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Optimizing User Pairing in NOMA Using K-Medoids Clustering for Enhanced Spectral Efficiency

Shiv Kumar Yadav [1], Puneet Gangal [2], Anil Khandelwal [3]
[1,2] Department of Electronics and Communication Engineering, Shubham University, Bhopal, India
[3] Department of Electronics and Communication Engineering, VNS Group of Institutions, Bhopal, India
[1]shivkumaryadav330@gmail.com, [2]puneetgan@gmail.com, [3]akhandelwal7@gmail.com

Abstract

Non-Orthogonal Multiple Access (NOMA) has emerged as a pivotal technology for 5G and beyond wireless networks, which promises the significant enhancements in spectral efficiency through power-domain multiplexing. However, the practical realization of benefits of NOMA critically depends on solution of the complex user pairing problem, which determines which users should be grouped for simultaneous transmission. This paper basically addresses the critical user pairing challenge in NOMA systems by proposing a novel K-Medoids clustering algorithm. The proposed algorithm optimizes user pairing based on a comprehensive feature vector incorporating channel gain magnitude, angular separation, and potential the signal-to-interference-plus-noise ratio (SINR). The pairing problem is formulated as a clustering optimization with a custom distance metric that balances the channel gain differences and spatial characteristics. The simulation results show the proposed method achieves higher spectral efficiency than the exhaustive search, random pairing, and channel gain difference (CGD), and reduces complexity. The proposed algorithm maintains a Jain's index at excellent level. The proposed algorithm demonstrates robustness across varying user densities while maintaining excellent fairness.

Keywords: NOMA, User Pairing, K-Medoids, Spectral Efficiency, Clustering, 5G

1 Introduction

The exponential growth of mobile data traffic with the modern emerging applications such as augmented and virtual reality, autonomous vehicles, and the Internet of Things (IoT) has imposed huge and unprecedented demands on the wide capacity of wireless networks [1, 2]. According to recent data from the "International Telecommunication Union" 2025 [3], there are 6 billion Internet users worldwide, which is around 74% of the world's population. This staggering growth requires revolutionary advancements in spectral efficiency, which have emerged as a critical performance metric for fifth-generation (5G) and beyond wireless networks.

The Orthogonal Multiple Access (OMA) techniques, which include Orthogonal Frequency Division Multiple Access (OFDMA) and Time Division Multiple Access (TDMA), have been the cornerstone of conventional cellular generations [4, 5]. However, these orthogonal techniques inherently limit the number of simultaneously served users to the number of available orthogonal resources, it fundamentally constrains the network capacity. The NOMA overcomes this limitation through non-orthogonal resource sharing, which enables multiple users to be served simultaneously on the same time-frequency resource block through power-domain multiplexing [6, 7]. NOMA is mainly a transformative technology for 5G wireless networks. The key features such as low latency, massive connectivity, and extremely high data rates are largely supported by NOMA-based systems designed principles [8, 9]. By operating in the power domain, NOMA enables multiple users to share the same time, frequency, or code resources that are already assigned to a particular mobile device [10]. The core operational principle of the NOMA

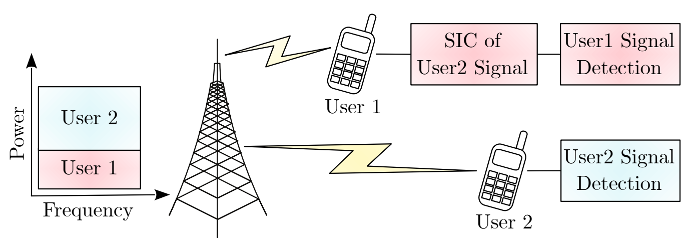

Fig. 1: Operational Principle of Non-Orthogonal Multiple Access

(as illustrated in Fig. 1) technique involves these two key components:

- **Superposition Coding:** It works at the transmitter, where signals for multiple users are combined with different power levels.
- **Successive Interference Cancellation (SIC):** It mainly works at the receivers, where the users sequentially decode and subtract interference from stronger

users before decoding their own signals.

This paradigm shift from the orthogonal to the non-orthogonal access allows the NOMA technique to achieve the capacity region of broadcast channels, which offers substantial improvements in spectral efficiency, user fairness, and massive connectivity.

However, the practical realization of the benefits of the NOMA critically depends on solution of these two fundamental challenges:

- **Optimal User Pairing:** It basically determines which users should be grouped together for superposition coding.
- **Efficient Power Allocation:** It assigns appropriate power levels to paired users.

