bandwidth, B	500 MHz
Total TX power gNB	23 dBm
Noise figure of gNB	5 dB
Number of UEs tested	15
Cyclic interval	50 ms
Noise Figure of UE	9 dB
Height of UE	1.5 m
Antenna gain of UEs	0 dB
3 dB beam width	65 degrees
No. of antenna for UEs	1
Type of antenna for UEs	Omni-directional
Length of cyclic prefix	Normal

If an RLF is detected, the radio link connection status is monitored repeatedly and updated in the gNB service. The procedure of re-establishing radio resource control will be initiated, whereby the received signals will be checked by the UE for all neighboring cells. The target cell that can meet the lowest essential signal level will be verified. The UE will determine which cell that offers the highest received signal level if several cells fulfil the standards. When the cell is generally selected through the UE, the radio resource control regeneration procedure to configure the connection is initiated during the T311 interval (equal to 10 s). The recovery procedure of non-access layer (NAS) is enabled if none of the cells meet the lowest requirements. However, UE continues to select an appropriate target cell during the recovery process of NAS. This work is repeated until an appropriate cell is specified and reconnected. At the termination of every simulation round, the system performance is evaluated.

5. Performance evaluation criteria

In wireless networks, there are various performance criteria those can be used to evaluate network service quality. In this work, three major performance criteria's (MPCs) are used for performance appraisal of HO and LB algorithms. They represent key criteria usually employed for evaluating the performance of HO algorithms in wireless network through user mobility. These MPCs are PPHP, RLF and SE. These three MPCs have been selected due to their importance. The results are displayed and discussed according to the performance of these criteria. For sure there are other MPCs can be considered such as the RSRP, SINR, HOP, HOF probability, interruption time, and throughput. Also, Energy Efficiency can be considered as one of the evaluated MPC, but to the best of our knowledge, this MPC is not commonly used directly in evaluating handover load balancing algorithm studies. Meanwhile, any enhancement in the PPHP and RLF is an imposes indication for enhancing the energy consumption efficiency. This is because the reduction in PPHP and RLF are both lead to decrease the overhead of signaling, and this means the consumption of energy is reduced further at both the UE and the base station sides. Also, these three considered MPCs give an indication about throughput and interruption time. Accordingly, the PPHP, RLF and SE are considered in this study and they are further discussed below.

5.1. Ping-Pong handover probability (PPHP)

The PPHP is also known as the unnecessary HO possibility that may result from user mobility. It is a significant metric for computing the occurrence of unnecessary HOs between two neighboring cells. This occurs for various reasons, such as inappropriate HCP settings or inaccurate HO decisions. If this situation originates through mobility of user, it causes the connection is unstable with poor connection quality. This represents a critical problem in wireless networks. However, it can also stem from PPHP when traveling across small cells. This causes the UE percentage to be transmitted across the small cell and delivered to a macro cell base station (MBS). It is then delivered back to the MBS where the residence time within the small cell is less than a predetermined threshold made in advance [82]. However, PPHP is calculated when mobile user disconnects its connection link from the original serving gNB and creates a new communication link to the target gNB. It then falls back again to the service gNB within a period of time less than the critical Ping-Pong period (T_{PP}). This is defined as the short period of time required to compute the Unnecessary Handover (UHO) that may occur between two adjacent cells, and it is supposed to take few seconds depending on the system settings. As a conclusion, PPHP is one of the key MPCs commonly utilized to assess the performance of mobile network over the user mobility within the deployed cells, thus, it is considered in this work. In the simulation, the HPPP is considered if the following condition is met [83]:

$$PPHP = P_s\left[(T_i - T_r) \leq T_{PP}\right] \tag{5}$$

where T_i represents the time that the UE will pass to initiate (start) HO process from the service gNB, and T_r is the necessary time for the UE to return to the same gNB. Therefore, $(\mathrm{T_i} - \mathrm{T_r})$ is less than $\mathrm{T_{PP}}$ if the UE is switch the connection back to the previous serving gNB and HO is registered as a Ping-Pong Handover (PPH) for every UE in the mobile network. The average level of PPHP for all UEs in each simulation time is expressed by:

$$\overline{\mathrm{PPHP}} = \frac{\mathrm{M_{PPH}}}{\mathrm{M_s} + \mathrm{M_f}} \tag{6}$$

where M_{PPH} represents the number of PPHs throughout the whole simulation. M_s and $\mathrm{M_f}$ represent the number of successful and failed HO, respectively.

5.2. Radio link failure (RLF)

Also known as outage probability (OP), is the recorded rate of dropped connections through mobility of user because of deteriorating level of the RSRP. The RLF is recorded if the RSRP service drops below a certain threshold level before the user changes its communication link to a target BS successfully. The threshold range is usually determined by certain criterion which usually differs from one communication system to another system. It is considered as an important MPC that is generally utilized to compute the performance of mobile network through mobility of user since user mobility may lead to rapid and varied changes in the received signal strengths level. This may lead to increasing the calls drop rate before the mobile user switching its connection to a new target cell due to the poor quality of signal or, sometimes, lack of cell resources. This problem is sometimes occurred because of improper HCP settings or non-compliant HO decision algorithms, therefore, RLF is a necessary MPC to consider when assessing the network performance during user mobility. Similar to PPHP with various orientations, inappropriate HCP settings can be automatically predicted. The RLF occurs in the static case if HCP settings are manually specified at maximum levels. It happens if improper HCP levels/settings have been defined or estimated automatically by an HPSO function. Either way, inappropriate HCP settings that cause RLF usually happen when HCP settings are set at exciting levels. This leads to delayed HO which may cause increased RLF in some cases, particularly when mobile utilizers are at cell edges or moving at high speeds with their mobile devices. This will subsequently lead to increased waste the resources of network and reduced the network performance. The RLF must be minimized as much as possible to conserve network resources. However, the RLF is considered when UEs lose contact with the BS through the HO operation. The key source of OP is the initialization failure of HO, which leads to wireless link disruption or failure. The average OP for all UEs $(\overline{\mathrm{OP}})$ can be expressed as follows:

$$(\overline{OP}) = \frac{\sum_{i=1}^{M_n} P_i(OP)}{M_n}\ \forall\, i^{th}\ UE \tag{7}$$

where i is the number corresponding for the measured utilizer, and M_n is the total number of UEs in the whole simulation.

5.3. Spectral efficiency (SE)

The SE of UEs is a key performance metric utilized to assess the throughput in UE mobility studies for mobile communication networks. At the cell edge, the UE's SE is defined as the fifth percentile of the cumulative distribution function (CDF) of normalised SE [84]. The SE can be mathematically represented through assembly the total utilizer throughput that the user receives properly during a certain period and divided by the total Bandwidth (B.W) of the user's channel. It is measured in bits per second per Hertz (bps/Hz). Consequently, the UE's SE of the cell edge is a measure of the perceived QoS for 5% of UEs with less UE throughput. The normalized user SE can be explained with the following expression [85]:

$$\xi_i = \frac{\mu}{T_i \times N \times B} \tag{8}$$

where $\boldsymbol{\xi_i}$ is the SE for user i, while $\boldsymbol{\mu}$ is the number of properly received bits in a system for user i and B is the user's channel B.W. The maximum SE of a single-input single-output (SISO) network for infinite decoding complexity and block length in the additive white Gaussian noise (AWGN) channel can be mathematical gained through the Shannon capacity model, as follows [86]:

$$SE = log_2(1 + SINR) \tag{9}$$

This mathematical formula can be modified to estimate the maximum system/channel capacity according to certain presumptions specific to every technology of radio access.

6. Results and discussions

In this main section, the simulated outcomes for PPHP, RLF rate and spectral efficiency are presented through a comparison based on various load balancing algorithms, which are: Distance [87,88], Cost Function [89] and Fuzzy Logic [90] algorithms. The simulations have been conducted in MATLAB based on system model explained at Section 3. The simulation with all system models are utilized to investigate the execution of different handover self-optimization algorithms from the literature, which are proposed to be investigated for managing load balancing issue in this study. The simulation results are analyzed, and the performance of the algorithms are compared for various mobile speeds in 5G mobile network. The simulation began according to the settings described previously. The parameters of the required network are first defined, followed by the construction of the simulated network environment in its entirety. Next came the mobility model where user directions and locations are updated periodically in the simulation. Their Euclidean distances from the gNB in the network are computed by the distance matrix.

