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RESEARCH ARTICLE

Optimal Handover Optimization in Future Mobile Heterogeneous Network Using Integrated Weighted and Fuzzy Logic Models

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ABSTRACT High mobility travelling trains and drones connected via ultra-dense mobile networks may lead to frequent handovers (HOs). As a consequence, this could arise the mobility problems of the serving network such as handover ping-pong (HOPP), radio link failure (RLF), handover probability (HOP), and handover failure (HOF). Mobility robustness optimization (MRO) function can contribute for fixing such related problems. This can be performed by self-optimization process for the handover control parameters (HCPs), that including time-to-trigger (TTT) and handover margin (HOM). Although various proposed solutions available in the literature, the issues have not been addressed efficiently. Thus, this study proposes a fuzzy logic controller (FLC) along with weighted function (WF) to perform efficient HO self-optimization process for the HCPs over the heterogeneous networks (Het-Nets). The proposed algorithm is defined as velocity-aware-fuzzy logic controller-weighted function (VAW-FLC-WF) algorithm. Additionally, a trigger timer is used along with the proposed algorithm for the purpose of reducing the ratio of HOPP. The objective of the integrated algorithms is to minimize the connections issues such as HOPP, RLF, and received signal reference power (RSRP). Besides, this study highlighted the significant of categorizing the speed scenarios in reducing the mobility issues by comparing the results with non-categorized speed scenarios (proposed FLC-WF). The proposed integrated algorithms show a significant enhancements as compared to the algorithms investigated from the literature. The average RLF probability of the proposed (VAW-FLC-WF) was reduced to 0.006 which was the lowest probability compared to the other HO algorithms. Besides, RSRP, HOPP were shown noticeable improvements compared to other HO algorithms.

INDEX TERMS Heterogeneous networks, 6G, 5G, mobility, handover, mobility robustness optimization, handover control parameters, handover margin, time-to-trigger.

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I. INTRODUCTION

Large numbers of connected devices that require high demands due to their high computational abilities, online gaming, and video conferencing have increased [1], [2]. Therefore, ultra-dense heterogeneous networks (HetNets) with millimeter wave (mm-wave) communication have been proposed to accommodate high network data rate for future mobile HetNets. In contrast, the network complexity of the different radio access technologies (RAT) will remain a challenge for the network operators since deploying an ultra-dense HetNet may cause high interference with high frequent handovers (HOs) compared to homogeneous networks. Hence, a large number of HOs may lead to an increase in the ratio of handover ping-pong (HOPP) and radio link failure (RLF) [3], [4].

HO is accountable for preserving the user equipment's (UE) quality connection during the transitions between base stations (BSs). However, the HO procedure is one of the significant processes in mobility management to conduct the network. Therefore, to avoid the mobility issues (i.e., too late HO, too early HO, and HO to wrong cell), several control parameters are necessary to be well configured for system reliability and stability.

Mobility robustness optimization (MRO) functions may significantly contribute to enhancing the quality of the connection as well as preserving the network resources if the handover control parameters (HCPs) are configured accurately [4]. There are two parameters for HCPs. They are time-to-trigger (TTT) and handover margin (HOM). Besides, a proper setting value mitigates a contradiction in objectives that may occur when optimizing the HCPs. For instance, a high TTT setting leads to RLF, whereas a low TTT setting leads to HOPP probability [5], [6]. Therefore, there is a trade-off between RLF and HOPP during the HO optimization process [7].

Mobile speed scenarios and received signal reference power (RSRP) values need to be taken into consideration when optimizing the HCPs in order to control the MRO issues. Low-speed scenarios with a low HCPs setting value may cause too early HO, whereas high-speed scenarios with a high HCPs setting value may cause too late HO. Moreover, a medium RSRP value at the cell edge needs high HCP setting value to maintain the current connection, whereas a low HCP setting is required for a weak RSRP value to speed up the HO process. In addition, traffic load and signal-to-interference-plus-noise ratio (SINR) are the two input parameters that have been investigated in MRO function to determine the suitable setting value for the HCPs. However, various algorithms with different deployment scenarios, simulators, and key performance indicators (KPIs) have been developed all through the past years. Therefore, several conventional and artificial intelligence optimization methods have been applied, as addressed in these works [7], [8].

Fuzzy logic controller (FLC) methods have been addressed to optimize HCPs of the MRO function, such as in [9], [10], [11], [12], [13], [14], and [15]. These methods applied different KPIs over a different deployment scenario for LTE networks. Furthermore, studies [10], [11], [12], [13], [14], [15] have been extensively addressed in [7] mainly under a section entitled HO optimization based on FLC. In addition, each study shows different system accuracy from other studies due to the differences in KPIs, simulation environment, inputs and outputs parameters.

Article [9] has proposed an FLC technique to auto-tune HOM and TTT over the fifth generation (5G) network and used RSRP, UE's speed, and received signal reference quality (RSRQ) as input parameters for optimization. The UE's speed was assumed to be from 20 km/hr to 140 km/hr.

Besides, the UEs were moving in a straight way in eight directions. Furthermore, handover probability (HOP), handover failure (HOF), HOPP, HO latency, and HO IT were used as KPIs in this study.

The FLC technique has been used to self-optimize the TTT and HOM based on three input parameters (i.e., SINR, BS load, and UE's load) [16]. Besides, this study manages the contradictions in objectives between the MRO and load balancing optimization. Furthermore, several metrics (i.e., HOPP, RLF, and HO latency) have been used as indicator to measure the system performance over a HetNet using several mobile speed scenarios.

Article [17] has proposed a FLC method for automatically optimizing the TTT and HOM over ultra-dense SBSs using the two input parameters (i.e., SINR and UE's speed). Furthermore, the number of HOs, system throughput, and HOPP were used as KPIs in this study. Moreover, the proposed algorithm was compared with the conventional scheme (A3 event).

Several methods have used weighted function (WF) as a solution technique to self-optimize the HCPs. Reference [16] introduces a self-optimizing HO method that uses fuzzy coordination to achieve a seamless HO for users who move across multiple radio access networks. Furthermore, [16] has applied two self-optimization functions (i.e., MRO and load balancing optimization) using three inputs (i.e., SINR, cell load, and mobile speed scenarios). Through simulation, the proposed method is shown to effectively optimize mobility by reducing issues like HOPP, RLF, and HO latency over different mobile speed scenarios. Furthermore, recently, Shayea et al. came up with an algorithm that aims to self-optimize HO parameters (i.e., TTT and HOM) in 5G networks by focusing on individual user performance [18]. The algorithm is based on automatic weight function and input metrics such as UE SINR, speed, and cell load to improve key performance indicators such as RSRP, HOP, HPPP, and RLF. Moreover, a method called weighted fuzzy self-optimization technique has been addressed which relies on factors such as the SINR ratio, the traffic load of the serving and target BSs, and the velocity of the UE. This method was presented to enhance TTT and HOM with the goal of reducing RLF and HOPP.

To enhance system performance, a proper HCP setting value should be addressed to avoid degradation in quality connection due to improper configuration of the HCPs. Therefore, auto-tuning TTT and HOM are a significant process during HO since no optimal HO triggering points were achieved up-to-date. However, the HCPs setting values should be changed automatically based on user experience, such as mobile speed scenarios, changes of RSRP values, and the traffic load. Therefore, self-optimizing the HCPs with different mobile speed scenarios over a HetNet environment requires an essential HO optimization algorithm that is able to optimize the HCPs effectively.

In this paper, an integrated algorithms (FLC and WF) were proposed to self-optimize the HCPs of the MRO (i.e., TTT and HOM). The proposed algorithm is compared with different algorithms addressed in the literature [12], [18]. Furthermore, MRO issues are investigated over a HetNet at different mobile speed scenarios over HetNet for speed values between 20 km/hr and 200 km/hr. Moreover, a trigger timer was proposed for reducing the HOPP when the received signal strength indicator (RSSI) above threshold. The objective of the trigger timer is to prevent the user from executing the HO to the target base station (BS) that has the same ID as the serving BS. In addition, RSRP, RLF, HOPP, and HOP are investigated in this study. Moreover, with more focus on the mobile speed scenarios, a velocity-aware-fuzzy logic controller-weighted function (VAW-FLC-WF) is proposed based on three input parameters, including RSRP, traffic load, and mobile speed scenarios.

The rest of this paper is organized as follows. Section II presents the MRO. Section III describes the related works. Section IV provides the challenges of MRO in next-generation mobile HetNet. Section V addresses a system model. Section VI presents the proposed adaptive system for the HCPs. Results and discussion are addressed in Section VII. Section VIII concludes the paper.

II. MOBILITY ROBUSTNESS OPTIMIZATION

MRO has been implemented and enhanced as a crucial self-optimization network feature in future mobile HetNets. The primary objective of MRO is to tackle the challenges related to mobility management that arise when users are on the move. Additionally, MRO has the capability of establishing a seamless connection by controlling the HCPs (i.e., TTT and HOM). Fig. 1 represents three issues that MRO is able to detect and correct. These issues include too early HO, too late HO, and HO to the wrong cell. However, controlling the HCPs values have a great impact on minimizing the MRO issues, which subsequently lead to a reduction in the ratio of the RLF and HOPP. Therefore, Fig. 1 highlights the inappropriate setting of the HCPs, where a low setting value of the TTT and HOM leads to too early HO, whereas too late HO occurs due to a high setting value of the TTT and HOM. Besides, mobile speed scenarios for individual connected users require high consideration. For instance, during high speed scenarios, low setting values of the TTT and HOM are needed to avoid too late HOs, while high setting values are required during low speed scenarios in order to avoid too early HOs. Furthermore, user experience (i.e., mobile speed scenarios, interference) is required to assign the HCP setting value to each user individually. Therefore, optimal HO triggering necessitates an efficient HO self-optimization decision algorithm to preserve the quality connection during HO. Fig. 2 represents the HO decision based on A3 events, where the TTT and HOM require an accurate configuration to avoid the issues addressed in Fig. 2 [7].

The HO decision algorithm is a set of rules and criteria used in wireless communication networks to determine when and how connected devices should switch from one BS to another. However, the key goals of the HO decision algorithm include maintaining the quality of service, reducing RLFs, HOPPs, optimizing resource utilization, and improving overall network efficiency. For the HO decision, the algorithm takes into account various parameters and measurements, as shown in Fig. 3. Some of these parameters are as follow.

Signal strength: The strength of the signal from the serving and the target BSs is a fundamental parameter. The HO might be triggered when the signal strength falls below threshold or the target BS has higher signal strength compared to the serving BS.

Signal quality: In addition to signal strength, the quality of the received signal, which includes factors such as SINR and RSRQ, is crucial for ensuring a smooth HO.

Load balancing: The algorithm considers the load on different BSs to distribute the traffic and prevent congestion. If a BS is heavily loaded, the algorithm might initiate the HO to a less congested BS.

