MAR ATHANASIUS COLLEGE OF ENGINEERING

(Affiliated to APJ Abdul Kalam Technological University, TVM)

KOTHAMANGALAM

Department of Computer Applications

Seminar Report

NOMA MOBILITY SUPPORT

Done by

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Under the guidance of

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MAR ATHANASIUS COLLEGE OF ENGINEERING

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CERTIFICATE

NOMA MOBILITY SUPPORT

Certified that this is the bonafide record of seminar presentation done by

VARSHA U

Reg No: MAC22MCA-2028

During the academic year 2023-2024, in partial fulfilment of the requirements for the award of the degree,

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ABSTRACT

Non-orthogonal multiple access (NOMA) is a promising technology for future wireless systems that can improve spectral efficiency by grouping users into clusters based on channel gain-difference. However, user mobility changes channel gain, requiring re-clustering. This study focus on three re-clustering methods- Arbitrary, One by one ,Kuhn-Munkres assignment algorithm (KMAA), which automatically dissociates identified users within clusters when the gain-difference is lower than a given threshold, followed by a re-association procedure that integrates users into different clusters while maintaining an appropriate gaindifference. Experimental results show that KMAA improves efficiency and capacity by minimizing re-clustering events, improving resource utilization, and lowering signaling overhead. Additionally, KMAA provides throughput and outage probability gains across a wide range of mobility scenarios. KMAA analysis for Multiple input multiple output (MIMO)-NOMA demonstrates its link resiliency and ability to maintain an average gain-difference among users in clusters. Overall, KMAA is a promising re-clustering method for NOMA systems that can improve performance in a variety of ways.

Contributions encompass a mobility management scheme, re-association methods, theoretical analysis, simulations, and comparisons of clustering techniques. The overarching objective is to optimize NOMA technology in dynamic wireless environments, offering insights into system models, mathematical descriptions, resource allocation procedures, and concluding with a detailed exploration of challenges and potential solutions.

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1. INTRODUCTION

Cellular communication systems have undergone significant evolution, employing various multiple access techniques like Time Division Multiple Access (TDMA) and Orthogonal Frequency Division Multiple Access (OFDMA) to enable multiple users to share bandwidth resources. While these methods have greatly enhanced data rates and spectral efficiency in earlier generations like 4G and LTE, the burgeoning use of smartphones, Internet of Things (IoT) devices, and similar technologies has led to escalating traffic, saturating available frequency bands.

This saturation has prompted the exploration of novel approaches to alleviate spectrum congestion. Non-Orthogonal Multiple Access (NOMA) has emerged as a promising solution aimed at improving spectral efficiency by employing superposition coding at the transmitter and Successive Interference Cancellation (SIC) at the receiver end. SIC allows decoding of multiple transmissions at a single receiver by decoding the strongest signal first and treating the rest as interference.

However, the seamless implementation of NOMA faces challenges, particularly in handling the high mobility of users within cellular networks. Wireless channels exhibit rapid variations in channel quality due to factors such as user mobility, changes in device location, and movement of objects in the communication space. These variations influence channel gain differences, potentially leading to incorrect user pairing or clustering, consequently impacting overall system throughput.

To address these challenges, this seminar report investigates the efficacy of NOMA technology in dynamic wireless environments. The report focuses on understanding the impact of user mobility on NOMA clusters and proposes mechanisms to manage mobility-induced changes effectively. Specifically, the report explores continuous per-cluster analysis to ensure the validity of clusters and introduces a dissociation mechanism for ineffective clusters. This dissociation process involves removing users from clusters and swiftly merging them with new suitable clusters to maintain NOMA operations.

Moreover, considering the complexity introduced by user mobility in NOMA clusters, the report compares different clustering methods and their effectiveness in dense urban environments. Additionally, it delves into the challenges posed by Multiple-Input Multiple-Output (MIMO) NOMA setups, where users within a cluster share the same beam, complicating the maintenance of gain differences under mobility.

The contributions of this report encompass a mobility management scheme for NOMA, re-association methods, theoretical analysis, simulations, and comparisons of clustering techniques, all aimed at optimizing NOMA technology in the face of dynamic wireless environments. In addition to addressing the challenges posed by user mobility, the report delves into the potential applications and benefits of Non-Orthogonal Multiple Access (NOMA) technology in future wireless systems. NOMA's unique approach of superposition coding and Successive Interference Cancellation (SIC) not only aims to improve spectral efficiency but also opens avenues for accommodating a massive number of devices and diverse communication requirements. The study explores how NOMA can adapt to the growing demand for connectivity from smartphones, Internet of Things (IoT) devices, and emerging technologies. It emphasizes the role of NOMA in optimizing resource utilization and overcoming spectrum congestion challenges, providing a forward-looking perspective on its role in the evolution of cellular communication systems. The report thus offers insights into both the challenges and the transformative potential of NOMA technology in the ever-evolving landscape of wireless communications.The subsequent sections detail the system model, mathematical descriptions, resource allocation procedures, challenges in MIMO-NOMA setups, simulation results, and concluding remarks.

2. SUPPORTING LITERATURE

2.1. Literature Review

Paper 1: Naeem, Muhammad Kamran, et al. "Mobility Support for MIMO-NOMA User Clustering in Next-Generation Wireless Networks." IEEE Transactions on Mobile Computing (2022).

The research paper explores the impact of user mobility in advanced wireless systems, specifically integrating Non-Orthogonal Multiple Access (NOMA) in Multiple-Input Multiple-Output (MIMO) setups. Using the Kuhn-Munkres assignment algorithm (KMAA) and other re-clustering techniques, the study addresses challenges arising from user movement and channel variations. The paper showcases KMAA's effectiveness in optimizing cluster formation, maintaining gain differences, and enhancing network efficiency through theoretical analyses, simulations, and practical implementations.

Examining beam-switching strategies in NOMA-MIMO configurations, the paper highlights the influence of beamwidth variations on link resilience and data throughput. Emphasizing efficient cluster design, resource allocation, and re-association mechanisms, the study aims to maximize spectral efficiency, minimize interference, and enhance overall system reliability in next-generation wireless networks. The research contributes insights into mobility management schemes, clustering algorithms, and beamforming techniques, providing valuable knowledge for the ongoing evolution of wireless communication technologies.

