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QoS-aware Power Allocation in Mixed-numerology NOMA

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Abstract

Mixed Numerology Non-Orthogonal Multiple Access (MN-NOMA) is a promising technique for beyond-5G wireless networks, but practical deployments face two major challenges: inter-numerology interference (INI) caused by overlapping subcarriers and residual interference due to imperfect successive interference cancellation (SIC). Most existing studies address these two issues separately. This paper proposes a QoS-aware power allocation framework that jointly mitigates INI and imperfect SIC in downlink MN-NOMA systems. The resource allocation problem is formulated with a logarithmic utility function, that aims to balance the overall spectral efficiency and user fairness. The resulting optimization problem is highly non-convex because of the coupled interference terms. To solve it efficiently, an alternating optimization and successive convex approximation (AO-SCA) framework is developed, where the original problem is iteratively transformed into tractable convex sub problems. Simulation results demonstrate clear performance gains over Equal Power Allocation (EPA) and Fixed Power Allocation (FPA) schemes. The proposed framework improves spectral efficiency, particularly in the low-to-moderate SNR region, while maintaining reliable performance under practical interference conditions. Unlike schemes that favor only strong-channel users, the proposed method provides a balanced fairness-efficiency tradeoff, maintaining a Jain's fairness index of approximately 0.67 while reducing outage probability to near-zero levels at SNR values above 30 dB. These results indicate that the proposed AO-SCA framework provides an effective and practical solution for fairness-aware resource allocation in interference-limited MN-NOMA networks.

Keywords: Alternating Optimization, Imperfect SIC, Inter-numerology Interference, Mixed Numerology NOMA, QoS-Aware Power Allocation, Successive Convex Approximation.

Introduction

The rapid growth of heterogeneous wireless applications in fifth-generation and beyond wireless networks has significantly increased the demand for flexible and efficient radio resource management (1). Emerging services such as enhanced mobile broadband (eMBB), ultra-reliable low-latency communication (URLLC), and massive machine-type communication (mMTC) have diverse QoS requirements in terms of throughput, latency, reliability, and connectivity (1–3). The Mixed Numerology (MN) transmission supports these heterogeneous services, by allowing simultaneous coexistence of different subcarrier spacings and symbol durations (4–8). Although MN transmission improves flexibility and scalability, it also creates INI, which degrades spectral efficiency and system reliability (2). The impact of INI becomes more severe when adjacent numerologies operate with overlapping spectral resources or insufficient guard bands (2, 9). Non-Orthogonal Multiple Access (NOMA) has attracted considerable attention for improving spectral efficiency and resource utilization in wireless communication systems (10–13). Unlike conventional orthogonal access schemes, NOMA allows multiple users to share the same time-frequency resources through power-domain multiplexing (14, 15). NOMA performance entirely depends on accurate SIC at the receiver (16, 17). Imperfect SIC leads to residual interference that significantly affects user fairness, outage probability, and achievable data rates (18). Hence, the integration of MN and NOMA introduces additional challenges due to the simultaneous presence of inter-numerology interference and residual SIC interference. Mixed numerology transmission provides significant flexibility for accommodating heterogeneous services; however, the coexistence of multiple numerologies creates complex interference interactions that are not present in conventional OFDM systems (7, 9). The severity of INI depends on factors such as subcarrier spacing,

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guard-band allocation, user distribution, and transmit power levels (19). As a result, resource allocation decisions directly influence both interference levels and QoS satisfaction. Therefore, efficient interference-aware optimization techniques are essential for maintaining reliable communication performance while preserving the flexibility advantages offered by MN operation. Several studies have investigated resource allocation and interference mitigation in MN systems. Energy-efficient resource allocation schemes for multi-numerology wireless networks have been developed, demonstrating improvements in throughput, QoS satisfaction, and energy efficiency through optimization-based resource management (1). Significant improvements in throughput, QoS satisfaction, and latency performance have been reported through Coordinated Multi-Point enhanced subcarrier and power allocation strategies for multi-numerology 5G-NR networks (4). However, these studies focused primarily on MN resource allocation and INI mitigation without considering NOMA transmission and imperfect SIC effects. The effects of INI and ICI in mixed-numerology MIMO-OFDM systems operating over time-varying wideband channels have been analyzed, and a joint mitigation framework based on statistical precoding and power allocation has been proposed (9). However, their work focused on MIMO-OFDM transmission and did not consider NOMA-based user multiplexing, imperfect SIC, or QoS-aware fairness optimization.

