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Proposed Handover Algorithm for Mobility and Congestion Aware in 5G Communication Systems

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ABSTRACT

Conventional handover schemes in 5G networks, such as Event A3-based triggering, usually rely on a limited set of radio measurements, particularly Reference Signal Received Power (RSRP), together with a fixed hysteresis margin. Such schemes may become less effective in dense heterogeneous networks (HetNets) where user mobility, cell congestion, and service requirements vary dynamically. This study proposes a mobility- and congestion-aware handover algorithm based on a dynamic weighted utility function implemented in the MATLAB 5G Toolbox. The proposed algorithm jointly considers RSRP, Reference Signal Received Quality (RSRQ), Channel Quality Indicator (CQI), Doppler shift, transmission delay, service priority, cell load, user mobility, and a controlled randomization factor. The weighting coefficients are adaptively adjusted according to service type, mobility level, and congestion status, enabling context-aware target-cell selection. A simulation framework was developed to represent a realistic 5G HetNets composed of macro and small cells, mobile users, and time-varying traffic loads. Compared with the conventional Event A3 handover mechanism, the proposed algorithm increased the handover success rate from 88.8% to 96.3%, reduced the ping-pong handover rate by approximately 70%, improved the load-balancing index from 0.64 to 0.86, increased the overall throughput from 7.3 to 9.5 Mbps, and reduced latency from 55.1 to 37.7 ms. Additional benchmarking against recent adaptive handover-control and machine-learning-based approaches further indicates that the proposed method provides a practical and computationally tractable solution for handover optimization in dense 5G HetNets deployments.

1. INTRODUCTION

The utilization of mobile networks keeps on rising with the development of 5G elements, making near-flawless connectivity and maximum quality of experience (QoE) a predominant requirement, particularly due to the frequent mobility of users between overlapping cells [1]. The conventional handover operation (e.g., based on Event A3 triggers) usually experiences excessive handovers (i.e., ping-pong effects) and insufficient reaction to congested conditions or signal deterioration [2]. These constraints are further increased to the point in high-density heterogeneous networks (HetNets) that have a mixture of macro and small cells due to the fact that users are in continual transition in coverage areas to diverse loads and diverse signal strengths [3, 4].

Although several studies proposed many handover approaches, which cover weighted or cost-function-based schemes by considering multiple radio metrics [5], or include congestion-aware and Non-Orthogonal Multiple Access (NOMA)-based load balancing techniques to enhance spectrum in dense HetNet scenarios [6, 7], they offered solutions that typically only improved mobility or congestion independently. However, despite the existence of integrated handover approaches in the literature, most either rely on static weighting schemes, lack real-time adaptability to user mobility and network congestion simultaneously, or introduce high computational overhead due to complex optimization or machine learning models [8]. This limits their practical deployment in dynamic 5G HetNet environments.

The contributions of this study, on the other hand, address a critical gap present in the literature by offering a unified, practically viable solution that equally optimizes signal quality, mobility, and congestion, unlike the previous strategies that focused on parts of handover optimization. The proposed model is a combination of real-time signal quality measurements (Reference Signal Received Power (RSRP), Reference Signal Received Quality (RSRQ), Signal-to-Interference-plus-Noise Ratio (SINR)), and mobility profiling and network congestion indicators into a composite utility-based decision algorithm with measurable dependencies, so the novelty of the proposed approach lies in its ability to integrate mobility prediction, congestion awareness, and signal quality metrics within a single adaptive decision framework. Unlike existing integrated handover methods that rely on fixed weighting schemes or treat these factors separately, the proposed model dynamically adjusts decision parameters based on mobility patterns, congestion levels, and signal quality variations, without requiring computationally intensive optimization or machine learning techniques. The main contributions of this work can be summarized as follows:

(1). Uses MATLAB-5G Toolbox-based simulation of more than 200 mobile user equipment (UEs) across HetNet deployment settings to reproduce real-world deployment details.

(2). Combines mobility prediction with congestion identification in the same decision loop to enhance the accuracy of handover.

(3). Shows an increase in baseline models in handover efficiency, which is quantified through simulation results.

The proposed work would lead to the development of a mobility and congestion-aware handover algorithm for 5G networks that would consider the signal quality, people movement, and network congestion in the dynamic assessment inside the MATLAB-based simulation model. To validate the proposed framework, the following implementation objectives are defined:

•Objective 1: To design and implement a multi-cell 5G HetNet simulation in MATLAB 5G Toolbox that can capture the dynamics of the network in real time.

•Objective 2: To incorporate the estimation of user mobility based on change of position and categorize different types of users based on their speed to find the expected sojourn duration.

•Objective 3: To identify the level of congestion at the base stations by determining the number of active users, availability of resource blocks, and throughput evaluation.

•Objective 4: To develop a multi-criteria handover decision algorithm to calculate the utility scores with reference to the signal and load parameters, which are weighted.

•Objective 5: To compare the proposed algorithm with the conventional methods based on Key Performance Indicators (KPIs), including handover success rate, ping-pong rate, throughput, and latency.

2. LITERATURE REVIEW

Handover in 5G networks has remained a key research area as mobility of the users rises, networks densify, and quality of service (QoS) demands rise [9]. Many studies have suggested mechanisms that deal with either signal quality, congestion awareness, or mobility management, but not many have provided an integrated approach. This review presents an overview of significant works associated with the mobility-aware handover, congestion management, signal metric optimization, and HetNet management. The problem of mobility management in 5G presents significant challenges, because in dense HetNets, the process of cell switching is frequent. Several studies have investigated adaptive handover control parameter optimization, such as dynamic tuning of hysteresis and time-to-trigger (TTT), mainly to improve mobility robustness in dense networks, while congestion awareness at the target cell is either implicitly considered or entirely neglected [10]. Regarding 5G, Shayea et al. [2] carried out an extensive survey about the issues of mobility management, including loss of handovers, failure in calls, and scalability. Oh et al. [1] provided insights on the impact of user active mobility in load balancing at Long Term Evolution (LTE) systems; the study showed that speed and mobility patterns among the users determine the LTE capability of self-organizing handover procedures.

One of the proposed solutions indicates that the convolutional neural network-based technique built on a handover mechanism using deep learning offers enhanced accuracy in the network prediction [11] in 5G vehicle-to-vehicle (V2V) communications. This direction reflects the emergence of machine learning-based handover approaches, which aim to enhance decision accuracy under complex mobility scenarios [5]. The studies [12, 13] examined multi-radio dual connectivity in mobile networks and demonstrated that mobility supporting concepts can integrate fast data recovery methods to decrease handover interruption. Testing the interruptions that take place during vertical handovers in the 3rd Generation Partnership Project (3GPP)-standardized networks, Shin et al. [14] demonstrated the ineffectiveness of legacy handover procedures. Tuysuz and Aydin [15] stated that QoE-based mobility-aware decision making is essential in streaming services at the edge, which underlines the necessity to consider the context assumed by the user in mobility models. Traffic congestion is a very critical factor that contributes to poor handover operation and impaired user experience. Duan et al. [16] proposed an adaptive approach of congestion control that is optimized for machine-type communication in LTE. Salama et al. [17] offered a collaborative edge computing model of 5G, which helps to enhance the usage of resources by utilizing distributed processing in case of congestion-aware handover. Cheung et al. [18] solved the issue of congestion by using a DNS-based network selection scheme that can distribute the load between the Wi-Fi and cellular networks. The traffic offloading was addressed effectively by Cheung et al. [18], who developed a congestion-aware user-cell association algorithm in multi-tier HetNets. Liu et al. [19] proposed a congestion-aware Wi-Fi offloading framework (CAWO) that dynamically redirects data depending on observed live congestion. Similarly, Nikhita and Mohan [20] suggested the same in software-defined vehicular networks to support QoS in mobile situations by providing a congestion-based routing mechanism. Zhang et al. [21] proposed a user-centric base-station selection scheme in ultra-dense networks, in which the congestion awareness aspect is involved, which delivers improved cell allocation. Simultaneously, Zhao et al. [22] presented a model of context-aware, multi-criteria handover to service differentiation by confirming the relevance of dynamic context awareness in mobility decision results.