Moreover, the user pairing identification is particularly crucial, as improper pairing can lead to severe inter-user interference, SIC failure, and ultimately, performance degradation that negates the advantages of the NOMA technique.

1.1 Problem Statement and Research Gap

The user pairing problem in the NOMA can be formulated as a combinatorial optimization problem where K users must be partitioned into M clusters of size N, with the objective of maximizing the sum spectral efficiency under power constraints. The exhaustive search approach to this problem has computational complexity of $\mathcal{O}\left(\frac{K!}{(N!)^M M!}\right)$, which becomes prohibitively complex for practical networks with tens or hundreds of users.

Existing approaches to user pairing can be broadly categorized as:

1. **Channel Gain Difference (CGD)-based Method**: It usually pair users with large channel gain differences to facilitate SIC.
2. **Random Pairing**: It is a simple but sub-optimal approach and its performance is unpredictable.
3. **Greedy Algorithms**: These iteratively select user pairs based on immediate gain.
4. **Matching Theory-based Approaches**: These are formulated as bipartite matching problems.
5. **Deep Learning (DL) Method**: It is neural network-based learning method to learn pairing patterns.

Despite these advancements, there are some significant limitations and research gaps. Most of the existing methods only focus on channel gain differences, they ignore spatial correlation and angular characteristics. Many methods lack robustness to channel outliers and variation in the user distributions. There are limited consideration on maximization of the spectral efficiency. There is a notable trade-off between computational complexity and optimal solution that has not been adequately addressed in the modern research.

2 Related Work

NOMA is a crucial technology for 5G and future wireless communications and networks, which provides the facilities of massive connectivity and high-speed data transmission within the limited spectral resources. This section presents a comprehensive literature review on NOMA systems with AI techniques.

Alajmi and Ghandoura [11] introduced a practical deep reinforcement learning (DRL)-based multi-carrier grant-free NOMA scheme for IoT that works for imperfect successive interference cancellation (SIC). By allowing each user to learn its own resource allocation policy, the scheme improves spectral efficiency and increases user fairness by up to 62% compared to existing approaches. Khan *et al.* [12] proposed a power-domain NOMA-based resource optimization scheme for IoT. This scheme jointly allocates the frequency blocks and the power under practical constraints, which achieves higher spectral efficiency than existing NOMA and OMA methods.

Perdana *et al.* [13] proposed an adaptive user pairing framework for multi-IRS–assisted massive MIMO-NOMA. It applies iterative optimization and deep learning to efficiently maximize the spectral efficiency under practical constraints. Periyathambi and Ravi [14] discussed the role of MIMO-NOMA to fulfill 5G capacity and efficiency demands, so they proposed a hybrid salp swarm and crowd search algorithm for downlink power allocation. This approach improves the spectrum utilization, throughput, and energy efficiency and achieves notable spectral and energy efficiency gains across different antenna configurations.

Wang *et al.* [15] proposed a deep reinforcement learning (DRL)-based resource allocation framework for mmWave massive MIMO-NOMA. It jointly optimizes the user grouping, subchannel assignment, and power allocation. This approach combines enhanced K-means clustering, a dueling deep Q-network (DQN) for subchannel allocation, and a "deep deterministic policy gradient" (DDPG)-based power control scheme. This approach achieves faster convergence and higher system capacity than existing algorithms.

Cui *et al.* [16] proposed K-means-based offline and online user clustering algorithms for mmWave-NOMA systems, combined with optimal power allocation, to maximize sum rate. This approach improves the spectral efficiency, handles dynamic user arrivals efficiently, and balances performance with computational complexity. A. Vijay [17] proposed a MIMO technique with a "multi-carrier code-division multiple access (MC-CDMA)" framework combined with SIC, enhanced by DL and bio-inspired optimization, for improving spectrum and energy efficiency in 5G. This approach enables dynamic resource allocation, interference reduction, lowered latency, and increased throughput, hence improving overall 5G network performance.

Prameela and Srilakshmi [18] proposed the "hybrid attention-aware spectrum predictor (HASP)," which is a combination of DL and ML framework for mmWave massive MIMO-NOMA systems. It predicts spectrum availability and attention-enhanced user clustering. The approach improves the spectral efficiency by 28%, the prediction accuracy is improved by 35%, and the computational load reduction is 45%, which finally meets the QoS requirements of the users and hence allows for more efficient 5G and beyond communications.

