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APPLIED RESEARCH

Enhancing Performance of Downlink NOMA-Based C-RAN Topology Through Optimal User Pairing and Dynamic Power Allocation Scheme

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ABSTRACT This research introduces cutting-edge advancements in non-orthogonal multiple access (NOMA) technology. It begins by presenting a state-of-the-art user localization algorithm based on trilateration, which accurately determines user positions in NOMA systems. Additionally, two innovative algorithms, MP (maximize number of paired users) and ME (maximize pairing efficiency), are introduced to optimize system performance by addressing challenges in localization, user pairing, and dynamic power allocation. These algorithms enhance system capacity, reduce interference, and improve quality of service (QoS) for all users. To further optimize system performance, a dynamic power allocation scheme is developed to seamlessly integrate with NOMA pairing optimization. This scheme ensures optimal power allocation based on user-specific factors, leading to enhanced data transmission efficiency and overall system performance. The research also pioneers a mathematical formulation for the NOMA pairing problem, taking into consideration the variability of user demands. This unique contribution improves system performance for users with diverse data rate requirements, addressing a critical aspect of NOMA research. Furthermore, the NOMA pairing optimization problem is formulated as a graph maximum weighted sum problem. This formulation enables the use of efficient low-complexity algorithms, contributing to the advancement of algorithmic approaches in NOMA systems.

INDEX TERMS NOMA, localization, user pairing, dynamic power allocation, optimal fairness, capacity maximization.

I. INTRODUCTION

Non-orthogonal multiple access (NOMA) is a communication technique that enables simultaneous transmission and reception of multiple signals over the same frequency band [1]. Unlike orthogonal multiple access (OMA), where each user is assigned a separate orthogonal channel, NOMA assigns each user a unique power level and utilizes superposition coding. This allows for the decoding of signals using successive interference cancellation (SIC) based on their power levels. NOMA offers several advantages over OMA, including increased spectral efficiency, improved network capacity, and enhanced energy efficiency. By accommodating more users on the same frequency band, NOMA boosts network capacity and reduces the need for additional spectrum resources. Moreover, NOMA improves energy efficiency by enabling multiple users to share the same resources, thereby reducing the energy consumption required for communication [2].

Localization refers to the use of mobile technologies and cellular networks to determine the precise location of a mobile device or user. In the context of NOMA, accurate

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localization of users can bring several advantages to wireless networks [3]. It can enhance the performance of various algorithms, including resource allocation, interference management, and context-aware services. Moreover, it can optimize critical factors such as user pairing, power allocation, and the selection of appropriate transmission modes based on the user's location, mobility, and channel conditions [4]. The incorporation of efficient user pairing and dynamic power allocation (DPA) in NOMA systems offers numerous benefits over traditional approaches. User pairing can minimize inter-user interference, thus improving the overall system capacity. Simultaneously, DPA ensures that each user receives an adequate amount of power according to their quality of service (QoS) requirements, reducing the probability of system outage and enhancing reliability. However, the widespread adoption of NOMA with user pairing and DPA faces challenges that must be addressed. One significant challenge is the development of efficient user pairing algorithms that minimize inter-user interference and maximize system capacity. Additionally, DPA implementation may be computationally demanding and require significant processing power, posing practical limitations [5], [6].

Several research studies have investigated the performance of NOMA with DPA in different scenarios. For instance, a study by Lv et al. [7] investigated the performance of NOMA with DPA in a cognitive radio network. The study showed that NOMA with DPA can improve spectrum efficiency and user fairness compared to conventional cognitive radio schemes. Li et al. [8] proposed a joint optimization framework for power allocation, resource allocation, and joint user clustering in NOMA-based mobile edge computing, which can significantly reduce the average latency of the system. They proposed heuristic algorithms for user clustering and resource allocation. Then they used particle swarm optimization to optimize average system latency with constraints on energy consumption, user deadline, and computing resources. Song et al. [9] studied the performance of NOMA systems with imperfect channel state information (CSI) for Downlink NOMA Heterogeneous Networks and proposed a DPA algorithm that can adapt to the uncertainty of the channel information. The closed-form expressions of power allocation factors are derived by the Lagrangian multiplier method. The simulation results show the superiority and efficiency of the proposed scheme compared with the traditional algorithms. Wang et al. [10] evaluated the performance of NOMA with DPA in a multi-cell environment. The proposed model is analyzed under several key constraints for optimization objectives and then derived from the optimal power allocation coefficients. The study showed that DPA-NOMA could significantly improve the system throughput and user fairness compared to fixed power allocation schemes (FPA-NOMA).

Zhang et al. [5] studied the problem of energy-efficient resource allocation using a two-step optimization algorithm. They first model the user scheduling problem as a dynamic matching between sub-bands and users. Given the user schedule, the power allocation problem was written as a convex optimization problem and solved using gradient assisted binary search algorithm. Ghafoor et al. [6] considered energy efficiency optimization under total power and minimum user data rate constraints. They used the Charnes-Cooper transformation to convert their non-linear concave fractional programming problem to a mixed-integer non-linear programming problem (MINLP). The MINLP problem was solved using a two-phase ϵ-optimal outer approximation algorithm. Akhtar et al. [11] propose Q-learning-based algorithm for sub-band and power allocation for users with different data requirements for sum-rate maximization. Their technique showed better results than Q-learning-based techniques that ignored the QoS requirements of different users. All mentioned techniques do not consider fairness as part of their resource allocation problem.

Liao et al. [12] studied the problem of balancing between energy efficiency and user long-term fairness as measured by the Jain index fairness. They proposed using a particle swarm optimization algorithm for achieving near-optimal solutions in linear time complexity. Ali et al. [13] developed a fair energy-efficient resource allocation approach in downlink femtocell NOMA-HetNets. A Greedy Algorithm (GA) was used to obtain a low-complex suboptimal solution during the user-pairing process. Simultaneously, the max-min energy efficiency optimization was employed to maximize the minimum energy efficiency of the femtocell users to achieve the optimal power allocation solution. The results showed that the proposed NOMA-SCP-GA had low complexity and fast convergence with more user fairness. However, both [12] and [13] do not consider resource allocation for users with heterogeneous data rate demands. Rezwan and Choi [14] used a deep-Q learning framework for priority-based channel assignment in NOMA systems with heterogeneous services. Their method maximizes the channel sum rate while achieving a minimum per-user data rate for fairness. Although different user demands are considered, all users receive the same minimum data regardless of whether this minimum is below the minimum requirement of the service or not. Therefore, users with high demands may get blocked while others operate, causing unfairness.