An important part of the handover decision is signal quality measures, RSRP, RSRQ, and SINR. Khan and Portmann [23] suggested backhaul-aware Software Defined Network-based QoS-control and handover optimization in LTE network, which is comprised of the signal quality metrics that facilitate the optimization of handover operations and ensure that they are maintained efficiently. Musa et al. [24] discussed how information-centric networking and edge intelligence can be combined in vehicular systems, and presented real-time measurement of the quality of links and channel dynamics. Khan and Portmann [23] also claimed that signal strength, latency, and edge conditions for multi-criteria handover are critical factors that could become a significant driver of network performance enhancement. Lohan et al. [25] conducted an elaborate survey of the existing jamming and interference detection solutions, revealing the relevance of signal monitoring in attaining QoE of 5G and 6G networks. Kumar et al. [26] also added a rank-based data scheduler (Reinforcement Learning-based Multipath Transmission Control Protocol (R-MPTCP)) that accounts for signal conditions to distribute wireless traffic on multiple paths.

Furthermore, Zaidi et al. [27] designed a data-driven, model-based framework towards QoE-aware EN-DC (E-UTRA-NR Dual Connectivity) activation process of optimizing dual connectivity via real-time signal assessment. On the same note, an automatized contextually-aware mechanism to select routes in HetNets was proposed by Monteiro et al. [28] using user preferences and conditions of the signals in order to make more informed connectivity decisions. With the maturity of 5G and the appearance of 6G, intelligent and adaptive mobility mechanisms are becoming popular. Ghonge et al. [29] pointed to 5G/6G difficulties and future architectural changes, such as AI-powered improved network decision optimization. According to the study conducted by Johnson [30], software-defined networking, intelligent automation, and edge computing contributed to the redefinition of mobility management.

However, these solutions typically enhance either mobility or reduce congestion, or they build on complex models that introduce high computational complexity. In order to provide a comprehensive overview and a structured comparison of previous studies, the key handover mechanisms are summarized in Table 1. The table categorizes research by its main focus (mobility management, congestion management, and signal metric optimization), outlining the objective, methodology, and key results of each study, thus highlighting the research gaps that this work aims to address.

Table 1. Comparison table of handover mechanisms

Category	Reference	Objective	Methodology	Results	Strengths / Limitations	Technology
Mobility Management	[1, 14]	Analyzing handover behavior to identify weaknesses	Standard analysis of movement patterns and vertical handover procedures	Improving understanding of the impact of user speed and revealing the ineffectiveness of traditional procedures	Analyzing the weakness of traditional handover / not suitable for dynamic and high mobility scenarios. Therefore, there is a need for more modern solutions	Long Term Evolution (LTE) 3rd Generation Partnership Project (3GPP)
	[5, 11]	Improved handover in vehicle-to-vehicle (V2V) communications in 5G and 6G mobile networks	Using machine learning-based handover and deep learning (Convolutional Neural Networks (CNNs)) to predict the handover decision	Achieving high accuracy in delivery prediction, which improves the reliability of the mobile network	Better prediction of handover points and reduced failures / requires massive training data and high computational complexity	V2V,5G, 6G
	[10, 12, 13, 15]	Fast data recovery to improve motion support	Advanced architectural solutions (dual connectivity, edge computing, adaptive handover control parameters) to ensure service continuity	Reduces handover interruption time and improves service continuity	Improves reliability in dense deployments/ requires support for multiple networks and architectural modification, which increases complexity and cost	Multi-Radio Dual Connectivity, 5G, Edge Computing
Congestion Management	[16, 18-20, 31, 32]	Controlling congestion in cellular networks and Wi-Fi	Using different algorithms for Congestion-aware and network selection, such as the congestion-aware Wi-Fi offloading framework (CAWO) and software-defined network routing	Improved performance by intelligently distributing the load between cellular and Wi-Fi networks based on congestion conditions	Effectively reduces congestion/solution may introduce latency or handover failure	LTE, Machine-to-Machine (M2M), heterogeneous networks (HetNets), Wi-Fi, 5G
	[17, 21]	Resource management and user allocation in advanced architectures (Multi-access Edge Computing (MEC), Ultra-Dense Network (UDN))	A collaborative model between edge computing nodes for managing resources during congestion	Improved resource utilization and reduced the impact of congestion through distributed processing	Improving resource utilization during handover / requires a robust infrastructure	5G
Signal Metrics Optimization	[22, 28]	Context-aware mechanism combining multiple metrics	A multi-criteria, context-aware delivery mechanism at the edge of a software-defined network	Combines signaling metrics (latency and real-world conditions)	Improving delivery performance. / Computational complexity caused an increase in decision-making latency	Edge Computing, HetNets
	[23]	Optimize handover using signal quality metrics	Integration of Reference Signal Received Power (RSRP) and Signal-to-Interference-plus-Noise Ratio (SINR) for handover decision	Ensuring service quality and delivery efficiency by considering signal quality metrics and network status	High resolution accuracy / Centralized control condition	LTE
	[25]	AI interference and jamming detection	AI-based signal monitoring and anomaly detection	Highlighting the importance of signal monitoring to achieve good quality of experience (QoE) in next-generation networks	Improving QoE in 5G & 6G / requires significant computational resources and diverse training data	5G, 6G
(Mobility + Congestion + Signal Metrics)	Our paper	Develop an integrated and adaptive handover framework	Developing a new handover algorithm that overcomes the shortcomings of traditional methods by integrating congestion, mobility, and signal metrics into the handover decision	Achieving a significant improvement in all performance indicators: increased handover success rate, reduced ping-pong effect, improved productivity, reduced response time, and better load balance	Compatible with 6G trends / MATLAB simulation	5G

3. METHODOLOGY

This section includes two main parts: Part 1 describes the components of the proposed mobility and congestion-aware handover algorithm in the 5G network, which is simulated with the help of a framework based on MATLAB. On the other hand, part 2 offers an explanation of signal quality metrics so that the discussion of the performance of the proposed system can be clearer.

The proposed algorithm aims to optimize handover utilization through a collective assessment of user motion, signal quality, and the base station congestion in a dynamic HetNet setup.

