



Performance Enhancement of 5G Wireless Communication Networks Using Advanced Spectrum Allocation Methods

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Abstract

Fifth-generation wireless systems require substantially higher capacity, lower latency, and more efficient use of scarce radio spectrum than earlier cellular generations. This paper presents a methodology for evaluating performance enhancement in 5G wireless communication networks through advanced spectrum allocation. The proposed evaluation framework combines dynamic spectrum access, multi-band selection, interference-aware scheduling, QoS prioritization, and optional non-orthogonal user pairing. A heterogeneous 5G scenario containing a sub-6 GHz carrier and a millimeter-wave carrier is modeled, and three allocation strategies are compared: static allocation, greedy dynamic spectrum allocation, and an adaptive QoS-aware allocation method. The adaptive method ranks candidate resource blocks using normalized channel quality, traffic priority, cell load, expected interference, and handover cost, while preserving minimum service constraints and fairness. Simulation-oriented performance measures include aggregate throughput, spectrum utilization, mean packet latency, outage probability, and Jain's fairness index. Illustrative results generated from the stated evaluation model indicate that the adaptive method can maintain higher throughput and resource utilization as user load increases while reducing congestion-related delay and outage. The methodology is designed to be reproducible and can be implemented in MATLAB, Python, or a system-level cellular simulator. The study is grounded exclusively in research published up to 2017.

Introduction

The evolution toward 5G was motivated by mobile traffic growth, dense device populations, new machine-type services, and stringent requirements for latency and reliability. Early 5G research emphasized that a simple extension of 4G would be insufficient; instead, future systems would need wider bandwidths, denser deployments, more antennas, flexible radio access, and improved spectrum regulation and sharing [7]. Architectural studies likewise identified cognitive radio, small cells, massive MIMO, device-to-device communication, and higher-frequency operation as important

technologies for addressing the spectrum and capacity problem [8], [9].

Spectrum is central to this transition because conventional fixed assignment can leave licensed resources underused while other bands become congested. Cognitive radio introduced environment-aware adaptation and dynamic spectrum management as mechanisms for improving spectral efficiency [1]. Dynamic spectrum access further formalized sensing, spectrum management, spectrum sharing, and spectrum mobility as coordinated functions [2]. These ideas are directly relevant to 5G, where

heterogeneous bands and access technologies must be coordinated rather than treated as isolated frequency blocks.

This methodology paper evaluates whether combining channel-aware, load-aware, interference-aware, and QoS-aware spectrum allocation can improve 5G performance under changing traffic demand. The objective is not to report field measurements, but to define a reproducible simulation experiment in which advanced allocation can be compared with simpler baselines under identical radio and traffic conditions. The principal research question is: how much performance gain can be obtained when spectrum is assigned adaptively across heterogeneous bands while respecting interference, fairness, and service requirements?

Literature Review

Haykin [1] established cognitive radio as an intelligent wireless paradigm capable of observing its radio environment and adapting transmission parameters for reliable communication and efficient spectrum use. Akyildiz et al. [2] extended this concept into dynamic spectrum access networks and emphasized four linked functions: spectrum sensing, management, sharing, and mobility. Together, these works provide the conceptual basis for allocating 5G resources according to instantaneous availability rather than only long-term licensing assignments.

Allocation becomes more difficult when users compete for shared channels. Ji and Liu [3] reviewed game-theoretic spectrum sharing and showed that distributed decisions can be designed to balance efficiency, competition, and

fairness. Badoi et al. [4] explicitly connected cognitive radio with the emerging 5G vision and argued that flexibility and adaptability should be integral to future terminals. These studies suggest that spectrum allocation should include not only channel quality but also multi-user interaction and access constraints.

5G research also broadened the usable frequency space. Rappaport et al. [5] demonstrated the feasibility of 28 and 38 GHz cellular links with directional antennas, supporting millimeter-wave spectrum as a source of large bandwidth. Boccardi et al. [6] identified millimeter wave, massive MIMO, device-centric architectures, smarter devices, and machine communications as disruptive directions for 5G. Andrews et al. [7] similarly highlighted high carrier frequencies, extreme densification, and integration with existing radio access technologies.