User grouping and power allocation techniques have been proposed for NOMA downlink systems, resulting in improved throughput and resource utilization through optimized power-domain multiplexing (14). Fairness maximization in downlink NOMA systems under imperfect SIC has been investigated, demonstrating improvements in user fairness and achievable rates through optimization-based resource allocation (20). Nevertheless, these studies were developed for conventional NOMA systems and did not account for mixed numerology operation and the resulting inter-numerology interference. QoS-constrained resource allocation problems often involve strongly coupled optimization variables and non-convex formulations, requiring advanced optimization or machine-learning-based solution techniques (21, 22). Improving spectral efficiency may adversely affect fairness or outage performance, while stringent QoS requirements can further restrict feasible resource allocation solutions (23). Consequently, advanced optimization frameworks are required to achieve an effective balance among competing performance objectives under practical interference conditions. Optimization techniques such as AO, SCA, and other iterative optimization frameworks have demonstrated strong potential for solving non-convex wireless resource allocation problems efficiently (1, 20, 24, 25). Despite these advances, most existing studies address MN interference and imperfect SIC independently. As a result, the joint optimization of spectral efficiency, fairness, and QoS in MN-NOMA systems under simultaneous INI and imperfect SIC remains insufficiently explored.

Motivated by this research gap, this paper proposes a QoS-aware power allocation framework that jointly considers INI, imperfect SIC, and QoS requirements while balancing spectral efficiency and user fairness.

The proposed AO-SCA framework jointly incorporates INI, imperfect SIC, QoS constraints, and fairness-aware resource allocation within a unified optimization framework. The proposed approach improves spectral efficiency, fairness, and outage performance while maintaining practical computational complexity.

The objective of the proposed AO-SCA framework is to develop a QoS-aware power allocation framework for MN-NOMA systems that jointly considers INI and imperfect SIC. The study aims to formulate an interference-aware optimization problem, develop an efficient AO-SCA-based solution approach, and evaluate its impact on spectral efficiency, fairness, energy efficiency, and outage performance.

The main contributions of this work are summarized as follows:

(a) A MN-NOMA system model incorporating INI and imperfect SIC is developed.

(b) A QoS-aware power allocation problem is formulated to jointly optimize spectral efficiency and fairness under practical interference conditions.

(c) An AO-SCA-based optimization framework is proposed to efficiently solve the resulting non-convex optimization problem.

(d) Extensive simulations are conducted to evaluate the proposed framework in terms of spectral efficiency, fairness, energy efficiency, and outage probability.

Methodology

In the proposed methodology, the MN-NOMA system is modeled in the presence of INI and imperfect SIC. Based on this system model, SINR and achievable rate expressions are derived, and a QoS-aware power allocation problem is formulated. Since the resulting optimization problem is non-convex, it is transformed using SCA and solved iteratively through an AO framework implemented in CVX. The performance of the optimized scheme is then evaluated through Monte Carlo simulations in terms of spectral efficiency, energy efficiency, fairness, and outage probability. The overall workflow of the proposed AO-SCA-based QoS-aware power allocation framework is illustrated in Figure 1.

