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Adaptive handover control parameters over voronoi-based 5G networks

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ABSTRACT

Various speed scenarios such as high-speed travelling trains and connected drones over ultra-dense heterogeneous networks (HetNets) may result in a large number of handovers (HOs), which may cause further mobility challenges. Therefore, mobility robustness optimization (MRO) function has been proposed to contribute for detecting and correcting the mobility issues including too late HO, too early HO, and HO to the wrong cells. This function can be more effective in reducing these challenges related to mobility when proper optimization settings is performed for the handover control parameters (HCPs) (i.e., time-to-trigger (TTT) and handover margin (HOM)). In this paper, a trigger timer is proposed to reduce the unnecessary HOs. Meanwhile, this work proposes a weighted algorithm for optimizing the HCPs automatically based network experiences. The proposed algorithm rely on various factors for performing the optimization process. That includes, mobile movement speed, network traffic load, and the measurement report of the received signal reference power. Research work conducted by Matlab simulator that implement HetNets that consider Fifth Generation (5G) network and system settings based on 3GPP. Besides, 15 users were investigated using several mobile speed scenarios over Voronoi 5G network. The simulation results show that a significant achievement has been performed by the proposed algorithm as compared to the other algorithms investigated from the literature. The proposed algorithm has minimized the Radio Link Failure (RLF), Handover Ping-Pong (HOPP), Handover Probability (HOP), and handover interruption time by 8.8 %, 6.9 %, 6.7 %, and 344 %, respectively, lower than the other algorithms presented.

1. Introduction

Over the past decades, there has been a significant development in the advancements of mobile cellular network. The Fifth Generation (5G) network supports high data rates (up to 10Gbps), extremely low latency (1 ms), high mobile speed scenarios (500 km/hr) [1,2]. The target of 5G networks to offer data traffic volume that is 1000 times greater than the current cellular network (Fourth Generation (4G)). Furthermore, 9.21 billion 5G mobile subscriptions are forecasted by end of 2029 [3,4]. In contrast, the massive growth of the connected devices in ultra-dense networks leads to high handover (HO) ratio [5]. This in turn will raise the HO issues.

In cellular networks, a smooth HO process is a fundamental necessity in mobility management to preserve the quality connection without any disruptions. In addition, HO is defined in Third-Generation Partnership Project (3GPP) protocol [6]. A HO is process in wireless communications, in which the User Equipment's (UE) network resources are transferred from the Serving Base Station (SeBS) to the Target Base Station (TBS) for maintaining the quality connection to the user [7]. The UE is instructed to initiate the HO process when the potential TBS achieves an acceptable level of radio signal quality. The HO triggering is performed based on HO events which rely on several measurement reports and HO control parameters such as Time-To-Trigger (TTT) and Handover Margin (HOM).

In 5G mobile networks, the measurement report plays a pivotal role in assessing the Received Signal Reference Power (RSRP) from neighboring Base Stations (BSs). This process occurs at a high frequency, typically every 40 ms, to ensure real-time and accurate data for seamless handovers and network optimization. The Measurement Report involves the UE periodically measuring the RSRP from nearby BSs and compiling

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this data into a report. The RSRP represents the power level of reference signals received from various neighboring gNBs and is crucial for evaluating signal strength and quality, by then, one BS is selected to be the candidate target BS that will serve as a serving cell. These reports serve as a vital input for making the HO decision. When the RSRP of a target BS exceeds certain thresholds or HOM, and this measurement has been performed in sequence for a period of time greater than or equal to TTT the network can trigger a HO. This process is essentially needed through the mobility of user to maintain a stable and high-quality connection as the user moves within the coverage area [8]. By collecting and analyzing these measurements at such a rapid rate, 5G networks can dynamically adapt and ensure a seamless user experience, particularly for applications demanding low latency and high reliability, such as autonomous vehicles and augmented reality. After that, the HO decision can be initiated based on the periodic measurement report.

Mobility Robustness Optimization (MRO) is one of the HO optimizations entities used for detecting and correcting mobility issues using TTT, HOM, and Cell Individual Offset (CIO) as the Handover Control Parameters (HCPs). Our works [7,9] have discussed the MRO functions extensively. Furthermore, Radio Link Failure (RLF), Handover Failure (HOF), Handover Ping-Pong (HOPP), and Handover Probability (HOP) are considered as the mobility issues which used as Key Performance Indicators (KPIs) to measure the network performance. Therefore, suboptimal setting of the HCPs leads to increasing in the ratio of RLF, HOPP, and HOF.

Stability and reliability of the network system can be achieved by proper settings of the TTT and HOM. In addition, RSRP, HOPP, RLF, and HOP have a relationship between each other when applying a HO optimization of the TTT and HOM [10–12]. For, instance, high average of RSRP leads to high HOPP which will subsequently increases the HOP. This is because of low setting values of TTT and HOM. Furthermore, low average of RSRP leads to high RLF and decreased HOP because of high setting values of TTT and HOM. Moreover, controlling the TTT and HOM for speed scenarios can contribute for seamless transition of the UE from BS to another without causing too late HOs due to high-speed with high HCPs values. Also, preventing too early HOs during low-speed with low HCPs values [13].

HO decision is a crucial process for ensuring seamless and uninterrupted connectivity as users move within the coverage area of different base stations (gNBs) [14]. These decisions are typically based on key parameters, including the and the HOM. RSRP is a metric that quantifies the power level of the reference signals received from neighboring gNBs. It provides an indication of the signal strength and quality, aiding in the selection of the target gNB for HO. The HOM is a predetermined threshold that determines when a HO should occur. When the RSRP of a neighboring gNB exceeds the RSRP of the serving gNB by the HOM, a HO decision is triggered. Therefore, the HO decision algorithm in 5G networks is taken based on these parameters. The system is continually evaluating these parameters and decides when to initiate a HO, ensuring that the UE connects to the most suitable gNB [15]. This can be represented simply in a mathematical expression as illustrated in Equation (1).

High mobility, unplanned ultra-dense 5G networks, and sub-optimal setting of the HCPs have impacted the robustness of the communication networks. Signal quality degradation occurs rapidly, particularly with higher frequencies (i.e., mm-Wave communications), which will be increasingly employed in 5G networks. However, a proper HO self-optimization algorithm for optimal HO triggering is required. Therefore, high mobility over BSs that uses high operating frequencies (small geographical area) necessitate an accurate HO setting value for the HCPs (i.e., TTT and HOM).

The main contributions of this study are summarized as follows:

- Weighted function (WF) is presented as a solution method for optimizing HCPs settings that include the TTT and HOM. The proposed algorithm is compared with other algorithm addressed in the literature.
- Triggering Timer is deployed to contribute for reducing the unnecessary HOs by preventing the HO executions to the TBS that has the same ID as the SeBS.
- 15 users have been investigated using several mobile speed scenarios over 5G network. Furthermore, RLF, HOP, and HO interruption time are used as the KPIs and different simulation times are applied to investigate the behavior of KPIs on the system performance.