Distance: The physical location of the connected device in relation to neighboring BSs is considered. Some research works has taken the distance as a factor for HO decision.

Mobile Speed Scenario: The speed of the connected devices is a significant factor. High-speed movement may require more frequent HOs to maintain connectivity.

Quality of Service Requirements: Different applications and services have varying requirements for latency, data rate, and reliability. The algorithm may consider these requirements when setting the HO decisions.

HO History: The algorithm may also take into account the history of HOs for a particular device to avoid unnecessary and frequent HOs.

III. RELATED WORKS

MRO has attracted considerable interest from the research community. For instance, surveys [7], [8], and [19] have discussed the HO self-optimization, mainly the MRO functions. We have addressed several summary tables related to MRO studies in our surveys [7] and [8]. Each study in these tables includes a solution method, scenario, mobility model, HCPs, KPIs, simulator, and achievements. Besides, challenges, solutions, topologies, and future directions were outlined in our surveys. Moreover, to highlight the differences between the evaluated approaches, various researchers have applied different HO decision algorithms with different solution methods, such as weight function [16], [18], [20], [21], [22], [23], FLC [10], [12], [13], [14], [15] velocity-aware [24], [25], [26], [27], [28], [29], [30], UE speed

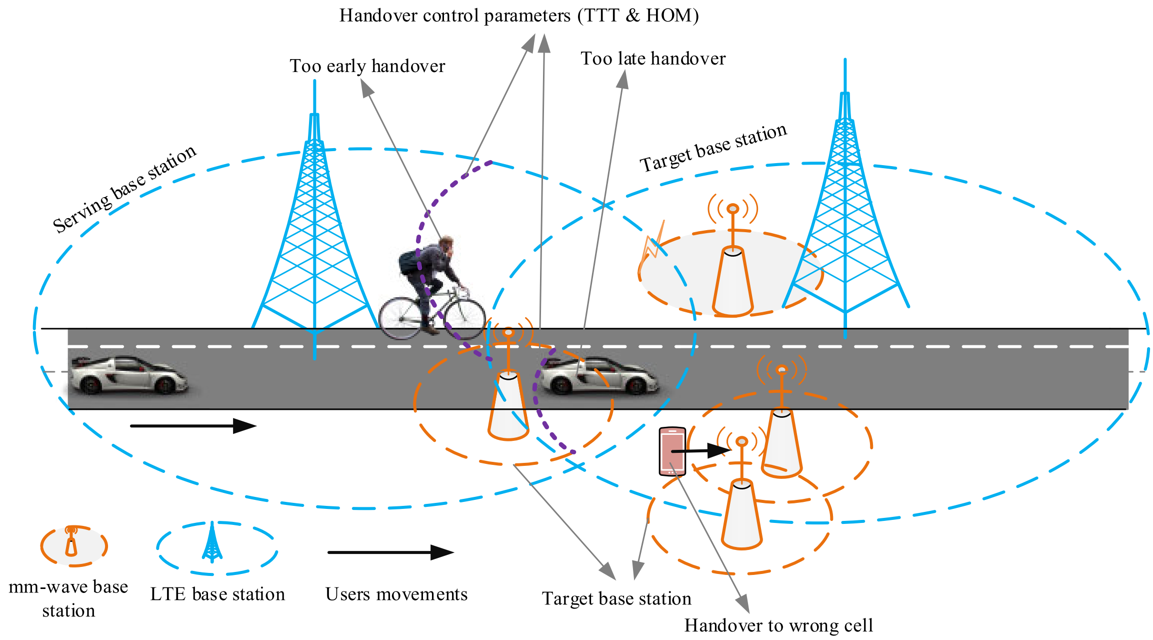


FIGURE 1. **Mobility robustness optimization issues.**

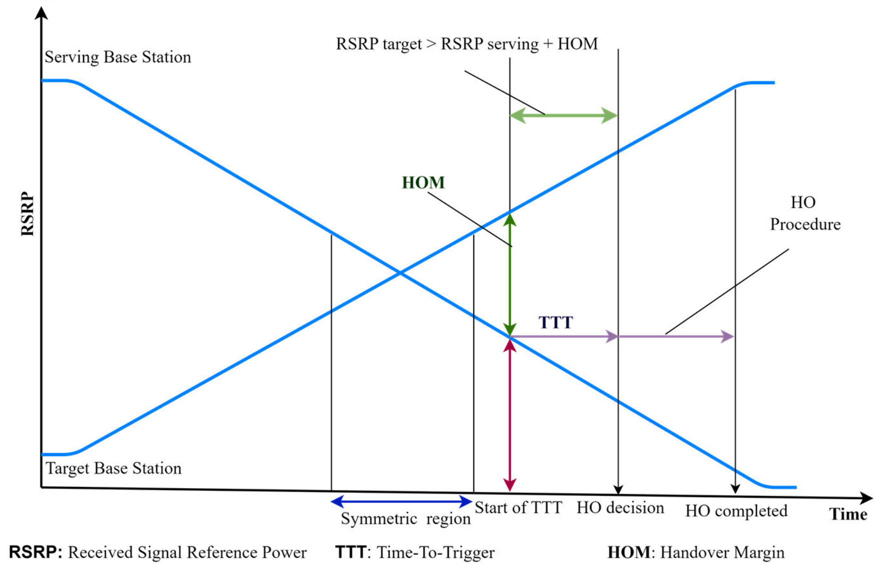


FIGURE 2. **Handover decision with handover control parameters of the MRO.**

with traffic load [13], dwelling time [31], RSRP-based [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], supervised machine learning (ML) in [42], [43], [44], [45], [46], [47], and [48], unsupervised ML in [49], and reinforcement learning in [5], [50], [51], [52], [53], [54], [55], [56], [57], [58], and [59]. Moreover, several mobile speed scenarios over a different deployment scenarios have been investigated using various KPIs. Therefore, the main objective is to achieve the optimal HO triggering point which subsequently improves the system's performance.

To avoid the redundancy work done in [7] and [8], several up-to-date MRO studies have been addressed in this study such as in [4], [21], [60], [61], [62], [63], [64], [65], and [66]. Besides, Table 1 summarizes various studies by addressing the problem, system, HCPs, mobility model, KPIs, solution method, drawback, and the operating frequency for each study.

Huang et al. [4] have presented a deep reinforcement learning algorithm to self-optimize the TTT and HOM. Besides, HOF and HOPP have been used as an indicators for

TABLE 1. Summary of MRO studies.

Ref., Year	Problem	HCPs	System	Mobility model	KPIs	Solution method	Drawback	Operating frequency
[64], 2024	Mobility issues (HOP, HOPP, HOF) over 5G network	TTT, HOM	5G	Random way point	HOP, HOPP, HOF, and throughput	Artificial intelligence multiple linear regression	RLF should be investigated due to the conflict in objectives with HOPP	28 GHz
[65], 2023	Minimizing HOPP and HOF	TTT	LTE-A/5G	Random way point	HOPP and HOF	FLC	A partial optimization process may affect on system performance due to not taking HOM as a HCP.	-
[66], 2023	Reducing RLFs and HOPPs	TTT, HOM	LTE	Random way point	RLF and HOPP	Multi-agent double deep Q-network	Over all simulation time and simulation steps should be taken into consideration to validate the system performance.	-
[21], 2023	HOPP reduction over 5G network	TTT, HOM	5G	Random way point	HOPP	Weighted function	Evaluation of the RLFs is required due the trade-off occurrence between HOPP and RLF	28 GHz
[60], 2023	Auto-tuning the HCPs at cell edge to minimize the MRO issues (HOP, HOPP, and HOF)	TTT, hysteresis, and threshold	5G	Directional mobility	HOP, HOPP, and HOF	Analytical closed-form expression to self-optimize the HCPs	The ratio of RLF is inversely proportional to the ratio of the HOPP. Hence, the ratio of RLF should be investigated	3.5 GHz
[61], 2023	Improving the capacity and minimizing the latency of 5G new radio	Fixed TTT	5G	Constant speed	Capacity and latency	Mixed integer linear programming	TTT should be self-optimized with HOM to increase the system performance	28 GHz
[62], 2023	Improving KPIs (HOF and HOPP) for reliable system	TTT, HOM	-	-	HOF and HOPP	Deep Q-learning with long-short-term-memory	RLF should be investigated since it has a trade-off with HOPPs	-
[16], 2022	Reducing mobility issues are required over a HetNet	TTT, HOM	HetNet	Street forward direction	HOPP, RLF, and HO latency	Weighted Function	Requires further enhancement for reducing HO latency by addressing conditional HO	2.1 GHz and 28 GHz for 4G and 5G network, respectively
[4], 2022	Complexity of modeling and analyzing the HO	TTT, HOM	Ultra-dense small BSs	Random waypoint	Throughput, HOF and HOPP	Deep reinforcement learning	The effects of speed scenarios on the occurrence of the RLFs should be discussed	-
[63], 2022	High mobility in 5G network	TTT, HOM	5G	Constant speed	Throughput, HO latency, and HOF	Reinforcement learning	The primary KPIs were not verified such as RLF and HOPP	26 GHz
[9], 2022	Optimal HO triggering over 5G network	TTT, HOM	5G	Street forward direction	HOP, HOF, HOPP, HO latency, and HO interruption time	FLC	RLF should be investigated because when the ration of the HOPP deceases, the ratio of RLF increases.	28 GHz

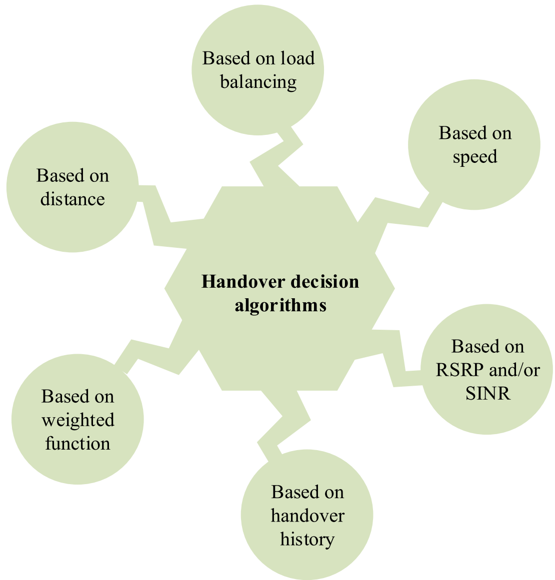


FIGURE 3. **Handover decisions.**

measuring the system's performance. Furthermore, random way point mobility has been employed over ultra-dense small BSs. Additionally, the technique for order of preference by similarity to ideal solution (TOPSIS) has been introduced to preselect the optimal target BSs based on three criteria: RSRP, SINR, and traffic load. The aim of the proposed approach was to decrease the HOF rate and minimize unnecessary HOs while allowing UE to fully utilize the advantages of a dense deployment of BSs.