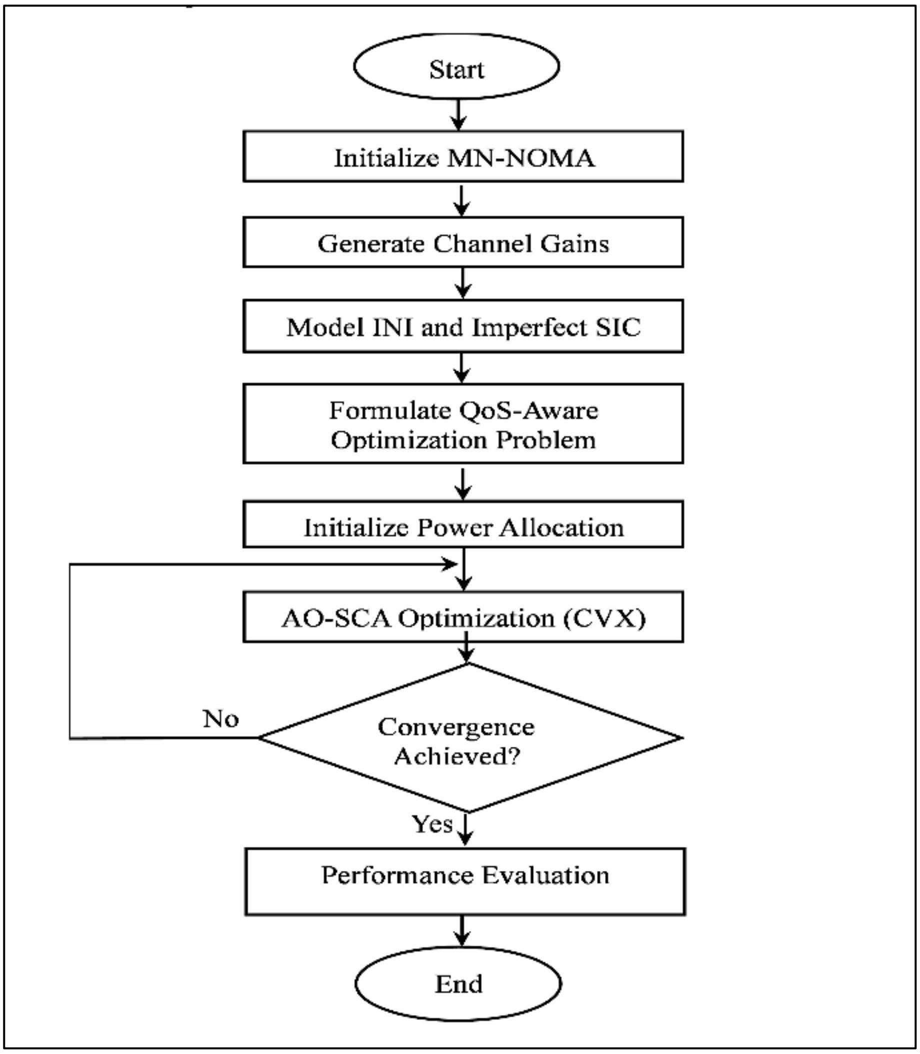

Figure 1: Workflow of the Proposed AO-SCA-based QoS-aware Power Allocation Framework

System Model

We consider a downlink MN-NOMA system, where a base station serves users grouped across M numerologies. Each numerology $m \in 1,2,\dots,M$ supports K users using power-domain NOMA. The total number of users is given by Equation [1]:

$$K_{total} = M\,K \qquad [1]$$

Let $P_{m,k}$ denote the transmit power allocated to user k in numerology m, and $H_{m,k}$ denote the effective channel gain. The transmitted superposed signal for numerology m is given in Equation [2].

$$x_m = \sum_{k=1}^{K} \sqrt{P_{m,k}}\;\; s_{m,k} \qquad [2]$$

Where, $s_{m,k}$ is the unit-power symbol, such that $E\left[\left|s_{m,k}\right|^2\right] = 1$

Users are ordered according to their channel gains as defined in Equation [3], ensuring proper SIC decoding order.

$$H_{m,1} \leq H_{m,2} \leq \cdots \leq H_{m,K} \qquad [3]$$

The effective channel gain for user k in numerology m is defined in Equation [4], where $h_{m,k} \sim CN(0,1)$ represents Rayleigh fading, d_k is the user distance and η is the path-loss exponent.

$$H_{m,k} = \left|h_{m,k}\right|^2 \cdot d_k^{-\eta} \qquad [4]$$

The received signal at user (m, k) given in Equation [5], consists of the desired signal, intra-numerology interference, INI, and noise.

$$y_{m,k} = \sqrt{H_{m,k}} \sum_{j=1}^{K} \sqrt{P_{m,j}} s_{m,j} + \sqrt{\alpha} \sum_{m'=1,m'\neq m}^{M} \sum_{j=1}^{K} \sqrt{P_{m',j}} \sqrt{H_{m',k}} s_{m',j} + n_{m,k} \qquad [5]$$

Where, $n_{m,k} \sim CN(0, \sigma^2)$. The interference-plus-noise term is defined in Equation [6].

$$D_{m,k} = H_{m,k}\left(\sum_{j=k+1}^{K} P_{m,j} + \beta \sum_{j=1}^{k-1} P_{m,j} + \alpha \sum_{m'=1,m'\neq m}^{M} \sum_{j=1}^{K} P_{m',j}\right) + \sigma^2 \qquad [6]$$

The first term in Equation [5] represents uncancelled intra-numerology interference, the second term models residual SIC interference, and the third term captures aggregated INI.

The SINR for user (m, k) is defined in Equation [7],

$$SINR_{m,k} = \frac{P_{m,k} H_{m,k}}{D_{m,k}} \qquad [7]$$

Where, σ^2 is the noise variance, $\beta \in [0,1]$ denotes the SIC imperfection factor and α is the INI coefficient. The SINR formulation follows the SIC decoding order inherent to NOMA systems, where interference from users with indices $j > k$ remains uncanceled, while interference from users with indices $j < k$ is partially removed via SIC with residual interference modeled by β.

The INI is defined in Equation [8].

$$I_{m,k} = \alpha\, H_{m,k} \sum_{m' = 1,m'\neq m}^{M} \sum_{j=1}^{K} P_{m',j} \qquad [8]$$

The INI power term is obtained from the received interference signal in Equation [4] after power-domain aggregation. The INI expression in Equation [8] models the aggregate interference contributed by users belonging to adjacent numerologies. The resulting interference power is scaled by the coupling coefficient α, which characterizes the degree of interaction between different numerologies. Furthermore, the interference experienced by a user is proportional to its effective channel gain $H_{m,k}$, reflecting the dependence of the received interference power on the propagation conditions of the victim user.

The achievable rate for user (m, k) is defined in Equation [9].

$$R_{m,k} = \log_2\left(1 + SINR_{m,k}\right) \qquad [9]$$

The minimum SINR requirement is expressed in Equation [10]. Using the SINR definition in Equation [6], the equivalent linearized QoS constraint can be written as Equation [11].

$$SINR_{m,k} \geq \gamma_{min} \qquad [10]$$

$$P_{m,k} H_{m,k} \geq \gamma_{min} D_{m,k} \qquad [11]$$

To improve feasibility of the optimization problem, a non-negative slack variable is introduced as given in Equation [12].

$$\{P_{m,k} H_{m,k} + s_{m,k} \geq \gamma_{min} D_{m,k}\ s_{m,k} \geq 0 \qquad [12]$$

A non-negative slack variable $s_{m,k}$ is introduced in Equation [11] to maintain feasibility of the QoS constraints during optimization. The total transmit power constraint is given by Equation [13].

$$\sum_{m=1}^{M} \sum_{k=1}^{K} P_{m,k} \leq P_{total} \quad [13]$$

The proposed system model represents INI as the aggregated interference originating from adjacent numerologies. Imperfect SIC is incorporated through a linear residual interference factor (β). QoS requirements are enforced using SINR-based constraints that are compatible with convex optimization techniques.