The rest of this article is structured as follows. Section 2 provides the research background. Section 3 addresses the related works. Section 4 presents the system model. Section 5 provides the proposed HO self-optimization algorithm. Section 6 presents the results and discussions. Section 7 provides the simulation challenges. Section 8 concludes the study.

2. Research background

A brief description including 4 subsections will be provided in this section.

2.1. 5G network

The world of telecommunications is undergoing a paradigm shift with the advent of 5G. This groundbreaking innovation promises to revolutionize the way we communicate, connect, and interact with the digital world. As 5G takes its first steps in commercialization, global research institutions are already setting their sights on the next frontier. The key driver behind the 5G to 6G transition lies in meeting new service requirements and adapting to the relentless growth in mobile data traffic [16,17]. The international telecommunication union, which predicts an increase of 5 zettabytes by 2030, underlines the need for ultra-high data rates (up to 1 Tbps), ultra-low latency, high energy efficiency, and ubiquitous global network coverage in next-generation wireless networks. The evolution of mobile communication networks from 1G to 5G is setting the stage for the quantum leap expected in 6G. The first-generation mobile network, designed for voice services, has evolved through digital modulation technologies, high-speed data transmission (3G), and fully IP-based 4G networks [18]. With their revolutionary advances in data rates, latency, reliability, and connectivity, the ongoing deployment of 5G networks serves as a foundation for the research and development of 6G.

In 5G mobile networks, the signal path loss is a fundamental component used to accurately replicate real-world radio propagation scenarios. Path loss models are indispensable for predicting signal strength, optimizing network design, and evaluating coverage and interference in 5G networks. By accurately modeling these path losses, researchers and network planners can develop strategies to enhance network performance and ensure that 5G systems deliver reliable and efficient connectivity across diverse environments.

2.2. Handover issues in 5G

The challenges of the HO in 5G network are associated with the preservation of the quality connection of the UEs when they move from one BS to another within the network. Unlike the existing mobile networks, 5G introduces higher operating frequencies and ultra-dense SBSs, which pose unique HO challenges as shown in Fig. 1. These include increased HO frequency due to the smaller coverage areas of small cells, leading to potential disruptions in services like voice calls and video streaming. Moreover, the integration of multiple radio access technologies, including mm-Wave and sub-6 GHz bands, complicates the HO procedures, which require an efficient HO decision algorithm. In addition, addressing the HO latency becomes an essential factor in ensuring uninterrupted connectivity for latency-sensitive applications like real-

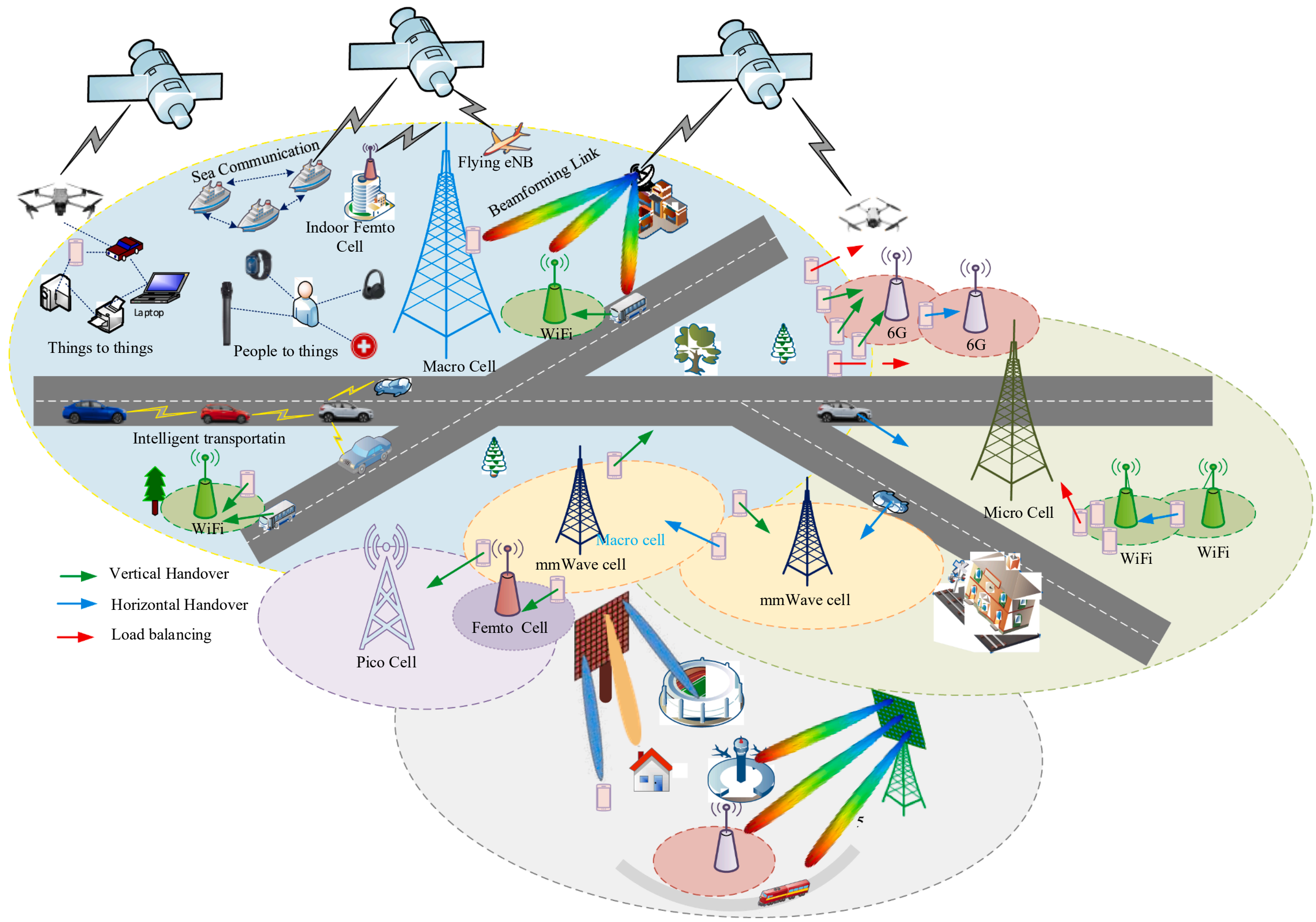

Fig. 1. Handover concept in a deployed Heterogeneous Networks with 5G technology.

time gaming. However, it is necessary that HO issues in the 5G network be handled through smart algorithms that aid the BSs in carrying out predictive HO, avoid interferences, and use coordination techniques that guarantee quality of service among the network users.