The scientific contributions of the presented results are as follows:

- Enhancing NOMA System Performance: This research introduces a user localization algorithm that accurately determines user positions in a NOMA system, enabling optimized resource allocation. Additionally, innovative algorithms address challenges in techniques like localization, user pairing, and dynamic power allocation, maximizing system capacity and improving user quality of service.
- Optimal Power Allocation for NOMA Systems: A dynamic power allocation scheme is developed to seamlessly integrate with NOMA pairing optimization.

This scheme optimizes power allocation based on user positions, channel conditions, and data rate requirements, enhancing data transmission efficiency and overall system performance.

- Addressing User Heterogeneity in NOMA Pairing: This study devises a novel mathematical formulation for NOMA pairing optimization, considering the diverse data rate demands of users. This formulation represents a significant contribution to NOMA pairing research and improves system performance for users with variable data rate requirements.
- Graph-Based Optimization for NOMA Pairing: The research formulates the NOMA pairing optimization problem as a graph maximum weighted sum problem, enabling the utilization of efficient low-complexity algorithms. This approach offers an effective solution for optimizing resource allocation in NOMA systems and contributes to the advancement of algorithmic approaches in the field.

Overall, these scientific contributions significantly enhance our understanding and practical implementation of NOMA systems by introducing a novel user localization algorithm, developing an effective dynamic power allocation scheme, addressing heterogeneous user demands, and formulating the NOMA pairing optimization problem as a graph maximum weighted sum problem.

The remaining sections of this paper are structured as follows: In Section II, we provide a comprehensive explanation of the NOMA network, including details about its localization, dynamic power allocation, and optimal user pairing algorithms. In Section III, we present and thoroughly discuss the results obtained from the conducted research. Finally, in Section IV, we conclude the paper by summarizing our findings and highlighting the research outcomes.

II. SYSTEM MODEL & ALGORITHMS

This section introduces implementing a NOMA-based cloud radio access network (C-RAN) topology by investigating the signal-to-interference-and-noise ratio (SINR). The list of symbols and notations used in this paper is summarized in 1.

A. DOWNLINK NOMA-BASED C-RAN TOPOLOGY

C-RAN is a centralized network architecture that separates the processing of signals from the radio hardware. It involves using a pool of virtualized baseband processing resources, which can be shared among multiple remote radio heads (RRHs) at different locations. The RRHs are key components of the C-RAN architecture, as they perform the radio frequency (RF) processing and convert the digital baseband signals into analog radio signals that are transmitted over the air. In NOMA technology, the RRH transmits the combined signal for all users (N), including those using NOMA. For the L user-pairs selected for NOMA, the RRH transmits the combined signals with different acceptable power coefficients depending on channel condition and SINR of each user, as presented in Fig. 1. The users with the best channel condition and highest transmission power can immediately recover their signal without or with minimal interference from other users. However, other users must use SIC techniques to extract their signals from the combined signal.

TABLE 1. The list of symbols and notations used in this paper.

Notation	Definition
N	Number of served users by RRH
L	Number of paired users
S	The combined transmitted signal at the RRH
α_i	The power allocation coefficient for user i
k_i	The transmitted information of user i
P_s	The transmitted power by RRH
h_l	The channel coefficient of l^{th} user
y_l	The received signal of of l^{th} user
n_l	The zero mean complex additive Gaussian noise with σ^2
$\gamma_{j\to l}$	The instantaneous SINR of l^{th} user to detect j^{th} user
γ_l	The SINR of l^{th} user
γ_L	The SINR of the L^{th} user
R	The sum data rate
d_i	The direct distance between the UE to RRH$_i$
(x_{bi}, y_{bi})	The location of reference RH$_i$
(x_m, y_m)	The unknown position of the UE
P_r	The received power Level in dB_m
f	The transmission frequency of the signal in MHz
H_m	The effective receiving mobile device antenna in meters
H_b	The effective height of transmitting RRH antenna in meters
C	The correction factor for open rural areas
$a\,(H_m)$	The correction function
γ_f	The SINR for far user
γ_n	The SINR for near user
$\gamma_f(i,j)$	The SINR for far user in the pair (i, j)
γ_{th}	The minimum acceptable SINR for far user
α_f	The PA coefficients for far user
α_n	The PA coefficients for near user
ξ	The ratio between PA coefficient of the far and near user
ξ_{ij}	The ratio between PA coefficient of the far and near user in the pair (i, j)
ξ_{th}	The minimum acceptable ratio between PA coefficient of the far and near user
P	The pairing matrix
p_{ij}	The element in pairing matrix P
η_{ij}	The efficiency of pair
β	The fairness coefficient
$J(x)$	The Jain fairness index

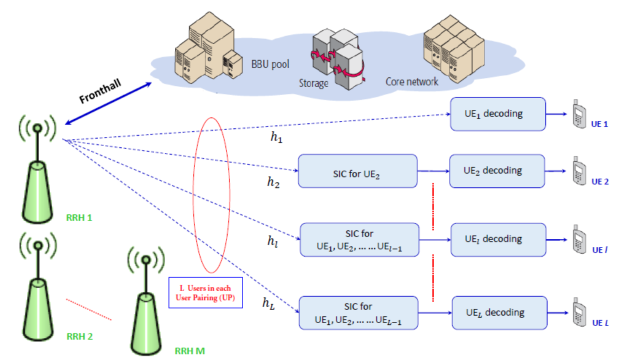

FIGURE 1. Schematic Diagram for Downlink NOMA Network integrated with RRH.

