System-Level Simulation of Multi-User CBR Traffic in Standalone Full-Duplex 5G NR Networks

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***Abstract*—This paper presents a simulation-based analysis of a Single-Cell Standalone 5G network under varying user load conditions using the Simu5G framework. The network comprises a gNodeB at the center of a 1000m × 1000m area with 20 User Equipments (UEs) distributed dynamically. Initially, 10 UEs are active, while the remaining are activated at 50s and 100s to simulate dynamic user behavior. Both uplink and downlink Constant Bit Rate (CBR) traffic are used to evaluate network performance. UE mobility is modeled using the MassMobility model with speeds between 1–3 m/s. Propagation effects are simulated using the Cost 231 path loss model, Rayleigh fading, shadowing, and the TwoRayGround reflection model to reflect realistic radio environments. Key performance indicators (KPIs) such as Signal-to-Interference-plus-Noise Ratio (SINR), throughput, packet loss, and MAC layer delay are recorded. The study provides insights into how user mobility, propagation effects, and dynamic activation influence the performance and reliability of 5G networks.**

***Index Terms*—5G New Radio (NR), 3GPPP, Simu5G, OMNeT++, Multiple User Equipments**

I. Introduction

As the global rollout of 5G technology accelerates, it is becoming increasingly important to understand how these networks behave in dynamic, real-world conditions—especially under varying user densities and traffic demands. With the growing integration of 5G in smart cities, autonomous systems, and the Internet of Things (IoT), ensuring consistent Quality of Service (QoS) across diverse scenarios is now a central challenge for telecom engineers and researchers [1]–[3].

Unlike previous generations, 5G introduces new expectations in terms of ultra-low latency, high throughput, and massive device connectivity, making network performance analysis a crucial area of study [4], [5]. This project focuses on the simulation of a standalone 5G New Radio (NR) network comprising up to 20 User Equipments (UEs) within a single cell. The main goal is to analyze how the addition of more users and the presence of full-duplex traffic flows (both uplink and downlink) affect key performance indicators such as throughput, latency, packet loss, and Signal-to-Interference-plus-Noise Ratio (SINR) [6], [7].

By simulating both constant and dynamic traffic scenarios, the project reflects a more realistic model of actual network environments, where user activity is rarely uniform or predictable. Leveraging the Simu5G framework built on OMNeT++ with INET 4.2.5 and 4.5.4, this study designs a system-level simulation that represents detailed network behavior [6], [7]. The selected simulation tools are particularly suited to evaluating the performance of 5G systems under a wide range of configurations and traffic models. Constant Bit Rate (CBR) traffic flows are used to mimic real-time services such as voice, video, and IoT sensor communications, all of which are sensitive to latency and require stable bandwidth [3], [8].

Particular attention is given to two core 5G service categories: Ultra-Reliable Low-Latency Communication (URLLC) and Enhanced Mobile Broadband (eMBB). These services are representative of modern application demands, from autonomous vehicle coordination to high-definition video streaming [9], [10]. As user load increases, the network's ability to handle these demands while maintaining acceptable QoS levels becomes a defining factor of its effectiveness.

The motivation behind this study stems from the increasing need to simulate dense deployment scenarios and identify potential performance bottlenecks before real-world implementation. Through in-depth analysis and KPI tracking, the simulation helps uncover the network's adaptive behaviors and limitations, offering insights into how resource allocation, scheduling, and radio propagation affect overall reliability. Ultimately, this project contributes to the development of more resilient and efficient 5G infrastructures by providing practical guidelines for managing full-duplex, multi-user traffic in standalone architectures [10].

II. Objectives

The primary objective of this project is to develop and simulate a standalone 5G New Radio (NR) network using the Simu5G framework within the OMNeT++ environment. The simulation aims to model uplink and downlink Constant Bit Rate (CBR) traffic flows between 1 to 20 User Equipments (UEs) in a single-cell setup. This study focuses on analyzing how varying user loads affect key Quality of Service (QoS) metrics, including latency, throughput, Signal-to-Interference-plus-Noise Ratio (SINR), and packet loss. The specific objectives of the project are as follows: 1)To identify and explain the fundamental features of 5G NR technology, including its architecture and key performance enhancements. 2)To review recent advancements in 5G development, particularly in high-density deployment scenarios, and identify current research challenges. 3)To design and conduct a system-level simulation using Simu5G that replicates realistic 5G network conditions with multiple UEs acting as CBR traffic generators. 4)To evaluate 5G network performance indicators under different user load conditions and provide insights into the impact of user density on network efficiency.

III. Background and Literature Review

With 5G becoming a core part of modern communication systems, it's important to understand how these networks actually perform in the real world—especially as more users and devices connect at the same time. Before diving into the simulation work, it's helpful to look at what 5G New Radio (NR) offers, what challenges come with deploying it in dense environments, and what other researchers have already explored. This section builds a foundation for the project by reviewing the key concepts, identifying gaps in the existing research, and explaining why this study is necessary.