3.1 System modeling in MATLAB

In MATLAB, a custom 5G simulation environment is developed to model a multi-cell HetNet topology [3], which consists of:

- Small cells and macro cells are configurable in their power transmission, coverage range, and resource bandwidth.
- Mobile UEs that move through the network at different mobility classes (pedestrian, medium, and high-speed mobility).
- Real-time signal quality Tracking, which includes:

(a) RSRP
(b) RSRQ
(c) SINR
(d) Channel Quality Indicator (CQI)

The simulator reproduces shadowing, fast fading, and path loss. Each base station dynamically monitors its load and the number of physical resource blocks (PRBs) that may be scheduled, thus enabling an accurate simulation of congestion situations.

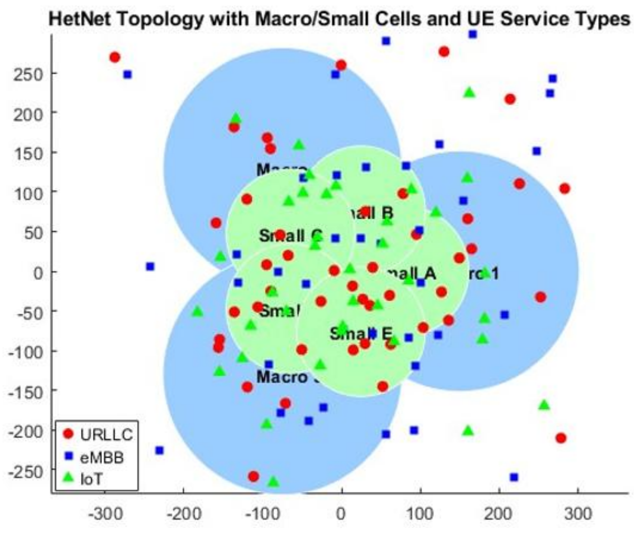


Figure 1. Heterogeneous network (HetNet) topology with macro/small cells and user equipment (UE) service types

Figure 1 illustrates the layout of the non-uniform, clustered distribution of users across the HetNet topology, which consists of three large macro cells (marked in blue) and five smaller cells (marked in green), which act as cluster centers. These represent areas of high user density, such as shopping malls, campuses, or dense urban spots within a heterogeneous 5G environment, with all cells functioning at 28 GHz in the millimeter wave (mmWave) band. Due to the physical nature of mmWave channels, which are characterized by poor penetration and high path loss, a precise cell distribution was adopted based on 3GPP standards. According to the recommendations of 3GPP TR 38.901, macro cells in the Urban Macro (UMa) scenario are preferably spread over a radius of 150 to 200 meters to provide wide coverage in a moderately dense urban environment. In contrast, small cells under the Urban Micro (UMi) scenario were deployed within areas with high data demand, such as shopping malls or busy intersections. A radius of 60 to 100 meters per small cell was adopted to improve performance in dense areas and enhance signal quality. Small cells within the coverage areas of large cells are arranged in an overlapping manner to ensure communication continuity, support handover decisions effectively, and reduce interruptions resulting from signal loss in this high-frequency range. This model is realistic and consistent with modern trends in 5G network design, as indicated by recent studies [33-35]. Most UEs are concentrated near small cells, while others are distributed randomly across the wider area; this configuration simulates realistic user movement across overlapping cell coverage.

3.2 Signal quality metrics collection

All the UEs also report the main signal indicators of the surrounding cells:

•RSRP (dBm): the signal strength, employed in cell choice.

•RSRQ (dB): Shows the signal quality considering interference and noise.

•SINR (dB): Measures the quality of the connections, taking co-channel interference into account.

•CQI (integer between 1 and 15): Indicates the quality of the wireless channel from the user equipment to the base station.

The values are constantly updated every $T_{\text{measurement}}$ milliseconds and sent to the signal quality evaluation module, where the potential of QoS is set by ranking the candidate cells.

Figure 2 shows the simulation results for the measured values of the Signal Quality Metrics. Figure 2(a) includes the value of the RSRP indicator ranging between-85 dBm and-45 dBm, a range consistent with the models approved in the 3GPP TR 38.901 for mmWave channels in dense urban environments (Dense Urban). These values reflect the high attenuation behavior resulting from the use of the 28 GHz frequency, which causes the signal power to be lost rapidly as the distance increases, especially in the case of no direct line of sight [33].

The SINR indicator, as shown in Figure 2(b), ranging between-20 dB and +15 dB, is a realistic results that reflect the combined effects of inter-cell interference and different propagation conditions among users. These values confirm that users close to the cell under the line of sight conditions enjoy high SINR levels, while the index drops significantly in the case of interference or outside the coverage area.

For RSRQ, as shown in Figure 2(c), the values range from − 6 dB to + 13 dB, which is the range expected within physical characteristics of the 28 GHz frequency used in mmWave networks, where the signal propagation capacity is reduced, while the need for precise steering using beamforming techniques increases, resulting in reduced inter-cell interference and increased reference signal concentration.

RSRQ is calculated according to the equation:

$$RSRQ = N \times RSRP/RSSI$$

where, *N* represents the number of resource blocks, *RSRP* is the Reference Signal Received Power, and *RSSI* is the total received power, including interference and noise.