The transmitted signal by the RRH can be expressed as follows [15]:

$$S=\sum_{i=1}^{L}\sqrt{\alpha_i P_s}k_i \quad , \tag{1}$$

where k_i is the transmitted information by user i, P_s is the transmission power by the RRH, and α_i is the power coefficient allocated for user i. The power coefficient α_i is used to allocate the transmission power among different users. The DPA scheme uses to determine the power coefficient α_i in order to maximize the overall system capacity subject to individual user's QoS constraints. Suppose that the channel noise is additive white Gaussian noise (AWGN) with a variance of σ^2; thus, the SINR of l^{th} user can be given by

$$\gamma_l=\frac{\alpha_l \rho\,|h_l|^2}{1+\rho\,|h_l|^2\sum_{i=l+1}^{L}\alpha_i} \quad , \tag{2}$$

where $\rho = P_s/\sigma^2$ and h_l is the channel coefficient of user l. Therefore the achievable throughput of l^{th} user can be expressed by

$$R_l^{\mathrm{NOMA}}=\log_2\left(1+\frac{\alpha_l \rho\,|h_l|^2}{1+\rho\,|h_l|^2\sum_{i=l+1}^{L}\alpha_i}\right), \tag{3}$$

The achievable throughput of each user is determined by the modulation and coding scheme used and the channel conditions. Thus, the overall throughput of downlink NOMA can be written as

$$\begin{aligned}R_{\mathrm{sum}}^{\mathrm{NOMA}}=&\sum_{l=1}^{L-1}\log_2\left(1+\frac{\alpha_l \gamma_l\,|h_l|^2}{1+\gamma_l\,|h_l|^2\sum_{i=l+1}^{L}\alpha_i}\right)\\&+\log_2\left(1+\alpha_L\gamma_L\,|h_L|^2\right) \ .\end{aligned} \tag{4}$$

This equation takes into account the number of users, their channel conditions, and the power allocation technique. Optimizing these parameters makes it possible to achieve higher throughput and better spectral efficiency in downlink NOMA systems.

B. LOCALIZATION ALGORITHM

The localization algorithm computes the user's position using the received signal strength indication (RSSI) and trilateration method. The RSSI represents the amount of energy lost during signal transmission. It can be used to calculate the direct distance between the RRH and the target user, where its value corresponds to the amount of signal attenuation, which could be calculated using various models. Okumura-Hata is one of the most useful models for calculating RSSI [3]. The Okumura-Hata model can be used for predicting the path loss of cellular transmissions into three modes urban, suburban, and open areas. It is an empirical propagation model based on extensive drive test measurements made in Japan at several frequencies ranging from 150 to 3000 MHz in a range from 1 to 100 km. The formula for the Okumura-Hata model is expressed as follows

$$\begin{aligned}L_p(dB)=&\,69.55+26.16\log(f)-13.82\log(H_b)-a(H_m)\\&+(44.9-6.55\log(h_b))\log(d)+C\end{aligned} \tag{5}$$

where f is the transmission frequency in MHz, d is specified in kilometers, H_b is the effective height of transmitting RRH antenna in meters, H_m is the effective receiving mobile device antenna in meters, C is a correction factor for open rural areas and $a(H_m)$ mobile antenna height correction factor that depends on the environment which is given by

$$\begin{aligned}&1: Smallandmedium-sizecities\\&a(H_m)=(1.1\log f-0.7)h_m-1.56\log f+0.8\\&C=0,\end{aligned} \tag{6}$$

$$\begin{aligned}&2: Metropolitanareas\\&a(H_m)=\begin{cases}8.29\,(\log 1.54\,H_m)^2-1.1 & (f\le 300\mathrm{MHz})\\ 3.2\,(\log 11.75\,H_m)^2-4.97 & (f>300\mathrm{MHz})\end{cases}\\&C=0,\end{aligned} \tag{7}$$

$$\begin{aligned}&3: Ruralarea\\&a(H_m)=(1.1\log f-0.7)H_m-1.56\log f+0.8\\&C=-4.78(\log f)^2+18.33\log f-40.98\ .\end{aligned} \tag{8}$$

Trilateration is a method of determining the precise positions of objects using the geometry of triangles. It uses the known locations of three reference points and the measured distance between the object and each reference point. Fig. 2 shows the concept of trilateration on an x-y plane by considering the three RRHs as the three available reference points, the x and y coordinates of the user equipment (UE) can be calculated as follows:

$$\begin{aligned}(x_m-x_{b1})^2+(y_m-y_{b1})^2&=d_1^2\\(x_m-x_{b2})^2+(y_m-y_{b2})^2&=d_2^2\\(x_m-x_{b3})^2+(y_m-y_{b3})^2&=d_3^2.\end{aligned} \tag{9}$$

where, (x_{bi}, y_{bi}) , $i\in\{1,2,3\}$ are the locations of references RRH$_i$, and (x_m, y_m) is the unknown position of the UE. The d_i is the direct distance between the UE and RRH$_i$, and it calculates by (5). The three equations in (9) could be mathematically solved to determine the precise location of UE.

C. DYNAMIC POWER ALLOCATION (DPA)

Static power allocation (SPA) is a power allocation scheme in NOMA where the power is fixed for each user and remains constant during the transmission. In SPA, the power is allocated to each user based on their channel quality, whereas users with better channel quality are allocated more power than those with worse channel quality. The DPA technique enables the NOMA system to adapt the power allocated to each user according to the network conditions, such as user location, data rate, and channel quality. By monitoring

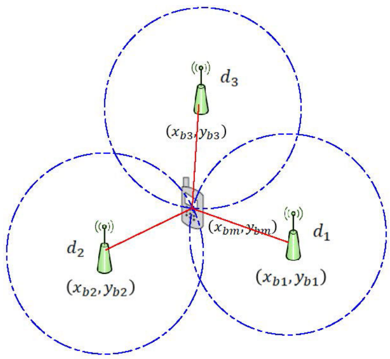

FIGURE 2. Trilateration technique on *x*-*y* plane.

