

Adaptive Cell Pride Traffic Load Balancing for Reliable 5G Mmwave Handovers

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Abstract: Handover (HO) management in millimeter-wave (mmWave) fifth-generation (5G) networks faces critical challenges including limited propagation distance, blockage, and frequent disconnections, particularly in dense urban environments. Most existing solutions target high mobility scenarios, while dense urban traffic with low-speed heterogeneous environments and frequent stop-and-go scenarios remains under-explored. This study proposes a novel concept of cell pride where the neighbouring cells cooperate and select the best performing cell for each user equipment (UE) instead of competing with each other. Based on this idea, the Adaptive Cell Pride Traffic Load Balancing (ACPT-LB) framework is developed to enhance the reliability of handover and connection stability in 5G mmWave networks by combining cooperative cell selection, adaptive load balancing, and a neighbour discovery mechanism. The simulated results showed Handover Success Rate (HSR) of 100%, Ping-Pong Avoidance Rate (PPAR) of 100%, and Connection Stability (CS) of more than 88% for all simulations with UE densities ranging from 1000 to 5000, highlighting the effectiveness of the framework in low mobility and high-density urban environments. These results confirm that ACPT-LB offers a scalable and robust solution for mobility and traffic management in 5G and Beyond 5G networks.

Index Terms: 5G mmWave, Handover Management, Traffic Load Balancing, Cell Pride, Connection Stability, Mutualistic Cell Selection

1. Introduction

The advent of 5G mmWave technology facilitates very high data rates, ultra-low latency, and massive connectivity of devices [5, 18, 42]. mmWave is a key building block of the next-generation wireless networks [8]. Despite these benefits, the high frequency of the spectrum poses critical challenges to mmWave deployment, such as short propagation range, severe sensitivity to blockage, and frequent handovers [10, 14, 27].

5G mmWaves suffer from high path loss and have limited diffraction and penetration through obstacles such as buildings, vehicles, foliage, and human bodies [23, 37]. As a result, mmWaves signals are easily blocked and prone to significant variations [40]. These issues are especially severe in high-density urban areas and in high mobility situations, where the presence of buildings, vehicles, and human traffic can quickly reduce the quality of links [8, 32].

Due to the above propagation characteristics, the coverage area of the cells is expected to be much smaller compared to traditional networks that operate at sub 6 GHz [17, 18]. This causes frequent switching between cells, an increase in handover event rate, and contention for available resources even at a low mobility rate [10, 32]. In scenarios

of high mobility, such as vehicular communication, frequent handovers may cause disconnections, loss of packets, and disruptions of services [4, 5, 24].

The mmWave communication is highly directional, which further complicates it, since slight displacement of the user or change in orientation can have a drastic influence on the quality of the link [37]. These issues not only result in service disruption to the users but also inefficient use of resources, increased interference, and poor network reliability [26, 31]. This complicates the operation of a stable connection, especially in dense urban deployments and in dynamic situations where the users are moving rapidly [12, 18, 38]. With more devices getting connected, it is necessary to ensure high stability in connections, a reduction in handover failures, and fewer ping-pong events in mmWave 5G networks to maintain a high quality of user experience [16, 17, 24].

Under these circumstances, traditional cell selection and handover mechanisms have low reliability and cause radio link failures (RLF), handover failures (HOF), unstable connections, and ping-pong events. Handovers and ping-pong switching between cells increase dramatically for higher density of users, making the problem more severe [17]. Several methods that are entirely based on received signal power or received reference signal power are shown to perform poorly in mmWave networks due to fast signal fading and severe blockage conditions [21, 39].

In order to address these shortcomings, this study proposes the concept of cell pride, which is a collaborative group of cells that share network resources in a Next Generation Node B (gNB) or across multiple gNBs. The proposed framework is inspired by mutualistic behaviour in nature, in which cells cooperate instead of competing, using a mutualistic cell selection approach. The most efficient cell is chosen among the cells, ensuring equal allocation of resources, less interference and higher reliability of the network. Once a serving cell hits capacity, an adaptive load-balancing system will redirect the incoming UEs to the subsequent optimum cell to ensure continuous service delivery and eliminate congestion. This cooperative technique is effective in dense urban environments and in scenarios involving low mobility, in which network is congested and handover is a major issue for link stability.

The main objective of the research is to design a powerful, versatile and scalable architecture of 5G mmWave networks that would increase the reliability of handovers, eradicate ping-pong phenomena, and maintain stable connections even at different levels of traffic density and mobility. The proposed framework offers coordinated resource management to reduce the interference that arises as a result of competitive cell behaviour in dense mmWave deployments. Therefore, this work makes ACPT-LB a load-aware cooperative handover system designed to operate in dense and low-mobility mmWave networks.

The general contribution of this work can be summarized as follows:

1. It proposes a new concept of cell pride that enables cooperative working among neighbouring cells, mutualistic cell selection and enhanced resource coordination in 5G mmWave networks.
2. It proposes an Adaptive Cell Pride Traffic Load Balancing (ACPT-LB) framework which integrates handover management and load balancing to enable dynamic and load aware redirection of user equipment to suitable cells.
3. The study develops a Cell Pride Score model that combines the signal strength and cell load into a single decision metric for efficient and scalable handover decisions.
4. It incorporates a neighbour discovery mechanism which limits candidate cell selection to nearby high quality cells, thus improves the accuracy of handover and enhances stability of connections.
5. It presents a scalable and extensible framework for 5G and beyond mmWave networks, by simulating the performance of the ACPT-LB system and validating it through simulation, high Handover Success Rate (HSR), Ping-Pong Avoidance Rate (PPAR) and strong Connection Stability (CS) in low mobility and dense urban scenarios are obtained.