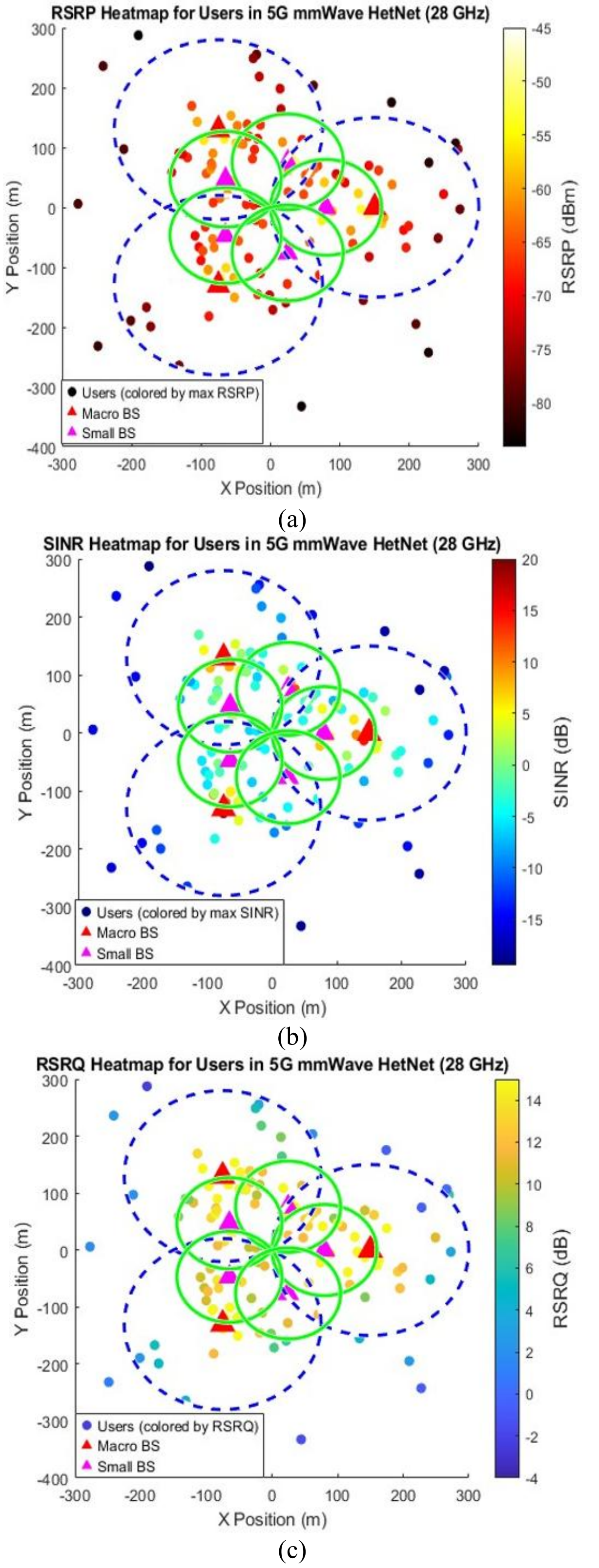


Figure 2. Signal quality metrics heatmap

An improved RSRQ indicates a decrease in RSSI resulting from less interference or a reduced number of connected users. Higher values, such as + 10 dB or more, indicate a low-interference environment and stable signal strength, while lower values (such as – 6 dB) indicate areas at the edge of coverage or near interference from neighboring cells. Overall, these results demonstrate the reliability of the model used to represent the behavior of HetNet networks operating at 28 GHz, and its ability to simulate a realistic next-generation 5G mmWave environment that takes into account attenuation, interference, diversity of traffic characteristics, and spatial distribution of users [33, 35, 36].

3.3 Mobility estimation

To estimate UE mobility, the following approaches are employed:

1) Position tracking: The movement of the UE is tracked over time by recording its position at each time step. The instantaneous velocity is calculated based on the change in position between two consecutive time steps and is then used, along with the direction of motion, to predict the future position, as follows [31]:

$$Pos(t + \Delta t) = Pos(t) + \left(\frac{||Pos(t) - Pos(t - \Delta t)||}{\Delta t}\right)[\cos\theta, \quad \sin\theta].\Delta t \tag{1}$$

2) Mobility classification: It is based on the velocity (v) of the UEs and Doppler shift estimation (based on the observed frequency change due to UE motion). It is defined as follows:

$$v(t) = (||Pos(t + \Delta t) - Pos(t)||)/\Delta t \tag{2}$$

Based on the magnitude of $v(t)$, UEs are classified into three mobility classes:

- Pedestrian: $v \leq 3$ km/h
- Medium Mobility: 3 km/h $< v \leq 30$ km/h
- High Mobility: $v > 30$ km/h

Additionally, the Doppler shift experienced by each UE due to mobility is calculated as follows [37]:

$$f_D = (v\,.f_c/\,c).\cos\theta \tag{3}$$

where,

f_D: Doppler shift (in Hz)
v: relative velocity by each UE (in m/s)
f_c: carrier frequency (in Hz), e.g., 28 × 109 for mmWave 5G
c: speed of light, 3 × 108 m/s
θ: angle between the direction of motion and the direction of signal propagation.

i. Doppler shift is positive if the mobile is moving towards the source.
ii. Doppler shift is negative if the mobile is moving away from the source, as illustrated in Figure 3(a). The distribution of Doppler shift values under mobility is shown in Figure 3(b).

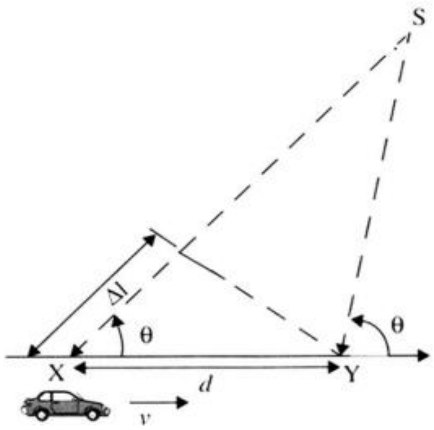
These categories allow the system to estimate users' sojourn time and adapt handover decisions accordingly.

3) Estimated sojourn time

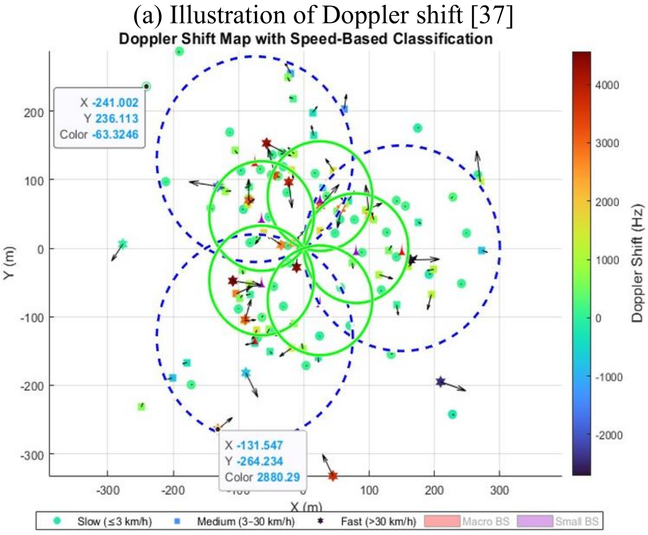
An estimated period for which a UE is likely to remain in the target cell:

$$T_s = R_{cell}/v \tag{4}$$

in which R_{cell} is the radius of the candidate cell.



(a) Illustration of Doppler shift [37]



(b) Doppler shift heatmap

Figure 3. Doppler shift with speed and direction classification

3.4 Congestion detection

To assess the congestion level per candidate base station, the following measurements are required:

- Active users: The number of UEs connected.
- Available PRBs: Mirrors the availability of scheduling.
- Uplink/Downlink throughput: Expressed in Mbps.
- Queue length and buffer occupancy: Instantaneous traffic load.

For cell i, the congestion factor is defined as $L_i \in [0,1]$:

$$L_i = Current\ PRBs\ Used\ /\ Total\ PRBs\ Available \tag{5}$$

where, a higher L_i indicates a higher level of congestion.

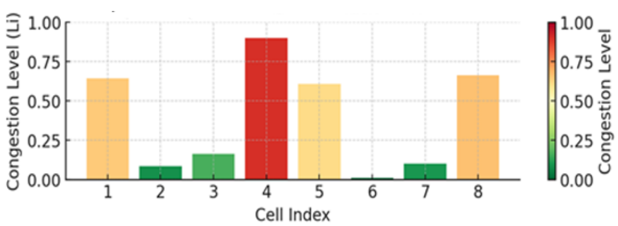


Figure 4. Congestion load distribution across cells

Figure 4 visualizes the congestion level across the active base stations in the network. The heatmap uses a color gradient where green indicates low congestion (L_i near 0), and red indicates high congestion (L_i near 1). This allows an identification of overloaded cells and demonstrates the congestion-aware load balancing of the proposed algorithm.

3.5 Multi-criteria handover decision algorithm

A weighted utility function is calculated for each neighboring candidate cell (i): signal strength, congestion, and mobility.