A. 5G New Radio Overview

The evolution of wireless communication has ushered in the era of 5G, enabling unprecedented capabilities for emerging technologies, particularly in smart cities and Internet of Things (IoT) applications. With the deployment of 5G New Radio (NR), enhanced features such as Ultra-Reliable Low-Latency Communication (URLLC), massive Machine-Type Communication (mMTC), and Enhanced Mobile Broadband (eMBB) have become foundational for next-generation connectivity [6]. 5G NR, standardized by 3GPP, introduces advanced features including massive MIMO, beamforming, network slicing, and millimeter-wave (mmWave) communication to support these use cases [6], [11]. Smart city infrastructure—comprising surveillance systems, intelligent transportation, energy grids, and healthcare services—demands highly dynamic and responsive networks that efficiently manage heterogeneous traffic patterns and Quality of Service (QoS) requirements [12]. Similarly, IoT deployments generate vast uplink data transmissions from distributed sensor nodes and UEs. These fluctuating traffic loads significantly strain the Radio Access Network (RAN) [11], making system-level simulations essential to analyze performance under varying conditions.

B. Challenges in High-Density 5G Deployments

High user density in 5G NR deployments introduces several performance challenges. Increasing the number of active UEs in a standalone single-cell network causes congestion, uplink-downlink contention, and increased interference [13]. These effects are particularly pronounced when supporting Constant Bit Rate (CBR) applications that demand strict QoS guarantees. Managing both uplink and downlink CBR traffic in such environments requires efficient radio resource management, adaptive scheduling algorithms, and potential use of features like Supplementary Uplink (SUL) to maintain performance, especially at the cell edge [14], [15]. Moreover, real-world applications such as smart city services and industrial IoT involve varying UE activity patterns, which exacerbate the dynamic nature of traffic loads. Ensuring consistent latency and throughput across such deployments necessitates flexible and scalable 5G architectures [16].

C. Related Work on 5G Network Simulation

Various researchers have explored simulation-based approaches to evaluate 5G NR performance. Simu5G, an OMNeT++-based simulator with INET integration, provides 3GPP-compliant features for evaluating end-to-end QoS metrics in a realistic system-level context. Nardini et al. [6], [16], [17] introduced Simu5G to support the analysis of multi-UE traffic scenarios. Patriciello et al. [13] and Boutiba et al. [11] extended this work by implementing slicing and dynamic traffic models, offering frameworks like NRflex and 5G-RCOLAB to simulate diverse urban and rural scenarios. Dangi et al. presented a broader survey highlighting how simulation tools help track the development and optimization of 5G NR deployments. In addition, recent studies have leveraged deep reinforcement learning to enable QoS-guaranteed joint resource allocation for NR with SUL [18], and researchers have also investigated the use of Software-Defined Networking (SDN) and Network Function Virtualization (NFV) to create flexible, scalable testbeds for 5G research [19].

D. Gaps in Existing Research

Despite these advancements, current literature often overlooks standalone 5G NR deployments with high user loads (e.g., 20 UEs) that include both uplink and downlink CBR traffic models. Simulations frequently simplify traffic patterns or focus solely on downlink behavior, leading to an incomplete understanding of total system performance [20]. Furthermore, while slicing and adaptive scheduling have been explored individually, fewer studies have jointly optimized multiple layers of the stack (e.g., physical, MAC, network) under heavy UE loads [21], [22]. This project addresses these gaps by modeling a single-cell, standalone 5G NR network using Simu5G, simulating up to 20 UEs generating both uplink and downlink CBR traffic. The study systematically evaluates latency, throughput, SINR, and packet loss to provide comprehensive insights into network performance under dense traffic conditions.

IV. System Description and Methodology

This section presents the simulation framework and methodology designed to assess the performance of a standalone 5G New Radio (NR) network under varying user load conditions. The model is implemented using the Simu5G simulation environment built upon OMNeT++, enabling detailed system-level analysis across multiple Key Performance Indicators (KPIs).

A. Network Architecture Overview

The simulated environment consists of a single gNodeB (gNB) deployed in the center of a 1000 m $\times$ 1000 m area, surrounded by multiple User Equipment (UE).hese UEs engage in full-duplex communication, generating Constant Bit Rate (CBR) traffic for both uplink and downlink flows. Key simulation parameters such as area size, number of UEs, and mobility model used are summarized in Table I.

TABLE I: Network Layout and Node Parameters

Parameter	**Value**
Area Size	1000 m × 1000 m
Number of UEs	20
gNB Position	(500 m, 500 m)
UE Speed	Uniform(1 m/s, 3 m/s)
UE Mobility Models	MassMobilityLinearMobility
UE Activation Times	0 s, 50 s, 100 s
Traffic Pattern	CBR, full-duplex UL/DL
Simulation Type	Dynamic user activation

Figure 1 shows a schematic of the simulated system.

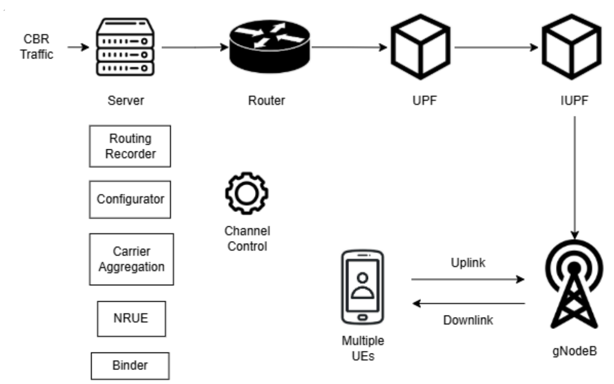

Fig. 1: System Architecture for Standalone 5G Network

B. Simulation Setup

The simulation environment was configured using the Simu5G framework, with a Single-Cell Standalone 5G network model. The cell is represented by a single gNB (gNodeB) fixed at the center of a 1000m x 1000m square area. User equipment (UEs) were distributed within this area, and their positions changed dynamically during simulation. Figure 2 shows a simulation setup in Omnet++.