2. Related Works

2.1. Handover Management Approaches

Several algorithms and frameworks have been proposed to improve handover decision-making in mmWave networks, which deals with the issues of fast signal attenuation, blockage, and high mobility that occur in mmWave [23, 38]. Some of the techniques used are signal strength-based handovers, prediction algorithms, mobility-based techniques, machine learning (ML) algorithms, and context-aware techniques [25, 37]. Signal strength-based algorithms primarily depend upon real-time Received Signal Strength (RSS) and/or Signal-to-Interference-plus-Noise Ratio (SINR) value measurements in real-time, while prediction and ML-based algorithms utilize historical connectivity, user trajectory, and network behaviour in terms of predicting a connection degradation or a degradation in link quality [12, 16, 17, 39]. The mobility-aware approach relies on UE speed and direction of travel and location history in order to differentiate between a transient and an ongoing loss in signals [6, 19]. These metrics are augmented by factors related to beam alignment, interference, and blockage predictions to improve handover decisions in mmWave networks [4, 29]. The primary objective is to ensure a minimum number of handover errors and a reasonable level of connection quality while handing over in fast-changing mmWave channels [9, 23, 36].

However, in spite of these developments, the current methods tend to fail in their endeavors to create efficiency in the network. Channel fluctuations are prone to trigger unstable or premature handovers and frequent back-and-forth handovers (also referred to as ping-pong events) lead to more signaling overhead and poor user experience [17, 31]. Radio link failures can also be experienced even in dense or high-mobility cases, which implies that predictive, mobility-aware, ML-driven, and context-aware approaches are also unable to ensure continuous connectivity [24]. Those constraints suggest that more powerful, smarter, and scalable handover management systems should be developed to provide consistent and efficient mmWave network operation in realistic and large-scale deployments [14, 16].

2.2. Traffic Load Balancing in Dense Networks

Adaptive traffic load balancing has been extensively studied as a system to deal with congestion in high-density networks, where many UEs compete with a limited radio resource pool [12, 22, 33]. This mechanism usually strives to transfer users in the overloaded cells to underutilized cells in the neighbourhood so that the total network throughput can be enhanced and the service degradation can be alleviated [7, 13, 41]. Load balancing can maximize the use of resources and alleviate congestion impacts at localized points by balancing traffic across available infrastructure [1, 15, 17, 30].

However, the present load balancing methods primarily focus on traffic distribution; they also perceive cells as self-autonomous, disregarding cooperation or joint decision-making among cells located in proximity to each other [11, 34]. Moreover, the methods fail to offer efficient overall integration in regard to highly significant mobility-related issues, such as handover failures, radio link failures, ping-pong, and connection stability [3, 41]. This leads to inefficiency in environments characterized by mobile conditions and full density, where the distribution of users and changes in link conditions tend to have coordinated and holistic perspectives in managing the networks [2].

2.3. Cell Cooperation and Mutualistic Approaches

There have been a number of recent studies that have investigated the concept of cooperation and mutualism where a number of cells work together for handoff decisions and resource allocation [28, 34]. Instead of competing individually, cells cooperate with each other to observe the network conditions such as traffic load, user location, and the actual status of the communications channel that could enhance overall network performances [11, 20, 35].

Despite these potential benefits, a large number of existing studies dealt with either high mobility or balancing of traffic loads separately, instead of addressing both issues simultaneously [28]. Furthermore, highly important performance factors such as the handover failure rate, radio link failure rate, ping-pong behaviour, and long-term link stability are hardly taken into account simultaneously [20]. This shows a huge void in the existing literature because holistic and scalable solutions to mmWave network management have not been developed yet.

2.4. Gap Identification and Motivation for ACPT-LB

Table 1. Comparison of Other Approaches with ACPT-LB¹

Approach / Study	High-Mobility Support	Low-Mobility Support	Load Balancing	Cooperative Cell Selection	Handover Failures	Ping-Pong Avoidance	Connection Stability	Scalability
Conventional Cell Selection	Low	Not considered	No	No	Moderate	Low	Moderate	Moderate
Signal Strength / Predictive Handover	Moderate-High	Not considered	Yes	No/Yes	Low-Moderate	Moderate-High	Moderate-High	Moderate-High
Adaptive Load Balancing	Moderate-High	Not considered	Yes	No/Yes	Low-Moderate	Moderate-High	Moderate-High	Moderate-High
Cooperative / Mutualistic Approaches	Moderate-High	Not considered	Yes	Yes	Low	Moderate-High	Moderate-High	Moderate-High
ACPT-LB (Proposed)	Not considered	High	Yes	Yes	Low	High	High	High

Despite the developments made on handover management, load balancing of traffic, and cell cooperation, gaps are still observable in current solutions [23, 25]. Most frameworks do not collaboratively maximize the reliability of handovers, connection stability, and ping-pong reduction as they process dynamic and high-density traffic [9, 16]. The level of spatial awareness and adaptive process is usually inadequate, while the decisions of the handover are not effective, and network resources are not used efficiently [36]. These shortcomings point to the necessity of a universal, scalable framework that will support UEs mobility, balancing of loads, cooperation between cells, reduce HOF, decrease RLF,

¹ Note: The qualitative ratings in Table 1 are based on reported trends and general findings from the respective studies. There is no direct numerical comparison of the works because of the differences in the simulation environment, mobility assumption, network configuration, and evaluation metrics in the referenced works.

avoid ping-pong events, and increase connection stability. Table 1 provides a brief overview of the performance of current methods in consideration of these metrics, which can be used to show the shortcomings of conventional, predictive, adaptive, and cooperative methods. The proposed Adaptive Cell Pride Traffic Load Balancing (ACPT-LB) solution fills the above gaps with the incorporation of a mutualistic cell pride scheme for cooperative cell selection, coupled with an adaptive load balance and the use of a neighbour discovery radius in favouring cells that are closer by. As illustrated in Table 1, ACPT-LB outperforms current techniques in all major metrics, which offers a highly feasible and efficient handover and traffic control system in low-mobility mmWave 5G networks with high density.

3. Methods and Material

3.1. Simulation Environment

The simulation environment is composed of 61 gNB sites spread across 3000m x 3000m with an inter-site separation of 100 m. Each site has three sectors that have a beamwidth of 70 degrees and a highest beamforming gain of 18 dB. The Carrier Frequency (CF) is configured to 30 GHz, and the overall system bandwidth is 100 MHz. The transmit power used is 45 dBm, and the antenna heights for gNB and UE are set at 10 m and 1.5 m, respectively.

