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Downlink Power Allocation for CR-NOMA-Based Femtocell D2D Using Greedy Asynchronous Distributed Interference Avoidance Algorithm

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Abstract: This paper focuses on downlink power allocation for a cognitive radio-based non-orthogonal multiple access (CR-NOMA) system in a femtocell environment involving device-to-device (D2D) communication. The proposed power allocation scheme employs the greedy asynchronous distributed interference avoidance (GADIA) algorithm. This research aims to optimize the power allocation in the downlink transmission, considering the unique characteristics of the CR-NOMA-based femtocell D2D system. The GADIA algorithm is utilized to mitigate interference and effectively optimize power allocation across the network. This research uses a fairness index to present a novel fairness-constrained power allocation algorithm for a downlink non-orthogonal multiple access (NOMA) system. Through extensive simulations, the maximum rate under fairness (MRF) algorithm is shown to optimize system performance while maintaining fairness among users effectively. The fairness index is demonstrated to be adaptable to various user counts, offering a specified range with excellent responsiveness. The implementation of the GADIA algorithm exhibits promising results for sub-optimal frequency band distribution within the network. Mathematical models evaluated in MATLAB further confirm the superiority of CR-NOMA over optimum power allocation NOMA (OPA) and fixed power allocation NOMA (FPA) techniques.

Keywords: device-to-device (D2D); greedy asynchronous distributed interference avoidance (GADIA); power allocation

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1. Introduction

Wireless communication technology is rapidly evolving towards 5G and beyond to meet the increasing demands for higher spectrum efficiency, ultra-low latency, improved reliability, and enhanced communication [1,2]. In this context, femtocells, characterized by lower transmission power and higher density compared to macrocells, enable efficient utilization of network resources. By employing appropriate interference management techniques, a heterogeneous network structure can significantly enhance system capacity [3,4]. However, load imbalance poses a significant challenge in heterogeneous networks, as most users prefer to connect to macro base stations with higher power, resulting in the underutilization of small cells and inefficient resource allocation [5].

One widely adopted approach is to artificially expand the coverage area of microcells and consolidate edge users into the microcell service, allowing resource reuse across multiple cells and improving overall network performance, particularly for edge users [6]. Network capacity can be increased by serving multiple users in the same resource dimension [7]. With the exponential growth in user service requirements and the number of connected devices, enhancing the throughput of microcells has become a major concern in academic and industrial circles. Multiple access technologies have always played a critical role in advancing wireless communications [8].

The Non-orthogonal multiple access (NOMA), an innovative multiplexing technique, has emerged as a promising solution the technology sector recommends. It ensures high system throughput while keeping reception costs low [9,10]. Unlike the frequency-diverse orthogonal multiple access (OMA) technologies used from 1G to 3G and in 4G LTE, NOMA actively introduces interference information at the transmitter. This fundamental difference allows multiple users to share frequency resources and distinguish users based on power and interference management [11]. The successive interference cancellation (SIC) is a key method used in NOMA to separate the signals of multiple users. Although the useful signal strength may be reduced, each user gains access to increased channel resources, leading to improved quality of service (QoS) [12].

By employing a heterogeneous architecture with small cells (SCs) and macro cells (MCs), multi-TIER networks can enhance spectrum efficiency and increase the capacity of existing cellular systems [13,14]. Interference management in HetNets has become a vital research area to address the various forms of interference, including cross-tier and co-tier interference, caused by frequency reuse between tiers [15]. Recently, the spatial domain for user multiplexing in HetNets has been identified as NOMA. The NOMA allows multiple devices to utilize the same frequency resources simultaneously by adjusting the broadcast power requirements for each subscriber and leveraging the receiver's capability to handle inter-user interference. The SIC is one of the methods employed in NOMA.

This paper's main contribution is the study of interference and noise-limited cognitive radio-based non-orthogonal multiple access (CR-NOMA) networks under system constraints. Additionally, this paper proposes a method for determining the best power allocation (PA) variables to ensure symmetrical availability while considering preset factors. This approach aims to enhance the QoS for all NOMA subscribers. The integration of femtocell networking with CR-NOMA is also addressed, suggesting a joint optimal channel allocation and power allocation control for femtocell subscribers. The contributions developed in this paper can be summarized as follows:

1. *Development of a greedy asynchronous distributed interference avoidance (GADIA) algorithm*: The proposed GADIA algorithm provides a solution for downlink power allocation in cognitive radio (CR)-based device-to-device (D2D) communication using NOMA. It addresses the challenges of interference mitigation and efficient resource allocation by employing a distributed and asynchronous approach.
2. *Enhanced user fairness*: The GADIA algorithm aims to achieve fairness among D2D users by considering their QoS requirements. By dynamically adjusting the transmit power levels based on local observations, the algorithm ensures that each user receives a fair share of network resources while maintaining interference control.
3. *Distributed and asynchronous operation*: The GADIA algorithm operation is distributed and asynchronous, allowing each D2D user to make power allocation decisions based on local information independently. This decentralized approach reduces signaling overhead and complexity compared to centralized algorithms, enabling faster convergence and adaptability to changing network conditions.
4. *Evaluation and performance analysis*: The contributions include evaluating the performance of the GADIA algorithm through simulations or analytical models. Performance metrics such as system throughput, interference management, user fairness, and spectral efficiency are analyzed to assess the effectiveness and benefits of the proposed power allocation scheme in CR-NOMA-based D2D networks.

These contributions collectively aim to optimize downlink power allocation in CR-NOMA-based D2D systems, user fairness, and overall system performance. They provide insights into the development of efficient algorithms for power allocation in emerging wireless communication technologies.

2. Related Works

Table 1 summarizes recently related studies and their contributions in the field of downlink power allocation for CR-NOMA-based D2D communication, highlighting their shortcomings. Based on the literature review, our proposed study aims to provide improved power control and throughput in NOMA based on D2D. In [16], the authors focused on avoiding interference between cellular and D2D users. They proposed a solution for multicast D2D communication in the uplink wireless connections, incorporating power control and resource management. Their approach achieved better throughput and reduced overall power usage compared to traditional methods.

The interference issue caused by resource sharing between cellular networks and D2D in HetNets was examined in [17]. The study investigated the effects of co-tier and cross-tier interference and introduced a matching technique with distributed resource allocation to minimize interference and improve system performance. In [18], interference control in multi-tier D2D communication was observed. The authors proposed an interference control system where only D2D UEs in an accessible group can reuse wireless connection resources. This technique effectively decreases interference while providing QoS.

The authors in [19] addressed the problem of cross-tier interference for underlay D2D users, particularly in the presence of channel estimation errors. They employed fractional programming (FP) to optimize small-cell power consumption while ensuring minimal QoS for macrocell users. A Lagrangian duality functional was introduced to reevaluate the power management issue, improving system efficiency.