2.3. Mobility robustness optimization (MRO)

The purpose of the HO optimization networks is to enhance the system performance by achieving a HO triggering points. One essential aspect of this optimization lies in improving the mobility robustness, which plays a significant role in reducing the HO issues. However, MRO contributes in correcting and detecting the mobility issues by optimizing the HCPs such as TTT and HOM [7]. In addition, the HOM is used to measure the signal strength threshold at which a HO is triggered, while the TTT determines the duration before a HO decision is made. Furthermore, several factors can be used as input parameters for auto-tuning the HCPs. These factors including RSRP, SINR, mobile speed scenarios, and traffic loads. Therefore, appropriate configuration of the HCPs through MRO may deliver enhanced reliability, reduced latency, improved quality connection of the users during HOs.

2.4. Research gap

Although advanced technological progress has been achieved, the problem of HO optimization and MRO is still a challenge for 5G and future HetNets. The integration of unplanned ultra-dense SBSs, different cell sizes, high operating frequencies, and high UE's mobility creates more complexity for 5G and HetNets. The complexity includes propagation challenges, signal blockages, and maintaining smooth HOs. Besides, the number of HOs is increasing due to densification networks, which subsequently increases the ratio of HOPP, RLF, and HOF. To meet these challenges, the development of innovative solutions is necessary for the HO algorithm design, interference management, and predictive analytics to achieve optimum handover control parameter values dynamically. Along with 5G network development and heterogeneous deployment enlargement, further research and development are required to overcome these challenges and offer seamless connectivity and quality of service for users in different use cases and scenarios.

3. Related works

Several MRO studies were comprehensively addressed in our surveys [7] and [9]. These studies were classified into several groups based on the solution method applied such as RSRP-based [19–28], weight function [1], [29–31], Fuzzy Logic Controller (FLC) [32–36], supervised machine learning (ML) in [37–43], unsupervised ML in [44], and reinforcement learning in [45–55]. Furthermore, Several solution methods were proposed in MRO for auto-tuning the HCPs (i.e., TTT and HOM) [11,12], [56–59]. However, our study has focused on addressing the most recent MRO investigations in order to avoid duplicating the work already presented in our published surveys.

Kwong et al. [60] have proposed a deep reinforcement learning algorithm to adjust the HOM to achieve HO optimality over the 5G network. Several KPIs, including the number of HOs, HOPP, HOF, throughput, and latency, have been investigated for system performance. Furthermore, the study has applied a random-way point mobility model to a 6x6 km2 coverage area. In addition, several mobile speed scenarios (i.e., 3 km/hr, 30 km/hr, 60 km/hr, 72 km/hr, 90 km/hr, 120 km/hr, and 300 km/hr) have been applied. Moreover, FR1 (between 4.1 GHz and 7.125 GHz) and FR2 (between 24.25 GHz and 52.6 GHz) were the carrier frequencies evaluated by [60]. The number of BSs deployed for FR1 and FR2 was 30 and 20, respectively. The study should include the TTT as a significant HCP in order to control the mobility issues such as HOPPs and the number of HOs. In addition, RLF requires an investigation to measure the effectiveness of this study. Improper configuration of the HOM may lead to high RLFs.

Saad et al. [61] have proposed a linear regression model to automatically adapt both TTT and HOM. Additionally, several metrics including HOP, HOPP, and RLF have been used as system indicators to display the effectiveness of the implemented algorithms. The presented algorithm investigates the user experience based on the Signal-To-Interference-Plus-Noise-Ratio (SINR). Mobile speed scenarios ranging from 40 km/hr to 140 km/hr have been applied. In addition, 15 users were examined over the 5G network using 200 m as a cell radius. Furthermore, 50 ms and 28 GHz are used as the measurement time and operating frequency, respectively. However, the speed scenarios and BS's load should be investigated during HOs to increase the robustness of the system and to achieve optimal HO triggering.

A HO self-optimization algorithm has been proposed in [62] for auto-tuning the HCPs (i.e., threshold, HOM, and TTT). Besides, HOP, HOPP, and HOF were applied as the KPIs over a deployed 5G network. Furthermore, the users are moving in a directional mobility over 0.6x0.6 km^2 using mobile speed scenarios between 0 km/hr and 120 km/hr. In addition, 3GPP release 16 has been used as the standard for the 5G simulating environment. Moreover, 4 users have been investigated using 4 BSs, each BS has a radius of 200 m. However, increasing the average of the HOPP leads to decreasing the average of the RLF. Therefore, the ratio of the RLF should be examined in this study.

Alhammadi et al. [11] have applied two self-optimization functions including MRO function and load balancing optimization function to adapt the HCPs. Furthermore, the study has proposed the FLC using three input parameters which are SINR, UE'S velocity, and BS load. In addition, urban Heterogeneous Networks (HetNet) is deployed as the simulation environment where the UEs are moving in a fixed directions using speed scenarios between 10 km/hr and 160 km/hr. In addition, to measure the robustness of the system compared to other algorithm presented in the literature [63], HOPP, RLF, HO latency, and outage probability were presented as the KPIs. Moreover, the operating frequencies applied for the 4G macro BS and 5G small BS were 2.1 GHz and 28 GHz, respectively.

FLC algorithm is proposed in [12] to automatically adjust the TTT and HOM using the measured parameters including RSRP, UE'S velocity, and Received Signal Reference Quality (RSRQ). HOF, HOP, HOPP, and handover interruption time were considered as the measurement indicators of the proposed algorithm over the 5G network. Moreover, the UEs were moving in a random way points over 3x3 km^2 simulation area using different mobile speeds (between 20 km/hr and 160 km/hr). In addition, 28 GHz operating frequency is applied to 183 5G small BSs which has radius of a 200 m each. The investigation of RLF is required due to the inverse relationship between the ratio of HOPP and the ratio of RLF.

To preserve the quality connection of the UEs during HO, efficient HO decision algorithm is required. So, Article [56] has proposed an approach for optimizing the Cell Individual offset (CIO) to increase the UE's capacity using reinforcement learning (i.e., Q-learning). Besides, deep reinforcement learning mainly actor-critic-based has been applied. Three KPIs (i.e., capacity, HOF, and HOPP) have been used to measure the effectiveness of the proposed algorithm. Multiple ground and flying BSs were deployed over 1x1 km^2 using suburban scenario. Furthermore, the 150 users are moving in a random way points at mobile speed scenarios between 1 and 3 m/s. Moreover, the study has considered 2 GHz as the operating frequency. Besides, 0.16 s and 3 dB were the fixed values assigned for the HCPs (TTT and HOM), respectively. However, the HCPs (i.e., TTT and HOM) should be auto-tuned in [56]. Assigning fixed values to the TTT and HOM will negatively impact on system operators in terms of operational expenses (OPEX) and capital expenses (CAPEX). Thereby, influencing the network performance. Another effect is the time consumption which results in higher operational costs and less revenue.

Farooq et al. [57] have proposed a ML mainly XGBoost model using three KPIs including edge RSRP, HO successful rate, and traffic load. Therefore, 3GPP events including A3 and A5 events were discussed in [57]. Different radio access technologies were applied using 3 different operating frequencies (i.e., 1.7 GHz, 3.1 GHz and 3.5 GHz). In addition, the users are moving in four speed scenarios (i.e., 3 km/hr, 60 km/hr, 120 km/hr, and 240 km/hr) over a simulation coverage area of 4 km^2. However, HOPP and RLF are significant KPIs that should be investigated to measure the system performance and the user satisfaction.