Luo *et al.* [19] proposed a distributed "multi-agent double deep Q-network and double multi-agent deep deterministic policy gradient (MADDQN-DMADDPG)" for "simultaneous wireless information and power transfer (SWIPT)" systems. They used massive MIMO-NOMA with optimization of user scheduling, power allocation, and power splitting. Their approach improves energy efficiency, mitigates the multi-user interference, and achieves a fast, stable convergence. Farghaly *et al.* [20] proposed a "wavelet packet transform (WPT)-NOMA" system with a "complex valued convolutional neural network" (CVNN)-based SIC receiver that pairs users via wavelet packet transform to improve spectral and energy efficiency and reliability. The approach outperforms conventional NOMA in bit error rate (BER), spectral efficiency, energy efficiency, and outage probability by efficient detection of signals using DL-enhanced receivers.

Zhang *et al.* [21] proposed a NOMA-assisted aerial edge computing system using a DRL-DGSN algorithm to optimize UAV trajectories, power allocation, and user association jointly. By taking advantage of multi-agent DRL and successive interference cancellation, their approach improves the system throughput, balances the UAV workloads, and outperforms existing methods in efficiency and training stability. Nguyen *et al.* [22] proposed a multi-cell, multi-subband NOMA resource allocation framework that basically combines meta-learning, federated learning, and multi-agent reinforcement learning. It jointly optimizes power and sub-band allocation, which enables rapid adaptation to dynamic network conditions, improves energy efficiency, and outperforms benchmark methods in scalability and robustness.

Beena and Sameer [23] presented a DL-based MIMO-NOMA receiver for vehicular communications using "long-short-term memory (LSTM)" for joint channel estimation and signal detection. It achieves higher accuracy, lower outage probability, better fairness, improved symbol error rate (SER) performance, greater robustness to channel variations, and lower computational complexity as compared to the traditional SIC methods. Rezwan and Choi [24] proposed a Q-learning-based resource allocation with priority-based device clustering for 5G NOMA. It prioritizes the ultra-reliable and low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communication (mMTC) devices. This approach meets quality of service (QoS) requirements and achieves a higher sum rate compared to other methods.

Chebbi *et al.* [25] investigated mmWave mMIMO integrated with NOMA for IoT in 5G and introduced joint user clustering and power control algorithms that exploit spatial channel correlations. Their approach enhances the spectral efficiency, supports more users with limited RF chains, and improves the utilization of wireless resources while meeting the requirements of QoS. Ji *et al.* [26] proposed a CNN-LSTM-based NOMA algorithm for train-to-train (T2T) communication, which optimizes the channel modeling and the power allocation. Their approach improves the spectral efficiency compared to traditional zero forcing (ZF) and minimum mean square error (MMSE) methods, reduces errors with training, and meets low-SNR T2T requirements.

H.M. and Anuradha [27] proposed a "multi-carrier index keying NOMA (MCIK-NOMA)" system that basically combines NOMA with index modulation to improve the spectral and energy efficiency. The performance analysis under various fading channels and channel state information (CSI) conditions shows that MCIK-NOMA outperforms traditional NOMA and OMA in BER, spectral, and energy efficiency. Karem and Chaitanya A. [28] proposed a low-complexity DNN-based resource allocation scheme for single-cell NOMA-IBFD systems. It uses input preprocessing and a penalty-based custom loss to handle constraints. It also uses a projection method to balance sum-rate performance and achieves feasible power allocation with reduced computational complexity.

He *et al.* [29] proposed a NOMA maritime network using "federated multiagent deep Q-network (FLMADQN)" for power allocation. Their approach improves system throughput, spectral efficiency, and convergence speed while preserving data privacy. It outperforms the conventional DRL and DQN methods in maritime IoT scenarios. Hamedoon *et al.* [30] proposed a RIS-assisted downlink NOMA framework for IoT networks, which optimizes power allocation and RIS phase shifts to enhance the energy efficiency and system throughput. This framework basically combines clustering, alternating optimization, Karush-Kuhn-Tucker (KKT)-based refinement, and ML-DL-RL approaches to significantly improve the sum rate and the energy efficiency in dynamic 6G environments.