Also, UEs move at an independent speed ranging from 0 to 4 km/h to simulate stop-and-go traffic conditions and the simulation runs for 300 seconds with a time step of 0.05 seconds, generating a large dataset for in-depth analysis. This mobility range is used to model congested urban vehicular traffic that is characterized by stop-and-go traffic where traffic signals and intersection delays results in low but dynamic speed distributions. This study is based on low-mobility dense urban conditions rather than high-speed vehicular mobility.

This study makes use of an Adaptive Cell Pride Traffic Load Balancing (ACPT-LB) framework in a 5G mmWave simulation using MATLAB. The ACPT-LB framework proposed is depicted in Fig. 1. and demonstrates the hybrid handover mechanism with mutualistic cell pride, adaptive load balancing, and neighbour discovery.

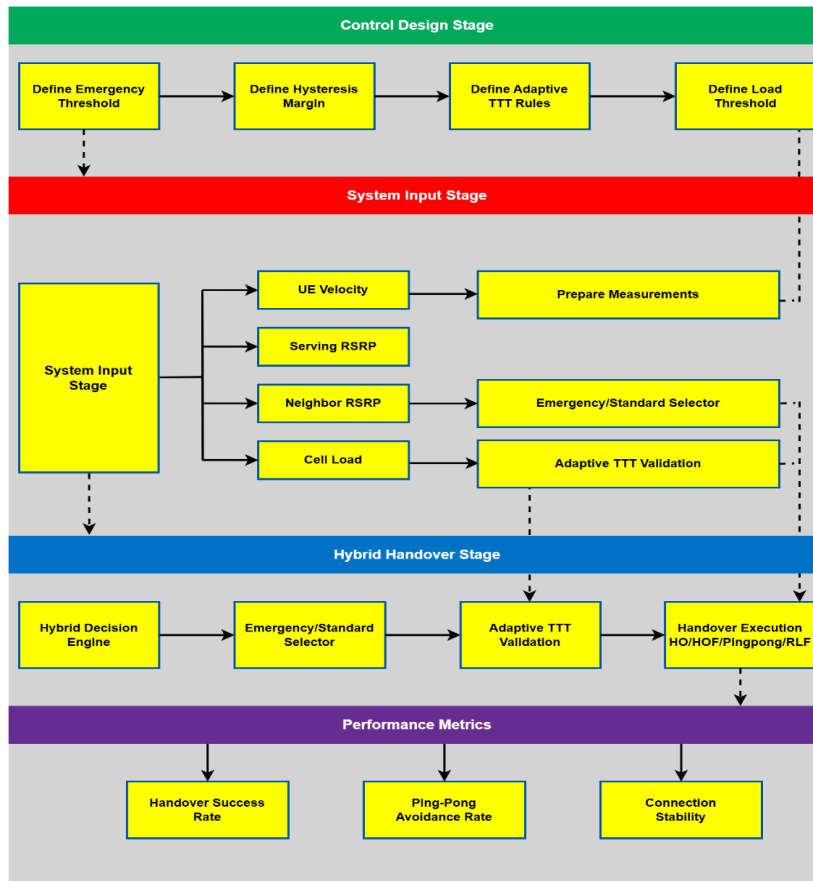


Fig. 1. Block diagram of the proposed ACPT-LB hybrid handover framework

Moreover, each of the 61 different gNodeB sites offers mmWave spectrum, which offers high speeds in terms of transfer rates, high directionality, and high risks of blockage due to building, road, and pedestrian obstructions. The simulation supports various types of traffic such as Video, IoT, and URLLC and the arrival of packets is modeled as a Poisson process. The power consumption, battery level, and Mobile Edge Computing (MEC) delay, are monitored to determine the energy efficiency and latency of each simulation scenario.

Radio propagation is modelled based on Urban Micro (UMi) Path Loss standard established by the 3rd Generation Partnership Project (3GPP) [1, 2], which is a standardized channel model of 5G mmWave. These models individually consider Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) conditions, log-normal shadowing, and sector antenna gains, which guarantee realistic and comparable simulation outcomes of the UEs scenarios considered in this work.

The simulation is based on large scale propagation properties and load aware handover behaviour. System level is abstracted to include detailed procedures during the physical layer like beam sweeping and alignment, Frequency Range 2 (FR2) high frequency mmWave operations, Synchronization Signal Block (SSB) transmission structures and Channel State Information Reference Signal (CSI RS) measurement structures, Layer 1 and Layer 3 filtering, and 3GPP radio link failure timers including N310, N311 and T310. The goal is to assess the effectiveness of cooperative and load-aware handover decisions under controlled low mobility conditions. It does not aim at implementing the whole protocol stack or any detailed physical layer procedure.

During the simulation, a set of network and user equipment metrics is continuously monitored and logged in the system throughout the simulation. The major parameters such as UE states, handover events, SINR, reference signal received power (RSRP), channel quality indicator (CQI), resource block allocations, power consumption, and buffer occupancy statistics are logged systematically into a structured dataset. The records obtained represent the dynamic nature of the network, UEs, and network infrastructure interactions and also give a detailed basis to analyze the network. The data collected is then processed with visualization modules that generate the graphical representations in order to make the interpretation easy. These visualizations allow the quantitative assessment of the performance of the framework under various network conditions and performance optimization.

3.2. Control Design Stage

The Control Design Stage defines the offline configuration parameters and control policies that define the behaviour of the handover system. They are not obtained based on real-time measurements of the network, but rather are a set of predefined rules that determine the decision-making process. These predefined rules include the emergency threshold, which is the minimum tolerable reference signal received power that initiates an immediate handover to prevent radio link failure. The minimum difference required between the serving cell and target cell for a signal to prevent unnecessary handovers caused by temporary signal fluctuation is set by the hysteresis margin. The time of handover is adaptively controlled by implementing Adaptive Time-to-Trigger (TTT), where the handover decision is adjusted according to the speed of the mobile users. This ensures faster handovers for UEs moving at high-speed and stable handovers for slow-speed users. In addition, the cell loading threshold limits the maximum number of mobile users that the cell can support.