(1) Signal quality sub-utility

$$Usig_i = w1 \cdot RSRP_i + w2 \cdot CQI_i + w3 \cdot RSRQ_i \tag{6}$$

(2) Mobility stability sub-utility

$$Umob_i = w4 \cdot T_s, i - w5 \cdot f_{D(i)} \tag{7}$$

(3) Congestion-aware sub-utility

$$\begin{aligned} Ucong_i = w6 \cdot (1 - L_i) - w7 \cdot Delay_i \\ - w8 \cdot thrPenalty_i \end{aligned} \tag{8}$$

(4) QoS and randomization component

$$Uqos_i = w9 \cdot QoS_i + \ w10 \cdot rand(i) \tag{9}$$

(5) Weighted utility function

$$Utility_i = Usig_i + Umob_i + Ucong_i + Uqos_i \tag{10}$$

where:

- $w1$–$w10$: weights that can be adjusted according to the weight of each criterion are dynamically adapted based on real-time user and cell characteristics to enable context-aware handover decisions in a 5G environment:

(a) Speed-Aware Adjustment
(b) Service-Aware Adjustment
(c) Congestion-Aware Adjustment

- L_i: Congestion factor of cell i.
- $T_{s,i}$: Sojourn time in cell i as an estimator.
- QoS: a priority factor depending on user type (Ultra-Reliable Low-Latency Communication (URLLC), enhanced Mobile Broadband (eMBB), Internet of Things (IoT)).
- Delay: Transmission Delay – latency experienced in the cell.
- thrPenalty: Throughput penalty – inversely related to expected rate.

Handover is only done when:

- The utility of a target cell (candidate cell) is more than that of the serving cell by a margin of δ.
- Metrics on signal exceed minimum QoS requirements.
- At least the hysteresis margin (H) and TTT are met to prevent a ping-pong effect.

$$\begin{aligned} Handover\ if\colon Utility_i - Utility_{current} > \delta \\ \text{and } duration > TTT \end{aligned} \tag{11}$$

Proposed Handover Algorithm (Pseudo-code):
To further clarify the implementation of the proposed

method, Algorithm 1 presents the pseudo-code corresponding to the MATLAB-based simulation model. This explicitly demonstrates how the utility function and dynamic weight adaptation are applied during each decision interval.

Algorithm 1: Adaptive Context-Aware Handover Decision

Input:
U: Set of UEs
B: Set of base stations (BSs)
M: Network metrics (RSRP, SINR, RSRQ, CQI, Load, PRB, Delay)
T: Thresholds $\{v_{th}, L_{th}, H, T_{TTT}\}$
Output: Optimal serving BS assignment
Begin
For each time step t do
For each UE $i \in U$ do
Context Extraction:
$\mu_i \leftarrow \|v_i(t)\|$
$s_i \leftarrow \text{ServiceType}(i)$
$\mathcal{N}_i \leftarrow \text{NeighborCells}(i)$
Context Indicators:
$\chi_v \leftarrow \mathbf{1}(\mu_i > v_{th})$
$\chi_q \leftarrow \mathbf{1}(s_i = \text{URLLC})$
Adaptive Weight Functions:
$w_{sig} \leftarrow \Phi_{sig}(\chi_v, \chi_q)$
$w_{mob} \leftarrow \Phi_{mob}(\chi_v)$
$w_{qos} \leftarrow \Phi_{qos}(\chi_q)$
$w_{exp} \leftarrow \Phi_{exp()}$
Initialize:
$U_{max} \leftarrow -\infty$
$b^* \leftarrow b_{serv(i)}$
Candidate Evaluation:
For each BS $j \in \mathcal{N}_i$ do
Raw Feature Vectors:
$x_{sig}(i,j) \leftarrow [\text{RSRP}_{ij}, \text{SINR}_{ij}, \text{RSRQ}_{ij}, \text{CQI}_{ij}]$
$x_{mob}(i,j) \leftarrow [T_{sojourn,ij}, f_{Doppler,ij}]$
$x_{net}(j) \leftarrow [\text{Load}_j, \text{PRB}_j, \text{Buffer}_j, \text{Delay}_j]$
Normalization (min-max scaling to [0,1]):
$\tilde{x}_{sig}(i,j) \leftarrow \text{Normalize}(x_{sig}(i,j))$
$\tilde{x}_{mob}(i,j) \leftarrow \text{Normalize}(x_{mob}(i,j))$
$\tilde{x}_{net}(j) \leftarrow \text{Normalize}(x_{net}(j))$
Context-Aware Network Weight:
$\chi L \leftarrow \mathbf{1}(\text{Load}_j > L_{th})$
$w_{net} \leftarrow \Phi_{net(\chi L)}$
Utility Function:
$U(i,j) = \langle \tilde{x}_{sig}(i,j), w_{sig} \rangle + \langle \tilde{x}_{mob}(i,j), w_{mob} \rangle - \langle \tilde{x}_{net(j)}, w_{net} \rangle - w_{qos} \cdot \tilde{x}_{net,}(\text{Delay})(j) + w_{exp} \cdot \xi$
ξ: exploration factor (random or learning-based)
Best BS Selection:
If $U(i,j) > U_{max}$ then
$U_{max} \leftarrow U(i,j)$
$b^* \leftarrow j$
End if
End for
Handover Decision:
$U_{current} \leftarrow U(i, b_{serv}(i))$
$\Delta U \leftarrow U_{max} - U_{current}$
If $(b^* \neq b_{serv}(i)) \wedge (\Delta U > H)$ then
$\tau_i \leftarrow \tau_i + \Delta t$
If $\tau_i \geq T_{TTT}$ then
$b_{serv}(i) \leftarrow b^*$
UpdateResources(b^*)
$\tau_i \leftarrow 0$
End if
Else
$\tau_i \leftarrow 0$
End if
End for
End for
End

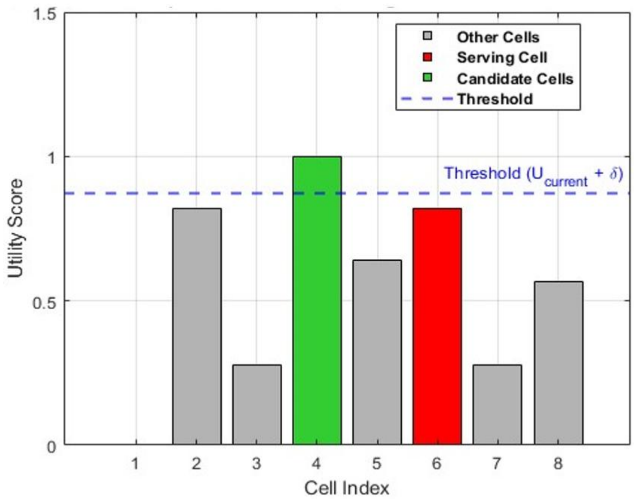


Figure 5. Utility score comparison between cells

Figure 5 shows a comparison of the utility scores of candidate cells of the UE at a time slot. A proposed algorithm would be used to select the cell with the highest utility score beyond a preconceived QoS that could be used to make intelligent handover decisions.