By offering a comprehensive analysis of mobility management paradigms, clustering algorithms, and beamforming techniques, the research contributes valuable insights to the ongoing evolution of wireless networking paradigms, paving the way for enhanced network adaptability, optimized resource utilization, and seamless connectivity experiences in dynamic and highly mobile communication landscapes.

Paper 2: Naeem, Muhammad Kamran, et al. "Towards the mobility issues of 5G-NOMA through user dissociation and re-association control." 2020 IEEE 21st International Symposium on" A World of Wireless, Mobile and Multimedia Networks"(WoWMoM). IEEE, 2020.

The paper addresses mobility challenges in 5G-NOMA networks by proposing user dissociation and re-association strategies. These approaches dynamically update user clusters to preserve optimal gain differences, crucial for NOMA technology success. By dissociating users with low channel gain differences and re-associating them in real-time, the algorithms aim to minimize outages and enhance system performance. Three re-association methods are introduced - arbitrary, one-by-one, and simultaneous. The simultaneous technique shows superior performance in reducing re-associations and transition durations.

The research underscores the significance of these clustering techniques in managing mobility within NOMA clusters, providing a practical alternative to complex power allocation methods. Leveraging user dissociation and re-association, the paper addresses diminishing gain differences between users due to high mobility in cellular networks. Simulations and analysis demonstrate the effectiveness of the proposed algorithms in maintaining cluster integrity and optimizing system performance. The findings suggest the applicability of these techniques to various NOMA-based networks, emphasizing efficient mobility management for enhanced connectivity and performance in modern communication systems.

In conclusion, the paper offers a comprehensive framework for handling mobility issues in 5G-NOMA networks, emphasizing the role of user dissociation and re-association in maintaining cluster coherence and improving spectral efficiency. The proposed algorithms provide a practical solution to the dynamic nature of mobile networks, ensuring optimal gain differences between users and minimizing disruptions during transitions.

Paper 3: Kim, Ha-Ryung, Jiasi Chen, and Jongwon Yoon. "Joint user clustering and beamforming in non-orthogonal multiple access networks." IEEE Access 8 (2020): 111355-111367.

The paper "Joint User Clustering and Beamforming in Non-Orthogonal Multiple Access Networks" presents a comprehensive analysis of the synergistic benefits of user clustering and beamforming in NOMA networks. The authors highlight the significance of considering multiple factors such as client location, channel difference, and channel coefficients in optimizing network throughput. By conducting experiments in various network topologies, they demonstrate that a joint approach to user clustering and beamforming significantly enhances network capacity compared to traditional methods. The study emphasizes the importance of minimizing beamforming interference and leveraging NOMA gains to achieve substantial improvements in network performance.

The paper introduces a novel clustering algorithm that effectively balances system throughput and user fairness in NOMA networks. By addressing the challenges of beamforming interference and NOMA interference, the proposed Joint User Clustering and Beamforming (JUCAB) scheme outperforms existing approaches in terms of network throughput. The authors provide a detailed comparison of different clustering schemes. Through a systematic evaluation of various factors affecting network performance, the study underscores the critical role of joint user clustering and beamforming in optimizing spectral efficiency and enhancing overall network capacity.

In conclusion, the research presented in this paper contributes significantly to the advancement of NOMA technology by proposing a holistic approach that integrates user clustering and beamforming. The findings underscore the importance of considering multiple factors simultaneously to achieve optimal network performance in NOMA systems.

2.2.Literature Summary Table

Sl. No.	Year	Author	Title	Summary
1	2022	Muhammad Kamran Naeem Raouf Abozariba Md Asaduzzaman Mohammad Patwary	Mobility Support for MIMO-NOMA User Clustering in Next-Generation Wireless Networks	The paper discusses the integration of NOMA in MIMO systems to tackle user mobility challenges in wireless networks. It introduces the KMAA algorithm and re-clustering methods to optimize cluster formation and network efficiency. Beam-switching strategies in NOMA-MIMO setups are explored to enhance link resilience and data throughput, emphasizing the significance of efficient cluster design and resource allocation for improved system reliability in dynamic environments.
2	2020	Muhammad Kamran Naeem, Raouf Abozariba, Md Asaduzzaman, Mohammad Patwary	Towards the Mobility Issues of 5G-NOMA Through User Dissociation and Re-association Control	The paper proposes innovative methods for managing mobility challenges in 5G-NOMA networks through user dissociation and re-association strategies. By dynamically updating user clusters based on channel gain differences, the algorithms aim to minimize outages and enhance system performance, with the simultaneous re-association method showing promising results in reducing re-clustering needs and improving resource utilization in dynamic mobile environments.
3	2020	Ha-Ryung Kim, Jiasi Chen, Jongwon Yoon	Joint User Clustering and Beamforming in Non-Orthogonal Multiple Access Networks	The paper presents a scheme that optimizes signal power in NOMA networks and reduces interference to enhance network utility. Through experimentation, the study demonstrates the effectiveness of this approach in improving system throughput and fairness, highlighting the significance of integrating user clustering and beamforming for enhanced spectral efficiency in wireless networks.

2.3.Findings and Proposal

The three referenced papers collectively contribute valuable insights into the challenges and advancements in the field of wireless communication systems, specifically focusing on Non-Orthogonal Multiple Access (NOMA) and its integration with mobility and beamforming strategies.

First Introduces the Kuhn-Munkres assignment algorithm (KMAA), showcasing its efficiency in minimizing re-clustering events, maintaining gain differences, and enhancing adaptability in dynamic scenarios.

Second paper addresses mobility challenges in 5G-NOMA networks through user dissociation and re-association, minimizing outages and optimizing system performance in real-time.

Third paper explores the benefits of simultaneous user clustering and beamforming, presenting the Joint User Clustering and Beamforming (JUCAB) scheme to improve network throughput by mitigating interference challenges.