Once these rules are defined, they are injected into the real-time system by configuration links and held constant throughout the entire duration of the simulation. This enables a stable behaviour in the system, and handover occurs based on different conditions in the network.

3.3. System Input Stage

The System Input Stage is responsible for the collection and processing of real-time network measurements required for making the handover decision. During each interval of the simulation, the UEs continuously monitor the reference signal power of the serving cell and the neighbouring cells. User velocity and current cell load were also recorded.

These measurements are processed in the measurement preparation module, where the data is filtered, synchronized, and normalized. The system selects the cell that has the maximum signal power as the best candidate for each UE, but when the cell reaches its load threshold, it starts rejecting users, and this causes the system to select the next best candidate cell.

3.4. Hybrid Handover Stage

The Hybrid Handover Stage is the intelligence center of the proposed ACPT-LB framework. It presents a mutualistic cell pride system in which neighbouring cells cooperate to choose the most suitable cell for a UE as illustrated in Fig. 1. The network derives a Cell Pride Score of a candidate cell as a result of the RSRP measurements of the UE and the current load of the respective cell. The Cell Pride Score is used to evaluate candidate cells in terms of signal quality and load. Neighbouring gNBs share RSRP and load information between Xn interfaces at the predetermined time intervals that are synchronized with TTT settings to achieve coordinated handover decisions that are consistent with 3GPP near real-time (near-RT) control.

In order to ensure consistency of the combination, received signal power (RSRP) is re-scaled to 0-1 scale across all the candidate cells as shown in (1).

$$RSRP_{norm} = \frac{RSRP - RSRP_{min}}{RSRP_{max} - RSRP_{min}} \quad (1)$$

The load term is quantified in terms of the proportion of the maximum number of users per cell $\left(\frac{U_c}{U_{max}}\right)$. The final Cell Pride Score of a candidate cell c is defined as (2).

$$\text{Cell Pride}_c = \text{RSRP}_{\text{norm}} - \lambda \left(\frac{U_c}{U_{\text{max}}} \right) \quad (2)$$

where $\text{RSRP}_{\text{norm}}$ represents the received signal power of candidate cell c , U_c is the current number of UEs connected to a cell c , U_{max} is the maximum supported number of UEs across all candidate cells, and λ is a weight factor that balances the impact of load relative to signal strength. This calculation uses real-time RSRP and load information between neighbouring gNBs over Xn interfaces, thereby allowing the utilization of Cell Pride Scores within 3GPP specifications.

λ and other important parameters including U_{max} , hysteresis margin and Time to Trigger (TTT) were selected through preliminary tuning to ensure stable handover performance under the low-mobility conditions considered in this study. The following key parameters were used: load weight factor (λ) of 15; the Time-to-Trigger (TTT) was set adaptively in the range of 0 to 40 ms, adjusting based on UE velocity; the handover margin (Δ) of 3 dB in accordance with 3GPP recommendations, and a maximum users per cell (U_{max}) of 240. The results indicated that the framework was not too sensitive to these parameter choices as the tested UE densities varied from 1000 to 5000. These parameter choices offer a controlled and repeatable environment, while still retaining a realistic network behaviour.

The cell with the best Cell Pride Score is identified as the target used in handover assessment. When this cell has reached its load limit, it starts rejecting more users, so the network selects the next good candidate cell according to the new Cell Pride Scores. This scoring ensures that UEs focus on good quality cells and not on overloaded cells, so that they can have balanced resource use and connection stability.

Each time a handover decision is made, the Cell Pride Score is calculated independently for each candidate cell, making the computational complexity of the ACPT-LB framework linear with the number of candidate cells and connected UEs. The cooperation between neighbouring inter-gNB is limited to exchanging RSRP and load information periodically over Xn interfaces, in synchronization with TTT intervals, keeping signaling overhead manageable and in line with the 3GPP near real-time control specifications. The simulation validated the framework performance for UE densities up to 5000, and the linear nature of the scoring system implies that performance should be consistent beyond this density.

The hybrid handover mechanism presented in Fig. 1 is implemented in Algorithm 1, which shows the step-by-step process of UE handover decision and load balancing. This handover decision procedure is guided by cooperative updates from neighbouring gNBs, which occur with intervals corresponding to TTT settings, ensuring near-RT compliance and minimizing signaling overhead.

Algorithm 1. ACPT-LB: Handover Decision with Load Balancing

A. Parameter Definitions for Algorithm 1	B. Algorithm 1 ACPT-LB: Handover Decision
λ : Load weight factor (balances signal vs. load) Δ : Handover margin (minimum RSRP improvement threshold) θ_{danger} : Emergency RSRP threshold U_{max} : Maximum users per cell (soft capacity limit) T_{TTT} : Time-to-Trigger duration RSRP : Reference Signal Received Power U_c : Number of connected UEs in a cell mean_users : Average number of UEs across candidate cells bestC : Best candidate cell serving : Current serving cell t_timer : Time-to-Trigger countdown timer t_target : Target cell being evaluated timeStep : Simulation time step	<pre> 1. Initialize system parameters and UE states 2. if t == 1 then HandoverDecision = false 3. else 4. % Cell Pride Score Calculation 5. for each site in network 6. site_scores = RSRP_norm - $\lambda * (U_c / U_{\text{max}})$ 7. recommended_cells.add(best_sector) 8. end 9. bestC = argmax(site_scores) 10. % Handover Trigger Check 11. if RSRP[bestC] > RSRP[serving] + Δ OR RSRP[serving] < θ_{danger} 12. if ttt_target == bestC 13. ttt_timer = ttt_timer - timeStep 14. if ttt_timer ≤ 0 AND $U_c[\text{bestC}] < U_{\text{max}}$ 15. serving = bestC 16. HandoverDecision = true 17. end 18. else 19. ttt_target = bestC; ttt_timer = T_TTT 20. end 21. end 22. end </pre>