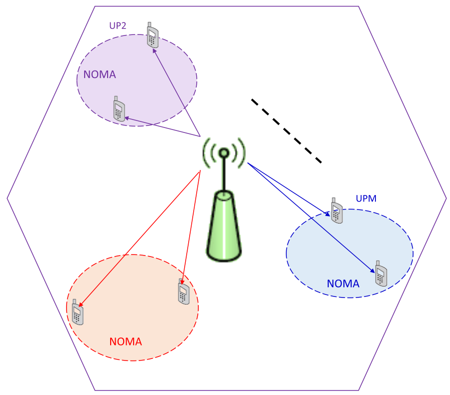

FIGURE 3. Two-user pairing for downlink NOMA system.

these factors, the system can adjust the transmission power of each user's device in real-time to optimize the overall system performance. This can improve the system capacity, energy efficiency, and QoS for the users, leading to better user experiences and increased network utilization. The DPA has been shown to outperform SPA in terms of system capacity and energy efficiency. However, DPA requires more signaling overhead and complexity compared to SPA [16], [17].

With the integration of DPA and localization algorithm into a NOMA system, the system can accurately estimate the location of each user, which uses to adjust the power allocation between different users. Users closer to the RRH can be assigned lower power levels, while those farther away can be assigned higher ones. This can improve the system's overall energy efficiency and reduce interference levels. In the DPA scheme, the power allocation coefficient is determined based on the instantaneous channel conditions, which can change over time as follows:

$$\alpha_i = \frac{d_i^2}{\sum_{j=1}^{L} d_j^2} \tag{10}$$

where d_i is the distance between the RRH and the i^{th} UE and L is the number of users assigned the same resource (paired users).

As shown in Fig. 3, the RRH simultaneously transmits multiple signals to two users in the same frequency and time resource. In NOMA-downlink-SIC with two users, the RRH assigns different power levels to the two signals based on the channel quality of each user. The signal transmitted at a higher power level is intended for the "strong or far" user, while the signal transmitted at a lower power level is intended for the "weak or near" user. The strong user decodes its own signal first by subtracting the interference caused by the weak user's signal using SIC. After decoding its signal, the strong user sends feedback to the weak user indicating the received signal quality. Then the weak user decodes its own signal after receiving feedback from the strong user, which cancels out the interference caused by the strong user's signal using SIC and then decodes its own signal using the residual signal. By canceling out the interference from the strong user's signal, the weak user achieves a better SINR and a higher data rate.

The SINR for the user with the highest power allocation coefficient (far-user) can be expressed as:

$$\gamma_f = \alpha_f \rho \left|h_f\right|^2 \tag{11}$$

Similarly, the SINR for the second user (near-user) can be expressed as:

$$\gamma_n = \alpha_n \rho \left|h_n\right|^2 \tag{12}$$

where $\alpha_f = d_f^2 / \left(d_f^2 + d_n^2\right)$ and $\alpha_n = d_n^2 / \left(d_f^2 + d_n^2\right)$ denote the PA coefficients for far and near users, respectively and $\alpha_f > \alpha_n$ and $\alpha_f + \alpha_n = 1$. Finally, h_f and h_n represent the Rayleigh fading coefficient for far-user and near-user (paired users). To achieve high system performance in NOMA, the power allocation coefficients must be carefully designed and optimized to maximize the SINRs of all users while ensuring that the total transmission power does not exceed the available power budget. In some cases, it may not be possible for a particular user to pair with another user, i.e., to share the same time-frequency resources. In such cases, the NOMA system can serve that user individually by assigning it a dedicated resource block or time slot (unpaired or individual user). After the computation of the PA coefficients, the parameter (ξ) is determined as the ratio between the PA coefficient of the far user and the PA coefficient of the near user as follows:

$$\xi = \frac{\alpha_f}{\alpha_n} \tag{13}$$

In the proposed DPA scheme, the power consumed by the far-user can be expressed as:

$$P_f = \frac{10^{\frac{\gamma_t h}{10}} \times \sigma^2}{\alpha_f \left|h_f\right|^2} \tag{14}$$

Similarly, the power consumed by the near-user is written as:

$$P_n = \frac{10^{\frac{\gamma_t h}{10}} \times \sigma^2}{\alpha_n \left|h_n\right|^2} \tag{15}$$

In the case of an individual user v, the power allocated is given by:

$$P_v = \frac{10^{\frac{\gamma_{th}}{10}} \times \sigma^2}{|h_v|^2} \tag{16}$$

These formulas indicate that the power consumed by the user is inversely proportional to the distance and channel condition while directly proportional to the threshold SNR (minimum SNR required to detect and decode the transmitted information successfully). Algorithm 1 shows the localization scheme used to calculate the position and distance of each user by using the Trilateration method and the allocated power coefficients for near and far users to optimize system performance while achieving the required data-rate, maximizing spectral efficiency, and satisfying power limit constraints. The power efficiency of the NOMA system is boosted, and the user pairing can be used effectively depending on the DPA. The main objective is to maximize the number of paired users and decrease the number of unpaired users by optimizing the pairing. Furthermore, the sum rate will be maximized. The following two subsections discuss the optimal user pairing algorithm and fair resource allocation.

Algorithm 1 Localization and DPA

Initialization f; P_s; G_t; H_b; H_m **for** *each user i* **do**
- Sorting P_r descending;
- Select the maximum three received power;
- Calculate the UE distances, (5);
- Apply the Trilateration method (9);

Calculate α_f & α_n (10);
Calculate γ_f (11) and γ_n (12);
Calculate ξ (13) ;

D. OPTIMAL USER PAIRING ALGORITHM

The optimal user pairing algorithm in NOMA aims to pair users with different channel qualities such that they can share the same resources while ensuring a minimum quality of service for all users. In the case of a 2-user NOMA scenario, we introduce a pairing matrix P where each element p_{ij} in P is a binary value representing the following [18]:

$$p_{ij} = \begin{cases} 1 & \text{if user } i \text{ is paired with user } j \\ 0 & \text{o.w} \end{cases} \tag{17}$$

Since we assume a 2-user pairing scheme, the matrix should be symmetric. Additionally, we denote an unpaired user by $p_{ii} = 1$. Hence, any row or column's sum must equal one. Assuming the requested data rates of the i^{th} user described by $r_i, i = 1, 2, \ldots, N$, the requested data rate (demand) of pair (i, j) is equal to $max(r_i, r_j)$. Therefore, the total data rate demand (R_{demand}) in the system after user pairing can be given by:

$$R_{\text{demand}} = \sum_{i=1}^{N}\sum_{j=i}^{N} p_{ij} \times max(r_i, r_j) \tag{18}$$