Building on these findings, the proposed research direction involves integrating advanced machine learning for dynamic mobility prediction and user behavior modeling in NOMA systems. This approach aims to enhance re-clustering algorithms' adaptability to changing conditions and user mobility patterns. Additionally, exploring reinforcement learning for optimizing resource allocation and beamforming strategies could further improve network performance.

In summary, NOMA optimizes wireless systems by clustering users based on channel gain, but user mobility requires re-clustering. This research studies three methods - Arbitrary, One by one, and KMAA. KMAA automatically adjusts clusters to maintain optimal gain differences, reducing re-clustering and improving efficiency. Overall, KMAA emerges as a promising re-clustering solution for NOMA, offering versatile performance improvements.

3. EVOLUTION OF ACCESS TECHNIQUES

3.1. Time Division Multiple Access(TDMA)

Time Division Multiple Access (TDMA) is a channel access method used in communication networks to enable multiple users to share the same frequency channel efficiently. The fundamental concept behind TDMA lies in dividing the available transmission time of a single channel into distinct, fixed-length time slots, each assigned to different users. This allocation strategy allows multiple users to access the channel during their designated time slots, ensuring that each user has exclusive access to transmit their data without interference from others.

3.2. Orthogonal Frequency Division Multiple Access(OFDMA)

Orthogonal Frequency Division Multiple Access (OFDMA) is a modulation technique widely utilized in modern wireless communication systems, renowned for its efficiency in handling multiple users and diverse data types within the same frequency band. At its core, OFDMA relies on a principle of splitting the available spectrum into numerous smaller subcarriers, each operating orthogonally to the others. These subcarriers collectively form a multi-carrier system that facilitates parallel data transmission to multiple users simultaneously. OFDMA's flexibility in resource allocation and its ability to handle varying data rates and multiple users concurrently make it highly efficient in next-generation wireless networks. It is prominently used in 4G LTE and WiMAX systems for high-speed data transmission, enabling enhanced spectrum utilization and improved overall network performance. Moreover, its adaptability and robustness have positioned OFDMA as a fundamental technology in 5G networks, facilitating the delivery of high-bandwidth, low-latency services and accommodating the diverse requirements of emerging applications such as IoT, ultra-high-definition video streaming, and augmented reality.

3.3. Challenges in NGN

Next-Generation Wireless Networks (NGN) face a myriad of challenges impeding their seamless integration and optimal functionality. The surging demand for high-speed data, augmented by data-intensive applications, strains existing bandwidth capacities. Spectrum scarcity exacerbates this, limiting available frequencies and causing interference issues. Balancing bandwidth and latency poses a conundrum: while high data rates are crucial, achieving low latency for real-time applications remains equally vital. Ensuring robust security measures against cyber threats looms large as networks grow increasingly interconnected. Interoperability challenges arise with the integration of diverse technologies and the need to maintain backward compatibility. the integration of Next-Generation Wireless Networks faces multifaceted challenges, including the need to efficiently manage IoT devices, address diverse communication paradigms, consider environmental sustainability, deploy intelligent network management, and navigate regulatory landscapes As NGNs evolve, the need for seamless integration of these paradigms becomes apparent, demanding advanced network architectures and protocols. Moreover, the continuous evolution of wireless standards and technologies adds complexity, necessitating frequent updates and adaptations to ensure NGN remains at the forefront of technological advancements. Addressing these evolving challenges is essential to harness the full potential of NGNs and provide users with a future-proof, adaptable, and high-performance wireless communication experience.

4. NOMA

4.1. Introduction to NOMA

Non-Orthogonal Multiple Access (NOMA) enhances spectral efficiency by allowing multiple users to share the same time-frequency resource block. It functions on the principle of power domain multiplexing, allocating different power levels to different users within the same resource block. At the transmitter, NOMA employs a power-domain encoding technique. It allocates different power levels or signal strengths to multiple users, even within the same resource block. At the receiver, NOMA employs successive interference cancellation (SIC). SIC is a signal processing technique that enables the receiver to decode multiple signals sent from different users in the same resource block. It starts by decoding the signal of the user with the strongest received power.

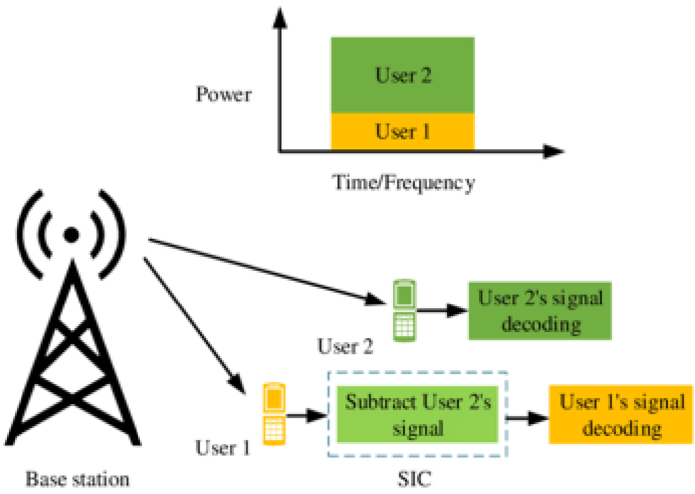

Fig 4.1 NOMA Wireless Communication with two users

In Figure 4.1, the power allocation in a Non-Orthogonal Multiple Access (NOMA) system is depicted. The antenna transmits signals (x1 and x2) to users U1 and U2, respectively. Power levels (P1 and P2) are assigned based on user proximity, allocating lower power to the closer user. The combined signal (s) is created by superimposing these signals. Successive Interference Cancellation (SIC) is illustrated, showing that U1 can directly decode its signal, while U2 needs to decode x1 first, subtract it, and then isolate x2. This SIC process is crucial in NOMA, allowing users to decode signals sequentially based on their strengths, optimizing resource utilization and minimizing interference.