3.5. Performance Metrics

The last stage of the proposed ACPT-LB framework is the performance metrics stage, during which the effectiveness of the handover and load balancing mechanisms will be quantified. This is the stage where the results of the simulation are evaluated to determine the extent to which the framework has sustained a seamless connectivity, ensured connection stability, and reduced unnecessary handover events within the dynamism of the traffic and channel environment. The

chosen metrics aim at capturing the main features of mobility management, such as the efficiency of handover, connection strength, and the reliability of signaling. Network performance is measured based on outcomes of handover events and radio link behaviour observed during the simulation and is evaluated using the following metrics:

3.5.1. Handover Success Rate (HSR)

The Handover Success Rate is the percentage of successful handovers compared to the total attempted handovers and is given as (3).

$$HSR (\%) = \frac{N_{HO}}{N_{HO} + N_{HOF}} \times 100 \quad (3)$$

where N_{HO} is the total number of successful handovers and N_{HOF} is the total number of handover failures. This metric gives a direct indication of how the framework will sustain smooth connectivity of UEs transiting between cells. An increase in HSR shows that there is efficient and reliable execution of handovers, which is very important in high-mobility and dense traffic conditions where handovers frequently occur. Monitoring HSR makes it possible to measure the efficiency of ACPT-LB on a quantitative level based on its capability to minimize interruptions and provide continuous network coverage.

3.5.2. Ping-pong Avoidance Rate (PPAR)

The Ping-pong Avoidance Rate measures the effectiveness of the framework in avoiding unnecessary back and forth handovers and is expressed as (4).

$$PPAR (\%) = \frac{N_{HO} - N_{PP}}{N_{HO}} \times 100 \quad (4)$$

where N_{PP} is the total number of ping-pong events. Ping-pong effect usually happens when a UE rapidly switches between two cells because of signal quality variation and this may result in the wastage of network resources, signaling overhead, and even user experience degradation. An increase in the PPAR means that the framework is becoming effective in stabilizing the decisions in handover, reducing unwarranted oscillations, and providing more stable connections to users.

3.5.3. Connection Stability (CS)

The Connection Stability or RLF-free rate measures the reliability of the UE connections over time and is defined as (5).

$$CS (\%) = \frac{N_{samples} - N_{RLF}}{N_{samples}} \times 100 \quad (5)$$

where N_{RLF} is the total number of radio link failures and $N_{samples}$ is the total number of recorded samples across all UEs. This measure is used to evaluate the overall stability of the network from a user's point of view. CS demonstrates the robustness of the ACPT-LB framework in the management of congestion, mobility, and changing channel conditions by accessing the duration of time that the UEs maintain continuous connectivity. A consistently high CS indicates a persistent characteristic signifying the system ability to maintain a certain acceptable threshold of reliable links under challenging high-density or high-mobility conditions which are vital in enabling the applications of low-latency and high-reliability.

4. Results and Discussion

The Adaptive Cell Pride Traffic Load Balancing (ACPT-LB) framework was tested in five vehicular user equipment (UE) density scenarios which included 1000 UEs, 2000 UEs, 3000 UEs, 4000 UEs, and 5000 UEs. These conditions depict different traffic concentrations in mmWave 5G vehicular communication conditions. Three of the performance metrics evaluated were Handover Success Rate, Ping-Pong Avoidance Rate, and Connection Stability. These metrics have been chosen to measure the capability of the framework to maintain stable connectivity, minimize any unnecessary handovers, and minimize radio link failure in dynamic traffic and mobility scenarios. The framework is evaluated under low-mobility, stop-and-go urban vehicular conditions (0-4 km/h), and the research on the conditions of higher mobility regimes is to be conducted in the future. Fig. 2. to 6 show the simulation outcomes of each traffic density scenario and Table 2 sums up the results.

A fixed random seed was used to ensure repeatability of all simulation results. This ensures that the results are consistent and reproducible, but statistical confidence intervals and variance analysis were not carried out across the multiple independent simulation runs and remains a direction for future work.

Table 2. Handover Success Rate, Ping-Pong Avoidance, Link Stability, and Simulation Time for Different UE Densities.

UEs samples	HSR (%)	PPAR (%)	CS (%)	Time (s)
1000	100	100	89.7	1217.4
2000	100	100	89.6	2571.0
3000	100	100	89.4	3457.2
4000	100	100	88.5	6814.1
5000	100	100	89.3	8970.6

The findings demonstrate that the HSR and PPAR were 100 percent in all the conditions, which suggests that the ACPT-LB framework can effectively manage low mobility users during congestion. This remarkably good performance is indicative of the constrained environment of simulation, involving low-mobility stop-and-go vehicular traffic and simplified models for blockage and interference. Although these findings show that ACPT-LB can be used to handle mobility in the conditions tested, these measurements might be decreased by real-world unpredictability including increased mobility, random blockages and interference. CS was sustained at more than 88 percent with the highest at 1000 UEs with 89.7 percent and minimal reduction at 4000 UEs with 88.5 percent demonstrating temporary congestion effects. These trends, as shown in Fig. 2 to 6, and summarized in Table 2, confirm that the TTT-based handover logic in the framework, load-aware selection of cells, and RLF detection mechanisms are consistent in ensuring that network performance is maintained as the UEs increase.



Fig. 2. Handover Success, Ping-Pong Avoidance, and Link Stability for 1000 UEs

The simulation time grew linearly with an increase in the density of the UEs. The simulation time varied from 1217.4 seconds for 1000 UEs to 8970.6 seconds for 5000 UEs. Such incremental growth is caused by the rise in the complexities of calculations involving SINR and handover processes. However, in a real network deployment, the ACPT-LB decision process is executed per UE at each TTT interval and not across the whole network, drastically reducing the per-node computational load. Signaling overhead is also kept minimal by the periodic exchange of information between inter-gNB synchronized to TTT settings. However, a proper assessment of the feasibility of real-time execution in large scale live deployments remains an area of interest for future research.