Different settings values for the TTT and HOM were investigated over 5G mobile network using several KPIs such as HOPP, HOP, and outage probability [58]. Furthermore, this study is addressed to investigate the impact of several mobile speed scenarios on the system performance when different HCPs setting values are applied. However, low HCP setting values leads to high HOPPs, the case becomes worse during high mobility. The assessment of the RLFs is required in this study because of the trade-off that arises between HOPP and RLF.

FLC algorithm over ultra-dense 5G network has been proposed by [59] to self-optimize the TTT and HOM. SINR and UE's velocity were the two FLC input parameters that determine the setting values of the TTT and HOM. NS-3 was used as the simulation tool to conduct this study over an area of 0.3 km^2. Furthermore, number of HOs, HOPP, and throughputs were investigated as the KPIs. In addition, for the mobility model, the users (5 users) are moving in two-dimensional random walk using several mobile speed scenarios (between 2 m/s and 20 m/s). The traffic load of the TBS should be investigated to avoid HO execution to the congested TBS.

4. System model

The simulation has been conducted using MATLAB 2021b. One reused operating frequency has been used in the simulation environment (i.e., 28 GHz) which make the users moves under one radio access technology. Furthermore, 200 m is the cell radius since operating frequency is high and the path-loss is increasing [64]. Moreover, 183 BSs are deployed using 30 dBm transmission power. Besides, the minimum assigned power for the received signal is −101.5 dBm. Fig. 2 displays the Voronoi-based simulation environment used for the deployment of the 5G mobile network. 2x2 km^2 is the study simulation area. Therefore, the user is allowed to connect only to one cell. Furthermore, we have used the voronoi environment for unplanned deployments of the locations of the BSs. The simulation environment is a practical deployment where the locations of the BSs are randomly distributed. Thereby, the calculated input parameters (i.e., RSRP, UE's speed, and traffic) from the voronoi simulation environment determine the output values of the HCPs (i.e., TTT and HOM).

The users (15 users) are moving in a random way points using several mobile speed scenarios (between 40 km/hr and 140 km/hr). Furthermore, the.

Euclidian distances are calculated periodically (every 40 ms) for each user inside the coverage of the BSs. In this study, the signal's path losses, are calculated alongside the log-normal shadowing and Rayleigh fading. Table 1 represents the 5G simulation parameters. These parameters are applied based on 3GPP release 16 [65,66].

The simulation time to measure a large number of users may take a longer time. However, we have investigated 15 users to validate our proposed algorithm and to show the improvements of our algorithm compared to other algorithms presented. Each user experiences mobility issues including RLF, HOPP, and HOP, which may affect the system's

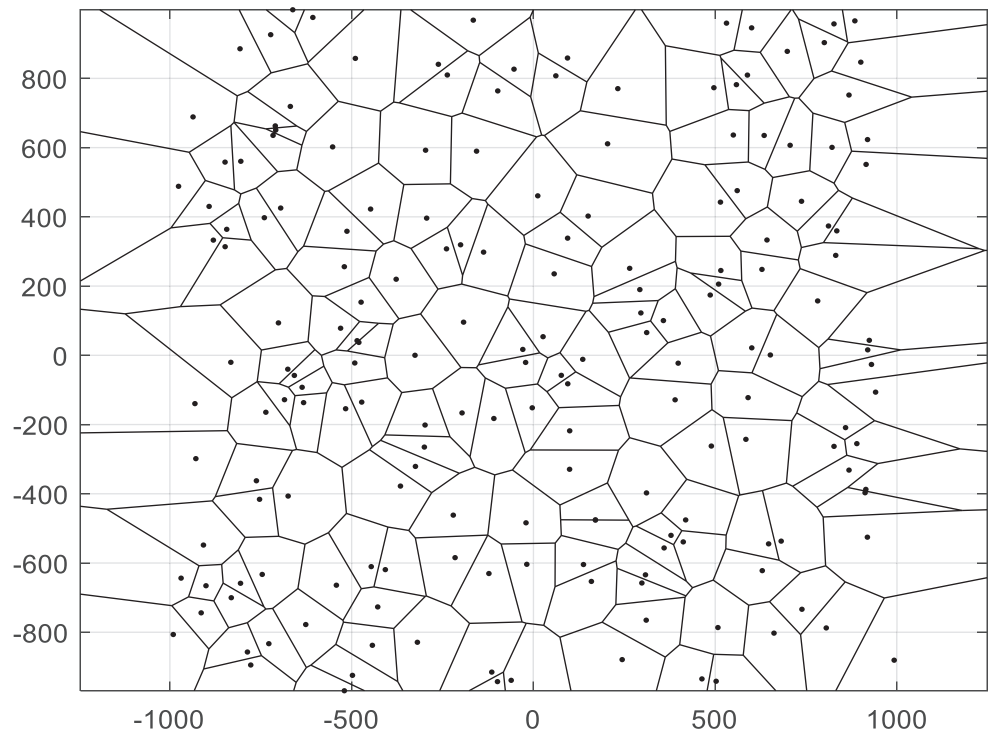

Fig. 2. Voronoi Simulation environment.

Table 1
Network parameters of the simulated 5G technology.

Network Parameters	Assumption **5G small BS**
Deployed BSs	183
Applied Frequency (GHZ)	28
transmitter Power (dBm)	30
Height of the BSs (meter)	15
Bandwidth (MHz)	500
Received Signal Strength Indicator (RSSI) (dBm)	−101.50
Height of the UE (meter)	1.5
Noise figure of the UE (dB)	9
HOM (dB)	Adaptive
TTT (ms)	Adaptive
Mobile speed scenarios (km/hr)	Between 40 and 200
Number of users	15
Measurement interval	40 ms
HO decision algorithm	$RSRP_{Target} \geq RSRP_{Serving} + HOM$ (1)
Environment	Urban areas, 5G network

performance. Investigating more or less than 15 users may affect the total average of the mobility issues (RLF, HOPP, and HOP). We have investigated the performance of the whole system so that, regardless of the number of users, our proposed algorithm will lead to better performance. Several researches have considered 1 user for the system validation such as in [67,68,69], and [70].

The movement steps between each simulation cycle differ depending on the speed situation. The step movements are directly proportional to the rise in mobile speed scenarios. Therefore, it is necessary to decrease the values of the HCPs. However, the HO procedure, consisting of HO preparation, HO execution, and HO completion, begins when the HO decision algorithm in (1) is met.