Problem Formulation

The objective of this work is to design an efficient power allocation scheme for MN-NOMA systems that maximizes system performance while satisfying user-specific QoS requirements under practical interference conditions. To jointly balance spectral efficiency and fairness, a logarithmic utility-based objective function is used. The optimization problem is formulated as given in Equation [14].

$$\max_{\{P_{m,k}\}} \sum_{m=1}^{M} \sum_{k=1}^{K} \log_2\left(1 + SINR_{m,k}\right) \quad [14]$$

The logarithmic utility formulation in Equation [14] provides a balance between spectral efficiency and user fairness. By maximizing the sum-log utility, excessive resource concentration toward strong users is avoided, while improving overall system efficiency under interference-limited conditions. The optimization problem is subject to total transmit power, QoS, and non-negativity constraints. Equation [15] represents the total power constraint. Using the SINR expression in Equation [6], the QoS constraint can be equivalently reformulated as Equation [16], where $D_{m,k}$ represents the interference-plus-noise term. Equations [16, 17] enforce the minimum SINR requirement, and Equation [18] ensures non-negative power allocation.

$$\sum_{m=1}^{M} \sum_{k=1}^{K} P_{m,k} \leq P_{total} \quad [15]$$

$$SINR_{m,k} \geq \gamma_{min} \quad \forall m,k \quad [16]$$

$$P_{m,k}H_{m,k} \geq \gamma_{min}D_{m,k}, \quad \forall m,k \quad [17]$$

$$P_{m,k} \geq 0, \quad \forall m,k \quad [18]$$

The formulated optimization problem is non-convex due to the following reasons. The SINR expression contains coupled interference terms in the denominator. The objective function involves a logarithmic utility function with coupled fractional SINR terms. QoS constraints introduce additional non-linear coupling. These factors make the problem difficult to solve directly using standard convex optimization techniques. Therefore, an AO-SCA framework is adopted to obtain a computationally efficient solution. AO decomposes the coupled variables into manageable subproblems, while SCA transforms the non-convex terms into convex approximations that can be efficiently solved using CVX (26). This combination enables stable convergence under INI and imperfect SIC conditions.

The adopted AO-SCA framework solves the problem iteratively as follows.

(a) Alternating Optimization: The problem is decomposed into tractable subproblems by iteratively optimizing power variables.

(b) Successive Convex Approximation: The non-convex terms are approximated using first-order convex approximations, enabling transformation into convex subproblems. The resulting convex subproblems are solved iteratively using the CVX optimization framework.

Proposed AO-SCA Optimization Framework

To solve the non-convex power allocation problem, an optimization framework based on alternating optimization (AO) and successive convex approximation (SCA) is employed.

For ease of analysis and convexification, the SINR expression in Equation [6] is rewritten in the compact form shown in Equation [19], where D_(m,k) denotes the interference-plus-noise term.

$$SINR_{m,k} = \frac{P_{m,k}H_{m,k}}{D_{m,k}} \quad [19]$$

The achievable rate can be written as a difference of concave functions as given in Equation [20].

$$R_{m,k} = \log_2\left(D_{m,k} + P_{m,k}H_{m,k}\right) - \log_2\left(D_{m,k}\right) \qquad [20]$$

This representation enables tractable convexification using SCA.
To solve the non-convex optimization problem, SCA is employed. The concave term $\log_2\left(D_{m,k}\right)$ is linearized via first-order Taylor approximation around the operating point $D_{m,k}^{(t)}$ as given in Equation [21]. Substituting this approximation yields a concave surrogate objective at iteration (t).

$$\log_2\left(D_{m,k}\right) \approx \log_2\left(D_{m,k}^{(t)}\right) + \frac{D_{m,k} - D_{m,k}^{(t)}}{D_{m,k}^{(t)}\ln(2)} \qquad [21]$$

After applying SCA, the resulting convex subproblem at iteration t can be expressed as follows. Let $\widetilde{D}_{m,k}$ denote the affine approximation of $\log\left(D_{m,k}\right)$ at $D_{m,k}^{(t)}$. At iteration (t), the approximated problem is expressed as given in Equation [22-25].

$$\max_{\{P_{m,k}\}} \sum_{m=1}^{M} \sum_{k=1}^{K} \left[\log_2\left(D_{m,k} + P_{m,k}H_{m,k}\right) - \widetilde{D}_{m,k}\right] \quad [22]$$

$$\text{s.t.} \sum_{m=1}^{M} \sum_{k=1}^{K} P_{m,k} \le P_{total} \quad [23]$$

$$P_{m,k}H_{m,k} \ge \gamma_{min} D_{m,k}, \quad \forall m,k \quad [24]$$

$$P_{m,k} \ge 0, \quad \forall m,k \quad [25]$$

Here, $\widetilde{D}_{m,k}$ denotes the affine approximation of the logarithmic term $\log_2\left(D_{m,k}\right)$. This problem is convex and can be solved efficiently using interior-point optimization methods.
The coupling among the interference terms is handled through an AO procedure, which iteratively updates the power allocation variables.

