Stimulating the Efficiency of Massive MIMO Cooperative NOMA Applying RIS in 6G Networks

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Abstract: *This study analyses Spectral Efficiency (SE) and throughput under varying user densities (50 to 200 users), mobility velocities (0 to 250 km/h), latency, packet loss, and fairness index at diverse Signal-to-Noise Ratio (SNR) levels for different scenarios. These scenarios encompass comprehensive massive Multiple-Input Multiple-Output (mMIMO) cooperative Non-Orthogonal Multiple Access (NOMA), mMIMO cooperative NOMA integrated with Cognitive Radio (CR), and CR-enabled mMIMO cooperative NOMA facilitated by Reconfigurable Intelligent Surfaces (RIS) using millimetre-Wave (mmWave) in 6G networks. The study investigates the enhancement of latency, packet loss, and fairness indexes in the proposed systems through a unique approach that dynamically optimizes power distribution via a Q-learning algorithm. The mathematical clarification of each equation offers a comprehensive understanding of signal reception by users, the dynamics and implications of CR, and the influence of intelligent RIS optimization on system performance. The findings demonstrate that the incorporation of RIS enhances resource allocation, improves user performance in high-density settings, increases average throughput, reduces latency and packet loss, and raises the fairness index by mitigating interference and optimizing channel access, particularly when employing the proposed optimization algorithm. These results support the advancement of scalable and efficient communication networks in the realm of 6G technology.*

Keywords: *Cooperative NOMA, massive MIMO, CR, RIS, SE, millimeter-wave.*

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1. Introduction

Every generation of wireless networks, from 1G to 6G, has improved capacity and quality of service [3, 15, 21]. Building the 6G network requires complex coding, broader frequency bands, and new antenna technologies. In 2023, the 3rd Generation Partnership Project (3GPP) developed the 6th-generation mobile system. At the March 2024 3GPP meeting in Maastricht, the Netherlands, the 6G standardization timeline was announced. In 2024, 6G technology began setting release 19 requirements. The ITU will create technical performance standards and performance evaluation processes for International Mobile Telecommunications 2030 (IMT-2030) between 2024 and 2026 [7, 26, 35].

Reduced latency, higher throughput, wide connectivity, and energy and spectrum efficiency are key goals for 6G wireless networks. As intelligent gadgets and equipment become more common, data transmission has expanded significantly. Several TeraHertz (THz) and millimetre-Wave (mmWave) advances have been achieved to fulfil the expected high demand [31, 32, 54]. Technological issues such as coding procedures, frequency band optimization, and antenna technology must be addressed to launch the 6G network.

There are several multiple-access algorithms, notably Non-Orthogonal Multiple Access (NOMA). According to [1, 33], NOMA improves Spectral Efficiency (SE) and user throughput. Mobile device receivers suppress beam-induced interference via Successive Interference Cancellation (SIC). [19] NOMA integrates multiple users by classifying them based on their power or code. With more NOMA users, orthogonal resources become inaccessible [10, 11]. The advancement of NOMA is anticipated to address these difficulties. These systems efficiently accommodate a substantial number of users owing to their optimized architecture and reduced resource consumption [12]. A strong option that shows promise for improving data transfer in mmWave and THz communication systems is massive Multiple-Input Multiple-Output (mMIMO) NOMA [2, 16].

Cognitive Radio (CR) technology is a useful way to manage radio frequencies, allowing flexible connections that help solve capacity issues in conventional licensed wireless networks. Primarily, in CR-based networks, there are Primary Users (PUs) or authorized users and Secondary Users (SUs) or unauthorized users. The SUs aims to exploit any opportunities that arise while they contend with the PUs for licensed spectrum [8, 20]. Consequently, CR technology will be essential in the advancement of future wireless networks and in meeting their increasingly rapid demands [13].

A Reconfigurable Intelligent Surface (RIS) is capable of producing intelligent and efficient radio setups [30, 53]. Passive Reflecting Elements (RE) in RIS alter the phase and amplitude of incoming signals. Traditional reflection-only RIS systems cannot provide complete spatial communication. STAR-RIS, which uses RIS for simultaneous transmission and reflection, is a proposed solution [42].

Recent studies on mMIMO-NOMA in mmWave/THz networks have mostly ignored user grouping and focused instead on performance analysis. To meet the increased expectations for SE and multiple user connections in 6G, NOMA-enabled networks must also include organized user grouping. Moreover, user clustering in networks functioning in low-frequency bands has garnered considerable research attention, but mmWave/THz networks remain largely unexamined. Nonetheless, user pairing investigations within a MIMO-NOMA system are limited to a restricted number of users [40, 52]. Recent studies classify users as cellular or Device-to-Device (D2D) via a cluster-matching technique grounded in channel correlation [56]. This method converts user clustering into a polynomial problem. Despite its general simplicity, a hurdle in learning-assisted clustering systems is the insufficient initialization of cluster heads.

A compendium of Xu *et al*. [49] and Chen and Yu [9] previously examined the efficacy of the STAR-RIS-based system for simultaneous transmission and reflection in fading channels. The results indicate that STAR-RIS performs better than regular RIS in NOMA systems, especially for users at the cell edge who cannot connect to the Base Station (BS) directly. They demonstrated that when the signal is weak, the uneven resource distribution in STAR-RIS can help balance the power received from the BS, showing that NOMA with STAR-RIS still functions effectively even without a direct link between the BS and users. In areas with a high Signal-to-Noise Ratio (SNR), the impact of resource allocation is negligible. The authors performed a comprehensive examination of the efficacy of entire transmit power systems with STAR-RIS [18, 23]. Yue *et al*. [51] evaluated performance for both fault-free and non-fault-free cascade interference cancellation. Elhattab *et al*. [14] conducted a comparison between NOMA and OMA communication systems within the context of phase-shifted coupled STAR-RIS.