5. Proposed handover self-optimization algorithm

When the TBS is greater than the SeBS, a trigger timer will be involved to identify the TBS's ID. If the TBS's ID has the same ID as SeBS, no HO decision algorithm will not be activated. The counter of a trigger timer

$$Timer\ counter_{max} = \frac{TTT}{Measurement\ intervel} \quad (2)$$

The measurement interval used in this study is 40 ms. In addition, the pre-defined value of the TTT is 120 ms. However, the maximum timer counter should be 3 according to (2). Then the TTT and HOM will be auto-tuned based on the proposed WF. The main objective of addressing the trigger timer is to prevent the user to transit to the BS that has the same ID as the previous BS. Subsequently, the unnecessary HOs will be reduced. Fig. 3 represents a trigger timer for reducing unnecessary HOs.

WF is proposed as a solution method for auto-tuning the TTT and HOM. In WF, three input parameters are addressed to determine the auto-tuning setting value of the TTT and HOM. These three input parameters are addressed below:

- RSRP function

Equation (3) represents the RSRP function where the SeBSs and the TBSs are calculated every 40 ms.

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

where T, S, and max subscripts represent the RSRP of the TBS, 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 ms.

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

where TL_T, TL_S, and TL_{max} represent the TBS's traffic load, serving

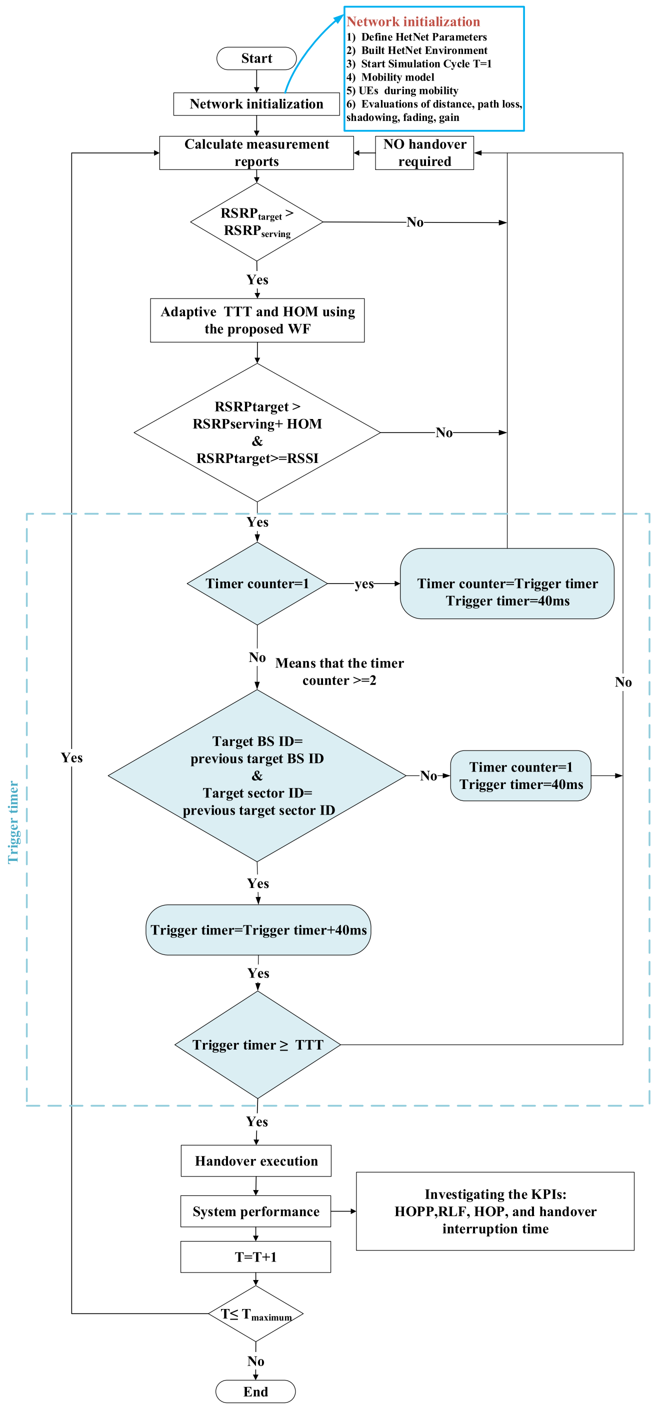

Fig. 3. Trigger timer for reducing unnecessary HOs (T represents the simulation cycle).

BS's traffic load, and maximum traffic load, respectively.

- Velocity function

Several mobile speed 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 the weight of function n, and n can be one of the three functions (i.e., RSRP, TL, or v). For simplifying (6), 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).