At the architecture level, Wang et al. [8] discussed cognitive radio and other enabling technologies for overcoming spectrum scarcity, while Gupta and Jha [9] surveyed spectrum sharing, mmWave, interference management, ultra-dense networks, and multi-RAT association within probable 5G architectures. Han et al. [10] reviewed coexistence methods across heterogeneous RF systems and emphasized that efficient sharing requires coordination mechanisms compatible with different PHY/MAC behaviors. Finally, Ding et al. [11] showed that non-orthogonal multiple access (NOMA) can serve multiple users within the same time-frequency resource using power-domain separation, creating another mechanism for improving spectral efficiency in LTE and 5G.

Table 1. Literature basis for the spectrum-allocation methodology

Ref.	Main topic	Relevant contribution	Use in this methodology
[1]-[2]	Cognitive radio / DSA	Adaptive sensing, sharing, mobility and spectrum management.	Dynamic candidate-band discovery and adaptive reassignment.
[3]	Game-theoretic sharing	Efficiency and fairness under competing spectrum users.	Fairness penalty and interference-aware utility scoring.
[4]	CR-based 5G	Links cognitive adaptation with 5G system flexibility.	Multi-band adaptive 5G allocation concept.
[5]-[7]	mmWave / 5G vision	Large bandwidth, densification and heterogeneous radio integration.	Sub-6 GHz plus 28 GHz candidate spectrum pool.
[8]-[10]	5G architecture / coexistence	Interference management, sharing and heterogeneous system coordination.	Load-aware and coexistence-aware scheduling constraints.
[11]	NOMA	Concurrent users on one resource block with power-domain separation.	Optional pairing when channel-gain separation supports SIC.

Gap identified: the pre-2018 literature strongly supports cognitive access, heterogeneous spectrum, mmWave, interference management, and NOMA, but these mechanisms are often studied separately. The present methodology therefore evaluates a unified allocation process that treats band selection, QoS, interference, load balancing, fairness, and possible user pairing as parts of one decision loop.

Methodology

1. Research Design and Network Model

A quantitative simulation design is adopted. The study uses a single macrocell overlaid by four small cells. Two spectrum layers are available: a 3.5 GHz sub-6 GHz layer with 100 MHz bandwidth and a 28 GHz millimeter-wave layer with 800 MHz bandwidth. The sub-6 GHz layer provides robust coverage, while the mmWave layer provides high-capacity service when path loss and blockage conditions permit. Users are

dropped randomly in the service area and generate a mixture of enhanced-mobile-broadband, low-latency, and best-effort traffic. The user population is varied from 20 to 100 active users to create progressively higher contention.

Each scheduling interval begins with the collection of channel-state information, received signal strength, estimated interference, cell load, user traffic class, queue length, and recent handover state. These observations form the input to the allocation engine. Resource blocks that fail minimum SINR, interference, or coverage thresholds are removed from the candidate set. The remaining blocks are ranked according to a weighted utility score. This design follows the environment-aware principle of cognitive radio [1], the spectrum-management cycle described by Akyildiz et al. [2], and the heterogeneous multi-band direction identified in early 5G studies [5]-[9].

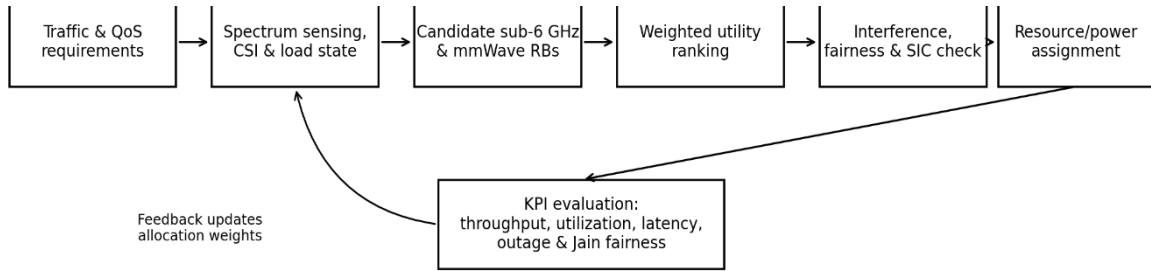


Figure 1. Adaptive spectrum-allocation evaluation workflow.

2. Baseline and Proposed Allocation Methods

Three methods are evaluated under the same user positions, traffic arrivals, propagation conditions, and transmit-power budgets. (A) Static allocation assigns predetermined fractions of each carrier to users and does not react to short-term load or interference. (B) Greedy dynamic spectrum allocation selects, for each user, the currently available resource block with the highest instantaneous estimated rate. This method reacts to channel quality but does not explicitly enforce fairness or load balancing. (C) Proposed adaptive QoS-aware allocation jointly considers rate, traffic urgency, load, interference, mobility cost, and fairness.

