Advanced RF Optimization Techniques for Enhancing Coverage, Throughput, and Quality of Service in LTE and 5G Networks

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Abstract: *The adoption of 5G New Radio (NR) in 2022 as an upgrade of the fourth-generation Long-Term Evolution (LTE) is a paradigm shift in telecommunication architecture, shifting towards a single fabric of the Internet of Things (IoT). This development presents considerable technical challenges, especially since 5G employs a tiered spectrum strategy using millimetre-wave (mmWave) frequencies, which are subject to high path loss and atmospheric absorption. This paper discusses advanced Radio Frequency (RF) optimization strategies that are needed to close the gap between the theoretical 5G capabilities and practical physical limitations. Some of the important strategies that are discussed are Massive MIMO and beamforming in order to achieve high spectral efficiency, Carrier Aggregation (CA) in order to increase peak data rates, and Self-Organizing Networks (SON) in order to achieve automated and real-time network refinement. Moreover, the paper discusses such key performance indicators as RSRP and RSRQ as Quality of Service (QoS) indicators. The document concludes that the key to the commercial and technical success of modern networks is rigorous RF optimization, which, however, is becoming more and more dependent on Artificial Intelligence (AI), despite the challenges associated with mmWave propagation, hardware power consumption, and 4G/5G interference in Non-Standalone (NSA) deployments.*

Keywords*: 5G New Radio (NR), Beamforming, Carrier Aggregation, Massive MIMO, Millimeter-wave (mmWave), Quality of Service (QoS), RF Optimization, Self-Organizing Networks (SON)*

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1. 0 Introduction

The transition from fourth-generation Long-Term Evolution (LTE) networks to fifth-generation New Radio (5G NR) represents a major paradigm shift in telecommunications, enabling not only enhanced mobile broadband services but also large-scale integration of Internet of Things (IoT) applications (David & Okhueleigbe, 2017). The rapid growth in mobile data traffic, cloud computing, smart devices, and latency-sensitive applications has intensified the demand for highly efficient and intelligent wireless communication systems

Kuboye (2019) reported that 5G NR was designed around three major service categories, namely Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low-Latency Communications (URLLC), and Massive Machine-Type Communications (mMTC), each targeting different performance requirements and application domains..

The expansion into new spectral frontiers is at the core of this evolution. LTE mainly worked on the sub-3GHz spectrum, which has a wide coverage but a small bandwidth (Bakare & Bassey, 2021). By contrast, 5G NR employs a tiered spectrum strategy, with low-band coverage to support wide-area coverage, mid-band (3.5GHz to 6GHz) coverage to provide a balance between capacity and range, and millimeter-wave (mmWave) coverage to support extreme data throughput in localized regions (Nigerian Communications Commission, 2020). This diversification necessitates advanced RF optimization techniques because higher-frequency mmWave signals suffer from severe propagation losses, atmospheric attenuation, signal blockage, and reduced penetration through physical obstacles Several studies have investigated optimization strategies for LTE and 5G networks, particularly in areas such as spectrum efficiency, interference mitigation, beamforming, and network densification. However, many of these studies focused on isolated optimization techniques without considering the combined effects of heterogeneous deployments, dynamic traffic conditions, and real-time Quality of Service (QoS) adaptation in hybrid LTE/5G environments

Another major advancement introduced by 5G is the migration from conventional hardware-centric network architecture to software-defined and cloud-native communication infrastructure." According to Eluwole (2018), Radio Access Network (RAN) was very inflexible in 4G networks, but 5G provides network slicing and service-based architecture. This enables operators to dynamically optimize RF resources in accordance with the needs of the user or application. Agboje et al. (2017) demonstrated that 5G networks can dynamically prioritize latency-sensitive applications such as remote surgery while simultaneously supporting high-throughput multimedia services. Abonyi (2018) assumed that the most noticeable shift in terms of Radio Frequency (RF) is the shift between passive and wide-beam antennas to active and Massive MIMO (Multiple-Input Multiple-Output) systems. Unlike conventional LTE sectorized transmission systems, 5G beamforming technology enables directional transmission of RF energy toward specific users, thereby improving spectral efficiency, signal quality, and network capacity As demonstrated by Jam (2017), this spatial multiplexing has a substantial spectral efficiency (the volume of data transmitted at a particular frequency) and thus improves the overall capacity of the cell and the Quality of Service (QoS) of the end-user.