Due to resource limitation, the maximum rate that the system could serve is $R_{\max}$. The system allocates a data rate for both paired and unpaired users represented by array X, such that the sum of elements in the array should not exceed $R_{\max}$. The elements of array X are the rates allocated for each user pair (i, j) denoted by x_{ij} and the rate allocated for each unpaired user i denoted by x_{ii}. The throughput delivered ($R_{\text{delivered}}$) by the system is the sum of the throughput used by unpaired users and the throughput used by each user within a pair. The throughput delivered can be mathematically written as:

$$R_{\text{delivered}} = \sum_{i=1}^{N}\sum_{j=i+1}^{N} p_{ij} \times (min(r_i, x_{ij}) + min(r_j, x_{ij})) + \sum_{i=1}^{N} p_{ii} \times min(r_i, x_{ii}) \tag{19}$$

Eq. 18 and 19 show that pairing can decrease the demand on system resources and increase the system efficiency. This performance enhancement is dependent on the pairing scheme used. In the next subsection, we mathematically formulate a general pairing problem and study two paining variants: pair count maximization and pairing efficiency maximization. We also propose an algorithm for solving these pairing problem variants.

1) PROBLEM FORMULATION

First, we consider the pair count maximization problem, which we call NOMA-maximize pairing (MP). The pairing problem in NOMA-MP can be mathematically formulated as:

$$\max_{P} \sum_{i=1}^{N}\sum_{j=i+1}^{N} p_{ij} \tag{20a}$$

$$\text{s.t.} \quad p_{ij} \in \{0, 1\} \tag{20b}$$

$$\sum_{j=1}^{N} p_{ij} \leq 1 \quad \forall i, \tag{20c}$$

$$\sum_{i=1}^{N} p_{ij} \leq 1 \quad \forall j, \tag{20d}$$

$$\xi_{ij} \times p_{ij} \geq \xi_{th} \times p_{ij} \tag{20e}$$

$$\gamma_f(i, j) \times p_{ij} \geq \gamma_{th} \times p_{ij} \tag{20f}$$

where ξ_{th} is the PA coefficient ratio between the far and near user in the pair (i, j), ξ_{th} is the minimum acceptable PA coefficient ratio, $\gamma_f(i, j)$ is the SINR of the far user in the pair (i, j), and γ_{th} is the minimum acceptable SINR for the far-user. Constraints 20c and 20d ensure that a user can be paired with at most one other user. Constraints 20e and 20f ensure that the chosen pair do not violate the pairing constraints.

As seen by its optimization problem, NOMA-MP only cares about the number of pairs created and ignores the difference in throughput demand between the paired users. Therefore, NOMA-MP wastes a portion of the throughput equal to $|r_i - r_j|$. We define a pairing efficiency maximization scheme called NOMA-maximize efficiency (ME) to solve this problem. The objective of NOMA-ME is to maximize the pairing efficiency for all pairs in the system. The efficiency of pair (i, j) is denoted by η_{ij} and defined as:

$$\eta_{ij} = \frac{r_i + r_j}{\max(r_i, r_j)} \tag{21}$$

To define the pairing problem in NOMA-ME, we apply constraints 20c, 20d, 20e, and 20f and reformulate Eq. 20a as follows:

$$\max_{P} \sum_{i=1}^{N} \sum_{j=i+1}^{N} p_{ij} \times \eta_{ij} \tag{22}$$

From Eq. 22, we can see that NOMA-ME tries to balance between maximizing the number of pairs and decreasing demand differences within the pairs.

2) PROPOSED SOLUTION

Representing the problem as an undirected graph, where the nodes represent the users, edges represent feasible pairings between users, and edge weight equal to the pair importance, allows exploring graph theory-based solutions. The importance of a user pairing changes according to the pairing problem variant considered. Since edges represent only feasible pairings p_{ij}, the problem can be defined as finding the group of non-adjacent edges with the maximum weighted sum. This redefined problem is similar to general graphs' maximum weighted matching problem. The NetworkX [19] library's implementation of Edmond's blossom [20] and primal-dual [21] algorithms, which solves the problem in $O(N^3)$, was used due to its optimality and reasonable time complexity. Paired users are added by placing ones at p_{ij}, while unpaired users are added by placing ones in p_{ii}.

Algorithm 2 summarizes the steps for achieving optimum pairs according to Eq. 20a for any user setting. The condition in line 4 refers to the constraints 20e and 20f.

Algorithm 2 NOMA Pairing Algorithm

```
Create graph G with all users as nodes ;
for each user i do
    for each user j > i do
        if user i and j can be paired then
            add edge (i,j) to G ;
            if NOMA-MP used then
                weight of edge (i,j) = 1 ;
            else
                weight of edge (i,j) = (r_i + r_j) / max(r_i, r_j) ;
p_ij ← apply maximum weight matching algorithm
  for G ;
```

E. FAIR RESOURCE ALLOCATION

Resource blocks must be allocated for a given paired user to serve the demand calculated for paired and unpaired users. The resource allocation algorithm needs to distribute the resource blocks reasonably and fairly. We use the β-proportional fairness-based resource allocation derived by Wang et al. [22]. However, we use resource allocation to distribute a portion of the total system resource blocks instead of allocating a portion of the time slot. The data rate allocated to each user pair (i, j) (x_{ij}), where $j = i$ in case of unpaired users, is expressed as [22]:

$$x_{ij} = \frac{p_{ij} * (max(r_i, r_j))^{\frac{1}{\beta}-1}}{\sum_{i=1}^{N} \sum_{j=i}^{N} p_{ij} * (max(r_i, r_j))^{\frac{1}{\beta}-1}} \times R_{\max} \tag{23}$$

where β is the fairness coefficient. Fairness is measured with respect to the benefit given to each user compared to the benefit given to others. Since different users have different data rate demands, defining the user benefit in terms of their demand is only logical. Hence, we define the benefit received by user pair (i, j) from the rate allocation x_{ij} as:

$$b_{ij} = \frac{x_{ij}}{max(r_i, r_j)} \tag{24}$$

To assess the fairness of the resource allocation approach defined in Eq. 23 at different values of β, we use the Jain fairness index given by the following equation [23]:

$$J(x) = \frac{(\sum_{i=1}^{N} \sum_{j=i}^{N} p_{ij} * b_{ij})^2}{\sum_{i=1}^{N} \sum_{j=i}^{N} p_{ij} * b_{ij}^2} \tag{25}$$

