Semantic Utility Aware User Grouping for 6G NOMA Networks

Derek Chui†, Wei Wang‡ and Krishna Murthy Kattiyan Ramamoorthy†
†*Department of Computer Science and Engineering, Santa Clara University,* California, USA.
‡*Department of Computer Science, San Diego State University,* California, USA.
dchui2@scu.edu, wwang@sdsu.edu, kkattiyanramamoorthy@scu.edu

***Abstract*—This paper looks into optimal algorithms for user pairing and triplet grouping in Non-Orthogonal Multiple Access (NOMA) wireless systems, aiming to maximize total utility by unifying channel characteristics with semantic relevance. As 6G wireless systems move toward task-oriented communication, it becomes increasingly important to consider the meaning and importance of user data in resource allocation. We evaluate several existing algorithms including brute force, Hungarian, and greedy approaches under a utility model that incorporates semantic value. Our study show that many traditional algorithms, designed without semantics in mind, perform suboptimally in this setting. Therefore, we propose a greedy algorithm called Semantic Greedy NOMA (SG-NOMA) that considers both channel diversity and semantic value, and demonstrate through simulations that it closely approximates brute force performance with significantly lower complexity. These findings highlight the importance of integrating semantic considerations into user grouping strategies for 6G wireless NOMA deployments.**

***Index Terms*—Non Orthogonal Multiple Access (NOMA), Semantic Aware Communication, NOMA Algorithms, SG-NOMA.**

I. Introduction

The continuous demand for higher data rates, low latency, and massive connectivity in wireless communications has established NOMA as a fundamental technique for next-generation networks. NOMA improves spectral efficiency and supports multiple simultaneous users by allowing them to share the same time and frequency resources, leveraging successive interference cancellation (SIC). This is achieved by allocating different power levels to users with diverse channel conditions. Compared to Orthogonal Multiple Access (OMA), NOMA offers better spectrum utilization and fairness, making it a key enabler for technologies like 6G and beyond.

A key aspect of NOMA is pairing a strong (near) user with a weak (far) user, enabling efficient use of power-domain multiplexing and improving overall system performance. Since grouping directly affects both throughput and fairness, optimal user pairing is central to NOMA's effectiveness. As the number of users increases, however, finding the best groupings becomes computationally challenging. A wide range of strategies have been proposed in prior work, from brute force methods that guarantee optimality to heuristics that reduce complexity at the cost of some performance. Most existing studies focus on physical-layer factors like channel gain or user distance.

This work was supported by the 2FURS (Faculty-mentored Undergraduate Research) Grant, Santa Clara University, 2024.

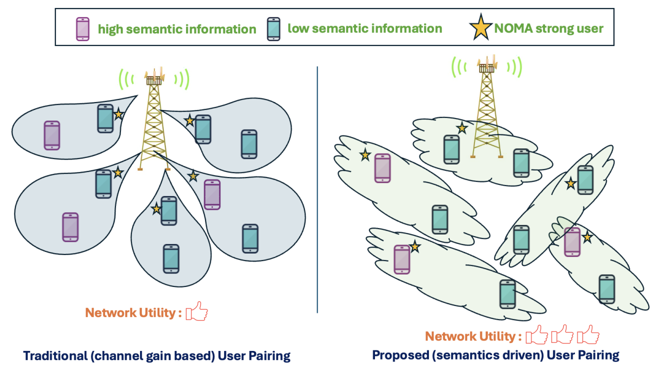

Fig. 1. Traditional vs. semantic-aware grouping in NOMA. Semantic-aware pairing considers both channel conditions and data importance for more meaningful groupings.

Beyond simple pairs, grouping can be extended to user triplets, which offer greater flexibility in handling diverse user requirements.