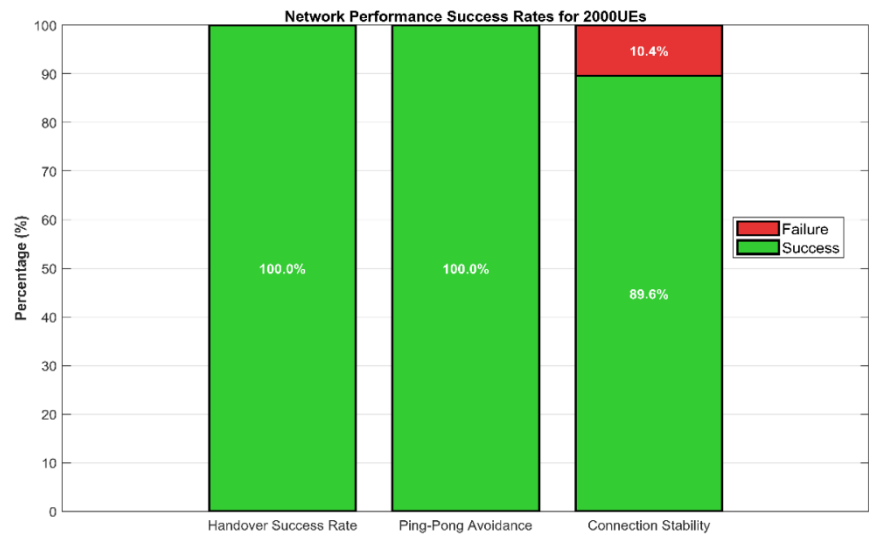


Fig. 3. Handover Success, Ping-Pong Avoidance, and Link Stability for 2000 UEs



Fig. 4. Handover Success, Ping-Pong Avoidance, and Link Stability for 3000 UEs

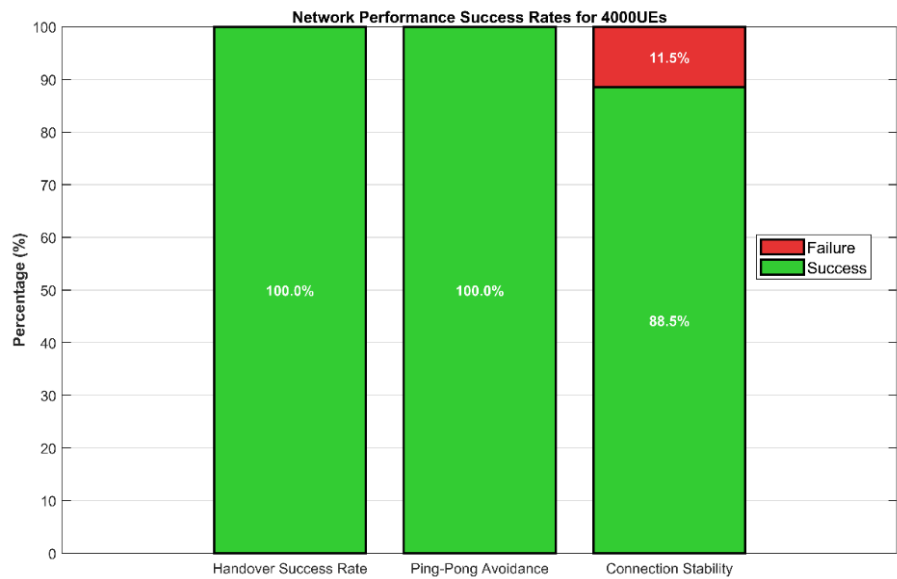


Fig. 5. Handover Success, Ping-Pong Avoidance, and Link Stability for 4000 UEs

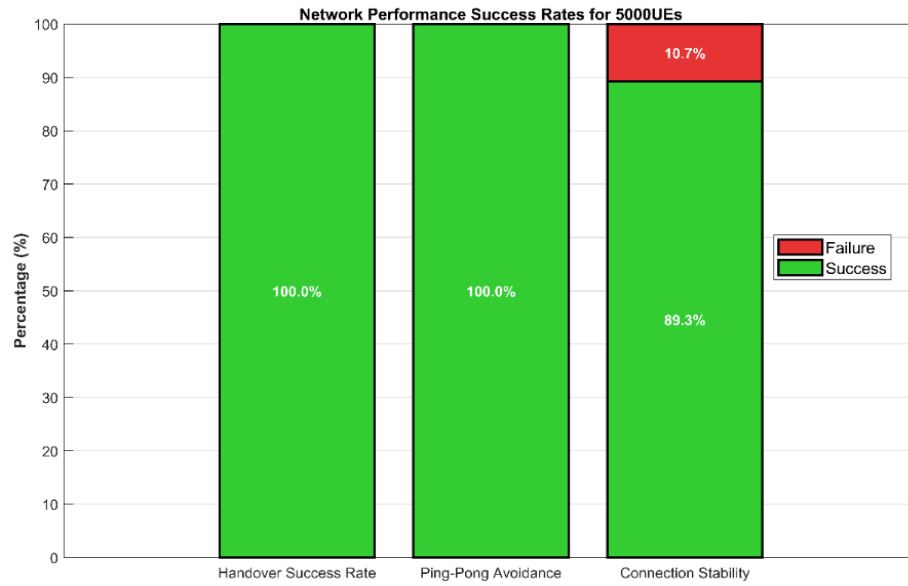


Fig. 6. Handover Success, Ping-Pong Avoidance, and Link Stability for 5000 UEs

Table 3. Average Per-UE Throughput, MEC Delay, and Packet Loss Rate for Different UE Densities

UEs	Avg Per-UE Throughput (Mbps)	Avg MEC Delay (ms)	Avg Packet Loss Rate
1000	14.91	12.81	0.0000095
2000	7.35	19.85	0.0000150
3000	4.91	27.06	0.0000548
4000	3.69	34.58	0.0000911
5000	2.97	41.57	0.0001790

Table 3 shows the average UE throughput, MEC delay, and packet loss rate for all UE density scenarios. The throughput values in Fig. 7. indicate shared per-UE radio resources, dropping from 14.91 Mbps at 1000 UEs to 2.97 Mbps at 5000 UEs as the number of users competing for the available bandwidth increases. As the density of the traffic increases from 1000 UEs to 5000 UEs, the MEC delay increases gradually from 12.81 ms to 41.57 ms, as illustrated in Fig. 8, due to increased communication overhead, queuing effects and edge-server processing load. The maximum packet loss rate observed across all scenarios was only 0.000179 when the number of UEs reached 5000, as depicted in Fig. 9, further demonstrating the robustness and scalability of the proposed ACPT-LB framework as the number of UEs increases.