Fig. 5 presents the PPHP as the average rate of all measured UEs against time with several scenarios of mobile velocity (40 to 140 km/h) and different optimization algorithms. These outcomes are generally taken by users who are monitored with six various mobile phone velocities. The results revealed that the PPHP levels were high in the initial run-up period. The situation became more evident with low mobile speed scenarios of less than 100 km/h.

This is because the network operation is based on initially specified the settings of HCP. After a certain period, the settings of HCP are optimized and updated automatically by the considered algorithms in this work. This has various effects on PPHP depending on the robustness and reaction of the optimization algorithm. The outcomes explain that the Distance optimization algorithm with mobile velocities of less than 100 km/h produces lower PPHP comparison with the Cost Function and Fuzzy Logic algorithms. However, the Distance optimization techniques produce a different range of PPHP which quickly varies over time with the increase of mobile speed scenarios especially above 100 km/h, because it aims to optimize HCPs according to the load of traffic cell that brings mobile speed up. This refers that the Distance Optimization technique sets a high margin to avoid the early HO causing PPHP. However, setting very low HO margin values when a user experience poor RSRP regardless of the cell and the speed of the user. In this case, the Distance Optimization technique addresses smooth HO to the target cell and avoids delayed HO. The predicted results are performed by utilizing linear regression model.

Fig. 6 presents the average PPHP for different algorithms investigated from the literature. Fig. 6 (a) presents the average PPHP rates overall all mobile speeds scenarios for various HO optimization algorithms. The average values are taken first overall all the measured UEs at each measured record time for each mobile speed scenario independently, then they are taken as average over all mobile speed scenarios at each record time. Fig. 6 (b) presents the final average PPHP rates values for various HO optimization algorithms. The average values are taken first overall all the measured UEs at each record time for each mobile speed scenario independently, then they are taken as average over all mobile speed scenarios at each record time, and then they are taken as final average overall simulation time. These final average values are useful to illustrate the differences between the performances achieved by each algorithm clearly.

The results indicate that PPHP levels are high in the initial operation period. This case is more evident for the Fuzzy Logic optimization algorithm compared to the other techniques for all mobile speed scenarios, as shown in Fig. 6 (b). The predicted results are performed by utilizing linear regression model. Thus, the Fuzzy Logic technique archives an average PPHP of 0.22, whereas the Optimization Cost function and Optimization Distance obtain 0.2 and 0.0173 for all mobile user speeds, respectively. This shows that the Optimization Distance technique achieves the lower rate of PPHP compared to other Optimization algorithms because other algorithms do not work effectively on optimize HCPs based on the experience of user, particularly when utilizers move close to the edge of the cell. On other words, the results further reveal that optimization based on the Distance algorithm provides noticeable reduction gains in PPHP, particularly when compared to the Cost Function and Fuzzy Logic techniques for all considered movement speed scenarios due to the optimized HCPs. The average drop achieved by the Distance optimization technique is approximately 12% and 20% lower than that of the Cost Function and Fuzzy Logic algorithms, correspondingly. But, the lowest PPHP rate may be considered occasionally as a bad indicator. This is due to the trade-off between PPHP and OP, as explained in the following figures. The studied algorithms generally reacted more to updated optimizations and mobile speed scenarios with time. However, the performances of the Distance and Cost Function optimization algorithms did not provide marked reactions, neither with various scenarios of mobile speed nor with optimizations updated with time. This is because of the robustness of the optimization algorithm's design.

Figs. 7 and 8 show the average recorded RLF probability according to different HO self-Optimization algorithms investigated from the literature. The results presented for different mobile speeds scenarios. Fig. 7 presents the average RLFs rate verses time for different algorithms with different mobile speed scenarios. The average values are taken over all measured UEs at every time record. In

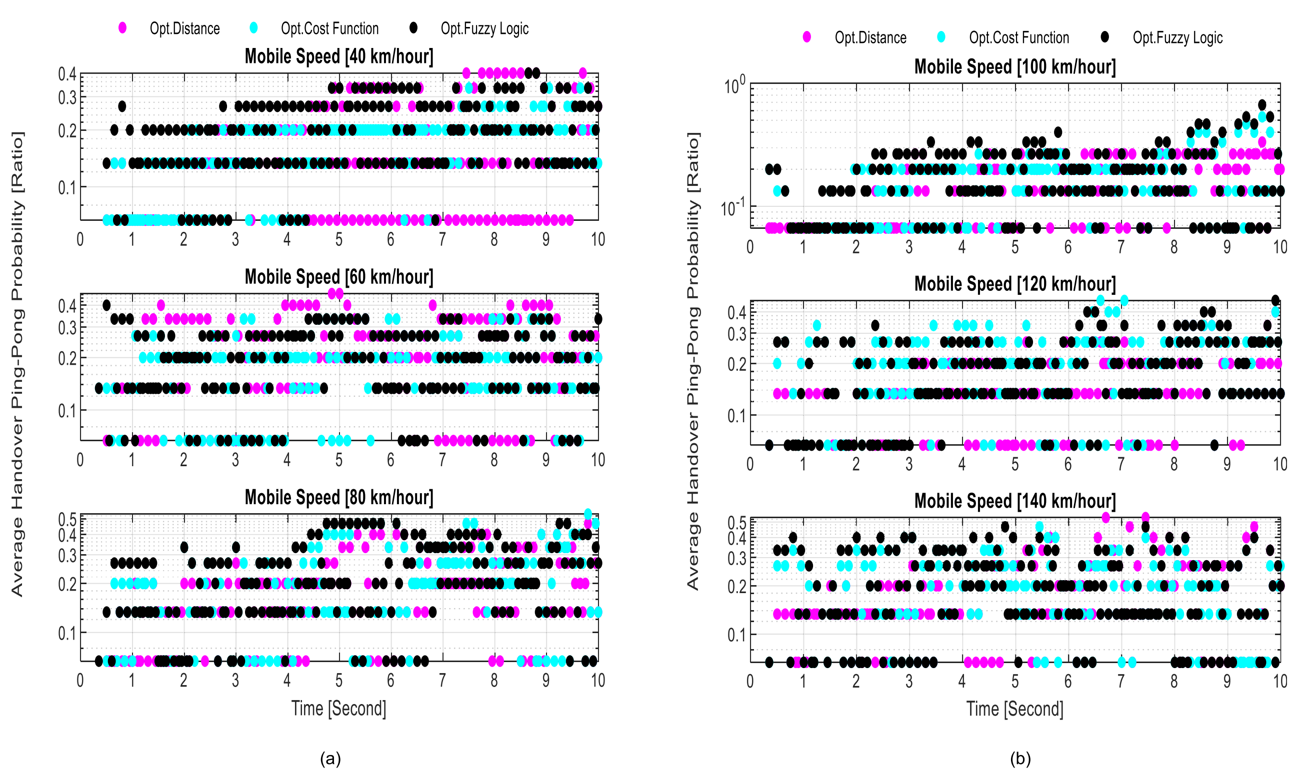


Fig. 5. The PPHP versus time for various mobile speeds.