Constant Bit Rate (CBR) traffic was used to simulate the downlink (server to UE) and uplink (UE to server) communication. For each UE, CBR applications were set up with specific packet sizes and sampling times, ensuring a consistent data flow throughout the simulation.

User Equipment (UEs) were configured with and without varying mobility patterns. A total of 20 UEs were considered, where the first 10 UEs are active from the start, and the remaining 10 UEs are dynamically activated at specific time intervals (50s and 100s). Their mobility is modeled using a MassMobility model, where the UEs move at speeds between 1m/s to 3m/s.

C. Traffic Modeling

CBR traffic is used to emulate real-time applications like voice and video, which demand consistent transmission rates.

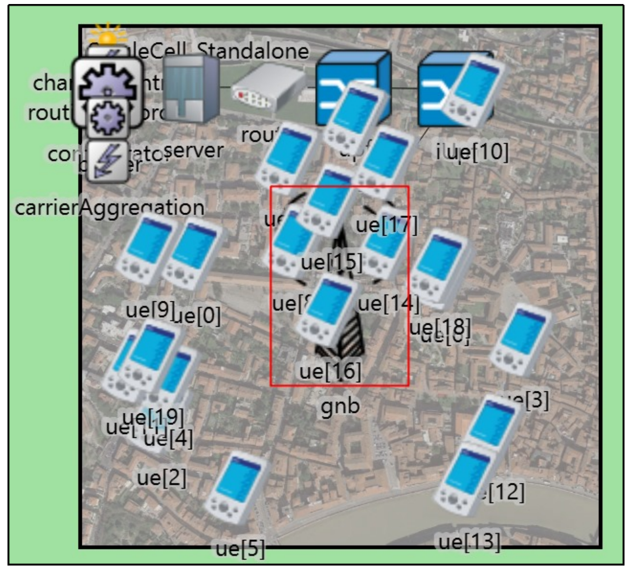

Fig. 2: Simulation Setup in Omnet++

Each UE is configured with two applications:

- **Downlink:** Server sends to UE
- **Uplink:** UE sends to server

As shown in Table II, the CBR traffic characteristics are identical for both uplink and downlink directions.

TABLE II: CBR Traffic Characteristics

Direction	**Packet Size (Bytes)**	**Sampling Time (s)**
Downlink	Uniform(600, 1500)	Uniform(0.01, 0.05)
Uplink	Uniform(600, 1500)	Uniform(0.01, 0.05)

Some UEs are also configured to stop their applications mid-simulation to simulate user churn, e.g., UE-2 deactivates at 75 s.

D. Propagation and Channel Modeling

The radio propagation environment is modeled using the Cost231 path loss model for urban scenarios and the Two-Ray Ground Reflection model for mmWave analysis. Fading and shadowing effects are added to simulate real-world variability.The propagation parameters used in the simulation are summarized in Table III.

TABLE III: Propagation Settings

Parameter	**Value**
Carrier Frequencies	2.4 GHz, 28 GHz
Path Loss Models	Cost231, Two-Ray
Fading	Rayleigh
Shadowing Std Dev	4 dB
Antenna Gain (UE/gNB)	5 dB
Transmit Power (UE)	23 dBm
Transmit Power (gNB)	30 dBm

E. Simulation Scenarios

Two primary types of traffic load scenarios are analyzed:

- **Constant Load Scenario:** All 20 UEs active from the start.
- **Load Scenario:** 10 UEs active at 0 s, 5 more at 50 s, remaining 5 at 100 s.

These variations allow the observation of traffic bursts, resource contention, and latency in real time.

F. Network Performance Metrics

To comprehensively evaluate the performance of the simulated standalone 5G NR network, several Key Performance Indicators (KPIs) were recorded during the simulation. These metrics provide insight into signal quality, transmission efficiency, delay characteristics, and overall network behavior under varying user loads. The KPIs are described as follows:

1) Signal-to-Interference-plus-Noise Ratio (SINR): SINR is a critical metric that quantifies the quality of the wireless channel by measuring the ratio of useful signal power (P_s) to the sum of interference power (P_i) and noise power (P_n). It is defined in Equation (1):

$$\text{SINR} = \frac{P_s}{P_i + P_n} \tag{1}$$

Higher SINR values indicate better link quality and support for higher-order modulation schemes, directly influencing throughput and reliability [23].

2) Throughput: Throughput represents the rate at which data is successfully received at the destination. It includes both downlink (gNB to UE) and uplink (UE to gNB) transmissions. The throughput is computed using Equation (2):

$$T = \frac{\sum \text{Packets}_{\text{received}} \times \text{PacketSize}}{\text{SimulationTime}} \tag{2}$$

This metric captures the effective data rate achieved over the air interface and reflects the system's efficiency in handling traffic [24].

3) Packet Loss: Packet loss quantifies the fraction of transmitted packets that fail to reach their intended destination, often due to congestion, interference, or retransmission timeouts. It is calculated using Equation (3):

$$P_L = \frac{\text{Packets}_{\text{sent}} - \text{Packets}_{\text{received}}}{\text{Packets}_{\text{sent}}} \tag{3}$$

A lower packet loss ratio indicates better reliability and system stability, particularly under high-load conditions [25].

