Evaluation of User Allocation Techniques in Massive MIMO 5G Networks

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***Abstract*—Massive MIMO (Multiple Input Multiple Output) is a fundamental technique for improving the efficiency of 5G wireless networks. At the base station, it calls for the use of numerous antennas—usually in the dozens or even hundreds. In addition to better coverage and less interference, this enables a large increase in the amount of data that can be delivered and received simultaneously. By enabling more precise signal transmission and reception, Massive MIMO can also result in significant energy savings. The use of optimization techniques can further improve the performance of 5G networks. The aim of this paper is to investigate a signal quality optimization technique for MIMO in which users are allocated to antennas according to different algorithms. For our research, the DeepMIMO simulator produced a dataset that sets up all necessary parameters. In our study, we examine different techniques for user allocation in 5G MIMO Networks. We conclude that transforming the problem of user allocation to a linear assignment problem in order to find the most efficient connection between the users and the base stations is one of the best ways to optimize user allocation.**

Keywords—Resource management, allocation and scheduling, smart antennas: MIMO, massive MIMO, beamforming

I. INTRODUCTION

Massive MIMO (MM) is one of the core technologies of the fifth generation of cellular technology (5G) networks [1],[2],[3],[4]. MM is the extension of traditional MIMO technology to antenna arrays having large number of controllable transmitters. The 3rd Generation Partnership Project (3GPP) defines MM as more than eight transmitters and eight receivers [5]. A multitude of antennas are used at the base station MM, a potential wireless technology, to simultaneously serve many customers. An essential technology for 5G networks, the utilization of several antennas enables a significant improvement in capacity and coverage.

MM offers a significant boost in system capacity, allowing for the simultaneous service of more consumers, which is one of its main benefits. Additionally, it increases coverage, allowing the signal to go further and navigate barriers more successfully. Because less power is required to transmit the same quantity of data with MM, the system's energy efficiency can be increased. Research on 5G MM environments has been a highly active area of investigation in recent years. A significant body of literature has been devoted to understanding the performance of MIMO systems, the effects of antenna configurations, and the impact of different environments on signal propagation [6].

One area of research in 5G MM environments focuses on the optimization of resource allocation, which includes techniques for assigning users to base stations, selecting appropriate transmission modes, and allocating power and bandwidth. The fast growth of mobile data and the extensive use of smartphones have created previously unimaginable challenges for wireless service providers as they aim to overcome a global bandwidth crisis [7], [8]. Optimizing resource management and allocation is considered to be a critical factor in improving the efficiency of 5G radio access networks and minimizing transmission latency, as emphasized by several research studies [9].

Researchers have examined various performance metrics like data rates, throughput, and Signal-to-Noise Ratio (SNR) to evaluate antenna configurations and modulation schemes. Simulations have assessed the impact of different propagation environments on system performance. Studies indicate that using the Hungarian algorithm for user allocation in MM 5G networks can enhance total user throughput compared to simple sorting algorithms [10]. We employ a linear assignment problem algorithm to optimize our MM system, efficiently assigning users to base stations.

The main goal of this work is to demonstrate how applying the Hungarian algorithm can optimize user allocation in a 5G Massive MIMO (MM) system. The aim is to minimize interference, enhance signal quality, and improve user throughput. The motivation behind this research is to explore the Hungarian algorithm's potential in efficiently assigning users to antennas in MM 5G networks. As 5G technology advances, the need for higher data rates and increased network capacity is crucial. MM, which utilizes numerous antennas at base stations, offers promise in meeting these demands. However, efficiently assigning users to antennas in such a complex system presents challenges. This study aims to evaluate the effectiveness of the Hungarian algorithm and the Minimum Cost Flow algorithm [11] in enhancing the performance and efficiency of MM 5G networks, contributing to wireless communication system advancements.