The study in [20] focused on spectral efficiency (SE) and examined the reliability of enhanced inter-cell interference coordination (eICIC). The authors proposed an algorithm for allocating spectrum resources to macrocell users (MUEs) by employing D2D to assist in downlink data delivery while overcoming transmission discontinuity during almost blank subframes (ABS). The suggested method outperformed standard eICIC techniques in terms of sum rate.

In [21], an interference issue encountered by IoT devices was highlighted. The authors proposed a signal-supported communication technique that involved creating a channel selection algorithm to increase device throughput, particularly in regions with favorable interference conditions. The results demonstrated that increasing the number of IoT nodes responding simultaneously boosted system throughput. Madani et al. [22] investigated the effectiveness of NOMA in a fixed-power underlay D2D connection mechanism. Zhai et al. [23] presented a link optimization method for NOMA-based D2D communication in wireless networks.

Large-scale underlay CR networks with the NOMA system were studied in [24], showing enhanced SU communication. Supplying better channel conditions can also improve the performance of both users. Alhamad et al. [25] calculated the NOMA throughput in CR-NOMA using an adaptive power level. Power distribution to nearby and distant consumers was adjusted to optimize CR-NOMA throughput. In terms of performance evaluation, both [22,25] papers provide numerical results to illustrate the effectiveness of their proposed power allocation policies. They both compare the performance of their proposed strategies against other methods of OMA in Madani's paper [22] and fixed power allocation in Alahmed's paper [25] to demonstrate their superiority.

These related works provide valuable insights into various aspects of downlink power allocation in CR-NOMA-based D2D communication [26]. However, challenges and research opportunities remain to be addressed, such as fairness metrics, rate optimization, interference management, energy efficiency, practical implementation considerations, and the specific requirements of D2D-enabled heterogeneous wireless networks (HetCNets) [27].

Table 1. Comparison and benchmarks between the closely related works and proposed solution.

References	Contributions	Comparison with the Proposed Solution
Ningombam et al. [16], 2019	A resource management and power control system based on frequency reuse was developed in a multicast D2D link.	Preserving cellular user throughput while increasing the number of D2D users is required.
Xu et al. [19], 2019	To manage interference, different communications mechanisms were defined: D2D, femtocells, and macrocell.	The accessibility of secondary users is not accounted for in the proposed model.
Maher et al. [19], 2019	In order to determine the optimal power for a macro-D2D pair (MD), a cross-tier D2D pair (CD), and a small cell wireless UE (SUE), fractional programming (FP) is utilized.	The decreased distance between cross-tier D2D and SUE may result in increased interference.
Dao et al. [21], 2019	A technique to power communication with interference avoidance is proposed.	To allow strong connectivity and more IoT stations at the same time.
Madani et al. [22], 2019	Enhance the data rate and individual rate.	The system is only available to two users.
Zhai et al. [23], 2019	Reduce resource utilization.	Distinguish cross-interference.
R. Alhamad [25], 2020	An optimum power level in CR-NOMA.	Maximize CR-NOMA throughput.
Y. Liu [26], 2015	Improve bandwidth efficiency while significantly lowering the complexity of PA design.	Improve SU communication under CR NOMA.

Developing a fairness index based on the rate for downlink in CR-NOMA with D2D communication using the GADIA presents several areas for exploration. Key challenges and research directions include:

1. *Fairness metrics*: Defining appropriate fairness metrics that capture the fairness requirements in CR-NOMA with D2D is essential. Metrics such as index fairness [28], max-min fairness, or proportional fairness can be considered depending on the system objectives and constraints.
2. *Rate optimization*: Designing an efficient algorithm to optimize achievable rates in CR-NOMA with D2D is crucial. The GADIA approach can be explored to find optimal or near-optimal solutions considering interference management, power allocation, user scheduling, and resource allocation to maximize the sum rate while ensuring fairness among users [29].
3. *Interference management*: Managing interference is critical in CR-NOMA with D2D. Research focuses on interference-aware resource allocation and power control techniques to mitigate interference and enhance system performance [30]. Advanced interference cancellation and suppression techniques can be explored to improve user achievable rates.
4. *Energy efficiency*: Developing energy-efficient techniques for CR-NOMA with D2D is important [31]. This includes optimizing power allocation and user scheduling strategies to minimize total power consumption while maintaining fairness and system performance.
5. *Practical considerations*: Practical aspects of real-world implementation should be considered [32]. This involves addressing channel estimation and feedback overhead, hardware impairments, limited computational resources, and system scalability. The proposed solutions should be practical and adaptable to different deployment scenarios.

In summary, the challenges and research directions for developing a fairness index based on the rate for downlink in CR-NOMA with D2D using GADIA involve optimizing rate performance while considering interference management, user, fairness metrics, energy efficiency, and practical implementation considerations.

3. Materials and Methods

This section introduces the CR-NOMA model, channel model, and achievable rate in a femtocells CR-NOMA network. The model is depicted in Figure 1, which represents a downlink underlay CR-NOMA communication scenario with a macrocell and a femtocell system [33]. The macrocell system consists of a Macrocell Base Station (MT) and Macrocell Devices (MDs). At the same time, the femtocell network includes a Femtocell Base Station (FBS) with NOMA functionality and K Femtocell Devices (FDs). The MT facilitates communication between the FBS and MDs. The FDs are randomly distributed in a two-dimensional plane following a Poisson distribution.

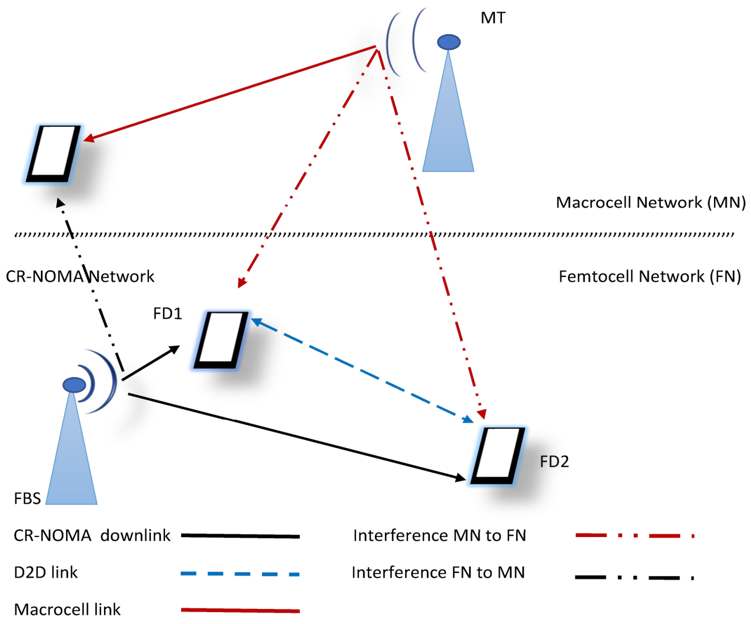

Figure 1. System model of CR-NOMA femtocell D2D link.