Kara *et al.* [31] analyzed the error performance of "NOMA-based cooperative relaying systems (NOMA-CRS)" over Nakagami-m fading and derived closed-form bit error probability (BEP) expressions. They also proposed an ML-assisted joint power sharing and allocation scheme that minimizes BER with low complexity and outperforms previous strategies. Li *et al.* [32] proposed a UAV-assisted NOMA relay scheme that jointly optimizes user scheduling, power allocation, and UAV trajectory to maximize energy efficiency. This scheme basically decomposes the non-convex problem into subproblems and solves it using integer programming, convex optimization, and successive convex approximation (SCA). This scheme outperforms benchmarks and extends the network lifetime.

Hu *et al.* [33] proposed a NOMA-enabled "federated edge learning (FEEL)" framework for 5G IoT networks to reduce the energy consumption of devices. This framework improves the energy efficiency using optimization of resource allocation and device pairing while preserving the data privacy. Their simulations show it outperforms TDMA-based FEEL in terms of energy savings. Gupta *et al.* [34] proposed an "energy-efficient downlink multicarrier NOMA" framework. It introduces a least user sum gain-based user assignment algorithm and a hybrid power allocation scheme combining penalty methods, particle swarm optimization, and bisection. Their approach significantly improves energy efficiency, throughput, fairness, and outage performance. It achieved up to 48.67% energy efficiency gains over existing resource allocation methods.

3 System Model

This section presents the mathematical model, which provides the fundamental concept and purpose to evaluate K-Medoids clustering to improve spectral efficiency by forming the clusters that basically minimize the intra-cluster interference differences while maximizing the inter-cluster separation.

A downlink NOMA system with a single base station (BS) is considered to serve K number of users. The users are grouped into M number of clusters, where each cluster contains N users ($K = M \times N$). The transmitted signal from the BS to the m^{th} cluster is expressed as:

$$x_m = \sum_{n=1}^{N} \sqrt{P_{m,n}} s_{m,n} \tag{1}$$

where, $P_{m,n}$ denotes the allocated power for the user n in cluster m, and $s_{m,n}$ denotes the message signal for the user n in cluster m with $\mathbb{E}[|s_{m,n}|^2] = 1$.

3.1 Channel Model

The channel gain basically quantifies how much a wireless signal is amplified or attenuated as it travels from the transmitter to the receiver. The channel gain between the BS and user k is expressed as:

$$h_k = \sqrt{\beta_k} g_k \tag{2}$$

where β_k represents the large-scale fading (path loss and shadowing), and $g_k \sim \mathcal{CN}(0,1)$ represents the small-scale Rayleigh fading component. Without any loss of generality, the users are ordered based on their channel gains:

$$|h_1|^2 \geq |h_2|^2 \geq \cdots \geq |h_K|^2 \tag{3}$$

3.2 Received Signal and SINR

The received signal at user n in cluster m is:

$$y_{m,n} = h_{m,n} x_m + \underbrace{\sum_{j \neq m} h_{m,n} x_j}_{\text{Inter-cluster inference}} + w_{m,n} \tag{4}$$

where $w_{m,n} \sim \mathcal{CN}(0, \sigma^2)$ is additive white Gaussian noise (AWGN).

For NOMA with successive interference cancellation (SIC), the signal-to-interference-plus-noise ratio (SINR) for user n in cluster m to decode its own signal after perfect cancellation of stronger intra-cluster signals is:

$$\gamma_{m,n} = \frac{P_{m,n}|h_{m,n}|^2}{\underbrace{\sum_{i=n+1}^{N} P_{m,i}|h_{m,n}|^2}_{\text{Uncancelled intra-cluster}} + \underbrace{\sum_{j \neq m} \sum_{i=1}^{N} P_{j,i}|h_{m,n}|^2}_{\text{Inter-cluster}} + \sigma^2} \tag{5}$$

The interference modeling captures both the intra-cluster and inter-cluster interference.

3.3 Spectral Efficiency

The spectral efficiency for user n in cluster m is given by:

$$R_{m,n} = \log_2(1 + \gamma_{m,n}) \tag{6}$$

The total spectral efficiency of the system is:

$$R_{\text{total}} = \sum_{m=1}^{M} \sum_{n=1}^{N} R_{m,n} \tag{7}$$

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3.4 Problem Formulation

The user pairing optimization problem is formulated as:

$$\begin{aligned}
\max_{\mathcal{C}} \quad & R_{\text{total}}(\mathcal{C}) \\
\text{s.t.} \quad & \mathcal{C} = \{C_1, C_2, \ldots, C_M\} \\
& C_i \cap C_j = \emptyset, \quad \forall i \neq j \\
& \bigcup_{m=1}^{M} C_m = \mathcal{U} \\
& |C_m| = N, \quad \forall m = 1, \ldots, M \\
& \sum_{n=1}^{N} P_{m,n} \leq P_{\text{total}}, \quad \forall m
\end{aligned} \tag{8}$$

where $\mathcal{U} = \{1, 2, \ldots, K\}$ is the set of all users, and $\mathcal{C}$ represents the clustering configuration.