Semantic communication has gained increasing attention in recent years, especially as wireless systems move toward task-oriented and context-aware transmission. In these systems, the goal is not just to deliver raw bits but to ensure that the transmitted content carries meaningful and relevant information. This shift makes it important to include semantic awareness in user grouping decisions. Many existing user pairing strategies in NOMA have been designed with physical parameters like distance and channel gain in mind, but overlook the importance of the transmitted content [1]. Research has shown that different users may carry different levels of semantic concentration, where some transmit more meaningful data than others. Semantic-aware communication has also been shown to reduce communication overhead while preserving task performance [2]. Figure 1 illustrates this shift in perspective. Traditional grouping may favor users with better channel conditions, but semantic-aware grouping prioritizes those whose content is more important.

In this paper, we study how existing user grouping algorithms perform when utility is defined using both channel characteristics and semantic importance. We use a simple model where each user is assigned a semantic value between 0 and 1, and utility is computed as the weighted sum of achievable rates. Several well-known algorithms discussed in section III are evaluated under this semantic-aware setting. Our results show that many of these traditional methods, which were not designed with semantics in mind, struggle to produce meaningful groupings. We then propose a new semantic greedy algorithm named SG-NOMA that prioritizes both channel diversity and semantic value when forming user pairs and triplets. Our study shows that this approach closely tracks brute force performance, while running at much lower complexity. This makes it suitable for practical real-time NOMA deployments where both performance and efficiency matter.

II. System Model and Problem Formulation

A. Channel Gain

The goal of NOMA is to essentially have multiple users share the same time and frequency resources, but with various power levels. This is best done by pairing a strong (close) user with a weak (far) user. We can mimic this relationship by grouping from a set of users with distances between the users being the maximum possible total distance when summed up as a set.

We first calculate the channel gain h based on the path loss model. This will give us the relationship between channel gain and distance. $\mathrm{h}_i = \frac{\sigma_i}{d^{\eta/2}}$, where d is the distance to the base station, σ_i as the Rayleigh fading coefficient sampled from Rayleigh distribution, and η the path loss exponent. The path loss exponent η models the propagation environment in wireless communication. It quantifies the decay in signal strength over distance, varying depending on the surrounding terrain and obstructions.

In our investigation, we vary η from 2 to 6, observing the impact on utility over different conditions. Specifically $\eta = 2$ corresponds to free space environments with ideal line of sight (LOS). This can be the likes of rural or open field settings. 2.7 to 3.5 reflects urban or suburban outdoor LOS conditions, while 3.5 to 5 are typically urban non line of sight (NLOS) cases. Indoor environments and residential areas exhibit values between 3 and 4, and lastly dense office buildings may push it as high as 6 because of more significant obstructions in signal. Such variations lets NOMA's performance and it's algorithms to be evaluated under a plethora of channel conditions.

B. Pairing Utility

With channel gain h, we can now plug it into utility U For pairs, utility U_{pair} is given by

$$U_{\text{pair}} = R_1 + R_2, \tag{1}$$

where R_1 and R_2 are the achievable rates of the weak and strong users, respectively. For each pair, the achievable rate for the weak user R_1 (decoded first) is given by

$$R_1 = \log_2\left(1 + \frac{\alpha_1 P h_1^2}{\alpha_2 P h_1^2 + N_0}\right), \tag{2}$$

and the achievable rate for the strong user R_2 (decoded after performing successive interference cancellation) is given by

$$R_2 = \log_2\left(1 + \frac{\alpha_2 P h_2^2}{N_0}\right), \tag{3}$$

where α_1 and α_2 are the power allocation factors for the weak and strong users, respectively, satisfying $\alpha_1 + \alpha_2 = 1$ with $\alpha_1 > \alpha_2$ to ensure the weak user receives more power. Here, P is the total transmission power, h_1 and h_2 are the channel gains of the weak and strong users, respectively, and N_0 is the noise power. For instance, α_1 can be 0.6 while α_2 can be 0.4. Total transmission power P can be set to 1, and N_0 can be set to 10^{-4}, thus acting as constants. Because of this the only variables would be the distances and Rayleigh fading.