Many studies mention various cooperative NOMA designs that utilise RIS systems as a cost-effective solution for 6G wireless networks. The concept of employing cooperative NOMA resulted in a reduction of the overall transmit power. A study by Ren *et al*. [38] looked at how using RIS can improve the performance of users at the edge of a cell in a SWIPT NOMA system, where information is sent from a user in the center of the cell to a user at the edge. Liu *et al*. [28] proposed a two-step method using RIS to support cooperative NOMA networks with SWIPT, which could enhance the rate for strong users while still meeting the service needs of weak users.

The future of wireless networks is characterized by CR NOMA. Multiple networks can share a single frequency due to CR's sophisticated monitoring and decision-making, enhancing spectrum utilization [27]. NOMA improves connectivity, equity, and SE by allowing many users to share time, code, and frequency resources [29]. The ergodic capacity and Outage Probability (OP) were assessed from the fundamental critical path to evaluate the performance of the NOMA-enhanced network [5]. To promote the use of NOMA systems among users with equivalent transmission power, the creators of [25] enhanced uplink communication through the incorporation of active and passive RIS. The objective of formulating a hybrid user clustering and RIS allocation approach was to improve the implementation of the NOMA scheme and optimize the system's aggregate rate [50]. The effectiveness of the RIS-enhanced NOMA network was analyzed by Vu *et al*. [47], concentrating on energy efficiency in both delay-tolerant and delay-constrained modes. Wu and Zhang [48] developed a deep learning framework and assessed a RIS-assisted CR-NOMA system to forecast ergodic performance.

Most research currently focuses on beamforming designs that use RIS. While no CR-NOMA network system model [36] presently exists, passive beamforming on RIS is the preferred approach after some simplifications. Therefore, the optimization procedures differ from our work. Thus, the characteristic optimization problem presented by Huang *et al*. [22] remains relevant even when using analogue conventions. The approach discussed by Tin *et al*. [44] is quite different from ours because we focus on improving SE using the CR cooperative NOMA mMIMO network with Down-Link (DL) supported by intelligent RIS. The principal contributions encompass the following:

- The study presents a new method for integrating the mMIMO DL cooperative NOMA system for multiple users in a 6G mmWave communication environment, using CR and RIS.
- The effects of different mobility speeds on the performance of CR mMIMO DL cooperative NOMA networks are examined, considering both RIS-equipped and RIS-free scenarios.
- This work employs a Q-learning algorithm to enhance power distribution in a novel manner, enabling the system to learn and adapt power levels based on network conditions, thereby reducing

delays and packet loss while ensuring fairness.

2. Related Work

Song *et al*. [41] proposed a STAR-RIS-assisted NOMA system for mobile edge computing that employs hybrid deep reinforcement learning. Song *et al*. [41] research focuses on energy-efficient computing utilizing RIS and NOMA; however, it operates within static environments and lacks CR integration. Our method, by contrast, adapts in real time based on user mobility and incorporates spectrum sensing.

Tran *et al*. [45] examined energy-saving solutions for 6G networks by employing deep reinforcement learning to optimize antenna tilt and transmission power. The paper addresses potential energy management; however, it omits RIS, NOMA, and CR, which are central to our research.

Bai *et al*. [6] developed a multi-agent deep reinforcement learning framework incorporating self-attention for opportunistic spectrum access in CR networks. This research omits RIS and NOMA and does not consider cooperative learning-based resource management with respect to user mobility.

Umer *et al*. [46] proposed a method using reinforcement learning to manage resources in systems that use RIS and coordinated multi-point NOMA. It employs RL for NOMA and RIS within a coordinated multi-point context, although it does not consider CR or DL cooperative transmission.

Our study introduces a cohesive DL cooperative NOMA system, characterized by power control via Q-learning for real-time adaptation, distinguishing it from earlier research. It optimizes dynamic RIS phases in mobile environments, identifies cognitive spectrum for opportunistic access, and evaluates key performance metrics, including SE, latency, packet loss, and fairness. What makes this design unique is that it performs effectively in real 6G scenarios with diverse user types and varying mobility rates.

We contextualize our work by comparing our system to major recent advancements in RIS-NOMA and CR-based 6G systems. While our simulations utilize a bespoke model, Table 1 below outlines the principal characteristics of current research:

Table 1. Presents the principal characteristics of our work.

Study	Fundamental technologies	Reference scenario	Primary metric	Performance versus proposal system
Yue *et al*. [51]	STAR-RIS, NOMA	Delay-tolerant NOMA	Ergodic rate	In mobile environments, our system has a greater SE and a reduced latency.
Vu *et al*. [47]	DL-RIS, CR-NOMA	Static environment, deep learning	Ergodic performance prediction	Our technology demonstrates enhanced SE and reduced latency in mobile environments. Our system does real-time Q-learning-based adaptation, appropriate for dynamic networks.
Solaiman *et al*. [40]	mmWave, D2D NOMA	Clustered pairing, no RIS	SE, Power allocation	The system we use incorporates advanced RIS and CR technologies, resulting in enhanced user equity and throughput.
De Sena *et al*. [12]	mMIMO-NOMA	Fairness under imperfect SIC	Fairness index	The fairness scores under the RIS-Q-learning hybrid method exceed the baseline by around 10%.

3. Materials and Methods

The wireless network includes multiple groups of k users employing mMIMO DL cooperative NOMA, operating alongside CR integration and mmWave technology, as illustrated in Figure 1. Users are positioned at varying distances from the BS, resulting in a range of received power levels and utilizing 512-Quadrature Amplitude Modulation (QAM).