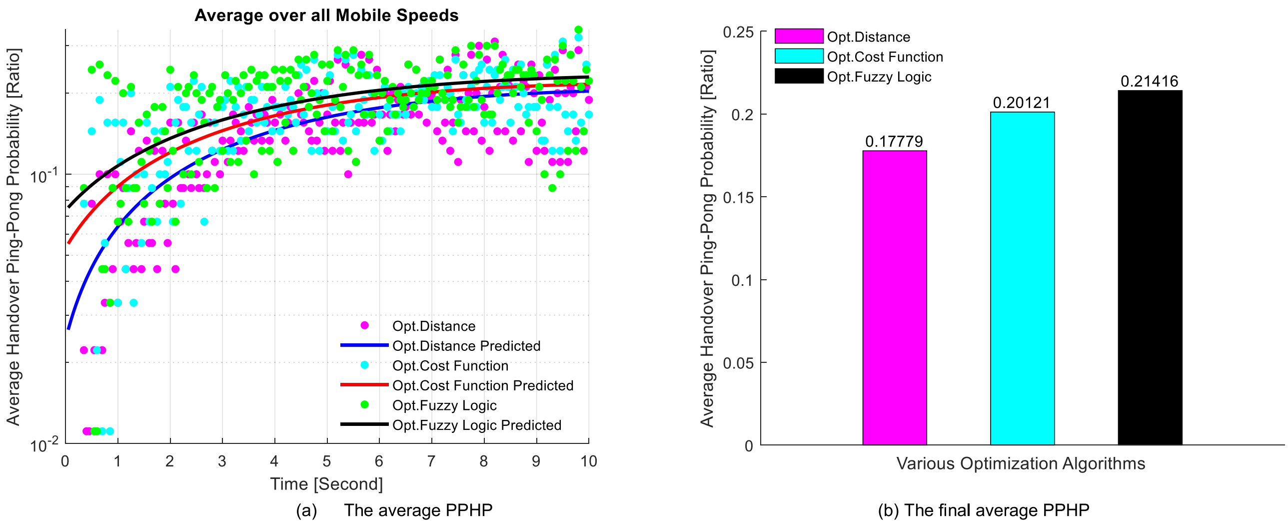


Fig. 6. The average PPHP and final average PPHP over all mobile speed's scenarios for various optimization algorithms.

Fig. 8, the RLFs is presented as a second and final average. Fig. 8 (a) presents the average RLF rates overall all mobile speeds scenarios for various HO optimization algorithms. The average values are taken first overall all the measured UEs at each measured record time for each mobile speed scenario independently, then they are taken as average over all mobile speed scenarios at each measured record time. Fig. 8 (b) presents the final average RLF rates values for various HO optimization algorithms. The average values are taken first overall all the measured UEs at each measured record time for each mobile speed scenario independently, then they are taken as average over all mobile speed scenarios at each measured record time, and then they are taken as final average overall simulation time. These final average values are useful to illustrate the differences between the performances achieved by each algorithm clearly.

The outcomes revealed that RLFs are mutable over time for all scenarios of mobile speed, where all algorithms are constantly reacting with time. Also, the results presented in Fig. 7 further show that no obvious differences are present between these algorithms and the probability of RLF increases with increasing the UEs speed due to the high-velocity UEs stays in the cell for a short time and needs HO to target the BS for avoiding the RLF. In Fig. 8, the Distance optimization algorithm provides remarkable reduction gain in the rate of RLF compared with other algorithms. Thus, the HO performance index causes the highest RLF rate on average across all scenarios of mobile speed. The average reduction gain achieved by the Distance optimization algorithm is about 3% and 11% lower than the Cost Function and Fuzzy Logic algorithms, respectively. This represents a great achievement for the Distance optimization algorithm. A lower RLF is not always a good sign. The use of low-HCP settings lead to reduced RLF. This will cause at the same time to early HO which, in turn increases PPHP. In some cases, a decreased RLF is a good indicator since it will be due to the use of self-optimization HO parameter algorithms which estimate optimal HCP settings. Mainly, the significant decrease is attributed to the efficient control of the HO process through avoiding the conflict between MRO and LBO. Therefore, the decision of correct HO helps the utilizers to connect seamlessly with full use for all resources of wireless network.

The SE link is a main parameter when designing and optimizing cellular networks. Regrettably, it is difficult to estimate this parameter since it depends on multiple factors that cannot be observed, and they significantly different from one cell to another. Figs. 9 and 10 display the results of spectral efficiencies for average UEs

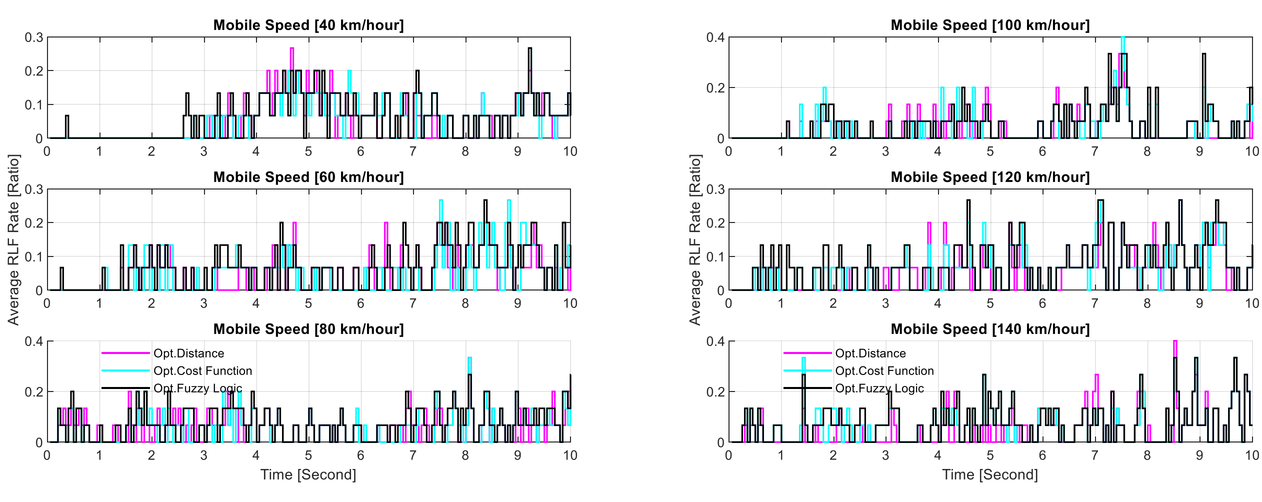
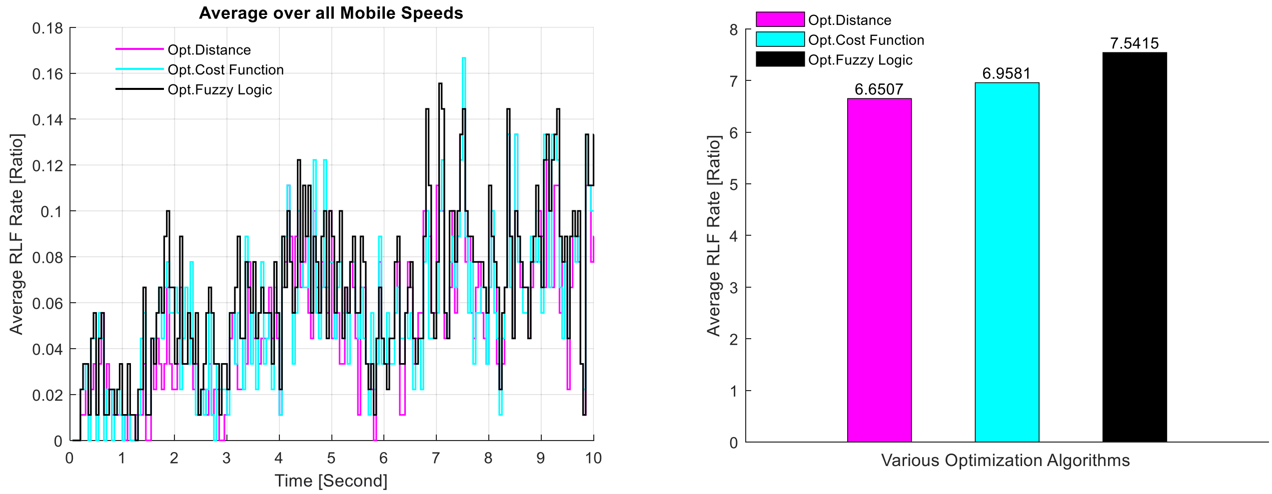


Fig. 7. The average RLF for different mobile speeds.



(a) The average RLF

(b) The final average RLF

Fig. 8. The average RLF and final average RLF for all mobile speed's scenarios and different optimization algorithms.

versus SINR specified to the range of [-10, 5 dB] in the x-axis for various mobile speed scenarios ranging from 40 to 140 km/h and different optimization algorithms, namely, opt. based on Distance, Cost function, and Fuzzy logic. In these figures, each point is a connection, and the links with the same SINR have a completely various SE. Furthermore, as can be observed that the Optimization based on the Distance algorithm is always better than the other algorithms used in this work. Thus, the HO decisions are made very quickly, and the impact of ping-pong appears. Moreover, the distance algorithm improves the SE even if the mobile phone is moving at higher speeds, so the decision becomes more complex. Also, when the speed of the mobile phone is higher, the channel changes faster because of the fastest environmental changes.

