CSEN 193 - Report

Semantic Aware NOMA with Q-Learning based User Grouping

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Section 1: Introduction

Imagine standing in a packed Levi's Stadium during the 2026 World Cup, trying to send a message to a friend across town. Thousands of devices competing for the same wireless channel. An invisible algorithm quietly decides whose messages go through first and whose can wait…

Figure 1: Levi’s Stadium during the 2023 CONCACAF Gold Cup

Now imagine that this algorithm not only allocates bandwidth, but also judges which messages are semantically important. Which users “say more with fewer words” and therefore appear more deserving of scarce resources. As a result, many are punished for not being able to communicate as effectively.

Would it still be ethical for algorithms to favor better communicators?

A concerned parent sending a message about a child’s medical symptoms. A frustrated worker communicates unsafe conditions. These are the kinds of ethical dilemmas that are often overlooked in next generation 6G protocols.

Traditional 4G or 5G systems optimize bit level throughput within physical constraints. On the other hand, semantic architectures rank users and messages via some sort of metric of meaning. This is in turn optimized via tools like machine learning, which decides user groupings and power allocation.

These design choices determine **who gets reliable service and who is left behind**. They carry often ignored ethical and social implications that are brushed over in light of technical ones.

Therefore, this state of the field will be both **technical** and explore the **digital humanities** aspect of 6G networks. This includes semantic aware user grouping, power allocation, and reflects how utility, fairness, and risks are modeled and compromised (via game theory).

The essay will first go over the background that led to the current state of the field (section 2), as well as innovations in semantic models (section 3.2). This is coupled with **reinforcement learning** based resource allocations (section 3.3), while drawing on both scholarly work and existing patents.

Technical limitations will then be addressed (section 4.1), along with **ethical issues** (section 4.2), especially those around fairness and perceived risk (via prospect theory). Finally the next steps (section 5), both in my own ongoing research and for the field, towards a more human centered 6G design.

Section 2: Description, History, Background

2.1 - User Grouping Problem

We can't talk about 6G communications without looking at non orthogonal multiple access.

Contrary to popular belief, 3G/4G/5G aren't actually a single protocol. These modern cellular standards are rather collections of many protocols. One of these protocols includes multiple access schemes that determine how users share time frequency resources.

Orthogonal multiple access (OMA) assigns each user non overlapping resources / power in time or frequency (see figure 2 left). This simplifies interference management, but limits the total number of supported users in dense environments.

In order to support more devices, especially in 6G scenarios like smart cities or packed stadiums, researchers began to implement **non orthogonal multiple access (NOMA)** instead.

NOMA occurs where multiple users share the same resource block (see figure 2 right) that transmits at different power levels. A "strong" user with better channel conditions decodes and sort of peels off the signal of a "weak" user via a method called successive interference cancellation (SIC). Afterwards it decodes its own message.

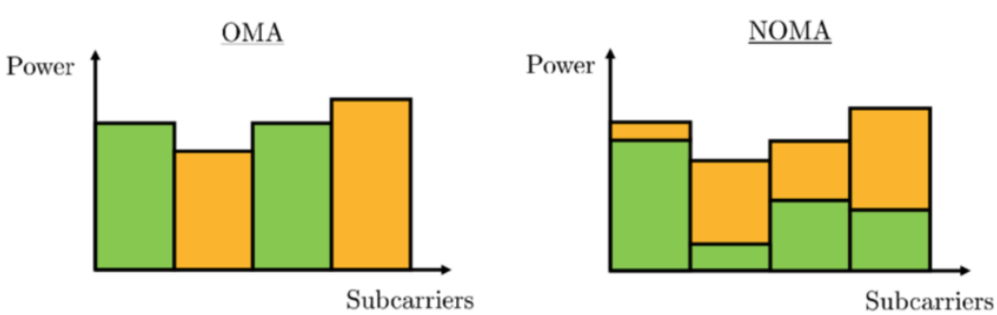


Figure 2: OMA vs NOMA. The two colors represent the transmit power of two different users' signals

Therefore, the central design problem is user grouping and power allocation. How do we decide which users share a resource? How much power should each user get?

This optimization problem quickly becomes unconventional if solved exactly, and thus researchers use heuristics, greedy algorithms, and now learning based approaches.

Classical work on NOMA grouping and power control, like Ali et al's dynamic user clustering and power allocation for 5G NOMA (NOMA was already a proposed protocol dating back to as early as 3G) frames the problem in terms of channel gain, path loss, and achievable rates [7]. Goal is to maximize sum rate or a weighted fairness metric, which is subject to power and other constraints. Examples of these optimized grouping schemes are shown below on figure 3.