C. Triplet Utility

For triplets, the utility U_{tri} extends to

$$U_{\text{tri}} = R_1 + R_2 + R_3, \tag{4}$$

where R_1, R_2, and R_3 correspond to the three users ordered by channel strength. Additional interferences are accounted for, but the general idea is the same as pairs. For triplet configurations, the rate for the weakest user R_1 (decoded first) is

$$R_1 = \log_2\left(1 + \frac{\alpha_1 P h_1^2}{\alpha_2 P h_1^2 + \alpha_3 P h_1^2 + N_0}\right), \tag{5}$$

the rate for the middle user R_2 (decoded second)is

$$R_2 = \log_2\left(1 + \frac{\alpha_2 P h_2^2}{\alpha_3 P h_2^2 + N_0}\right), \tag{6}$$

and the rate for the strongest user R_3 (decoded last, with all interference canceled) is

$$R_3 = \log_2\left(1 + \frac{\alpha_3 P h_3^2}{N_0}\right), \tag{7}$$

where $\alpha_1, \alpha_2, \alpha_3$ are the power allocation factors assigned to the weak, middle, and strong users, respectively, satisfying $\alpha_1 + \alpha_2 + \alpha_3 = 1$ with $\alpha_1 > \alpha_2 > \alpha_3$ to prioritize the weaker users.

D. Semantics

We can now introduce semantics to the equation by multiplying each rate R_i by a semantic weight $w_i \in (0, 1)$, which represents the importance of user i's data. This is essentially a simplified version of the semantic information concentration model $I/(K \times W)$ from [3], where I is the semantic information per sentence, K as the average number of mapped semantic symbols per word, and W being the average number of words per sentence. From such we approximate this value by assigning random weights w_i sampled uniformly between 0 and 1. This approach enables modeling diverse semantic priorities across users.

Therefore, the semantic aware now utility becomes

$$U_{\text{sem}} = \sum_{i=1}^{N} w_i R_i, \tag{8}$$

where $N = 2$ for pairs or $N = 3$ for triplets. This semantic weighting reflects application level priorities in the network utility by emphasizing more semantically meaningful data during resource allocation. It's important to note that in the simulations, the set of weights w_i and points are set constant, while the algorithm used will determine the rate R_i.

III. Algorithms for User Grouping

This following section looks into the various grouping algorithms sourced both from other research and new findings. It details the algorithms evaluated for optimal and heuristic user groupings in NOMA systems. During the simulations, the results of these algorithms will be plugged into R of $U_{\text{sem}} = \sum_{i=1}^{N} w_i R_i$, where weights, variables, and user locations will remain constant. The goal is to maximize total utility by grouping users with complementary channel conditions, while doing so efficiently for optimal scaling later on. The results will be compared with brute force to analyze its efficiency. Being largely determined by distances and weights, we first find the groupings that sum up to the largest total distances in a set. Then we plug it into (8) to compute the utility.

A. Brute Force Search

We can first look at the brute force solution as a baseline. Then we would notice the recurring patterns and optimize it from then on. For obvious reasons, this would have the worst complexity but will certainly provide the best pairing results consistently without fail. We can derive the time complexity for pairs with the following:

$$O\left(\frac{n!}{(n/2)! \cdot 2^{n/2}} \cdot n\right) = O(n^{n/2}). \tag{9}$$

Where n! are the permutations of all users, (n/2)! for unordered triplet groupings, and $2^{n/2}$ as permutations within each pair. The same applies to triplets:

$$O\left(\frac{n!}{(n/3)! \cdot 3^{n/3}} \cdot n\right) = O(n^{n}) \tag{10}$$

For example, there are 10395 ways to pair 12 users into 6 unique pairs, and 15400 ways to pair 4 pairs of 3 with 12 users as well. With that in mind, our goal now is to reduce the time complexity as much as possible, while keeping the same results without compromising anything else.

B. D-NOMA (Distributed NOMA)

D-NOMA algorithm [4] is studied, which introduces a structured user grouping method to enhance fairness and utility in denser environments. It is suitable to improve throughput for user pairs, with small channel gain differences. Instead of pairing users based on sorted channel gain, it divides users into four quartile based groups: First Nearest Near (FNN), Second Nearest Near (SNN), First Farthest Far (FFF), and Second Farthest Far (SFF). Pairings are then created across matching group indices by parity. As an example example, FNN is paired with FFF, and SNN with SFF. The algorithm complexity is $O(n \log n)$, dominated by the initial sorting of users by channel gain.