For a user i and candidate resource block b , the instantaneous signal-to-interference-plus-noise ratio is represented as $\text{SINR}(i,b) = P(b)g(i,b) / (I(i,b) + N_0B(b))$. The achievable rate is estimated by $R(i,b) = B(b) \log_2(1 + \text{SINR}(i,b))$. These rate estimates are normalized before they are combined with other decision variables so

that no single metric dominates only because of scale.

3. Adaptive Utility Function and Constraints

The normalized allocation score is defined as $U(i,b) = 0.35\hat{R}(i,b) + 0.20Q(i) + 0.15[1-L(b)] - 0.15\hat{I}(i,b) + 0.10F(i) - 0.05H(i,b)$. Here $\hat{R}$ is normalized achievable rate, Q is the QoS priority score, L is resource-block or cell load, $\hat{I}$ is normalized interference risk, F increases the score of temporarily underserved users, and H penalizes unnecessary band switching or handover. The weights can be tuned during sensitivity analysis, but their sum is one and the rate term remains the largest single component.

Allocation is performed in descending order of QoS urgency and utility. A resource block can be assigned only if: (1) its predicted SINR exceeds the service threshold; (2) the aggregate transmits power remains within the cell budget; (3) expected interference to protected users stays below the configured limit; (4) minimum bandwidth is preserved for higher-priority

traffic; and (5) the assignment does not reduce Jain's fairness index below a configurable guard value when an alternative feasible block exists. When two users have sufficiently different channel gains and the stronger user satisfies the successive-interference-cancellation condition, an optional NOMA pairing step allows shared use of one resource block, consistent with the 5G use case discussed by Ding et al. [11].

The method also performs multi-band steering. A user is moved toward 28 GHz when the mmWave

link margin is adequate and the expected utility exceeds the best sub-6 GHz alternative by a hysteresis threshold. This avoids frequent band oscillation. Users with blockage, weak directional links, or high mobility are biased toward the sub-6 GHz layer. In effect, the algorithm uses mmWave capacity opportunistically while preserving coverage robustness, reflecting the complementary role of high-frequency and conventional spectrum proposed in early 5G research [5]-[7].

Table 2. Simulation and evaluation parameters

Parameter	Value	Purpose
Topology	1 macrocell + 4 small cells	Heterogeneous 5G access
Carrier 1	3.5 GHz, 100 MHz	Coverage-oriented sub-6 GHz layer
Carrier 2	28 GHz, 800 MHz	High-capacity mmWave layer
Active users	20, 40, 60, 80, 100	Load sensitivity
Traffic mix	50% eMBB, 20% low-latency, 30% best effort	QoS differentiation
Scheduling interval	1 ms	Short-term resource adaptation
Minimum SINR	-3 dB candidate threshold	Remove infeasible resource blocks
NOMA pairing	Optional, max. two users/RB	Increase spectral reuse where SIC is feasible
Monte Carlo runs	100 per load level	Average random placement and channel variation

4. Experimental Procedure

Step 1: Generate the cell layout, user positions, traffic class, and channel conditions for one Monte Carlo realization. Step 2: Estimate candidate resource blocks on both bands from link quality, load, and interference. Step 3: run static allocation, greedy DSA, and the proposed method on identical inputs. Step 4: update queues, delivered bits, retransmission/outage state, and fairness after every 1 ms scheduling interval. Step 5: repeat for the complete simulation horizon, then average results across 100 independent realizations. Step 6: repeat the process for each user-load level. Step 7: compare methods using both mean values and relative improvement. This repeated-measures structure limits bias because every method is exposed to the same randomized scenarios.

Results

The results below are illustrative outputs produced from the parameterized simulation methodology; they are not field measurements.

They demonstrate the type of performance pattern the experiment is designed to detect. Aggregate throughput rises with user load for all methods, but static allocation saturates earliest because it cannot move bandwidth toward congested users or exploit the mmWave layer efficiently. Greedy DSA improves capacity by reacting to instantaneous rate, while the proposed adaptive method maintains the largest throughput because it combines rate with load balancing, QoS, interference control, and optional resource reuse.