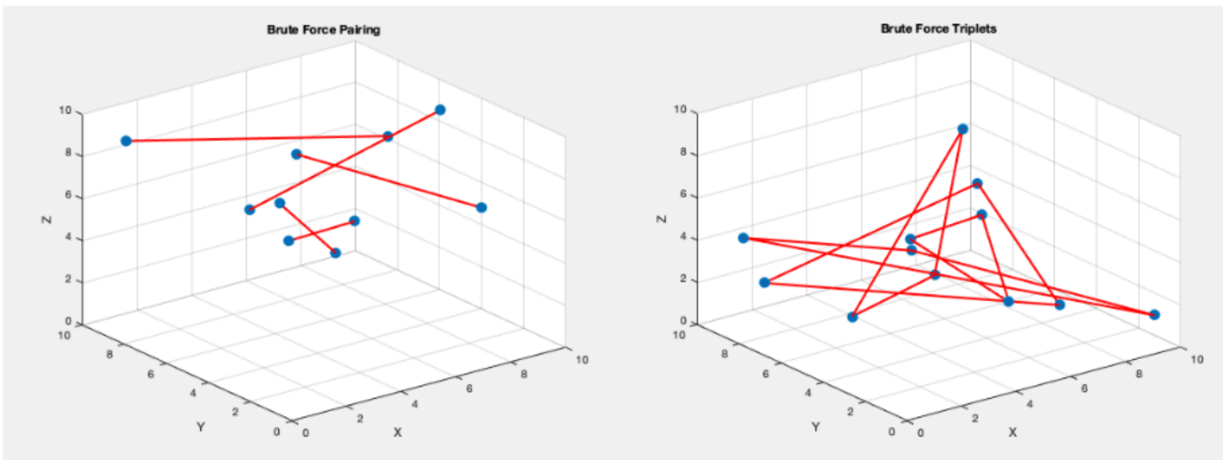


Figure 3: Optimal NOMA Grouping in Pairs & Triplets via a Brute Force Algorithm

2.2 - Semantic NOMA

Now we know the context and motivations behind NOMA, we can move on to its recent advancements.

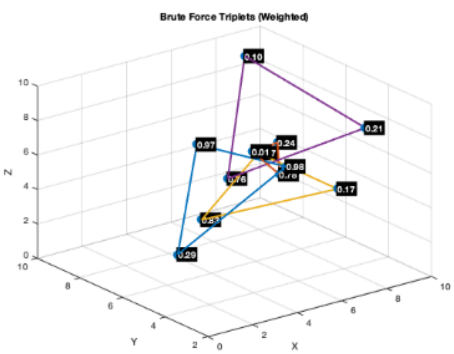
An emerging topic of **semantic communication** now asks a more radical question. What if we optimize meaning delivered per unit resource? These semantic models track how much information a message adds to the receiver's knowledge base. Like traditional NOMA, there are many ways to implement this, including ethical considerations as well.

For example, Mu and Liu propose architectures that explicitly separate semantic and bit level performance [6]. This shows that semantic aware designs can still preserve task performance, even when traditional metrics aren't optimal.

In another related work, Mu and other co authors also introduce semi NOMA schemes where some users are served with semantic methods while others with conventional transmission [6]. This reflects tensions between heterogeneous service types.

More directly correlated to NOMA resource allocation, Duan et al. models semantic NOMA power trading as a Stackelberg game [3]. The weak NOMA leader sets a power price, while the strong follower purchases power with a goal to maximize its semantic utility. This produces equilibrium power allocations, which differs from classic throughput driven solution.

Ma et al. takes this another step further [5]. They measured throughput in semantic units rather than bits, where performance depends on the user's knowledge base. This method adjusts to local context, improving fairness compared to traditional objectives. In figure 4 we can see the similar grouping schemes to figure 3, but with an additional **semantic weight** for each user.




```
 1     2     5
 3     6     8
 4     7    11
 9    10    12

Triplet Weights:
  Triplet 1: [0.29, 0.98, 0.97]
  Triplet 2: [0.01, 0.78, 0.24]
  Triplet 3: [0.17, 0.83, 0.07]
  Triplet 4: [0.76, 0.21, 0.10]
Total Score (Weighted Utility): 8.2600
```

Figure 4: Optimal Semantic NOMA Grouping in Triplets via a Brute Force Algorithm

These works alter the goal of optimization from simple SNR to more realistic utility functions. These functions mix semantic, context, and reliability together. This also begs the questions:

Whose semantics are encoded?
How are differences in language or knowledge treated in these models?

2.3 - Current Patents

At the implementation level, NOMA requires that users who share the same resource block to be distinguishable at the receiver.