Fig. 11 presents the CDF of SE probability to compare performance between various optimization algorithms. These outcomes represent the average values across all UEs for different HO optimization algorithms. Since different optimization algorithms from the literature are scenarios that contribute to enhanced throughput of the cell edge, the UE's spectral efficiency is evaluated in this work to determine which improvements can be achieved in each scenario. From these figures, it is clear that optimization based on the Distance deployment scenario provides further enhancements for UEs throughout the cell in terms of SE compared to the Cost Function and Fuzzy Logic algorithms. To demonstrate the benefit of using these optimization techniques, Fig. 10 compares the different approaches using the CDF of SE probability. For the Distance optimization algorithm, the achieved CDF of SE probability is approximately 20% and 28% lower than that of the Cost Function and Fuzzy Logic algorithms in each SINR band included, respectively. The connection distribution in the cell strongly affects the measured SE for that cell. The noticeable variations justify require to measure SE based on the cells. Overall, the Distance optimization algorithm reduces PPHP, RLF and SE, as well as achieves low waste network resources from switching back and forth of utilizer data because of lower overhead signals.

In Fig. 12, the Distance optimization algorithm provides remarkable enhancements in the final average of spectral efficiency compared with the other algorithms. The average enhancement gain achieved by the Distance optimization algorithm is about 11% and 18% higher than the Cost Function and Fuzzy Logic algorithms, respectively. This represents a good achievement for the Distance optimization algorithm. Higher spectral efficiency in 5G mobile networks allows for more data to be transmitted in a given amount of spectrum, which increases network capacity and supports faster data rates. This enables more devices to be connected simultaneously with improved reliability and reduced latency.

7. Future research opportunities and directions

LBSO is one of the most important functions that automatically optimizes HCP settings in 4G and 5G networks. Automatic self-optimization (ASO) operations will allow this technology to be part of the mobile phone network 6G. Additional advancements will be introduced, and new factors will be utilized. The following section provides a summary and general guidance for future research activities.

7.1. Mobility with the integration of satellite and 6G networks

One goal that must be investigated for future wireless networks is the integration between satellites and 6G technology. The goal is to enable the services of enhanced mobile broadband (eMBB) to be available anytime and anywhere with high quality of service. However, many satellite systems and the 6G network function use mm-wave ranges, leading to increased mobility problems [91–96]. Examining the SO techniques of these systems is an important research goal that must be conducted in future.

7.2. LB mechanisms for the internet of things (IoTs)

A vast number of connections from IoT devices have caused increasing loads on the network. It is crucial to provide solutions to current network issues to enhance IoT network services. Such solutions include energy conservation, scalability, security, the network age, reliability, congestion, QoS and heterogeneity. LB is an efficient way to balance workloads and extend the life of objects in the IoT design. The network's local information is utilized to implement the LB technique where data traffic is distributed between multiple paths. An efficient LB technique generally improves the extensive computing applications as well as system performance to prevent system overload. Despite the importance of LB in IoT, no systematic or comprehensive reviews are present to analyses this method's great potential [97,98].

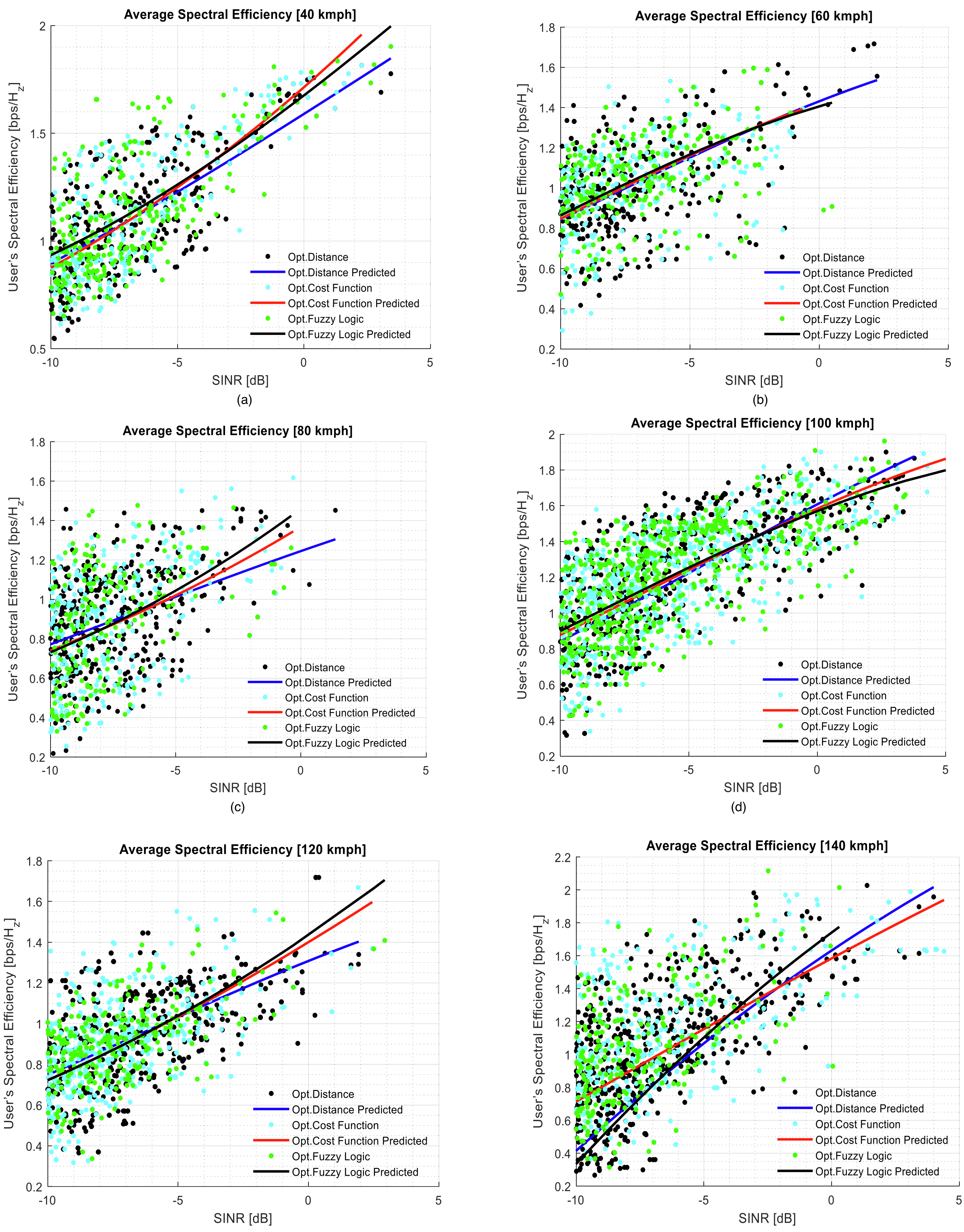


Fig. 9. The average UE spectral efficiency versus SINR with various mobile speeds.

7.3. Artificial intelligence & machine learning

The empowerment of artificial intelligence (AI) and machine learning (ML) as part of future solutions to address mobility problems will be a key direction. Designing the relevant AI/ML algorithms can enable the automatic learning of users' recorded experiences during mobility [99–103]. This system will enable SO and HO procedures to be accurately and quickly executed in the

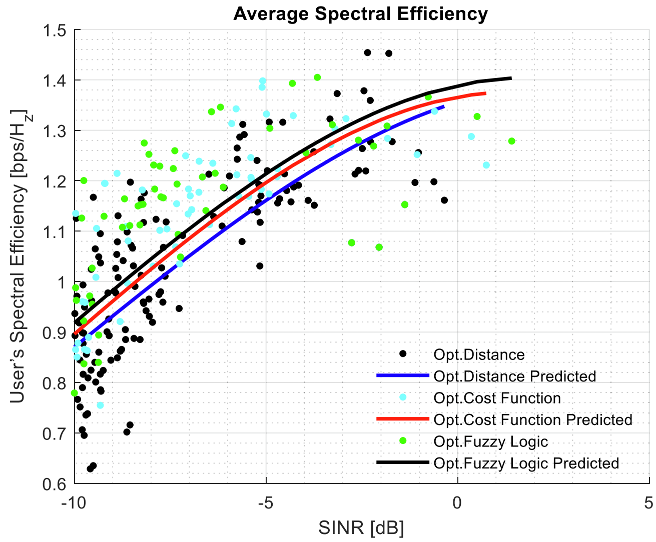


Fig. 10. The average UE's spectral efficiency verses SINR for different optimization algorithms and over all mobile speeds.

