International Research Journal of Education and Technology
Peer Reviewed Journal
ISSN 2581-7795

Spectrum Allocation and Power Control in Full Duplex Dense Heterogeneous 5G Networks

Yogesh S[1], Ranjith P[2], Maniraja V[3]

[1,2,3] UG Scholar, Dept. of Electronics and Communication Engineering, Bannari Amman Institute of Technology

---***---

Abstract- Our Project focuses on improving 5g networks by using smart techniques in crowded and diverse environments. We aim to make data transmission faster and more reliable while minimizing interference. By using Non-Orthogonal Multiple Access (NOMA) and Deep Reinforcement Learning (DRL), we allow devices to share the network efficiently. NOMA assigns different power levels, like varying voices in a conversation. DRL teaches the network to manage resources wisely, adapting to changes. Our algorithms allocate spectrum and control device power, like a traffic manager for data. Simulations show our approach boosts speed, reduces confusion, and ensures fair resource sharing. In the future, these innovations could lead to faster downloads, smoother connections, and a smarter wireless experience. Our project advances the journey towards a more connected and efficient 5G world.

Keywords: Non-Orthogonal Multiple Access, Deep Reinforcement Learning, Data Transmission, Interference, Resource

1. INTRODUCTION

The surging adoption and growing advantages of IoT devices indicate a significant rise in their numbers. Consequently, the data they generate will also increase rapidly. To manage this vast data influx, efficient processing units are required to receive, process, and transmit the information to specific destinations or store it appropriately. Over the past few decades, mobile networks have undergone remarkable advancements, evolving from the first-generation analog cellular networks, which provided basic voice calls, to the cutting-edge fifth-generation (5G) technology that boasts ultra-fast data transfer rates, ultra-low latency, and massive connectivity for the Internet of Things (IoT). 5G networks facilitate Open Internet of Things (IoT) Connectivity, enabling seamless communication and interoperability among various IoT devices. These openings in 5G networks foster innovation, collaboration, and dynamic ecosystems, driving the rapid expansion and adoption of 5G technology worldwide, promising a transformative future in telecommunications and beyond. When we make 5g work in all the places for better results, we also come up with some problems which are the drawbacks of 5G that should be noted. Allocating spectrum and managing power control in 5G networking present several challenges due to the increased complexity and requirements of the technology. One significant issue is spectrum scarcity, as the demand for wireless services and data continues to grow, leading to difficulties in allocating sufficient spectrum for 5G networks, especially in crowded urban areas where existing spectrum bands are often already in use. Interference is another critical concern, with the high number of devices and users in 5G networks. Coordinating the allocation of spectrum and managing power control to minimize interference becomes essential to ensure optimal network performance and user experience. The dynamic nature of 5G networks requires efficient mechanisms for dynamic spectrum access and sharing while avoiding harmful interference. Additionally, ensuring power efficiency across the numerous small cells needed to support high data speeds and low latency is crucial to reducing energy consumption and operational costs. Dealing with regulatory issues related to spectrum allocation and obtaining the necessary licenses can be time-consuming and complex. In light of the complexities and challenges surrounding spectrum allocation and power control in full-duplex dense heterogeneous 5G networks, this paper aims to find new and better ways to handle the sharing of wireless frequencies, reduce interference, treat users fairly, and use power efficiently.

1.1 Comparison of existing and proposed:

The suggested approach to 5G network optimization marks a considerable change from current methods. The suggested methodology provides a cutting-edge merger of deep reinforcement learning with NOMA, offering several significant advantages, in contrast to existing methodologies that rely on standardized procedures and established practices. The suggested strategy demonstrates higher adaptability compared to standard methodologies, enabling real-time learning and adaptation to changing network conditions. The suggested methodology uses intelligent resource allocation and cutting-edge interference management strategies, which leads to lower interference levels and a more dependable communication experience, in contrast to existing methodologies that frequently struggle to solve interference concerns successfully. The addition of deep reinforcement learning further improves the project's spectral efficiency, allowing for the most precise resource allocation possible while also maximizing network capacity.