Article [21] has proposed a WF as a solution method to self-optimize the TTT and HOM over the 5G network. Furthermore, the main objective of [21] is to reduce the HOPP probability using the input parameters (i.e., RSRP, mobile speed scenarios, and traffic load). Besides, a trigger timer has been introduced to minimize the HOPP effects by preventing the UE from initiating a HO decision to a BS with the same ID as the current serving BS. Moreover, various mobile speed scenarios (between 20 km/hr and 200 km/hr) have been applied using two simulation time intervals, including 150 sec and 400 sec.

Mbulwa et al. [60] have self-optimized the HCPs including TTT, hysteresis, and threshold using several metrics such as RSRP, speed, and UE's direction. Besides, the study was deployed over a 5G network using speed scenarios between 20 km/hr and 200 km/hr. Furthermore, a directional mobility model has been applied using speed scenarios between 0 km/hr and 120 km/hr. Moreover, the study aims to reduce the ratio of HOPP, HOF, and HOP.

Mixed integer linear programming has been proposed over the 5G network [61]. Furthermore, a fixed TTT has been assigned using speed scenarios between 30 km/hr and 90 km/hr. Besides, the study investigated the effect of blockage and speed scenarios on HO mechanisms over a vehicular network environment. However, the objective of the proposed approach was to reduce the HOPP probability, HO delay, number of HOs, and capacity.

A deep Q-learning technique has been proposed over a deployed ultra-dense network, taking into account various signal fading conditions [62]. Besides, a virtual system with long-short-term-memory was setup for predicting the occurrence of HOPPs and HOFs. However, the primary goal of [62] was to minimize the HOF, HOPP, and HOP.

Karmakar et al. [63] have proposed a reinforcement learning algorithm along with a Kalman filter using a deployed 5G network. Moreover, the Kalman filter is used for estimating the RSRP values of the serving and target BSs, whereas state action-reward-state-action reinforcement learning is used for selecting the proper target BS. Furthermore, a constant speed mobility model was applied using speed scenarios between 50 km/hr and 350 km/hr. However, the aim of this study was to minimize the HO latency and HOF while maintaining a high level of throughput.

Authors in [64] present an artificial intelligence multiple linear regression model designed to self-optimize the TTT and HOM over 5G networks. A random mobility model is applied to all users using five mobile speed scenarios, ranging between 40 km/hr and 140 km/hr in increments of 40 km/hr. However, the objective of this study was to reduce mobility issues including HOP, HOPP, and HOF while sustaining a high throughput level.

Haghrah et al. [65] have proposed FLC techniques based on RSRQ. The HO triggering was implemented over a coverage area of 1 km x 1 km. A random way point mobility model was applied to the 20 measured users using speed scenarios between 36 km/hr and 288 km/hr. Moreover, an ultra-dense SBSs outdoor environment has been taken into consideration. However, the study aims to reduce the ratio of the HOF and HOPP.

Article [66] has proposed a deep reinforcement learning approach to self-optimize the TTT and HOM. A random way point mobility model is used for all UEs (8 users) using various speed scenarios (i.e., 5 m/s, 10 m/s, 30 m/s, and 60 m/s). However, the main objective of [66] was to reduce the ratio of both HOPP and HOPP.

Several solution methods have been applied in the literature to accurately configure the HCPs of the MRO functions, as mentioned in Table 1. Additionally, these approaches were implemented using different systems, mobile speed scenarios, KPIs, and mobility models. Thereby, different accuracy levels were achieved. Furthermore, the next section presents various challenges related to mobility.

IV. CHALLENGES IN MOBILITY

Different deployed network environments, methods, and speed scenarios have been investigated by several studies during the last few years to optimize the HCPs. However, for achieving an accurate HCP setting value, several challenges have been raised which can be summarized as follows:

A. MASSIVE CONNECTED DEVICES

Ericsson has reported approximately 4.4 billion 5G subscriptions by 2027 [67]. Consequently, to guarantee the quality of experience (QoE), ultra-dense HetNets have been deployed for user satisfaction. In contrast, HO management problems may occur such as high HO ratio, HOPP, RLF, and high signaling loads due to the deployment of various types of BSs such as macro-BS (MBS), micro-BS, pico-BS, and femto-BS.

B. IMPLEMENTATION OF HIGH FREQUENCY BANDS

High frequency bands are gaining interest due to their capacity to achieve significant transmission capabilities in future wireless systems. In contrast, due to the characteristics of mm-wave communications, including limited transmission range, high sensitivity to obstacles, and large transmission loss, HO triggering conditions become more complex. Besides, several mobility issues have been raised, such as frequent HOs due to the requirement of delaying an ultra-dense SBSs to cover large areas. Subsequently, the ratio of RLF, HOP, and HOPP will increase [68], [69].

C. ULTRA-DENSE NETWORKS

One of the main motivations of HetNets is the substantial increase in data capacity. However, in recent years, there has been a significant demand for data capacity in mobile internet usage. However, the increase in requirements for data capacity is primarily driven by the widespread adoption of more sophisticated mobile devices. On average, the capacity required for a 3G smartphone approximately equals to 30 times the system capacity of a 2G voice phone, while 5 times the system capacity of tablet is needed compared to smartphone system capacity [70]. Therefore, mobile devices are an excellent platform for social networking applications like Facebook and instagram as they provide constant, always-connected coverage, making them highly accessible. In HetNets, usage of different RATs causes more signaling load, especially in HO cases due to the ultra-dense HetNets [71]. Furthermore, increasing the HO ratio in HetNet may lead to several mobility issues such as HOP, HOPP, and RLF which will subsequently deteriorate the system performance. Hence, an advanced HO optimization algorithm is required to maintain the UE's quality connections.

D. HIGH SPEED MOBILITY

The rise of innovative technologies like self-driving cars, unmanned aerial vehicles, and fast trains has led to a greater demand for uninterrupted connectivity when traveling at high speeds. As a result, mobility management systems are under increased pressure to guarantee a seamless transition between different network cells and minimize any negative effects on the user's overall experience.

E. LACK OF DATASET AVAILABILITY

ML predictions are more accurate when the dataset gets bigger and consist of more different cases. However, obtaining accurate and sufficient training dataset become a challenging problem due to the privacy of disclosing the wireless communication datasets. However, examining the user's mobility has been obtained by generating a synthetic dataset. But, the authenticity of the simulator's dataset may not be used as a benchmark for investigating the precision of ML models when applying the HO self-optimization processes.

F. DEVICE POWER CONSUMPTION

Due to the ultra-dense HetNet deployments, the UE's power consumption is raised. Moreover, different mobility systems (i.e., inter-system and intra-system) with mm-wave communications may contribute to power consumption negatively [72]. Therefore, high power consumption mostly occurs during the UE's updating and locating process which is called track area update and paging [73].

G. COVERAGE AND PROPAGATION ISSUES

As the utilization of mm-wave frequencies becomes more prevalent future mobile HetNets, characterized by high propagation losses and susceptibility to obstructions. Thereby, a proper HO decision algorithm is required to preserve the quality connection.

V. SYSTEM MODEL

This work is deployed over a HetNet environment that includes 61 MBSs, each MBS consists of 3 sectors, and 183 5G small BSs located in each sector. In addition, the simulation area covering 8×8 km^2 within an urban area. Furthermore, very small wavelength due to high frequency (i.e., 28 GHz) are applied for small 5G BS which requires a small geographical area [74].

The mobility scenario of this work is that the users are moving in fixed directions ($\theta = 0°$). To the best of our knowledge, utilizing one direction mobility model is better than using a random mobility model as this will enable the users to cross several BSs faster and this helps for raising the number of HOs during the simulation, since our system environment has a symmetrical form, θ value is insignificant. In addition, this model simulates the real network scenarios more logically. But, in the random mobility model the users will mostly keep moving in the same area, as a probability, and this means the HO probability will be so low. In the random mobility model, the users may move to other BSs and cross several cells, but this scenario still has a probability. Thus, the scenario is not as close to the real network. The black arrow presented in Fig. 4 shows the movement of the investigated users. Besides, 20 UEs whose starting points (x, y) are different over a HetNet have been investigated using several mobile speed scenarios. Furthermore, the movement steps between each simulation cycle varies from speed scenario to another. The step movements increase when the mobile speed scenarios increase. Hence, decreasing in the HCPs is required. Furthermore, 10 various mobility speed scenarios between 20 km/hr and 200 km/hr have been investigated. Table 2 highlights the network parameters which

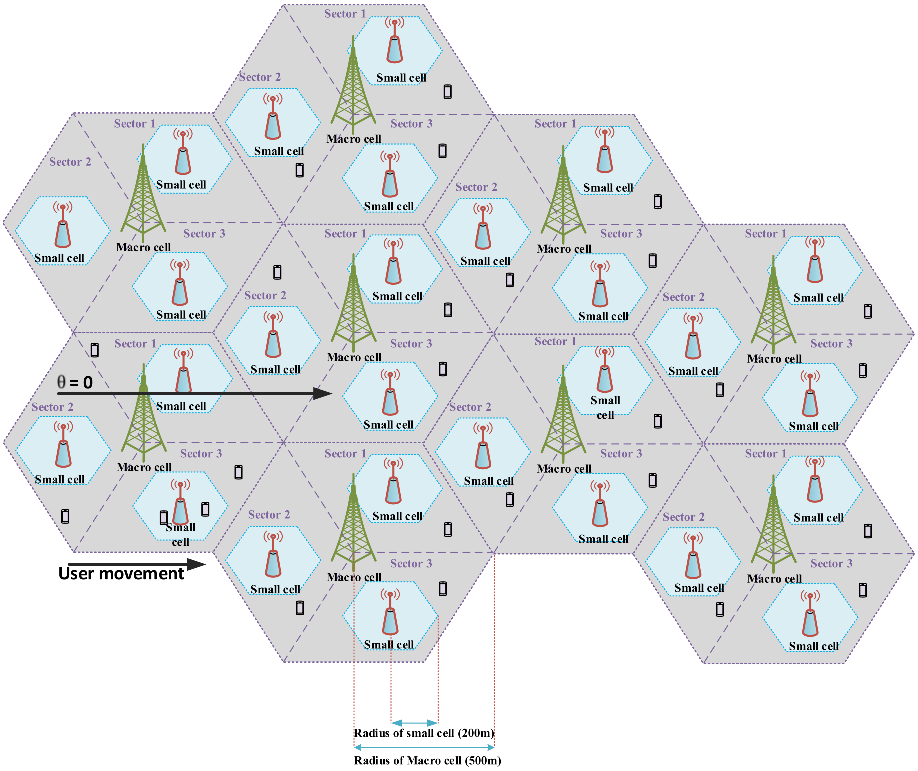


FIGURE 4. Proposed mobility model, in each sector, there is one SBS.