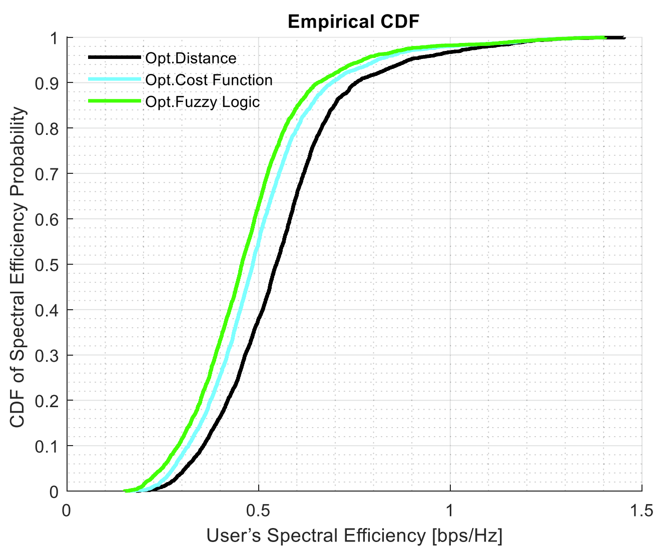


Fig. 11. The average CDF of UE's spectral efficiency probability over all mobile speeds for various optimization algorithms.

right place and time. This technology can also be applied to enable the system to recognize where and when balance is to be achieved, and which UE specifically needs optimization. ML can be employed to determine and address conflicting processing issues that may arise between LBO and HPO functions.

7.4. The consumption of battery life

Efficient battery usage is still a prominent challenge and a goal to be achieved in 5G technology. The use of carrier aggregation, mm-wave, high HOP, dual contact and signaling overhead will lead to an overall increase in the power consumption of the UE battery [104–108]. 5G technology aims to increase the battery life by 10x compared to 4G technology. This will require advanced technologies that can work more efficiency. Further research is needed despite the numerous studies conducted toward achieving this goal.

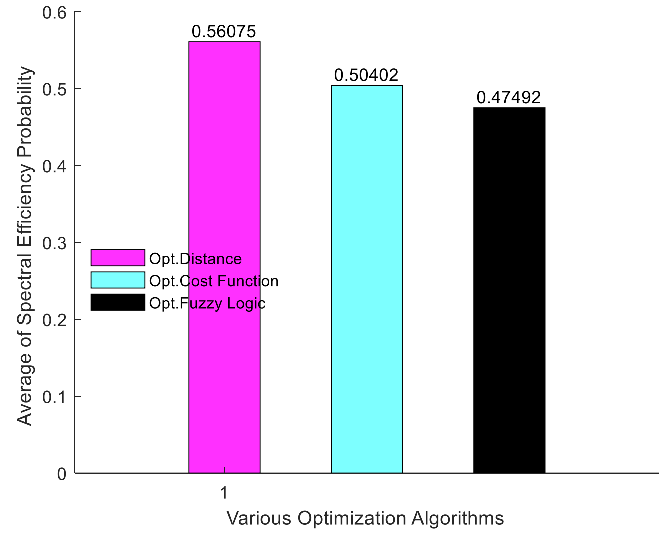


Fig. 12. The final average of UE's spectral efficiency probability over all mobile speeds and overall simulation time for various optimization algorithms.

7.5. Increased complexity

6G networks are expected to be even more complex than 5G networks, with more advanced features and capabilities. This increased complexity could make load balancing even more challenging. 6G networks are expected to have even more advanced features and capabilities than 5G networks, including higher data rates, lower latency, and more connected devices. These advanced features and capabilities will require more complex network infrastructures, such as a denser network of small cells, advanced beamforming techniques, and dynamic spectrum sharing.

The increased complexity of the network infrastructure could make load balancing even more challenging in several ways. Firstly, the denser network of small cells will require more precise and dynamic load balancing algorithms to ensure that the load is distributed evenly across the network. Secondly, the advanced beamforming techniques in 6G networks could result in highly directional connections that require careful management to ensure that the load is balanced evenly between the cells. Thirdly, the dynamic spectrum sharing in 6G networks could result in more complex interference management, which could affect load balancing performance.

Moreover, with the increasing number of connected devices in 6G networks, the load balancing algorithms will need to be more intelligent and adaptive to handle the varying demands of different devices and applications. The complexity of the network and the heterogeneity of the devices and applications will require more advanced artificial intelligence and machine learning techniques to optimize load balancing performance.

7.6. Ultra-low latency

6G networks are expected to have ultra-low latency, which could make it more difficult to balance loads across the network without introducing delays or other performance issues.

Ultra-low latency in 6G networks is expected to create load balancing issues because it requires fast and efficient data processing and communication. With ultra-low latency, data must be processed and transmitted across the network with minimal delay, which puts additional pressure on the network infrastructure. To achieve this, the network must ensure that the processing and communication resources are distributed optimally across the network.

LB algorithms will need to be able to respond quickly and dynamically to changes in network traffic to ensure that data is processed and transmitted as quickly as possible. This requires advanced machine learning and artificial intelligence techniques that can analyze real-time network traffic data and adjust resource allocation accordingly.

Additionally, with ultra-low latency, the time available for load balancing decisions is significantly reduced. This means that load balancing decisions must be made quickly and accurately, which requires more advanced and efficient algorithms. If load balancing decisions are not made quickly enough, it can lead to performance issues and increased latency. Therefore, load balancing in 6G networks will require even more sophisticated algorithms and technologies to handle the increased complexity and ultra-low latency requirements.

7.7. Massive IoT devices

Massive IoT devices can create load balancing challenges in a number of ways. First, the sheer number of devices can lead to a significant increase in network traffic, which can strain network resources and make it more difficult to balance loads effectively.

Second, IoT devices may have different data requirements and network behavior compared to traditional mobile devices, which can make load balancing more complex. For example, some IoT devices may require very low latency and high reliability, while others may have more relaxed requirements.

Third, IoT devices can be very diverse in terms of their connectivity requirements and capabilities, which can make it more difficult to balance loads across different types of devices and networks.

In general, the massive number and diverse nature of IoT devices can make load balancing in 6G networks more challenging and require new approaches and techniques to effectively manage network resources and ensure optimal performance.

7.8. Heterogeneous networks (HetNets)

HetNets refer to the deployment of different types of wireless access technologies such as macrocells, small cells, and Wi-Fi in a single network. While HetNets can provide significant improvements in network coverage and capacity, they can also create load balancing challenges due to the varying characteristics of the different access technologies.

For example, small cells have a smaller coverage area and can be used to offload traffic from macrocells. However, this can create an imbalance in the load distribution between the macrocells and small cells, leading to congestion in some areas and underutilization in others.

Moreover, different access technologies may have different radio access technologies (RATs) and different interference patterns, which can further complicate load balancing. For example, switching between Wi-Fi and cellular networks can introduce handover delays and affect the user experience.

Therefore, load balancing in HetNets requires the development of new algorithms and techniques that can take into account the heterogeneity of the network and balance the traffic load across different access technologies to ensure efficient utilization of network resources and optimal user experience.