Qualcomm's multiple access signatures for NOMA patent (US11089598) expands the pool of available spreading signatures (see figure 5 left), describing how a base station signals then configures such codes [11]. This notes practical challenges around managing these codebooks, overhead, and maintaining consistent performance even with interference.

Another patent assigned to Ericsson, message and rate based user grouping in NOMA (US11012177) groups users based on their message characteristics and required data rates instead of just channel conditions alone [12]. This shows that semantic application level information is already being considered at the patent level. They show that design decisions where users share resources and on what basis aren’t just based on academia, but worked into actual algorithms that will shape future wireless systems when scaled up (see figure 5 right).

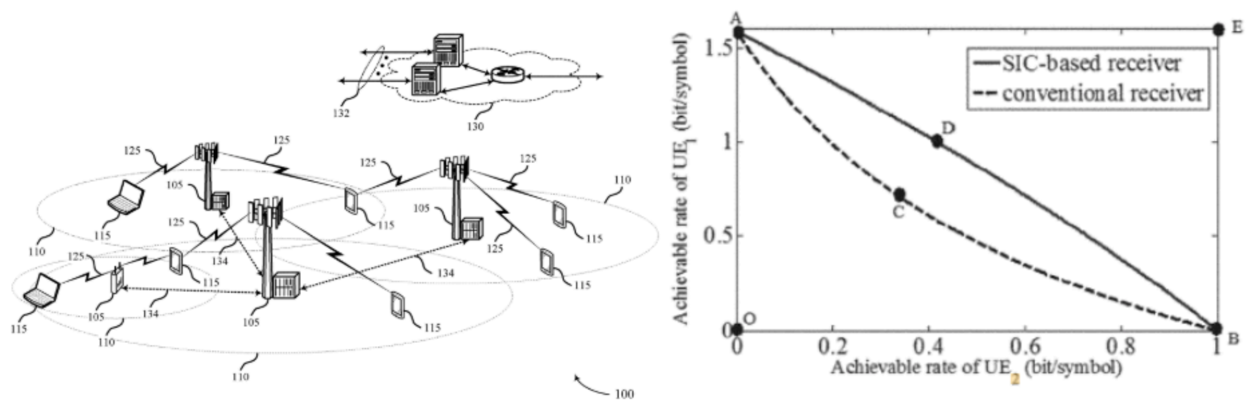


Figure 5: Illustrations of NOMA patents US11089598 & US11012177 [11][12]

Section 3: Current Innovations, Research

3.1 - Baseline NOMA Grouping

Building on previous work, my own research on semantic utility aware user grouping benchmarks several common NOMA grouping schemes. These include distance based heuristics, graph based models, and classic algorithms like Hungarian or Jonker Volgenant assignments. Simulations are adapted to pair or triplet users via channel conditions and proximity.

My study confirms that optimal **brute force grouping** yields **highest utilities but scales poorly**. On the other hand, low complexity heuristics are **fast but suboptimal**.

Referring back to Ali et al. once again, their dynamic user clustering shows how grouping interacts with power allocation [7]. Users are clustered based on channel gain, then power is in turn allocated within each cluster, balancing capacity and fairness.

Later works like Chen’s multi user grouping extends this to a greater scale and more sophisticated resources. Overall, these algorithms provide strong baselines. However, they still operate within physical metrics, meaning that all bits are equally valuable.

3.2 - Semantic Utility Aware Grouping

A simple semantic weighting model on top of these grouping schemes can then be introduced. For example, each user can be assigned a semantic weight between 0 and 1, which represents how important their traffic is in the system's perspective. The overall NOMA utility is therefore a function of both throughput and these semantic weights. Grouping decisions thus **trade off spectral efficiency with semantic priority**.