4 Proposed Methodology

The proposed method employs K-Medoids clustering to group users based on their channel characteristics for optimal NOMA pairing. The medoid represents the most centrally located user in each cluster, which provides robustness to the outliers compared to K-Means.

4.1 Feature Vector Design

For each user k, a feature vector $\mathbf{f}_k$ that captures the channel characteristics relevant for the NOMA pairing is defined as:

$$\mathbf{f}_k = \left[|h_k|^2, \angle h_k, \beta_k, \text{SINR}_k^{(\text{OMA})} \right]^T \tag{9}$$

where $\text{SINR}_k^{(\text{OMA})}$ is the SINR, which the user k experiences in an orthogonal multiple access system.

4.2 Distance Metric

The distance between two users i and j is defined as a weighted combination of the channel gain difference and the angular separation:

$$\begin{aligned} d(i,j) = \alpha \cdot \left| |h_i|^2 - |h_j|^2 \right| + \\ (1-\alpha) \cdot \min(|\angle h_i - \angle h_j|, 2\pi - |\angle h_i - \angle h_j|) \end{aligned} \tag{10}$$

where $\alpha \in [0, 1]$ is a weighting parameter that balances the importance of channel gain difference and angular separation.

The overall steps of the proposed method are illustrated in Fig. 2. Initially, the required system parameters are initialized and calculated, and the CSI is collected, which extracts the feature vectors. The K-Medoid is initialized randomly using these feature vectors, and users are assigned to their nearest Medoid. If the value of the Medoid is convergence, then NOMA clusters are formed; otherwise, the value of the Medoid of the cluster is updated. The power allocation method is applied to each NOMA cluster, and spectral efficiency is finally calculated.

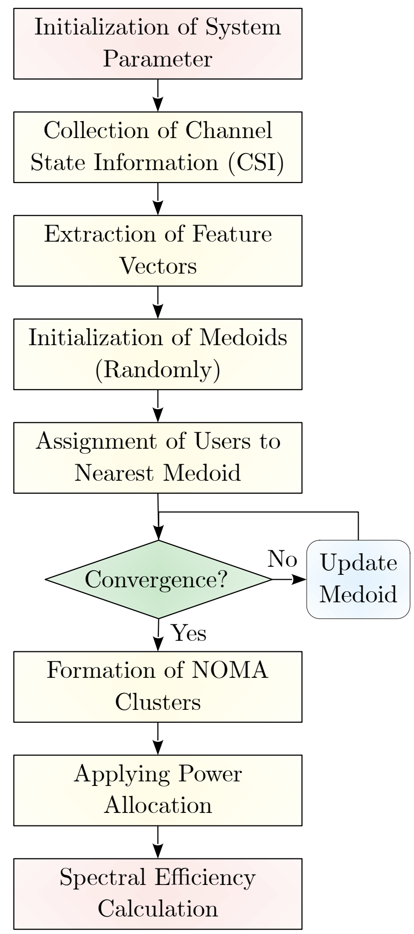

Fig. 2: K-Medoids-based User Pairing

4.3 Algorithm

The K-Medoids-based user pairing for NOMA clustering algorithm is presented in Algorithm 1.

4.4 Jain's Fairness Index Analysis

Jain's fairness index (0 to 1) [35] is a quantitative measure of how fairly resources are allocated among users in a system. For NOMA systems, it quantifies the equity of spectral efficiency distribution among all users.

$$\mathcal{J} = \frac{\left(\sum_{k=1}^{K} R_k \right)^2}{K \cdot \sum_{k=1}^{K} R_k^2} \tag{11}$$

where R_k denotes the spectral efficiency (achievable rate) of user k (total number of users in the system).