Given the coupling through $D_{m,k}$, AO is employed as follows:

a) Evaluate $D_{m,k}$ using current $P_{m,k}$.
b) Solve the convex subproblem obtained via SCA.
c) Update $P_{m,k}$ and repeat until convergence.

The step-by-step procedure of the proposed optimization framework is given in Algorithm 1.

Convergence and Complexity

Algorithm 1: SCA-Based Power Allocation

a) Initialize feasible $P_{m,k}^{(0)}$ satisfying constraints.
b) Set $(t = 0)$.
   Repeat i) Compute $D_{m,k}^{(t)}$ for all m, k.
   ii) Linearize $\log\left(D_{m,k}\right)$ at $D_{m,k}^{(t)}$.
   iii) Solve the convex subproblem to obtain $P_{m,k}^{(t+1)}$.
   iv) $t \leftarrow t + 1$.
c) Until convergence tolerance is satisfied or the maximum number of iterations is reached.

The iterative AO–SCA procedure exhibits stable convergence behavior and terminates when the change in the power allocation vector falls below a predefined tolerance. Each iteration solves a convex program with linear and logarithmic terms, which is tractable using standard solvers. The iterative procedure is terminated when the Euclidean norm of the difference between two consecutive power allocation vectors satisfies $\|P^{t-1} - P^{t}\|_2 < 10^{-2}$, or when the maximum number of iterations is reached.

Simulation Setup

A downlink MN system with $M = 2$ numerologies and $K = 3$ users per numerology is considered. The total transmit power is normalized to $P_{total} = 1$. Users are ordered according to channel gains to enable SIC decoding. The channel model follows the formulation in Section III, where users are randomly distributed within a distance range of 10–100 m, with path-loss exponent $\eta = 2$. Rayleigh fading is assumed for all users. INI is controlled by $\alpha = 0.3$. Both perfect and imperfect SIC conditions are evaluated. Unless otherwise specified, baseline simulations use $\beta = 0$, while other figure investigates imperfect SIC with $\beta > 0$. The QoS threshold is set to $\gamma_{min} = 0.1$ (linear scale). The system is evaluated over an SNR range of 0–40 dB with a step size of 5 dB. The proposed AO–SCA algorithm is executed with a maximum of 10 iterations and convergence tolerance 10^{-2}. A slack penalty parameter of 50 is used to improve feasibility under QoS constraints. Performance is evaluated in terms of spectral efficiency, energy efficiency, Jain's fairness index, outage probability, and fairness-efficiency tradeoff behavior. The simulation parameters are summarized in Table 1. For each SNR value, Monte Carlo simulations are performed using independently generated channel realizations. The proposed AO-SCA framework and benchmark schemes (EPA, FPA, and Random allocation) are evaluated under identical simulation conditions. Performance is compared in terms of spectral efficiency, energy efficiency, fairness index, and outage probability.

Table 1: Simulation Parameters

Parameter	Value
Number of Numerologies	2
Users per Numerology	3
SNR Range	0–40 dB
Path Loss Exponent	2
INI Coefficient (α)	0.3
SIC Factor (β)	0
QoS Threshold (γ_{min})	0.1
Total Power	1
Monte Carlo Runs	50
AO Iterations	10

Results

The proposed AO-SCA power allocation framework is evaluated against Equal, Fixed (FPA), and Random allocation schemes over an SNR range of 0–40 dB under Rayleigh fading with inter-numerology interference (INI) and imperfect SIC conditions.

Figures 2A and 2B show that the proposed AO-SCA scheme achieves better spectral and energy efficiency than Equal and FPA allocation in low-to-moderate SNR regions by adapting power allocation according to QoS and interference conditions. The improvement is most pronounced in the low-to-moderate SNR region, where AO-SCA achieves up to 33% higher spectral efficiency than Equal allocation and up to 61% higher spectral efficiency than FPA. The relative gain is most pronounced at low-to-moderate SNR values and decreases at higher SNR values as all schemes approach their performance limits. Although Random Allocation provides the highest efficiency at high SNR, this gain is achieved by favoring strong-channel users without fairness consideration.

Figure 2C shows that Equal and FPA allocation maintain higher Jain's fairness index due to more uniform resource distribution, whereas Random Allocation produces poor fairness performance.