Algorithm 1: Proposed 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 WF
               Update TTT and HOM according to (6)
               Auto-tunes TTT and HOM
                 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
```

The trigger timer is added to the HO decision algorithm as shown in Equation (8) and Fig. 3.

$RSRP_{Target} \geq RSRP_{Serving} + HOM\&\&$

Table 2
Mobility issues due to improper configurations of the HCPs.

MRO issues	TTT value	HOM value	Affected KPI levels
Too late HO	High	High	High RLF
To early HO	Low	Low	High HOPP
HO to wrong cell	Inappropriate	Inappropriate	High RLF or High HOPP

$$\textit{Trigger timer} \geq \mathrm{TTT} \tag{8}$$

Algorithm 1 shows general steps of the proposed WF algorithm. Therefore, the measurement reports were calculated every 40 ms for each user and for each mobile speed scenario over the whole simulation time. In Algorithm 1, the symbol T represents the number of simulation cycles. Line 13 indicates that.

there is no HO decision at simulation cycle = 1. However, when T > 1, the HO decision algorithm will be initiated.

The initial value of the TTT is 100 ms. Then, we have presented the optimization steps as 0.1. Equation (6) is evaluated in each simulation cycle T. The WF at T is compared with (T-1) to decide whether to add or subtract from the current TTT value. Furthermore, 25 ms have been used

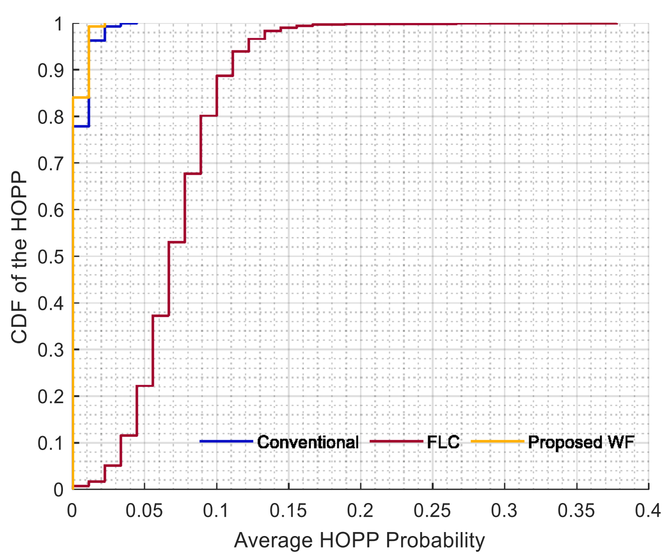

Fig. 4. CDF of the average HOPP probability.

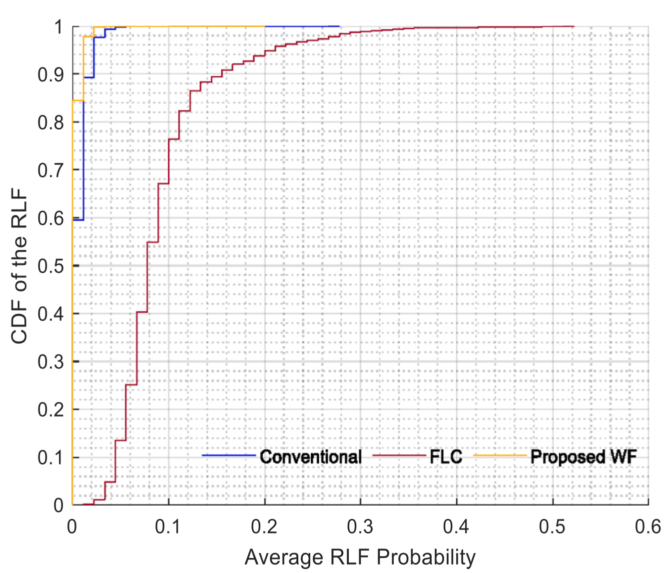

Fig. 5. CDF of the average RLF.

for the addition and subtraction processes based on equation (6). However, the TTT values range between 0 ms and 5120 ms [6]. The HOM optimization level is given by equation (9)

$$f(\overline{\boldsymbol{HOM}}) = \frac{\boldsymbol{HOM}_{max} - \boldsymbol{HOM}_{min}}{2} \tag{9}$$

where $\boldsymbol{HOM}_{max}$ and $\boldsymbol{HOM}_{min}$ are the maximum and minimum HOM, respectively. The prediction of the HOM is obtained by multiplying equation (6) by the average HOM level $\boldsymbol{f}(\overline{\boldsymbol{HOM}})$.

6. Results and discussions

In this section, the proposed WF algorithms is compared with other algorithms to show its effectiveness on reducing the applied KPIs. Therefore, the KPIs include HOPP, RLF, HOP, and HO interruption time.

Before discussing the results, we will provide an explanation of the relationships between the HCPs and mobility issues such as too late HO, too early HOs, and HO to wrong cell, as well as the connection between these issues and KPIs such as HOPP, RLF, and HOP. Table 2 shows the suboptimal settings of the HCPs (TTT and HOM). Assigning high values to the TTT and HOM will result in a decrease in the HOPPs. Thereby, increasing RLF due to too late HO. Assigning lower HCP settings will result in a decrease in RLFs and an increase in HOPPs due to too early HO. Subsequently, increasing the ratio of the HOPP leads to a high HOP probability. Improper configurations may cause the HO to wrong cell or lead to unnecessary HOs.

Fig. 4 presents the average HOPP probability in the form of the cumulative distribution function (CDF). The proposed algorithm in Fig. 4 shows a significant improvement compared to the conventional and the FLC [33] algorithms. Therefore, the increasing and decreasing the average probability of the HOPP relay on the configurations of the TTT and HOM. Low TTT and HOM setting values lead to high HOPPs whereas, high setting values lead to low HOPP but high RLFs. However, our algorithm gave an optimal reduction of the HOPPs and RLFs due to a proper configuration of the TTT and HOM.

Fig. 5 shows the CDF of the average RLF probability where the proposed algorithm shows the lowest average compared to another algorithm. In addition, Table 3 addresses the average RLF values using different time intervals and several speed scenarios. Therefore, a trade-off between RLF and HOPP need an optimal HO triggering value which has been achieved in our proposed algorithm. Based on the proposed algorithm in Table 3, it can be seen that the average values of both RLF and HOPP are the lowest values. Therefore, RLF can occur during the handover process, either because the UE did not receive the HO command or the network did not receive the measurement report. Additionally, the UE might experience difficulty in accessing the target cell which may lead to RLF. Moreover, Fig. 6 to Fig. 9 represents the average RLF probability where Fig. 6 represent the average RLF probability versus HO optimization algorithm. Besides, the figure displays