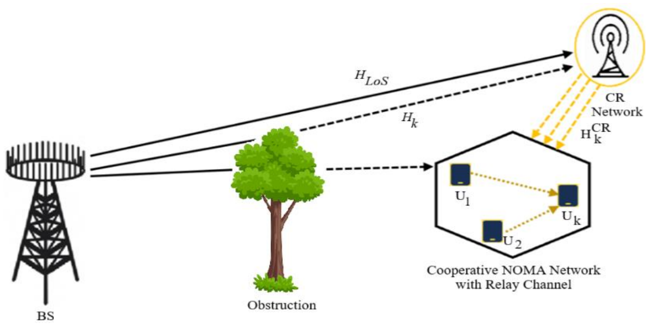


Figure 1. Displays mMIMO PD DL mMIMO cooperative NOMA with k users employing CR and mmWave technology.

In mMIMO, each BS possesses several antennas (M) and serves multiple users (N). mMIMO physically multiplexes many users and focuses energy into narrow beams directed at each user. For each user, the mMIMO channel manifests as a matrix exhibiting Rayleigh fading, resulting in the received signal comprising several distinct, scattered components. When modeling the BS (with M antennas) for user k channel, the $H_k \in \mathbb{C}^{M\times 1}$ channel vector connecting the BS to the *k-th* user [22].

$$H_k = [\, h_{k,1}, h_{k,2}, \dots, h_{k,M}\,]^T \tag{1}$$

where, k is the system user index. $h_{k,M}$ is the channel coefficient between the *kth* user and the *m-th* transmit antenna. M_T is the number of BS or transmit antennas.

The connection strength of the Rayleigh fading channel between the *m-th* antenna at the BS and the *k-th* user is represented by the complex Gaussian random variable $h_{k,m} \sim \mathcal{CN}(0, \beta k)$. User k perceives βk as large-scale route loss and shadowing.

$$y_k = H_k^H x + z_k \tag{2}$$

where x is the BS broadcast signal, $z_k \sim \mathcal{CN}(0, \sigma^2)$ is the AWGN with variance σ^2.

A method is used to check how busy a channel is by examining power levels, and the presence of PUs is identified using prior knowledge of their signal features, expressed mathematically as follows,

$$E = \sum_{n}^{N} = 1|\mathcal{Y}[n]|^2 \tag{3}$$

The receive signal $\mathcal{Y}[n]$, N samples.

The spectrum sensing decision rule is [34],

$$Decision = \begin{cases} H_0 & if\ E < \lambda(spectrum\ available) \\ H_1 & if\ E \geq \lambda(spectrum\ occupied)) \end{cases}$$

E is the signal energy and λ is the detection threshold.

The available bandwidth, B_{avail}, is determined as follows,

$$B_{avail} = B_{total} - B_{occupied} \tag{4}$$

$B_{occupied}$ represents the bandwidth utilized by PUs ascertained using spectrum sensing.

Channel conditions determine NOMA user power levels. The total power P_t is allocated among users based on their channel conditions.

$$P_k = P_t \cdot \frac{1}{k} \tag{5}$$

User index k (1st user has most power).

In cooperative NOMA, user k's received signal is,

$$y_k = H_k^H \sum_{n}^{k} = 1 \sqrt{P_k} x_k + z_k \tag{6}$$

x_k is the transmitted signal, P_k is the power (higher for poorer channel conditions), and z_k is noise at user k. SIC lets better channel users decode and delete weaker channel users' signals before decoding their own.

The SINR for k users as [10],

$$SINR_k = \frac{P_k . h_k}{\sum_{j=1, j\neq k}^{K} P_j . h_j + N_0} \tag{7}$$

For cooperative users, the SINR additionally accounts for relayed signals [12],

$$SINR_{coop} = SINR_k + \sum_{j=1}^{K-1} SINR_j \tag{8}$$

Calculate the k^{th} user's SE_k,

$$SE_k = \frac{B}{K} log_2 + (SINR_{coop}) \tag{9}$$

The diverse reflective elements of the intelligent RIS device can alter the phase of incoming electromagnetic waves, thereby improving communication quality, as shown in Figure 2.

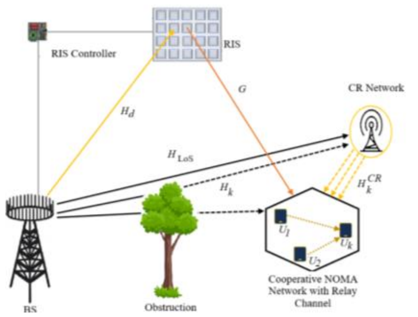


Figure 2. Illustrates mMIMO PD DL CR mMIMO cooperative NOMA with K users employing intelligent RIS and mmWave methodologies.

The RIS-assisted communication connection channel model is,

$$H_{RIS} = G\Theta H_d \tag{10}$$

The BS-RIS channel is represented by $H_d \in \mathbb{C}^{N_{RIS} \times M}$, whereas the RIS-user channel is $G \in \mathbb{C}^{N \times N_{RIS}}$. The diagonal matrix $\Theta = diag(e^{j\theta_1}, e^{j\theta_2}, \ldots, e^{j\theta_{N_{RIS}}})$ represents the phase shifts caused by the RIS elements.

The user k received this RIS signal [22],

$$\mathcal{Y}_k^{RIS} = \mathrm{H}_k^H x + \mathrm{g}_k^H \Theta H_d x + z_k \tag{11}$$

where g_k is the RIS-user channel.

$$SINR_{RIS} = \frac{P_k \cdot |H_{RIS}|^2}{I + N_0} \tag{12}$$

where I is user interference.

RIS signal intensity is greatly improved by optimizing phase shifts. Define the optimization problem,

$$\max_{\theta} |H_{RIS}|^2 \tag{13}$$

The user k's effective NOMA system with RIS channel is,

$$h_{eff,k} = H_k + g_k^H \Theta H_d \tag{14}$$

The SE for user k in a NOMA system with RIS [39] is,

$$SE_k = log_2\left(1 + \frac{P_k |h_{eff,k}|^2}{\sum_{i<k} P_i |h_{eff,i}|^2 + \sigma^2}\right) \tag{15}$$

Calculate throughput (T) as,

$$T = SE_{total} \times BW_{avail} \tag{16}$$

To calculate throughput with and without RIS, alter user density by changing the number of users k depending on area size A and density ρ, $K=\rho \times A$.