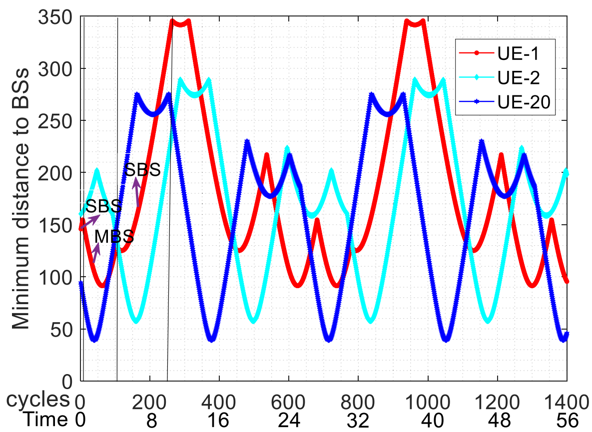


FIGURE 5. Minimum distance of the users versus simulation cycles and simulation time (v = 200 km /hr).

are estimated based on third-generation-partnership-project. (3GPP) specifications [18], [27], [32], [75], [76].

Since our simulation environment includes MBSs and small BSs, a UE can receive service from different BSs depending on its location. Fig. 5 shows the minimum distances of the users (UE1, UE2 and UE20) to the nearest BS in each simulation cycles. However, we are giving an example of one mobile speed scenario (200 km/hr) shown in Fig. 5. Therefore, the user moves 3.11 km overall the simulation time. Furthermore, x-axis of Fig. 5 shows the minimum distances of the user to the BS versus both the simulation cycle and simulation time. However, at the whole simulation cycles (1400 cycles), the user moves 56 secs. As seen from the figure, path-loss (PL) behavior for all UEs changes periodically, since the simulation environment is symmetrical. As the UE moves at each simulation instant, it moves away from the serving BS and approaches another BS. When the signal strength from the nearest BS is higher than the RSRP value of the serving BS plus the HOM value, the UE will want to HO to the nearest BS. The minimum distance value in Fig. 5, we can figure out that the considered UE makes HO to the BS which is closest when it has the minimum distance. However, for Fig. 5, UE1 will be described in more details as an example for easier understanding of the movement of the UEs inside the simulation environment. The annotations addressed in Fig. 5 are related to UE1. Therefore, according to Fig. 4, the initial position of UE1 x-axis and the y-axis are [-136.37, 91.38], respectively. Furthermore, at this initial position, the nearest BS was SBS with ID 185. Besides, 145.81 m was the minimum distance. The UE1 linked to ID 185 for six simulation cycles. Then, MBS with ID 1 was the nearest BS to UE1 starting from the simulation cycle number 7 to simulation cycle 103. The UE1 keeps moving to SBS from simulation cycle 104 to 263.

Fig. 6 shows the PL (dB) behavior of the UEs versus distance in meter as well as the PL versus the simulation time. The PL is calculated by using (1) when MBS is the serving cell by taking into account carrier frequency, BS antenna

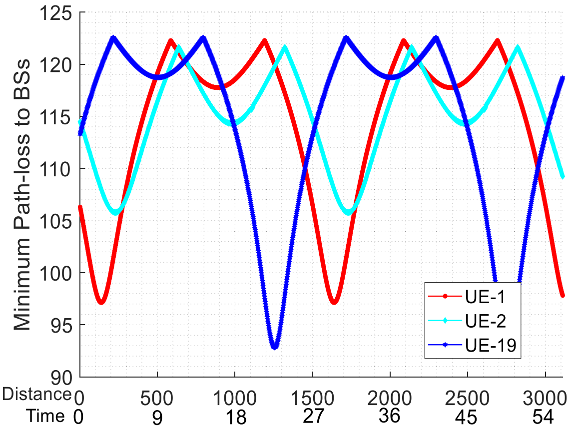


FIGURE 6. Minimum path-loss (dB) of the UEs versus distance and simulation time.

height and distance between the serving BS and the user [76].

We have presented three users among the 20 users as an example of the PL across all the BSs. Therefore, the mobile speed scenario used in Fig. 5 and Fig. 6 is 200 km/hr. However, the step movements for low-speed scenarios are small compared to high mobile speed scenarios.

$$PL_{dB} = 40\times\left(1-4\times10^{-3})d_{hb}\right)\log_{10}(R) - 18\times\log_{10}(d_{hb}) + 21\times log_{10}(f) + 80dB, \quad (1)$$

TABLE 2. HetNet parameters.

Network Parameter	Assumption: Macro Cell	Assumption: 5G small cell
Cell radius (meter)	500	200
Number of BSs	61	183
Operating Frequency (GHZ)	2.6	28
BS transmitter Power (dBm)	46	30
BS height (meter)	25	15
Bandwidth (MHz)	20	500
UE max Tx power (dBm)	21	
UE min Tx power (dBm)	-50	
Q_rxlevmin*(dBm)	-101.50	
UE height (meter)	1.5	
UE noise figure (dB)	9	
HOM (dB)	Adaptive (between 0 and 16)	
TTT (msec)	Adaptive (between 0. and 5120)	
Measurement interval	40ms	
HO decision algorithm	$RSRP_{Target} \geq RSRP_{Serving} + HOM$ (2)	
Environment	Urban areas, HetNet	

TABLE 3. Proposed algorithm for auto-tuning the HCPs over a HetNet.

```
Algorithm 1: Proposed FLC-WF Algorithm
Start
Initialize HetNet parameters
LOOP: for each mobile speed scenario
    Initialize network environment
  LOOP :for simulation cycles
    LOOP : for each user
      Initialize distance locations, path loss, fading, gains, RSRP, ...ect.
      Initialize traffic model
      Initialize mobility model
      Inputs: RSRP_serving, RSRP_target, UE's speed, traffic load
      Output: HOM, TTT
      Calculate the input parameters
      if T=1 then
        HO decision <------ false
      else
        if RSRP_target > RSRP_serving then
          Initialize FLC
          Convert the input parameters to fuzzy sets with ranges
          according to Fig. 5
          Formulate the fuzzy rules according to Table 5
          Auto-tunes HOM
          Initialize WF
          Update TTT according to (6)
          Auto-tunes TTT
            if RSRP_target > RSRP_serving + HOM then
              if trigger timer >= TTT then
                HO decision <------ true
                Send HO request
                Initialize preparation, execution, and completion HO
              elseif RSRP_serving < RSSI & RSRP_target > RSSI then
                  No trigger timer is initiated
                  HO decision <------ true
                  Send HO request
                  Initialize preparation, execution, and completion HO
              else
                  HO decision <------ false (The serving BS remain the same)
              end
          else HO decision <------ false (The serving BS remain the same)
          end
        else  HO decision <------ false (The serving BS remain the same)
        end
      end
    end LOOP of users
  end LOOP of simulation cycles
end LOOP of mobile speed scenarios
```

where R is UE-BS separation in km, f is the carrier frequency in MHz, and d_{hb} is the BS antenna height.

However, the operating frequency and the BS antenna height have been mentioned in Table 2. Moreover, two different PL models have been applied in this study by changing the operation frequency and BS antenna height in (1). For example, f and d_{hb} values used for MBS are different from those used for SBS as addressed in Table 2.

VI. PROPOSED INTEGRATED MODEL

In this paper, by taking into consideration UE's speed, RSRP, and traffic load, the TTT and HOM values of the MRO function, which are HCP settings, are automatically optimized. It is mentioned that UE's speed has been ignored by majority of researchers. However, it can lead a severe deterioration of connection quality. Two proposed methods were applied for auto-tuning the HCPs which vary in their simulation time,

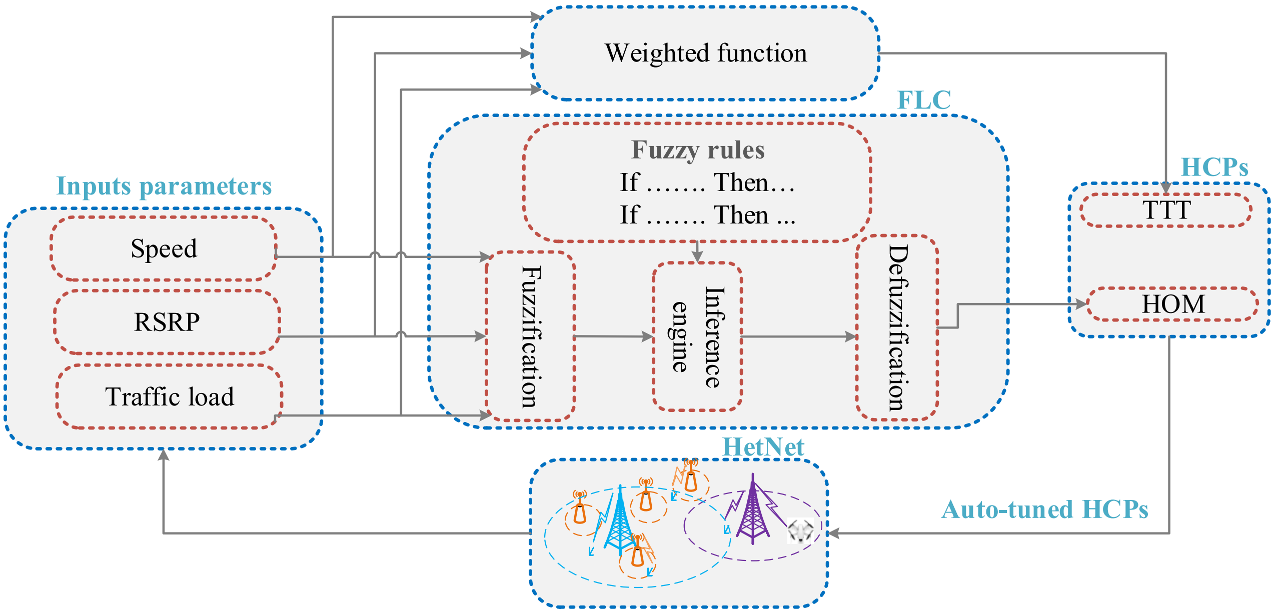


FIGURE 7. Proposed method 1 for HO self-optimization over the HetNet.

TABLE 4. Simulation parameters for the proposed method 1.

Parameters	Values
Number of simulation cycles	1400
Speed scenarios (km/hr)	from 20 to 200 with 20 km / hr steps
Number of users	20

TABLE 5. Events controlled by MRO [77].

Events	HOM	TTT
HOF/ RLF happened	Decrease	Decrease
HOPP happened	Increase	Increase
High or medium speed detected	Decrease	Decrease

number of users, and classification of input parameters. Furthermore, the investigation of the proposed algorithm is done using MATLAB 2021a and based on the network deployment and system setting defined by 3GPP Release 16. Therefore, Table 3 represents the proposed algorithm in sequential manner for self-optimizing the TTT and HOM.