The calculation of utility terms, as well as the process of decision making to execute a handover, is illustrated in the flowchart algorithm shown in Figure 6 below. This function gives the index of the candidate cell with the best value and states if it passes the handover criteria.

3.6 Proposed algorithm workflow

The proposed algorithm is carried out in MATLAB as shown below:

- Network initialization: Deploy various macro and small cells whose coverage areas overlap.
- Generation of UE: Implementation of 100+ UEs with random initial coordinates and distributed mobility classes.
- Measurement loop: At every time step:
  (a) UEs make reports of signal metrics.
  (b) Base stations update congestion status.
  (c) Utility scores are computed for each neighbor.
  (d) Handover decisions are made based on a multi-criteria evaluation.
- Performance metrics recorded:
  (a) Handover success rate
  (b) Ping-pong rate
  (c) Mean throughput
  (d) Latency (ms)
  (e) Load Balancing Index (LBI): To quantify the distribution of traffic across the network by using Jain's Fairness Index, which is defined as:

$$\text{LBI} = \frac{(\sum_{i=1}^{N} L_i)^2}{N \times (\sum_{i=1}^{N} L_i^{\,2})} \tag{12}$$

where, N represents the number of base stations, and L_i is the load (utilization) of cell i. The index ranges from 1/N (worst case, all load concentrated on one cell) to 1 (perfect load balancing).

- Handover Failure Rate (HOF): The percentage of handover attempts that fail to complete successfully, which can be calculated as:

$$HOF = \frac{N_{failed}}{N_{total}} \times 100\% \quad (13)$$

- Radio Link Failure (RLF): Occurs when the SINR drops below a critical threshold (Q_{out}) for a specific duration (T_{310}) before a handover can be executed.
- Handover Interruption Time (HOIT): The time interval during handover execution where no user data packets can be exchanged between the UE and the network (from the last uplink transmission in the source cell to the first downlink transmission in the target cell).

This combined MATLAB scenario model with the proposed handover algorithm effectively emulates signal, congestion, and mobility dynamics in realistic scenarios, thus providing a robust simulation framework to guide realistic 5G implementations.

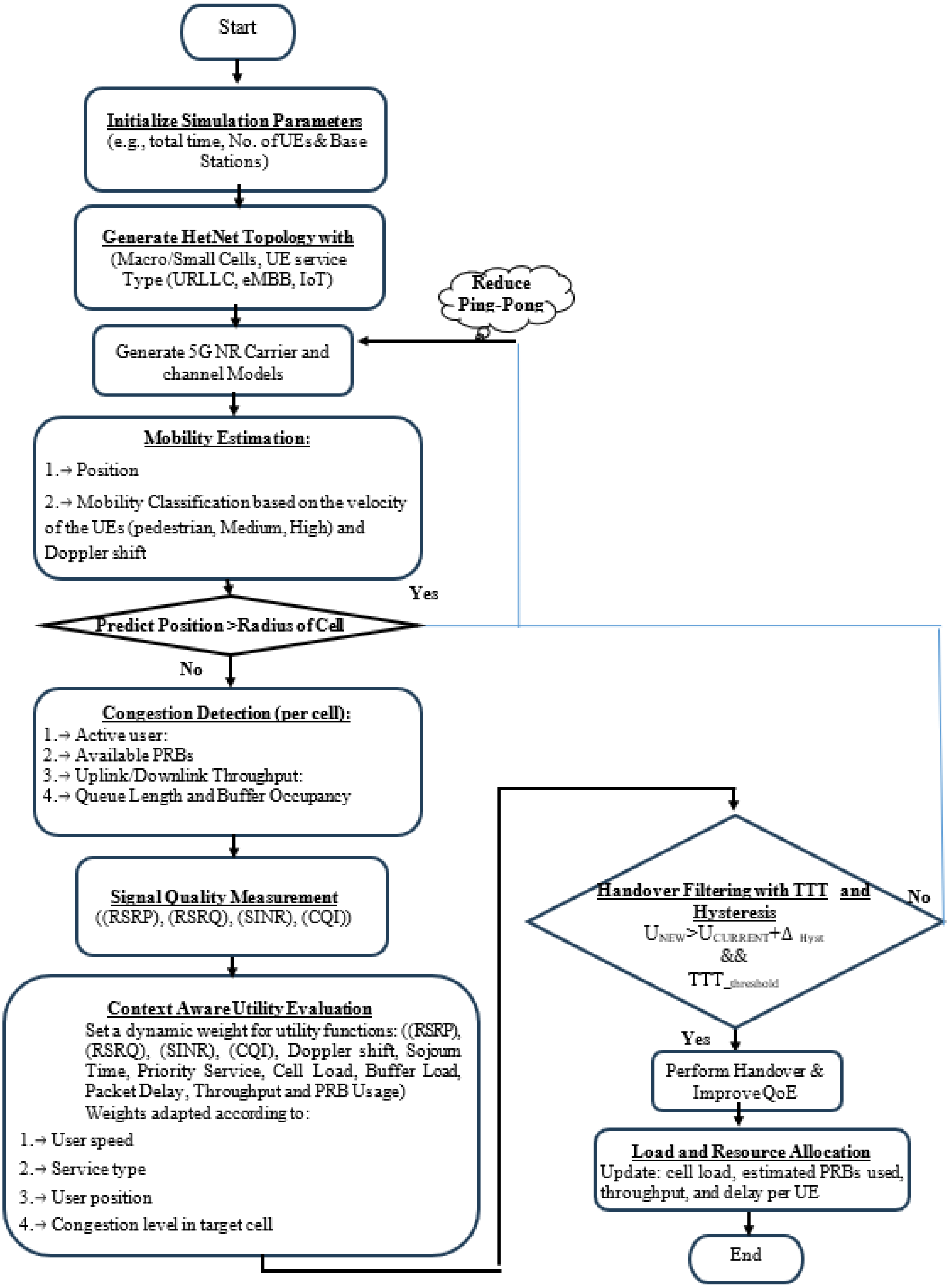


Figure 6. Context-aware multicriteria handover decision flow in 5G networks

4. RESULTS AND DISCUSSION

In this section, the results of the simulation are listed and analyzed, wherein the implementation of the recommended mobility and congestion-aware handover algorithm has been carried out in a 5G HetNet environment in MATLAB. The traditional A3 event-based handover mechanism is used as a benchmark for the performance. Key performance metrics considered include the success rate of the handover, ping-pong rate, average throughput, latency, and the load balancing index, RLF, HOF, and HOIT.