Thus, user density affects throughput [24],

$$T_{with/without\ RIS}(\rho) = \sum_{k=1}^{\rho \times A} SE_{with/without\ RIS,k} \tag{17}$$

Changes in distance and relative velocities alter channel conditions when users move randomly. Let, $p_k(t)=[x_k(t), \mathcal{Y}_k(t)]$ represent user k's position at time t. v_k represents user i's speed. θ_k represents user k's random movement direction. The position of user k at time $t+\Delta t$ is,

$$P_k(t + \Delta t) = P_k(t) + v_k \Delta t \cdot [cos(\theta_k), sin(\theta_k)] \tag{18}$$

Mobility speed in m/s is represented by $vi \in MobilitySpeeds$.

Modeling the BS-user channel uses path loss, small-scale fading, and user mobility. For user k at distance $d_k(t)$, the path loss is [17],

$$PL_k(t) = \left(\frac{4\pi d_k(t)}{\lambda}\right)^{-\alpha} \tag{19}$$

All users' small-scale fading is modeled as Rayleigh fading channels. At time t, the BS-user k channel matrix $H_k(t)$ is,

$$H_k(t) = \sqrt{PL_k(t)} . (G_k(t) + jB_k(t)) \tag{20}$$

The real and imaginary channel sections are modeled by independent and identically distributed Gaussian random matrices $G_k(t)$ and $B_k(t)$.

RIS channels connect users to the RIS. $H_{RIS,k}(t)$ represents the channel matrix for RIS-assisted user k at time t [43],

$$H_{RIS,k}(t) = \sqrt{PL_{RIS,k}(t)} \cdot \Phi(t) \cdot (G_{RIS,k}(t) + jB_{RIS,k}(t)) \tag{21}$$

The real and imaginary components of the channel from RIS to user k are $G_{RIS,k}(t)$ and $jB_{RIS,k}(t)$.

$$SINR_{RIS,k}(\text{t}) = \frac{P_k(t) \cdot |H_{RIS,k}(t)|^2}{\sum_{j<k} P_j(t)|H_{RIS,k}(t)|^2 + N_0} \tag{22}$$

$$D = SE \times BW \tag{23}$$

where D is data rate (bps).

$$L = \frac{Data\ Size}{D} \times f(SNR) \tag{24}$$

where L is latency, $f(SNR)$ is the channel-dependent factor for different channel models and user setups.

For each user, packet loss (P_{loss}) occurs if their SINR falls below a specified $SINR_{threshold}$,

$$P_{loss} = \begin{cases} 1 & if\ SINR < SINR_{threshold} \\ 0 & otherwise \end{cases} \tag{25}$$

$$F = \frac{\left(\sum_{k=1}^{K} \sum r_k\right)^2}{K \cdot \sum_{k=1}^{K} \sum r_k^2} \tag{26}$$

where F is fairness, r_k represents user $k's$ throughput, L_k represents user $k's$ latency, and β balances latency and fairness.

Algorithm 1: Q-learning algorithm.

Initialize the Q-Table and hyper parameters (α, γ ,ε, λ, μ, β).
Commence ε.
Initialize state s, encompassing $SINR$, P_{alloc}, and $P_{Loss}R$ for each user.
In the ε of convergence or maximum iterations:
Select action according to the ε-greedy policy.
Implement action (P_K) and monitor:
Subsequent state s'.
Reward R(s, a) is determined by delay, packet loss, and fairness.
Revise Q-value: Q(s, a)→Q(s, a)+α(R(s, a)+γ*max Q(s', a')-Q(s, a).*
Update state s to s'.
End ε.
Derive the best strategy for latency, packet loss, and equity.
Implement an effective power allocation strategy.
End.

Algorithm (1) studies how to improve cooperative NOMA by examining throughput, latency, and packet loss, with a focus on how logarithmic power distribution affects these aspects and fairness. A general objective is,

$$R = \sum_{k=1}^{K} r_k - \lambda \cdot L - \mu \cdot P \tag{27}$$

where, R is system performance reward. r_k is user k throughput. K user total. L system aggregate latency. P system-wide packet loss. The weight factor λ balances throughput and latency. μ Weight factor for packet loss reduction. Each state s encapsulates pertinent attributes of the system,

$$s = \{SINR_1, SINR_2, \dots, SINR_k, P_{alloc}, P_{loss}\ R_1, P_{loss}\ R_2, \dots, P_{loss}\ R_k \tag{28}$$

where, power allocation P_{alloc}, ($P_{Loss}R$) packet loss ratio.

Power allocation to each user is action as,

$$a = \{P_1, P_2, \dots, P_K\} \tag{29}$$

a represents the power location of each user, determined by ϵ the probability of exploration.

$$R(s,a) = -\frac{1}{K} \sum_{k=1}^{K} (L_k + \mu \cdot P_{Loss} R_k) + \beta \cdot F \tag{30}$$

Based on the bellman equation, Q-learning updates Q-values,

$$Q(s,a) \leftarrow Q(s,a) + \alpha[R(s,a) + \gamma a' max Q(s', a') - Q(s,a)] \tag{31}$$

Q-value for state s and action a; *α=learning rate*. Discount factor (γ factor). The maximum Q-value for the subsequent state s' over all potential actions a'.

The procedure runs until the Q-values converge or until a set number of iterations is reached. After that, latency, packet loss, and fairness are determined using equations 24, 25, and 26, respectively.