The FBS employs the NOMA approach by providing higher power in the downlink to devices with poor channel conditions and lower power to devices with favorable channel conditions [34]. The power allocation is based on the distance between the FBS and the FDs. That assumes that BW denotes the downlink channel bandwidth, and all channels are affected by independently distributed Rayleigh fading. In the underlay spectrum utilization paradigm of CR-NOMA, the MD and other FDs operating in the same frequency band may interfere with the access of all FDs. The NOMA's successive cancellation interference (SCI) technology is employed to mitigate this interference, which eliminates signal interference among FDs until the desired signal is decoded.

Figure 2 illustrates the decoding processes in the CR-NOMA system. The CR-NOMA combines the principles of CR and NOMA to improve spectrum efficiency and user capacity in D2D communications.

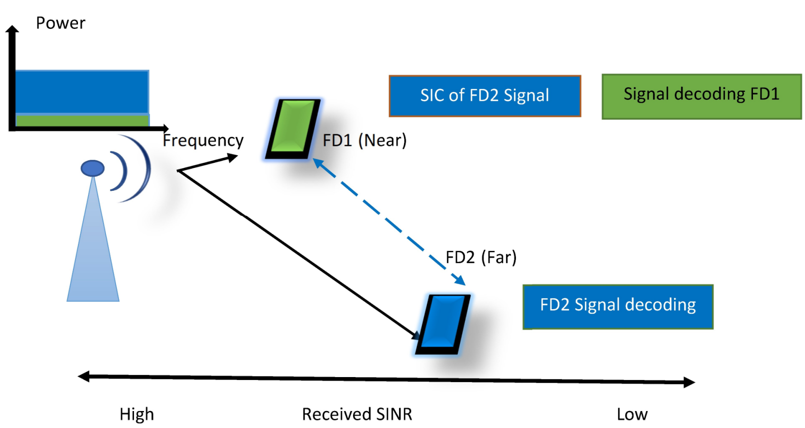

Figure 2. Decoding processes for the CR-NOMA system.

The proposed power allocation scheme in CR-NOMA-based D2D networks typically involves the following key steps:

- ***Spectrum sensing***: In a cognitive radio system, the first step is spectrum sensing, where devices (secondary users) detect and identify available frequency bands that primary users are not using. This ensures that secondary users do not cause harmful interference to licensed users and utilize the spectrum opportunistically.

User pairing: NOMA allows multiple users to share the same resources simultaneously and frequently. User pairing involves grouping two or more D2D users together, where one user acts as the stronger (near) user and the others as the weaker (far) users. The near user assists in decoding the signals of the far users.

- ***Power allocation***: Once user pairing is determined, the power allocation scheme decides how much power each D2D user should use to transmit its data. The goal is to maximize the system's sum rate while meeting the QoS requirements of individual users.

The FBS simultaneously transmits signals to K (FDs) separated by different distances on the same frequency band. The power allocation is such that the FBS allocates higher transmission power to a signal from a remote FD than to a signal from a nearby user (FD_i). The order of the channel gains from the FBS to the i-th receiver FD_i is arranged in descending order, and the SCI technique is used to reduce the power of users with higher channel gains gradually.

3.1. The Channel Model

Before transmission, the base station assigns different power levels to users. The overlaid signal x_i on the radio spectrum x can be expressed as in [26,27]:

$$x_{FBS,FDi} = \sqrt{P_{FBS}}\sqrt{\alpha_{FD_i}}x_{FDi} \tag{1}$$

where α_{FD_i} represents the power allocation coefficient for the i-th user,

$$\sum_{i=1}^{k} \alpha_{FDi} = 1,\ i = 1,\ 2,\ 3,\ \ldots\ k \tag{2}$$

$0 < \alpha_{FDi} < 1$ and P_{FBS} is the max transmit power of the Femtocell Base Station (FBS). The received signal of user K on frequency band BW at the receiving end is:

$$Y_{MD} = \sqrt{P_{MT}}H_{MT,MD}x_{MT,MD} + nn \tag{3}$$

where $P_{MT} = Transmitpowe\ rmacrocell\ basestation.$ $H_{MT,MD}$ = denotes the integrated channel gain from the MT to MD.

nn = white Gaussian noise between mean value of zero and variance of σ^2.

$$Y_{FBS} = \sqrt{P_{MT}}H_{MT,FBS}x_{MT,FBS} + nn_{MT,FBs} \tag{4}$$

The received signal of user i on the frequency band BW can be written as:

$$Y_{FDi} = H_{FBS,FDi}x_{FBS,FDi} + \sqrt{P_{MDi}}H_{MDi,FDi}x_{MDi,FDi} + \sum_{j=1_{j\neq i}}^{N-1} \alpha_{FDj}\ \sqrt{P_{FBS}}H_{FBS,FDi}x_{FDj,FDi} + \text{nn} \tag{5}$$

where $H_{FBS,FDi}$ denotes the channel gain from the FBS to the i-th receiver and $nn_{FBS,FDi}$ represents the white Gaussian noise with zero mean and variance σ^2. The received signal can be further simplified as:

$$Y_{FDi} = H_{FBS,FDi}\sqrt{P_{FBS}}\sqrt{\alpha_{FDi}}x_{FDi} + \sqrt{P_{MDi}}H_{MDi,FDi}x_{MDi,FDi} + \sum_{j=1_{j\neq i}}^{N-1} \alpha_{FDj}\ \sqrt{P_{FBS}}H_{FBS,FDi}x_{FDj,FDi} + \sigma^2 \tag{6}$$

where j denotes the set of users excluding user i. The interference caused by other devices is represented by the term $\sum_{j=1_{j\neq i}}^{N-1} \alpha_{FDj} \sqrt{P_{FBS}} H_{FBS,FDi} x_{FDj,FDi}$, and the overall received signal Y_{FDi} contains both the desired signal and interference.

In accordance with NOMA characteristics, the SIC technique is employed to remove interference. The SIC detector evaluates multiple users in the incoming signal one by one, removing the signal's multiple access interference if the device is successfully decoded. The sequence of operations is determined by the power levels, with the signal with higher power and poorer quality being decoded first, followed by the signals with lower power and better quality.

$$SINR = \mu_{MD} = \frac{P_{MT,} |H_{MT.MD}|^2}{nn_{MT,MD}^2} \tag{7}$$

This iterative process gradually achieves a better channel condition for each user's Signal to Interference Noise Ratio (SINR)

$$SINR = \frac{P_{FBS,} \alpha_{FDi} |H_{FBs.FDi}|^2}{H_{MD,FDi} P_{MD} + \sum_{j=1_{j\neq i}}^{N-1} \alpha_{FDj} \sqrt{P_{FBS}} H_{FBS,FDi} x_{FDj,FDi} + \sigma^2} \tag{8}$$

thereby removing interference and improving system performance. PU and FD's transmission rate (bits/s/Hz) can be calculated using the Shannon theorem.

$$R_{MD} = \mathrm{BW}\log_2(1 + \mathrm{SINR}) \tag{9}$$

Each user's throughput can be expressed using NOMA as:

$$R_{FDi} = \sum_{i=1}^{k} BWlog_2(1 + SINR_{FDi}), \mathrm{i} = 1,\ 2,\ 3,\ \ldots\ \mathrm{k} \tag{10}$$

3.2. SIC Technology

The SIC is a key technology used in CR-NOMA systems to mitigate interference. In CR-NOMA, different users are assigned different power levels and non-orthogonal spreading codes to transmit their signals over the same time and frequency resources. This results in overlapping signals at the receiver, causing interference between users. The SIC separates and decodes individual user signals, progressively improving the receiver's ability to decode weaker signals.