4) MAC Layer Delay: MAC delay refers to the time a packet spends at the Medium Access Control (MAC) layer before successful transmission. This delay is computed using Equation (4):

$$D_{\text{MAC}} = T_{\text{departure}} - T_{\text{arrival}} \tag{4}$$

This metric helps evaluate the scheduling efficiency and queuing delays at the MAC layer [26].

5) RLC Layer Performance: The Radio Link Control (RLC) layer ensures reliable packet delivery and contributes to quality of service (QoS). Performance is evaluated through RLC throughput, delay, and packet loss:

- **RLC Throughput:** Same computation as in Equation (2), but specific to the RLC layer.
- **RLC Packet Loss:** Fraction of packets dropped or unacknowledged at the RLC layer, computed similarly to Equation (3).
- **RLC Delay:** Time between packet arrival at RLC buffer and successful delivery.

Monitoring RLC metrics provides deeper insights into user experience, especially in conditions with varying user load [27].

6) PHY Layer Interference: While not always associated with a direct equation, PHY layer interference represents the cumulative unwanted signal power received by a UE or gNB, caused by neighboring transmissions within the same frequency band [26]. High interference levels can degrade SINR (see Equation (1)), increase retransmissions, and ultimately reduce overall throughput as mentioned above in Equation (2).

7) Data Collection Method: All KPIs were extracted using scalar files for aggregated statistics and vector files for time-series analysis. These outputs were automatically generated by Simu5G's metrics recording framework during simulation runs, providing fine-grained insights into system dynamics over time.

G. Simulation Execution and Runtime Events

The simulation was executed under two contrasting load conditions to analyze system performance under realistic and idealized scenarios.

In the dynamic user load scenario, the simulation begins with only 10 active User Equipments (UEs). At runtime, the Scenario Manager is employed to progressively activate additional UEs—5 at 50,s and another 5 at 100,s. These UEs are dynamically assigned initial mobility positions and immediately begin generating Constant Bit Rate (CBR) traffic. Meanwhile, a subset of UEs already in operation are deactivated at scheduled intervals (e.g., UE-2 at 75,s, UE-5 at 125,s, and UE-8 at 150,s), effectively simulating user churn. This approach emulates real-world 5G conditions where users join, move within, and leave the network continuously.

In the non-varying user load scenario, all 20 UEs are active from the start of the simulation and remain engaged throughout the runtime. Each UE consistently transmits uplink and downlink CBR traffic using randomized packet sizes and sampling intervals. This setup is useful for baseline evaluation, offering a steady traffic profile without sudden load spikes or drops.

These two scenarios allow for a comprehensive performance comparison, highlighting the effects of dynamic user behavior on metrics such as throughput, SINR, delay, and packet loss.

V. Results and Discussion

This section presents a comparative analysis of system performance under varying and non-varying user load conditions in a Simu5G network. Key performance indicators include throughput, delay, packet loss, and SINR.

A. Scenario 1: Varying User Load

This scenario simulates a dynamic environment where user equipment (UE) is introduced in intervals, leading to changes in traffic load and network performance.

1. Downlink MAC Throughput: The throughput exhibits fluctuations as user load varies, reflecting the dynamic allocation of resources. Peaks in throughput correspond to lower user contention, while dips indicate increased competition for bandwidth.The downlink MAC throughputs of both path loss models are shown in Figs. 3 and 4. below.

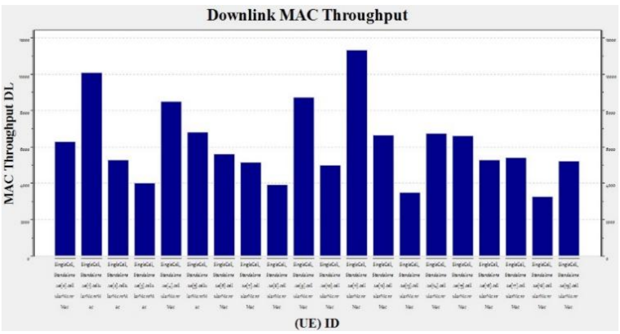

Fig. 3: Downlink MAC Throughput with Varying User Loads Using Cost231

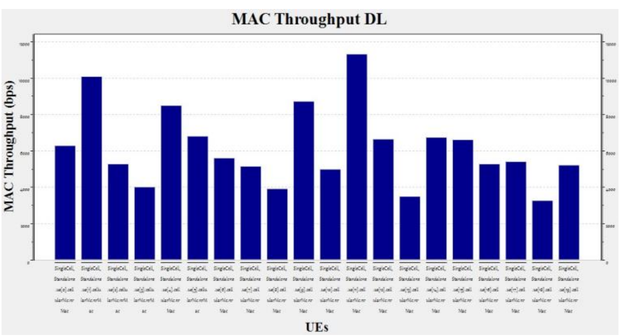

Fig. 4: Downlink MAC Throughput with Varying User Loads Using Two Ray Ground Reflection

2. Uplink MAC Throughput: The throughput remains relatively stable but slightly decreases during peak load periods. Efficient MAC scheduling ensures acceptable performance even under load spikes. The uplink MAC throughputs of both path loss models are shown in Figure 5 and Figure 6.

3. Downlink RLC Delay: Delay increases with higher user load due to queuing and retransmissions. This highlights the trade-off between system capacity and latency under fluctuating demand (see Fig. 7).

4. Uplink RLC Delay: Similar to the downlink, uplink RLC delay escalates as more users contend for access. However, uplink delays show slightly higher variance, suggesting greater sensitivity to traffic dynamics as illustrated in Fig. 8.