4.2. Uplinking in NOMA

In NOMA (Non-Orthogonal Multiple Access), the uplink involves multiple users transmitting data to a common receiver, such as a base station, over the same frequency-time resource. In the uplink scenario:

- Power Domain Multiplexing: Users send their data using different power levels allocated by the base station. This allocation considers each user’s channel conditions, assigning lower power to users with better channel conditions and higher power to users experiencing weaker channels. This power allocation is critical in ensuring that signals can be separated at the receiver.
- Successive Interference Cancellation (SIC): At the receiver, SIC plays a crucial role. It decodes the signals one by one, starting with the user transmitting the strongest signal. Once the strongest signal is decoded and removed, the receiver proceeds to decode the next strongest signal. This iterative process continues until all the users’ signals are successfully recovered.

NOMA’s uplink operation optimizes the spectral efficiency by allowing multiple users to simultaneously transmit their data, overcoming interference challenges through power allocation and successive interference cancellation techniques at the receiver

4.3. Downlinking in NOMA

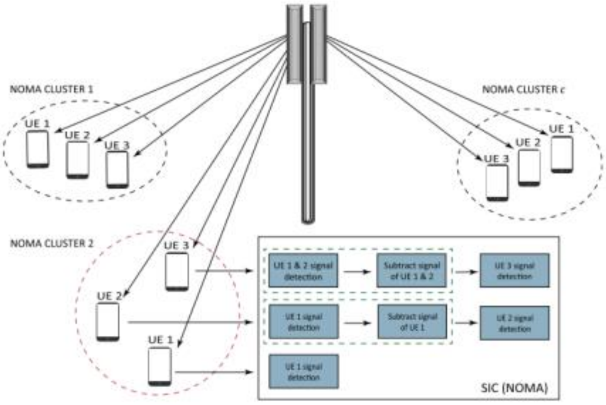

Fig 4.2: Downlinking in NOMA

In NOMA, the downlink involves a base station transmitting data to multiple users over the same frequency-time resource. Here's how the downlink process typically occurs in NOMA:

- Power Allocation: Similar to the uplink, the base station allocates different power levels to users based on their channel conditions. Users with better channels may receive lower power, while those with weaker channels are assigned higher power levels. This power allocation aims to optimize the overall spectral efficiency.
- Superposition Coding: The base station uses a technique called superposition coding to combine multiple users' data into a single composite signal. This composite signal contains the individual data intended for each user, superimposed onto each other.
- Successive Interference Cancellation (SIC): Similar to the uplink scenario, SIC might be employed at the user equipment side to decode and remove the signals of users with better channel conditions first, followed by decoding the signals of users with weaker channels.

Downlinking in NOMA allows the base station to serve multiple users simultaneously over the same resource, leveraging power allocation strategies and advanced signal processing techniques at the user equipment to manage interference and decode individual users' data from the composite signal.

4.4. User Pairing in NOMA

In NOMA (Non-Orthogonal Multiple Access), user pairing plays a pivotal role in optimizing system performance. It involves grouping users in a way that enhances the gain difference between them within the same cluster. This pairing is crucial for efficient superposition coding and successive interference cancellation (SIC). Here’s why user pairing holds significance:

- Enhanced Gain Difference: Pairing users with distinct channel conditions and disparate quality of service requirements results in a notable difference in their channel gains within a cluster. This gain difference is pivotal for successful implementation of NOMA techniques. Users with significant gain differences allow for more effective superposition coding and decoding through SIC.
- Spectral Efficiency: User pairing directly impacts the overall spectral efficiency of the system. When users are appropriately paired based on their channel conditions, the superposition coding technique can efficiently combine their signals, allowing simultaneous transmission in the same resource block. This efficient use of resources enhances the system’s capacity to serve multiple users concurrently.
- SIC Effectiveness: The gain difference between users aids in the effectiveness of the SIC process. Users with higher channel gains can be decoded first, and their signals can be removed from the received signal before decoding signals from users with lower channel gains. This stepwise interference cancellation relies on the gain difference to achieve better decoding performance.

Overall, user pairing in NOMA is crucial for maximizing the gain differences between users within a cluster. This gain diversity facilitates better utilization of the shared resources, improves spectral efficiency, and enables more efficient implementation of superposition coding and SIC, ultimately enhancing the system’s overall performance and capacity.

5. CHALLENGES WITH USER MOBILITY

User mobility poses several challenges in NOMA systems, affecting channel gain differences and user pairing accuracy, often necessitating re-clustering methods:

- Channel Gain-Difference Impact: User mobility causes fluctuations in channel conditions, altering the gain differences between users within a cluster. As users move, their positions relative to the base station change, impacting the received signal strength and channel characteristics.
- Incorrect User Pairing: Mobility introduces dynamic changes in channel conditions, leading to potential mismatches in user pairing. Users initially paired for optimal gain difference might experience altered channel conditions due to mobility. Incorrect user pairing diminishes the effectiveness of NOMA, affecting SIC and reducing the benefits of superposition decoding, ultimately degrading system performance.
- Re-Clustering Necessity: To mitigate the impact of user mobility and maintain efficient NOMA operation, re-clustering methods become essential. These methods dynamically adjust user clusters based on updated channel information or mobility patterns. Re-clustering allows for realignment of users into clusters that optimize gain differences, enhancing spectral efficiency and maintaining system performance.

Effective power control mechanisms and interference management strategies are crucial to adapt to these changes and ensure that the benefits of NOMA, such as increased spectral efficiency and capacity, are sustained. Adaptable and intelligent re-clustering methods need to consider these diverse scenarios to maintain the effectiveness of NOMA across different use cases, highlighting the importance of robust mobility management in the design and deployment of NOMA systems.

6. SYSTEM MODEL

The system model often incorporates mechanisms for user association, dissociation, and re-association within clusters to optimize performance. It accounts for factors like bandwidth availability, throughput requirements, and mobility intensity to ensure efficient resource utilization and minimize interference. The model's objective is to optimize cluster formations, considering various constraints and network dynamics, ultimately enhancing the overall performance of the wireless communication system.

Fig 6.1: An example of dissociation and re-association in shared clusters.

The diagram shows a cluster of clusters, arranged in a grid and connected by lines. Each cluster contains four positions: vacant, occupied, dissociated UE, and association.

Vacant position: A position that is not currently occupied by a user equipment (UE).