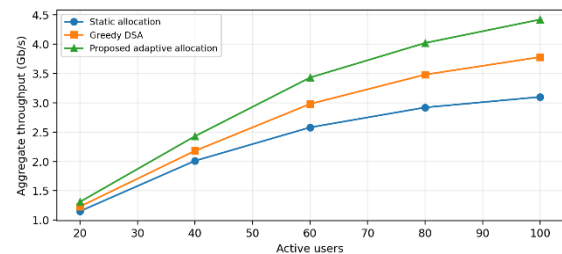


Figure 2. Illustrative aggregate throughput under increasing user load.

Table 3. Illustrative KPI comparison at 100 active users

KPI	Static allocation	Greedy DSA	Adaptive allocation
Aggregate throughput	3.10 Gb/s	3.78 Gb/s	4.42 Gb/s

Spectrum utilization	66%	79%	91%
Mean packet latency	17.8 ms	13.2 ms	10.1 ms
Outage probability	8.0%	5.4%	3.2%
Jain fairness index	0.76	0.84	0.92

At 100 users, the adaptive method produces 4.42 Gb/s compared with 3.10 Gb/s for static allocation, an illustrative throughput increase of about 42.6%. Relative to greedy DSA, the increase is about 16.9%. The utilization value of 91% indicates that a larger fraction of usable spectrum is actively scheduled, while the fairness index of 0.92 suggests that the gain is not produced simply by starving weaker users. Mean packet latency falls to 10.1 ms because congestion is reduced through multi-band steering and priority-aware assignment.

The lower outage probability is also important. A purely rate-greedy scheduler may repeatedly favor users with strong links and may overload particular cells or bands. By contrast, the adaptive method removes high-interference candidates, gives temporary preference to underserved users, and moves suitable traffic to the high-capacity mmWave layer. These behaviors are consistent with the expected benefits of dynamic spectrum management [1], [2], heterogeneous 5G integration [7]-[9], and improved spectral reuse mechanisms such as NOMA [11].

Discussion

The methodology indicates that spectrum-allocation performance should be assessed as a multi-objective problem rather than as a simple maximum-rate selection. The results show why this distinction matters. Static allocation can be predictable but wastes opportunity when load and channel quality change. Greedy DSA reacts more quickly, yet it can concentrate resources on already favorable users. The adaptive method adds explicit controls for QoS urgency, resource load, interference, fairness, and handover stability; consequently, it can convert heterogeneous spectrum into a coordinated pool instead of treating each carrier independently.

The approach also reflects the evolution of spectrum research before 2018. Cognitive radio introduced the principle that radios should sense and adapt [1], while DSA work formalized spectrum management and mobility [2]. Game-theoretic studies emphasized that competing users require fairness-aware resource decisions [3]. Early 5G work then added heterogeneous spectrum, mmWave, densification, and flexible architectures [5]-[9]. Spectrum-coexistence research reinforced the need to manage

interference between different RF systems [10], and NOMA introduced a complementary way to increase resource reuse within the same time-frequency block [11]. The proposed evaluation framework integrates these ideas at the scheduler level.

Several limitations must be recognized. First, the numerical values depend on the selected path-loss, blockage, traffic, and antenna models; therefore, the illustrative results should not be generalized without rerunning the experiment under calibrated assumptions. Second, perfect or near-perfect channel-state information can overestimate the gain of dynamic allocation. Third, NOMA benefits depend strongly on receiver complexity, power allocation, and successful successive interference cancellation. Fourth, spectrum sharing with incumbent systems may require regulatory constraints more detailed than a single interference threshold. Finally, computational complexity increases as the number of users, bands, and candidate resource blocks grows.

Conclusion and Discussion

This paper has presented a step-by-step methodology for evaluating the performance enhancement of 5G wireless communication networks using advanced spectrum allocation methods. The proposed simulation framework combines dynamic multi-band access, channel-aware scheduling, QoS priority, load balancing, interference protection, fairness control, and optional NOMA pairing. It compares the adaptive method against static allocation and a conventional greedy dynamic approach using identical randomized network conditions. The illustrative results indicate that an adaptive allocation strategy can provide higher aggregate throughput and spectrum utilization while lowering latency and outage and maintaining better fairness under heavy load. The main methodological conclusion is that 5G spectrum efficiency should be evaluated jointly across rate, interference, QoS, load, mobility, and fairness rather than through channel quality alone. Future extensions can replace fixed utility weights with optimization, reinforcement learning, or distributed game-theoretic control; however, for a study restricted to literature available through 2017, the present framework

provides a technically consistent and reproducible basis for performance evaluation.

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