Dynamic Bandwidth Allocation in Multi-Cell Massive MIMO-NOMA System

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Abstract - *This paper investigates the problem of dynamic bandwidth allocation in multi-cell massive multiple-input multiple-output (MIMO) under non-orthogonal multiple access (NOMA) systems. In this research, a novel joint optimization framework that dynamically allocates bandwidth across cells and clusters is proposed. It also simultaneously optimizes the power control to maximize the sum spectral efficiency under user fairness constraints. The proposed framework basically incorporates a realistic system model that accounts for pilot contamination, channel estimation errors, intra- and inter-cell interference, and NOMA-specific successive interference cancellation. Recognizing the non-convex and combinatorial nature of the problem, we employ successive convex approximation (SCA) to transform it into a series of tractable convex subproblems and develop an iterative algorithm with guaranteed convergence. Extensive Python simulations demonstrate that the proposed dynamic bandwidth allocation method significantly outperforms the static allocation and orthogonal multiple access (OMA) benchmarks. The proposed method achieves significant improvement in the sum spectral efficiency and maintains high user fairness across varying traffic loads and interference conditions.*

Key Words: Non-Orthogonal Multiple Access (NOMA), Dynamic Bandwidth Allocation, Multi-Cell Network, Massive MIMO, Successive Convex Approximation (SCA), Spectral Efficiency.

1. INTRODUCTION

Emerging applications, such as the Internet of Things (IoT), streaming ultra-high-definition videos, virtual reality, and other high-speed online activities, have created exponential growth in mobile data traffic. These technological advancements require the unprecedented capacity and connectivity of fifth-generation (5G) and beyond wireless networks [1,2]. Massive multiple-input multiple-output (MIMO) and non-orthogonal multiple access (NOMA) have been widely investigated to fulfill these transformative technological requirements. Massive MIMO basically equips base stations (BSs) with a large number of antennas to serve multiple users simultaneously and provides substantial gains in spectral and energy efficiency through spatial multiplexing [3-6]. Conversely, NOMA allows multiple users to share the same time-frequency resource by superposing their signals in the power domain. Therefore, it enhances user connectivity and spectral efficiency compared to conventional orthogonal multiple access (OMA) [7,8].

In addition to the individual merits of massive MIMO and NOMA, their integration poses significant challenges due to intricate inter-cell interference and the requirement for sophisticated resource allocation. Pilot contamination caused by the reuse of pilot sequences across cells in a multi-cell massive MIMO system degrades channel estimation accuracy and limits the achievable rates [9-11]. The problem becomes even more complex when it is combined with NOMA because the superimposed signals in each cell generate additional intra- and inter-cluster interference that must be carefully managed through power control, user clustering, and successive interference cancellation (SIC) [12-14].

Fig. 1 illustrates a concept of multi-cell massive MIMO-NOMA system. Each base station is generally equipped with a large antenna array that serves multiple NOMA clusters. The bandwidth is dynamically allocated across multiple cells and clusters to adapt to variations in traffic and channel conditions.

Resource allocation plays a significant role in unlocking the full potential of massive MIMO-NOMA systems. Power control and user clustering have been extensively investigated to mitigate interference and maximize the sum rate [15,16]. Dynamic user clustering algorithms for NOMA mainly enhance the spectral efficiency by dynamically creating a group of users based on the time-varying channel conditions, such as channel gain differences, to optimize SIC and power allocation [17]. In practice, traffic loads and channel conditions are highly dynamic across cells and over time. Static bandwidth allocation usually generates inefficient resource utilization, particularly in the presence of asymmetric inter-cell interference and heterogeneous user demands [18]. Therefore, dynamic bandwidth allocation is a crucial to explore the dimensions in multi-cell massive MIMO-NOMA systems.

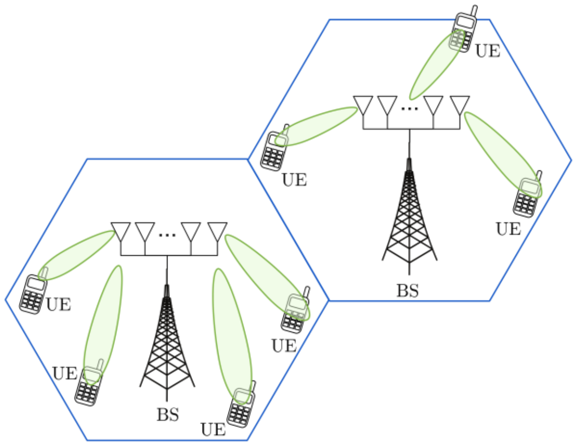

Fig. 1 Multi-Cell Massive MIMO System

Fig. 2 illustrates the concept of dynamic bandwidth allocation across cells over time (t_1, t_2, t_3, t_4). The bandwidth allocated to each cell (B_1, B_2, B_3) varies according to traffic load, channel conditions, and interference levels, that enable adaptive resource utilization.

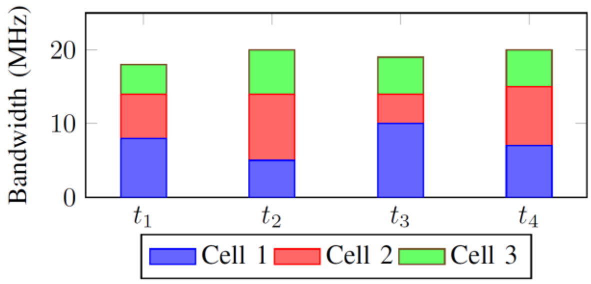

Fig. 2 Dynamic Bandwidth Allocation across Multiple Cells over Time

The remainder of this paper is organized as follows. Section II reviews related work on massive MIMO, NOMA, and resource allocation. Section III presents the system model, including channel estimation, signal model, and the bandwidth allocation framework. Section IV details the proposed joint optimization method and algorithm. Section V provides simulation results and discussions. Finally, Section VI concludes the paper with future directions.

2. RELATED WORK

The evolution of fifth-generation (5G) and beyond wireless networks is driven by high spectral efficiency, massive connectivity, and low latency requirements. Two foundational technologies, MIMO and NOMA, have attracted significant research interest. This section mainly reviews the existing studies on massive MIMO, NOMA, their integrated technologies, and resource allocation strategies that highlight the research gaps that motivate this work.