Our differs from the previous ones in the field due to our novel algorithms for allocating users to base stations based on their SNR values. These up-to-date algorithms offer improved results in real-life scenarios. Our efficient algorithm considers user's SNR to select the optimal base station. Additionally, we incorporate the Hungarian algorithm that adapts to changing conditions and makes real-time decisions about user allocation. This approach ensures accurate simulation of real-life scenarios and superior results compared to prior studies. We will also evaluate results using the Minimum Cost Flow algorithm. Our algorithms can boost existing network performance, promising more efficient and reliable future communication.

Our study presents new algorithms for user allocation to base stations based on SNR values. We compare these algorithms to gain insights into optimal user allocation, considering time complexity in high-density Massive MIMO scenarios. We evaluate the potential advantages of using the Hungarian and Minimum Cost Flow techniques. We conducted our research using the DeepMIMO simulation environment [12], obtaining a suitable dataset with the required parameters. Our proposed algorithm optimizes this dataset, ensuring minimized path loss and maximized throughput for each user.

The rest of this paper consists of the following sections. In Section II, we examine the proposed sorting algorithms which are a version of quick sort, the Hungarian algorithm and the Minimum Cost Flow algorithm. In Section III we analyze our DeepMIMO simulation environment, its features and parameters. In Section IV we present the comparative evaluation between the proposed algorithms in terms of user allocation, throughput and pathloss. Finally, in section V we present our conclusion and future work.

II. Proposed Algorithms

This section presents the algorithms that we are going to compare using one or more active base stations in terms of user allocation. The first algorithm is a sorting algorithm developed for a single base station. The second algorithm is a reordering algorithm specifically designed for scenarios with multiple active base stations. The third algorithm is the Hungarian algorithm, a combinatorial optimization algorithm for solving assignment problems. The fourth algorithm is the Minimum Cost Flow which aims to minimize the overall cost of allocating resources while satisfying capacity constraints and user demands, making it a valuable tool for efficient resource allocation in complex network scenarios.

A. Algorithm 1 - With One Base Station Active

In our first algorithm, we focus on user assignment to a single base station. The goal is to allocate users to the base station based on their pathloss values, ensuring better distribution and optimizing network performance. To achieve this, we utilize a sorting algorithm that organizes the users' pathloss values in ascending order. By doing so, we can identify the users with the lowest pathloss, indicating stronger signal quality. These users are prioritized for assignment to the base station.

Pseudocode for storing the pathloss for each user to an array of structs – Algorithm 1

```
counter = 0
for bs = 1 to numBS:
  pathloss_bs = sorted_pathloss_bs_ue([sorted_pathloss_bs_ue.basestation]== bs)
  usernumber =[pathloss_bs.usernumber]
  basestation = pathloss_bs.basestation]
  pathloss = [pathloss_bs.pathloss]
  for i = 1 to min(num_tx_antennas, length(usernumber)):
    counter    = counter + 1
    basestation, and pathloss using the current user's values
    success_pathloss(counter) =  struct('usernumber', usernumber(i),
    'basestation', basestation(i), 'pathloss', pathloss(i))
    counter = 0
for bs = 1 to numBS:
  pathloss_bs = pathloss_bs_ue([pathloss_bs_ue.basestation] == bs) usernumber
  = [pathloss_bs.usernumber]
  basestation = [pathloss_bs.basestation]
  pathloss = [pathloss_bs.pathloss]
  [~, index] = sort(pathloss, 'ascend')
  sorted_usernumber = usernumber(index)
  sorted_basestation = basestation(index)
  sorted_pathloss = pathloss(index)
  for i = 1 to length(sorted_usernumber):
      counter = counter + 1
      sorted_pathloss_bs_ue(counter) = struct('usernumber',
      sorted_usernumber(i), 'basestation', sorted_basestation(i), 'pathloss',
      sorted_pathloss(i))
```

To assign users to a single base station, the algorithm involves creating an array for user data (user number, base station, pathloss), grouping users by base station, sorting by ascending pathloss, adjusting info using the sorted pathloss index, and creating a new array for optimal user mapping based on path loss. This promotes fair user distribution, optimizing 5G network performance with signal quality in mind.

B. Algorithm 2 - With Many Base Stations Active

Furthermore, to expand our research, we will examine how will users be allocated when multiple base stations are active. The algorithm must traverse through an array which will store for each user the SNR value if he eventually connects to one of the multiple active base stations.