8. Conclusion

This paper focused on MLB since it is one of the most significant self-optimization problems in 5G mobile networks. The dynamic estimation of HCP settings has been evaluated based on different optimization algorithms from the literature: the Distance, Cost Function and Fuzzy Logic algorithms. These algorithms estimated the optimization values according to the UE speed. All UEs acquire HCP settings differently from other UEs due to their independent setting of HCP values. Performance has been evaluated on the basis of PPHP, RLF and spectral efficiency under different mobile speeds. The simulation results demonstrate that optimization based on the Distance algorithm yielded remarkable results in system performance compared to the Cost Function and Fuzzy Logic algorithms for all scenarios of mobile speed. For the PPHP rate, the optimization performance in terms of Distance algorithm was lower than the Cost Function and Fuzzy Logic algorithms in the final average. However, this reduction is not always an advantage nor is it a good indicator since the use of higher HCP settings will cause a decrease in PPHP. This will simultaneously cause a delay in HO which, in turn, increases the RLF. A decrease in PPHP is sometimes a good indicator when effective self-optimization algorithms of HO parameters are utilized to estimate optimal settings of HCP. For the RLF rate, the performance of the Distance optimization algorithm was lower in the final average when compared to the Cost Function and Fuzzy Logic algorithms. A lower RLF is not always a good sign since the use of low settings of HCP causes a reduced RLF. This will cause the early HO which in turn, leads to an increased PPHP rate. The results further illustrate that optimization based on Fuzzy Logic deployment scenario provides a significant enhancement in terms of CDF of SE probability throughout the cell compared to the Cost Function and Distance algorithms.

Declaration of Competing Interest

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

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References

[1] J.G. Andrews, S. Singh, Q. Ye, X. Lin, H.S. Dhillon, An overview of load balancing in HetNets: Old myths and open problems, IEEE Wirel. Commun. 21 (2014) 18–25.
[2] A.J. Fehske, I. Viering, J. Voigt, C. Sartori, S. Redana, G.P. Fettweis, Small-cell self-organizing wireless networks, Proc. IEEE 102 (2014) 334–350.
[3] W.K. Saad, W.A. Jabbar, B.J. Hamza, Adaptive modulation and superposition coding for MIMO data transmission using unequal error protection and ordered successive interference cancellation techniques, J. Commun. 14 (2019).
[4] "Universal Mobile Telecommunications System (UMTS), Mobility Enhancementsin Heterogeneous Networks; 3GPP TR 36.839," Tech. Report; 3GPP: Valbonne, France, 2012.
[5] J. Sun, Z. Qian, X. Wang, X. Wang, Es-dqn-based vertical handoff algorithm for heterogeneous wireless networks, IEEE Wireless Commun. Lett. 9 (2020) 1327–1330.
[6] S. Wang, H. Deng, R. Xiong, G. Liu, Y. Liu, H. Liu, A multi-objective model-based vertical handoff algorithm for heterogeneous wireless networks, EURASIP J. Wirel. Commun. Netw. 2021 (2021) 1–18.
[7] M. Ding, D. Lopez-Perez, H. Claussen, M.A. Kaafar, On the fundamental characteristics of ultra-dense small cell networks, IEEE Netw. 32 (2018) 92–100.