2.1 Massive MIMO Systems

Thomas L. Marzetta [19] envisioned massive MIMO, which equips base stations (BSs) with many antennas to serve multiple users simultaneously, which offers substantial gains in spectral and energy efficiency. Their seminal work established the fundamental concept of non-cooperative cellular systems with many antennas. Ngo *et al.* [20] analyzed the energy and spectral efficiency of massive MIMO under perfect and imperfect CSI. Subsequently, their research addressed the practical challenges such as channel estimation and pilot contamination. Fernandes *et al.* [21] investigated the effects of pilot contamination and proposed pilot assignment schemes to minimize the inter-cell interference. Björnson *et al.* [22] provided a comprehensive analysis on the massive MIMO, which basically covers the signal processing, resource allocation, and implementation aspects.

Massive MIMO boosts efficiency in 5G/6G, while generative diffusion models (GDMs) are the powerful AI tools. Jin *et al.* [23] used GDMs to improve channel estimation in massive MIMO, which exhibited promising results and highlighted future challenges. Shi *et al.* [24] proposed a cell-free massive MIMO system using "six-dimensional movable antennas (6DMA)," where distributed access points cooperatively serve users, and it can adjust antenna orientations. Their system optimizes antenna rotations based on user locations using a Bayesian optimization approach to maximize network performance. Their results show that the adaptive setup significantly improves the data rates by boosting signal strength and reducing interference and outperforms the fixed-antenna and centralized systems, particularly when users are widely distributed.

Tian and Zheng [25] proposed a hybrid deep learning model for channel estimation in MIMO systems. This model mainly combines the convolutions and gated recurrent units (GRUs) to improve the performance across different channel conditions. They basically used techniques like data augmentation and regularization to prevent overfitting and are trained using stochastic gradient descent. Their simulation results under both static and time-varying channels represent that the model outperforms traditional and existing deep learning methods and demonstrates better accuracy and generalization. Mashdour *et al.* [26] addressed the performance issues in cell-free massive MIMO, which is basically caused by the imperfect CSI. They proposed a robust resource allocation framework that has user scheduling and power allocation strategies particularly designed to maximize the data rates and reduce errors under uncertain CSI. Their simulation results represent that their approach significantly improves the performance by up to 30% compared to the existing methods.

2.2 Non-Orthogonal Multiple Access (NOMA)

NOMA originated as an auspicious 5G multiple-access technique that enables power-domain multiplexing to enable multiple users to share the same resource block. Saito *et al.* [27] presented the fundamental principles of NOMA and demonstrated its superiority over OMA in terms of sum rate and user fairness. Ding *et al.* [28] conducted a comprehensive NOMA survey and discussed power allocation, user pairing, and cooperative NOMA. Islam *et al.* [29] analyzed SIC as a key NOMA enabler. They comprehensively surveyed the recent advancements in NOMA for 5G and examined current research on capacity analysis, power allocation methods, user fairness, and user-pairing techniques. The integration of NOMA with other technologies, such as MIMO and millimeter-wave, has been explored in [30], which examined the impact of user pairing on the performance of NOMA systems.

Shi and Ouyang [31] proposed a "NOMA-enabled MEC system" where devices offload tasks to multiple edge servers simultaneously, thereby reducing delay. They introduced an optimization algorithm to efficiently manage resources, achieve lower latency and cost than traditional methods, and extend well to multidevice IoT scenarios. Benjebbour *et al.* [32] reviewed NOMA as a downlink multiple access technique for LTE and 5G networks. They explained its advantages over traditional OFDMA and its integration with MIMO. Through simulations and experimental tests, NOMA achieved more than 30% performance gains in both link- and system-level evaluations compared to OFDMA.

Chen *et al.* [33] presented a NOMA with reconfigurable intelligent surfaces (RIS) approach that optimizes transmission to boost spectral efficiency. Their proposed algorithm efficiently allocates resources, and their results show significant improvements, particularly when a unicast-first decoding strategy is applied. Abuajwa *et al.* [34] reviewed ways to improve energy efficiency in NOMA and explored notable gains from power allocation, relaying, and energy harvesting. However, trade-offs, such as higher complexity and reduced fairness for edge users, were highlighted.

Srivastava *et al.* [35] proposed a "low-complexity machine learning-based receiver" for NOMA to overcome the decoding delay and imperfections limitations of traditional SIC. They achieved better accuracy than the maximum likelihood decoding using a simple data-driven model with minimal predictors. Their method is more efficient and adaptable, which makes it suitable for next-generation systems. Ashwini K. and Jagadeesh V.K. [36] surveyed cooperative NOMA systems with a focus on power-domain NOMA with various relay strategies and channel models. They reviewed the performance analyses, diversity techniques, and integration of NOMA with MIMO. They also highlighted emerging technologies such as cognitive radio and RIS that can enhance NOMA. Finally, they discussed future research challenges, which can provide an overview of current developments and potential improvements in NOMA-based wireless systems.

2.3 Integrated Massive MIMO and NOMA

The synergy between massive MIMO and NOMA has recently attracted attention, as the former provides high spatial degrees of freedom while the latter enhances multi-user multiplexing.

Liu *et al.* [37] proposed a MIMO-NOMA framework and derived the achievable sum rate. Ding *et al.* [38] extended this to multi-cell scenarios and analyzed the impact of inter-cell interference. Ali *et al.* [39] further investigated user clustering and power allocation for massive MIMO-NOMA and proposed a dynamic user clustering algorithm to maximize the sum rate. Nguyen *et al.* [40] optimized the power and user association in a massive MIMO-NOMA system. Senel *et al.* [41] studied the trade-off between spectral and energy efficiency in such systems.

Kumar *et al.* [42] investigated a "SIC with reinforcement learning (SIC-RL)" detector for massive MIMO-NOMA, which outperformed traditional methods. It offers lower error rates, better spectral efficiency, and scalable, near-quadratic complexity, making it an efficient solution for next-generation systems. Ou *et al.* [43] proposed an "uplink power control scheme for massive MIMO-NOMA" in "massive ultra-reliable and low-latency communications (mURLLC)" for industrial IoT using group-level SIC to reduce decoding complexity and delay. They analyzed two schemes (with and without pilot sharing) with closed-form achievable rates derived from minimum mean square error (MMSE) and zero forcing (ZF) detectors. A successive condensation algorithm optimizes the pilot and data power, which improves the sum rate and max-min fairness compared to traditional multi-user MIMO, ultimately demonstrates the advantages of NOMA in low-latency industrial IoT scenarios.