A. FUZZY WEIGHTED OPTIMIZATION FUNCTION

In our study, we have used the proposed FLC-WF algorithm for self-optimizing the TTT and HOM over a HetNet scenario. Fig. 7 represents the proposed solution method which includes FLC and weighted function. Moreover, the FLC is used to auto-tune the HOM parameter, whereas the weighted function is used for optimizing the TTT. Furthermore, Table 4 presents the supplementary estimated parameters that have been incorporated into Table 2 to support the proposed method illustrated in Figure 7. However, 20 users have been analyzed using 10 different mobile speed scenarios.

Table 5 presents the way of controlling the HCPs of the MRO to preserve the network resources and keeping the quality connection. Besides, it represents the actions needed to be considered when different events happen. Furthermore, the table illustrates the relation of mobile speed scenarios and the HCPs. For example, low-speed scenarios require low settings of HCPs, while high setting value for HCPs is required for high-speed scenarios. Therefore, the enhancement of the performance metrics can be achieved by adapting the HOM and TTT to achieve optimal HO triggering point as shown in Table 5.

1) FUZZY LOGIC CONTROLLER (FLC)

For the proposed FLC-WF, the proposed FLC algorithm is used for the decision-making process to self-optimize the HOM. In FLC, several processes are taken into considerations which are as follow:

- **Fuzzification:**
  It is the process of transforming the input crisp quantity into fuzzy sets. The linguistic variables define the inputs and outputs in the FLC. However, a set of membership functions for the inputs should be generated. For example, mobile speed scenario is an input which has been converted to fuzzy sets with ranges. Therefore, the fuzzy membership function of our proposed algorithm is addressed as follow:
- **Inputs membership function:**
  Three membership functions are applied as shown in Fig. 8. Each membership function includes several fuzzy sets and each fuzzy set has its own range. In Fig. 8 (a), the

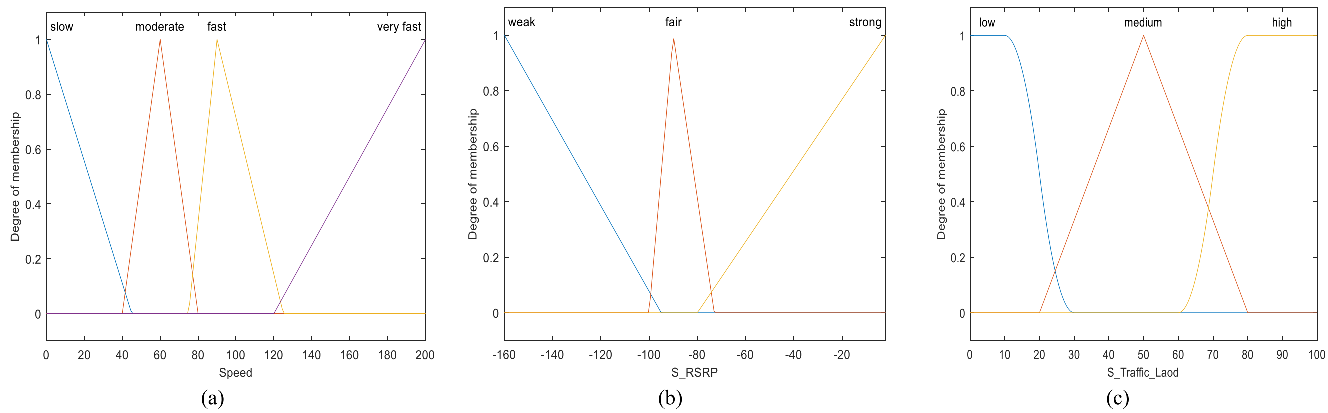


FIGURE 8. Inputs membership functions (a) UE's velocities (b) UE's RSRP (c) Traffic load.

speed membership function has four fuzzy sets which defined as slow, moderate, fast, and very fast. We called the fuzzy input slow when UE speed is between 0 and 50 km/hr, while called it moderate for UE speed is between 40 and 80 km/hr. It is assumed that the mobile speed scenarios range between 0 km/hr and 200 km/hr. Furthermore, Fig. 8 (b) represents the serving RSRP (dBm). Three fuzzy sets are applied which includes weak, fair, and strong. In addition, Fig. 8 (c) represents the cell loads which are classified into three fuzzy sets (i.e., low, medium, and high). However, the generated fuzzy rules are applied according to the fuzzy sets of the input parameters. Therefore, Fig. 8 is generated by creating a new fuzzy inference system and then adding our input parameters with ranges.

- **Fuzzy rules:**
A set of rules is then applied to the membership functions to yield to output value. Furthermore, "and" logic gate "or" logic gate are initiated based on the designer's interest. We have "and" logic gate for this study. However, the fuzzy rules are changed according to the ranges of output membership functions. Therefore, we have generated fuzzy rules as addressed in Table 6. Furthermore, the HOM values are tuned based on the input parameters. For example, if the speed is slow and RSRP is weak and load is low set, then HOM should be assigned to low set as highlighted in Fig. 9. Therefore, Table 6 shows 36 rules which are all possible rules that can be obtain from 4 fuzzy sets in speed, 3 fuzzy sets in RSRP, and 3 fuzzy sets in load. Furthermore, the output value obtained from the output fuzzy sets (HOM) can determine the performance of the system. However, accurate configuration of HOM value leads to reduction in HOP, HOPP, and RLF. Besides, the RSRP will be kept in acceptable level.
- **Defuzzification:**
Defuzzification is a procedure used to transform the ambiguous output of an FLC, expressed as a membership function, into a distinct numerical or crisp value that can be implemented as a control action or decision.

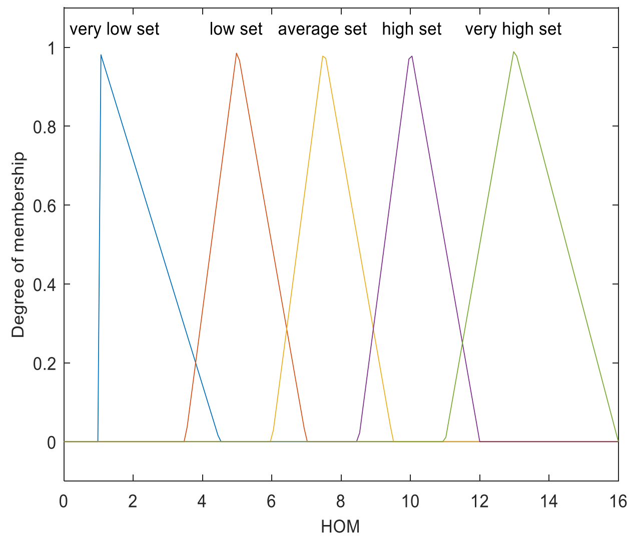


FIGURE 9. Output membership function of the proposed FLC.

- **Output membership function:**
The output membership function for HOM value (dB) is addressed in Fig. 9 which consists of several fuzzy sets ranging between 0 dB and 16 dB. Therefore, the fuzzy sets include very low set, low set, average set, high set, and very high set. However, HOM's fuzzy sets are assigned according to the input linguistic variables addressed in Table 6. Therefore, high HOM values have been used carefully in the applied FLC's rules to avoid high HOPPs and/or high RLFs.

2) WEIGHTED OPTIMIZATION FUNCTION

The second control parameter that is required to be self-optimized is the TTT. Therefore, the weighted function is used to self-optimize this parameter. The weighted function (WF) is used to self-optimize the TTT parameter. However, three function have been used as addressed below:

TABLE 6. Fuzzy rules for auto-tuning HOM.

Rule No.	Speed	RSRP	Load	HOM
1	Slow	Weak	Low	Low set
2	Slow	Weak	Medium	Low set
3	Slow	Weak	High	low set
4	Slow	Fair	Low	low set
5	Slow	Fair	Medium	low set
6	Slow	Fair	High	Average set
7	Slow	Strong	Low	Very high set
8	Slow	Strong	Medium	low set
9	Slow	Strong	High	High set
10	Moderate	Weak	Low	Very low set
11	Moderate	Weak	Medium	Very low set
12	Moderate	Weak	High	Very low set
13	Moderate	Fair	Low	average set
14	Moderate	Fair	Medium	average set
15	Moderate	Fair	High	average set
16	Moderate	Strong	Low	high set
17	Moderate	Strong	Medium	average set
18	Moderate	Strong	High	average set
19	Fast	Weak	Low	Very low set
20	Fast	Weak	Medium	Very low set
21	Fast	Weak	High	Very low set
22	Fast	Fair	Low	low set
23	Fast	Fair	Medium	low set
24	Fast	Fair	High	average set
25	Fast	Strong	Low	average set
26	Fast	Strong	Medium	average set
27	Fast	Strong	High	high set
28	Very fast	Weak	Low	Very low set
29	Very fast	Weak	Medium	Very low set
30	Very fast	Weak	High	Very low set
31	Very fast	Fair	Low	average set
32	Very fast	Fair	Medium	average set
33	Very fast	Fair	High	average set
34	Very fast	Strong	Low	high set
35	Very fast	Strong	Medium	high set
36	Very fast	Strong	High	high set

RSRP function: The maximum RSRP is pre-determined by -20 dBm and will be updated according to the maximum RSRP value of the measurement report.

$$f\,(RSRP) = \left(\frac{RSRP_T}{RSRP_{max}}\right) - \left(\frac{RSRP_S}{RSRP_{max}}\right) = \frac{RSRP_T - RSRP_S}{RSRP_{max}}, \tag{3}$$

where T, S, and max subscripts represent the RSRP of the target BS, the RSRP of the serving BS, and the maximum value of the RSRP, respectively.

Traffic load's function: The loads of the BSs are updated periodically in every simulation cycle which stated as 40 msec.

$$f\,(TL) = \left(\frac{TL_T}{TL_{max}}\right) - \left(\frac{TL_S}{TL_{max}}\right) = \frac{TL_T - TL_S}{TL_{max}}, \tag{4}$$

where TL_T, TL_S, and TL_{max} represent the target BS's traffic load, serving BS's traffic load, and maximum traffic load, respectively.

Velocity function: Several mobile speed (v) scenarios are applied to the following velocity function.

$$f\,(v) = 2\log_2\left(1 + \frac{v}{v_{max}}\right) - 1, \tag{5}$$

where v_{max} is the maximum velocity applied which is 200 km/hr. However, the mathematical model is addressed as below:

$$w_n = \frac{1 - f(x_n)}{\sum_{i=1}^{F}(1 - f\,(x_i))}, \tag{6}$$

where w_n is the weight of function n, and n can be one of the three functions (i.e., RSRP, TL, or v). For simplifying (4), the below equation is addressed:

$$w_{RSRP} = \frac{1 - f(RSRP)}{(1 - f\,(RSRP)) + (1 - f\,(TL)) + (1 - f\,(v))} \tag{7}$$

However, w_{TL} and w_v can be simplified easily from (6). According to the weights of the functions, the TTT values are self-optimized. Therefore, the main objective is to reduce MRO issues (i.e, too late HOs, too early HOs, and HO to wrong cell).