Despite these technological advancements, early 5G deployments predominantly adopted Non-Standalone (NSA) architecture, which depends on existing LTE core infrastructure and introduces additional challenges related to interference management, mobility coordination, and dual connectivity. (Petrescu, 2019). This hybrid architecture relies on the 4G core network as a reference point of 5G signaling to form a multifaceted interference environment in which LTE and 5G have to coexist harmoniously. Yaacoub and Alouini (2020) wrote that RF optimization in this generation does not only concern tuning a new signal, but rather how to deal with the complex handovers and dual-connectivity between two generations of technology to make sure that the gains in throughput and latency that have been promised to the consumer are actually achieved.

Although substantial progress has been made in LTE and 5G optimization research, limited attention has been given to integrated RF optimization frameworks capable of simultaneously improving coverage, throughput, interference management, and QoS in heterogeneous LTE/5G environments. Furthermore, the increasing complexity of AI-driven adaptive networks and dynamic spectrum allocation requires more robust optimization strategies capable of supporting real-time network intelligence. This study aims to evaluate advanced RF optimization techniques for enhancing coverage, throughput, and Quality of Service (QoS) in LTE and 5G networks, with emphasis on Massive MIMO, beamforming, carrier aggregation, and self-organizing network architectures The significance of this study lies in its potential contribution to the development of intelligent and adaptive wireless communication systems capable of supporting future smart city infrastructure, industrial automation, autonomous transportation, and large-scale IoT applications. The findings may also assist network engineers, researchers, and telecommunication operators in designing more efficient RF optimization frameworks for next-generation wireless systemsWith the ever-increasing data requirements, the capability to optimize the Coverage, Throughput, and QoS by refining it with digital and physical tuning is the key to the commercial and technical success of a network. Table 1 presents a comparative overview of the major performance improvements associated with the transition from LTE to 5G networks.

Table 1: Key Performance Leaps from the 4G Era into the 5G Standard

Parameter	**LTE (4G)**	**5G NR (2022 Standards)**
Peak Data Rate	**1 Gbps**	**10–20 Gbps**
Latency	**10–50 ms**	**1–10 ms**
Connection Density	**105 devices/km^2**	**106 devices/km^2**
Spectrum Range	**450 MHz – 3.8 GHz**	**450 MHz – 52.6 GHz (incl. mmWave)**

(Source: Attar *et al.*, 2022)

2.0 Conceptual Framework: The RF Optimization Loop

The RF Optimization Loop conceptual framework is a continuous four-stage cyclical process designed to maintain optimal network performance under dynamic environmental and traffic conditions. Donà & Ciuffo (2022) noted that this optimization loop transforms a newly conFig.d ‘golden cluster’ into a stable high-performance production network through continuous monitoring and adjustment. The process begins with extensive data collection, followed by detailed performance analysis, strategic parameter tuning, and post-optimization verification (Hock et al., 2018). The iterative nature of the framework ensures that RF optimization remains a continuous and adaptive process capable of responding to evolving subscriber behavior, mobility patterns, and traffic demands. “The first stage involves data collection using two major sources: drive testing and Operations Support System (OSS) statistics. Drive testing is a field measurement technique used to evaluate real-world radio network performance through specialized hardware and software installed in moving vehicles, and handover performance across specific geographic routes (Carlsson & Sonesson, 2017). At the same time, OSS statistics give a network-side perspective, which is a summation of bulk data at the base stations (eNodeBs in LTE or gNodeBs in 5G). Riener et al. (2022) reported that OSS counters monitor critical Key Performance Indicators (KPIs) such as Call Drop Rate (CDR), Handover Success Rate (HOSR), and Radio Resource Control (RRC) setup success rate , providing a comprehensive picture of the health of the network throughout the cluster.

Following data acquisition, the analysis phase focuses on identifying the root causes of network degradation, including pilot pollution, overshooting cells, hardware malfunction, and interference issues (Hamrouni, 2020). This phase is particularly important in 5G mid-band deployments where inter-cell interference and LTE–5G transition management significantly affect network performance Wayessa (2020) explained that post-processing tools are used to generate signal heat maps and correlation analyses that help determine whether throughput degradation originates from poor signal coverage or excessive interference. This diagnostic stage is essential because improper or non-targeted tuning may unintentionally degrade the performance of neighboring cells. The third stage involves parameter tuning, which includes both physical and logical optimization of network resources. Ojugo and Eboka (2020) explained that physical tuning involves modifying antenna tilt angles, azimuth orientation, and transmission parameters to reshape coverage areas and reduce inter-sector interference interference across overlapping sectors. Logical tuning involves adjusting software-defined network parameters such as handover thresholds, transmit power levels, scheduling priorities, and neighbor cell relations. In 5G systems, this stage also includes beamforming weight optimization, where digital beam patterns are dynamically adjusted to concentrate signal energy toward high-demand traffic zones (Olatunde-Thorpe *et al*., 2022). “In 5G systems, this stage also includes beamforming weight optimization, where digital beam patterns are dynamically adjusted to concentrate signal energy toward high-demand traffic zones.”