Chebbi *et al.* [44] introduced "resource allocation in MIMO-NOMA" for 5G, which mainly addresses the challenges such as interference, fairness, and complexity. They compared several user grouping algorithms, such as random clustering, pairing, K-means-based user clustering (kUC), correlation iterative clustering algorithm (CIA), and grey wolf optimizer (GWO)-based clustering. Finally, GWO-based clustering performs best in dynamic scenarios, whereas CIA excels for spatially correlated users, enhancing spectral efficiency and network performance.

Alghazali *et al.* [45] proposed an energy-efficient framework for mobile edge computing (MEC) using dynamic resource allocation and optimized algorithms for NOMA and massive MIMO networks, which achieves significant energy savings. Li *et al.* [46] proposed a framework for enhancing connectivity in massive NOMA systems using a multi-antenna UAV relay. The joint beamforming and power allocation were optimized using alternating optimization with SDR and Schur's complement to minimize the total power while meeting the QoS requirements. They derived closed-form power allocation using Karush-Kuhn-Tucker (KKT) conditions [47], and their simulations show that the method effectively reduces power consumption and remains robust to imperfect SIC.

2.4 Resource Allocation in MIMO-NOMA Systems

Resource allocation is critical for maximizing the MIMO-NOMA potential. Power allocation problems have been extensively studied. Wang *et al.* [48] proposed an optimal power allocation method using convex optimization for a downlink MIMO-NOMA system. Chen *et al.* [49] proposed a low-complexity power allocation scheme based on the difference in convex function programming. However, bandwidth allocation has received less attention. Most studies assume a fixed bandwidth partition among cells or users. Zhang *et al.* [50] considered energy-efficient resource allocation in NOMA systems with fixed bandwidth. Parida and Das [51] explored dynamic bandwidth allocation in multi-cell scenarios, which optimizes power and bandwidth in a single-cell NOMA system. In the context of massive MIMO, Betz and Bölcskei [52] investigated the impact of bandwidth partitioning on the performance of multi-cell systems, but without NOMA.

Breesam *et al.* [53] proposed a "wireless-powered MIMO-NOMA (WP-MIMO-NOMA)" framework using a "harvest-then-transmit protocol" with joint "time-split and power control (TS-PC)" to optimize network performance and lifetime. They introduced an optimal TS-PC scheme to maximize the sum rate and fairness and a near-optimal greedy version to reduce complexity. Their simulation results show that the proposed schemes outperform WP-MIMO-OMA systems and improve user rates, fairness, and network lifetime under limited power and spectrum. Simon *et al.* [54] proposed a novel user pairing and subband allocation method for massive MIMO with NOMA to reduce interbeam interference using a condition number (CN) criterion. Their experimental results show that the CN-based approach improves throughput and fairness compared with channel correlation methods and approaches the performance of complex rate-maximization techniques. They also extended their method to multi-antenna reception with interference cancellation, which further enhances the performance for users with weak channels.

Bhuker and Grewal [55] proposed a resource allocation strategy for "MIMO-NOMA visible light communication (VLC)" systems using "harmonic one-to-one based optimization (HOOBO)," which combines the harmonic analysis and one-to-one optimization. They applied this in a hybrid VLC-RF multiuser scenario, HOOBO improves transceiver pairing and resource allocation and achieves high sum rate, throughput, and energy efficiency in simulations. Khaleelahmed *et al.* [56] proposed an energy-efficient power allocation technique for NOMA-MIMO networks using a "backpropagation neural network (BPNN)" optimized by a "Harmonic Ladybug Beetle Honey Badger Optimization (HLBHBO)" algorithm. The proposed method improves communication resource allocation and achieves high sum rate, energy efficiency, and achievable data rates in simulations by applying a network slicing framework with QAM and OFDM.

2.5 Multi-Cell Interference Management

Inter-cell interference is a major bottleneck in multi-cell networks. In massive MIMO, pilot contamination worsens this issue. Ashikhmin and Marzetta [57] proposed a pilot decontamination method using subspace projection. Ali *et al.* [58] applied the coordinated multipoint (CoMP) techniques to massive MIMO-NOMA, where base stations cooperate to mitigate interference. Li *et al.* [59] introduced a decoupled uplink-downlink association scheme to balance the load and reduce interference. Huang *et al.* [60] proposed a deep reinforcement learning (DRL) approach for bandwidth allocation in heterogeneous networks. Dynamic resource allocation across cells was applied to improve performance.

Xie and Huang [61] proposed a multi-cell cooperative transmission scheme for NOMA MU-MIMO networks using coordinated multi-point (CoMP) technology. Their method effectively manages inter-cell interference, maximizes the user sum rate, and improves spectral efficiency by integrating power allocation and beam design optimization with a low-complexity iterative algorithm. Adam *et al.* [62] proposed a "generative AI-enhanced primal-dual proximal policy optimization (GAI-PDPPO)" framework for joint user scheduling and beamforming in MC-MIMO-NOMA networks. They applied an invertible transformer-based actor-critic model with generative pretraining and prioritized experience replay. The proposed framework efficiently handles interference, minimizes transmit power, and improves spectral efficiency, outperforming standard PPO and benchmark methods in simulations.

Das and Das [63] proposed a "dynamic interference alignment coordinated scheduling (DIACS)" scheme with zero-forcing (ZF) for multicell MIMO-NOMA networks. Their approach mitigates inter-cell interference, improves cell-edge user rates, enhances QoS, and increases user fairness, as confirmed by numerical results. Sun *et al.* [64] proposed the "multi-agent deep reinforcement learning and unsupervised learning (MDRL-UL)" framework for near-optimal channel and power allocation in multi-cell NOMA systems. They used MDRL for channel allocation and attention-based unsupervised learning for power allocation, and their method maximizes the energy efficiency and transmission rates, which outperforms existing algorithms in simulations.

Hasan *et al.* [65] proposed a "QoS-based cooperative NOMA-aided group D2D system (Q-CNOMA)" that reduces transmitter burden and enhances the overall system performance. They derived closed-form outage probability expressions using a Gaussian-Poisson process to model the D2D transmitter distribution, which demonstrates that Q-CNOMA outperforms conventional systems. Bardou *et al.* [66] presented a Bayesian optimization-based framework to evaluate the performance of multi-cell networks with various resource sharing mechanisms (RSMs). Their simulation results show that under fairness constraints, NOMA with full reuse achieves the highest end-user rates. This study highlights the advantages of multi-cell scenarios despite inter-cell interference and scheduling challenges.