Algorithm 1 K-Medoids Based User Pairing for NOMA

Require: Set of users $\mathcal{U} = \{1, 2, \ldots, K\}$, number of clusters M, maximum iterations $T_{\max}$, convergence threshold ϵ
Ensure: Clustering configuration $\mathcal{C} = \{C_1, C_2, \ldots, C_M\}$, total spectral efficiency R_{total}
Collect CSI for all users $h_k, \forall k \in \mathcal{U}$
Extract feature vectors $\mathbf{f}_k$ using (9)
Initialize medoids: Randomly select M users as initial medoids $\mathcal{M}^{(0)} = \{m_1^{(0)}, m_2^{(0)}, \ldots, m_M^{(0)}\}$
$t \leftarrow 0$
$\Delta \leftarrow \infty$
while $t < T_{\max}$ and $\Delta > \epsilon$ **do**
  Assignment Step:
  for each user $k \in \mathcal{U}$ **do**
    Find closest medoid: $c_k^{(t)} = \arg\min_{m \in \mathcal{M}^{(t)}} d(k, m)$
    Assign user k to cluster $C_{c_k^{(t)}}$
  end for
  Update Step:
  for each cluster $C_i, i = 1, \ldots, M$ **do**
    Compute new medoid: $m_i^{(t+1)} = \arg\min_{k \in C_i} \sum_{j \in C_i} d(k, j)$
  end for
  Compute change: $\Delta = \sum_{i=1}^{M} d(m_i^{(t)}, m_i^{(t+1)})$
  $t \leftarrow t + 1$
  $\mathcal{M}^{(t)} \leftarrow \{m_1^{(t)}, m_2^{(t)}, \ldots, m_M^{(t)}\}$
end while
Power Allocation:
for each cluster $C_i, i = 1, \ldots, M$ **do**
  Sort users in C_i by channel gain: $|h_{i,1}|^2 \geq |h_{i,2}|^2 \geq \cdots \geq |h_{i,N}|^2$
  Allocate power using fractional transmit power allocation (FTPA):
  $P_{i,n} = \frac{P_{\text{total}} \cdot |h_{i,n}|^{-\eta}}{\sum_{j=1}^{N} |h_{i,j}|^{-\eta}}, \quad n = 1, \ldots, N$
end for
Performance Evaluation:
Compute SINR $\gamma_{m,n}$ using (5)
Compute spectral efficiency R_{total} using (7)
return $\mathcal{C}, R_{\text{total}}$

The Jain's fairness index basically exhibits its range $\frac{1}{K} \leq \mathcal{J} \leq 1$, where $\mathcal{J} = \frac{1}{K}$ is the maximum unfairness (worst fairness), where all the resources are allocated to a single user, and $\mathcal{J} = 1$ is considered the best fairness, where all users achieve identical rates. This index is scale independent, which means it is unaffected by the absolute magnitude of rates. It has the continuity property, small changes in the rate distribution result in small changes in the value of $\mathcal{J}$.

For NOMA systems with K users partitioned into M clusters of size N, the fairness index is expressed as:

$$\mathcal{J} = \frac{\left(\sum_{m=1}^{M} \sum_{n=1}^{N} R_{m,n}\right)^2}{K \cdot \sum_{m=1}^{M} \sum_{n=1}^{N} R_{m,n}^2} \tag{12}$$

where $R_{m,n} = \log_2(1 + \gamma_{m,n})$ is the spectral efficiency of the user n in the cluster m, and $\gamma_{m,n}$ is its corresponding SINR.

For scenarios with different quality-of-service (QoS) requirements, a weighted Jain's index can be employed:

$$\mathcal{J}_w = \frac{\left(\sum_{k=1}^{K} w_k R_k\right)^2}{K \cdot \sum_{k=1}^{K} (w_k R_k)^2} \tag{13}$$

where w_k represents the priority weight assigned to the user k, with $\sum_{k=1}^{K} w_k = 1$.

Table 1 provides guidelines for interpreting Jain's index values in NOMA systems:

Table 1: Interpretation of Jain's Fairness Index in NOMA Systems

Jain's Index Range	**Fairness**	**Interpretation in NOMA Context**
$\mathcal{J} > 0.9$	Excellent	All the users receive comparable service quality
$0.8 < \mathcal{J} \leq 0.9$	Good	Acceptable for most applications
$0.7 < \mathcal{J} \leq 0.8$	Moderate	Potential user dissatisfaction at cell edge
$0.6 < \mathcal{J} \leq 0.7$	Poor	Cell-edge users severely get disadvantage
$\mathcal{J} \leq 0.6$	Unacceptable	Requires immediate remedial action

4.5 Computational Complexity Analysis of the Proposed Algorithm

The computational complexity of the proposed algorithm is mainly dominated by the K-Medoids clustering. The assignment step involves $\mathcal{O}(K \cdot M)$ per iteration. The update step require $\mathcal{O}(|C_i|^2)$ steps for each cluster, total $O(K^2/M)$ in the worst case. Finally, the overall complexity represents $\mathcal{O}(T \cdot (K \cdot M + K^2/M))$, where T is number of iterations.