According to Ituma *et al*., (2020), the optimization cycle concludes with post-optimization verification, during which network performance is reassessed against the baseline measurements. This stage may involve additional drive tests or continuous 24-hour OSS monitoring to determine whether the implemented changes achieved the desired improvements in coverage, throughput, and Quality of Service (QoS). When the KPIs reach the target thresholds, the cycle is stabilized; when new bottlenecks are observed (which is a frequent consequence of the dynamism of radio waves), the cycle instantly returns to the collection stage. Continuous optimization enables LTE and 5G networks to maintain reliable high-speed performance even in complex urban propagation environments characterized by dense infrastructure and dynamic user mobility.

The conceptual framework presented in this study provides a systematic approach for understanding the interaction between data acquisition, network analysis, parameter optimization, and performance validation in modern wireless communication systems. The framework also highlights the importance of adaptive and intelligent optimization strategies in maintaining network stability and user satisfaction in heterogeneous LTE/5G deployments. Fig. 1 illustrates the closed-loop RF optimization framework, showing the continuous interaction between data collection, analysis, parameter tuning, and verification processes in LTE and 5G network optimization.

3. 0 Advanced Optimization Techniques

This section discusses the advanced RF optimization techniques employed to improve network coverage, throughput, spectral efficiency, and Quality of Service (QoS) in LTE and 5G systems.

3.1 A. Massive MIMO and Beamforming

Massive Multiple-Input Multiple-Output (Massive MIMO) is one of the core technologies responsible for the significant capacity improvement observed in 5G networks. (Chataut & Akl, 2020). Unlike conventional antenna systems that transmit broad sector-wide signals, Massive MIMO enables simultaneous transmission and reception of multiple independent data streams over the same frequency resources (Ishteyaq & Muzaffar, 2022). By exploiting spatial multiplexing, Massive MIMO significantly improves spectral efficiency, increases cell capacity, and enhances network reliability. Elijah et al. (2022) reported that Massive MIMO plays a crucial role in supporting high user densities in urban environments without requiring additional spectrum allocation. Complementing Massive MIMO technology is beamforming, a signal processing technique that enables directional transmission of radio signals toward specific users. According to Sowande, et al. (2022), instead of radiating energy in all directions, "Beamforming utilizes advanced signal processing algorithms to dynamically adjust signal phase and amplitude across antenna arrays, thereby forming narrow directional beams toward user equipment (UE). According to Popoola (2022), this focused transmission can significantly improves the Signal-to-Interference-plus-Noise Ratio (SINR), extends effective coverage for high-frequency bands, and enhances Quality of Service (QoS), particularly at cell edges.

Afolalu (2021) explained that by actively driving these beams in real-time, the network reduces the amount of noise experienced by other users. As a result, overall interference levels are reduced, leading to more efficient spectrum utilization and improved network performance,

Fig. 2 compares Signal-to-Interference-plus-Noise Ratio (SINR) performance in wireless networks with and without active beamforming implementation.

3.2 Carrier Aggregation (CA) & Spectrum Refarming

Carrier Aggregation (CA) is a key LTE-Advanced and 5G optimization technique used to increase peak data rates and improve spectrum efficiency (Randhawa & Jain, 2017). During the transition period in 2022, CA played a key role in the process of aggregating the capacity of the old 4G bands with the new 5G New Radio (NR) spectrum. This multi-band transmission approach enables user devices to simultaneously receive data across multiple frequency bands, thereby significantly improving throughput and network reliability (Kamath *et al*., 2020). This resource pooling strategy enables operators to support high-bandwidth applications while maintaining stable network performance during periods of heavy traffic demand.