The basic principle of SIC technology is as follows: the receiver initially treats all signals as interference and tries to detect the strongest signal. After successfully decoding the strongest signal, the receiver subtracts its contribution from the received signal, reducing the interference caused by that signal. The receiver then repeats the process to detect and decode the next strongest signal from the modified received signal. This iterative process continues until all individual user signals are separated and decoded.

The order in which users' signals are decoded and canceled depends on their power levels. The user with the strongest signal is decoded first, followed by the next strongest, and so on. By canceling the interference caused by previously decoded signals, the receiver progressively improves its ability to decode weaker signals. SIC in NOMA enables multiple users to efficiently share the same time and frequency resources while mitigating interference, thereby achieving higher spectral efficiency.

The SIC technology in NOMA is not without limitations. It is sensitive to power levels, and if multiple users have identical power levels, the performance may be significantly degraded. The SIC also relies heavily on the successful decoding of the first user, and if the first user fails to decode correctly, it can propagate decoding errors to lower-order users, reducing system efficiency [35]. The SIC receivers also introduce decoding latency for lower-order users due to the complexity of parallel decoding operations. These limitations need to be considered when implementing and optimizing NOMA systems using SIC technology [36].

3.3. Fairness Index in Femtocell Based on Rate

In this paper on CR-NOMA systems, a fairness index is used to assess the fairness of communication among wireless FDs. A higher fairness index indicates a more equitable sharing of resources in the system. This study proposes a novel fairness index based on the rate variation of mobile users' transmission rates in a downlink NOMA system [37].

The FI is a commonly used metric for assessing fairness in wireless communication. It aims to achieve equitable sharing of information in NOMA networks through effective resource allocation strategies. The FI is defined as [38]:

$$FI_{R_i} = \frac{\left(\sum R_i\right)^2}{\left(K * \sum {R_i}^2\right)}, \qquad \text{i} = 1,\ 2,\ 3,\ \ldots,\ \text{k} \tag{11}$$

where R represents the data rate of individual users,

$$R_{avg} = \frac{R_{sum}}{K} \tag{12}$$

R_{avg} is the average data rate across all users [39].

Mean square of femtocell user rate is

$$R_{avg}^2 = \frac{1}{k}\sum\nolimits_{i=1}^{k} R_i^2 \tag{13}$$

$$\text{Var (R) Variable of users V} = \frac{1}{k-1}\sum\nolimits_{i=1}^{k}\left(R_i - R_{avg}\right)^2 \tag{14}$$

where V is the variance of the data rates and the fairness index ranges between 0 and 1, with 0 representing unfairness and 1 representing perfect fairness. A higher fairness index indicates a more equitable distribution of data rates among users. This index and the fairness index (FI) provide a comprehensive evaluation of fairness based on both rate and power allocation. The FI can be calculated as:

$$FI_{R_{avg}} = 1 - \left(\text{Var(R)}/R_{avg}\right. \tag{15}$$

where Ri represents the data rate of the i-th user, and K is the total number of users in the system. The FI ranges between 0 and 1, with 0 representing unfairness and 1 representing perfect fairness [40]. The FI is dependent on both power distribution and channel parameters, ensuring fairness by allocating higher data rates to users with increased power allocation. The proposed fairness index based on rate variation provides better sensitivity and can evaluate the fairness of systems with different user levels. It considers user rate variations and provides a comprehensive measure of fairness in NOMA systems.

However, the FI in Equation (11) is based on the rate variation among users in the downlink NOMA system. It is calculated as the square of the sum of individual data rates divided by the product of the total number of users (K) and the sum of the squares of individual data rates. This formulation assesses the fairness based on the absolute data rates of individual users without considering the variations or distribution of these data rates. As a result, FI calculated using Equation (11) can never be 0, even if the data rates of all users are zero.

The FI in Equation (15) is designed to evaluate fairness by considering both power distribution and channel status. It is computed as 1 minus the ratio of the variance of data rates to the average data rate across all users. In our formulation, Var(R) represents the variance of data rates among users, and Ravg is the average data rate across all users. Unlike the FI in Equation (11), the FI in Equation (15) takes into account the rate variations among users and provides a more comprehensive measure of fairness. The FI in Equation (15) offers a more sensitive and comprehensive measure of fairness by considering rate variations among users in the downlink NOMA system. It provides valuable insights into how data rates are allocated and shared among users, making it a more suitable metric for assessing fairness in wireless communication simulations.

3.4. The Greedy Asynchronous Distributed Interference Avoidance Algorithm (GADIA)

The GADIA algorithm is a technique used in NOMA systems to mitigate interference and improve system performance. It specifically focuses on resource allocation and power control for Femtocell Device (FD) communications in coexistence with a mobile network [41]. In a NOMA-based D2D communication system, multiple devices share the same time and frequency resources to transmit simultaneously. However, this can lead to interference between devices and with the cellular network. The GADIA algorithm addresses this issue by dynamically adjusting the devices' power levels and resource allocations.

The GADIA algorithm operates asynchronously, allowing devices to update their power levels and resource allocations independently without strict synchronization. This provides flexibility and efficiency in resource management in dynamic communication environments. The algorithm includes the following key steps:

- *Initialization*: The algorithm begins by initializing the power levels and resource allocations for each device and base station in the system. Interference measurement: Each device measures the interference caused by other devices in the system. This information is shared with the base station [42]. Resource allocation: The base station collects the device interference measurements and calculates each device's resource allocation. The goal is to allocate resources in a way that minimizes interference. Power control: The base station determines the power levels for each device based on the interference measurements and resource allocation. The power levels are adjusted to minimize interference and ensure reliable communication.
- *Iterative optimization*: Steps are performed iteratively to improve the resource allocation and power control. The algorithm dynamically adjusts the parameters until a desired level of performance is achieved.

4. Optimization Problems

In this section, the optimization problems for maximizing the number of accessed FDs in the system and maximizing the rate of FDs under fairness constraints are formulated. The specific mathematical formulations and optimization algorithms may vary depending on the research context and underlying assumptions.