C. D-NLUPA (Divide and Next Largest User Pairing)

The D-NLUPA algorithm introduced in [5] presents a two step method for maximizing sum throughput in NOMA systems. This is done by decoupling user clustering from power allocation. It first uses low complexity suboptimal user clustering scheme, leveraging channel gain disparities, and pairs high channel gain users with low channel gain users. This also maximizes the benefits coming from SIC.

The dominant operation is sorting n users based on channel gain, which has a time complexity of $O(n \log n)$. After sorting, forming the $n/2$ pairs is a linear operation, requiring only $O(n)$ time. Thus the overall time complexity of this pairing strategy is: $O(n \log n)$ which makes it highly efficient and scalable for real time user grouping.

D. MUG (Multi User Grouping)

We also include the MUG algorithm from [6], which uses a path cover approach to maximize user multiplexing on sub-channels, forming larger user groups in a graph theoretic framework. This addresses the problem with user grouping in down link NOMA systems. The core concept is to construct a directed graph where each node represents a user, edges represent feasible pairings based on sufficient channel gain and power availability. It when splits each user into two nodes, searches the graph for disjoint paths of limited length K where K is the max number of users per group. It applies depth first search (DFS) and matching logic, covering the graph with fewest number of disjoin paths, representing a valid user group. The time complexity of this method is mostly determined by graph traversals, being bounded by $O(n^2)$.

E. LCG (Low Complexity Greedy)

Proposed in [7], LCG sorts through sub channels based on lowest channel gain throughout users, iteratively matching each sub channel with the user with the highest channel gain. Users are then excluded from future pairings. The process is repeated until all users are assigned to sub channels. The greedy approach makes sure users with strong channel conditions are efficiently utilize, while maintaining fairness. It therefore runs in polynomial time because of its sorting and sequential matching structure, being $O(n \log n)$ for n users. LCG is able to consistently provide high rates in lower SNR environments, especially when computational simplicity is prioritized.

F. DEC (Deep Embedded Clustering)

On the other hand, [7] also references the DEC algorithm. It essentially integrates deep learning and clustering, optimizing sub channel user assignments in a NOMA system. It transforms raw channel gain data into a latent space, then performing clustering in such space, finding similar channels, and grouping accordingly. It assigns users by matching strong channel conditions in high gain clusters with weaker, low gain clusters, ensuring fairness and reducing interference. However it's more intensive than LCG, but shows better performance in high SNR scenarios.

G. Hungarian

Hungarian has been widely applied to optimal user pairing in downlink NOMA systems [8], especially for solving linear assignment problems. It builds a cost matrix, each entry representing a pairing score between users in two clusters. The algorithm maximizes total pairing utility by minimizing total cost with matrix reduction and iterative optimization.

This is done by matrix normalization, row and column reductions, covering zeros with min number of lines, and doing so until an optimal assignment is found. However, it's high computational cost of $O(n^4)$ makes it unsuitable for real time or large scale scenarios.

H. JV (Jonker Volgenant)

JV then improves and builds on the Hungarian algorithm, making it a shortest path based min cost flow problem. It reduces the cost matrix and finds augmenting paths for unassigned rows, completing the pairings. It speed comes from steps like column reduction. From the results on [8], JV has similar performances to Hungarian, but improves weak user capacity by prioritizing short distance pairings for fairness.

I. Proposed Algorithm - SG-NOMA

Taking inspiration from literature research, we propose a new algorithm named SG-NOMA that maximizes the semantic aware utility function. Unlike prior structural methods like DNOMA or LCG, SG-NOMA evaluates groupings based on the approximate version of weighted utility, which prioritizes both channel diversity and semantic contribution.