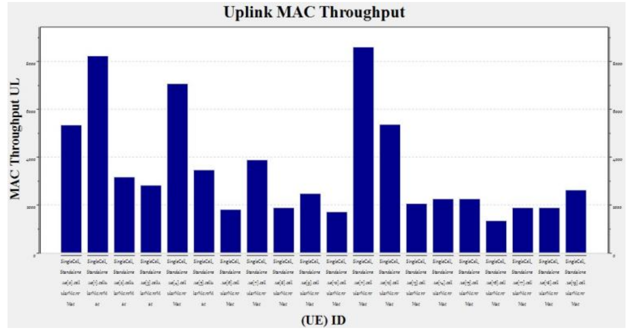

Fig. 5: Uplink MAC Throughput with Varying User Loads Using Cost231

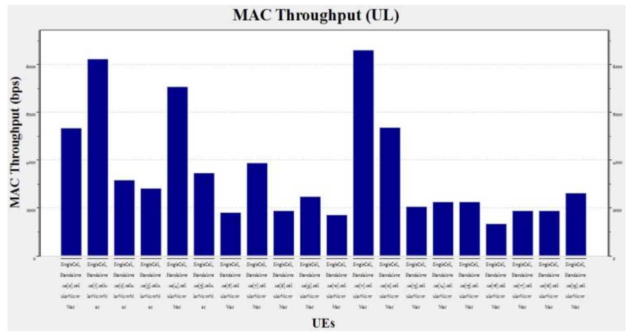

Fig. 6: Uplink MAC Throughput with Varying User Loads Using Two Ray Ground Reflection

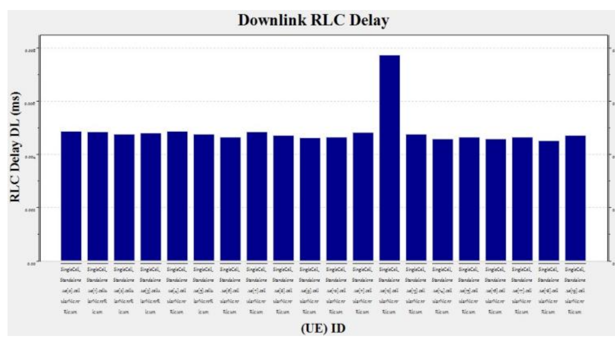

Fig. 7: Downlink RLC Delay with Varying User Loads Using Cost231

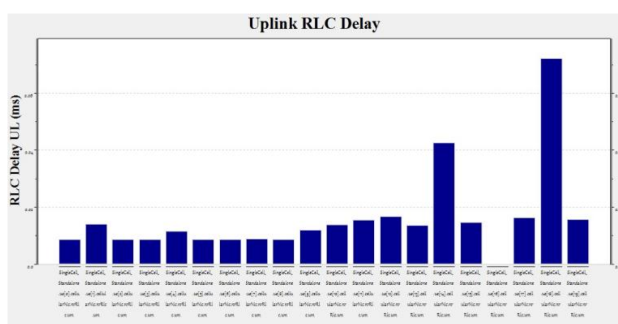

Fig. 8: Uplink RLC Delay with Varying User Loads Using Cost231

5. RLC Packet Loss: Packet loss increases with user count, indicating buffer overflows and retransmission thresholds being exceeded. This emphasizes the need for adaptive congestion control in high-load situations (see Fig. 9).

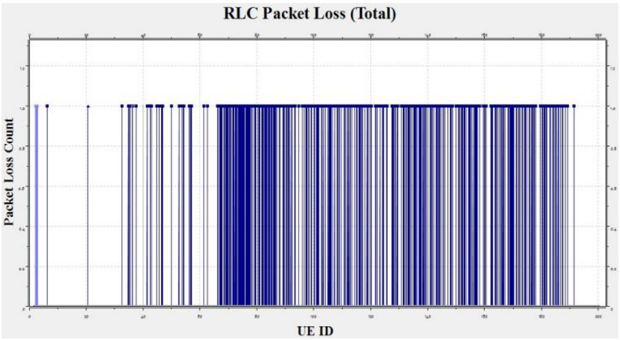

Fig. 9: Uplink RLC Packet Loss with Varying User Loads Using Cost231

6. RLC Throughput (Downlink and Uplink): Both DL and UL RLC throughputs follow expected trends—improving under light loads and degrading during peak user activity. This metric effectively captures the end-to-end performance under dynamic load conditions (see Fig. 10 and Fig. 11).

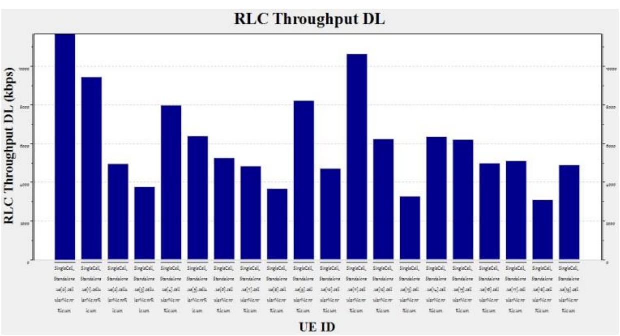

Fig. 10: Downlink RLC Throughput with Varying User Loads Using Cost231

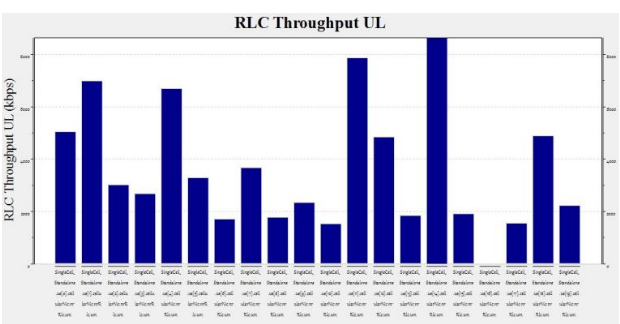

Fig. 11: Uplink RLC Throughput with Varying User Loads Using Cost231

7. MAC Delay: For the Two Ray Ground Reflection Model, the downlink MAC delay was zero, and the uplink MAC delay is shown in Fig. 12