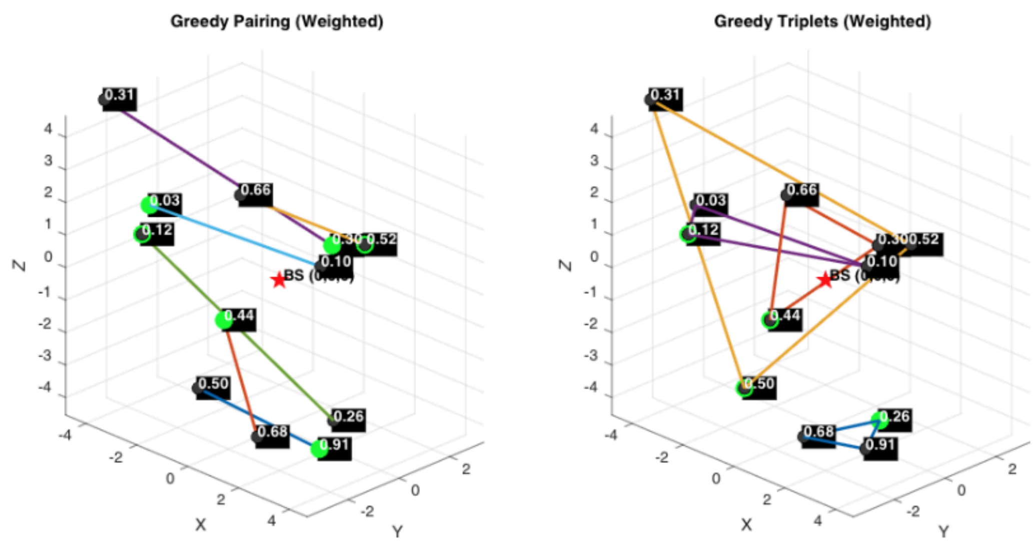


Figure 6: Semantic NOMA Grouping in Triplets via a Greedy Algorithm

My core contribution to this is a **semantic greedy NOMA (SG NOMA) algorithm** which builds user groups by considering both distance based interference structures and semantic weights (see figure 6 above). My 3D simulations, as seen below in figure 7, show that **SG NOMA (in red)** achieves utility close to **brute force level optimization (in blue)** while running in quadratic time, making it more practical for dense deployments.

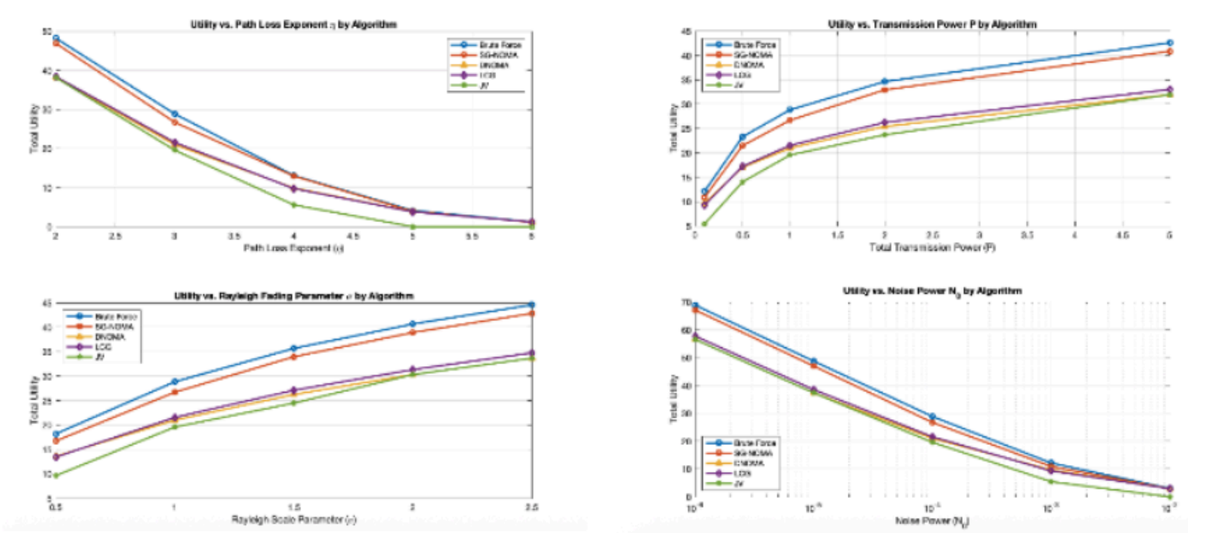


Figure 7: Semantic Greedy NOMA algorithm results are near optimal

Unfortunately, as seen in figure 7, peer feedback on this work noted that the semantic model itself (single random weight per user) was way too simplified, and that the algorithmic novelty could be strengthened by integrating **learning based methods** (more on that in section 3.3).

> 1. Lack of technical contribution: The proposed utility function, U_sem = sum of w_i R_i, is mathematically equivalent to the classic 'weighted sum-rate maximization' problem, which is well-studied in wireless communications. The primary novelty here is the re-framing of the weights.

Figure 7: Excerpt from IEEE CCNC 2026 Submission Feedback

Other recent work extends semantic power allocation as well. Once again, Duan's Stackelberg formulation reflects how introducing economic incentives where users bid for power according to their semantic valuations (see figure 8), can improve total semantic utility compared to basic allocations [3]. In fact, a part of my simulation metrics were drawn from this. Ma shows that this allows systems to prioritize meaning preserving transmissions, adjusting strategies based on differences in user knowledge bases [5].