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5 Results Analysis

The Table 2 represents basic parameters for simulation and their values. The simulations were conducted in Python on a computer system with the specifications presented in Table 3:

Table 2: Simulation Parameters

Parameter	Value
Cell radius	500 m
Number of users, K	30, 60, 90
Users per cluster, N	2
Carrier frequency	2 GHz
Bandwidth	10 MHz
Transmit power, P_{total}	46 dBm
Path loss model	$128.1 + 37.6 \log_{10}(d)$ dB
Shadowing standard deviation	8 dB
Small-scale fading	Rayleigh
Noise power spectral density	-174 dBm/Hz
Number of Monte Carlo runs	5000

Table 3: Hardware Configuration for NOMA Simulation

Component	Specification
Processor	Intel Core i5-12400 @ 2.5 GHz
CPU Cores	6 Cores / 12 Threads
RAM	16 GB DDR4 @ 3200 MHz
Cache	18 MB Intel Smart Cache
Storage	1 TB NVMe SSD
Operating System	Linux (Ubuntu 24.04 LTS)

The Fig. 3 illustrates the sum spectral efficiency in bps per Hz over transmit power for proposed and different pairing algorithms. The proposed K-Medoids method represents the maximum spectral efficiency compared to the exhaustive search, random pairing, and CGD.

The Fig. 4 illustrates the computational complexity of proposed method with comparison of different pairing algorithms. The execution time of proposed method is lower compared to the exhaustive search, random pairing, and CGD.

The fairness performance is a critical metric in NOMA systems, as aggressive spectral efficiency optimization can lead to starvation of cell-edge users. The Fig. 5 illustrates the Jain's fairness index for different pairing algorithms across varying user densities.

The proposed K-Medoids algorithm maintains a Jain's index 0.94 for 30 users and above 0.87 even for 100 users, which demonstrates excellent fairness characteristics. This robustness stems from the use of proposed method for actual users as medoids, which prevents the formation of extreme clusters.

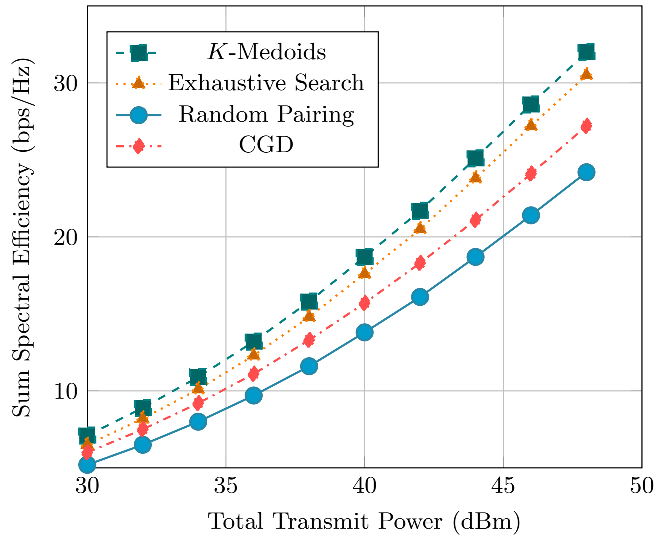

Fig. 3: Sum spectral efficiency vs. transmit power for different pairing algorithms ($K = 30$)

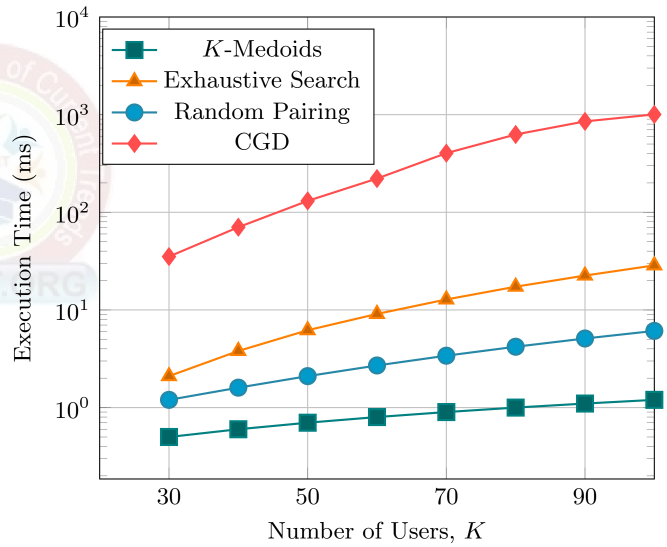

Fig. 4: Computational Complexity Comparison of Different Pairing Algorithms

The convergence behavior of proposed K-Medoids method for different user densities is illustrated in Fig. 6.