To select the best SNR value for each user and sort SNR values for individual base stations, the algorithm creates a struct array called single_users. It iterates through the sorted_pathloss_bs_ue array for each user, checking if a user with the same ID exists in single_users. If not, it adds the current user to the end of the array. When it finds a matching user, it compares their SNR with the highest SNR among matching structures in single_users. If the current user has a higher SNR, it updates the corresponding structure in single_users with the current user's information.

Next, it iterates through each base station in the array and sort each user's information based on the SNR value of that specific base station. It creates a new structure called single_sorted_pathloss_bs_ue to store each user's sorted pathloss value along with user number, base station number, distance between base station and user, and SNR value. It uses a counter variable to track the number of elements in the single_sorted_pathloss_bs_ue structure.

Pseudocode for identifying if a user already exists - Algorithm 2

```
single_users = create_empty_struct_array()
single_users[1] = sorted_pathloss_bs_ue[1]
for ii = 1 to length(sorted_pathloss_bs_ue):
  user = sorted_pathloss_bs_ue[ii]
  idx = find_matching_user(single_users, user.usernumber)
  if  is_empty(idx):
   append_user(single_users, user)
  else:
    if user.SNR > get_max_SNR(single_users, idx):
       max_idx = get_max_SNR_index(single_users, idx)
       update_user(single_users, idx[max_idx], user)
return single_users
for bs = 1 to numBS:
  pathloss_bs =
```

```
 filter_single_sorted_pathloss_bs_ue(single_sorted_pathloss_bs_ue, bs)
 if length(pathloss_bs) > capacity:
   for i = 1 to capacity:
     append_to_success_pathloss(success_pathloss,
     pathloss_bs[i])
   for i = (capacity+1) to length(pathloss_bs):
     append_to_bs_overflow(bs_overflow, pathloss_bs[i])
   ovf = length(bs_overflow)
 else:
   for i = 1 to length(pathloss_bs):
   append_to_success_pathloss(success_pathloss, pathloss_bs[i])
 for user = 1 to length(bs1_overflow):
   user_num = bs1_overflow[user].usernumber
   user_pathloss = filter_sorted_pathloss_bs_ue(sorted_pathloss_bs_ue,
   user_num)
   [~, idx] = sort_pathloss_by_SNR_descending(user_pathloss)
for z = 1 to length(idx):
 number_bs = 0
 for z1 = 1 to length(success_pathloss):
   if success_pathloss[z1].basestation == idx[z]:
     number_bs = number_bs + 1
 if number_bs < capacity:
   append_to_success_pathloss(success_pathloss,
   user_pathloss([user_pathloss.basestation] == idx[z]))
   break
```

Each base station has a maximum user capacity. The algorithm we'll use checks each base station to see if the received pathloss values exceed their capacity threshold. Users not exceeding this threshold are added to the success_pathloss structure, while the rest go to bs_overflow. If the received pathloss values are within the capacity, all go to success_pathloss. In cases where users exceed a base station's capacity, the code sorts SNR values in sorted_pathloss_bs_ue in descending order. It then adds the highest SNR pathloss value to success_pathloss while ensuring the base station's capacity isn't exceeded.

C. *Linear Assignment Problem Algorithm*

The third and fourth algorithms address linear assignment problems, aiming to minimize the overall cost of allocating rows to columns. We transform the resource allocation issue into a linear assignment problem. Utilizing the Hungarian algorithm with MATLAB's matchpairs function, we identify the most suitable base station for user connections. The Cost matrix, sized N by M (N users and M active base stations multiplied by their capacity), is crucial. Additionally, the CostUnmatched parameter of the matchpairs function specifies costs for unallocated rows and columns, enhancing problem resolution [13].