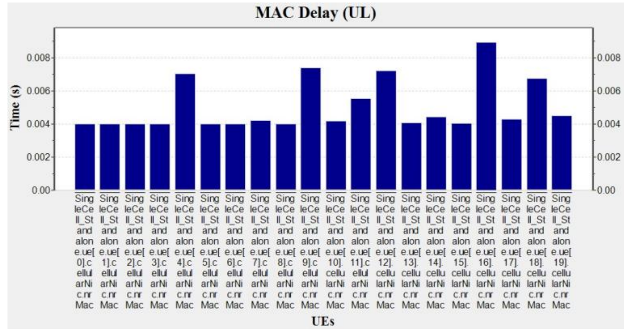

Fig. 12: Uplink MAC Delay with Varying User Loads Using Two Ray Ground Reflection

8. MAC Packet Loss: For the Two Ray Ground Reflection Model, the downlink MAC packet loss was zero, and the uplink MAC packet loss is shown in Fig. 13:

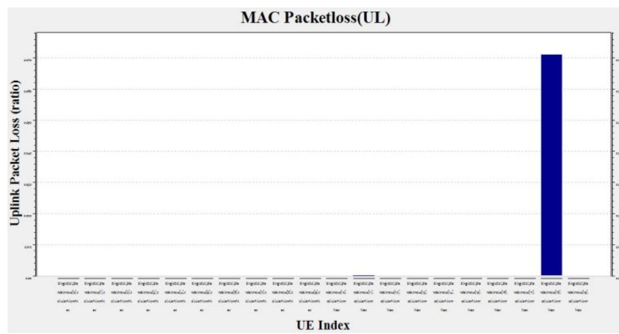

Fig. 13: Uplink MAC Packet Loss with Varying User Loads Using Two Ray Ground Reflection

9. Mean SINR per Module with Overall System SINR: The average SINR varies across modules due to changing interference and user positions. The overall system SINR remains within a tolerable range, but dips slightly during high user density, affecting modulation and coding schemes (see Fig.14 and Fig.15.

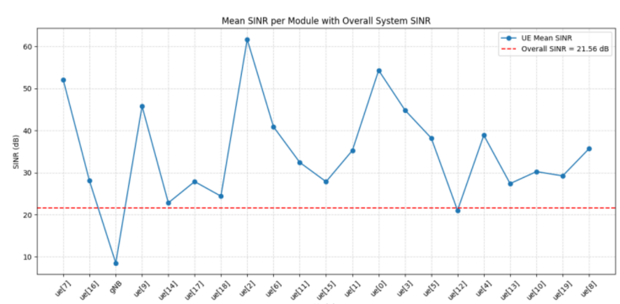

Fig. 14: Mean SINR per Module with Overall System SINR with Varying User Loads Using Cost231

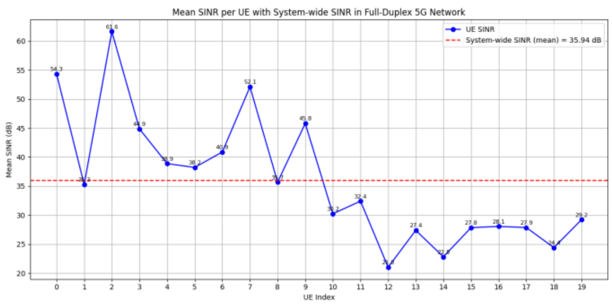

Fig. 15: Mean SINR per Module with Overall System SINR with Varying User Loads Using Two Ray Ground Reflection

B. Scenario without Varying User Loads

In the static load scenario, network behavior was evaluated under consistent traffic conditions, allowing for more controlled analysis:

1. MAC Throughput (Downlink and Uplink): Throughput remains stable, with the downlink achieving higher values due to more favorable scheduling and channel conditions. Uplink throughput is consistent, indicating balanced resource distribution, as shown in Figs. 16 and 17.

