

IS-Wireless Take Home Assignment

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1 Introduction

This report highlights the design decisions, assumptions made, and results obtained from the implementation of the research paper by Kooshki et al. [1] on the cell-less approach for efficient radio resource management in future 6G mobile networks. It also highlights improvements to the algorithm and the tooling used.

2 Design Decisions and Assumptions made

2.1 Number of UEs, RUs, and PRBs

The number of UEs and RUs was kept the same as in the paper except for the case with 24 RUs. This was replaced with 12 RUs and 36 UEs, 120 UEs, and 360 UEs. Since the paper investigates increasing number of RUs and UEs by certain factors (3, 10, and 30), this configuration was sufficient for the analysis and reduces complexity.

The number of PRBs was also reduced to 10. The number of PRBs was not explicitly analyzed in the paper, thus making this reduction reasonable for the scope of this work. The number of generations for the modified genetic algorithm was set to 8 and the population size was set to 12.

A single TTI is used in the simulation, and fifty independent simulations were performed for each configuration.

2.2 Tooling Used

Python was used as the programming language because of its ability to handle tensor computations efficiently.

2.2.1 Large-Scale Fading - Path Loss

The path loss was modelled according to ITU-R requirements for Non-Line-of-Sight (nLOS) scenarios for both the indoor and the urban-micro (outdoor) environments [2].

2.2.2 Small-Scale Fading - Multipath Fading

A Rayleigh fading model was used to estimate the small-scale multipath fading under nLOS scenarios for both environments.

For the indoor scenario, fading was done on a per RU-UE basis, resulting in a constant fading coefficient across all PRBs for a given RU-UE link. This models a flat-fading channel where the coherence bandwidth is greater than the channel bandwidth.

For the urban micro/outdoor scenario, fading was applied independently for each RU-UE-PRB combination. This was done to introduce diversity across the PRBs; however, with this simplification, the fading coefficients are uncorrelated across the frequencies, and it does not capture the frequency correlation present in more realistic frequency-selective channels.

2.3 Modified Genetic Algorithm

2.3.1 Initial Population

The initial population was generated by associating each UE with the RU that provides the maximum RSRP. Round-robin was then used to randomly allocate PRBs to the RUs to which the UEs were attached, until the number of individuals in the population was achieved.

2.3.2 Fitness Function

The fitness value of each individual is computed as the sum of the achievable throughput of all users, explicitly taking into account the interference caused by other RUs, PRBs, and UEs that are also active (i.e., those with their values in the matrix equal to 1). In addition, the fitness calculation considers cases where a PRB of the same RU serves multiple UEs. In such cases, the PRB's power is split equally amongst the UEs it serves, and each UE contributes interference to the other co-scheduled UEs on the same PRB.

A minimum data-rate threshold of 0.3Mbps is used for each user. If, for an individual, a user does not satisfy this constraint, the data rate of that user is set to zero.

2.3.3 Selection

Roulette wheel selection was used to select the fittest individuals to go further to the next stage. Each individual was assigned a selection probability proportional to its fitness, which is computed as the ratio of the individual's fitness to the total fitness of the population. As a result, individuals with higher fitness values had a higher chance of being selected.

2.3.4 Crossover

The selected individuals then went through the crossover process. Two parent individuals were chosen from the population, and a single-point crossover was applied at a randomly selected point within the RB allocation. The crossover operation was done according to a predefined probability, which was set to 0.7 in order to encourage diversity between the RBs.

2.3.5 Mutation

The children generated through crossover then went through an adaptive mutation, in which random bits were flipped with a probability that depends on the individual's fitness. The mutation probability is defined as

$$\text{mutation probability} = 0.1 \times \frac{(\text{maximum fitness} - \text{fitness})}{(\text{maximum fitness} - \text{average fitness})}$$

where individuals with lower fitness values have a higher probability of mutation, which allows the algorithm to explore other solutions for less fit individuals while keeping the good solutions.

2.3.6 Final Solution

After all generations are complete, the best individual from the final generation is selected as the solution to the optimization problem.

2.3.7 Elitism

In each generation, elitism was applied before selection, to allow the best individual from each generation to be retained through the next generation.

2.4 Results

The results derived from the simulation are shown in Figure 1. The legacy scheduler was simulated with UEs associated to the RU with maximum RSRP and resource blocks allocated via round-robin scheduling. Fifty independent simulations were done and the CDF for each scenario was plotted. In general, the results show great improvements in system capacity of the MGA compared to the legacy for majority of the simulations across all cases. There was a very small percentage having slightly negative values, likely due to the randomness of the algorithm.