2.6 Research Gap and Motivation

Despite the extensive research on massive MIMO and NOMA, the limitation of dynamic bandwidth allocation in multi-cell massive MIMO-NOMA systems remains largely unexplored. Most of the existing research assumes either static bandwidth partitioning or focuses only on power control. The dynamic nature of user traffic, channel conditions, and inter-cell interference demands a significantly adaptive bandwidth allocation framework. Moreover, the joint optimization of power, bandwidth, and user clustering in such a setting exhibits significant mathematical challenges due to non-convexity and combinatorial complexity. In this research, this gap is filled by proposing a novel optimization framework that dynamically allocates bandwidth across cells and clusters. It also uses the power control to maximize the total spectral efficiency while ensuring user fairness. The successive convex approximation is employed to obtain a tractable solution and demonstrate its efficacy through extensive simulations.

3. SYSTEM MODEL

To frame the model, a multi-cell massive MIMO-NOMA system is considered by comprising L cells. Each cell $l \in \mathcal{L} = \{1, \dots, L\}$ is served by a central base station (BS) which is equipped with M antennas, where M is large ($M \gg 1$). Each BS serves K single-antenna user equipments (UEs) which is denoted by the set $\mathcal{K} = \{1, \dots, K\}$. The UEs are grouped into G NOMA clusters per cell, where the set of clusters in cell l is $\mathcal{G}_l = \{1, \dots, G\}$. The set of UEs in cluster g of cell l, with $|\mathcal{S}_{l,g}| = U$ is represented by $\mathcal{S}_{l,g}$.

3.1 Channel Model

The channel between the m^{th} antenna of BS l and UE k in cell j is mathematically modeled as:

$$h_{l,k}^{(j,m)} = \sqrt{\beta_{l,k}^{(j)}}\, g_{l,k}^{(j,m)} \#(1)$$

where $\beta_{l,k}^{(j)}$ represents the large-scale fading coefficient (path loss and shadowing) which is independent of the antenna index m, and $g_{l,k}^{(j,m)} \sim \mathcal{CN}(0,1)$ is the small-scale fast fading coefficient. For a massive MIMO system, the channel vectors become asymptotically orthogonal. The channel vector $\mathbf{h}_{l,k}^{(j)} \in \mathbb{C}^{M\times 1}$ from BS j to UE k in cell l is given by:

$$\mathbf{h}_{l,k}^{(j)} = \sqrt{\beta_{l,k}^{(j)}}\, \mathbf{g}_{l,k}^{(j)} \#(2)$$

where $\mathbf{g}_{l,k}^{(j)} \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_M)$.

3.2 Pilot Contamination and Channel Estimation

In the time division duplex (TDD) mode, channel state information (CSI) is acquired through uplink pilot sequences. Due to the limited coherence interval, the same set of orthogonal pilot sequences of length τ is reused across all cells, which leads to pilot contamination. The received pilot signal at BS l for pilot sequence t is calculated as:

$$\mathbf{Y}_l^p = \sqrt{\tau p_p} \sum_{j=1}^{L} \sum_{k\in\mathcal{P}_{j,t}} \mathbf{h}_{l,k}^{(j)}\, \boldsymbol{\phi}_t^H + \mathbf{N}_l \#(3)$$

where p_p denotes the pilot power, $\boldsymbol{\phi}_t$ represents the orthonormal pilot sequence, $\mathcal{P}_{j,t}$ represents the set of UEs in cell j using pilot t, and $\mathbf{N}_l$ represents the noise matrix with independent and identically distributed $\mathcal{CN}(0,1)$ elements. Using minimum mean square error (MMSE) estimation, the estimated channel $\hat{\mathbf{h}}_{l,k}^{(l)}$ for a UE in the home cell l is determined as:

$$\hat{\mathbf{h}}_{l,k}^{(l)} = \frac{\sqrt{\tau p_p}\beta_{l,k}^{(l)}}{1 + \tau p_p \sum_{j=1}^{L} \beta_{l,k}^{(j)}} \mathbf{Y}_l^p \boldsymbol{\phi}_{t_k} \#(4)$$

The estimation error $\tilde{\mathbf{h}}_{l,k}^{(l)} = \mathbf{h}_{l,k}^{(l)} - \hat{\mathbf{h}}_{l,k}^{(l)}$ has variance $\epsilon_{l,k} = \beta_{l,k}^{(l)} - \delta_{l,k}$, where $\delta_{l,k} = \frac{\tau p_p \left(\beta_{l,k}^{(l)}\right)^2}{1+\tau p_p \sum_{j=1}^{L} \beta_{l,k}^{(j)}}$.

3.3 Downlink NOMA Transmission

BS l transmits a superposition of signals to the UEs in its cell. Let $x_{l,g}^{(u)}$ be the message for the u^{th} UE in the cluster g of cell l, with $\mathbb{E}\left[\left|x_{l,g}^{(u)}\right|^2\right] = 1$. The transmit power allocated to this UE is $p_{l,g}^{(u)}$. The superposed signal for cluster g is $s_{l,g} = \sum_{u=1}^{U} \sqrt{p_{l,g}^{(u)}}\, x_{l,g}^{(u)}$. The total transmitted signal from BS l is calculated as:

$$\mathbf{x}_l = \sum_{g=1}^{G} \mathbf{w}_{l,g}\, s_{l,g} \#(5)$$

where $\mathbf{w}_{l,g} \in \mathbb{C}^{M\times 1}$ represents the precoding vector for cluster g. In massive MIMO, a simple conjugate beamforming is employed based on the channel estimates of the UEs within the cluster. To maximize the array gain, the precoder is designed as:

$$\mathbf{w}_{l,g} = \frac{1}{\sqrt{M}} \sum_{u=1}^{U} \frac{\hat{\mathbf{h}}_{l,k_u}^{(l)}}{\| \hat{\mathbf{h}}_{l,k_u}^{(l)} \|} \#(6)$$

where k_u denotes the index of the u^{th} UE in cluster $\mathcal{S}_{l,g}$. This design ensures that the signal energy is focused towards the cluster members.