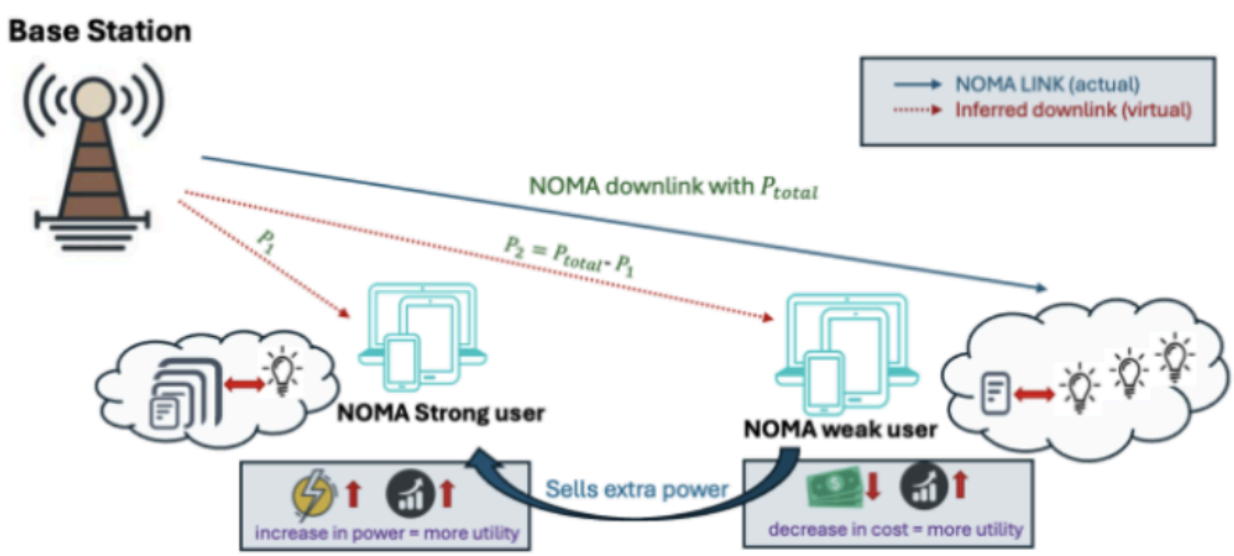


Figure 8: Illustration of Duan's Game Theoretic & Stackelberg formulation [3]

Pereira and Lima's work in rate splitting multiple access (RSMA) provides an important parallel development [8]. Rather than being strictly orthogonal or purely NOMA, it splits each user's message into common and private streams, using low complexity user matching and power allocation to manage interference and fairness.

Many of the original contributors of NOMA actually created RSMA due to NOMA unsuccessfully being pushed as a protocol when 5G rolled out. This shows a sort of tension, but also that flexible sharing and splitting of streams may be effective for future semantic aware schemes as well.

3.3 - Reinforcement Learning

In order to address limitations with heuristic and game theoretic methods, the next progression seems to be through **reinforcement learning (RL)** for resource allocation.

Aermsa-Ard eta al. formulates NOMA power allocation as a **Q learning** problem [4]. In their simulations, the base station acts as the agent, power coefficients as actions, and rewards are tied to minimum signal to noise ratio which encourages fair user rates.

Their results show that Q learning achieves more balanced rates, but also highlight a major limitation. Q table grows rapidly with the size of the state action space, and thus suggests the need for more compact representations or function approximations.

Deep reinforcement learning (DRL) offers one approach. Song et al. combines adaptive user pairing and power allocation in a DRL framework [9]. They let a neural network approximate the value function, which enables the system to adapt to changing channel conditions & user distributions. However, this introduces additional challenges with training stability and interpretability.

Recall in the section where I mentioned feedback I received on my previous work. It argued that my algorithm lacks novelty. Also recall how Q tables grow rapidly in previous methods. These two insights inspired me to build on top of my existing work.

In my latest work, I extend my SG NOMA algorithm to include Q learning for grouping. This is done over thousands of episodes, where the state encodes which users have already been assigned and features of a partially formed group. The action then selects the next user to join a group, rewarding the utility of the completed grouping (see figure 9 flow chart below).