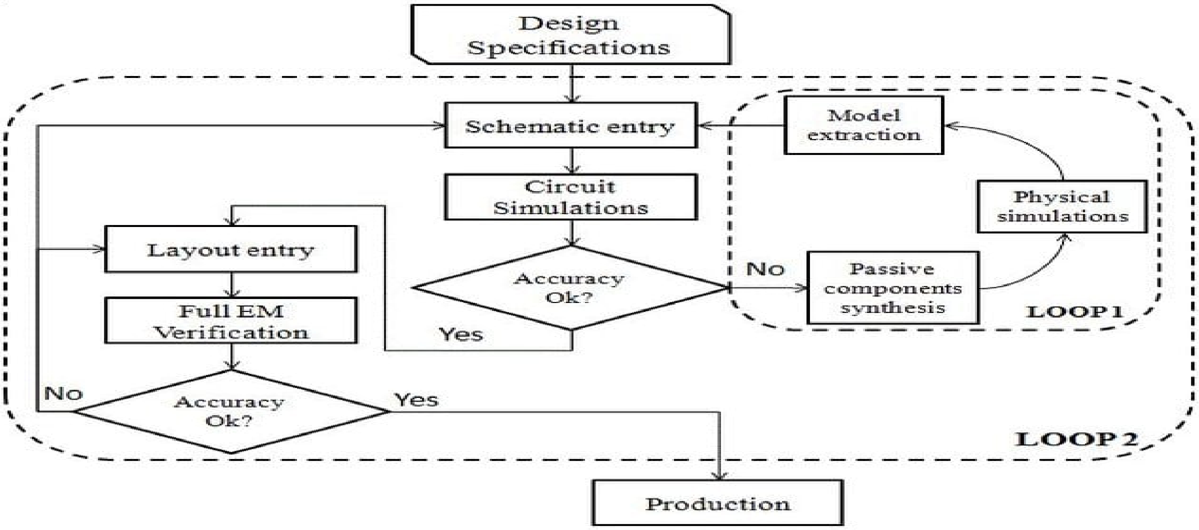

Fig. 1: A Flowchart illustrating the "Close-Loop RF Optimization Process." (Ahyoune et al., 2013)

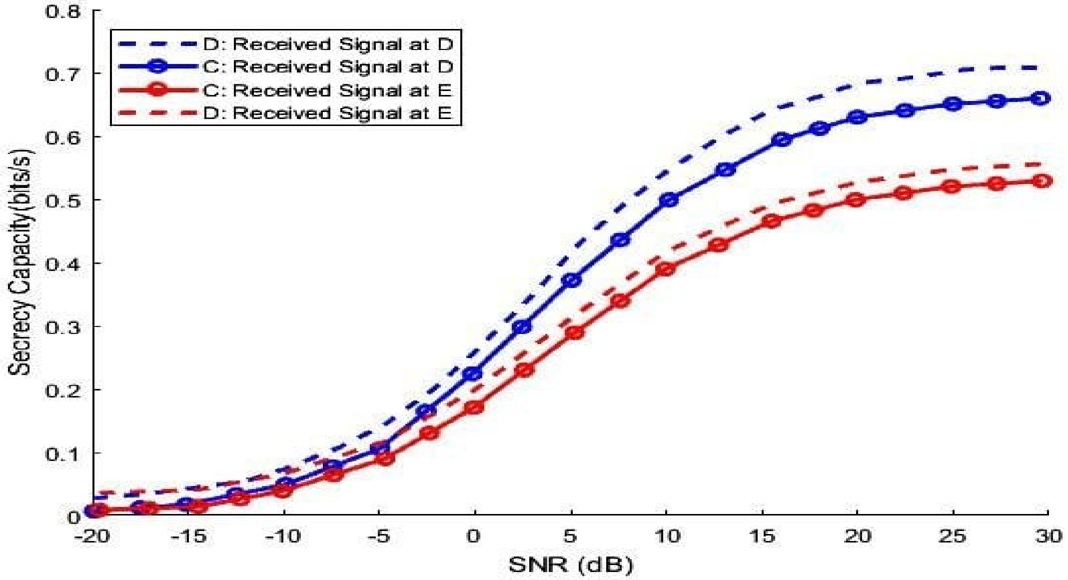

Fig. 2: A Comparison Chart (Bar Graph) showing Signal-to-Interference-plus-Noise Ratio (SINR) levels with vs. without Active Beamforming

Also, Spectrum refarming refers to the strategic reallocation of legacy frequency bands originally assigned to 2G or 3G services for more spectrally efficient LTE and 5G technologies. (Lehr, 2020). These lower-frequency bands provide superior propagation characteristics, including wider coverage range and improved indoor penetration compared to higher-frequency C-band and mmWave spectrum.(Luttinen, 2022). Successful spectrum refarming requires careful RF optimization to ensure coexistence between legacy systems and newly deployed 5G layers without service degradation. Together, Carrier Aggregation and spectrum refarming maximize spectrum utilization efficiency and improve overall network capacity. Table 2 illustrates common carrier aggregation combinations used in 5G NSA deployments.