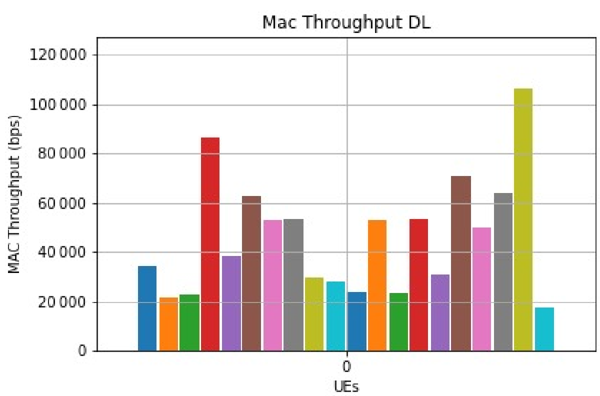

Fig. 16: MAC Throughput Downlink

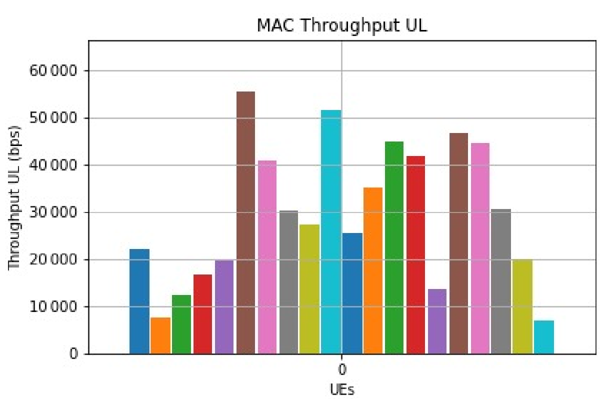

Fig. 17: MAC Throughput Uplink

2. MAC Delay (Downlink and Uplink): Delay metrics remain low and predictable, showcasing the advantage of uniform traffic distribution. This also confirms the efficiency of the scheduler in steady-state conditions, as illustrated in Figs. 18 and 19.

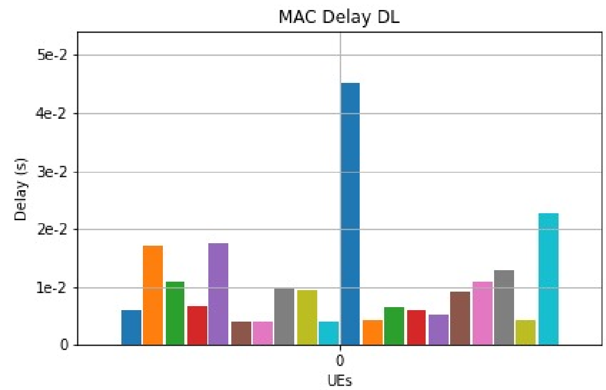

Fig. 18: MAC Delay Downlink Using Cost231

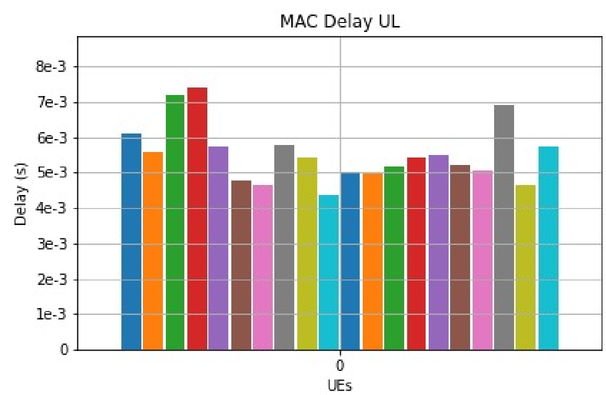

Fig. 19: MAC Delay Uplink Using Cost231

3. Received SINR (Downlink and Uplink): SINR values remain stable with minor fluctuations. Downlink SINR is generally higher due to better antenna configurations and power allocation. These values correlate directly with consistent throughput performance, as illustrated in Fig. 20.

4. MAC Packet Loss (Uplink): Uplink packet loss is minimal in the non-varying scenario, underscoring the system's ability to handle steady traffic without significant buffer overflows or retransmission penalties, as shown in Fig. 21.

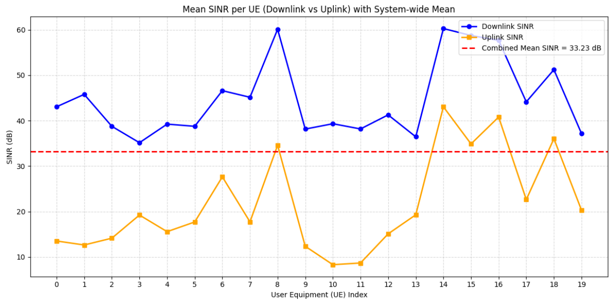

Fig. 20: Per-UE uplink and downlink SINR with overall system-wide average

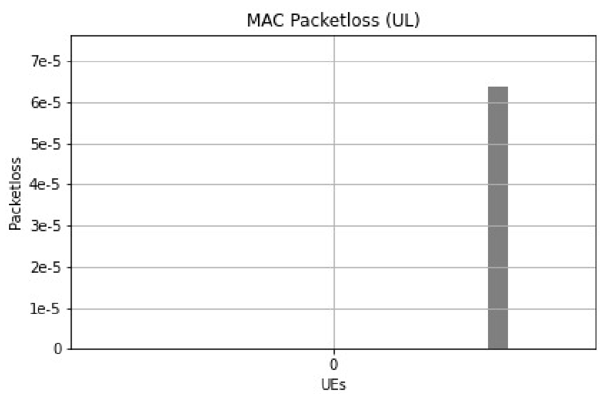

Fig. 21: MAC Packetloss Uplink

VI. Discussion

This section discusses the observed performance of the simulated 5G standalone network under different traffic conditions. By comparing results from varying and non-varying user loads, we aim to highlight how user density, traffic behavior, and propagation environments impact key performance indicators such as throughput, latency, packet loss, and SINR. The analysis helps in understanding the network's adaptability and efficiency under realistic deployment scenarios.