4.1 Implementation setup summary

- Cells: 3 macro + 5 small cells
- UEs: 200
- Simulation duration: 300 seconds
- UE mobility classes: Pedestrian low, medium, high
- Measurement interval: 200 ms
- Traffic model: full buffer per UE
- Comparison of handover algorithms:
  (a) Event-based baseline A3
  (b) Proposed mobility + congestion-aware utility-based

4.2 Performance comparison

A thorough simulation determined the effectiveness of the proposed mobility and congestion-aware handover algorithm. The performance of the algorithm was compared with the traditional A3 event-based handover mechanism. Since a variety of KPIs have been considered, i.e., handover success rate, ping-pong rate, throughput, latency, and load balancing index, Radio Link Failure (RLF), Handover Failure (HOF), and Handover Interruption Time (HOIT) were investigated in several conditions of UE mobility to ensure robustness. All results were averaged over 10 independent simulation runs with different random seeds. Standard deviations (σ) are reported to indicate consistency, and a paired t-test was performed to confirm statistical significance ($p < 0.05$) [38].

$$t_{test} = \frac{\mu_{propsed} - \mu_{\mu_{A3}}}{\sqrt{\frac{\delta^2{}_{proposed} + \delta^2{}_{A_3}}{N}}} \quad (14)$$

where,

- $\delta_{proposed}, \mu_{propsed}$: Mean and standard deviation of the proposed method.
- μ_{A3}, δ_{A_3}: Mean and standard deviation of the A3 baseline.
- N: Number of samples. For the "Average" rows (which aggregate the three speed classes: Pedestrian, Medium, High), we used $N = 3$. For specific class rows (e.g., High Mobility), we used $N = 10$.

Table 2 shows the handover success rates of the traditional A3-based method along with the proposed algorithm in various classes of user mobility. The success rate is high, indicating the stability and reliability of the handover operations.

The results showed that the improved performance of high-speed users was due to the use of Sojourn Time and Doppler shift to prevent frequent handovers, while the improved performance of pedestrians was due to load balancing (Congestion awareness). It can avoid crowded cells and make improved decisions since it considers the congestion and signal quality, while also accounting for UE speed.

Table 2. Handover success rate (%)

UE Speed Class	A3-Based Handover	Proposed Method	T-Test	P-Value
Pedestrian	94.1 ± 1.5	98.3 ± 1.1	7.14	< 0.05
Medium	89.7 ± 1.8	96.5 ± 1.4	9.42	< 0.05
High	82.6 ± 2.2	94.0 ± 1.6	13.25	< 0.05
Average	88.8 ± 1.9	96.3 ± 1.4	10.04	< 0.05

Note: UE = User Equipment.

Table 3. Ping-pong rate (% of total handovers)

UE Speed Class	A3-Based Handover	Proposed Method	T-Test	P-Value
Pedestrian	7.4 ± 0.9	2.1 ± 0.6	− 15.4	<0.001
Medium	12.9 ± 1.1	3.7 ± 0.8	− 21.3	<0.001
High	18.6 ± 1.4	6.0 ± 0.9	− 23.9	<0.001
Average	13.0 ± 1.2	3.9 ± 0.8	− 19.9	<0.001

Ping-pong handover rate, as shown in Table 3, indicates the unnecessary handovers and the frequency of short-term handovers. The low values imply more stable handover choices and that there are fewer fluctuations across the cells.

Reducing ping-pong effects is done by incorporating a utility function with considerations of hysteresis and TTT, whereby the effects are minimized within the proposed approach. This results in a more reliable handover process and fewer problems for the end users.

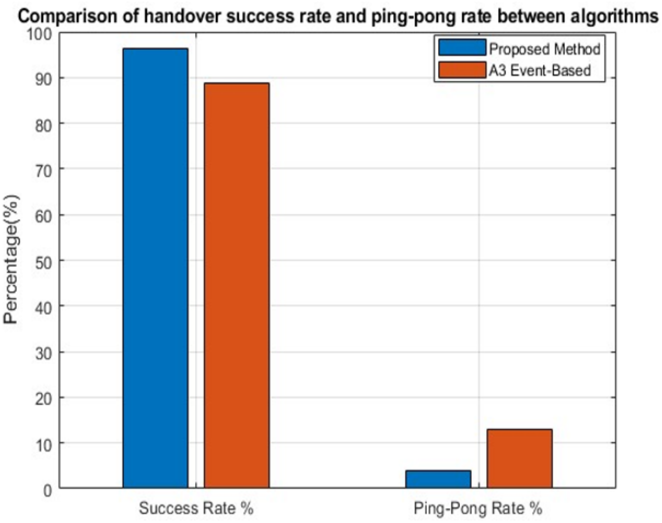


Figure 7. Handover success and ping-pong rate comparison

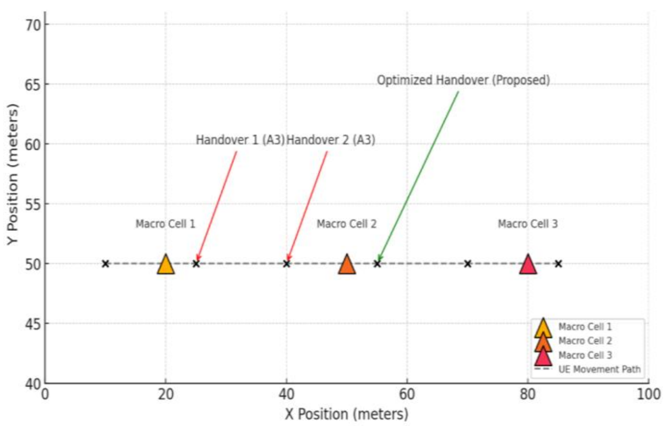


Figure 8. Handover behavior: A3 event-based vs. proposed algorithm

Figure 7 shows the visual comparison of the success rate of handover and the ping-pong rate between the traditional A3-based approach and the proposed algorithm. The offered strategy is rather effective in performance as it shows improvements in both measures.

Figure 8 focuses on handover behavior: A3 event-based vs. proposed algorithm. This figure compares user movement through overlapping cells. The A3 algorithm results in multiple early handovers, while the proposed method intelligently delays until conditions are optimal, thus minimizing disruptions.

Table 4 shows the measurements of RLF, HOF, and HOIT. The proposed algorithm reduces RLF and HOF by proactively handing over users before signals degrade critically and avoiding overloaded cells.

Table 5 shows a comparison of the average throughput per user with the two methods. The proposed method, through the absence of overloaded cells, will result in improved overall resource utilization as well as improved data rates.

The proposed method will not cluster cells and distribute UEs to less occupied base stations with superior signal conditions, leading to increased average throughput per user.

Table 6 reflects the latency experienced between the two schemes of handover. The reduction in latency in the suggested approach indicates more effective data processing because of the adequate distribution of the loads.

The lower latency in the proposed method can be attributed to even cell load balancing of traffic, hence reducing the queueing length and transmission delays. Along with the sensitivity to congestion, the algorithm is important to counteract latency.

Table 4. RLF, HOF, and HOIT metrics

Metric	A3-Based Handover	Proposed Method	T-Test	P-Value
RLF Rate (%)	4.8 ± 0.6	1.2 ± 0.4	12.90	< 0.05
HOF Rate (%)	11.2 ± 1.1	3.7 ± 0.8	− 13.43	< 0.05
HOIT (ms)	32.5 ± 3.2	24.8 ± 2.1	− 8.64	< 0.05

Note: RLF = Radio Link Failure; HOF: Handover Failure; HOIT: Handover Interruption Time.