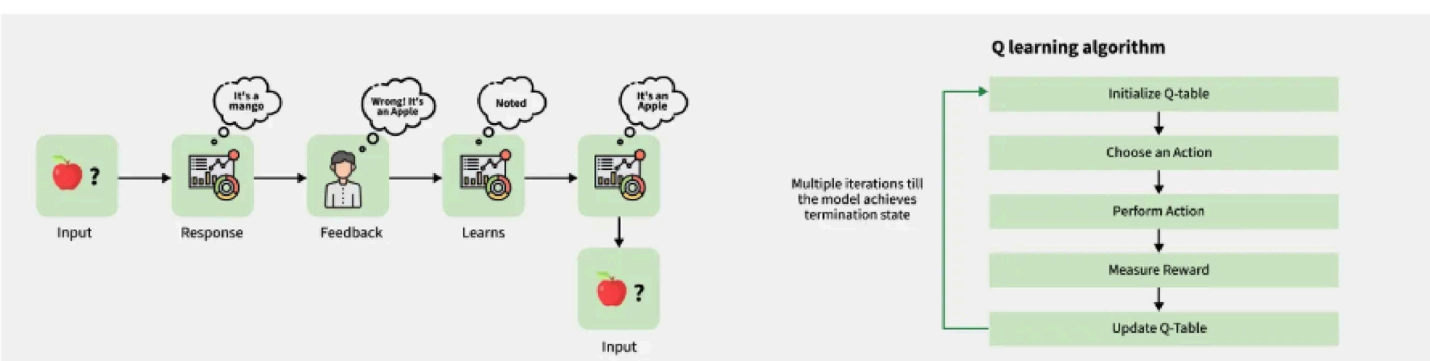
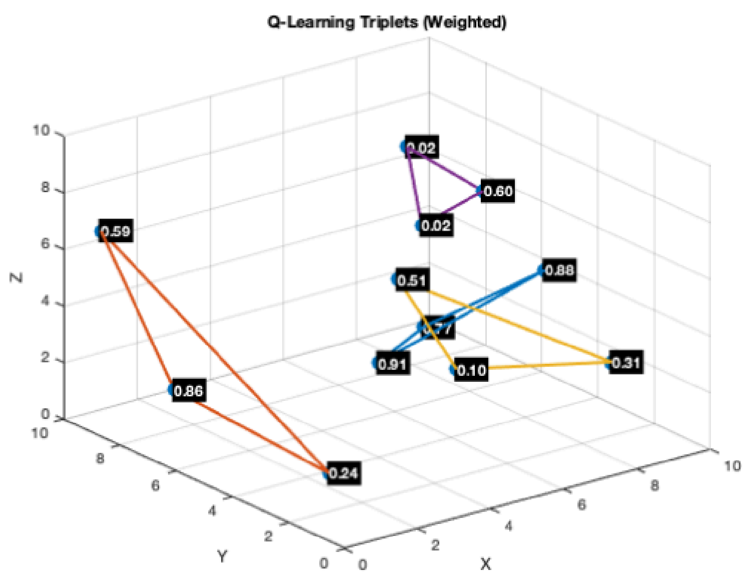


Figure 9: Flow Chart of the Q learning Algorithm

To deal with rapidly growing Q tables, I implemented key value pairs instead, which compresses the presentation of states rather than laying out a table with many unused states as criticized in Aermsa-Ard's future work section [4].

Simulations reveal that this RL based grouping achieves even better (and sometimes optimal) hybrid utility, while requiring **significantly less computation time than brute force**, even as the number of users grows. Results suggest that learning based grouping captures complex trade offs like channel conditions, semantics, and fairness, all without manually tuning heuristic rules that we started off with (figure 10 shows that Q Learning returns highest average utility scores).




```
Greedy Grouping (O(n^3)):
     1     3     4
     2     8    10
     5     6    11
     7     9    12

Triplet Weights:
  Triplet 1: [0.24, 0.91, 0.86]
  Triplet 2: [0.10, 0.77, 0.88]
  Triplet 3: [0.51, 0.31, 0.60]
  Triplet 4: [0.02, 0.59, 0.02]
Total Score (Weighted Utility): 8.3116

QLearning Grouping (O(E·n^2)):
     3     8    10
     9     1     4
     2     5     6
     7    11    12

Triplet Weights:
  Triplet 1: [0.91, 0.77, 0.88]
  Triplet 2: [0.59, 0.24, 0.86]
  Triplet 3: [0.10, 0.51, 0.31]
  Triplet 4: [0.02, 0.60, 0.02]
Total Score (Weighted Utility): 9.6318
```

Figure 10: Semantic NOMA Grouping in Triplets via the Q Learning Algorithm

Section 4: Issues

4.1 - Complexity, Generalization, Deployment

Even with smart algorithm design, NOMA user grouping and semantic aware variants still add further dimensions into the state space. Brute force search is unrealistic beyond small user counts. While efficient, greedy approaches miss high utility configuration, especially in dense settings like a packed stadium where interference patterns are complex. Lastly, RL dismisses some of this, but at the cost of training time and convergence.

Once again, Aresma-Ard's Q learning work explicitly states how the Q table grows with the number of users and actions, identifying table size as a key scalability challenge. My own key value design partially addresses this, but as networks scale to thousands or even millions of devices, even compressed RL models will eventually have to deal with this. Therefore, generalization to real world 6G environments remains open.