Table 2: Typical Carrier Aggregation Configurations in 5G Non-Standalone (NSA) Networks

Combination Type	Frequency Bands	Theoretical Throughput Gain
Intra-band Contiguous	3.5 GHz + 3.5 GHz	~100% (Doubles bandwidth)
Inter-band (Mid+Low)	1800 MHz + 3.5 GHz	~60% (Balanced Coverage/Speed)
Inter-band (Low+Low)	700 MHz + 900 MHz	~30% (Enhanced Deep Indoor)
3-Layer CA	800 MHz + 1800 MHz + 3.5 GHz	~150% (Premium User Experience)

(Source: Oughton et al., 2021)

The results indicate that combining low-band and mid-band spectrum provides a balance between coverage and throughput, while multi-layer aggregation significantly enhances user experience and network capacity.

Self-Organizing Networks (SON) represent intelligent network management systems that utilize automation and Artificial Intelligence (AI) to optimize radio access network performance with minimal human intervention (Imoize, et al., 2021). Recent advancements in AI and Machine Learning (ML) have transformed SON from a rule-based framework into a predictive and adaptive optimization system. “According to Omolaye *et al.* (2017), SON functionality can be categorized into self-configuration, self-optimization, and self-healing operations. By processing large volumes of real-time network data, SON algorithms can detect network anomalies, predict congestion trends, and automatically implement corrective actions across multiple cell sites (Papidas & Polyzos, 2022).

One major application of SON is Mobility Load Balancing (MLB), which dynamically redistributes traffic from congested cells to underutilized neighboring cells (Jouini, 2017). (Machine learning-based SON controllers can predict traffic fluctuations and proactively adjust handover parameters to prevent Quality of Service (QoS) degradation. At the same time, Coverage and Capacity Optimization (CCO) makes use of automated tilt and power control to reduce interference and eliminate coverage gaps (Marzouk, Barraca & Radwan, 2020). This adaptive optimization approach enables the network to dynamically respond to changing traffic distribution and user mobility patterns in real time.”

Table 3: Comparison Between Manual and SON-Driven RF Optimization

Feature	Manual Optimization	SON-Driven (AI/ML) Optimization
Response Time	Days to Weeks (Post-Analysis)	Seconds to Minutes (Real-Time)
Data Scope	Localized (Cluster-based)	Network-Wide (Holistic)
Scalability	Limited by Human Resources	Highly Scalable via Cloud Compute
Error Margin	Prone to Human Oversight	High Precision via ML Algorithms
Operational Cost	High (Field Visits/Drive Tests)	Low (Automated Remote Tuning)

Source: Farooq, Riaz & Abid (2022).”

Fig. 3 illustrates the spatial distribution of wireless traffic density within a heterogeneous network environment.

Despite the significant improvements offered by Massive MIMO, Carrier Aggregation, and SON technologies, challenges such as computational complexity, energy consumption, inter-cell interference, and real-time optimization scalability remain critical concerns in dense LTE and 5G deployments.

4.0 Coverage and Quality of Service (QoS) Analysis

Coverage and Quality of Service (QoS) are critical indicators used to evaluate the effectiveness of RF optimization strategies in LTE and 5G networks. Musa & Adeniran (2022) reported that the evaluation of network performance in modern wireless systems primarily depends on Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) metrics.

According to Idris (2017), Reference Signal Received Power (RSRP) is a primary coverage metric used to measure the average received power of reference signals transmitted by a serving cell. High RSRP values indicate strong signal coverage and improve the ability of user equipment (UE) to maintain reliable connectivity in both outdoor and indoor environments. However, Zinno (2018) emphasized that signal strength alone does not guarantee high network performance, since signal quality and interference levels also significantly influence user experience.”