4.1. Problem State 1: Maximization of Accessed FDs in the System

The problem can be stated as follows:

$$\text{Maximize} \sum_{i=1}^{k} K \tag{16}$$

Subject to:

$$P_{FDi} \le P_{max,}\ SINR \ge SINR_{th,},\ \alpha_i \in [0,1],\ \text{i} = 1, 2, \ldots, \text{k},\ 0 < \alpha_{FDi} < 1$$

where K is the total number of available FDs, P_{FBS} represents the maximum transmit power of the FBS, and $\alpha_i \in$ denotes the power allocation factor for the i-th FD. The power allocation factor constraint in Equation (16) ensures that the power allocated to each FD does not exceed the maximum power resource available.

Based on the information provided in Equation (16), it seems to describe the power allocation process for FDs in a system. Increase in power allocation factor is as follows:

- According to Equation $\alpha_i \in [0, 1]$, i = 1, 2, ..., K, the power allocation factor for each femtocell is gradually increasing. This implies that more power is allocated to femtocells with better channel gains than those with weaker ones.
- Sequential iterations for power allocation: To achieve the purpose of power allocation, sequential iterations are performed on the femtocells. Each device in femtocell's power

allocation factor is determined based on the power allocation factors of the previous FDs with better channel gains. This iterative process helps in achieving an optimized power allocation scheme.

- Total transmit power constraint: The total transmit power of the Femtocell Base Station (FBS) is denoted as P_{FBS}, and it is constrained by the sum of power allocation factors (α_i of all the FDs (i ∈ {1, 2, . . ., K}). This constraint ensures that the total transmit power of the FBS is controlled during the power allocation process.

$$\alpha_{FDi} P_{FBS} \leq P_{max,} \tag{17}$$

- Power allocation limit: The power allocation factor for each FD $\alpha_i \in$ is limited by a maximum power threshold denoted as Pmax. This constraint ensures that the power allocated to each FD does not exceed the maximum allowable power. Overall, the process involves sequentially adjusting the power allocation factors for each FD based on the power allocation factors of the previous FDs with better channel gains. The goal is to achieve an efficient power allocation scheme while considering each FD's total transmit power constraint and individual power limits.

$$\alpha^*_{\mathrm{FDi}} \leq \min\left(\frac{P_{max,}}{P_{FBS}}\right) \tag{18}$$

4.2. Problem State 2: Maximization of FDs' Rate under Fairness Constraints

The problem can be formulated as follows:

$$\text{Maximize } \Sigma(R_i) = \sum_{i=1}^{k} BWlog_2\,(1 + SINR), i = 1,\ 2,\ \ldots,\ \mathrm{K} \tag{19}$$

Subject to:

$$\alpha_{FDi} P_{FBS} \leq P_{max,}, \quad \alpha_i \in [0,1], \mathrm{i} = 1,2,\ldots,\mathrm{K}, 0 < \alpha_{FDi} < 1,\ FI \geq F$$

where R_i represents the rate of the i-th FD, P_{FBS} denotes the maximum transmit power of the FBS, α_i is the power allocation factor for the i-th FD, and F represents a lower bound on fairness index. The power allocation factor constraint in Equation (19) ensures that the total transmit power of the FBS does not exceed the power allocated to each FD. The fairness index constraint ensures that the fairness index meets the minimum fairness requirement [43]. The objective is to maximize the total rate of FDs while satisfying the fairness constraints.

Once the challenge of problem state 1 is addressed, it becomes possible to estimate and optimize the minimal throughput of the accessed device. Consequently, the optimization problem of problem state 2 in Equation (19) can be identified under conditions.

In this femtocell system, the variable FI represents user fairness, serving as a lower bound to ensure that the fairness value does not fall below this threshold. The range of F is defined from 0 (representing unfairness) to 1 (representing perfect fairness). The objective is to allocate power to the FDs by the Femtocell Base Station (FBS) while considering both the best channel gain FD and the lowest channel gain FD. The power allocation factor (α) is used to manage power distribution for the closest FD and the edge FD, respectively.

To solve the problem effectively, it can be decoupled into two subproblems: power allocation for the nearest user and power allocation for the farther user. This approach allows for separate optimization of power allocation for each user category.

Regarding throughput maximization in wireless systems, providing consumers with improved channel conditions and greater power can lead to higher data rates and achieve higher throughput. The calculation FDi, based on the previously discussed conditions and problems, can be determined using Equation (15).

These optimization problems can be solved using appropriate optimization techniques, such as iterative algorithms. The specific solution approach depends on the problem formulation, system constraints, and desired performance criteria. It is worth noting that the proposed optimization problems aim to achieve the highest network throughput and fairness in the femtocell system while considering power control and the specific requirements of CR-NOMA. The solution to these problems can provide valuable insights into power allocation, rate optimization, and overall system performance in CR-NOMA-based communication scenarios.

4.3. Maximum Rate under Fairness (MRF) Algorithm

The specific algorithm for solving the optimization problems can vary depending on the chosen optimization technique and the system constraints that can provide a high-level overview of possible algorithmic approaches for each problem.

4.3.1. Maximization of Accessed FDs in the System:

One possible algorithm for solving this problem is as follows:

1. Initialize the power allocation factors α_i for each FD i, α_{FDi} i = 1, 2, . . ., k; set the iteration count t = 0.
2. While the constraint in Equation (16) is not satisfied,
    - Calculate the current sum of power allocations $\sum \alpha_{FDi}$
    - Find the FD with the smallest α_i and increase its α_i value.
    - Update the power allocation factors for other FDs to maintain the fairness among them $\alpha_{FDi} P_{FDi} \leq P_{max,}$.
3. Count the number of FDs with non-zero power allocation factors as the maximum number of accessed FDs that K. t = t + 1.
4. Return the optimized power allocation factors. $\alpha^*_{FDi} \leq min\left(\frac{P_{max,}}{P_{FBS}}\right)$.

This algorithm iteratively adjusts the power allocation factors until the constraint in Equation (7) is satisfied, while ensuring fairness among the femtocell devices.

4.3.2. Maximization of FDs' Rate under Fairness Constraints (MRF):

One possible algorithm for solving this problem is as follows:

1. Initialize the power allocation factors α_i for each FD i.
2. While the fairness index constraint FI $\geq$ F is not satisfied,
    - Calculate the current sum of power allocations ($\sum \alpha_{FDi}$).
    - Calculate the current fairness index FI based on the power allocation factors α_i.
    - If FI $\geq$ F, break the loop and continue to the next step t = t + 1.
    - Find the FD with the largest α_i and decrease its α_i value. α^*_{FDi}.
    - Update the power allocation factors for other FDs to maintain the fairness among them.
3. Calculate the rates R_i for each FD_i based on the optimized power allocation factors α^*_{FDi}. Equation (18).
4. Return the optimized power allocation factors α_i, $0 < \alpha_{FDi} < 1$ and the rates R_i.

This MRF algorithm (MRF) iteratively adjusts the power allocation factors until the fairness index constraint in FI $\geq$ F is satisfied, while maximizing the total rate of FDs.