The statistical analysis reported in Table 4 reveals that the proposed K-Medoids achieves the smallest standard deviation among the the exhaustive search, random pairing, and CGD algorithms ($\sigma = 0.03$), which indicates consistent performance across channel realizations. The 95% confidence interval [0.90, 0.92] demonstrates that fairness with increasing user count is both predictable and graceful.

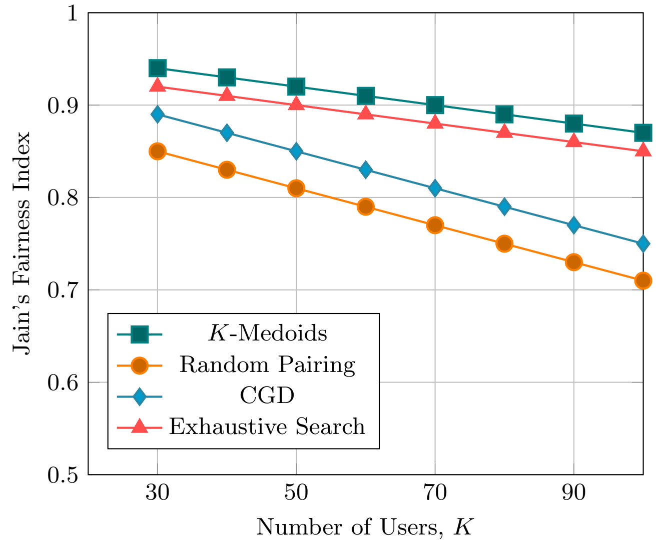

Fig. 5: Fairness Performance Comparison using Jain's Fairness Index

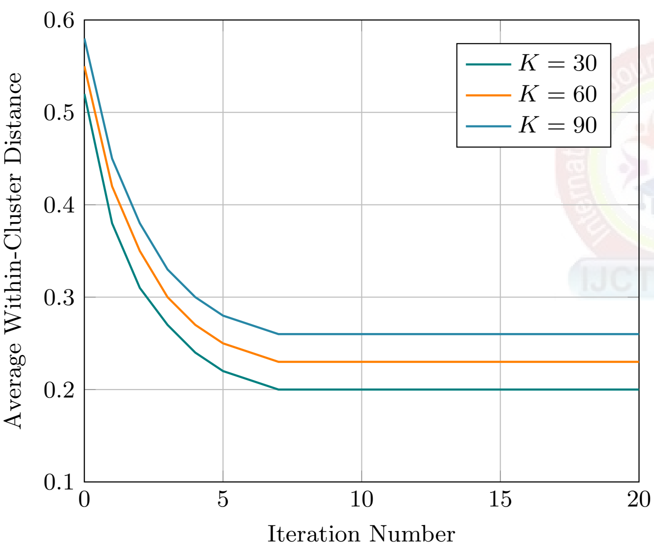

Fig. 6: Convergence Behavior of K-Medoids Algorithm for Different User Densities

Table 4: Statistical distribution of Jain's fairness index

Metric	K-Medoids	Exhaustive	CGD	Random
Mean (μ)	0.91	0.89	0.83	0.79
Median	0.89	0.83	0.91	0.79
Std. Dev. (σ)	0.02	0.03	0.06	0.08
95% CI	[0.90, 0.92]	[0.88, 0.90]	[0.81, 0.85]	[0.77, 0.81]
Min	0.86	0.82	0.70	0.65
Max	0.95	0.94	0.90	0.88

6 Conclusion

This paper has addressed the critical challenge of user pairing in downlink NOMA systems through a novel K-Medoids clustering-based approach. The proposed methodology fundamentally transforms the user pairing problem from a combinatorial optimization with exponential complexity to the other clustering problem with polynomial-time complexity, while maintaining near-optimal performance.

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