Occupied position: A position that is currently occupied by a UE.

Dissociated UE: A UE that is not currently associated with a cluster.

Association: The process of a UE connecting to a cluster.

The lines connecting the clusters represent the possible associations between UEs and clusters. A UE can only be associated with one cluster at a time.

The overall purpose of the diagram is to show how clusters can be arranged and interconnected to provide service to UEs.

Here is a possible scenario for how the diagram could be used: A UE is initially in a dissociated state. The UE scans for available clusters and selects the cluster with the strongest signal. The UE sends an association request to the selected cluster. The cluster assigns a vacant position to the UE and the UE becomes associated with the cluster. The UE can now access the services provided by the cluster. If the UE moves out of the coverage area of the current cluster, it will dissociate from the cluster and scan for a new cluster to associate with.

6.1.Dissociation

Dissociation in a wireless network refers to the process of removing or separating users from a cluster when their channel conditions deteriorate to a point where the Successive Interference Cancellation (SIC) technique can no longer effectively mitigate interference between them. SIC is a key feature in NOMA (Non-Orthogonal Multiple Access), enabling simultaneous data transmission and reception by multiple users within the same resource block. When the channel conditions between users within a cluster degrade substantially, it impacts the efficiency of SIC. If the channel gain difference between users becomes too small or if the channel quality deteriorates significantly, it impedes the successful decoding of multiple signals. Dissociation aims to maintain a sufficient gain difference between users within a cluster to support the SIC process. By dissociating users experiencing poor channel conditions, the network ensures that the remaining users in the cluster can continue to benefit from the advantages of NOMA, maximizing spectral efficiency and overall system performance. Dissociation allows for the reassignment of users to new clusters or positions where their channel conditions better support the principles of SIC, optimizing the utilization of network resources and improving data transmission reliability.

6.2.Re-association

Re-association in a wireless network involves integrating dissociated users into new clusters to maintain the effectiveness of Successive Interference Cancellation (SIC), a fundamental technique in NOMA (Non-Orthogonal Multiple Access). When users are dissociated from their original clusters due to deteriorating channel conditions that hinder SIC, re-association aims to reallocate these users to new clusters where their channel conditions are more conducive to the SIC process. The goal is to find suitable host clusters for the dissociated users where the channel gain difference between users is sufficiently large to support simultaneous transmission and reception. This process helps optimize the overall system performance by preserving the advantages of NOMA, such as improved spectral efficiency and increased capacity. Re-association involves algorithms or procedures that identify vacant positions or clusters with better channel conditions to accommodate the dissociated users. By strategically assigning these users to new clusters, the network mitigates interference and enhances the likelihood of successful simultaneous transmission and reception, thereby maintaining the efficiency of the SIC technique across the network.

6.3.Re-association Methods

Re-association methods in wireless networks aim to efficiently reintegrate dissociated users into new clusters to maintain system performance. These methods vary in their approaches to finding suitable host clusters for dissociated users.

6.3.1 Arbitrary Method

The Arbitrary Method in wireless networks focuses on reintegrating dissociated users into clusters in a straightforward manner. When users are dissociated due to deteriorating channel conditions, this method randomly assigns them to available clusters that meet predefined criteria, often related to maintaining a specific threshold of gain difference between users. Its simplicity lies in the basic rule applied: the dissociated users are placed in clusters that ensure a certain level of gain difference, facilitating successful simultaneous transmissions and receptions through NOMA. While it’s easy to implement and requires less computational complexity compared to more advanced algorithms, its drawback lies in potential suboptimal network performance. The method lacks precision in optimizing gain differences among clusters, which might lead to less efficient resource utilization. Nonetheless, it remains suitable for scenarios requiring rapid decision-making and limited computational resources, prioritizing quick user reintegration over meticulous optimization.

6.3.2 One-by-One Method

The One-by-One Re-association Method in wireless networks involves a systematic approach to reintegrating dissociated users into clusters. When users are dissociated due to deteriorating channel conditions, this method examines each dissociated user individually and identifies suitable clusters based on predefined gain difference criteria. Unlike the arbitrary method, this approach aims for a more refined allocation by evaluating the gain differences between a dissociated user and potential clusters, prioritizing the one offering the highest gain difference within the set thresholds. By sequentially assessing each dissociated user and placing them in clusters with the best gain difference, this method seeks to optimize cluster performance, enhancing the efficiency of simultaneous transmissions through NOMA. While computationally more intensive than the arbitrary method, the one-by-one approach potentially yields better overall network performance by maximizing gain differences and resource utilization, ensuring a more optimal re-association of users.

6.3.3 Kuhn-Munkres Assignment Algorithm(KMAA) Method

The Kuhn-Munkres Assignment Algorithm (KMAA) method, also known as the Hungarian algorithm, is a sophisticated approach used in wireless networks to re-associate dissociated users with clusters, ensuring optimal pairings based on channel conditions. It's a more complex yet highly efficient technique compared to other re-association methods.

This algorithm operates by constructing a cost matrix that represents the association between dissociated users and available clusters. The matrix's elements denote the cost or gain difference between a dissociated user and a specific cluster. The KMAA method then identifies the optimal assignment by finding the maximum gain differences , aiming to pair each dissociated user with the most suitable cluster. KMAA systematically evaluates all possible combinations of user-cluster pairings to determine the optimal association that maximizes gain differences within predefined thresholds. By leveraging computational optimization techniques, like the Hungarian algorithm, it ensures that each user is re-associated with a cluster that maximizes the overall gain difference, enhancing the efficiency of NOMA based transmissions in wireless network.

In addition to its role in optimizing user-cluster associations for enhanced Non-Orthogonal Multiple Access (NOMA) transmissions, the Kuhn-Munkres Assignment Algorithm (KMAA) also contributes to the overall stability and reliability of wireless networks. The algorithm's ability to systematically evaluate and determine optimal pairings ensures that network resources are efficiently utilized, minimizing interference and congestion. This, in turn, leads to improved network performance, reduced latency, and increased throughput. The KMAA method's sophisticated approach is particularly valuable in dynamic wireless environments where channel conditions and user mobility can change rapidly.