that the proposed algorithm has the lowest RLF probability with value of 0.002. Furthermore, Table 3 addresses the averages of probabilities using several mobile speed scenarios and simulation time. In addition, Fig. 7 displays the average RLF probability at different mobile speed scenarios where the proposed algorithm shows the lowest average RLF probability at all mobile speed scenarios. Moreover, Fig. 8 and Fig. 9 represent the average RLF probability using different simulation time. Besides, Fig. 8 and Fig. 9 show that the proposed algorithm has the lowest RLF probability over all the simulation time. Therefore, by increasing the simulation time to 400 sec, the behavior of the system in term of RLF is shown below Fig. 9 using three mobile speed scenarios (i.e., 40 km/hr, 120 km/hr, 200 km/hr). Therefore, by extending the simulation time to 400 s, the proposed algorithm has shown a significant reduction in all KPIs applied (HOPP, RLF, HOP, and HO interruption time).

Fig. 10 and Fig. 11 display the average HOP where the proposed algorithm shows a significant reduction compared to the conventional

Table 3
Investigated KPIs using different simulation time, speed scenarios, and HO algorithms.

HO Algorithm	Speed scenarios (km/hr)	Simulation time	HOPP	RLF	HOP	Interruption time (ms)
FLC	[40, 60, 80, 100, 120, and 140]	150 sec.	0.07	0.09	0.07	3.78
	[40,120, and 200]	400 sec	0.1	0.06	0.12	6.25
Conventional	[40, 60, 80, 100, 120, and 140]	150 sec.	0.003	0.062	0.15	0.75
Proposed WF	[40, 60, 80, 100, 120, and 140]	150 sec.	**0.001**	**0.002**	**0.003**	**0.17**
	[40,120, and 200]	400 sec	**0.004**	**0.007**	**0.006**	**0.34**

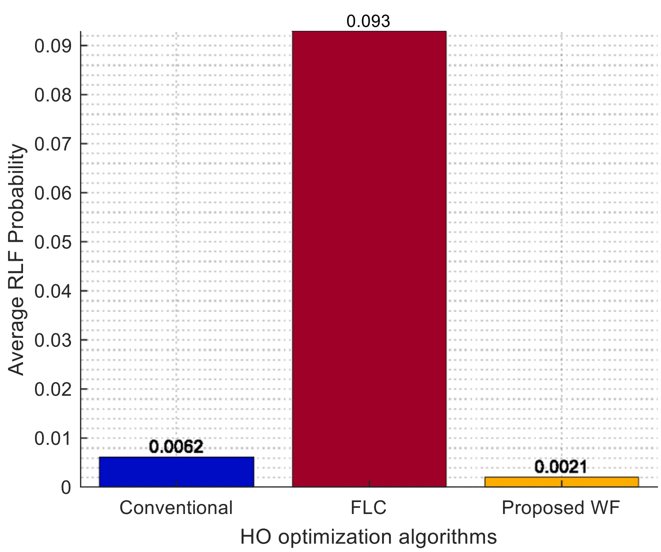

Fig. 6. Average probability of the RLF vs HO algorithms.

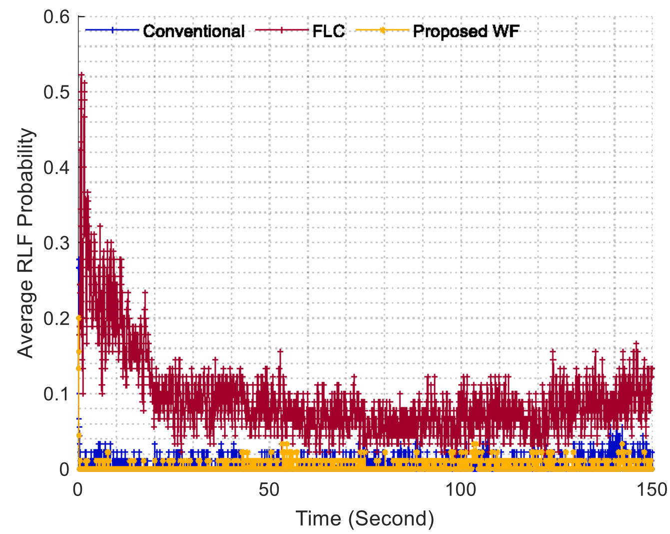

Fig. 8. Average probability of the RLF vs simulation time.

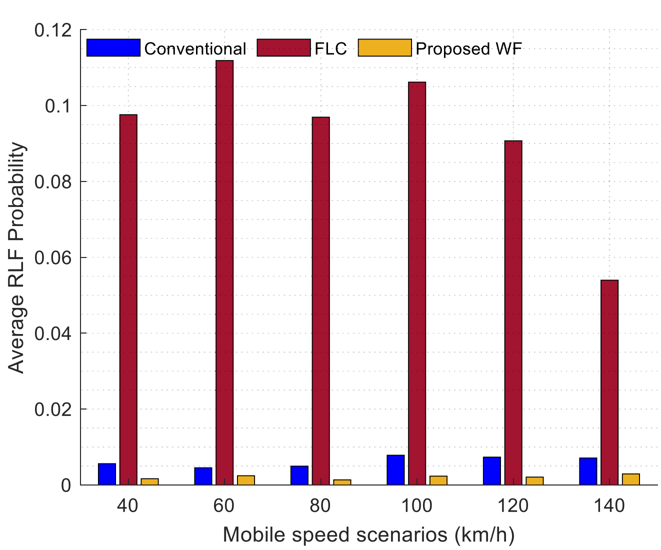

Fig. 7. Average probability of the RLF at different speed scenarios.

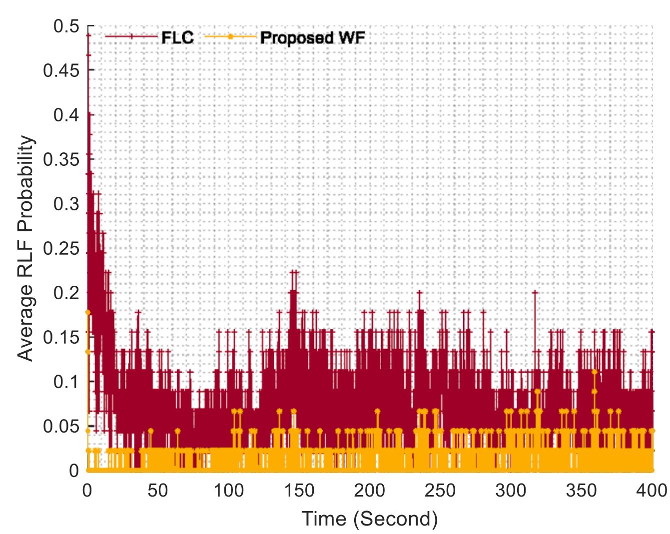

Fig. 9. Average probability of the RLF vs simulation time.

and FLC algorithms. Furthermore, Table 3 highlights the values of the HOP where the proposed WF has the lowest average HOP. Moreover, Fig. 10 shows the average HOP using various mobile speed scenarios. It can be observed that the proposed algorithm has achieved the lowest HOP over all mobile speed scenarios compared to other algorithms. Therefore, the proposed algorithm has self-optimized the TTT and HOM properly by assigning a different setting value according to the mobile speed scenario.

For instance, at low mobile speed scenarios a high TTT and HOM setting values were assigned to avoid too early HOs whereas, low setting value were assigned to the TTT and HOM during high mobility in order to avoid too late HOs.

Fig. 12 represents the HO interruption time overall the simulation cycles (i.e., 150 sec.). Besides, the proposed algorithm shows the lowest average with 0.17 ms compared to 0.75 ms and 3.78 ms for the conventional algorithm and FLC, respectively. Furthermore, Table 3 shows the average HO interruption time at various mobile speed scenarios and

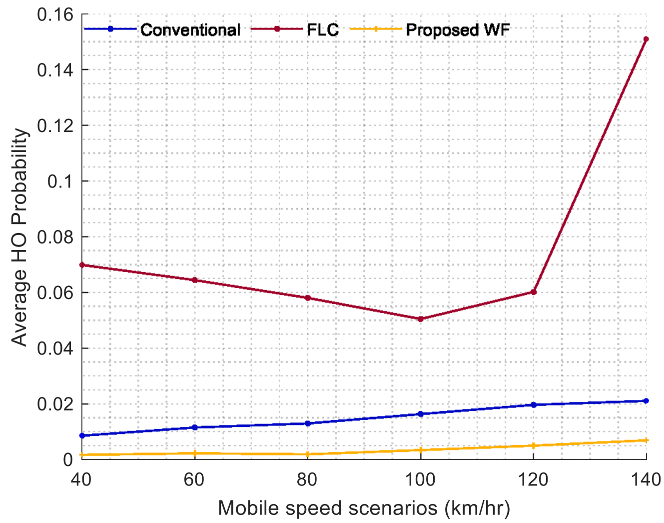

Fig. 10. Average handover probability at different speed scenarios.

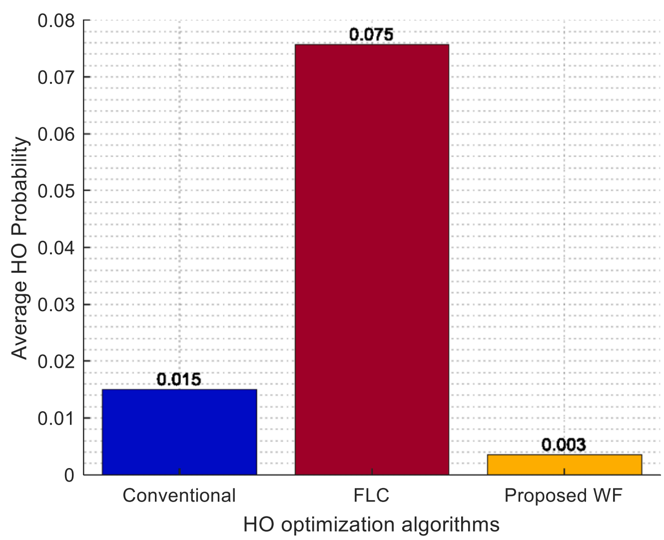

Fig. 11. Average handover probability vs HO algorithms.

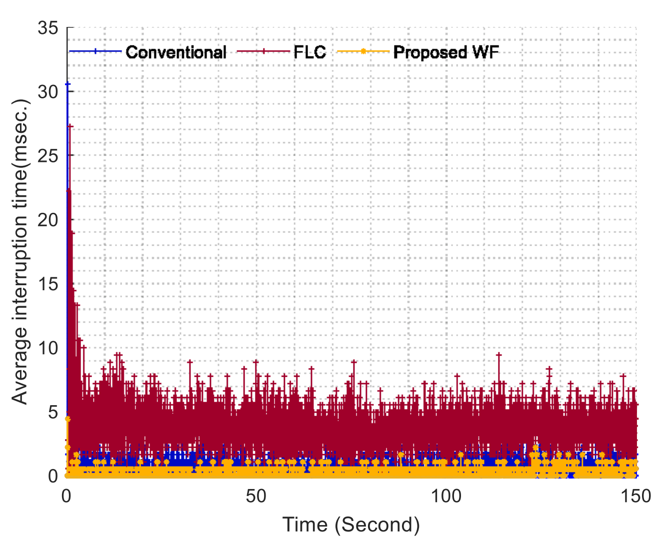

Fig. 12. Average HO interruption time vs simulation time.

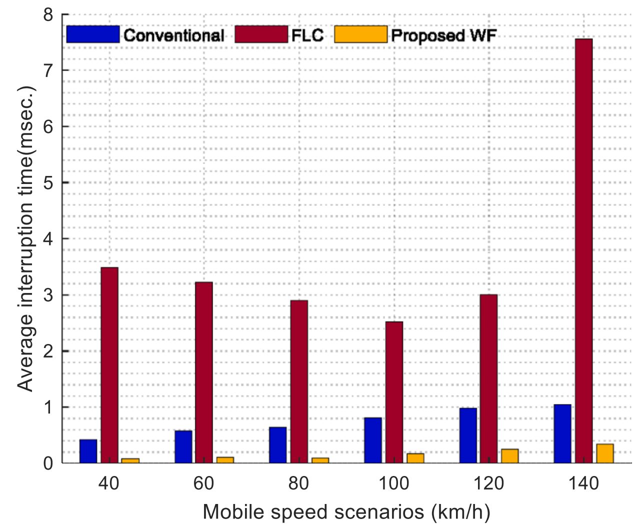

Fig. 13. Average HO interruption time for all UEs with different mobile.

different simulation time. However, the proposed WF algorithm in Table 3 shows the lowest average values compared to another algorithm. Moreover, Fig. 13 presents the average HO interruption time at different mobile speed scenarios. In addition, the proposed algorithm shows a significant reduction in the average interruption time at all mobile speed scenarios compared to the other algorithms.

7. Simulation challenges

Several challenges during the simulation phase have been faced. These challenges are summarized as follow:

7.1. Simulation time

The simulation time depends on some parameters applied in our study. These parameters include the number of simulation cycles, the number of users, and mobile speed scenarios applied. However, increasing one of these parameters leads to increasing the simulation time. The simulation time highly increasing if all of these parameters are applied with large number of both simulation time, users, and mobile speed scenarios.

7.2. Memory storage and processor