D. *Minimum Cost Flow Algorithm*

To further optimize the user allocation process, this paper explores the application of the Minimum Cost Flow algorithm. The minimum cost flow algorithm is a well-established optimization technique that aims to determine the optimal flow of resources through a network while minimizing the total cost associated with the flow. In the context of this study, the Minimum Cost Flow algorithm can be utilized to allocate users to base stations based on factors such as signal quality, user demand, and network conditions. By incorporating the Minimum Cost Flow algorithm into the optimization framework, it is expected to enhance the efficiency and accuracy of user allocation in the 5G MM scenario.

III. SIMULATION ENVIRONMENT

The DeepMIMO dataset generation framework has two important features. A Ray-tracing scenario and the parameters for this scenario.

A. *DeepMIMO Features*

First, the DeepMIMO channels are constructed based on accurate ray-tracing data obtained from Remcom Wireless InSite [14]. The DeepMIMO channels, therefore, capture the dependence on the environment geometry/materials and transmitter/receiver locations, which is essential for several machine learning applications [15]. To be more specific, A Ray-tracing Scenario which is generated by using the Accurate 3D Ray-tracing Simulator Wireless InSite by Remcon is used for generating the dataset. In our example this scenario is the O1 scenario which is available in the DeepMIMO website. The software we used for the simulations was MATLAB where we generated a channel model which included the path loss of our users, and a traffic model to simulate user behavior.

B. *Scenario*

In order to test our algorithms and to accurately simulate a real-world scenario, various parameters need to be taken into account. These parameters include the base stations and their capacity, the transmission power, the noise power, the number of transmission (TX) antennas on the base station, the user and antenna gain, and the available bandwidth which will be divided by the User number and "handed" to the users so that everyone can have the same resource blocks. This happens because in our scenario, all users require the same resources.

The DeepMIMO dataset can be completely defined by (i) the adopted ray-tracing scenario and (ii) the set of parameters, which enables the accurate definition and reproduction of the dataset. The scenario we will use in this paper is the O1 (Outdoor 1) Scenario from DeepMIMO with the operating frequency to be 60 GHz. This scenario consists of 18 base stations and 3 user grids with 1,184,923 maximum users that are scattered through the site map (181 users per row) to provide an accurate representation of a real scenario. Fig. 1 depicts the site map of the scenario which will be used to create the dataset needed for our algorithm testing.

Fig. 1. DeepMIMO O1 scenario outdoors.

Using these parameters and modifying them as we show in Table 1, we calculate the SNR of each user, the average per user throughput and the total throughput in order to show how the per user throughput can be affected by the numbers of users that are connected in the base station. The environment consists of a small map with 18 base stations that is divided into 3 grids. Each grid is divided into rows and each row has 181 users. Below we describe the modification of our parameters for our simulation.

TABLE I.

Simulation Parameters	*Value*
Network Bandwidth	20 Mhz
Subcarrier Spacing	60 Khz
NR blocks	24
Active Subcarriers	64
User Gain	0
User Antenna	1
Antenna Gain	21 dBi
Tx Antennas	1000
Transmission Power	45 dBm

Fig. 2. Simulation Parameters

To ensure reliable communication and emulate a real life scenario, we have set the user gain to 0 which implies that the base station's presence does not enhance the user experience or extend the coverage area significantly. The antenna gain to 21 dBi so the antenna can focus or concentrate its radiation pattern in a specific direction more effectively. The noise power is given from the formula $-174 + 10 * log10(bandwidth)$. The base station deploys 1000 Tx antennas with a 45dBm transmission power to extend coverage and serve more users. Each base station is assigned a fixed capacity of 1000 users, reflecting real-world scenarios where a single base station serves diverse users with varying signal strengths and communication needs. These parameters ensure a precise evaluation of our proposed algorithms' performance.

In our simulations, we concentrate on User Grid 1 and evaluate the proposed methodology using a testbed comprising base stations. Each base station, except for the first algorithm, has a capacity of 1000 users; the first algorithm utilizes one base station with a 3000-user capacity (capable of accommodating up to 2534 users). This testbed mirrors a realistic scenario often encountered in 5G MM deployments. The user dataset varies in size, encompassing 181, 362, 905, 1267, 2353, and 2534 users, reflecting diverse load conditions. We assess user allocation algorithms, including sorting and Hungarian algorithms, based on metrics such as time, complexity, fairness, and overall system capacity utilization. Our testbed and parameter choices ensure the relevance and validity of the obtained simulation results.