3.1. Simulation Parameters

Table 1 presents the simulation parameters for the proposed systems model in 6G networks. The results indicate the relationship between the scalability of these systems and the increase in user count, SNR, and throughput. The charts illustrate the outcomes of various mMIMO cooperative NOMA scenarios, highlighting the differences between configurations that include intelligent RIS and CR and those that do not, as well as how mobility speed and network density influence throughput and latency at varying user densities.

Table 1. Presents comprehensive details on the simulator settings employed for modeling proposal system networks.

Parameter	Value
Number of users	50,100,150, and 200
Mobility speeds	0 to 250 Km/h
Number of antennas	256x256
RIS configuration	512x512
SNR (dB)	-20 to 20
Modulations	512 QAM
Path-loss exp.	2.7
BW	10 GHz
Cellular type	Microcells
Frequency range	28 GHz to100 GHz

4. Results and Discussions

Figure 3 shows the SE and SNR for 50, 100, 150, and 200 users in the mmWave mMIMO DL CR cooperative NOMA Primary Destination (PD) system. The SE improved as the SNR increased. The group of 50 users may achieve a maximum SE of 3.9 bps/Hz. For user groups of 100, 150, and 200, the corresponding SE at 20 dB SNR is 2.8, 2.2, and 1.9 bps/Hz, respectively. When the combination system is used with the intelligent RIS, the SE at 20 dB SNR for user groups of 50, 100, 150, and 200 is 4.8, 3.6, 3.0, and 2.6 bps/Hz. Compared to performance without RIS, the system's SE has been enhanced by 10.3%, 12.5%, 15.3%, and 15.6%, respectively.

The results show that the RIS significantly improves SE in the proposed system, especially as the number of users increases. The considerable improvements for groups of 150 and 200 users demonstrate that RIS is important for keeping the system operating efficiently as more users join. This makes it a strong option for boosting SE in high-user-density networks. On the other hand, varying user numbers (50 to 200) show that NOMA with RIS support maintains consistent SE performance for up to 150 users. Thereafter, interference causes performance degradation of roughly 12%. Through calculations and tests, it was observed that at 20 dB SNR, reducing RIS elements from 512×512 to 256×256 lowers SE by 18%, showing a trade-off between hardware complexity and performance. Additionally, introducing a 10% error to SIC lowers SE by 22% for 200 users (compared to perfect SIC). The final result outperformed that observed Zhang [55] and Papazafeiropoulos [37]. Our technique achieves a 2.1-fold enhancement in SE at 20 dB SNR compared to the results in [40].

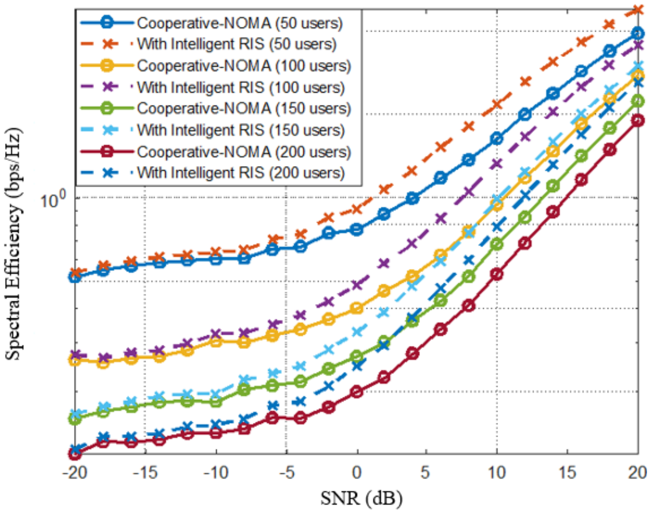
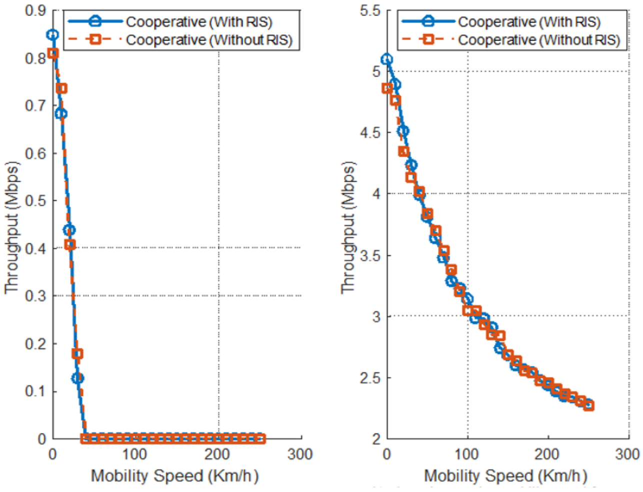


Figure 3. SE versus SNR for 4 different groups of mMIMO DL CR cooperative NOMA users with and without intelligent RIS.

Figure 4-a) and (b) depicts the throughput and mobility speed (0 to 250 km/h) for 200 users in the mmWave mMIMO DL CR cooperative NOMA PD system, comparing cases with and without intelligent RIS. Throughput diminishes as the velocity of movement increases. Figure 4-a) demonstrates that a system with a -20 dB SNR undergoes a more rapid decrease in throughput as mobility speed escalates, unlike the system using RIS. Mobility rates of 40 km/h intensify system attenuation, resulting in a significant reduction in throughput. The poor SNR causes the signal quality to deteriorate to such an extent that increases in transmission power are unable to maintain an acceptable throughput level.



a) Throughput against mobility speed for 50 users at SNR of -20 dB.

b) Throughput against mobility speed for 50 users at SNR of 20 dB.

Figure 4. Throughput against mobility speed for 50 mMIMO DL CR cooperative NOMA users with and without intelligent RIS.