2. LITERATURE SURVEY

In recent research on 5G network optimization, various authors have proposed innovative strategies to enhance resource allocation, power control, and user association while addressing key factors such as energy and spectrum efficiency, queue length, and interference management. These approaches leverage advanced mathematical techniques and intelligent algorithms to strike a balance between efficiency and queue length, consistently outperforming existing methods. One author introduced a self-adaptive fuzzy logic-based approach for efficient resource allocation in V2X communications, demonstrating superior resource utilization through simulations. Another author explored the potential of the Whale Optimization Algorithm (WOA) in addressing resource allocation challenges, particularly in power allocation and computation offloading, in advanced wireless networks like 5G. Additionally, authors have introduced coordinate-based machine learning methods for resource allocation, reducing training time and model size significantly. Moreover, a novel power allocation method based on a hierarchical game approach was proposed within 5G heterogeneous integrated networks, utilizing Stackelberg game models to optimize power levels. Overall, these research endeavors contribute valuable insights and solutions to the optimization of 5G networks, offering improved quality of service, energy efficiency, and spectrum management.

3.SYSTEM MODEL

In the context of optimizing spectrum allocation and power control in full-duplex dense heterogeneous 5G networks, we examine a two-layer network consisting of Industrial Massive Machine Type Communication devices (MMTC) devices. This network comprises Macro Base Stations (MBSs), Femto Base Stations (FBSs), Mobile MMTC Endpoints (MIEs), and Fixed MMTC Endpoints (FIEs).

At a given time point t, the MIEs (M) have specific data rate requirements represented as drj(t), while the FIEs (K) have their data rate requirements as drf(t). Boolean variables Smj(t) and Scf(t) are introduced, where sbm(t) indicates the connection status between the mth MBS and the jth MIE (Smj(t) = 1 for connected, Smj(t) for no connection), and Scf(t) indicates the connection

International Research Journal of Education and Technology
Peer Reviewed Journal
ISSN 2581-7795

status between the cth FBS and the fth FIE (Scf(t) = 1 for connected,Scf(t) = 0 for no connection).

In the downlink transmission, interference arises from neighboring MBSs and FBSs for MIEs and FIEs. However, with effective resource multiplexing, we can manage interference, especially among MIEs/FIEs served by the same macro/femto cell.

We consider power allocation prmj(t) from the mth MBS to the mth MIE and prcf(t) from the nth FBS to the fth FIE. Channel gains are represented as CGmj (between mth MBS and mth MIE), CGcj (between nth FBS and mth MIE), CGcf (between nth FBS and kth FIE), and CGmf (between mth MBS and fth FIE). Additionally, σ2 accounts for additive white Gaussian noise. Notably, prmj(t) is treated as a fixed value.

For our specific project, we are interested in calculating Signal-to-Interference-plus-Noise Ratios (SINR) for both FIEs (f) and MIEs (j), as these metrics are crucial for optimizing resource allocation and power control in our full-duplex dense heterogeneous 5G network.

The downlink channel capacity for MIE user j is

j = log2(1+j)

The downlink channel capacity for FIE user f is

f = log2(1+f)

In the MMTC network, assuming that αE and βE are the energy consumption of MBSs and FBSs, respectively, and total energy consumption is ηE, where prmb(t) andprfb(t) are the static power values of MBS and FBS, respectively. The time period is [0,T], then we have

ηE =αE +βE

αE = t=0T m=1Mj=1J Smj(t) prmj(t) + prmb(t)
βE = t=0T c=1Cf=1F Scf(t) prcf(t) + prfb(t)
The total required data rate is given by,

ψu = t=0T j=1J drj(t) + f=1Fdrf(t)