III. SIMULATION & RESULTS

To comprehensively evaluate the efficacy of our proposed pairing approaches, we conduct a rigorous assessment by considering multiple performance metrics. Firstly, we calculate the average demanded rate (R_{demand}) and power consumption for three distinct system configurations: a system without pairing (referred to as "individual"), a system implementing NOMA-MP, and a system employing NOMA-ME pairing technique. These calculations are performed for various numbers of users, enabling us to analyze the impact of user population on these metrics. Additionally, we assess the efficiency and fairness of the resource allocation methods by measuring two key performance indicators: the delivered rate ($R_{\text{delivered}}$) and the Jain index. By evaluating $R_{\text{delivered}}$ and the Jain index for different numbers of users, we gain valuable insights into the efficiency and fairness achieved by our proposed resource allocation strategies. It is important to note that

TABLE 2. Simulation parameters.

	Parameter	Value
Threshold SNR	γ_{th}	30
AWGN variance	σ^2	$7.9621^{-}16$
The transmitted power by RRH	P_s	0.0013 W
Threshold PA ratio	ξ_{th}	1.5
Maximum Throughput	$R_{\max}$	100 Mbps

these evaluations involve varying the value of β–a parameter influencing the resource allocation scheme–and the number of users (N).

To ensure the statistical robustness of our analysis, we meticulously constructed a dataset comprising a total of 124, 828 records. This expansive dataset encompassed a cell radius of 200 m, maintaining a uniform distance of 1 m between any two consecutive users. Within our simulation results, we systematically performed iterations for each unique combination of β and N, systematically exploring individual β and specific N values in isolation. In each iteration, we randomly select the N users from the conducted dataset. By varying the number of iterations, we conducted an investigation to identify the ideal quantity that would yield representative and reliable outcomes while remaining cognizant of time constraints. As a result, we found that conducting 50 iterations proved to be sufficient to obtain representative results within a manageable timeframe. During each iteration, we selected N users and their corresponding positions randomly from the constructed dataset that we had generated. In order to effectively model diverse data rate demands, we assigned each user a randomly generated requested data rate using a discrete uniform distribution within the range of [1, 5]. This method ensured a realistic representation of diverse data rate requirements, further enhancing the fidelity of our simulations.

The system is thoroughly tested across a range of N values, ranging from 10 to 150 users, while utilizing various β values such as 0.5, 0.8, 1, 2, 4, 6, 8, and 10. The SNR threshold is set at 30 dB as a result of a comprehensive analysis and rigorous simulations to achieve a resilient performance with a BER of 10^{-3} for every user within the cell, particularly those residing at the cell-edge, operating in a multipath Rayleigh fading channel. By encompassing a wide spectrum of user populations and β values, we ensure a comprehensive evaluation of the proposed approaches under diverse scenarios. For a complete understanding of the simulation setup, please refer to Table 2, which outlines the remaining critical simulation parameters. These parameters play a vital role in defining the simulation environment and guaranteeing consistent and reliable results.

Fig. 4 presents a comprehensive analysis of the behavior of the demanded rate (R_{demand}) when utilizing different pairing techniques in the system. Regardless of the specific pairing technique employed, our findings demonstrate a positive correlation between the number of users (N) and the demanded rate R_{demand} due to an increased number of requests within the system. Additionally, our results indicate

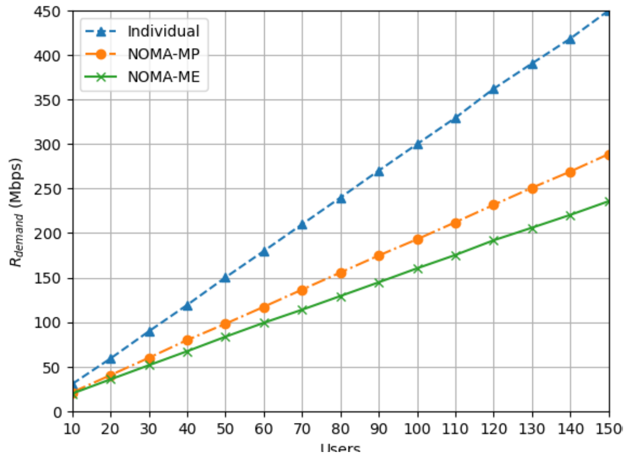

FIGURE 4. R_{demand} needed by different pairing techniques under different users N.

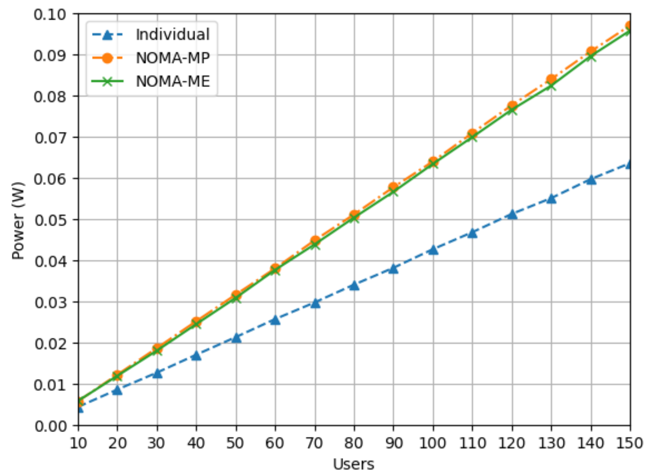

FIGURE 5. Power consumed by different pairing techniques under different users N.

a significant decrease in the required data rate achieved through the implementation of user pairing. Pairing users together leads to a substantial reduction in the demanded rate compared to scenarios without pairing. This reduction in required data rate highlights the effectiveness of user pairing techniques in optimizing resource utilization and efficiently meeting user demands. Notably, the NOMA-ME pairing technique stands out as the most efficient in reducing the required data rate, as intended. Particularly at higher user rates, where a greater number of pairs are likely to exhibit a low value of the channel quality parameter η_{ij} (between user i and user j) under the NOMA-MP pairing technique, the NOMA-ME approach proves to be highly effective.