A. Comparative Analysis of Cost 231 and Two-Ray Ground Reflection Model

A comparative assessment of the Cost 231 and Two-Ray Ground Reflection propagation models under different user load scenarios indicates notable differences in the performance of 5G networks. One of the most prominent differences is seen in the SINR results. The Cost 231 model, created for urban settings, yielded an average SINR of about 21.56 dB. However, the SINR figures varied significantly among different User Equipments (UEs), ranging from under 20 dB to over 60 dB. This fluctuation illustrates the effects of multipath fading, shadowing, and interference commonly encountered in densely populated urban environments. Conversely, the Two-Ray Ground Reflection model displayed a much more consistent and noticeably higher average SINR of around 35.94 dB. Specifically, UEs activated later in the simulation UE-11 to UE-19 consistently experienced SINR values within the 25–30 dB range, emphasizing the model's capability in representing environments with better line-of-sight conditions and fewer obstructions, such as open or semi-urban locales.

An evaluation of throughput at the MAC layer further highlights the advantages of the Two-Ray model. In the context of the Cost 231 scenario, both downlink and uplink throughput displayed greater variability, particularly during times of escalating user demand. The increase in contention and interference contributed to significant declines in throughput as more UEs became active. In contrast, the Two-Ray Ground Reflection model demonstrated more stable throughput performance, especially in the downlink, where higher SINR levels facilitated more effective spectrum use and diminished retransmission rates.

Delay metrics also underscored the differing performances of the two models. Under the Cost 231 model, delays for both uplink and downlink at the RLC layer grew as user numbers increased. This was mainly due to queuing and congestion occurring at elevated traffic volumes. The uplink RLC delay exhibited greater variability, indicating increased sensitivity to changes in user activity and interference. Meanwhile, the Two-Ray Ground Reflection model showed a notable enhancement in delay performance, particularly at the MAC layer. The downlink MAC delay was virtually zero, benefiting from the stronger and more reliable channel conditions provided by this model.

Packet loss trends supported these conclusions. With the Cost 231 model, RLC packet loss surged significantly during periods of high load due to buffer overflows and surpassing retransmission limits. Uplink MAC layer packet loss was also considerable. In contrast, the Two-Ray Ground Reflection model experienced minimal packet loss in the downlink and considerably reduced loss in the uplink, again due to enhanced link quality and more consistent SINR.

To summarize, the Cost 231 model presents an accurate representation of challenging urban conditions, with its performance reflecting the complexity of the environment and user density. Nonetheless, the Two-Ray Ground Reflection model offers superior SINR, reduced delay, and negligible packet loss under equivalent load situations, making it more appropriate for mmWave research or simulations in open areas. Consequently, the decision between the two models should be based on the deployment context and the specific performance metrics of interest in 5G network evaluations.

B. Performance Comparison Between Variable and Non-Variable User Load Scenarios

A comparative examination of scenarios with variable and non-variable load reveals essential insights into how user behavior affects the performance of 5G networks. In the variable load scenario, users were activated at specific intervals (10 UEs initially, 5 at 50 seconds, and another 5 at 100 seconds), reflecting real-world traffic spikes. This dynamic setup generated fluctuating traffic patterns, resulting in variations in throughput, increased delays in the RLC and MAC layers, and heightened packet loss rates, particularly during user activation phases. As the network load increased, resource contention intensified, leading to temporary reductions in SINR, longer queuing delays, and occasional surges in retransmissions. These fluctuations emphasize the system's sensitivity to live user activity and highlight the challenges of maintaining consistent Quality of Service (QoS) in variable environments.

On the other hand, the non-variable load scenario had all 20 UEs active from the beginning of the simulation, creating a steady and uniform traffic pattern throughout. This consistency enabled more predictable characteristics in throughput and delays, with minimal variance across key performance indicators (KPIs). Delays in MAC and RLC remained relatively low and stable, and packet loss was minimal. Additionally, SINR values stayed stable due to the lack of sudden changes in interference or traffic volume. The non-variable scenario effectively acts as a benchmark, demonstrating the network's optimal performance under controlled and balanced conditions.

In summary, while the non-variable scenario illustrates ideal operational conditions, the variable load scenario offers a more realistic representation of user behavior in actual 5G settings. The latter highlights the necessity for adaptive scheduling and congestion control mechanisms to manage traffic surges effectively and ensure resilience. Consequently, the differences observed between the two scenarios emphasize the importance of dynamic resource allocation strategies in future 5G implementations to address load variability without sacrificing service quality.

VII. Conclusion

This study investigated the performance of a 5G standalone network under varying and non-varying user load conditions using the Simu5G simulation framework. Key QoS parameters—throughput, delay, packet loss, and SINR—were analyzed in both uplink and downlink directions. Under varying user loads, the network exhibited dynamic performance fluctuations. Throughput peaked during low contention but declined with increased user density. RLC delays and packet losses increased significantly due to queuing and retransmissions, revealing the system's sensitivity to congestion. Mean SINR remained within acceptable bounds but decreased slightly at high loads, indicating rising interference. These results highlight the challenges in maintaining consistent QoS during unpredictable traffic conditions. In contrast, the non-varying user load scenario showed stable and optimal performance across all metrics. Throughput and delay remained consistent, SINR levels were steady, and packet loss was minimal, reflecting the network's ability to deliver high performance under controlled traffic conditions. The comparative analysis emphasizes the importance of adaptive resource allocation and congestion management mechanisms to sustain 5G performance in real-world, dynamic environments. These findings can guide the design and tuning of scheduling and QoS strategies in future 5G deployments.

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