5. Simulation and Numerical Results

The proposed MRF technique is simulated and evaluated using MATLAB simulation, and the algorithm from the related research is compared. The optimization technique in Figure 3 did not enforce an appropriate rate constraint, so these two scenarios had higher throughput. In comparison, it considers fairness and the data rate constraint. The proposed algorithm nevertheless outperforms the other schemes in terms of data rate.

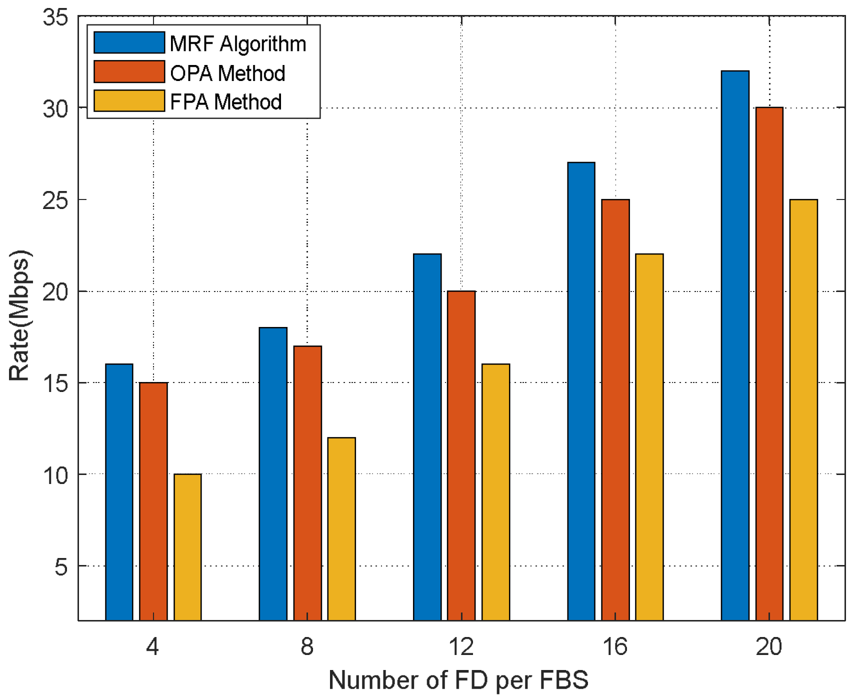

Figure 3. Sum rate vs. number of FD per FBS.

Fairness was emphasized in the system design for the MRF algorithm. However, it also showed higher throughput than optimal power allocation (OPA) [26] or fixed power allocation (FPA) [23] methods. In order to prevent constraint violation, the power optimization of the network was penalized by the framework of the system, which constrains the power ratio, rate of FD, and fairness. The proposed approach is the preferred choice due to the consequences and fairness weights utilized by the role.

Table 2 summarizes simulation system parameters. These simulation parameters define the characteristics of the simulated CR-NOMA system, including the coverage areas of the macrocell and 10 femtocells. These parameters are essential for setting up the simulation environment and evaluating the performance of the proposed technique in terms of accessed FDs, FDs' rates, fairness, and other relevant metrics.

Table 2. Simulation system parameters.

Parameter	Values
Macrocell radius	300 m
Femtocell radius	30 m
Bandwidth	5 MHz
PmaxMacrocell power	46 dBm
Femtocell devices	20
Path loss exponent	3
Channel model	Rayleigh Fading Channel
Number of FBS	10
Modulation	64 QAM
SINR minimum	5 dB
Noise power	−120 dBm/Hz
Min rate of user	1 Kbps

The performance of the MRF algorithm is evaluated and compared with the OPA and FPA methods [23,26]. The simulation results highlight the advantages of the MRF in terms of data rate, fairness, and power allocation. Figure 3 demonstrates that the rate exhibits an increasing trend when there is an increase in the number of devices per femtocell base station. In other words, as more FDs can access the system, the rate is significantly improved. The maximum number of K that can access a single FBS is 20.

When comparing the performance of different algorithms, it is observed that the MRF algorithm achieves a higher rate than the OPA and FPA algorithms. Additionally, it is noteworthy that the MRF algorithm outperforms the FPA algorithms by a significant margin in terms of throughput. These findings suggest that the proposed algorithm and OPA scheme effectively enhance the rate.

Figure 4 compares the Minimum Rate (R_{min}) for various (FD) values with the user's location. With increasing rate constraints as FD grows, the R_{min} of all simulated schemes degrades. This paper emphasizes the importance of optimizing transmit power for three algorithms, particularly when the coefficient power (potentially related to SINR or channel conditions) is low. Additionally, carefully selecting the SIC decoding order is crucial for improved system performance. Power allocation and transmit power optimization effects become more pronounced with higher SINR, indicating their significance under better signal conditions.

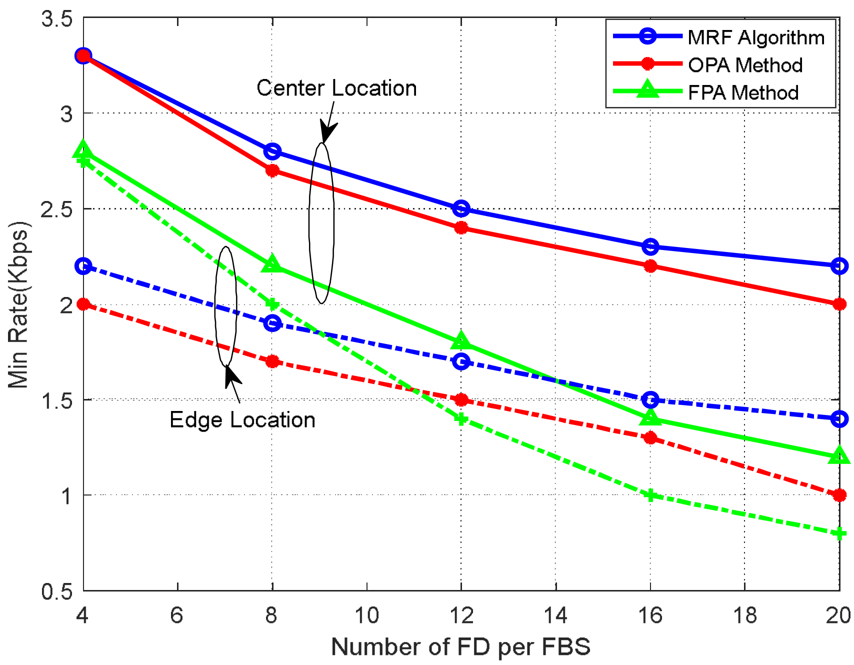

Figure 4. Min rate vs. number of FD per FBS.

Figure 5 depicts the relationship between fairness and the power allocation coefficients for users with strong channel gains. Power allocation coefficients are used to distribute power among users or channels in wireless communication systems. Allocating more power to users with strong channel conditions is crucial as it ensures reliable communication and maximizes overall system performance. The fairness index of the MRF algorithm and optimal power allocation increases as the rate of near users within the femtocell rises. This indicates that as the rates of users closer to the femtocell increase, the fairness among users also improves.