7. RE-ASSOCIATION METHODS

7.1. Initial Clustering and Dissociation Procedure

Algorithm 1. Initial Clustering and Dissociation Procedure

1: **Phase 1: Choosing initial clusters**
2: **Input:** Number of UEs $|\mathcal{V}'|$, cluster size $k_{\max}$ ⊳ e.g., $(1 \leq |K| \leq k_{\max})$, λ_0 and λ_1 gain-difference threshold values, $\mathcal{N}$ is a set of available positions and $\mathcal{M}$ is a set of dissociated and new UEs
3: **Output:** $\mathcal{C}$;
4: **for** $i \in \{1, 2, \ldots, |\mathcal{V}'|\}$ **do**
5: calculate the distance between UE v_i and BS and save it in set $\mathcal{D}$
6: sort $\{\mathcal{D}\}$
7: sort $\{\mathcal{V}'\}$ according to $\{\mathcal{D}\}$
8: **for** $j \in \{1, 2, \ldots, k_{\max}\}$ **do**
9: $l = j \times k$
10: **if** $l \leq |\mathcal{V}'|$ **then**
11: $\mathbf{c}_j = \{(k \times (j-1)) + 1, (k \times (j-1)) + 2, \ldots, (k \times (j-1)) + k_{\max}\}$ assigning UEs to the clusters $\{1, 2, \ldots, k\}$.
12: **else**
13: $\mathbf{c}_j = \{(k \times (j-1)) + 1, (k \times (j-1)) + 2, \ldots, |\mathcal{V}'|\}$ assigning UEs to the clusters $\{1, 2, \ldots, |\mathcal{V}'| - (k \times (j-1))\}$.

14: **Phase 2: Managing clusters**
15: **for** $k = 1 \rightarrow |\mathcal{C}|$ **do**
16: $\mathbf{s} \leftarrow \mathbf{s}_{emp}$ ⊳ an empty array.
17: $\mathbf{W} \leftarrow ((1 : (|\mathbf{c}_k| - 1)) \times (1 : |\mathbf{c}_k|))$ ⊳ is a matrix of zeros, where each υ represents the status of UE interference.
18: **for** $i = 1 \rightarrow (|\mathbf{c}_k| - 1)$ **do**
19: **for** $j = i + 1 \rightarrow |\mathbf{c}_k|$ **do**
20: $d_{ij} = |(h_{x_i} - h_{y_j})|$ ⊳ d_{ij} is a function to find the gain-difference between all the UEs in a cluster.
21: **if** $\lambda_0 \leq d_{ij} \leq \lambda_1$ (where $\lambda_0 < \lambda_1$) **then**
22: $\mathbf{c}_k \leftarrow \mathbf{c}_k$
23: increase the rate of channel feedback measurements.
24: **else if** $d_{ij} \leq \lambda_0$ **then**
25: $\mathbf{s} \leftarrow [\mathbf{s}, \upsilon_{(i,j)}]$ ⊳ save index of interfering UEs in $\mathbf{s}$.
26: $\mathbf{W}(i, j) \leftarrow 1$ ⊳ interference status of UEs becomes 1 when their gain-difference is less than λ_0.
27: **for** $l = 1 \rightarrow (1 : |\mathbf{c}_k|)$ **do**
28: $\psi \leftarrow \mathbf{W}(:, l)$ ⊳ identify the UEs which are causing interference by analyzing each column of $\mathbf{W}$.
29: $\mathbf{c}_k \leftarrow (\mathbf{c}_k \setminus \psi)$ ⊳ disassociate UE with desired criteria
30: check $\mathbf{s}$ if all the interfering UEs are dissociated from k^{th} cluster otherwise go to 27.
31: $\mathcal{M} \leftarrow \psi$ ⊳ set of all the dissociated UEs
32: $\mathcal{N} \leftarrow$ save cluster number k
33: **if** $|\mathbf{c}_k| < k_{max}$ **then**
34: $\mathcal{N} \leftarrow$ save cluster number k

Fig 7.1: Initial Clustering and Dissociation Procedure

The algorithm is used for initial clustering and dissociation. It is used to choose initial clusters for a set of UEs, and to dissociate UEs from clusters when they move out of the coverage area of the current cluster.

This algorithm is designed to choose initial clusters that are well-balanced and to dissociate UEs from clusters in a timely manner. It is commonly used in cellular networks to manage the handoff of UEs between different cells.

Clustering algorithm is used for wireless networks. It is used to group user equipment (UEs) into clusters, based on their signal strength and other factors. The goal of clustering is to improve the performance of the network by reducing interference and increasing throughput. Once the clusters have been created, the network can use this information to improve its performance. For example, the network can use the cluster information to determine which UEs to schedule for transmission and which UEs to place in power save mode.

Overview of Algorithm 1

Phase 1. The algorithm computes an approximate solution based on distance from the base station in order to initialize the maximization of the objective function of P2. Phase 1 performs the initial clustering and is composed of the following steps:

- Step 1: Construct the set D, which consists of the distances between each UE and the BS and sort all the UEs, based on their distance from BS (Line 4–7).
- Step 2: Construct k groups containing UE from V0 , where each group consists of l number of UEs. We assign the first l UEs to form group 1, then the next set of l UEs to form group 2 and so on. The first (second) user in each group will form the first (second) cluster and so on (Line 8–13).

NOMA will benefit from the location and positioning Ehancements which are new features for wireless standards [29]. Future studies will also define more accurate sets of positioning techniques for both indoor and outdoor environments. The form of clustering in Algorithm 1

(Phase 1) is the de facto method in NOMA allocation and used by several researchers [30]. However, this user clustering technique would inevitably be invalid in networks where users are mobile. Our next algorithms deal with this problem. The detailed pseudo-code is presented in Algorithm 1.