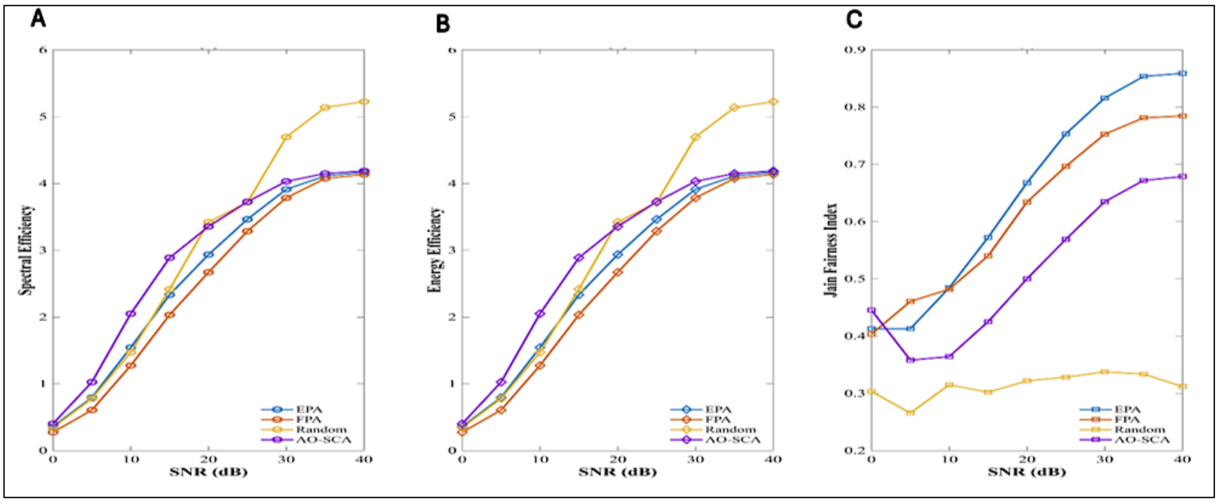

Figure 2: Performance Comparison of Equal, FPA, Random, and AO-SCA schemes.
(A) Spectral Efficiency versus SNR, (B) Energy Efficiency versus SNR, (C) Jain Fairness Index versus SNR

The fairness–efficiency tradeoff in Figure 3 indicates that the AO-SCA framework operates between the high-efficiency Random scheme and the high-fairness Equal scheme, providing a balanced compromise between user fairness and spectral efficiency. Each point in Figure 3 corresponds to a different QoS threshold value.

Figure 4 shows that the proposed AO-SCA method achieves outage performance close to Equal and FPA schemes while maintaining improved efficiency. In contrast, Random Allocation exhibits considerably higher outage probability because of uncontrolled power assignment and lack of QoS awareness.