To investigate the capacity limits of the system and observe any performance degradation due to congestion or interference, a testbed would need to be set up with a base station capable of supporting a large number of users and providing adequate coverage for the desired area. Additionally, a realistic number of user devices would need to be included in the testbed. The testbed would also need to include equipment such as base stations. A description of our testbed would need us to specify our hardware, which will be a single macrocell base station with 1000 Tx antennas and a transmission power of 45dBm. User devices with a gain of 0dB and capable of connecting to the base station over a 20MHz bandwidth. Our simulation environment is based on MATLAB that provides a comprehensive model of 5G network which includes a channel model which includes the path loss of our users, a traffic model to simulate user behavior. We also have to specify our Test Scenarios:

- A baseline scenario with a single user connecting to the base station to establish a reference performance level.
- Scenarios with 181, 362, 905, 1267, 2353 and 2534 users connecting to the base station to observe the effect of increased user load on total and per-user throughput to investigate the capacity limits of the system and observe any performance degradation due to congestion or interference.

And the Evaluation Metrics:

- Throughput (data rate) per user which measures the amount of information that can be transmitted over a given bandwidth and SNR.
- Algorithm time complexity.
- User allocation.

The MatchPairs function in MATLAB is employed in this study to optimize the user allocation process in a 5G MM scenario. By leveraging advanced matching strategies and heuristic techniques, MatchPairs aims to efficiently assign users to base stations based on various criteria. The function is designed to handle large-scale user allocation tasks and delivers near-identical results compared to traditional algorithms while exhibiting improved time complexity. The MatchPairs function plays a crucial role in achieving accurate and efficient user allocation in the context of this study.

IV. Algorithms Evaluation

In this section, we assess different user allocation algorithms in MM 5G networks as discussed in Section II. Firstly, we evaluate Algorithm 1, emphasizing single base station user assignments. We present simulation results illustrating the effects of growing user connections on throughput, SNR, and network performance. Additionally, we validate the advantages of leveraging multiple base stations to enhance overall network throughput. We introduce the Hungarian algorithm to enhance user allocation efficiency and compare it with prior methods. Our goal is to identify the most optimized user allocation approach in MM 5G networks.

A. Algorithm 1 - User Assignment to One Base Station

We run simulations for 181, 362, 905, 1267, 2353 and 2534 users by selecting some of the rows that are the closest to our active base station and modifying their user number each time. Specifically for the simulations we used combinations of Rows 1090 up to 1103. In Fig. 2 that follows we can observe how the users' data rates are reducing, with more people connecting to the base station. The x-axis refers to the number of users that were simultaneously connected to the base station and on the y-axis, we see the average throughput in Mbps.

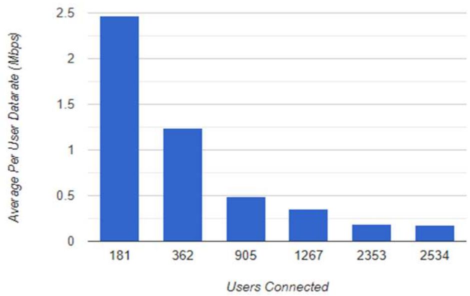

Fig. 3. Average per user throughput to User count Graph (1 active BS)

In general, in a 5G MM scenario with one active base station and a capacity of 3000 users, the use of multiple antennas allows for simultaneous transmission and reception of data, resulting in a higher per user throughput than traditional single antenna systems. As user numbers gradually rise from 181 to 2534, per-user throughput is likely to decrease due to increased interference. More users connected to the base station led to overlapping radio waves, causing interference.