Pairwise SG-NOMA algorithm builds on user pairs sequentially by selecting, per iteration, user pairs with the highest score. Scoring is defined as the sum of distances and difference in semantic weights. The goal is to promote pairs that are both spatially diverse and semantically unique. This tends to increase the effective channel difference needed for NOMA. Once the best pair is selected, both users are remove from the pool, and the process repeats until all users are grouped. This correlates well with channel gain diversity and relevancy, allowing it to approximate brute force utilities without being exhaustive. We can extend this idea to triplets, which considers valid three user combinations per step, assigning scores based on both distances and weights. Again, combination with highest score is selected, and removed from the pool. This approach scales polynomially, offering a balance between performance and complexity.

Despite the greedy nature, both algorithms produces utility curves that follow closely to brute force, as seen in the simulations below. In contrast, fixed rule methods exhibits a weaker correlation with semantic utilities, which means lower and more erratic trends in performance.

Algorithm 1 Proposed Optimized Grouping Algorithm

Require: User set $\mathcal{U} = \{u_1, u_2, \ldots, u_n\}$ with 3D positions, Rayleigh fading z_i, path loss exponent η, semantic weights w_i
Ensure: Grouped user sets (pairs or triplets), optimized utility U_{sem}
Computer distance d_i of each user to base station
Computer channel gain $h_i = \frac{\sigma_i}{d^{\eta/2}}$ for each user
Sort users by d_i in descending order (weakest to strongest)
if pairing mode **then**
  Initialize empty pairing list $\mathcal{P}$
  for $i = 1$ to $n/2$ **do**
    Pair u_i (weak) with u_{n-i+1} (strong)
    Compute R_1, R_2 using SIC formulas
    Compute $U_{\text{sem}} = w_i R_1 + w_{n-i+1} R_2$
    Store pair and utility
  end for
else {triplet mode}
  Initialize empty triplet list $\mathcal{T}$
  for $i = 1$ to $n/3$ **do**
    Form triplet $(u_i, u_{i+n/3}, u_{i+2n/3})$ in descending distance order
    Assign $\alpha_1 > \alpha_2 > \alpha_3$ to weak, mid, strong users
    Compute R_1, R_2, R_3 using SIC formulas
    Compute $U_{\text{sem}} = w_1 R_1 + w_2 R_2 + w_3 R_3$
    store triplet and utility
  end for
end if
Return groupings with maximum U_{sem} =0

IV. Simulation Results and Discussion

In order to evaluate the performance of the proposed and bench marked algorithms, we conducted MATLAB simulations with randomly generated user positions within a covered area. We first compute channel gain from distance, with the help of Rayleigh fading. The path loss exponent, which depends on the environment, could also be altered to compared simulation results. With channel gain, utility can be found using weak and strong users. The summation of these groupings will be our total network utility. With semantics, each user has a weight attached and will be multiplied to each grouping.

The simulation studies how the utility changes with various situations and compares those results to other algorithms. Specifically, brute force, SG-NOMA, D-NOMA, and LCG since they all have diverse algorithmic styles and time complexities. It's also important to note that D-NOMA, LCG, and JV were developed without semantics in mind. By default and unless noted otherwise, $\eta = 3$, $\alpha = 0.6$, $P = 1$, $N_0 = 1e-4$, and $\sigma = 1$. Pairs instead of triplets will be implemented for this for simplicity, and also makes it easier to follow.

A. Effect of Path Loss Exponent η on Brute Force Utility

We begin the simulations by evaluating the sensitivity of utility to environmental conditions, simulating the brute force utility across changing path loss exponents $\eta \in \{2, 3, 4, 5, 6\}$. All other variables and parameters are kept constants, which includes the positions of users, transmission power, and noise.