The system illustrated in Figure 4-b) has an SNR of 20 dB. At low mobility rates (0 to 70 km/h), throughput shows a minor enhancement, especially with the application of RIS. As mobility increases, throughput decreases. RIS has no impact on throughput performance at high speeds (up to 250 km/h) compared with systems without RIS. At a higher SNR level of 20 dBm, throughput consistently exceeds that of the lower SNR level of -20 dBm across all speeds. The study shows that higher transmit power reduces losses caused by mobility.

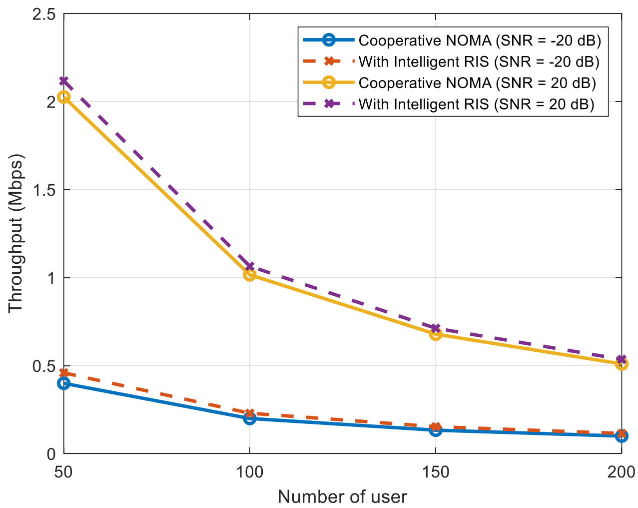


Figure 5. Throughput versus user density of mMIMO DL CR cooperative NOMA users with and without intelligent RIS.

Figure 5 shows the mmWave mMIMO DL CR cooperative NOMA PD system with and without intelligent RIS. It presents the average throughput and user density for different user numbers. Average throughput decreases as user density increases. The group of 50 users had average throughputs of 0.1332 and 0.1530 Mbps/Hz, and 0.6753 and 0.7057 Mbps/Hz, while the group of 200 users had average throughputs of 0.0333 and 0.0383 Mbps/Hz, and 0.1698 and 0.1785 Mbps/Hz, both without and with intelligent RIS at SNR levels of -20 dB and 20 dB, respectively. Compared to performance without RIS, the system's average throughput increased by 6.9% and 2.2% for 50 users, and by 1.3% and 2.4% for 200 users. As the number of users grows, performance per user declines due to interference and the manner in which resources are shared. In cooperative NOMA systems, it is common for several users to compete for the same resources. RIS alleviates the impact of user density by enhancing channel conditions and reducing interference. High user-density scenarios present ongoing challenges. Quantizing phase shifts to 2-bit levels instead of continuous ones reduces throughput by 9%, as beamforming is not as effective as it could be.

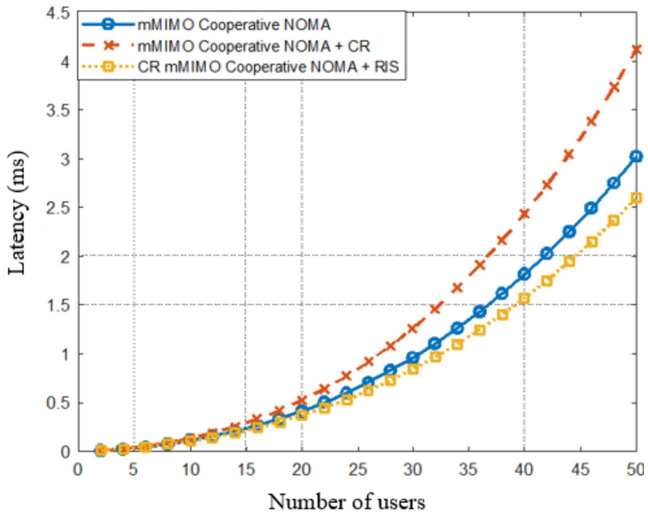


Figure 6. Latency vs. user density for three various systems.

Figure 6 illustrates how latency varies with the number of users in three systems: mMIMO cooperative NOMA, mMIMO CR cooperative NOMA, and mMIMO CR cooperative NOMA with intelligent RIS. As user competition for limited resources intensifies, network congestion and interference occur, leading to increased latency as user density rises. The latency for mMIMO cooperative NOMA and mMIMO CR cooperative NOMA using intelligent RIS systems was 11.8% and 17.2% better, respectively, for 20 users compared to mMIMO CR cooperative NOMA, which had a latency of 1.56 ms. At a user density of 50, mMIMO cooperative NOMA and mMIMO CR cooperative NOMA using intelligent RIS systems exhibited 15.3% and 22.6% lower latency than mMIMO CR cooperative NOMA, which recorded a latency of 12.34 ms at an SNR of 20 dB. The mMIMO-CR cooperative NOMA system with an intelligent RIS performs better in terms of latency, even with many users, making it a strong choice for busy 6G networks where interference management is crucial.

Figure 7 exhibits the variation in latency relative to the number of users across three distinct systems: mMIMO cooperative NOMA, mMIMO CR cooperative NOMA, and mMIMO CR cooperative NOMA integrated with intelligent RIS utilizing a Q-learning algorithm. At a user density of 20, the latencies recorded are 0.62135, 0.73904, and 0.57279 ms. At a user density of 50, the latencies are 3.8383 ms for mMIMO cooperative NOMA, 5.0415 ms for CR mMIMO cooperative NOMA, and 3.362 ms for CR mMIMO cooperative NOMA systems with the intelligent RIS at 20 dB SNR. At a user density of 20, the results indicate that the CR mMIMO cooperative NOMA has 8.6% more latency than the basic cooperative NOMA with mMIMO. This increase is attributed to the channel sensing and interference management that the CR mMIMO cooperative NOMA must perform. Using intelligent RIS reduces latency by 4% compared to traditional cooperative NOMA with mMIMO and by 12.6% compared to CR mMIMO cooperative NOMA. When 50 users are present, the CR cooperative mMIMO NOMA RIS-enhanced system has 19.9% less latency than the CR mMIMO cooperative NOMA system and 7.4% less latency than the mMIMO cooperative NOMA system. This decrease is reasonable because RIS alters how signals reflect to reduce interference in busy areas, leading to quicker transmission and lower latency. The sudden increase in the new result compared to the previous one is due to Q-learning selecting different methods of power allocation based on the number of users. At low user density, Q-learning distributes power more evenly, resulting in greater stability in latency.