Fig. 5 provides comprehensive data on the power consumption associated with different pairing techniques used at various values of N. This result elucidates the trade-off between the efficiency and power consumption in NOMA systems. Specifically, it demonstrates that the power consumption in a system without pairing is comparatively lower than systems that employ pairing techniques. However,

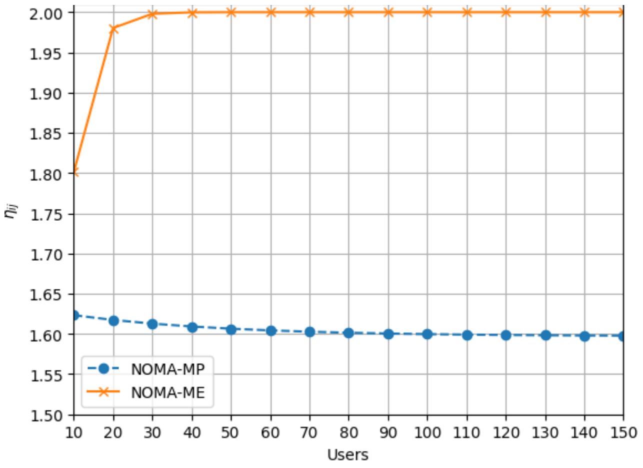

FIGURE 6. Average η_{ij} for pairs created by NOMA-MP and NOMA-ME pairing at different N.

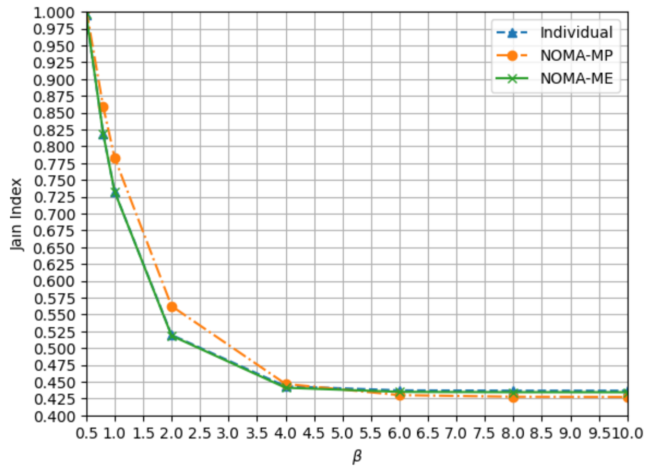

FIGURE 7. Jain index value for resources allocation under different pairing techniques using different β.

it is crucial to note that the unparsed system necessitates a greater allocation of system resources. The findings underscore the importance of considering the trade-off between power consumption and resource efficiency when determining whether to implement user pairing techniques. While these techniques contribute to enhanced resource utilization and system efficiency, they entail increased power consumption.

Therefore, the choice to employ pairing techniques should be determined by the specific needs and priorities of the system. The results also indicate that both NOMA-MP and NOMA-ME pairing techniques consume approximately equal levels of power. This finding offers an added benefit to using NOMA-ME because it utilizes fewer system resources while maintaining similar power consumption levels. This observation further supports the use of NOMA-ME as a preferred pairing technique, as it achieves resource efficiency and comparable power consumption, ultimately resulting in an optimized balance between power consumption and system performance.

Fig. 6 provides detailed insights into the average pair efficiency experienced by user pairs formed using the NOMA-ME and NOMA-MP techniques, across different numbers of users. The results obtained from this analysis support our initial hypothesis and confirm that NOMA-MP technique tends to waste resources due to the formation of inefficient pairs. In contrast, the findings consistently demonstrate that NOMA-ME achieves the highest pairing efficiency in most scenarios. Pairing efficiency is a crucial metric that reflects the effectiveness of forming user pairs, considering factors such as channel conditions and rate demands. The results strongly indicate that the NOMA-MP technique, which pairs users with differing rate demands, falls short in terms of achieving optimal pairing efficiency. This inefficient pairing strategy leads to suboptimal utilization of resources and compromises the overall efficiency of the system. Conversely, the NOMA-ME technique consistently exhibits superior performance in terms of achieving maximum pairing efficiency. By intelligently pairing users with compatible rate demands, NOMA-ME optimizes the allocation of resources, ensuring that each user pair can make the most efficient use of the available resources.

This approach significantly enhances the overall efficiency and performance of the NOMA system. These findings emphasize the importance of employing the NOMA-ME technique to achieve maximum pairing efficiency in NOMA systems. By selecting user pairs judiciously based on their rate demands and channel conditions, NOMA-ME maximizes the utilization of resources, resulting in enhanced system performance and improved overall efficiency. The results from this analysis offer valuable insights into the optimization of user pairing strategies and contribute to the development of more efficient and reliable NOMA systems in various communication scenarios.

Fig. 7 illustrates the Jain index, a measure of fairness, as a function of the parameter β. The Jain index quantifies the fairness of resource allocation techniques in a system. As β increases, our results indicate a decrease in fairness. For $\beta = 0.5$, the resource allocation algorithm distributes resources proportional to the requested rate of each user, resulting in equal benefits for all users. However, as β increases, the allocation strategy shifts towards maximizing the minimum rate provided to each user, irrespective of their request. Consequently, at high β values, users with low data demands benefit greatly, while those with high data demands receive fewer benefits. This disparity undermines the fairness of the system.