Total network utility decreased monotonically as η increased. This is because higher path loss weakens channel gains, especially for distant users. This reveals the importance of environment aware grouping when considering realism. The line plot shows utility versus η, illustrating such inverse relationship. Figure 2 show that increasing σ increases utility,

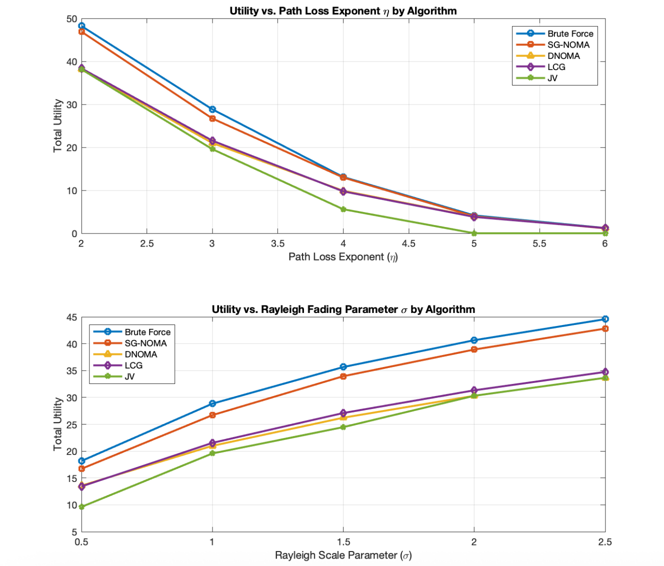

Fig. 2. Utilities as a function of path loss exponent and Rayleigh fading

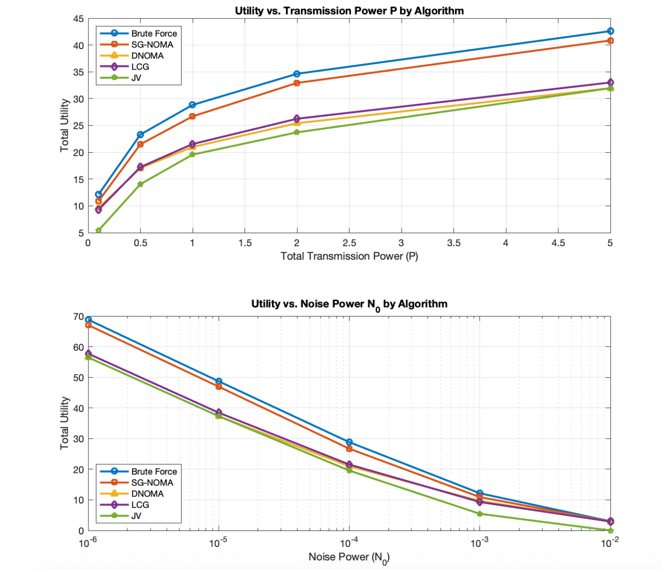

Fig. 3. Utilities as a function of power P and noise N_0

reflecting stronger channel gains for users. Like several other variables however, utility gains diminishes with higher σ.

B. Impact of Rayleigh Fading Parameter

In order to evaluate the effect of fading on NOMA utility, we analyzed the varying Rayleigh distribution parameter σ which directly affects the channel gain. Prior simulations assumed $\sigma = 1$ but σ is changed from 0.5 to 2.5 to observe its influence on utility. The remaining parameters are held constant. SG-NOMA however is more sensitive to random variations. Figure 2 shows utility trends as σ increases, where larger σ means higher channel gain variability, benefiting weaker users (randomly boosting fading gains). This means higher achievable rates R_1 and higher utility.

C. Effect of Total Transmission Power on Utility

Next we study how the total transmission power P influence achievable utility in NOMA. Again, all parameters are constant, and utility is simulated for $P \in \{0.1, 0.5, 1, 2, 5\}$.

Increasing P meant a noticeable boost in total network utility, mainly due to strong signal power at the receiver. The gain is nonlinear because of the ncrease in power produced by large utility jumps, with subsequent increments showing diminishing returns. This reflects the trade off between transmit power and spectral efficiency under fixed bandwidths as seen in Figure 3.

D. Effect of Noise Power on Utility

The addition of N_0 affects the utility in NOMA since it appears in the denominator of R_1 and R_2 rate equations. It thus directly degrades achievable results when increased. Utility is calculated across $N_0 \in \{10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2}\}$.