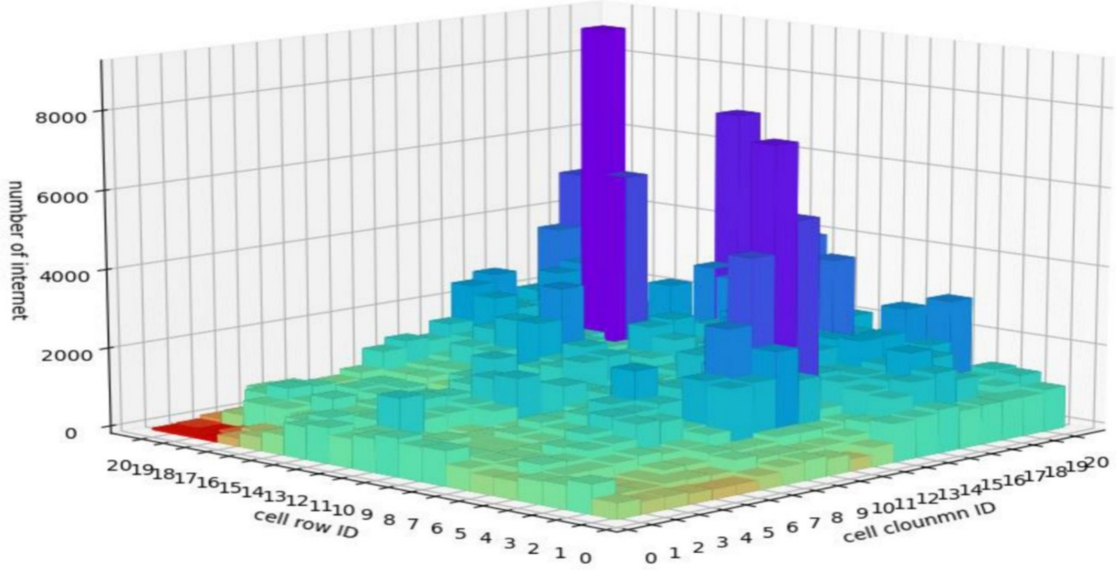

Fig. 3: Distribution of wireless traffic in Spatial distribution. (Chen et al., 2022)

Olatinwo & Joubert (2019) explained that Reference Signal Received Quality (RSRQ) is used to evaluate signal quality by accounting for interference and thermal noise within the radio environment. Although RSRP may be large, low RSRQ means that there is .high pilot signal pollution or interference by adjacent cells.“Such interference conditions directly reduce throughput, increase latency, and raise call drop probability. According to Eluwole (2018), the maintenance of an optimal signal-to-noise ratio becomes increasingly challenging in dense 5G deployments where overlapping Massive MIMO beams and closely spaced small cells introduce additional interference. . Cumulative Distribution Function (CDF) analysis is commonly used to evaluate the percentage of network users experiencing different levels of throughput and signal quality.

Table 4: RF Signal Strength Classification and QoS Interpretation

Signal Category	RSRP (dBm)	RSRQ (dB)	Expected Quality of Service (QoS)
Excellent	≥ -80	≥ -10	Ultra-fast throughput; seamless 4K/8K streaming.
Good	-80 to -90	-10 to -15	High-speed data; stable VOIP and video calls.
Mid-Cell	-90 to -100	-15 to -20	Moderate speeds; potential for buffering in 5G.
Cell Edge	≤ -105	≤ -20	Frequent disconnections; significant throughput drop.

(Source :Elrashidi *et al.*, 2022).

Fig. 4 illustrates the disparity in user throughput distribution between urban and rural environments. Dense urban regions generally experience higher peak throughput due to improved infrastructure density, although interference and congestion may negatively affect cell-edge users. In contrast, rural environments exhibit lower average throughput due to wider cell spacing and limited spectrum resources.

Despite the significant performance improvements achieved through advanced RF optimization techniques, several technical and operational challenges continue to affect large-scale 5G deployment.