The power distribution within the femtocell influences the fairness index associated with FPA. In other words, higher power distribution leads to greater fairness. It is important to note that the proposed fairness index has a wider range compared to other indices, making it more suitable for studying systems with changing user counts and channel conditions. It can effectively capture the impact of resource allocation changes on fairness in dynamic scenarios.

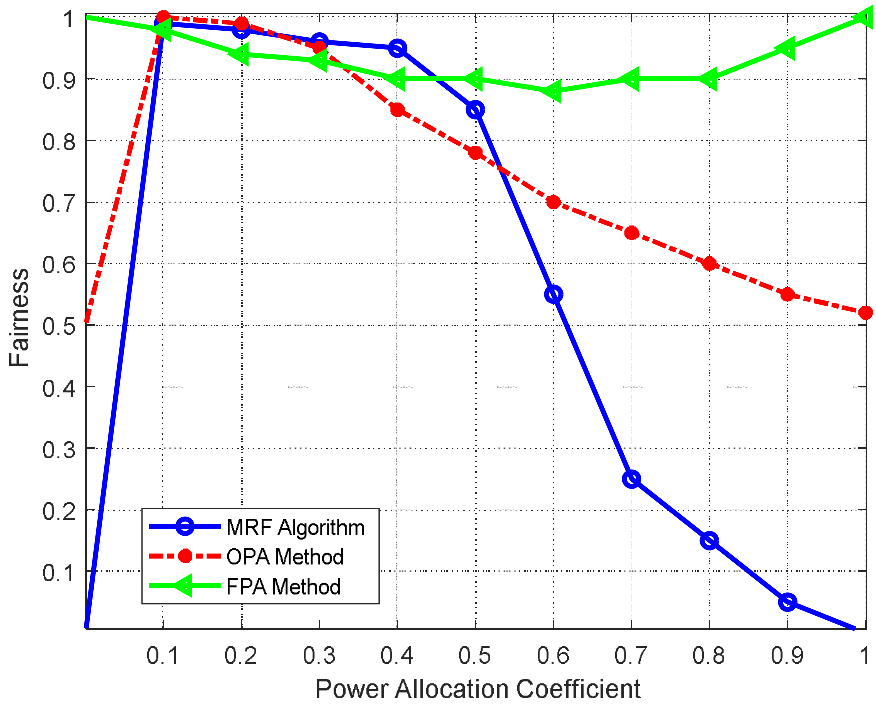

Figure 5. Fairness vs. coefficient power allocation with strong channel gain.

Considering the fairness index of the MRF algorithm and OPA, higher fairness is observed when the center user rate within the femtocell is higher. This suggests that as users' rates in the femtocell's central area increase, the system fairness improves. Similarly, the fairness index associated with FPA is influenced by the power distribution among users within the femtocell. Hence, the more users benefit from power distribution, the fairer the FPA becomes.

In terms of the fairness value range, the number of users affects the lower bound of OPA, making it suitable for analyzing systems with a fixed number of users. On the other hand, the lower bound of the FPA fairness index is influenced by both the number of users and channel conditions, making it appropriate for evaluating systems with fixed user counts and specific channel conditions.

In contrast, the MRF fairness index's range remains unaffected by the number of users or channel conditions. This characteristic makes it better suited for studying systems with changing user counts and channel conditions. Additionally, the proposed fairness index is more sensitive to changes in resource allocation within the system. In summary, Figure 5 provides insights into the relationship between fairness and power allocation coefficients. The MRF algorithm demonstrates higher fairness as the rate of near users increases.

Figure 6 shows the power allocation factor (denoted by α) for four FDs devices, considering their distance from the FBS. The range for α is $0 < \alpha < 0.45$. As per the characteristics of NOMA, more power is allocated to FDs that are farther away from the FBS. FD4 has the largest coverage area among the four FDs, followed by FD3. This means that FD4 can communicate over a larger distance compared to the other devices. FD1 has the smallest coverage area among them.

The Bit Error Rate (BER) increases as the communication distance increases. When the power allocation factor for all four FDs is less than 15 dB, the FD with a higher power allocation factor will have a higher BER. In this case, FD1 has the lowest BER, followed by FD2, FD3, and FD4. The power allocation strategy based on distance and the associated BER observations illustrates how NOMA efficiently allocates power to FDs based on their location from the FBS. This approach optimizes communication performance, ensuring that FDs with larger coverage areas receive higher power allocations while maintaining a balanced BER for reliable data transmission.

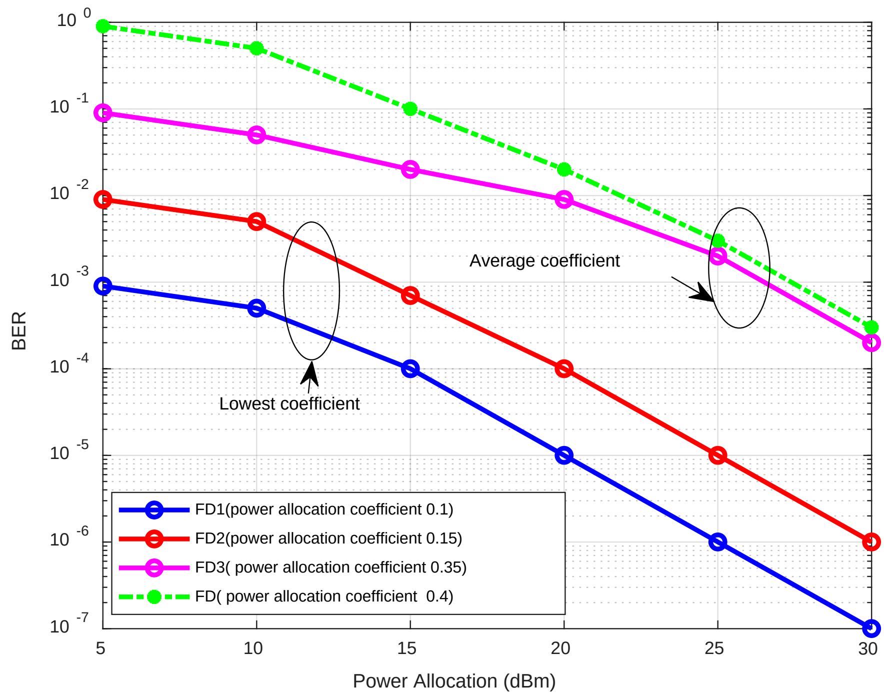

Figure 6. BER performance versus SINR.

Figure 7 showcases the performance of the MRF algorithm, OPA, and FPA concerning system fairness across varying user counts. As the number of users increases, the system's fairness eventually becomes stable. This phenomenon occurs because the channel gain difference between users tends to diminish with a larger user base. The MRF algorithm demonstrates significantly higher system fairness than OPA and FPA. This indicates that the proposed approach effectively balances user rates, leading to a fairer distribution of resources and benefits across the system. The higher system fairness achieved by the MRF algorithm is an important advantage that makes it a promising solution for real-world applications and scenarios with varying user populations.