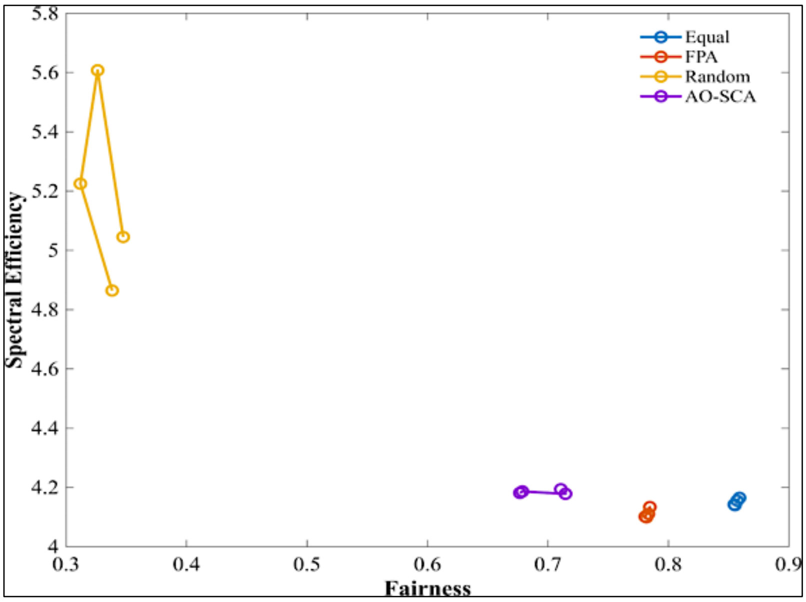

Figure 3: Fairness–Spectral Efficiency

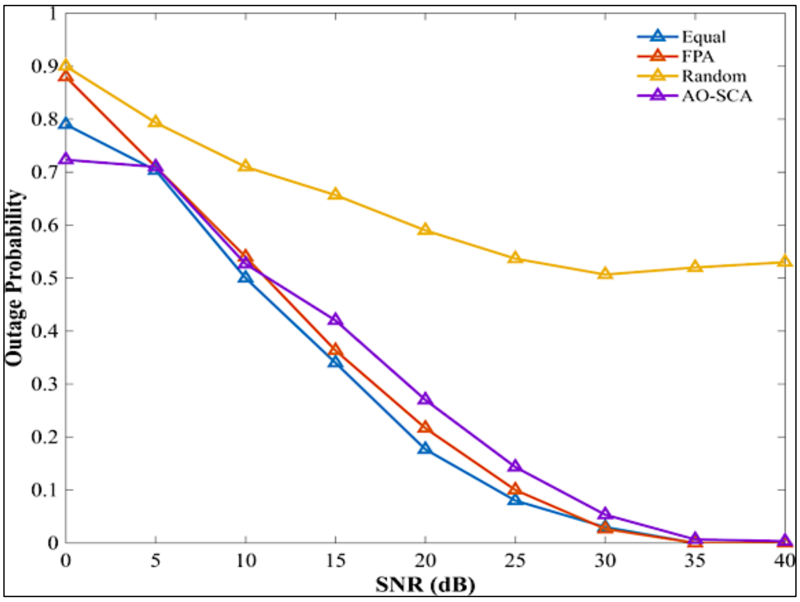

Figure 4: Outage Probability versus SNR (Tradeoff at SNR = 40 dB)

Figure 5 shows the effect of varying QoS thresholds. Equal, FPA, and AO-SCA schemes remain comparatively stable over the evaluated QoS range, whereas Random Allocation has performance fluctuations. Hence the proposed optimization framework can accommodate stricter QoS requirements with only minor impact on overall system performance. Figure 6 presents the impact of imperfect SIC on the AO-SCA framework. As the residual SIC factor β increases from 0 to 0.5, spectral efficiency decreases because of additional residual interference after SIC decoding. Even under imperfect SIC conditions, the AO-SCA scheme maintains stable performance across the evaluated SNR range.