Table 5. Average throughput per user equipment (UE) (Mbps)

UE Speed Class	A3-Based Handover	Proposed Method	T-Test	P-Value
Pedestrian	8.4 ± 0.5	10.2 ± 0.4	8.8	< 0.05
Medium	7.6 ± 0.6	9.6 ± 0.5	8.0	< 0.05
High	6.1 ± 0.7	8.7 ± 0.6	8.9	< 0.05
Average	7.3 ± 0.6	9.5 ± 0.5	8.9	< 0.05

Table 6. Average latency (ms)

UE Speed Class	A3-Based Handover	Proposed Method	T-Test	P-Value
Pedestrian	46.2 ± 2.6	32.1 ± 1.9	− 13.8	< 0.05
Medium	53.4 ± 2.2	37.7 ± 1.2	− 19.8	< 0.05
High	65.9 ± 1.8	43.2 ± 1.8	− 28.1	< 0.05
Average	55.1 ± 2.9	37.7 ± 1.6	− 16.6	< 0.05

Table 7. Load balancing index (0 = poor, 1 = optimal)

Scenario	A3-Based Handover	Proposed Method	T-Test	P-Value
Overall network	0.64 ± 0.04	0.86 ± 0.02	15.55	< 0.05

Table 7 shows the load balancing index of the entire network that gauges the merit of a distributed traffic load between the base stations; the higher the index, the better the load distribution.

The proposed method has a better way of maintaining load balancing because it actively avoids congested cells. This enhances network efficiencies, and it is fair, especially when there is a peak usage.

4.3 Expanded comparative analysis

In addition to the standard A3 baseline, we compare our proposed mobility and congestion-aware algorithm against two critical categories of state-of-the-art handover mechanisms: Adaptive handover control parameter-based methods and machine learning-based methods.

The comparison focuses on KPIs, mechanism complexity, and adaptability.

4.3.1 Comparison with adaptive handover control parameter-based methods

(1) Nasri and Altman [39] (LTE load balancing):

- Method: Dynamically adapts the Handover Margin (HM) based on the load difference between the serving and target cells.
- Performance: Reports a 15% increase in user throughput and improved access probability compared to fixed margins.
- Comparison with proposed: While Nasri's method [39] optimizes for load balancing via margin adjustment, it operates primarily on a single parameter (Margin). Our proposed method integrates multi-criteria weights (w_1 to w_{10}) that adapt simultaneously to signal quality, mobility (Doppler, speed), and congestion. This allows for finer granularity in decision-making (e.g., prioritizing low latency for URLLC users) rather than just adjusting a threshold.

(2) Gannapathy et al. [40] (Adaptive TTT handover (ATH)):

- Method: Adapts the TTT dynamically based on SINR measurements in a 5G mmWave-LTE dual connectivity environment.
- Performance: Reduces handover ping-pong and RLF compared to conventional methods.
- Comparison with proposed: The ATH mechanism focuses on adapting the timing of the handover (TTT) to cope with intermittent mmWave channels. Our proposed method includes TTT adjustment but goes further by pre-calculating the utility score of the target cell. Where ATH might delay a handover, our method might select a different target cell entirely if the congestion load (L_i) is too high, providing superior load balancing (Index 0.86) and throughput (9.5 Mbps) compared to the throughput gains typically seen in single-parameter tuning.

4.3.2 Comparison with machine learning-based methods

(1) Kabeer et al. [41]. (Sequence-based deep learning):

- Method: Uses Gated Recurrent Unit (GRU) / Long Short-Term Memory (LSTM) / transformer architectures to predict handovers based on RSRP sequences.
- Performance: Achieves 98% reduction in ping-pong effects and 46% reduction in unnecessary handovers.
- Comparison with proposed: While Kabeer et al. [41] achieve slightly higher ping-pong suppression, this comes

at the cost of high computational complexity (training deep neural networks). Our proposed method achieves a robust 70% ping-pong reduction using a deterministic utility function. This makes our method more practical for real-time implementation in resource-constrained 5G UE and base stations, avoiding the latency and energy consumption associated with neural network inference.

(2) Chien et al. [42]. (Privacy-preserving federated learning and LSTM):

- Method: Uses federated learning with LSTM to predict RSRP and adjust handover thresholds dynamically.
- Performance: Reduces handover ping-pong probability to 0.0333 (vs. A3's 0.0606).
- Comparison with proposed: Chien's method [42] focuses on privacy and prediction accuracy. However, it requires a federated learning framework, which introduces communication overhead. Our method achieves comparable handover ping-pong reduction (3.9% vs. 3.33%) with a lighter-weight algorithm that can be deployed locally without the need for model aggregation across devices.

(3) Khan et al. [43] (machine learning-based for Wi-Fi/cognitive networks):

- Method: Uses Random Forest for handover prediction and throughput estimation for access point selection.
- Performance: Reduces unnecessary handovers by 60% compared to received signal strength methods.
- Comparison with proposed: Although Khan's work [43] is in Wi-Fi, the machine learning principle applies. Our method achieves similar stability (70% ping-pong reduction) but is specifically optimized for 5G HetNets with mmWave characteristics and explicit congestion factors (L_i), which are less critical in standard Wi-Fi but vital in cellular 5G.

4.4 Summary of observations about the proposed method

(a) Handover efficiency: Handover was 9 percent more efficient on average because it offered improved cell selection.
(b) Stability: The ping-pong handovers were reduced by about 70 percent due to the addition of hysteresis, sojourn time, and TTT in decision making.
(c) QoS keeps improving: Greater throughput and low latency continue to improve user QoE.
(d) Network utilization: Equal utilization of resources prevents a weak and inelastic network environment.

5. CONCLUSIONS

This work proposes a new handover decision scheme in 5G networks which incorporates mobility prediction, congestion awareness, and signal parameters. As opposed to conventional A3 event-based handover protocols, the suggested approach dynamically considers the user speed, network traffic, and radio state differently, which ensures a utility-based allocation of decisions. The algorithm intends to use parameters like RSRP, RSRQ, CQI, Doppler shift, delay, buffer size, priority score, predicted position, base station load, and estimated sojourn time so as to minimize the handover failures and ping-pong effect, and ultimately enhance user QoE. Simulation results conducted with the aid of MATLAB demonstrate that all key performance indicators are enhanced to a considerable degree. The proposed scheme has better handover success rates, better throughput, lower latency, and lower ping pong rates. Moreover, the algorithm demonstrates excellent load balancing, which guarantees equitable and effective allocation of resources between macro and small cells of the HetNet. Additionally, the expanded benchmarking against recent Adaptive handover control parameters and machine learning-based approaches confirms that our integrated method provides a more holistic optimization than single-parameter tuning techniques. Crucially, the results demonstrate that the proposed algorithm achieves performance stability comparable to deep learning approaches but with significantly lower computational complexity, making it a highly practical solution for 5G deployments.

The proposed approach utilizes the information in real-time measurements of radio signals, the mobility behavior of users, and the existing congestion levels to support handover optimization in dense and dynamic 5G systems. Future research can deal with realistic conditions instead of simulation-only validation by using field-based testing to provide further analysis of adaptability and responsiveness, along with expanding the model to encompass uplink metrics and energy efficiency constraints, in the case of ultra-dense environments. Implementation in a standard open-source simulator, such as ns-3, which offers 3GPP-compliant channel and mobility models, can also be considered.

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