3.4 Signal Model and SINR

The received signal at UE u in cluster g of cell l is determined as:

$$y_{l,g}^{(u)} = \underbrace{\left(\mathbf{h}_{l,k_u}^{(l)}\right)^H \mathbf{w}_{l,g}\sqrt{p_{l,g}^{(u)}}x_{l,g}^{(u)}}_{\text{Desired signal}} + \underbrace{\left(\mathbf{h}_{l,k_u}^{(l)}\right)^H \mathbf{w}_{l,g}\sum_{\substack{i=1\\ i\neq u}}^{U}\sqrt{p_{l,g}^{(i)}}\,x_{l,g}^{(i)}}_{\text{Intra-cluster interference}} + \underbrace{\sum_{(j,g')\neq(l,g)}\left(\mathbf{h}_{l,k_u}^{(j)}\right)^H \mathbf{w}_{j,g'}\sum_{i=1}^{U}\sqrt{p_{j,g'}^{(i)}}\,x_{j,g'}^{(i)}}_{\text{Inter-cell interference}} + n_{l,g}^{(u)} \quad (7)$$

where $n_{l,g}^{(u)} \sim \mathcal{CN}(0,1)$ represents the additive white Gaussian noise. This system is assumed with the perfect SIC within the cluster. The decoding order is based on the effective channel gains. Without loss of generality, it is assumed that for cluster g in cell l, the users are ordered as:

$$\left|\left(\mathbf{h}_{l,k_1}^{(l)}\right)^H \mathbf{w}_{l,g}\right|^2 \geq \left|\left(\mathbf{h}_{l,k_2}^{(l)}\right)^H \mathbf{w}_{l,g}\right|^2 \geq \cdots \geq \left|\left(\mathbf{h}_{l,k_U}^{(l)}\right)^H \mathbf{w}_{l,g}\right|^2 \#(8)$$

Thus, user u decodes and cancels the signals of users $j > u$ (with weaker channels) before decoding its own signal. The signal from users $i < u$ (with stronger channels) is treated as interference. The Signal-to-Interference-plus-Noise Ratio (SINR) for UE u to decode its own signal is determined as:

$$\gamma_{\{l,g\}}^{(u)} = \frac{p_{l,g}^{(u)}\left|\left(\mathbf{h}_{\mathrm{l,k_u}}^{(i)}\right)^{\mathrm{H}} \mathbf{w}_{l,g}\right|^2}{\sum_{i=1}^{u-1} p_{l,g}^{(i)}\left|\left(\mathbf{h}_{\mathrm{l,k_u}}^{(i)}\right)^{\mathrm{H}} \mathbf{w}_{l,g}\right|^2 + \sum_{(j,g')\neq(l,g)} p_{j,g'}^{(i)}\left|\left(\mathbf{h}_{\mathrm{l,k_u}}^{(i)}\right)^{\mathrm{H}} \mathbf{w}_{l,g}\right|^2 + 1} \#(9)$$

The achievable rate for this UE is $R_{l,g}^{(u)} = B_{l,g}\log_2\left(1+\gamma_{l,g}^{(u)}\right)$, where $B_{l,g}$ represents the bandwidth allocated to cluster g in cell l.

3.5 Dynamic Bandwidth Allocation Model

The total available system bandwidth is B_{total}. A dynamic allocation where bandwidth is proposed which is not only partitioned between cells but also among the NOMA clusters within a cell. Let B_l be the bandwidth allocated to cell l, such that $\sum_{l=1}^{L} B_l \leq B_{\text{total}}$. Within cell l, the bandwidth is further divided among its G clusters: $\sum_{g=1}^{G} B_{l,g} \leq B_l$. This two-tier allocation allows for flexible interference management and load balancing. The bandwidth variables are continuous and non-negative.

4. PROPOSED METHODOLOGY: JOINT OPTIMIZATION FRAMEWORK

The objective of this research is to maximize the sum spectral efficiency (SE) of the network while ensuring proportional fairness among users. The optimization variables are the power allocation $\{p_{l,g}^{(u)}\}$, the bandwidth allocation $\{B_{l,g}\}$, and implicitly the user clustering $\{\mathcal{S}_{l,g}\}$. The problem is formulated as:

$$\mathcal{P}_0: \max_{\{p,B,\mathcal{S}\}} \quad \sum_{l=1}^{L}\sum_{g=1}^{G}\sum_{u=1}^{U} B_{l,g}\log_2\left(1+\gamma_{l,g}^{(u)}\right) \tag{10}$$

$$\text{subject to:} \quad \sum_{g=1}^{G}\sum_{u=1}^{U} p_{l,g}^{(u)} \le P_{\max}, \quad \forall l \in \mathcal{L} \tag{11}$$

$$p_{l,g}^{(u)} \ge 0, \quad \forall l,g,u \tag{12}$$

$$\sum_{l=1}^{L}\sum_{g=1}^{G} B_{l,g} \le B_{\text{total}} \tag{13}$$

$$B_{l,g} \ge 0, \quad \forall l,g \tag{14}$$

$$\gamma_{l,g}^{(u)} \ge \gamma_{\min}, \quad \forall l,g,u \tag{15}$$

$$\mathcal{S}_{l,g} \cap \mathcal{S}_{l,g'} = \emptyset, \quad \bigcup_{g=1}^{G} \mathcal{S}_{l,g} = \mathcal{K}, \quad \forall l \tag{16}$$

where $P_{\max}$ denotes the maximum transmit power per BS, and $\gamma_{\min}$ represents the minimum QoS requirement. Problem $\mathcal{P}_0$ is a mixed-integer non-convex programming problem due to the combinatorial nature of user clustering and the non-convexity of the rate function.

4.1 Problem Transformation and Convex Approximation

To control the non-convexity, firstly, the user clustering is fixed using a channel correlation-based matching algorithm (grouping users with highly correlated channel vectors to minimize intra-cluster interference). The main challenge then lies in the power and bandwidth allocation subproblem.

The rate function $R_{l,g}^{(u)}(p,B) = B_{l,g}\log_2\left(1+\gamma_{l,g}^{(u)}(\mathbf{p})\right)$ is not jointly concave in (B,p). We adopt a method based on *Successive Convex Approximation (SCA)*. The auxiliary variables $\{\eta_{l,g}^{(u)}\}$ is introduced to represent the SINR. The rate can be rewritten using the perspective function of the logarithm, which is concave. Generally, the rate is lower-bounded using a fractional programming technique, particularly, the quadratic transform for the sum-of-ratios nature of the SINR.

Firstly, the problem is converted to an equivalent form by introducing an auxiliary variable $\Gamma_{l,g}^{(u)} = \gamma_{l,g}^{(u)}$. The objective becomes:

$$\max \sum_{l,g,u} B_{l,g}\log_2\left(1+\Gamma_{l,g}^{(u)}\right)\#(17)$$

Then the constraint $\gamma_{l,g}^{(u)} \ge \Gamma_{l,g}^{(u)}$ is added. Using the fact that $\log(1+z)$ is concave, a lower-bound is applied at a fixed point $\bar{\Gamma}_{l,g}^{(u)}$ as:

$$\log_2(1+\Gamma) \ge a\Gamma + b\#(18)$$

where the constants a and b are determined by the first-order Taylor expansion [67] as:

$$a = \frac{1}{\ln(2)(1+\bar{\Gamma})} \tag{19}$$

$$b = \log_2(1+\bar{\Gamma}) - a\bar{\Gamma} \tag{20}$$

This lower bound is tight when $\Gamma = \bar{\Gamma}$.