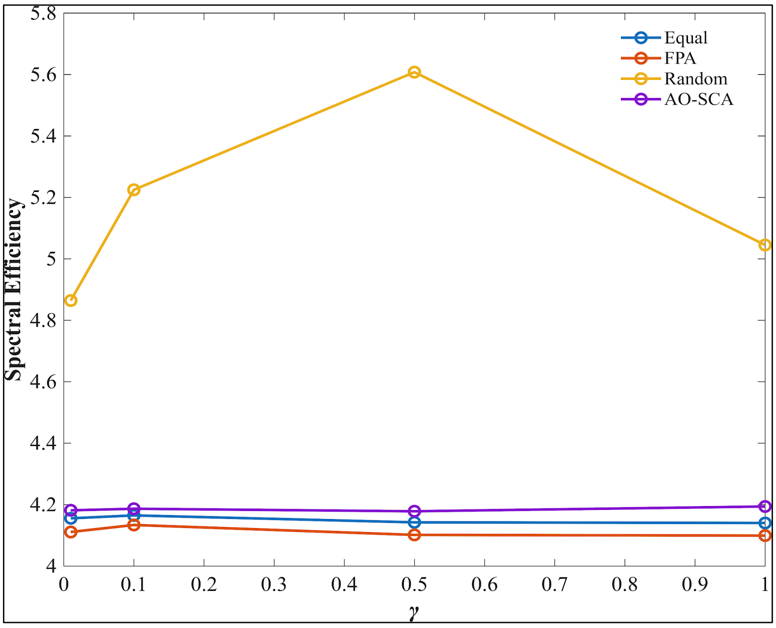

Figure 5: Impact of QoS Threshold Variation

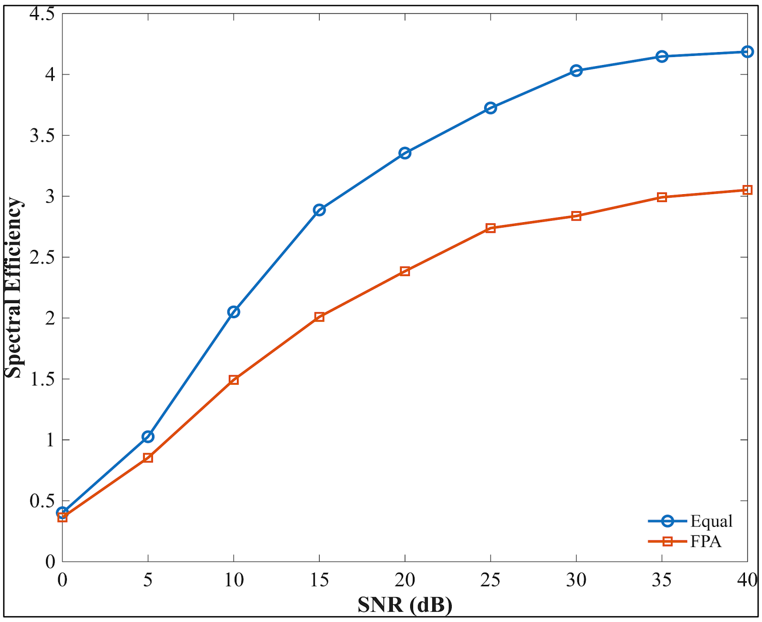

Figure 6: Practical Imperfect SIC Robustness

Discussion

The obtained results are consistent with earlier studies showing that optimization-based resource allocation improves spectral efficiency, QoS performance, and fairness in wireless networks (1, 20). Previous studies have investigated MN resource allocation and fairness optimization under imperfect SIC conditions (1, 20). In contrast, the proposed framework jointly addresses both INI and imperfect SIC within a unified QoS-aware optimization framework. The simulation results demonstrate that the proposed AO-SCA framework improves spectral efficiency, fairness, and outage performance compared with Equal and FPA allocation schemes. Significant improvements in user fairness under imperfect SIC conditions have been reported previously through fairness-aware optimization techniques (20). The results obtained in this work show that a reasonable level of fairness can be maintained even in the presence of additional inter-numerology interference while improving spectral efficiency. These gains arise from the ability of the proposed framework to adapt power allocation according to both QoS requirements and interference conditions, which is consistent with earlier optimization-based resource allocation studies in MN and NOMA systems (1, 4, 20). Improvements in system efficiency under MN operation have also been reported previously (4). However, the joint impact of INI and imperfect SIC was not considered in that study. Unlike fixed allocation strategies, the optimization process dynamically distributes resources among users, resulting in a better balance between efficiency and fairness. It has been shown that improving fairness in NOMA systems may reduce the achievable system throughput (23). The proposed AO-SCA framework operates at a balanced point between these competing objectives, maintaining acceptable fairness while improving spectral efficiency. This behavior is particularly important in mixed-numerology environments where inter-numerology interference and residual SIC interference jointly affect system performance.

The results also indicate that incorporating QoS constraints directly into the optimization problem improves reliability without causing a significant loss in spectral efficiency, which is consistent with the findings reported in QoS-aware resource allocation studies for wireless networks (1, 24). Furthermore, the framework remains relatively robust under imperfect SIC conditions, suggesting its suitability for practical receiver implementations. The importance of interference-aware mitigation techniques for mixed-numerology systems has also been demonstrated previously (9). Unlike earlier studies, the proposed framework jointly considers QoS constraints and imperfect SIC. These findings demonstrate that joint consideration of INI, imperfect SIC, and fairness can provide more effective resource management for future mixed-numerology NOMA networks. From a practical perspective, QoS-aware AO-SCA power allocation is recommended for MN-NOMA systems operating under significant INI and imperfect SIC conditions. The framework is well suited for heterogeneous 5G and beyond services, providing improved reliability and spectral efficiency while maintaining acceptable fairness without requiring additional spectrum resources.

Conclusion

This paper presented a QoS-aware AO-SCA power allocation framework for MN-NOMA systems operating in the presence of INI and imperfect SIC. The proposed formulation jointly considers spectral efficiency, fairness, and QoS requirements within a unified optimization framework. By combining AO and SCA, the original non-convex problem is transformed into a sequence of convex subproblems that can be solved efficiently using standard optimization tools.

The simulation results showed that the proposed framework consistently outperforms EPA and FPA schemes in terms of spectral efficiency while maintaining acceptable fairness and outage performance. The benefits of the proposed approach were particularly evident in the low-to-moderate SNR region, where adaptive power allocation provided noticeable performance gains under practical interference conditions. The results also demonstrated that the framework remains effective under different QoS requirements and varying levels of SIC imperfection. These observations highlight the importance of jointly addressing INI and imperfect SIC rather than treating them as independent problems.

Although the study considered a simplified downlink MN-NOMA scenario with a fixed number of users, static INI coefficient, and Rayleigh fading channels, the obtained results indicate that QoS-aware optimization can provide an effective mechanism for interference-aware resource allocation in future mixed-numerology wireless networks. Future work may extend the framework through adaptive numerology selection, dynamic user scheduling, hybrid beamforming, and AI-assisted optimization techniques, as well as through evaluation under more realistic channel and deployment conditions.

Abbreviations

None.

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Author Contributions

Sudhir Kumar Dhotre: Conceptualization, Methodology Development, Software Implementation, Simulations, Data Analysis, Result Interpretation, Manuscript Writing, Sanjay Nalbalwar: Research Supervision, Technical Guidance, Methodology Validation, Manuscript Review, Anil Nandgaonkar: Research Supervision, Technical Guidance, Validation of Results, Manuscript Review. All authors contributed to the development of the research, reviewed the manuscript, and approved the final version for publication.

Conflict of Interest

The authors declare no conflict of interest regarding the publication of this manuscript.

Data Availability

The data generated and analyzed during this study are available from the corresponding author upon reasonable request. The simulation codes and associated datasets used to support the findings of this research can also be made available for academic and research purposes.

Declaration of Artificial Intelligence (AI) Assistance

The author used AI tools for language refinement and grammar correction. The development of the research problem, mathematical modeling, simulation design, data analysis, interpretation of results, and final conclusions were carried out by the author. The author takes full responsibility for the accuracy, originality, and integrity of the content presented in this manuscript.

Ethics Approval

This study does not involve human participants, animals, human tissue, or personal data. Therefore, ethics committee approval and informed consent were not required for this research.

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