As also discussed in the reference paper, the RU level, RB level and UE level analysis is presented below and compared with the paper.

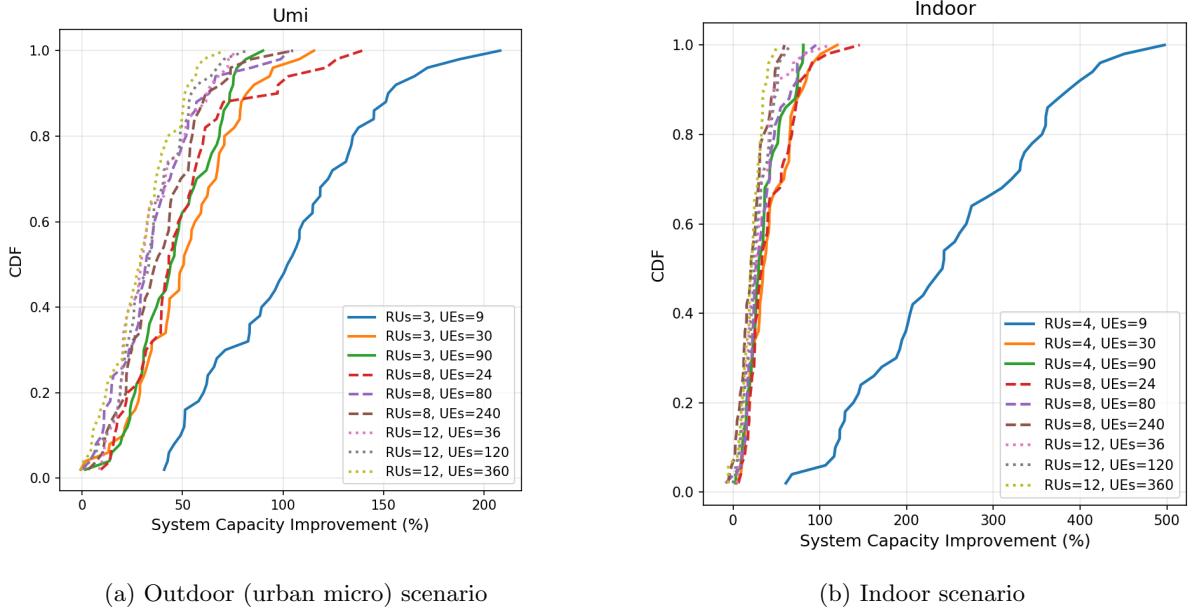


Figure 1: System capacity improvement compared with the legacy system.

RU level analysis: When comparing the performance at the RU level, the results are generally consistent with those reported in the reference paper. Lower number of RUs provide more capacity improvements, although the case with 8 RUs and 24 UEs shows similar trends to the cases with 3 RUs and 30/90 UEs. This is due to the higher number of users as will be discussed in the UE analysis. As stated in the reference paper, more competition for resources with higher gain creates opportunity for the algorithm to efficiently allocate resources. However, in this scenario, a larger number of RUs also provides flexibility for resource allocation for the legacy algorithm. This gives the legacy algorithm more space to allocate resources to the UEs with good channels and thus the gain is not as high as the case with lower RUs. Thus, with higher number of RUs, the gain of the MGA is comparatively lower than with lower number of RUs.

RB level analysis: The Rayleigh fading model used in this work applies independent fading per PRB without frequency correlation, which is a simplification compared to more realistic frequency-selective channels. Thus, in this work, there is a relatively large number of PRBs with good channel quality for the outdoor compared to the reference paper, which considers more realistic frequency-selective environments with deeper fading variations across the frequencies. The main difference between the two environments in Figure 1 is that the indoor has better channel conditions than the outdoor. Thus, the case with low RUs and UEs (4 RUs, 9 UEs) shows very high improvement for the indoor compared to the outdoor with 3RUs and 9UEs. The MGA algorithm can take advantage of these good channel conditions for the few UEs and allocate a high number of resources to them. For the remaining configurations with higher number of UEs, there is less difference between indoor and outdoor environments. Since the outdoor scenario still has a good number of PRBs with reasonable channel quality, the legacy algorithm can take advantage of the user diversity and allocate resources to users with good channel conditions, although it still performs worse than MGA. Thus, the relative gain of MGA is lower with high UEs, and is similar for both indoor and outdoor scenarios.