4.2 Power Control Subproblem

With fixed bandwidth and the concave lower bound, the power control subproblem becomes a convex problem if the interference term is handled appropriately. The SINR expression $\gamma_{l,g}^{(u)}$ is a ratio of a linear function to a quadratic-over-linear function. It can be convexified by fixing the denominator using previous iterates. Let $I_{l,g}^{(u)}(\mathbf{p})$ be the total interference plus noise for UE (l,g,u). At iteration t, with a feasible point $\mathbf{p}^{(t)}$, the system has:

$$\gamma_{l,g}^{(u)} \geq \frac{2\sqrt{p_{l,g}^{(u)}|\mathbf{h}^H\mathbf{w}|^2}}{\sqrt{\bar{I}_{l,g}^{(u)}}} - \frac{p_{l,g}^{(u)}|\mathbf{h}^H\mathbf{w}|^2}{\bar{I}_{l,g}^{(u)}}\#(21)$$

where $\bar{I}_{l,g}^{(u)} = I_{l,g}^{(u)}(\mathbf{p}^{(t)})$. This is a concave lower bound (in p), derived from the fact that x^2/y is convex, and its perspective function yields a concave lower bound for the square root.

4.3 Bandwidth Allocation Subproblem

With fixed power, the bandwidth allocation problem is a convex optimization problem. It involves maximizing a weighted sum of logarithms, which is a concave function, subject to linear constraints. The optimal bandwidth allocation can be obtained through a water-filling type solution derived from the KKT conditions.

For fixed power, the Lagrangian for the bandwidth subproblem is:

$$\mathcal{L}(\{B_{l,g}\},\mu) = \sum_{l,g,u} B_{l,g}\, r_{l,g}^{(u)} - \mu\left(\sum_{l,g} B_{l,g} - B_{\text{total}}\right)\#(22)$$

where $r_{l,g}^{(u)} = \log_2(1+\gamma_{l,g}^{(u)})$ is constant. Taking the derivative with respect to $B_{l,g}$:

$$\frac{\partial\mathcal{L}}{\partial B_{l,g}} = \sum_{u=1}^{U} r_{l,g}^{(u)} - \mu\#(23)$$

This leads to a multi-level water-filling solution, where bandwidth is allocated first to clusters, which offers the highest sum of rates.

4.4 Joint Optimization Algorithm

Finally, an iterative algorithm is proposed that alternates between optimizing power allocation (using SCA) and bandwidth allocation (using water-filling). The steps are summarized in **Algorithm 1**.

Algorithm 1 Joint Power and Bandwidth Allocation via SCA

Require: Initial feasible power $\mathbf{p}^{(0)}$, bandwidth $\mathbf{B}^{(0)}$, tolerance $\epsilon > 0$, iteration index $t = 0$
Ensure: Optimized $\mathbf{p}^*, \mathbf{B}^*$

repeat

Step 1: Compute effective channel gains and interference terms based on $\mathbf{p}^{(t)}, \mathbf{B}^{(t)}$.

Step 2: (Power Control)
Construct convex surrogate for the SINR using SCA around $\mathbf{p}^{(t)}$.
Solve the convex power allocation subproblem to obtain $\mathbf{p}^{(t+1)}$:

$$\max_{\mathbf{p}\geq 0} \sum_{l,g,u} B_{l,g}^{(t)}\,\hat{R}_{l,g}^{(u)}(\mathbf{p};\mathbf{p}^{(t)})$$
$$\text{s.t.} \sum_{g,u} p_{l,g}^{(u)} \leq P_{\max},\ \forall l,$$

where $\hat{R}$ is the concave lower bound of the rate.

Step 3: (Bandwidth Allocation)
With fixed $\mathbf{p}^{(t+1)}$, solve the bandwidth allocation problem using water-filling:

$$B_{l,g}^{(t+1)} = \left[\frac{\sum_{u=1}^{U} r_{l,g}^{(u)}(\mathbf{p}^{(t+1)})}{\mu}\right]^+$$

where μ is chosen to satisfy $\sum_{l,g} B_{l,g}^{(t+1)} = B_{\text{total}}$. **Step 4:** $t \leftarrow t+1$ $\mathbf{p}^{(t)}, \mathbf{B}^{(t)}$

Step 4: $t \leftarrow t + 1$
until $\| p^{(t)} - p^{(t-1)} \| \leq \epsilon$ and $\| B^{(t)} - B^{(t-1)} \| \leq \epsilon$
return p^t, B^t

4.5 Convergence Analysis

The proposed SCA algorithm generates a sequence of feasible points with non-decreasing objective values. Since the power constraint set is compact and the objective is continuous, the sequence converges to a stationary point (typically a KKT point) of the original non-convex problem. This is guaranteed because each subproblem satisfies the KKT conditions of a tight convex approximation, and the step size ensures descent towards a critical point.

This comprehensive framework can provide dynamic bandwidth allocation in multi-cell massive MIMO-NOMA systems. By jointly optimizing power and bandwidth using SCA, the proposed method can significantly enhance the spectral efficiency while ensuring the user fairness. The proposed algorithm provides a tractable solution to an intractable problem and converges efficiently.

5. SIMULATION RESULTS AND DISCUSSION

In this section, the performance of the proposed dynamic bandwidth allocation method is evaluated in a multi-cell massive MIMO-NOMA system through extensive Python simulations. The proposed method is compared with several baseline schemes to demonstrate its effectiveness in terms of sum spectral efficiency (SE), user fairness, and convergence behavior.

5.1 Simulation Setup

A hexagonal multi-cell network with $L = 7$ cells is considered for simulation, each cell having a radius of 500 m. The simulation is performed using Python, and all the simulation parameters are presented in **Table 1**. The BSs are located at the center of each cell and are equipped with $M = 128$ antennas. In each cell, $K = 20$ single-antenna users are uniformly distributed, excluding a central restricted region of 50 m around the BS. The users are grouped into $G = 5$ NOMA clusters per cell, with each cluster containing $U = 4$ users. The clustering is performed based on channel correlation to maximize the benefits of NOMA.