B. VELOCITY AWARE FUZZY WEIGHTED OPTIMIZATION FUNCTION

Assigning precise values to the HCPs (TTT and HOM) at different mobile speed scenarios is significant to avoid the mobility issues (i.e. too late HOs, too early HOs, HOs to wrong cell). However, the RSRP quickly decreases in high speed scenarios, which requires a low setting value for the TTT and HOM in order to avoid too late HOs. Moreover, since the mobile speed scenarios are low, the UE keeps connecting to serving BS longer compared to high mobile speed scenarios, which require assigning high values for the TTT and HOM in order to avoid too early HOs. However, in Table 8, we indicated that the values of the HCP are directly related to speed scenarios. For instance, low speed scenarios require high setting values to avoid too early HOs, whereas high speed scenarios require low setting values to initiate a fast triggering HO in order to avoid too late HOs. Furthermore, speed category 1 (slow speeds) has higher HOM values compared to speed category 4 (very fast speeds), as addressed in Table 8.

This proposed algorithm differs by the mobile speed categorization compared to the previous method mentioned in Fig. 8. Moreover, the mobile speed scenarios have been classified into four categories such as speed less than 60 km/hr, speed between 60 km/hr and 120 km/hr, speed between 120 km/hr and 160 km/hr, and speed between 160 km/hr and 200 km/hr. However, the membership function has been established for each speed category. Therefore, each mobile speed scenario applied in the simulation environment will fall into one of the four speed categories generated. The objective

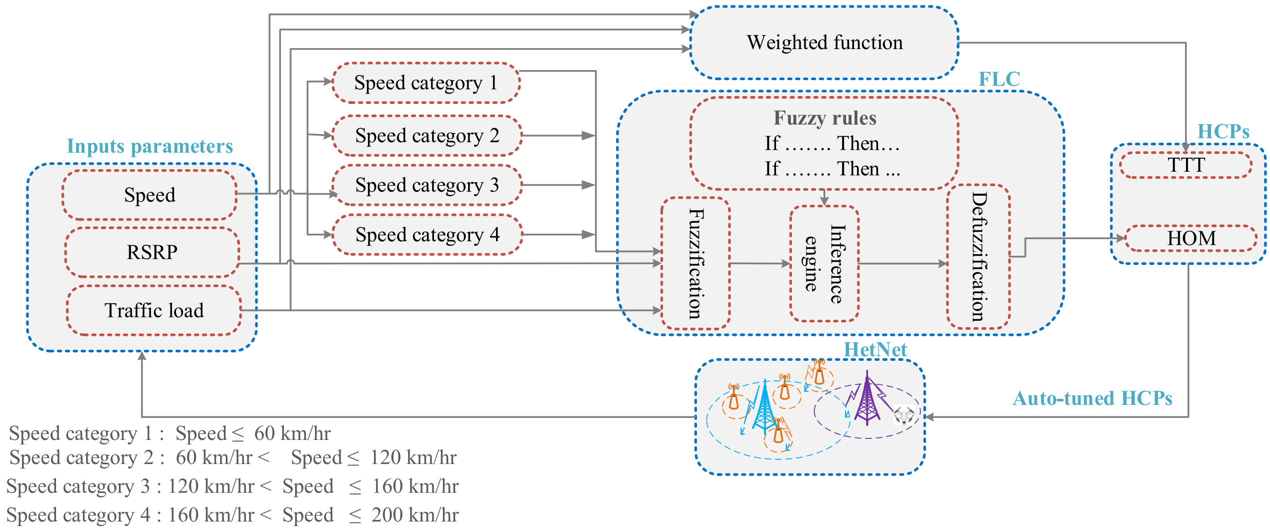


FIGURE 10. Proposed method 2 for HO self-optimization over the HetNet.

TABLE 7. Simulation parameters for the proposed method 2.

Parameters	Estimations
Number of simulation cycles	3750 (150 secs)
Speed scenarios (km/hr)	40, 60, 80, 100, 120, and 140
Number of users	15

of categorizing the mobile speed scenarios is to assign an accurate HOM. Furthermore, Table 7 presents the simulation parameters for the proposed Method 2 that shown in Fig. 10. Furthermore, the parameters in Table 7 are considered as a supplementary parameters to Table 2. The simulation cycles are increased in Method 2 which allow the user moving a longer distance with crossing more BSs. Subsequently, more HOs can be investigated. Besides, to prevent user edge crossing, the user is returning back when reaching to the last BS of the simulation environment.

In this section, the membership function of the mobile speed scenarios addressed in Fig. 12 was generated based on speed categories shown in Fig. 10. However, the speed membership function has 4 different levels of fuzzy sets specified as slow, moderate, fast, and very fast. Therefore, the mobile speed scenario will determine which fuzzy set will be chosen. Then, the output fuzzy set will be determined. However, the other input membership functions are addressed in Fig. 8 (b, c).

The output membership function shown in Table 8 will be determined based on the mobile speed scenario applied. However, the auto-tuning of the HOM is achieved by obtaining a HO triggering value from Table 8. Whereas the TTT

TABLE 8. Output membership function.

Linguistic Variable	Number of speed category	Linguistic fuzzy sets restrictions	Ranges of fuzzy set (dB)	
			From	To
HOM (dB)	1	Short	4	5
		Average	5	6
		Long	6	7
		Very long	7	7.5
	2	Short	3	3.5
		Average	3.5	4
		Long	4	4.5
		Very long	4.5	5
	3	Short	2	2.5
		Average	2.5	3
		Long	3	3.5
		Very long	3.5	4
	4	Short	1	1.5
		Average	1.5	2
		Long	2	2.5
		Very long	2.5	3

triggering value is achieved by the proposed weighted optimization function. Therefore, these HO triggering values (i.e., TTT and HOM values) have a significant impact in reducing the KPIs applied in this study (i.e., HOPP, RLF, and HOP) as well as obtaining high RSRP (dBm). Furthermore,

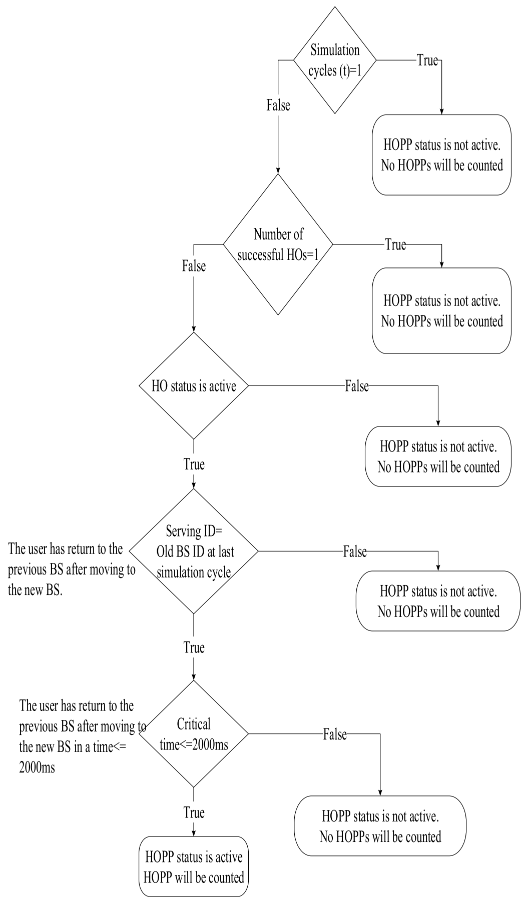


FIGURE 11. Flowchart of the HOPP's counter in HetNet.

the HOPPs is obtained using the algorithm given in Fig. 11. Therefore, low average probability of the HOPP and RLF indicate that the HCPs are configured accurately.

VII. RESULTS AND DISCUSSION

The results have been classified into two parts. The first part proposes the fuzzy weighted optimization function based on Fig. 7. The second part proposes a velocity aware fuzzy weighted optimization function based on Fig. 10.

A. FUZZY WEIGHTED OPTIMIZATION FUNCTION

10 mobile speed scenarios (i.e., 40 km/hr, 60 km/hr, 80 km/hr, 100 km/hr, 120 km/hr, and 140 km/hr) have been applied. In addition, 20 users have been measured over all the simulation cycles.

This subsection explains the results related to our proposed FLC-WF algorithm. However, the proposed solution method is addressed in Fig. 7 where the output parameters (TTT and HOM) have been auto-tuned by two algorithms (i.e., FLC and WF), HOM was tuned by FLC whereas WF is used to self-optimize the TTT. However, the simulation parameters of the proposed algorithm are addressed in Table 2 and Table 4.

Fig. 13 and Fig. 14 are simulated over all the mobile speed scenarios, all users, and over all simulation cycles. The average HOPP probability versus HO optimization algorithm is addressed in Fig. 13. However, decreasing the HOPP to 0 for the WF in Fig. 13 has impacted on both RLF and RSRP as we can see in Fig. 14 and Fig. 16, respectively. Therefore, the trade-off in our proposed algorithm is kept to 0.0002 for the HOPP in order to decrease the RLF effect as low as possible. However, the HOPPs have impact on network resources and it may not affect customer satisfaction.

The following points explain the HOPP level to justify why the HOPP values were low in this simulation study:

- The simulation time (56 sec.) which is 1400 cycles that used for evaluating the KPIs has also impact on HOPP level. However, increasing the simulation cycles allow the user to across a large number of BSs which will increase the number of HOs. Besides, increasing simulation time with increasing mobile speed scenarios will make the user even crossing more BSs.
- Proposing a trigger timer has a great impact of reducing HOPPs. The objective of the trigger timer is to avoid the HO from sector to the same sector or from SBS to the same SBS. This impacted on reducing the HOPP which subsequently reduces the HOP. However, as shown in Table 3, the trigger timer is initiated under a certain conditions such as when the HO decision is satisfied as well as the ID of the target BS is different from the ID of the serving BS.
- The setting value of the HCPs (i.e., TTT and HOM) has a great impact on increasing and decreasing the HOPPs. However, Table 4 shows the suboptimal settings of MRO parameters (i.e., TTT and HOM).