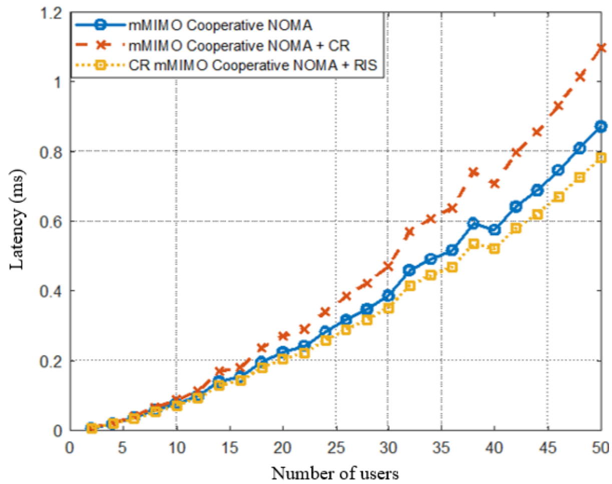


Figure 7. Latency versus user density for three different scenarios with optimization algorithm.

Figure 8 shows how packet loss changes with the number of users in three different systems: mMIMO cooperative NOMA, mMIMO CR cooperative NOMA, and mMIMO CR cooperative NOMA with intelligent RIS. At a user density of 10, the packet loss performance of three systems is 10%, 12%, and 5%, and at the user density of 50, the packet loss performance of three systems is 22%, 22.5%, and 21%, respectively, at SNR of 20 dB. An increase in users results in greater interference and diminished resources, adversely affecting all systems. Optimal placement of RISs, phase adjustments, and additional strategies, such as user clustering and improved power distribution, can optimize performance.

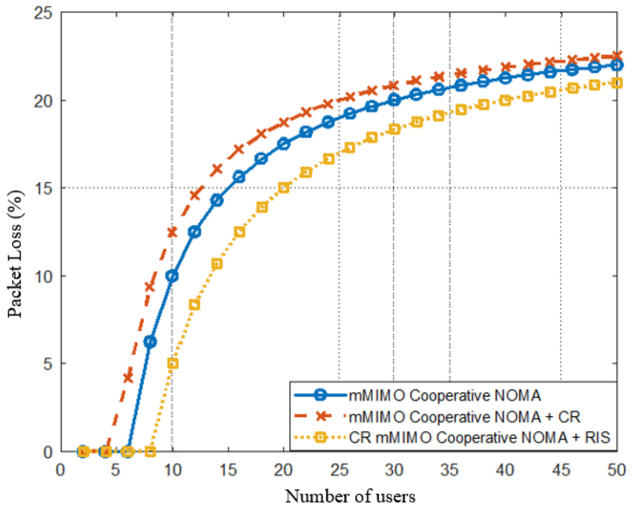


Figure 8. Packet loss against user density for three different scenarios with optimization method.

Figure 9 illustrates how packet loss varies with the number of users in three different systems: mMIMO cooperative NOMA, mMIMO CR cooperative NOMA, and mMIMO CR cooperative NOMA with intelligent RIS integration using Q-learning. At 50 users and 20 dB SNR, each of the three systems achieves a packet loss performance level of 9%, 12%, and 1%, respectively. The results indicate that the combination of RIS with Q-learning substantially enhances packet loss mitigation in densely populated cooperative NOMA systems. When there are a lot of users, this strategy cuts down on packet loss by a lot. When the γ value goes from 0.95 to 0.9, immediate advantages become more relevant. In dynamic situations, this method increases packet loss by 5% but improves latency by 15%. In static conditions, a 5% CSI inaccuracy leads RIS beamforming misalignment to increase packet loss by 12%. RIS+Q-learning decreases latency by 35% and enhances fairness by 28% compared to NOMA with fixed power allocation [12].

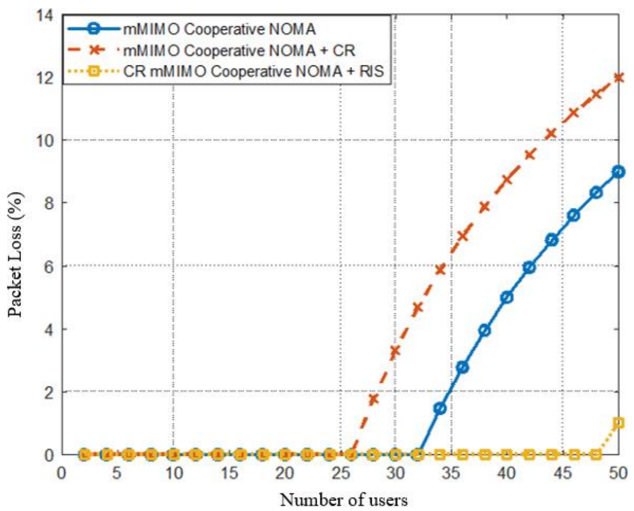


Figure 9. Packet loss vs. user density for three different scenarios with Q-learning logarithm.