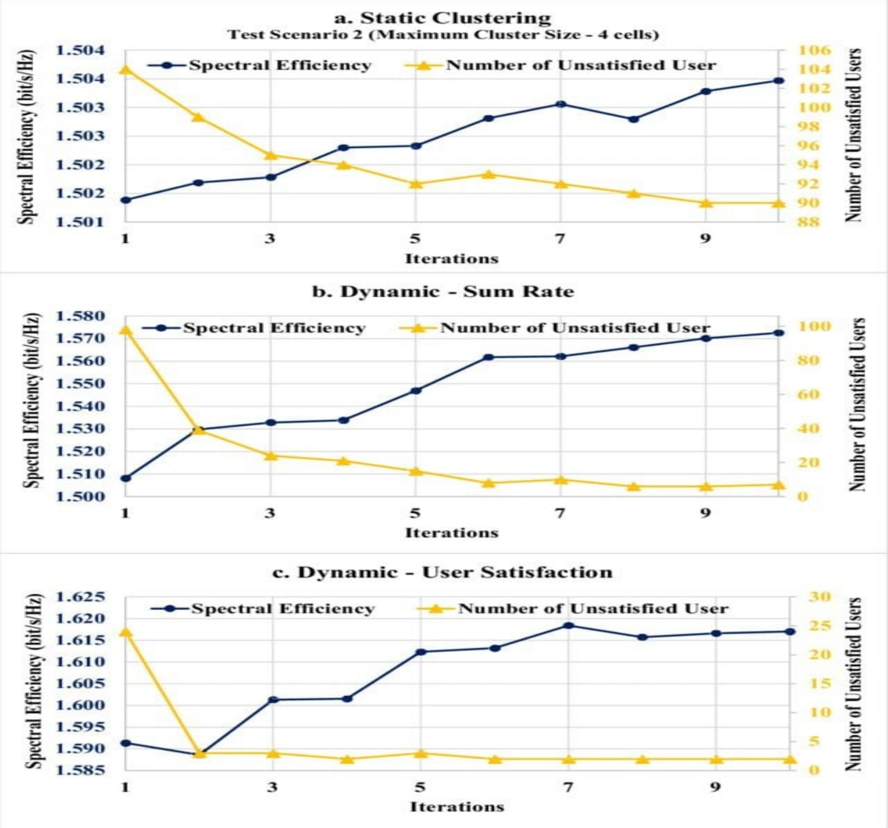

Fig. 4:A Cumulative Distribution Function (CDF) graph showing User Perceived Throughput in dense urban vs. rural 5G environments. (Ding et al., 2020)

5.0 Challenges in 2022 Deployments

The deployment of 5G networks in 2022 encountered several technical challenges associated with high-frequency propagation, infrastructure complexity, and heterogeneous network coexistence (Jam, 2017). Severe propagation loss at millimeter-wave (mmWave) frequencies remains one of the major limitations of 5G deployment. Although mmWave frequencies offer extremely high bandwidth, their short wavelengths are highly vulnerable to attenuation caused by buildings, vegetation, atmospheric moisture, and other physical obstructions (Agubor, et al., 2019). Consequently, dense deployment of small cells is required to maintain continuous connectivity and acceptable Quality of Service (QoS). Hinga & Atayero (2021) concurred that unless RF is optimized and reflective surfaces controlled, without effective RF optimization and intelligent beam management, multigigabit communication is largely restricted to line-of-sight transmission scenarios.

Apart from propagation-related challenges, energy consumption has become a major operational concern in modern 5G infrastructure. Ajibade & Alabi (2017) stated that the huge computational needs of 5G base stations, especially with Massive MIMO of 64T64R (64 Transmit, 64 Receive) antenna arrays. Large-scale Massive MIMO antenna systems, particularly 64T64R configurations, require extensive computational processing and consume significantly more electrical power than conventional LTE base stations. This additional power consumption not only added to the operational expenditures (OPEX) of service providers but also requires sophisticated cooling and stronger power grids at cell sites (Njoku, 2019). Moreover, Ugwuanyi, Paul and Irvine (2021) developed the notion that 4G/5G interference in Non-Standalone (NSA) deployments results in a spectral environment that is noisy. As 5G usually relies on existing 4G frequencies to signal, the balancing act in parameter tuning is incredibly delicate in order to manage the handovers and preserve the integrity of the LTE control plane and maximize the 5G data throughput.

The following radar chart illustrates the competing priorities engineers must balance during the optimization phase. Improving one vertex often requires a sacrifice in another.

(i) **Coverage:** Limited by mmWave and high-frequency path loss.
(ii) **Throughput:** Maximum potential, but constrained by interference.
(iii) **Energy Efficiency:** The "Cost" of 5G performance.
(iv) **Latency:** Highly optimized in 5G, but dependent on stable signal quality.