Due to the long simulation time required for the simulation, the computer getting stuck for completing the simulation due to the computer processor issues. Furthermore, storing large number of data leads to memory issues. Low on memory caused by saving data for the distance, path-loss, RSRP, and KPIs every 40 ms for each user in each BS for every mobile speed scenario. To cope up with these challenges, high quality computer may help to solve these challenges.

7.3. Scalability of network

Scalability is a critical consideration in the development and testing of 5G networks. The promise of 5G technology lies in its ability to support an unprecedented number of devices, from smartphones and IoT sensors to autonomous vehicles and industrial machinery. To assess and optimize network performance, simulating large-scale networks with numerous users and base BSs is essential. However, this ambition comes with computational challenges. Simulating massive 5G networks demands substantial computational resources. The sheer volume of interactions, data exchanges, and signal calculations between a multitude of users and BSs can strain even high-performance computers.

Researchers face the task of efficiently processing and analyzing enormous datasets, which can slow down simulations and hinder the research process. Addressing scalability challenges often involves advanced parallel computing, cloud-based solutions, and distributed simulation frameworks. Researchers must strike a balance between achieving a realistic representation of 5G network behavior and managing the computational complexities to enable meaningful analysis and optimization.

7.4. Realistic mobility models

Realistic mobility models are pivotal in the simulation of 5G networks, as they aim to mirror the dynamic nature of real-world user behavior and movement patterns. These models play a central role in evaluating network performance, especially in scenarios where mobility is a critical factor, such as urban environments, vehicular communication, and smart cities. Creating such models is a complex undertaking due to the multifaceted and unpredictable nature of human mobility. Factors like pedestrian and vehicular traffic, user density, user preferences, and environmental conditions must be considered. Mobility models need to replicate the random and non-uniform movement of users, considering sudden changes in speed, direction, and pauses, which occur in real life. Moreover, it's essential to account for different mobility scenarios, including urban, suburban, and indoor environments, each characterized by distinct movement patterns. Striking the right balance between complexity and simplicity in mobility models is crucial. While intricate models can capture the nuances of mobility, they can also demand substantial computational resources. Therefore, researchers must carefully design and calibrate these models to ensure that simulation results closely align with the real-world behavior of 5G network users and devices.

8. Conclusion

As a conclusion, it is noticeable that the investigated solution methods from the literature were not achieved the HO optimality due to their implementation drawbacks and limitation of considered input parameters and deployment scenarios. However, this study proposes a WF algorithm based on three input parameters (i.e., RSRP, speed scenarios, and network traffic load) to determine the auto-tuning setting value of the TTT and HOM. Additionally, HOPP, RLF, HOP, and HO interruption time were applied as KPIs to measure the robustness of the proposed algorithm. Furthermore, the proposed algorithm was deployed using several mobile speed scenarios over a 5G network. The simulation results demonstrated that the proposed algorithm achieved a crucial reduction in all addressed KPIs compared to the other algorithms presented. Therefore, the reduction achieved for the RLF, HOPP, HOP, and handover interruption time were lower than the other algorithm by 8.8 %, 6.9 %, 6.7 %, and 344 %, respectively.

CRediT authorship contribution statement

Waheeb Tashan: Software, Methodology, Writing – original draft. **Ibraheem Shayea:** Conceptualization, Writing – review & editing. **Muntasir Sheikh:** Funding acquisition, Writing – review & editing. **Hüseyin Arslan:** Project administration, Validation. **Ayman A. El-Saleh:** Validation, Writing – review & editing. **Sawsan Ali Saad:** Visualization, Writing – review & editing.

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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