We used brute force pairing to computer the optimal semantic unweighed utility at each noise level. As seen in Figure 3, it decreases as noise power increases. Lower N_0 means both users achieve higher SINR, which means improved data rates. As N_0 grows, well formed pairings result in limited performance too, showing the sensitivity in NOMA systems to noise elevation. As N_0 increases, the gap between brute force and SG-NOMA does too.

E. Pairing and Triplet Observations

Across both pairwise and triplet based simulations, several trends consistently emerge:

As expected, the exhaustive brute force approach achieves the highest total utility in all scenarios. Obviously there's always a chance that algorithms like SG-NOMA, hungarian, and jv can approach or even match it, but none can replicate the consistency. However this comes at the cost of factorial complexity, which

SG-NOMA closely tracks optimal performance. The proposed algorithm consistently achieves near optimal utility. All results follow the same trend as brute force across various path loss exponents, power allocation coefficients, fading parameters, and more. It's effective in approximating optimal solutions, significantly

Rule based algorithms deviate in shape. The likes of D-NOMA, LCG, and JV, while fast and simple to implement, lacks consistency. It fails to follow the trend in brute force results. The fixed pairing logic leads to suboptimal grouping, especially under dynamic channel or power conditions. Their utility trends appear more constant or jagged.

Triplet grouping amplifies sensitivity, where small variations in user position or channel gain lead to greater divergence in total utility across algorithms. The benefits of adaptive algorithms like SG-NOMA becomes amplified as group sizes increase.

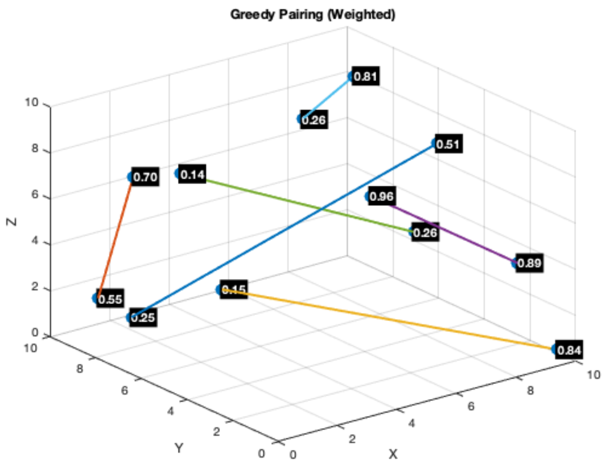

Fig. 4. Semantic Aware Greedy Pairings

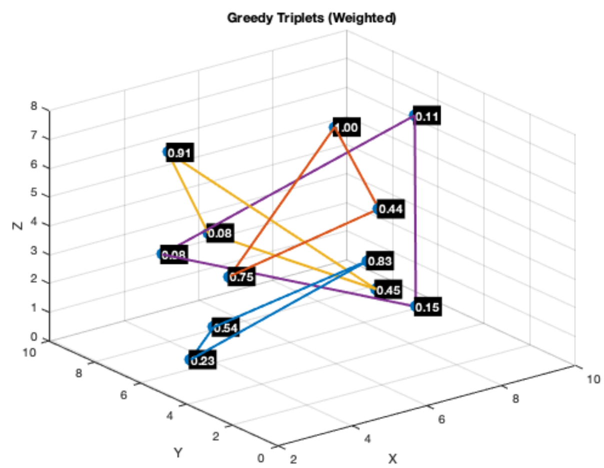

Fig. 5. Semantic Aware Greedy Triplets

The inclusion of semantic weights in utility prioritizes meaningful groupings. Algorithms that adapt to both quality and importance outperform those that rely solely on channel gain.

SG-NOMA scales well across dimensions, even in triplet settings. It maintains a competitive utility, being polynomial in complexity. It makes it a strong candidate for real time and resource constrained NOMA systems.

V. Conclusions and Future Work

This paper studied how incorporating semantic utility into user grouping can improve performance in NOMA systems. Several existing algorithms were evaluated under this semantic model. The results showed that many of these traditional approaches, which are based only on channel characteristics, do not perform well when semantic importance is considered. To address this, we proposed a SG-NOMA algorithm that considers both channel diversity and semantic value. Our simulations show that this approach closely matches brute force utility while being much more efficient to run, making it a practical solution for real-time NOMA grouping.