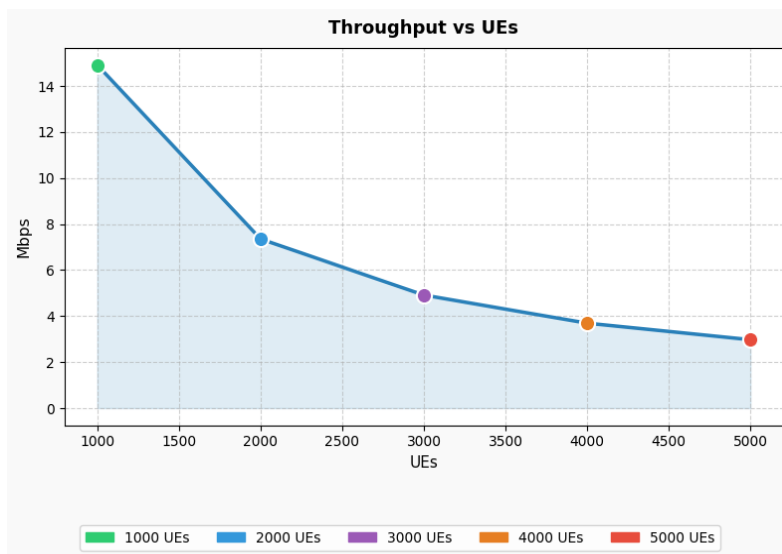


Fig. 7. Per-UE Throughput vs UE Density

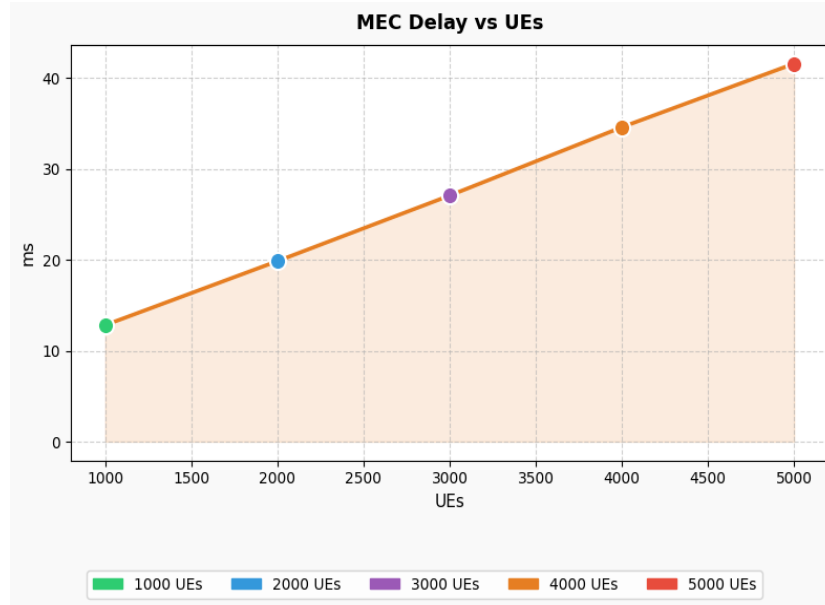


Fig. 8. MEC Delay vs UE Density

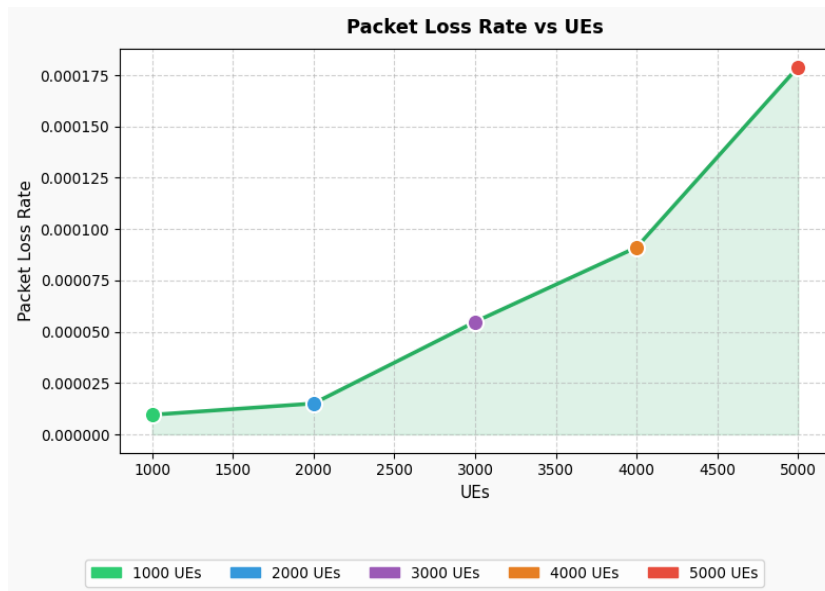


Fig. 9. Packet Loss Rate vs UE Density

In general, the findings validate the assumption that the ACPT-LB framework is an efficient method of distributing cell loads, facilitating smooth handovers, and ensuring strong connection stability, which makes it highly applicable to massive 5G mmWave applications. The three important parameters, HSR, PPAR, and CS, collectively give an overall measure of the performance of the network. In particular, HSR measures the effectiveness of single handover initiatives, PPAR indicates the effectiveness and consistency of handover decisions, and CS evaluates the overall persistence of user connections over time. Analyzing all these metrics at once give an idea of how effective this framework is in dealing with a high volume of traffic, resource utilization, and maintaining a constant connection in a fluctuating 5G mmWave network. In addition to the provision of quantitative measures of performance, these metrics also give an account of the ability of the framework to facilitate real-life applications where seamless mobility, high reliability, and efficiency are critical.