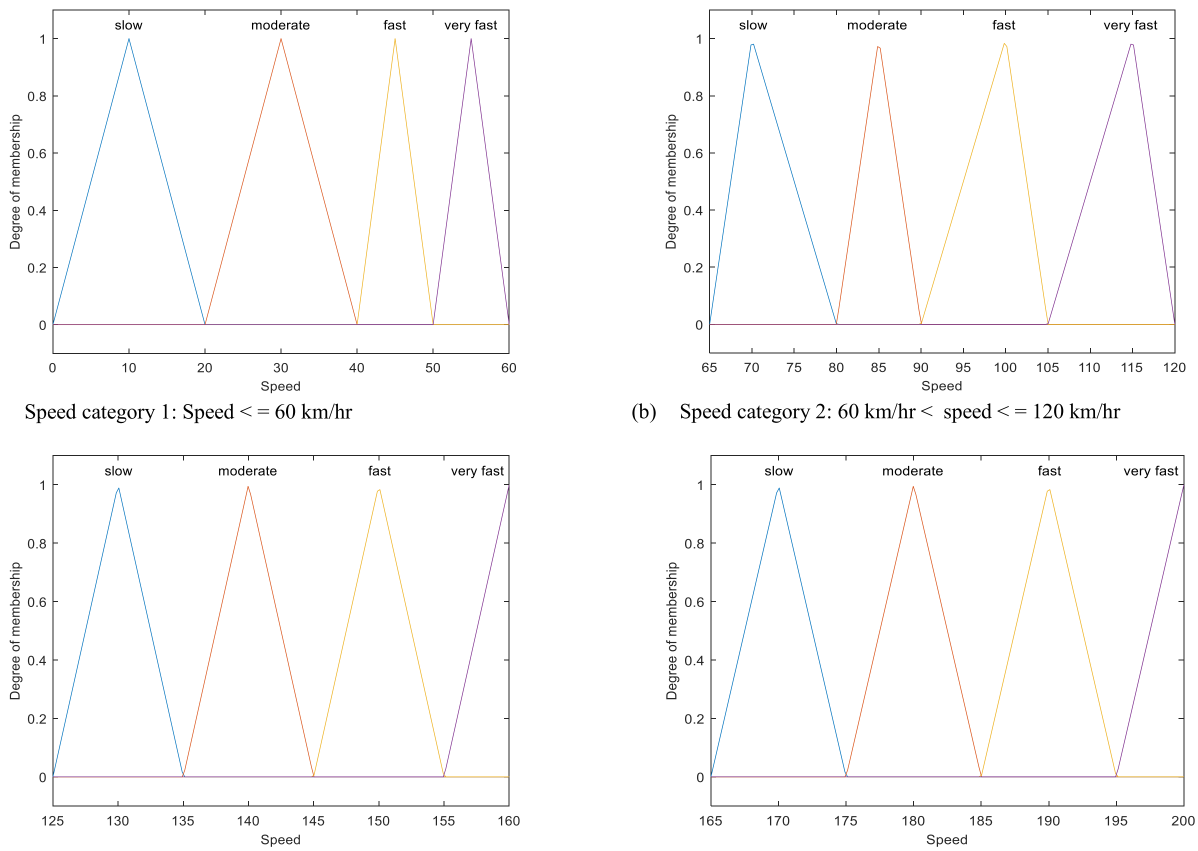
However, we have increased the simulation time in our proposed Method 2.

Fig. 14 shows the average RLF probability versus the presented self-optimization algorithms. However, the proposed algorithm shows that the WF algorithm has the highest average RLF with 0.02 while the proposed algorithm has 0.0084. However, the great concern for network operators is to reduce the RLFs of the network to keep the customer connected to the network.

The results presented in Fig. 13 and Fig 14 were obtained based on the proposed method 1, without categorizing the mobile speed scenarios. Utilizing a wide speed range (from 20 km/hr to 200 km/hr) with FLC may lead to inaccuracies in assigning optimal points for the TTT and HOM. Hence, minimal improvements have been achieved in Fig. 13 and Fig. 14. Therefore, we further enhanced the proposed method 1 by proposing the velocity-aware-FLC-WF (VAW-FLC-WF) algorithm as mentioned in Fig. 10.

Fig. 15 represents the average RLF probability for each mobile speed scenarios.

Besides, the simulation is implemented over all simulation time using 20 UEs. Moreover, it can be seen from Fig. 15 that the proposed algorithm has the lowest average RLF probability at all speed scenarios compared to WF algorithm. In addition, the proposed algorithm shows less RLFs in



(a) Speed category 1: Speed < = 60 km/hr

(b) Speed category 2: 60 km/hr < speed < = 120 km/hr

(c) Speed category 3: 120 km/hr < speed < = 160 km/hr

(d) Speed category 4: 120 km/hr < speed < = 200 km/hr

FIGURE 12. Input membership function of mobile speed scenarios.

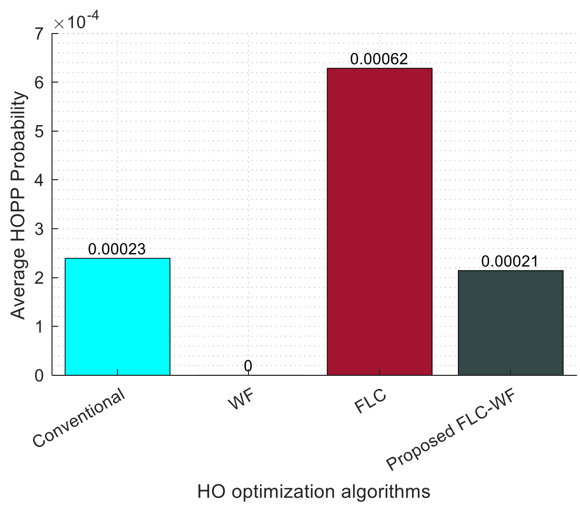


FIGURE 13. Average HOPP probability versus HO algorithms.

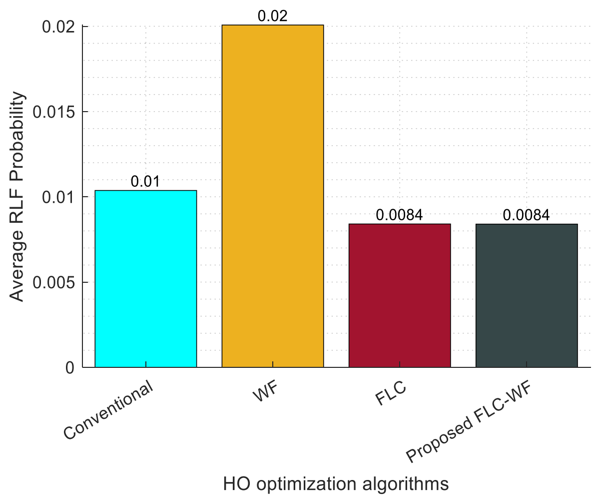


FIGURE 14. Average RLF probability versus HO algorithms.

several mobile speed scenarios such as in 40 Km/hr, 60 km/hr, and 140 km/hr compare to FLC. Therefore, accurate configuration of the HCPs (i.e., TTT and HOM) leads to low RLFs in several speeds of the proposed algorithm. High average HOPP has a direct impact on increasing the level of RSRP (dBm) because in HOPP the UE is triggering to the target BS that has the highest RSRP value which will subsequently lead to high average serving RSRP as shown in FLC of Fig. 16. Moreover, WF has the lowest average serving RSRP since it has 0 HOPPs. However, the average serving RSRP of our proposed FLC-WF was kept between -57 dBm and 49 dBm.

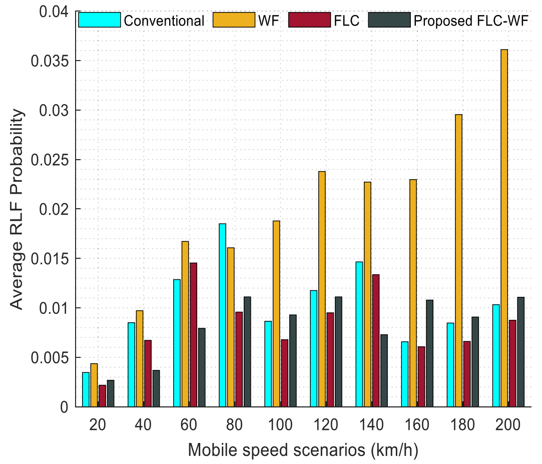


FIGURE 15. Average RLF probability versus mobile speed scenarios.

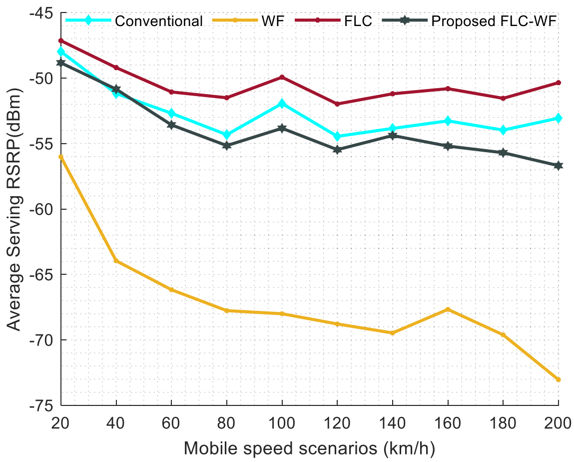


FIGURE 16. Serving RSRP (dBm) for all users and all mobile speed scenarios vs simulation time.

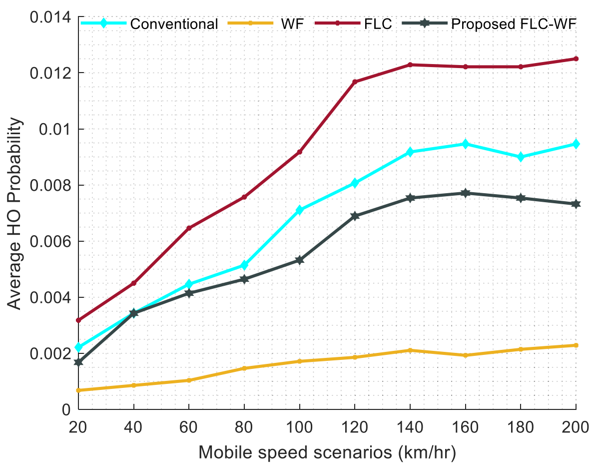


FIGURE 17. Average HO probability versus mobile speed scenarios.

Fig. 17 represents the average HOP over several mobile speed scenarios. However, increasing the mobile speed scenarios leads to increasing in HOP since the user is crossing more BSs compared to low-speed scenarios. Furthermore, increasing the amount of HOPPs increases the HOP which subsequently negatively impact on system performance since it leads to wasting the network resources.

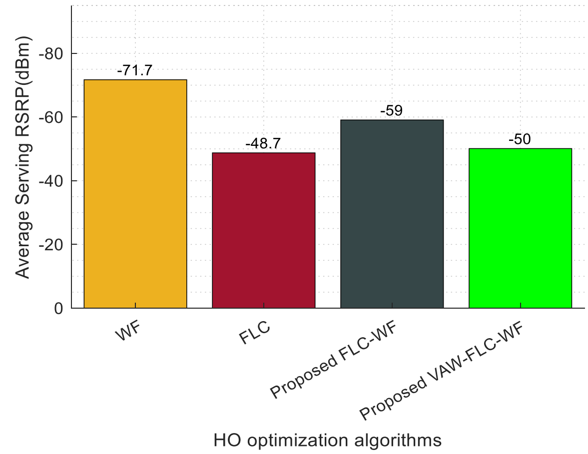


FIGURE 18. Average RSRP versus HO algorithms.