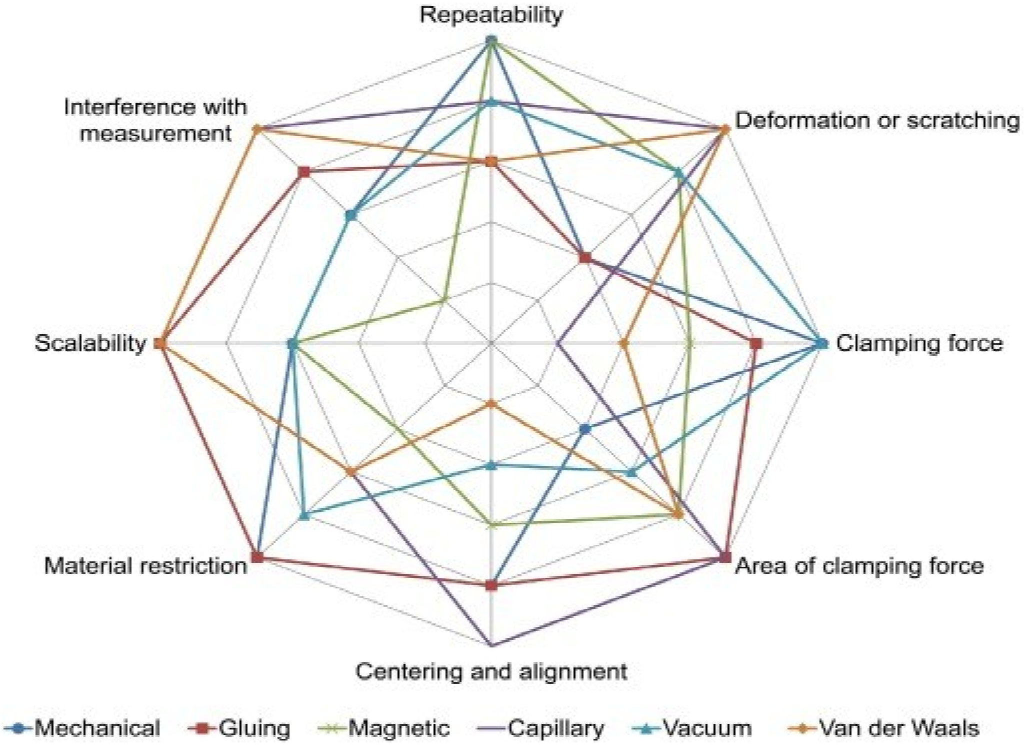

Fig. 5: A Radar Chart (Spider Chart) evaluating optimization trade-offs: ***Coverage vs. Throughput vs. Latency vs. Energy Efficiency. (Source :*****Ramkumar et al., 2022)**

6.0 Conclusion

This study has demonstrated that advanced RF optimization remains a fundamental requirement for achieving reliable and high-performance LTE and 5G network operations. Although 5G New Radio (NR) introduces remarkable improvements in throughput, spectral efficiency, latency reduction, and network capacity, the practical realization of these capabilities is strongly influenced by radio propagation limitations, interference conditions, environmental obstructions, and the increasing complexity of heterogeneous wireless infrastructures. Consequently, effective RF optimization serves as the critical bridge between the theoretical promises of 5G technology and its real-world operational performance.

The study highlighted the significant roles of advanced optimization techniques such as Massive MIMO, beamforming, Carrier Aggregation (CA), spectrum refarming, and Self-Organizing Networks (SON) in improving network coverage, throughput, and Quality of Service (QoS). Massive MIMO and beamforming were shown to enhance spectral efficiency and signal quality through spatial multiplexing and directional transmission, while Carrier Aggregation and spectrum refarming improved spectrum utilization and user throughput across heterogeneous frequency bands. In addition, SON-based automation demonstrated the growing importance of Artificial Intelligence (AI) and Machine Learning (ML) in enabling adaptive, real-time, and large-scale optimization of modern radio access networks.

The analysis of key performance indicators such as Reference Signal Received Power (RSRP) and Reference Signal Received Quality (RSRQ) further emphasized the importance of maintaining both strong signal coverage and acceptable signal quality in dense LTE and 5G deployment environments. The study also established that deployment challenges associated with millimeter-wave (mmWave) propagation, high energy consumption, infrastructure densification, and LTE/5G coexistence in Non-Standalone (NSA) architectures continue to affect network stability and operational efficiency.

Looking toward the future, RF optimization is expected to evolve from conventional parameter tuning approaches into fully intelligent and autonomous optimization systems driven by AI-native Radio Access Networks (RANs). The transition toward Standalone (SA) 5G architecture, Open Radio Access Network (O-RAN) frameworks, and zero-touch network management will further enable predictive resource allocation, automated fault recovery, intelligent beam management, and dynamic network slicing. These advancements are expected to improve scalability, reduce operational costs, and enhance user experience across emerging applications such as smart cities, autonomous transportation, industrial automation, and massive Internet of Things (IoT) ecosystems.

Furthermore, the anticipated evolution toward 6G communication systems and higher-frequency Terahertz spectrum bands will introduce additional propagation and optimization complexities that require more sophisticated RF management techniques. Therefore, future research should focus on AI-assisted RF optimization, energy-efficient Massive MIMO architectures, digital twin-assisted network planning, reinforcement learning for beamforming optimization, and intelligent O-RAN controllers capable of supporting next-generation wireless communication systems.

In conclusion, advanced RF optimization will continue to play a central role in ensuring sustainable, efficient, and reliable wireless communication networks. The ability to intelligently balance coverage, throughput, latency, energy efficiency, and Quality of Service will remain essential for supporting the increasing global demand for seamless high-speed connectivity and future digital innovation.

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