5. Conclusion

This paper proposed a framework of Adaptive Cell Pride Traffic Load Balancing (ACPT-LB) to tackle frequent handovers, short range, and congestion in dense 5G mmWave networks. ACPT-LB guarantees the efficient use of network resources and smooth connectivity by allowing cell groups to cooperatively manage the resources and dynamically redirecting traffic. The simulation outcomes of 1000, 2000, 3000, 4000, and 5000 UEs densities indicate that HSR, PPAR,

and CS are consistent, thus confirming the efficacy of the framework in a wide range of settings. The findings demonstrate the necessity of first building a solid and well-validated underlying framework. This should be the basis before machine learning or proactive optimizations are applied. Through this robust base, the effectiveness and reliability of future prediction models are guaranteed.

Practically, operators can deploy mobility detection sensors on gNB infrastructure to automatically detect low mobility congestion scenarios, like stop-and-go urban traffic. When such conditions are detected, the network can automatically switch to the ACPT-LB mode, which provides smooth and reliable connectivity for users experiencing traffic congestion without requiring manual intervention. This renders ACPT-LB a practical and effective solution for urban deployment where traffic congestion is a common problem.

6. Limitation and Future Work

Although ACPT-LB demonstrates a robust and feasible model for managing mobility and load balancing in 5G mmWave systems. It should be noted that the results of this study apply to urban vehicle traffic in low mobility conditions, from 0 km/h to 4 km/h, which represent stop-and-go traffic scenarios. Also, there was no experimental deployment or real hardware validation to evaluate the performance of ACPT-LB, only MATLAB-based simulations were used. The simulation assumes Poisson traffic arrivals, multiple service classes, LOS/NLOS propagation, and a statistical blockage and interference model based on neighboring cell RSRP contribution. However, it does not fully capture real-world effects such as dynamic multipath fading and complex interference patterns. Moreover, the simulation model includes several traffic classes such as URLLC, Video and IoT but a detailed and rigorous performance evaluation of the framework was not performed in this study for each traffic class and each mobility profile. Furthermore, the framework uses a high load-weighting factor, which was intentionally designed to prioritize load balancing at the expense of physical-layer signal quality, ensuring that overloaded cells are avoided even when their signal strength is marginally better than alternatives. While the results are encouraging in this context, simulation offers a controlled environment, albeit one that is limited, and factors like hardware-related impairments, protocol overhead, and channel conditions that are not predictable in the real world could affect real-world results. Thus, the performance of ACPT-LB under higher mobility conditions, such as highway driving or high vehicle speeds, is yet to be explored.

To overcome these limitations, future research will explore the performance of the framework under a wider range of mobility conditions, evaluate deployment in testbeds, and consider more realistic channel and traffic models. In addition, the analysis will be extended to accommodate different 5G service classes and dense urban microcell environments, and the scalability and applicability of the gNB coordination approach will be enhanced with the integration of machine learning to provide predictive handover decision making.

All the Declarations and Statements

Author Contribution Statement

Emmanuel O. Isatayo - Conceptualization, Methodology, and Writing: Drafting Original Manuscript, Proposed research ideas, Constructed the overall framework, and drafted the initial manuscript of the study.

Samuel I. Olotu - Supervision, Data Curation and Software Implementation: Handled overall supervision of the research, guided data acquisition, dataset preprocessing, and implementing the research model.

Mary T. Kinga - Co-Supervision, Validation, Performance Evaluation, Formal Analysis, Visualization, and Statistical Analysis: Assisted in supervision of the research, led the model training process, validated results using standard metrics, benchmarked performance against existing methods, performed in-depth analysis of experimental results, prepared performance charts, and ensured the statistical robustness of the evaluation.

All authors have read and agreed to the published version of the manuscript.

Conflict of Interest Statement

The authors declare no conflict of interest.

Funding Declaration

This research received no external funding.

Data Availability Statement

Not Applicable

Ethical Declarations

Not Applicable

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Declaration of Generative AI in Scholarly Writing

Generative AI tools were used to assist in improving the clarity, grammar, and readability of the manuscript. The authors take full responsibility for the content of the work.

Abbreviations

The following abbreviations are used in this manuscript:

5G - Fifth Generation
 6G - Sixth Generation
 ACPT-LB - Adaptive Cell Pride Traffic Load Balancing
 CF - Carrier Frequency
 CQI - Channel Quality Indicator
 CS - Connection Stability
 CSI-RS - Channel State Information Reference Signal
 FR2 - Frequency Range 2
 gNB - Next Generation Node B
 HO - Handover
 HOF - Handover Failure
 HSR - Handover Success Rate
 IoT - Internet of Things
 LoS - Line of Sight
 MATLAB - Matrix Laboratory
 MEC - Mobile Edge Computing
 ML - Machine Learning
 mmWave - Millimeter Wave
 NLoS - Non-Line of Sight
 PPAR - Ping-Pong Avoidance Rate
 RLF - Radio Link Failure
 RSRP - Reference Signal Received Power
 RSS - Received Signal Strength
 SINR - Signal to Interference plus Noise Ratio
 SSB - Synchronization Signal Block
 TTT - Time to Trigger
 UE - User Equipment
 UMi - Urban Micro
 URLLC - Ultra Reliable Low Latency Communication

Appendix A\B\C..., with appendix title

Not Applicable

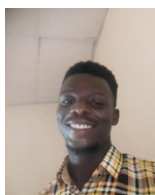
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