[8] I. Kosmopoulos, E. Skondras, A. Michalas, D.D. Vergados, An Efficient Mobility Management Scheme for 5G Network Architectures, in: *2020 5th South-East Europe Design Automation, Computer Engineering, Computer Networks and Social Media Conference (SEEDA-CECNSM)*, 2020, pp. 1-6.
[9] W.K. Saad, M. Ismail, R. Nordin, Survey of adaptive modulation scheme in MIMO transmission, JCM 7 (2012) 873–884.
[10] "User Equipment (UE) Radio Transmission and Reception," Part 1: Range 1 Standalone; 3GPP TR 38.101, Tech. Report; 3GPP: Valbonne, France, 2018.
[11] "Technical Specification Group Services and System Aspects, Release 15 Description; 3GPP TR 21.915, Tech. Report; 3GPP: Valbonne, France, 2019.
[12] H.E. Ericsson, "Modified RRH Arrangement for HST SFN," 3GPP: Valbonne, France, 2019.
[13] W. K. Saad, M. Ismail, R. Nordin, A.A. El-Saleh, On the Performance of Cooperative Spectrum Sensing of Cognitive Radio Networks in AWGN and Rayleigh Fading Environments, *KSII Transactions on Internet & Information Systems*, vol. 7, 2013.
[14] A. Damnjanovic, J. Montojo, Y. Wei, T. Ji, T. Luo, M. Vajapeyam, et al., A survey on 3GPP heterogeneous networks, IEEE Wirel. Commun. 18 (2011) 10–21.
[15] J. Hoadley, P. Maveddat, Enabling small cell deployment with HetNet, IEEE Wirel. Commun. 19 (2012) 4–5.
[16] W. Saad, M. Ismail, R. Nordin, A. El-Saleh, Spectrum sensing schemes for dynamic primary user signal under AWGN and Rayleigh fading channels, J. Commun. 11 (2016) 231–241.
[17] W. A. Jabbar, W. K. Saad, Y. Hashim, N. B. Zaharudin, M.F.B.Z. Abidin, Arduino-based buck boost converter for pv solar system, in *2018 IEEE Student Conference on Research and Development (SCOReD)*, 2018, pp. 1–6.
[18] M.B. Patil, R. Patil, A network controlled vertical handoff mechanism for heterogeneous wireless network using optimized support vector neural network, Int. J. Pervasive Comput. Commun. (2021).
[19] Y. Q. B. a. D. Rao, "Small cells big opportunities," Huawei Technol., Shenzhen, China, Tech. Rep., 2014.
[20] A. Imran, M.A. Imran, A. Abu-Dayya, R. Tafazolli, Self organization of tilts in relay enhanced networks: A distributed solution, IEEE Trans. Wirel. Commun. 13 (2014) 764–779.
[21] W.A. Jabbar, W.K. Saad, M. Ismail, MEQSA-OLSRv2: A multicriteria-based hybrid multipath protocol for energy-efficient and QoS-aware data routing in MANET-WSN convergence scenarios of IoT, IEEE Access 6 (2018) 76546–76572.
[22] Q. Ye, B. Rong, Y. Chen, M. Al-Shalash, C. Caramanis, J.G. Andrews, User association for load balancing in heterogeneous cellular networks, IEEE Trans. Wirel. Commun. 12 (2013) 2706–2716.
[23] S. Hämäläinen, H. Sanneck, C. Sartori, LTE self-organising networks (SON): network management automation for operational efficiency, John Wiley & Sons, 2012.
[24] 3GPP, "Nr and nr-ran overall description; stage 2, Tech. Rep. No. TS 38.300," 2018.
[25] J.G. Andrews, H. Claussen, M. Dohler, S. Rangan, M.C. Reed, Femtocells: Past, present, and future, IEEE J. Sel. Areas Commun. 30 (2012) 497–508.
[26] R. Kwan, R. Arnott, R. Paterson, R. Trivisonno, M. Kubota, On mobility load balancing for LTE systems, in: *2010 IEEE 72nd Vehicular Technology Conference-Fall*, 2010, pp. 1–5.
[27] H.-S. Jo, Y.J. Sang, P. Xia, J.G. Andrews, Heterogeneous cellular networks with flexible cell association: A comprehensive downlink SINR analysis, IEEE Trans. Wirel. Commun. 11 (2012) 3484–3495.
[28] S. Singh, F. Baccelli, J.G. Andrews, On association cells in random heterogeneous networks, IEEE Wireless Commun. Lett. 3 (2013) 70–73.
[29] 3GPP TR 36.902 V9.3.1, Evolved Universal Terrestrial Radio Access Network (EUTRAN); Self-Configuring and Self-Optimizing Network (SON) Use Cases and Solutions, Release 9, 2011.
[30] W.K. Saad, Y. Hashim, W.A. Jabbar, Design and implementation of portable smart wireless pedestrian crossing control system, IEEE Access 8 (2020) 106109–106120.
[31] M. Sheng, C. Yang, Y. Zhang, J. Li, Zone-based load balancing in LTE self-optimizing networks: a game-theoretic approach, IEEE Trans. Veh. Technol. 63 (2013) 2916–2925.
[32] P. Szilágyi, Z. Vincze, C. Vulkán, Integrated mobility load balancing and traffic steering mechanism in LTE, in: *2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2013, pp. 2148-2153.
[33] A. Aguilar-Garcia, S. Fortes, A. Garrido, A. Fernandez-Duran, R. Barco, Improving load balancing techniques by location awareness at indoor femtocell networks, EURASIP J. Wirel. Commun. Netw. 2016 (2016) 1–17.
[34] M. H. Ismeala, B. J. Hamzaa, and W. K. Saada, Comparison the performance evaluation of Xgpon-Rof System with Wdm and Scm for different modulation schemes, *Al-Qadisiyah J. Eng. Sci.*, 12, 240–245-240–245, 2019.
[35] J. Steuer, K. Jobmann, The use of mobile positioning supported traffic density measurements to assist load balancing methods based on adaptive cell sizing, in: *The 13th IEEE International Symposium on Personal, Indoor and Mobile Radio Communications*, 2002, pp. 339–343
[36] M.A. Abdulnabi, W.K. Saad, B.J. Hamza, Performance analysis of full-duplex NG-PON2-RoF system with non-linear impairments, J. Phys. Conf. Ser. (2020) 012158.
[37] F. Guidolin, I. Pappalardo, A. Zanella, M. Zorzi, A Markov-based framework for handover optimization in HetNets, in: *2014 13th Annual Mediterranean Ad Hoc Networking Workshop (MED-HOC-NET)*, 2014, pp. 134-139.
[38] H. Li, S. Habibi, G. Ascheid, Handover prediction for long-term window scheduling based on SINR maps, in: *2013 IEEE 24th Annual International Symposium on Personal, Indoor, and Mobile Radio Communications (PIMRC)*, 2013, pp. 917-921.
[39] W. K. Saad, M. Ismail, R. Nordin, A. A. El-Saleh, Optimality of the HDC rules in cooperative spectrum sensing for Cognitive Radio network, in *2015 1st International Conference on Telematics and Future Generation Networks (TAFGEN)*, 2015, pp. 22-27.
[40] K.M. Addali, S.Y.B. Melhem, Y. Khamayseh, Z. Zhang, M. Kadoch, Dynamic mobility load balancing for 5G small-cell networks based on utility functions, IEEE Access 7 (2019) 126998–127011.
[41] Z.H. Abbas, F. Muhammad, L. Jiao, Analysis of load balancing and interference management in heterogeneous cellular networks, IEEE Access 5 (2017) 14690–14705.
[42] A. Asghar, H. Farooq, A. Imran, On concurrent optimization of coverage, capacity and load balance in HetNets through joint self-organization of soft and hard cell association parameters, IEEE Trans. Veh. Technol. 67 (2018) 8781–8795.
[43] M. Alhabo, L. Zhang, Load-dependent handover margin for throughput enhancement and load balancing in HetNets, IEEE Access 6 (2018) 67718–67731.
[44] A. L. Yusof, M. A. Zainali, M. T. M. Nasir, N. Ya'acob, Handover adaptation for load balancing scheme in femtocell Long Term Evolution (LTE) network, in: *2014 IEEE 5th Control and System Graduate Research Colloquium*, 2014, pp. 242-246.
[45] M. Alhabo, L. Zhang, O. Oguejiofor, Inbound handover interference-based margin for load balancing in heterogeneous networks, in: *2017 International Symposium on Wireless Communication Systems (ISWCS)*, 2017, pp. 146–151.
[46] A.K. Gupta, H.S. Dhillon, S. Vishwanath, J.G. Andrews, Downlink multi-antenna heterogeneous cellular network with load balancing, IEEE Trans. Commun. 62 (2014) 4052–4067.
[47] Y.L. Lee, W.K. Saad, A.A. El-Saleh, M. Ismail, Improved detection performance of cognitive radio networks in AWGN and Rayleigh fading environments, J. Appl. Res. Technol. 11 (2013) 437–446.
[48] S. Singh, J.G. Andrews, Joint resource partitioning and offloading in heterogeneous cellular networks, IEEE Trans. Wirel. Commun. 13 (2013) 888–901.
[49] B.A. Bjerke, LTE-advanced and the evolution of LTE deployments, IEEE Wirel. Commun. 18 (2011) 4–5.
[50] S. Singh, H.S. Dhillon, J.G. Andrews, Offloading in heterogeneous networks: Modeling, analysis, and design insights, IEEE Trans. Wirel. Commun. 12 (2013) 2484–2497.
[51] W.K. Saad, I. Shayea, B.J. Hamza, H. Mohamad, Y.I. Daradkeh, W.A. Jabbar, Handover parameters optimisation techniques in 5G networks, Sensors 21 (2021) 5202.
[52] W.-S. Hwang, T.-Y. Cheng, Y.-J. Wu, M.-H. Cheng, Adaptive handover decision using fuzzy logic for 5G ultra-dense networks, Electronics 11 (2022) 3278.
[53] A. Alhammadi, W. H. Hassan, A. A. El-Saleh, I. Shayea, H. Mohamad, W. K. Saad, Intelligent coordinated self-optimizing handover scheme for 4G/5G heterogeneous networks, *ICT Express*, 2022.
[54] S. A. Khan, I. Shayea, M. Ergen, A. A. El-Saleh, M. Roslee, An Improved Handover Decision Algorithm for 5G Heterogeneous Networks, in: *2021 IEEE 15th Malaysia International Conference on Communication (MICC)*, 2021, pp. 25-30.
[55] I. Shayea, M. Ergen, A. Azizan, M. Ismail, Y.I. Daradkeh, Individualistic dynamic handover parameter self-optimization algorithm for 5G networks based on automatic weight function, IEEE Access 8 (2020) 214392–214412.
[56] R. Karmakar, G. Kaddoum, S. Chattopadhyay, Mobility management in 5G and beyond: a novel smart handover with adaptive Time-to-trigger and hysteresis margin, IEEE Trans. Mob. Comput. (2022).
[57] S. Mishra, N. Mathur, Load balancing optimization in LTE/LTE-A cellular networks: a review, *arXiv preprint arXiv:1412.7273*, 2014.
[58] A. M. Miyim, K. Umar, A. Ibrahim Kiyawa, A Fuzzy-based AHP approach to handover decision for mobility management in heterogeneous wireless network, *SLU J. Sci. Technol.*, vol. 2, pp. 46-57, 2021.
[59] R. Balakrishnan, B. Canberk, Traffic-aware QoS provisioning and admission control in OFDMA hybrid small cells, IEEE Trans. Veh. Technol. 63 (2013) 802–810.
[60] R. Hernandez-Aquino, S.A.R. Zaidi, D. McLernon, M. Ghogho, A. Imran, Tilt angle optimization in two-tier cellular networks—A stochastic geometry approach, IEEE Trans. Commun. 63 (2015) 5162–5177.
[61] W.K. Saad, I. Mahamod, N. Rosdiadee, I. Shayea, Thoughput performance of adaptive modulation and coding scheme with link adaptation for mimo-wimax downlink transmission, J. Asian Sci. Res. 2 (2012) 641.
[62] M. Chardy, M. B. Yahia, Y. Bao, 3G/4G load-balancing optimization for mobile network planning, in: *2016 17th International Telecommunications Network Strategy and Planning Symposium (Networks)*, 2016, pp. 7-12.
[63] M.J. Mohsin, W.K. Saad, B.J. Hamza, W.A. Jabbar, Performance analysis of image transmission with various channel conditions/modulation techniques, Telkomnika 18 (2020) 1158–1168.
[64] R.P. Ray, L. Tang, Hysteresis margin and load balancing for handover in heterogeneous network, Int. J. Future Comp. Commun. 4 (2015) 231.
[65] O. Aydin, Optimized carrier aggregation for handover, EP2373090 A1 2011.
[66] Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Requirements (Release 15), document TS 28.627 V15.0.0, 3GPP, Valbonne, France, 2018.