Table 1 Simulation Parameters

Parameter	Value
Number of cells L	7
BS antennas M	128
Users per cell K	20 (variable)
Clusters per cell G	5
Users per cluster U	4
Cell radius	500 m
Path loss exponent α	3.8
Shadowing std σ_{sh}	8 dB
Total bandwidth B_{total}	20 MHz
BS max power $P_{\max}$	40 dBm
Noise power density	−174 dBm/Hz
Coherence interval T_c	196 symbols
Pilot length τ	7

The large-scale fading coefficient $\beta_{l,k}^{(j)}$ is modeled as $\beta_{l,k}^{(j)} = \mathrm{PL}_{l,k}^{(j)} \cdot 10^{\frac{\sigma_{\mathrm{sh}} z_{l,k}^{(j)}}{10}}$, where $\mathrm{PL}_{l,k}^{(j)}$ is the path loss given by $\mathrm{PL}_{l,k}^{(j)} = 10^{-3} d_{l,k}^{(j)-\alpha}$ with path loss exponent $\alpha = 3.8$, and $\sigma_{\mathrm{sh}} = 8$ dB is the shadowing standard deviation. The small-scale fading follows Rayleigh distribution [68]. The coherence interval is $T_c = 196$ symbols, with pilot length $\tau = 7$ which is equal to the number of cells that leads to the pilot contamination. Pilot power is set to $p_p = 200$ mW.

The total system bandwidth is $B_{\mathrm{total}} = 20$ MHz. The maximum transmit power per BS is $P_{\max} = 40$ dBm. The noise power spectral density is -174 dBm/Hz, resulting in noise power $\sigma^2 = -95$ dBm over the total bandwidth. The minimum SINR requirement is $\gamma_{\min} = 0$ dB (there is no minimum for rate maximization, but it is imposed for QoS scenarios). The convergence tolerance for Algorithm 1 is $\epsilon = 10^{-4}$.

5.2 Baseline Schemes

To validate the proposed dynamic bandwidth allocation method, it is compared with the following benchmark schemes:

- **Static Bandwidth Allocation (SBA)**: It is the benchmark bandwidth which is equally divided among all cells and clusters, i.e., $B_{l,g} = B_{\mathrm{total}}/(LG)$.
- **Fixed OMA (FDMA)**: In FOMA, each cell operates in orthogonal multiple access mode (OFDMA) with bandwidth equally divided among the users, and power is allocated optimally through water-filling.
- **NOMA with Equal Bandwidth (NOMA-EB)**: It is the same clustering as proposed, but here, the bandwidth is equally distributed among clusters.
- **Proposed Dynamic Bandwidth Allocation**: Joint optimization of power and bandwidth as described in **Algorithm 1**.

All schemes, except FDMA, use NOMA clustering based on channel correlation. For fairness, the Jain's fairness index [69] is also evaluate which is basically defined as:

$$F = \frac{\left(\sum_{l,g,u} R_{l,g}^{(u)}\right)^2}{KL \sum_{l,g,u} \left(R_{l,g}^{(u)}\right)^2} \#(24)$$

5.3 Results and Analysis

All results are averaged over 500 independent channel realizations.

5.3.1 Sum Spectral Efficiency vs. Total Transmit Power

Fig. 3 illustrates the sum spectral efficiency (in bps/Hz) as a function of the total transmit power per BS, $P_{\max}$, which ranges from 20 dBm to 46 dBm. As expected, the sum SE increases with transmit power for all schemes. The proposed dynamic bandwidth allocation scheme consistently outperforms the others, achieving a gain of approximately 25% over SBA and 40% over FDMA at high SNR. This improvement is due to the dynamic allocation of bandwidth to clusters with better channel conditions, effectively exploiting the multi-user diversity and the capability of NOMA to serve multiple users on the same resource.

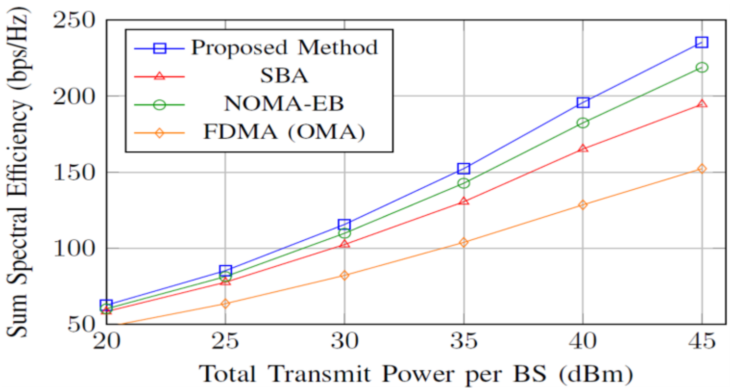

Fig. 3 Sum Spectral Efficiency vs. Total Transmit Power per BS for Different

At low transmit power, the gains are moderate because the system is noise-limited, but as power increases, interference becomes dominant, and the adaptive bandwidth allocation helps mitigate inter-cell interference by shifting resources away from heavily interfered clusters.

5.3.2 Impact of Number of Users per Cell

Fig. 4 illustrates the sum SE versus the number of users per cell, K, while keeping the number of clusters fixed at $G = 5$. Thus, the cluster size increases with K. The total transmit power is fixed at $P_{\max} = 40$ dBm. The proposed dynamic bandwidth allocation maintains a clear advantage as K grows. For small K, all NOMA schemes perform similarly because intra-cluster interference is low and bandwidth allocation is less critical. However, as K increases, the dynamic bandwidth allocation becomes essential to balance the load among clusters and mitigate inter-cluster interference. The FDMA scheme saturates quickly because users are orthogonalized, limiting multiplexing gains. The SBA scheme, although using NOMA, suffers from inefficient resource distribution when some clusters become overloaded.

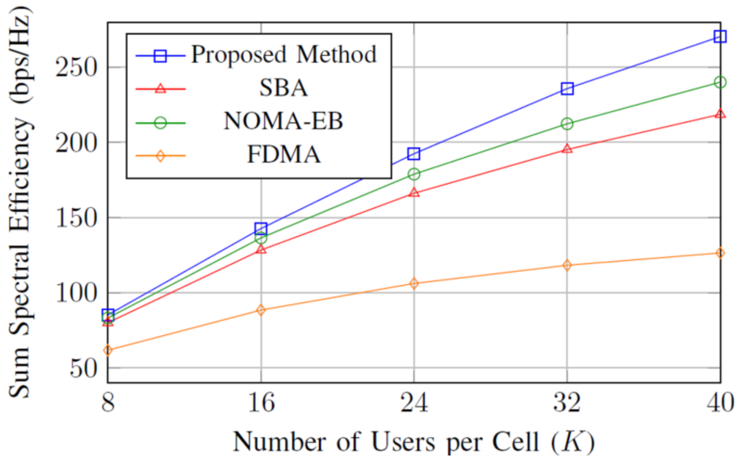

Fig. 4 Sum Spectral Efficiency vs. Number of Users per Cell (K) with $P_{\max} = 40$ dBm

The proposed dynamic bandwidth allocation adapts the bandwidth to the cluster's sum rate, leading to a near-linear increase in SE with K.