For future work, we plan to extend our semantic utility model using real-world data. We also aim to evaluate performance in more dynamic scenarios, such as with time-varying channels or when users arrive and leave the system. Another promising direction is to explore antenna activation strategies in pinch-antenna systems [9], where low-cost antennas are selectively activated to improve flexibility and sum rate. Lastly, reinforcement learning could be used to train agents that learn how to group users over time, improving semantic utility without needing exhaustive search [10].

Acknowledgment

This work was supported in part by the 2FURS (Faculty mentored Undergraduate Research) Grant at Santa Clara University.

References

[1] X. Mu and Y. Liu, "Exploiting semantic communication for non-orthogonal multiple access," *IEEE J. Sel. Areas Commun.*, vol. 41, no. 8, pp. 2563–2576, Aug. 2023, doi: 10.1109/JSAC.2023.3288242.

[2] X. Mu, Y. Liu, L. Guo, and N. Al-Dhahir, "Heterogeneous semantic and bit communications: A semi-NOMA scheme," *IEEE Journal on Selected Areas in Communications*, vol. 41, no. 1, pp. 155–169, Jan. 2023, doi: 10.1109/JSAC.2022.3224164.

[3] X. Mu, Y. Liu, L. Guo, J. Lin, and N. Al-Dhahir, "Heterogeneous semantic and bit communications: A semi-NOMA scheme," *IEEE J. Selected Areas in Commun.* vol. 41, no. 8, pp. 155–169, Aug. 2022.

[4] S. Mounchili and S. Hamouda, "New user grouping scheme for better user pairing in NOMA systems," in *Proc. IEEE International Conference on Communications (ICC)*, 2020, pp. 820–825.

[5] M. S. Ali, H. Tabassum, and E. Hossain, "Dynamic User Clustering and Power Allocation for Uplink and Downlink Non-Orthogonal Multiple Access (NOMA) Systems," *IEEE Access*, vol. 4, pp. 6325–6343, 2016, doi: 10.1109/ACCESS.2016.2604821.

[6] G. Chen, W. Zheng, J. Chu, Z. Zhang, and Y. Zhang, "Multi-user Grouping Algorithm in Multi-carrier NOMA System," in *Proc. IEEE 3rd International Conference on Electronics and Communication Engineering (ICECE)*, 2020, pp. 37–41, doi: 10.1109/ICECE51594.2020.9353027.

[7] P. Thakre, S. B. Pokle, R. Patel, N. Shrimankar, and M. Dubey, "Performance of Deep Embedded Clustering and Low-Complexity Greedy Algorithm for Power Allocation in NOMA-Based 5G Communication," in *Proc. IEEE International Conference on Electronics, Communication and Signal Processing (ICECSP)*, 2024, pp. 1–6, doi: 10.1109/ICECSP61809.2024.10698406.

[8] K. Katta, R. C. Mishra, and K. Deka, "Optimal User Pairing Using the Shortest Path Algorithm," in *Proc. IEEE International Conference on Advanced Networks and Telecommunications Systems (ANTS)*, 2021, pp. 1–6, doi: 10.1109/ANTS52808.2021.9937012.

[9] T. Kudo, K. Taki, Y. Sugimoto, and A. Iwase, "Low-Complexity User Grouping and Antenna Activation for Pinching-Antenna Multiple Access Using Dielectric Waveguide," in *Proc. IEEE Global Communications Conference (GLOBECOM)*, 2023, pp. 1736–1741, doi: 10.1109/GLOBECOM53935.2023.10443135.

[10] S. Song, M. Peng, Y. Li, and S. Yan, "Deep Reinforcement Learning Based NOMA for Adaptive User Pairing and Power Allocation in 5G Networks," *IEEE Transactions on Wireless Communications*, vol. 22, no. 1, pp. 511–525, Jan. 2023, doi: 10.1109/TWC.2022.3215703.