[67] Self-Organizing Networks (SON) Policy, Network Resource Model (NRM), Integration Reference Point (IRP); Information Service (IS) (Release 15), document TS 28.628 V15.0.0, 3GPP, Valbonne, France, 2018.
[68] Telecommunication management; Self-Organizing Networks (SON) Policy Network Resource Model (NRM) Integration Reference Point (IRP); Information Service (IS) (Release 11), document TS 32.522 V11.7.0, 3GPP, Valbonne, France, 2013.
[69] K.I. Pedersen, F. Frederiksen, C. Rosa, H. Nguyen, L.G.U. Garcia, W. Yuanye, Carrier aggregation for LTE-advanced: functionality and performance aspects, Commun. Magazine, IEEE 49 (2011) 89–95.
[70] Radio Frequency (RF) System Scenarios (Release 15), document TR 25.942 V15.0.0, 3GPP, Valbonne, France, 2018.
[71] I. Shayea, M. Ismail, R. Nordin, H. Mohamad, Handover performance over a coordinated contiguous carrier aggregation deployment scenario in the LTE-advanced system, Int. J. Vehicular Technol. 2014 (2014).
[72] 3GPP, TR 25.816 V8.0.0., UMTS 900 MHz Work Item Technical Report (Release 8)., ed. Franch: http://www.3gpp.org/DynaReport/25816.htm," 2009.
[73] 3GPP, TR 25.814 V7.1.0., Physical layer aspects for evolved Universal Terrestrial Radio Access (UTRA) (Release 7), ed. Franch: http://www.3gpp.org/DynaReport/25814.htm, 2006.
[74] Radio Frequency (RF) System Scenarios (Release 15), document TR 25.942 V15.0.0, 3GPP, Valbonne, France, 2018.
[75] Radio Resource Control (RRC); Protocol Speci_cation (Release 15), document TS 36.331 V15.3.0, 3GPP, 2018.
[76] M. Gudmundson, Correlation model for shadow fading in mobile radio systems, Electron. Lett 27 (1991) 2145–2146.
[77] A. Goldsmith, Wireless communications: Cambridge university press, 2005.
[78] a. G. L. D. Jiang, An overview of 5G requirements, 5G Mobile Communications, pp. pp. 3-26, 2017.
[79] D. Castro-Hernandez, R. Paranjape, Optimization of handover parameters for LTE/LTE-A in-building systems, IEEE Trans. Veh. Technol. 67 (2017) 5260–5273.
[80] Radio Resource Control (RRC); Protocol Specication (Release 15), document TS 36.331 V15.3.0, 3GPP, 2018.
[81] Radio Resource Control (RRC); Protocol Specication (Release 15), document TS 36.300 V15.3.0, 3GPP, Valbonne, France, 2018.
[82] 3GPP, Radio Frequency (RF) system scenarios (Release 15), TR 25.942 V15.0.0, ed. Valbonne - FRANCE: 3GPP, 2018.
[83] I. Shayea, M. Ismail, R. Nordin, H. Mohamad, T. Abd Rahman, N.F. Abdullah, Novel handover optimization with a coordinated contiguous carrier aggregation deployment scenario in LTE-advanced systems, Mob. Inf. Syst. 2016 (2016).
[84] P. J. S. a. J. Shin, Method for Handover in Multi-Carrier System, *Google Patents,* 2011.
[85] E. Dahlman, S. Parkvall, J. Skold, 4G: LTE/LTE-Advanced for Mobile Broadband, Academic Press, 2013.
[86] C.E. Shannon, Claude Elwood Shannon: Collected Papers, IEEE Press, 1993.
[87] Y.-F. Huang, H.-C. Chen, H.-C. Chu, J.-J. Liaw, F.-B. Gao, Performance of adaptive hysteresis vertical handoff scheme for heterogeneous mobile communication networks, J. Networks 5 (2010) 977.
[88] H. Zhu, K.-S. Kwak, Performance analysis of an adaptive handoff algorithm based on distance information, Comput. Commun. 30 (2007) 1278–1288.
[89] I.M. Bălan, B. Sas, T. Jansen, I. Moerman, K. Spaey, P. Demeester, An enhanced weighted performance-based handover parameter optimization algorithm for LTE networks, EURASIP J. Wirel. Commun. Netw. 2011 (2011) 1–11.
[90] P. Muñoz, R. Barco, I. de la Bandera, On the potential of handover parameter optimization for self-organizing networks, IEEE Trans. Veh. Technol. 62 (2013) 1895–1905.
[91] M. Abo-Zeed, J.B. Din, I. Shayea, M. Ergen, Survey on land mobile satellite system: Challenges and future research trends, IEEE Access 7 (2019) 137291–137304.
[92] A.M. Al-Samman, T.A. Rahman, M.H. Azmi, I. Shayea, Path loss model and channel capacity for UWB–MIMO channel in outdoor environment, Wirel. Pers. Commun. 107 (2019) 271–281.
[93] M. Giordani, M. Zorzi, Satellite communication at millimeter waves: A key enabler of the 6G era, in: *2020 International Conference on Computing, Networking and Communications (ICNC)*, 2020, pp. 383-388.
[94] I. Shayea, T. Abd. Rahman, M. Hadri Azmi, A. Arsad, Rain attenuation of millimetre wave above 10 GHz for terrestrial links in tropical regions, *Trans. Emerg. Telecommun. Technol.,* 29, e3450, 2018.
[95] I. Shayea, L. A. Nissirat, M. A. Nisirat, A. Alsamawi, T. Abd. Rahman, M. Hadri Azmi, *et al.*, Rain attenuation and worst month statistics verification and modeling for 5G radio link system at 26 GHz in Malaysia, *Trans. Emerg. Telecommun. Technol.,* 30, e3697, 2019.
[96] B. Zong, C. Fan, X. Wang, X. Duan, B. Wang, J. Wang, 6G technologies: Key drivers, core requirements, system architectures, and enabling technologies, IEEE Veh. Technol. Mag. 14 (2019) 18–27.
[97] T. A. Al-Janabi, H. S. Al-Raweshidy, Optimised clustering algorithm-based centralised architecture for load balancing in IoT network, in *2017 International Symposium on Wireless Communication Systems (ISWCS)*, 2017, pp. 269-274.
[98] B. Pourghebleh, V. Hayyolalam, A comprehensive and systematic review of the load balancing mechanisms in the Internet of Things, Clust. Comput. 23 (2020) 641–661.
[99] A. Aibinu, A. Onumanyi, A. Adedigba, M. Ipinyomi, T. Folorunso, M.-J.-E. Salami, Development of hybrid artificial intelligent based handover decision algorithm, Eng. Sci. Technol., Int. J. 20 (2017) 381–390.
[100] J. V. Cervantes Bazán, A. D. Cuevas Rasgado, S. Lazcano Salas, F. García Lamont, S. Cerquides Bueno, Artificial intelligence techniques in handover decision: a brief re-view, 2019.
[101] M. Ergen, What is artificial intelligence? technical considerations and future perception, Anatolian J. Cardiol 22 (2019) 5–7.
[102] B. Shubyn, N. Lutsiv, O. Syrotynskyi, R. Kolodii, Deep learning based adaptive handover optimization for ultra-dense 5G mobile networks, in: *2020 IEEE 15th International Conference on Advanced Trends in Radioelectronics, Telecommunications and Computer Engineering (TCSET)*, 2020, pp. 869-872.
[103] L. Yan, H. Ding, L. Zhang, J. Liu, X. Fang, Y. Fang, et al., Machine learning-based handovers for sub-6 GHz and mmWave integrated vehicular networks, IEEE Trans. Wirel. Commun. 18 (2019) 4873–4885.
[104] B.J. Hamza, W.K. Saad, I. Shayea, N. Ahmad, N. Mohamed, D. Nandi, et al., Performance enhancement of SCM/WDM-RoF-XGPON system for bidirectional transmission with square root module, IEEE Access 9 (2021) 49487–49503.
[105] A. Mahmood, W. A. Jabbar, W. K. Saad, Y. Hashim, H.B. Manap, Optimal nano-dimensional channel of GaAs-FinFET transistor, in *2018 IEEE Student Conference on Research and Development (SCOReD)*, 2018, pp. 1-5.
[106] B. Munir, V. Dyo, On the impact of mobility on battery-less RF energy harvesting system performance, Sensors 18 (2018) 3597.
[107] M. Tawalbeh, A. Eardley, Studying the energy consumption in mobile devices, Procedia Comput. Sci. 94 (2016) 183–189.
[108] A. Zahedi, M. Ergen, I. Shayea, Optimum time/power fraction of energy harvesting in TSR/PSR SWIPT-based cooperative communications with effective capacity maximization approach, AEU-Int. J. Electr. Commun. 111 (2019) 152889.