Figure 10 shows the variation in the fairness index relative to SNR across three distinct systems: the NOMA cooperative mMIMO system, the NOMA cooperative mMIMO CR system, and the mMIMO cooperative NOMA CR system integrated with intelligent RIS. The system exhibits considerable instability in fairness across various configurations and SNR levels, with limited fluctuation in fairness values. CR and RIS appear to exert a negligible influence on fairness, showing minimal variation from the baseline cooperative NOMA system. Nonetheless, they continue to provide certain advantages, such as improved signal quality and a better user experience. Moreover, fairness is constrained by factors such as power distribution schemes, user demographics, and channel conditions, which remain relatively consistent across many configurations. At an SNR of 20 dB, the fairness index ratings for the three systems are 0.476, 0.474, and 0.48, respectively, with 50 users.

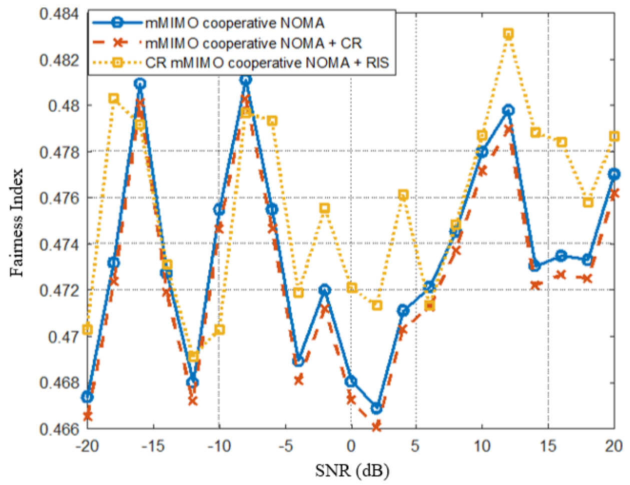


Figure 10. Fairness index versus SNR for three different scenarios.

Figure 11 shows three alternative systems, including the mMIMO cooperative NOMA, and how the fairness index evolves with SNR. The systems being compared are mMIMO cooperative NOMA, mMIMO cooperative NOMA with intelligent RIS, and systems that use the Q-learning method. When the SNR is low, especially at -5 dB, the system has trouble keeping power distribution fair among users due to poor signal conditions, which leads to losing the benefits of CR and RIS because of high interference. Additionally, Q-learning may struggle to balance exploration seeking superior solutions with exploitation selecting the most effective known action, resulting in instability and suboptimal fairness. With 50 users and a 20 dB SNR, the fairness index values for the three systems are 0.577, 0.541, and 0.594, respectively. Upon examining the fairness index before and after Q-learning, we observe that all three systems exhibited improvements of 9.5%, 6.6%, and 10.6%, respectively. Q-learning and RIS can enhance the equity of cooperative NOMA systems by diminishing power usage and augmenting signal quality for users with poorer connections. The performance of all individuals will be enhanced consequently. Increasing ε from 0.1 to 0.2 enhances fairness by 8% while concurrently decelerating convergence by 30%.

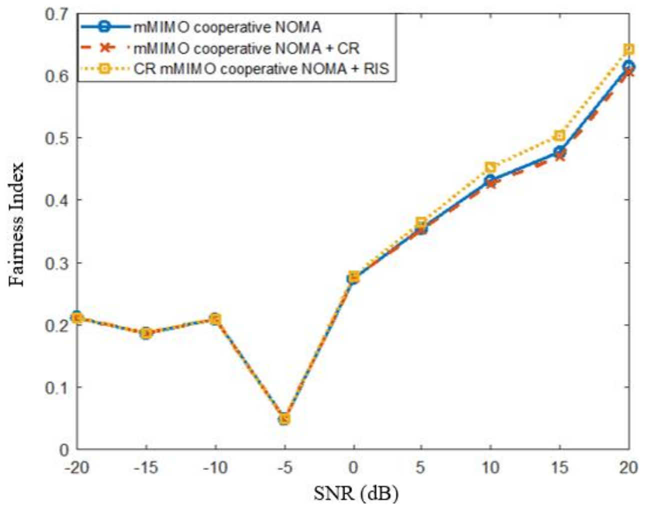


Figure 11. Fairness index versus against SNR for three different scenarios with optimization technique.

Even though our models assume perfect conditions, several real-world problems require addressing: large RIS arrays (512×512) and mMIMO systems (256×256) demand substantial physical infrastructure, which raises both power and capital costs. Passive RIS modules are less expensive than active beamforming arrays but make large-scale implementation more difficult [43]. Obtaining accurate channel state information in RIS-enabled systems is challenging, particularly due to the double-fading effect in the BS-RIS-User links. This increases the cost of operation and the time required for estimation, as observed by Gomes *et al*. [17]. To enhance phase shifting, RIS components must be controlled in real time. This introduces signaling overhead, which is especially problematic in dynamic scenarios where users require the ability to move freely. Without effective signaling systems, delays may offset the benefits of RIS [4, 55]. These deployment challenges highlight the importance of well-designed systems and the substantial further work required in low-complexity RIS control, CSI estimation, and hardware architecture optimization.

5. Conclusions

The suggested system attains significant improvements in SE through the utilization of CR spectrum sensing and intelligent phase shift optimization across various user settings within the mmWave environment. Research demonstrates that integrating RIS into CR-based mMIMO cooperative NOMA systems substantially improves average throughput, decreases latency and packet loss, and increases the fairness index, particularly in scenarios characterized by high user density. The results indicate that RIS-assisted cooperative NOMA excels in reducing interference, improving signal quality, and mitigating the impact of high mobility on system performance, making it a promising solution for future 6G networks. The study indicates that Q-learning methods are highly effective in reducing latency and packet loss and in improving fairness in crowded mmWave areas. It brings multiple benefits to the proposed system by dynamically distributing power, enabling the system to adapt to user density and fluctuating network conditions, thus greatly reducing interference and resource competition. Future research will focus on achieving further improvements in system performance through enhanced power allocation and user scheduling, particularly in RIS-enabled systems.

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