As user count rises, individual bandwidth decreases, leading to lower throughput. Signal-to-Noise Ratio (SNR), vital for signal quality, weakens with more connections due to signal degradation. Activating additional base stations extends coverage and reduces existing base station loads, potentially enhancing total network throughput. Overall network throughput increases when users connect to multiple base stations, rather than activating more base stations, indicating data transmission limitations in wireless channels. While wireless networks can accommodate more users than thought, individual data rates may slow during peak usage as users share available bandwidth. These findings are crucial for high-traffic wireless network performance, guiding more efficient network protocol and resource allocation strategy designs.

B. Algorithm 2 - With Many Base Stations Active

In our second simulation, we maintain the same dataset but modify certain parameters. Specifically, we use three base stations, each with a capacity of 1000 users (instead of 3000), allowing user allocation across base stations once the count exceeds 1000. Simulations were conducted separately for user counts of 181, 362, 905, 1267, 2353, and 2534, with calculated average per-user throughput for each case. In Fig. 3, we observe the expected trend: as user count rises, average throughput per user decreases. The x-axis represents the active user count, and the y-axis shows average throughput in Mbps. Fig. 4 illustrates user allocation to each base station in different scenarios.

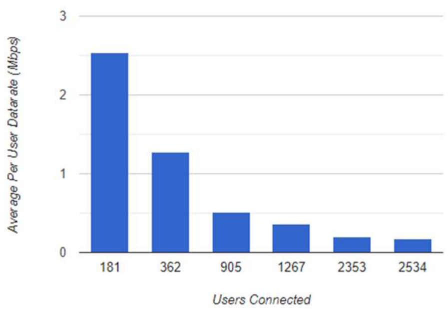

Fig. 4. Average per user throughput to User count Graph (3 active BS)

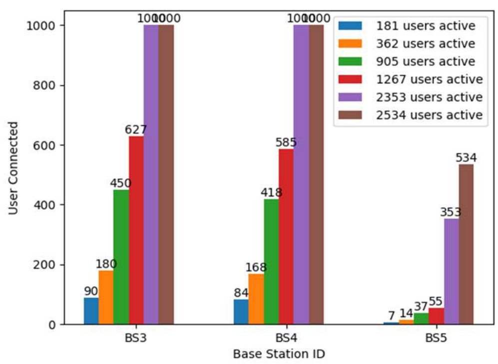

Fig. 5. User Allocation for each scenario (3 active BS)

With three active base stations, the average per-user data rate increases. Additionally, running the same simulation with four active base stations for user counts of 181, 362, 905, 1267, 2353, and 2534 shows a marginal (0.1%) increase in average data rate compared to the three-base station scenario. For instance, with 181 users and three active base stations, each user had a data rate of 2.54 Mbps, which slightly increased to 2.545 Mbps with four base stations. Fig. 5 illustrates an almost linear relationship between the reduction in average per-user throughput and the increase in user count. Fig. 6 shows user allocation for the four active base stations.

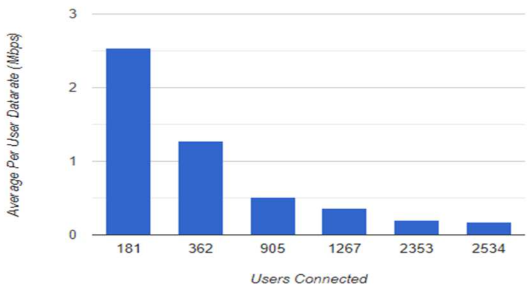

Fig. 6. Average per user throughput to User count Graph (4 active BS)

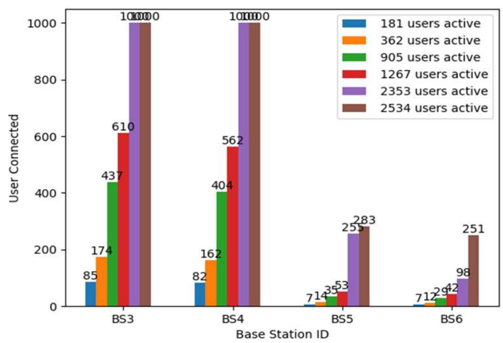

Fig. 7. User Allocation for each scenario (4 active BS)

Additionally, the challenge of maintaining high performance in larger wireless networks is evident through the nearly linear relationship between user count and throughput decrease. These findings can significantly impact wireless network design and optimization, particularly in densely populated areas where accommodating numerous simultaneous users is crucial. However, improving user management and connection to the most efficient base station for optimal per-user throughput can be achieved with more efficient algorithms. We will test this scenario with both the Minimum Cost Flow and Hungarian algorithms, comparing results to determine the most optimized approach.