B. VELOCITY AWARE FLC-WF

The results of this part are achieved based on our improved method shown in Fig. 10. Therefore, the developed algorithm velocity-aware-FLC-WF (VAW-FLC-WF) shows more results enhancement compared to the proposed FLC-WF obtained by Fig. 7. Moreover, the number of both simulation cycles, mobile speed scenarios, and users are presented in Table 7. Furthermore, the proposed VAW-FLC-WF was compared with other HO algorithms.

Fig. 18 represents the average RSRP (dBm) versus HO optimization algorithms. In addition, Fig. 18 shows the proposed algorithm (VAW-FLC-WF) has been improved compared to the proposed FLC-WF. Furthermore, VAW-FLC-WF shows more enhancement compared to WF. 1.3 dBm was the difference between VAW-FLC-WF and FLC because due to high HOPPs in FLC which made the users fluctuating between high RSRP.

Besides, Figs. 18, 21, and 20 have been implemented over all mobile speed scenarios, over all users, and all simulation time. In addition, Figs. 19 and 20 show the average RSRP versus different mobile speed scenarios and simulation time, respectively. Besides, these two figures show that VAW-FLC-WF has the highest RSRP compared to the other algorithms except that FLC achieves a small higher RSRP. However, it can be summarized that, high RLFs have an inverse proportion to RSRP value since the user keep connecting to the same BS until it goes to below the RSSI. Consequently, the average RSRP will be decreased. Moreover, high HOPPs have a direct proportion to RSRP value since the user keep fluctuating between BSs that have a high RSRP. Consequently, the average RSRP will be increased.

Fig. 21 shows the average HOPP versus HO algorithms where VAW-FLC-WF shows a significant enhancement by

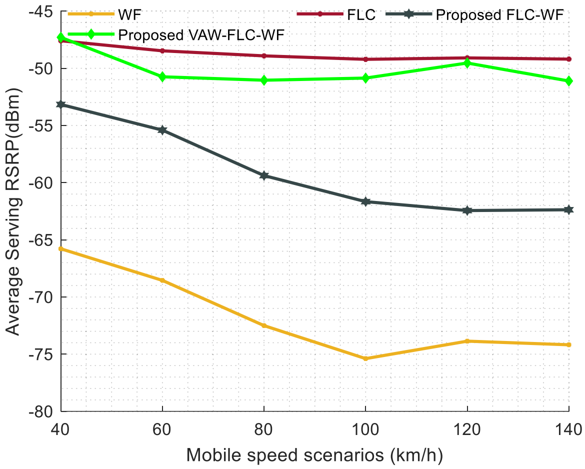


FIGURE 19. Average RSRP at different mobile speed scenarios.

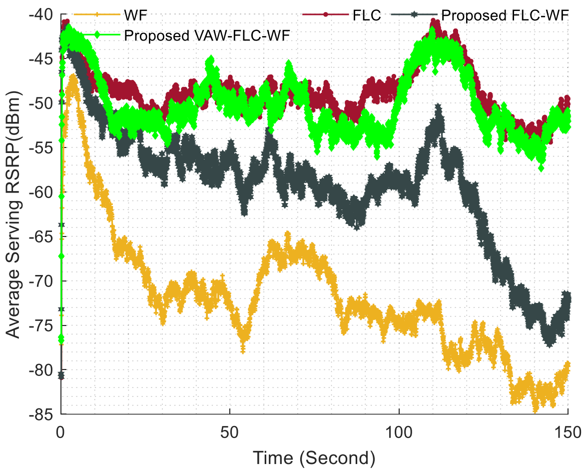


FIGURE 20. Serving RSRP (dBm) for all users and all mobile speed scenarios vs simulation time.

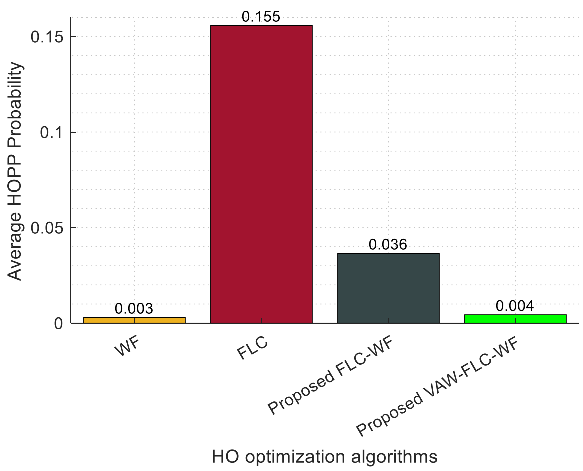


FIGURE 21. Average HOPP probability versus HO algorithms.

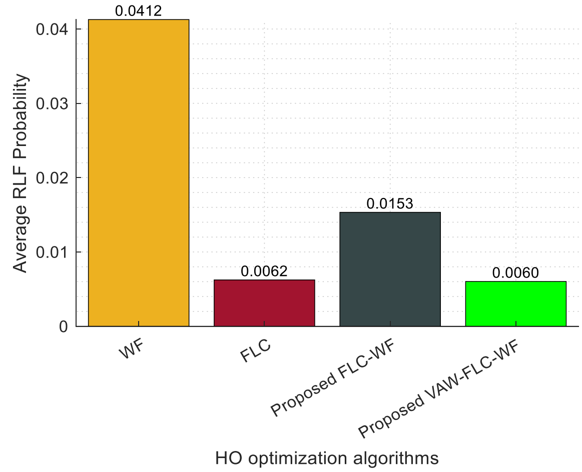


FIGURE 22. Average RLF probability versus HO algorithms.

TABLE 9. List of abbreviations in alphabetical order.

Item	Description
3GPP	Third-generation partnership project
5G	Fifth generation
BS	Base station
FLC	Fuzzy logic controller
HCP	Handover control parameters
HetNet	Heterogeneous networks
HO	Handover
HOF	Handover failure
HOM	Handover margin
HOP	Handover probability
HOPP	Handover ping-pong
KPI	Key performance indicator
MBS	Macro base station
ML	Machine learning
MRO	Mobility robustness optimization
PL	Path-loss
RLF	Radio link failure
RSRP	Received signal reference power
RSRQ	Received signal reference quality
RSSI	Received signal strength indicators
SINR	Signal-to-interference-plus-noise-ratio
TL	Traffic load
VAW-FLC-WF	Velocity-aware-fuzzy logic controller-weighted function
WF	Weighted function

0.004 compared to the other algorithms. However, a proper configuration of TTT and HOM of the proposed VAW-FLC-WF leads to less HOPPs. Consequently, enhancing the system's performance. Fig. 22 represents the average RLF probability versus HO algorithms. The proposed algorithm VAW-FLC-WF shows the lowest average RLF probability compared to the other HO optimization algorithms presented.

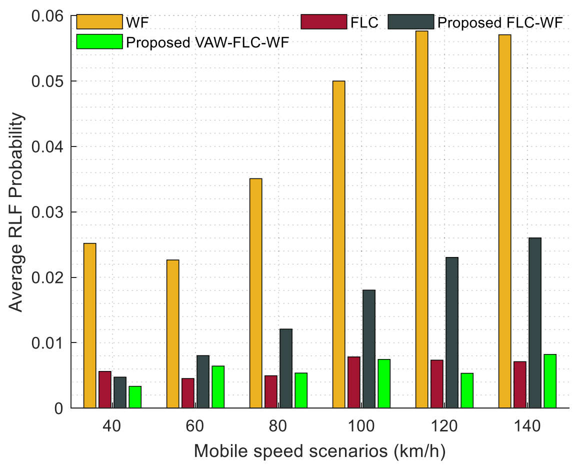


FIGURE 23. Average RLF probability versus different speed scenarios.

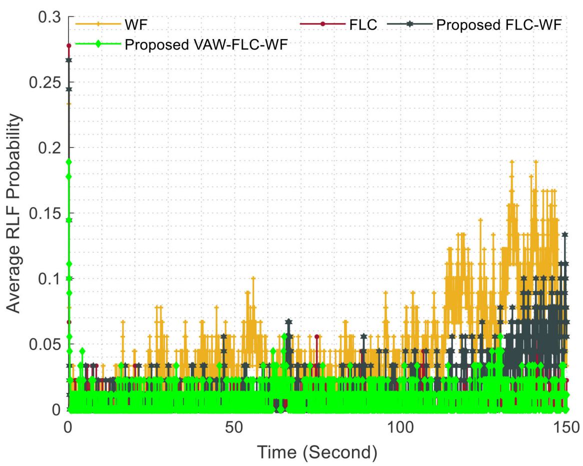


FIGURE 24. Average RLF probability versus simulation time.

This is due to the proper assignment of the values of TTT and HOM during HOs which made the VAW-FLC-WF algorithm decreases to 0.006. Furthermore, Figs. 23 and 24 address the average RLF probability versus different mobile speed scenarios and simulation time, respectively. Moreover, six mobile speed scenarios were applied over the whole simulation time (150 secs). However, an increase in the ratio of HOPP means the signaling load has increased as well as the network resources have been wasted. Subsequently, the cost and time for the network operators will increase. On the other side, to achieve user satisfaction, the ratio of the RLF must be decreased by having an optimal HO triggering algorithm. Therefore, the velocity aware consideration used in the proposed algorithm VAW-FLC-WF shows a significant improvement compared to other algorithms.

The proposed algorithm has the capability to be implemented in practice due to the proper configurations of the HCPs. Besides, the algorithm auto-tunes the HCPs to maintain the UE's quality connection during HOs. Additionally, the algorithm has been validated by measuring several users using different mobile speed scenarios. Furthermore, to enhance the robustness of the system, we have applied significant metrics as KPIs, such as RSRP, RLF, HOPP, and HOP.

VIII. CONCLUSION

In this study, a novel algorithm was proposed to self-optimize the TTT and HOM based on the three input parameters (i.e., UE's speed, TL, and RSRP). Furthermore, the proposed algorithm was implemented using several mobile speed scenarios over a HetNet. Assigning proper values to the TTT and HOM with taking mobile speed scenarios into consideration will lead to an improvement in the system's performance as addressed in our VAW-FLC-WF algorithm, where the average RLF is minimized to 0.006. Furthermore, RSRP, HOPP, RLF, and HOP were applied as the KPIs. However, the proposed algorithm shows an improvement in RSRP, HOPP, RLF compare to other HO algorithms. However, in our upcoming research, we will conduct further studies involving other algorithms described in the literature, explore new scenarios, and enhance the simulation model to improve the accuracy and comprehensiveness of our findings.

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