UE level analysis: For the UE-level analysis, the scenarios with lower number of UEs and RUs can take advantage of the availability of many good resources, allowing the users to be allocated to good channels more frequently. In the reference paper, the MGA for the outdoor scenarios with higher number of UEs benefit from the stronger frequency-selective environment, and thus the algorithm can efficiently select and allocate the good resources to a larger number of UEs. Since the channel model used in this work is a simplification of realistic frequency-selective environments, increasing the number of UEs does not provide the same level of performance gain. Instead, increasing the number of UEs provides more diversity for the legacy and since a large number of the PRBs are still good and as diverse, the legacy will still have some gains and thus the MGA algorithm will not be as effective compared to when the UE

is low. This could also explain why there are cases where the 8 RUs with 24 UEs has higher capacity improvements compared to the 3 RUs with 30 and 90 UEs. The same applies to the case with 8 RUs and 240 UEs in the indoor case, having a lower gain compared to 12 RUs with 36/120 UEs. Higher UEs creates more diversity for the legacy to find users with good channels. This could also explain the high gap in the performance between the case with 9 UEs and the rest.

In summary, for this simulation, when channel conditions are better and the number of UEs and RUs is low, the MGA takes greater advantage of the good channels and increases system capacity significantly more than the legacy. When the number of UEs is high and with good channel conditions, the MGA still performs better, but the legacy now has more user diversity to take advantage of and can then increase its system capacity more, thus reducing the relative gain of the MGA.

2.5 Improvements to the Algorithm

The algorithm currently only considers the minimum data rate for each UE as a QoS constraint. To make the algorithm more QoS-aware, it should also take latency-sensitive applications into account. In general, achieving a very high data rate can lead to increased latency if scheduling is not handled adequately. Similar to latency-aware schedulers, the genetic algorithm could be optimized for latency-sensitive applications while still maintaining a minimum data rate particularly for throughput-sensitive applications.

This can be achieved by adding an additional constraint for a subset of users based on their latency requirements, expressed as

$$L_{m,n} \leq L_{m,n}^{\text{max}}, \quad \forall m \in \mathcal{L},$$

where $L_{m,n}$ denotes the experienced latency of user m to RU n . $L_{m,n}^{\text{max}}$ is the maximum allowable latency, and \mathcal{L} is the subset of latency-sensitive users.

In practice, proportional fairness algorithms are widely used to ensure fairness among users. An additional constraint implementing a minimum fairness threshold could therefore be used in the algorithm. The performance of this approach could then be compared with current fairness-based schedulers.

Furthermore, in general, a larger search space requires a higher number of populations and generations to explore a large number of possible solutions. For example, the number of generations and population size suitable for an RU with 50 PRBs may not be optimal for an RU with 100 PRBs. This also extends to varying number of RUs and UEs. Using similar parameters for both small and large search spaces may lead to suboptimal results or unnecessary computational overhead. A more appropriate approach, which was not used in this simulation, could be to run the algorithm until convergence for each scenario while imposing a maximum number of generations.

2.6 Improvement to Tooling

In the simulation, some simplifications were made, especially with respect to fading and propagation environment computations. A more detailed mobile network was not simulated; instead, only the network layout, propagation environment, and the scheduling algorithms were modeled to estimate the achievable throughput. As a result, some detailed parts of the network were not considered. Python was used primarily due to its efficiency in tensor computations. MATLAB could have been a more suitable tool using the 5G Toolbox and system-level simulation, which takes care of system-level details. However, access to a MATLAB license is currently not available, as it expired after graduation.

Furthermore, in the reference research paper, an ORAN system which makes use of a near Real-Time Intelligent Controller (near-RT RIC) to control the scheduling was used. This was not used in this simulation, the algorithm was already assumed to be controlled centrally. Other tools such as MATLAB, which has ORAN related capabilities, could enable a more realistic implementation of the ORAN for this work.

References

- [1] F. Kooshki, M. A. Rahman, M. M. Mowla, A. G. Armada, and A. Flizikowski, “Efficient radio resource management for future 6g mobile networks: A cell-less approach,” *IEEE Networking Letters*, vol. 5, no. 2, pp. 95–99, 2023.
- [2] ITU-R, “Guidelines for evaluation of radio interface technologies for imt-2020,” International Telecommunication Union, Geneva, Switzerland, Tech. Rep. Rep. M.2412-0, Oct. 2017.