In terms of implementation, patents like Qualcomm also highlight that practical systems need to manage finite codebooks and overhead, as well as hardware limitations on SIC performance (that many ignore in pursuit of “optimal” simulations) [11]. Semantic aware grouping needs to respect these constraints, which reduces feasible allocation when compared to theoretic formulations.

Semantic models themselves are still questioned. Ma’s semantic throughput, Duan’s utility functions, and my own hybrid rate modelling all have specific forms based on **assumptions and analytic convenience / biases** [3]. This makes it hard to compare theories across research, raising questions on how robust these conclusions are to changes in the semantic model.

4.2 - Ethical and Social Issues

As promised, these technical limitations are also mixed in with ethical concerns regarding fairness, value, and risk. In my digital humanities initiative (DHI) grant proposal at SCU, I argued that NOMA effectively encodes a theory of whose communication matters by ranking messages and users based on their semantic utility.

Recall the Levi’s stadium example in the beginning of this essay. Those who can compress their intent into dense and more polished messages (native speakers) may be assigned higher semantic scores than others. This could systematically punish users even when their underlying needs are more urgent.

Game theoretic approaches like Duan’s Stackelberg model highlights yet another concern [3]. If access to power is moderated by price, users with **higher ability or willingness to pay** will receive better semantic service. This recreates economic inequalities in the design of wireless systems.

RL introduces its own risks as well. Let’s say the reward function is defined as an aggregate semantic utility. The agent then would learn to sacrifice consistently low utility users in favor of frequently high utility ones.

To combat this I thought about using **prospect theory** [10]. Though not conventionally used in NOMA, I think it provides a useful framework for our case. People are more sensitive to losses than equivalent gains (see figure 11), systematically overweighing certain probabilities. This is even with low probability or high impact events.

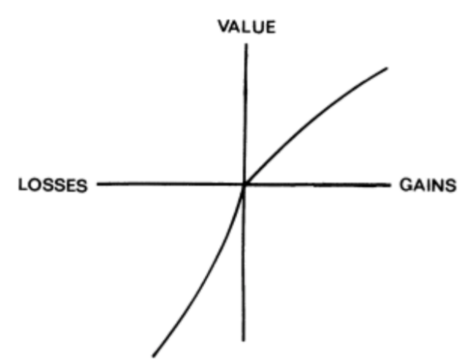


Figure 11: Gains and Losses vs Perceived Value [10]

Again in my DHI proposal, I argue that designing these algorithms solely around classic expected utility risks creating systems that appear optimal in **face value** but then means that some users are in a **persistent state of perceived loss** (ex. delaying messages even in high stakes contexts).

Prospect theory would suggest that we need to pay attention to both average throughput but how users experience delays relative to their expectations and context [10].

I really liked this example because it connects directly to questions of social justice.

Whose reference points and risk attitudes are encoded in the utility function? Who gets to decide? Further, **what sort of ethical lens can we look at this through (see figure 12)?** We talk a lot about utility in a technical NOMA sense, but utility in an ethical sense applies very well here. Do we learn more towards utilitarianism? Or virtue? Perhaps even with prima facie duties?

Without **intentional humanistic critique**, these aspects of NOMA will be overlooked. Designs will silently privilege users without anyone knowing.

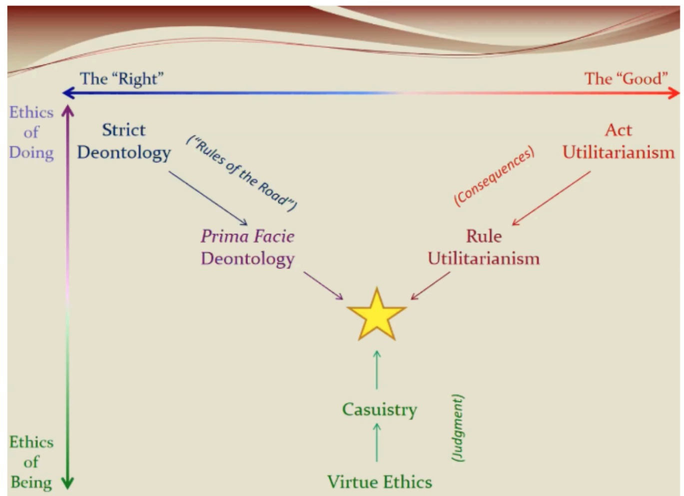


Figure 12: Ethical Roadmap Drawn from ENGR 19 Slides

4.3 - Gaps in Current Research

In my opinion, existing research does a really good job at pushing these methods, but there are still some noticeable gaps. Most works:

- Assume a fixed, designer chosen semantic utility model rather than exploring a range of value theories (which is what I tried to do in my research).
- They also focus on fairness metrics via utility, rather than human perceptions of fairness, risk, and loss.
- Lastly they rarely engage with ethical frameworks, even when these algorithms obviously encode normative choices when you really look into them.