The results depicted in Figures 8, 9, and 10 provide significant scientific insights into the behavior of the delivered rate ($R_{\text{delivered}}$) in various scenarios, namely no pairing, NOMA-MP, and NOMA-ME. These figures showcase the impact of different values of β on the

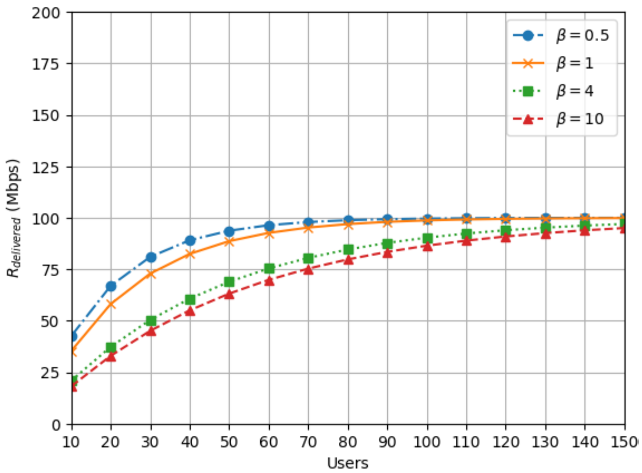

FIGURE 8. $R_{\text{delivered}}$ **at different** N **by resource allocation under no pairing using different** β**.**

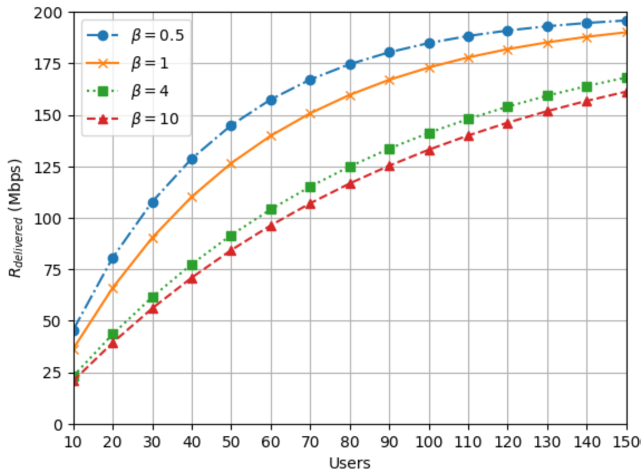

FIGURE 10. $R_{\text{delivered}}$ **at different** N **by resource allocation under NOMA-ME pairing using different** β**.**

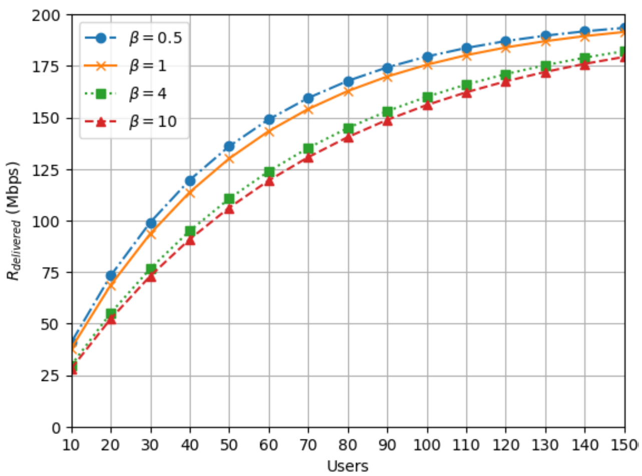

FIGURE 9. $R_{\text{delivered}}$ **at different** N **by resource allocation under NOMA-MP pairing using different** β**.**

allocation of rates. Consistent with prior research, when β assumes high values, users with lower data rate demands receive excessively high rates, leading to inefficient resource utilization and a decrease in overall system efficiency. The experimental outcomes reaffirm this observation and lend support to our earlier calculations. In the absence of pairing, the maximum value of $R_{\text{delivered}}$ equals R_{max}, as the available resources are solely allocated to a single user without any sharing or allocation considerations.

In terms of resource allocation, the utilization of proportional allocations (specifically observed at $\beta = 0.5$) is found to be the most efficient, as it minimizes resource waste while maximizing system performance. It is worth mentioning that the NOMA-ME approach outperforms others at $\beta = 0.5$ due to its effective user pairing mechanism. This mechanism ensures that users with compatible rate demands are paired together, resulting in optimal resource utilization and overall performance enhancement. On the other hand, the NOMA-MP approach shows relatively better performance at higher β values. This improvement can be attributed to the inefficient pairing strategy employed by NOMA-MP, where users with lower rate demands are paired with those requiring higher rates. However, it is important to acknowledge that this performance gain comes at the cost of reduced variation in benefits and a shift in the distribution of requested rates towards higher values.

Based on a comprehensive analysis of the data depicted in the previous figures, it can be inferred that the NOMA-ME approach, combined with efficient user pairing and the proportional allocation strategy at a specific value of β (i.e., $\beta = 0.5$), results in highly desirable performance outcomes. These findings highlight the crucial importance of selecting appropriate values for β and establishing optimal user pairing in order to achieve efficient allocation of resources in NOMA systems. Moreover, these strategies have the potential to significantly enhance system throughput and optimize the overall performance of NOMA systems.

IV. CONCLUSION

The research paper introduces a novel optimal user pairing and dynamic power allocation scheme for NOMA systems. The scheme consists of two algorithms that work together to improve system performance. The first algorithm accurately locates the positions of distributed users and determines the power levels required for each user based on their position and channel conditions. This precise power allocation ensures that each user receives an optimal power level, maximizing data transmission efficiency. The second algorithm focuses on achieving fairness among different user pairs by intelligently balancing data rates. It considers factors such as user channel conditions and data rate requirements to allocate resources in a way that ensures equitable distribution of bandwidth and throughput. Extensive simulations were conducted to evaluate the proposed scheme. The results showed that it outperformed conventional approaches in terms of system throughput and user fairness. The scheme demonstrated higher system throughput, allowing for more efficient resource utilization, and better fairness by balancing data rates among user pairings. In conclusion, the proposed optimal user pairing and dynamic power allocation scheme is a effective approach to enhance the performance of NOMA systems. It has potential applications in wireless communication, Internet of Things (IoT) networks, and 5G systems. By improving spectral efficiency and enhancing the user experience, this scheme contributes significantly to the advancement of wireless communication technologies in various real-world scenarios.

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