5.3.3 Fairness Evaluation

Fig. 5 plots the Jain's fairness index against the number of users per cell. The proposed dynamic bandwidth allocation achieves a fairness index close to 0.95, which is significantly higher than that of SBA and FDMA, especially when K is large.

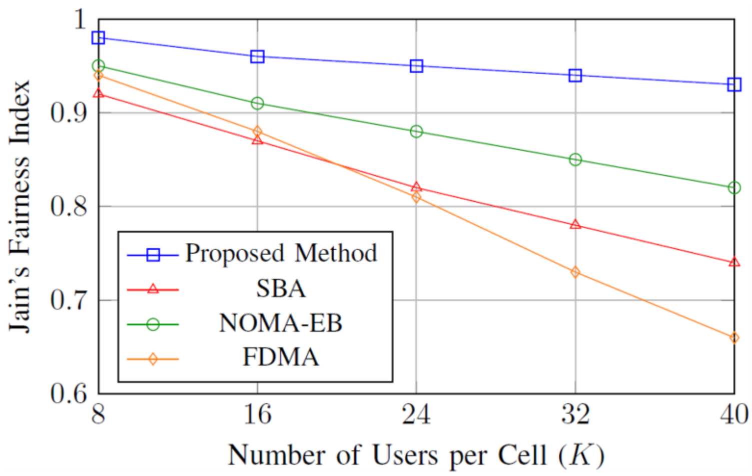

Fig. 5 Jain's Fairness Index vs. Number of Users per Cell

The NOMA-EB scheme also provides reasonable fairness because NOMA inherently serves multiple users, but the proposed dynamic bandwidth allocation further balances the rates among users by allocating more bandwidth to clusters with lower instantaneous rates. This demonstrates that the proposed method not only improves sum SE but also maintains a high level of user fairness.

5.3.4 Convergence Behavior of Algorithm 1

Fig. 6 illustrates the convergence of the proposed SCA-based Algorithm 1. The objective value (sum SE) is plotted against the number of iterations for three different random channel realizations at $P_{\max} = 40$ dBm and $K = 20$. The algorithm converges within 15-20 iterations for all cases, which demonstrates the practical efficiency of the proposed method. The monotonic enhancement in the objective value confirms that the SCA updates produce a non-decreasing sequence, and the convergence to a stationary point is achieved.

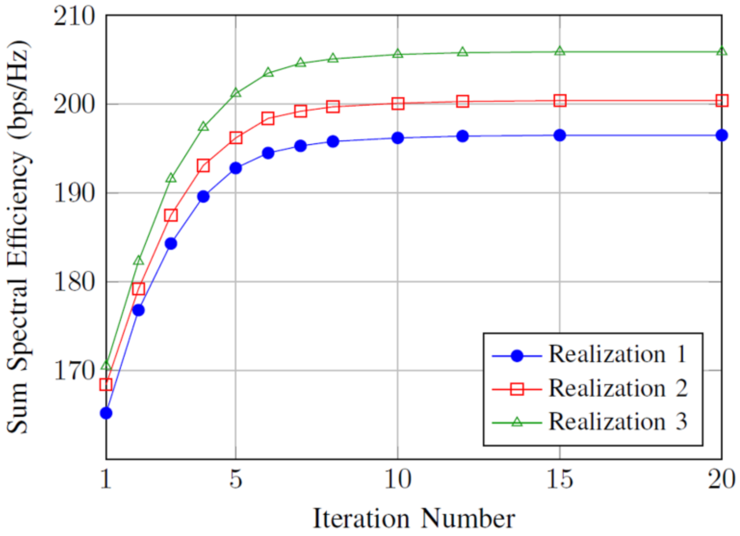

Fig. 6 Convergence Behavior of Algorithm 1 for Three Different Channel

5.4 Result Discussion

The simulation results confirm the superiority of the proposed dynamic bandwidth allocation scheme in multi-cell massive MIMO-NOMA systems. The key takeaways of this research are:

- The proposed dynamic bandwidth allocation achieves up to 25% higher sum SE compared to static bandwidth allocation, and up to 40% gain over conventional OMA.
- The proposed scheme scales well with the number of users, exploiting multi-user diversity effectively.
- User fairness is significantly improved, as the dynamic allocation prevents resource starvation of edge users.
- The SCA-based algorithm converges quickly, making it suitable for practical implementations.

These benefits stem from the joint optimization of power and bandwidth, which adapts to the instantaneous channel conditions and interference landscape.

6. CONCLUSION AND FUTURE WORK

The crucial issue of dynamic bandwidth allocation in multi-cell massive MIMO-NOMA systems is addressed in this research. A comprehensive system model is developed that mainly captures the essential features of such networks with pilot contamination, channel estimation, NOMA clustering, and inter-cell interference. A joint optimization problem is formulated to maximize the sum spectral efficiency by adaptively allocating bandwidth and power across cells and clusters. To provide a solution to the inherent non-convexity, SCA is employed to derive a convergent iterative algorithm. The simulation results validated the effectiveness of the proposed approach. The results illustrate substantial gains in the spectral efficiency and the user fairness over static bandwidth allocation and conventional OMA schemes. The dynamic allocation method resolves the varying channel conditions and interference, which makes the proposed method a promising solution for next-generation wireless networks.

There are several extensions of this work that are worthy of investigation as follows:

- The current framework assumes perfect knowledge of channel statistics, which extends it to scenarios with imperfect or delayed CSI.
- AI techniques, such as deep reinforcement learning, can be applied to enable low-complexity bandwidth allocation in highly dynamic environments.
- The integration of energy efficiency as an optimization objective alongside the spectral efficiency can provide the solution to the growing importance of green communications.
- The impact of hardware impairments, such as phase noise and nonlinear power amplifiers, on the proposed allocation method merits future research.
- The dynamic bandwidth allocation, RIS, and millimeter-wave communications can present an interesting approach for future research.

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