Bridging these gaps requires not just technical innovations but new ways of evaluation. Connecting technical performance with actual human experience and ethical principles.

Section 5: Next Steps

In my ongoing research, I think there are three different directions I can take in order to extend my research in NOMA: Refining the utility model, integrating prospect theoretic risks, or embedding results in narrative case studies for engineering ethics (as part of my DHI proposal).

5.1 - Technical

Redefining hybrid utility: Building on the hybrid rate modeling in my latest paper, I look to refine the semantic component to depend on density, tolerance, and knowledge bases (following ideas from Mu and Ma) [5][6].

Instead of a single random weight in 0,1 each user will hold a small vector of semantic attributes like urgency, status, or complexity. Grouping and power allocation algorithms will then consider these attributes instead of ignoring them completely.

Scaling RL grouping: I also plan to extend the Q learning framework with more compact state representation to better handle dense, world cup like, environments with millions of devices. By simulating extremely dense scenarios like global events streamed to billions, SG NOMA and Q learning can then be used as baselines, then comparing them to the likes of DRL based methods as proposed by Song et al [9].

Benchmarking against RSMA & patents: Implementing algorithms (as seen on figure 13) described by Pereira and Lima can show how our novel methods fare in similar scenarios [8]. Also to approximate grouping logic suggested by patents like Qualcomm and Ericsson, revealing how close academic algorithms have come to actual designs [11][12].

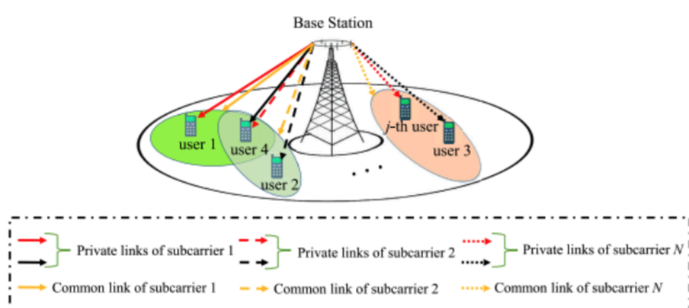


Figure 13: High Level Illustration of an Implemented NOMA Environment

5.2 - Prospect Theory

Another direction I'm looking to take would be to embed prospect theory directly into the utility function used by RL. Rather than maximizing standard utilities, it would optimize a prospect theory like value [10].

This allows simulations to explore how various risk attitudes (risk averse v risk neutral) change which users are prioritized under load. The goal is therefore not to just match human biases, but to make trade offs between efficiency and fairness that current models tend to hide.

RL is also a natural place to use these ideas. Reward function can be modified to penalize repeated or severe losses for vulnerable users, constraints enforce limits on the worst case utility. Over time the agent learns policies that respect both technical and ethical aspects of NOMA.

5.3 - Case Studies and Ethics in SCU

Lastly I feel this technical work could feed into case studies for courses like ENGR 19 at SCU.

I was taking ENGR 19 over fall quarter. Every week we would examine several cases with the ethical concepts we've learnt over the course. However, I noticed the lack of cases related to pure computer science principles.

Figure 14: Most ENGR courses are held in the SCDI Building at SCU

These cases can show how different, **unsuspecting algorithms** allocate resources, and what this means for their experience of risk and dignity. Cases can be analyzed with ethical frameworks learned in class, such as **casuistry, prima facie, virtue** (as mentioned earlier), and more. This connects abstract design choices into actual dilemmas. They aim to make ethics not only a topic in wireless engineering, but in other fields as well.

Section 6: Conclusion

Semantic aware NOMA grouping and power allocation represents a shift in wireless system design. Rather than treating all bits as equal, researchers encode models of meaning and significance into these very algorithms. Efforts on semantic utility, game theory, and RL shows that technical improvements are possible beyond physical constraints.

Conversely, the shift raises issues with fairness and risk. Models privilege certain users, which hide biases that many overlook. Prospect theory and digital humanities perspectives give us tools to address these issues [10]. Future 6G algorithms therefore should be judged not just technically but via the very human experiences they produce.

Figure 15: 6G Networks will Influence many beyond the technical level

Ultimately, my own research aims to contribute to broader considerations of NOMA. Instead of who gets the signal, it's about whose meaning, safety, and voice our wireless infrastructures are made to protect.

6G systems and beyond will only succeed if they integrate technical progress with **human centered design**.

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