Phase 2. In phase 2 of Algorithm 1, we applied a backtracking procedure to continuously monitor and update the clusters. The pseudo-code consists of the following steps:

- Step 1: Monitor the gain-difference between each pair of UEs within a cluster in real-time (Line 15–20).
- Step 2: If the gain-difference between any two UEs within a cluster falls below 1 but remain greater than 0, then the UEs in that cluster are prompted to increase the frequency of obtaining and reporting channel gain measurements. This minimizes channel feedback and communications overhead, when user mobility in the network is low (Line 21–23).
- Step 3: If the gain-difference between UEs within a cluster is less than the given threshold 0, the UE which is introducing interference to other UEs within the cluster is dissociated (Line 24– 30).
- Step 4: Assign the dissociated users to set M and save the cluster indexes from which the users are dissociated in N . Find all the clusters which are under-utilized and save their indexes in N (Line 31–34).

The dissociated UEs from the set M are then assigned to clusters in set N , using arbitrary, one-by-one or the KMAA algorithms, following the corresponding techniques therein. The dissociated users are assigned to new suitable positions in other clusters, within multiple position candidates. It is reasonable for the UEs to be placed to the position where the gain-difference between the users in the new cluster is higher than 1. The logic behind this algorithm is to keep track of the gain-difference changes between users which occur as a consequence of mobility and to maintain the clusters in working order, minimizing outages.

7.2. Arbitrary Method

Algorithm 2. Re-Association Algorithm Using Arbitrary Mechanism

Input: Let λ_0 gain-difference threshold value, $\mathcal{N}$ is a set of available positions and $\mathcal{M}$ is a set of dissociated and new UEs.
$\mathcal{M}^* \leftarrow \emptyset$
for $i = 1, 2, \ldots, |\mathcal{M}|$ **do**
  $\rho \leftarrow 0$
  for $j = 1, 2, \ldots, |\mathcal{N}|, \quad j \neq i$ **do**
    ⊳ So we will go through all the clusters except $\mathbf{c}_i$ from which ith user is dissociated
    $\psi \leftarrow (1 \times |K_j|)$ is a vector of zeros
    for $l = 1, 2, \ldots, |K_j|$, **do**
      $d \leftarrow |(h_{x_i} - h_{x_l})|$
      if $d \geq \lambda_0$ **then**
        $\psi_l = 1$
    if $\sum \psi = |K_j|$ **then**
      $\mathbf{c}_j \leftarrow \mathbf{c}_j \bigcup m_i$
      if $|\mathbf{c}_j| = k_{max}$ **then**
        $\mathcal{N} \leftarrow \mathcal{N} \setminus \mathbf{c}_j$
      $\rho \leftarrow 1$
    continue
  if $\rho = 0$ **then**
    $\mathcal{M}^* \leftarrow \mathcal{M}^* \bigcup m_i$
Add new clusters for UEs in $\mathcal{M}^*$ using Algorithm 1 from Line (4–13)

Fig 7.2: Re-Association Algorithm Using Arbitrary Mechanism

The Arbitrary Algorithm in NOMA re-association randomly assigns dissociated users to available clusters without considering the gain differences comprehensively. It operates by sequentially assessing all clusters for vacant positions and placing dissociated users in these positions. This method, while straightforward, lacks optimization based on gain differences between users and clusters. It does not guarantee the best allocation in terms of maximizing the channel gain differences or enhancing the performance of simultaneous transmissions. Consequently, the Arbitrary Algorithm might lead to suboptimal assignments, resulting in reduced spectral efficiency and potential interference issues within clusters. While simple and easy to implement, this method may not fully exploit the advantages of NOMA, as it overlooks the critical factor of gain differences between users, which are pivotal for effective superposition coding and successive interference cancellation (SIC).

7.3. One by One Mechanism

Algorithm 3. Re-Association Algorithm Using One-by-One Mechanism

Input: Let λ_0 gain-difference threshold value, $\mathcal{N}$ is a set of available positions and $\mathcal{M}$ is a set of dissociated and new UEs.
$\mathcal{M}^* \leftarrow \emptyset$
for $i = 1, 2, \ldots, |\mathcal{M}|$ **do**
  $\rho \leftarrow 0$, $\mathbf{d}' \leftarrow (|\mathcal{N}| \times 1)$ is an array of zeros,
  for $j = 1, 2, \ldots, |\mathcal{N}|, \quad j \neq i$ **do**
    $\triangleright$ So we will go through all the clusters except $\mathbf{c}_i$ from which ith user is dissociated
    $\psi \leftarrow (1 \times |K_j|)$ is a vector of zeros
    $\mathbf{d} \leftarrow (1 \times |K_j|)$ is a vector of zeros
    for $l = 1, 2, \ldots, |K_j|$, **do**
      $d \leftarrow |(h_{x_i} - h_{x_l})|$
      if $d \geq \lambda_0$ **then**
        $\psi_l \leftarrow 1$
        $\mathbf{d}_l \leftarrow d$
    if $\sum \psi = |K_j|$ **then**
      $\mathbf{d}'_j \leftarrow \sum \mathbf{d}_l$
  $\mu \leftarrow \max(\mathbf{d}')$ and save its position to υ
  re-associate the UE m_i with cluster $\mathbf{c}_\upsilon$
  $\mathbf{c}_\upsilon \leftarrow \mathbf{c}_\upsilon \bigcup m_i$
  $\rho \leftarrow 1$
  if $|\mathbf{c}_\upsilon| = k_{max}$ **then**
    $\mathcal{N} \leftarrow \mathcal{N} \setminus \mathbf{c}_\upsilon$
  if $\rho = 0$ **then**
    $\mathcal{M}^* \leftarrow \mathcal{M}^* \bigcup m_i$
Add new clusters for UEs in $\mathcal{M}^*$ using Algorithm 1 from Line (4–13)

Fig 7.4: Re-Association Algorithm Using One-by-One Mechanism

The One-by-One Algorithm in NOMA re-association systematically examines each dissociated user and searches for the best possible cluster to re-associate them with, considering the gain differences between users and clusters. This method evaluates clusters individually, identifying the one that maximizes the gain difference between the new user and the existing cluster users. By iteratively selecting the most suitable cluster for each dissociated user, this method aims to optimize the assignment based on gain differences, thereby enhancing the overall spectral efficiency of the system. However, while it provides a more tailored approach than the Arbitrary Algorithm, it might not always yield the globally optimal solution, as it focuses on local optimizations at each step. Nonetheless, it attempts to enhance the performance of NOMA by considering gain differences, contributing to better channel utilization and interference mitigation within clusters.