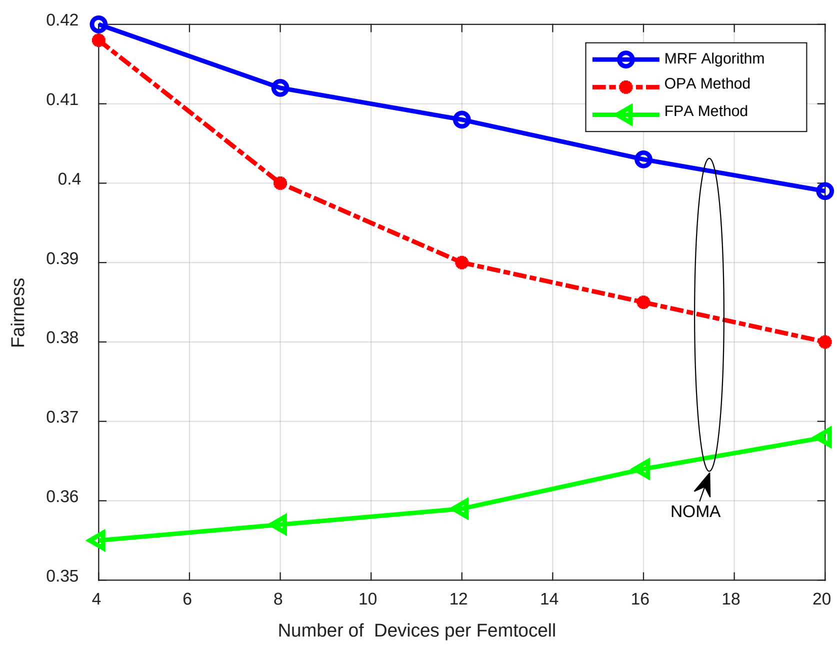

Figure 7. Number of femtocell device performance versus fairness.

Figure 8 illustrates the boundary rate comparison between the proposed power allocation scheme, which employs the MRF algorithm, and OPA and FPA. An example of FD communication engaging FBS over a channel gain is provided to facilitate understanding. The results in Figure 8 indicate that utilizing NOMA results in a larger capacity region compared to the other algorithms.

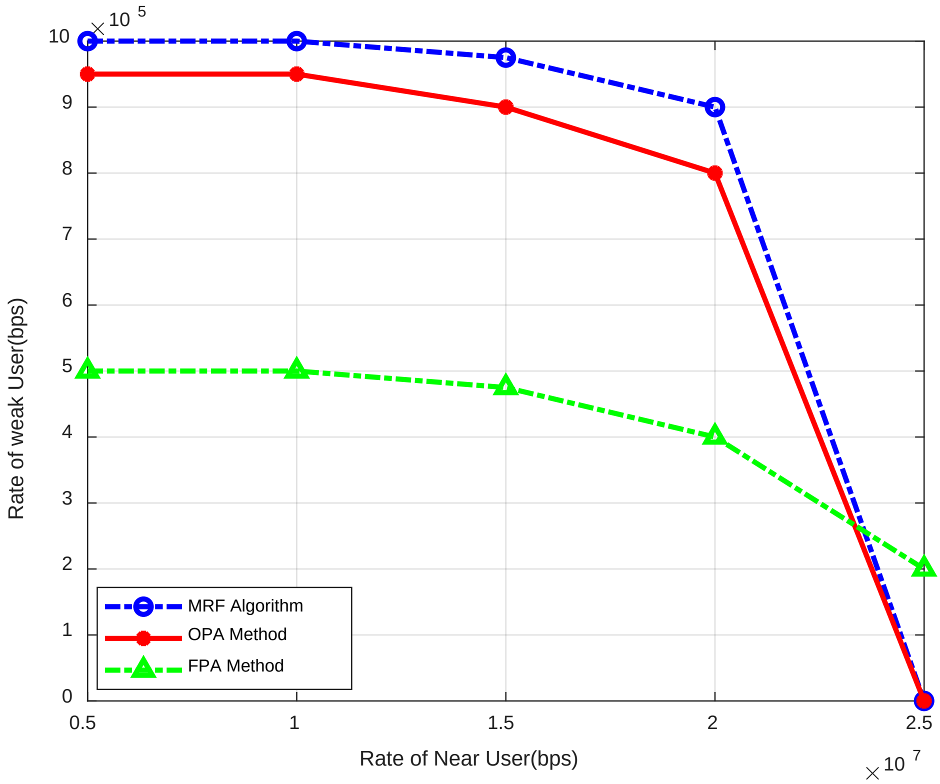

Figure 8. Rate weak FD vs. strongest FD.

Specifically, when comparing the MRF algorithm to FPA, it is evident that the rate of weak (FD) users with the proposed algorithm is approximately three times higher. This substantial rate improvement is considered a key advantage of the MRF algorithm over FPA. The rationale behind this advantage lies in the fact that users with low normalized channel gains should be given access to greater power levels to boost their reception. By allocating more power to weak FD users, their data reception quality is enhanced, leading to higher data rates.

A significant benefit of employing SIC in NOMA is that FDs with greater channel gains can utilize less power while still having an excellent chance of successfully detecting the data. This efficient power utilization allows NOMA to achieve a greater capacity region compared to OPA and FPA. That demonstrates that the proposed power allocation schemes, utilizing the MRF, outperform OPA and FPA, resulting in a larger capacity region and a higher rate for weak FD users. The intelligent power allocation strategy based on users' channel conditions, combined with the advantages of SIC in NOMA, contributes to the superior performance of the MRF algorithm.

6. Conclusions

This paper also addresses the problem of resource allocation in a downlink CR-NOMA system. It also proposes a fairness index based on the sample differences of users' transmission rates. Its concept of a fairness-constrained system combines the power allocation algorithm based on the proposed fairness index, which may optimize the system performance under the lowest fairness constraint. The simulation's findings show that the provided fairness index is appropriate for assessing systems' fairness with different user counts since it has a specified range with excellent responsiveness. The GADIA is a globally distributed algorithm for determining the network users' suboptimal frequency band distribution. So that interference can be avoided using the NOMA technique, each FD femtocell has several coupled devices. Then, theoretical and scenario simulations are evaluated to estimate the highest possible rate of MRF.

One potential limitation of the proposed fairness-constrained system and algorithm is scalability. As the number of users in the network increases, the complexity of the resource allocation process may grow significantly. Future work should address improving the algorithm's scalability to handle larger networks without compromising performance. The proposed approach may assume certain channel models or conditions. Wireless channels can be highly variable. Future work could investigate how the fairness index and allocation algorithm can adapt to dynamic channel conditions for more accurate resource allocation.

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