C. Hungarian Algorithm

As with our previous simulations for algorithms 1 and 2 we had to run the simulation for 181, 362, 905, 1267 and 2353 users. A small part of the algorithm 2 and 1 was used to create a Cost matrix which will be used for the linear assignment problem. The results from this simulation were the same as with the algorithm 2. In comparison to the algorithm used previously, the MatchPairs function demonstrates better time complexity. The previous algorithm suffered from high computational requirements, resulting in longer execution times. In contrast, the MatchPairs function incorporates optimized data structures and matching strategies, resulting in a significant reduction in computational burden. With a time complexity of $O(N^3)$, where N represents the number of users, MatchPairs offers enhanced efficiency and scalability in the user allocation process.

D. Minimum Cost Flow Algorithm

In our simulations we observed that the Minimum Cost Flow algorithm outperformed the Hungarian algorithm in terms of execution time and computational requirements. As the number of users increases, the time complexity of the Hungarian algorithm grows cubically, resulting in longer execution times. However, with the Minimum Cost Flow algorithm, the execution time scales more efficiently, resulting in reduced computational burden and faster user allocation. Reading the topology and constructing the directed graph, the complexity needed is $O(U + B)$ where U is the number of Users and B is the number of base stations. Printing the assignments for each user takes $O(B)$ time and so, the time complexity of the entire algorithm is dominated by finding the minimum cost flow in the graph, which is $O(U * (U + B + log(U + B)))$. Compared to the Hungarian algorithm's complexity of $O(N^3)$ where N is the $max(U, B)$, the minimum cost flow is more time efficient in allocating users to the correct base stations. Overall, our comparative analysis favors the Minimum Cost Flow algorithm for more efficient user allocation compared to the Hungarian algorithm. This adoption enhances wireless communication systems and optimizes MM technology utilization in 5G networks.

V. Conclusions and Future Work

In this article, we explored user allocation techniques in MM 5G networks using a DeepMIMO simulator. We focused on two algorithms: user allocation to a single base station and user allocation to multiple active base stations. Additionally, we implemented the Hungarian and the Minimum Cost Flow algorithm to optimize user allocation and compare their time complexity. In the first scenario with a single active base station, we noticed a decrease in user throughput as the number of connected users increased. This drop was due to increased interference caused by overlapping radio waves. In the subsequent scenarios with multiple active base stations, activating more base stations offloaded existing ones and expanded coverage, leading to a slight increase in network throughput. The nearly linear relationship between the number of users and throughput degradation highlighted the challenges of maintaining high performance in large wireless networks.

We introduced the Hungarian algorithm for optimizing user assignments based on the linear assignment problem. This algorithm demonstrated improved efficiency and scalability compared to our previous approach. The Hungarian Algorithm's MatchPairs function reduces complexity and offers higher time efficiency, making it a superior choice for user assignment. Additionally, the Minimum Cost Flow algorithm provided a more efficient solution to our problem in terms of time complexity. Consequently, the Minimum Cost Flow algorithm outperformed the Hungarian algorithm in execution time and scalability, especially in scenarios with numerous users and antennas.

Our study offers valuable insights into MM 5G user allocation techniques, with future research opportunities including exploring dynamic allocation adapting to changing conditions, enhancing real-time user-to-antenna allocation for optimal performance. Applying machine learning for adaptive user-to-antenna allocation, utilizing network parameters and historical data. Investigating scalability in large-scale 5G networks with numerous base stations and users, assessing performance as networks grow amid challenges like increased interference, resource constraints, and computational complexity. Further study will improve efficiency, capacity, and performance in MM 5G networks, maximizing this revolutionary technology's potential.

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