7.4. Simultaneous Mechanism

Algorithm 4. Re-Association Algorithm Using Simultaneous Mechanism

```
Input: Let λ0 gain-difference threshold value, 𝒩 is a set of available positions and ℳ is a set of dissociated and new UEs.
ℳ* ← ∅
G ← (|ℳ| × |𝒩|) is an array of zeros,
for i = 1, 2, . . . , |ℳ| do
    ρ ← 0, d′ ← (|𝒩| × 1) is an array of zeros,
    for j = 1, 2, . . . , |𝒩|,   j ≠ i do
        ▷ So we will go through all the clusters except c_i from which ith user is dissociated
        ψ ← (1 × |K_j|) is a vector of zeros
        d ← (1 × |K_j|) is a vector of zeros
        for l = 1, 2, . . . , |K_j| do
            d ← |(h_{x_i} − h_{x_l})|
            if d ≥ λ0 then
                ψ_l ← 1
                d_l ← d
        if ∑ ψ = |K_j| then
            g_j ← ∑ d_l
    G ← g
n ← number of rows in G
rowMin[i] ← i
colMin[j] ← j
assignMat ← G*
while Num < n do
    for i = 1, 2, . . . , n do
        for j = 1, 2, . . . , n do
            G_ij ← G_ij − rowMin[i]
    for i = 1, 2, . . . , n do
        for j = 1, 2, . . . , n do
            G_ij ← G_ij − colMin[i]
    Cover all 0 with the minimum number of horizontal and vertical lines
    Num ← Minimum number of lines to cover the 0s
Obtain the re-association G* and assign the status to users ρ ← 1
for i = 1, 2, . . . , |𝒩| do
    if |c_i| = k_max then
        𝒩 ← 𝒩 \ c_i
for j = 1, 2, . . . , |ℳ| do
    if ρ = 0 then
        ℳ* ← ℳ* ⋃ m_j
Add new clusters for UEs in ℳ* using Algorithm 1 from Line (4–13)
```

Fig 7.5: Re-association Algorithm Using Simultaneous Mechanism

The Kuhn-Munkres Assignment Algorithm (KMAA), also known as the Hungarian Algorithm, is an optimization algorithm used in association problems like the assignment of tasks or resources. In the context of NOMA re-association, it efficiently pairs dissociated users with suitable clusters, considering gain differences to optimize simultaneous transmissions.

Here’s an overview of how the KMAA works in the context of NOMA reassociation:

Constructing the Gain Matrix: Initially, a matrix is created with gain differences between dissociated users and potential clusters. This matrix represents the gain differences between each dissociated user and each available cluster.

Optimal Assignment: The KMAA aims to find the best possible pairing of users to clusters that maximizes the overall gain differences. It operates based on an iterative process to identify the most efficient pairings.

Hungarian Algorithm Steps: The algorithm operates by finding the optimal assignment through a series of steps:It reduces the gain matrix by subtracting the minimum value from each row and column to create zero elements. It covers all zeros in the matrix with the minimum number of lines (either horizontal or vertical) to create maximum possible zero entries. It checks for the minimal number of lines needed to cover all zeros. If it matches the number of rows/columns, the optimal assignment is achieved. If the minimal lines do not cover all zeros, it adjusts the matrix to create additional zeros and repeats the process until an optimal solution is found. Re-Association and Optimization: Once the optimal pairings are determined, users are re-associated with clusters, aiming to maximize gain differences for efficient simultaneous transmissions. The KMAA algorithm, unlike simpler methods, optimizes the assignment by considering gain differences, ensuring a more efficient and effective utilization of resources in NOMA-based systems.

Overview of Algorithms 2, 3 and 4

Following the scanning procedure to identify vacant positions, Algorithm 2 performs assigning UE to clusters randomly (Line 5-13) and update all the clusters accordingly.Algorithm 3 performs a search to find the maximum gain difference between users in clusters containing valid positions (Line 5-16) and update all the clusters accordingly. To optimize the assignment problem and to maintain the global maximum-gain difference, Algorithm 4 performs the best possible solution, which is achieved using the Hungarian algorithm in two steps: (1) Line 4-17, we construct matrix, G, which contains channel gain-difference values between the dissociated UE in M and UE in N . (2) The assignment of UE to clusters is determined by Line 18-31 and saved in G , followed by updating the sets M and N (Line 32-37).

8. CONCLUSION

In this work we highlighted the problem of mobility associated with NOMA clustering, where the gain-difference between users may decrease to a level, where the successive interference cancellation (SIC) fails. In this context we presented a new approach, fully-automatic, to manage and update clusters in a robust manner, through user dissociation and re-association procedure, which links dissociated users to new clusters. We have analyzed three solutions: (i) arbitrarily (ii) one-by-one and (iii) KMAA.

In conclusion, this seminar has delved into the intricate domain of Next Generation Wireless Networks (NGN), exploring the evolution from traditional access techniques like TDMA and OFDMA to the cutting-edge Non-Orthogonal Multiple Access (NOMA) systems. Through our investigation, we've uncovered the limitations of prior technologies, highlighting the necessity for advancements that address burgeoning challenges in wireless communication. We scrutinized NOMA's groundbreaking principles, emphasizing its ability to drastically enhance spectral efficiency through simultaneous transmission and reception by multiple users within a shared resource block. The encoding techniques at the transmitter and Successive Interference Cancellation (SIC) at the receiver were key focal points, showcasing NOMA's prowess in maximizing channel utilization and mitigating interference. However, despite its promising capabilities, we acknowledged the intricacies associated with user mobility, channel variations, and the criticality of accurate user pairing in NOMA clusters. Furthermore, the need for robust re-clustering methods to adapt to dynamic network environments became evident. In essence, this seminar underscores the pivotal role of NOMA in revolutionizing wireless communication, while also acknowledging the complexities that necessitate continual research and innovation in this rapidly evolving field.

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