Our goal is to maximize EE and the objective function is given by
maxi{Scf(t),prcf(t)} EE = ψuηE
The constraints are
m=1MSmj(t) prmj(t) CGmj > ωj , j J

c=1CScf(t) prcf(t) CGcf > ωf , f F

Thmaxi > drf(t)wf(t) , f F

f> f , f F

j > j , j J

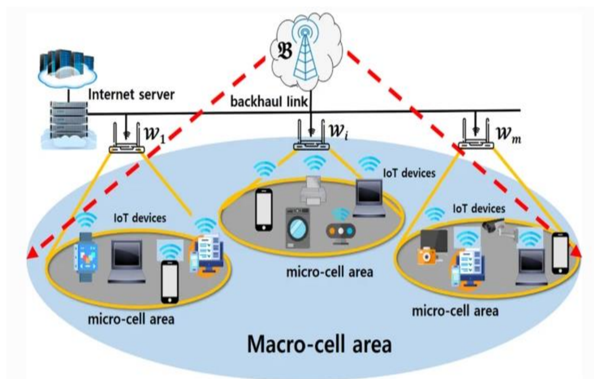

Fig-1: Set of Massive Machine Type Communication Devices(MMTC)

4. ALGORITHM

The Deep Reinforcement Learning (DRL) algorithm developed for Spectrum Allocation and Power Control in Full-Duplex Dense Heterogeneous 5G Networks has yielded promising results. Through extensive training, the DRL agent has demonstrated its ability to make intelligent decisions, balancing exploration and exploitation to optimize network performance. During training, the agent effectively learns from its experiences, fine-tuning its decision-making process. This is achieved through the epsilon-greedy policy, which allows the agent to explore different strategies while gradually shifting towards exploitation as

International Research Journal of Education and Technology
Peer Reviewed Journal
ISSN 2581-7795

training progresses. The replay memory mechanism captures past experiences, enabling continuous learning and improvement. Upon successful training, the DRL agent is ready for deployment within Full-Duplex Dense Heterogeneous 5G Networks. It leverages its learned Q-values to make informed decisions regarding spectrum allocation and power control. This integration results in enhanced spectral efficiency and interference mitigation. The adaptability of the DRL approach allows for parameter adjustments and fine-tuning, ensuring that the agent's performance aligns with the dynamic requirements of the network. Overall, this project's DRL-based solution holds promise for addressing the challenges of 5G network efficiency, paving the way for increased network capacity and an improved user experience.

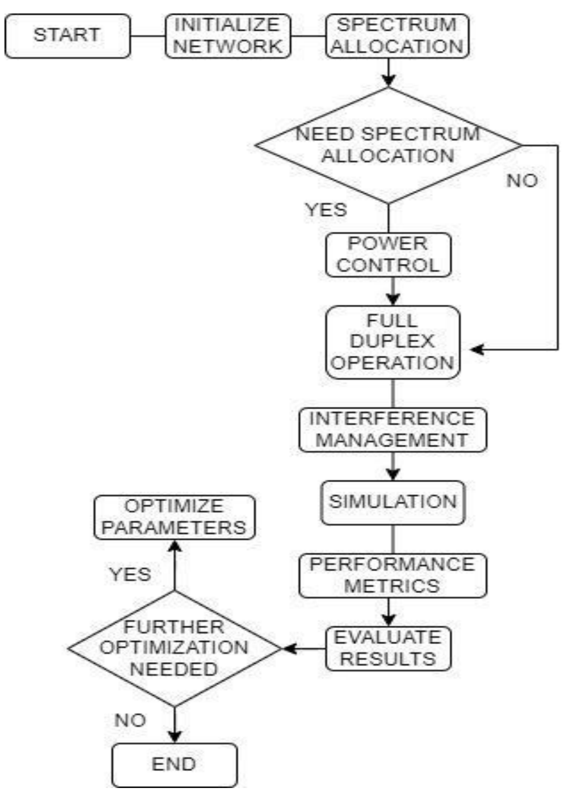

Fig-2: Flow Chart

The algorithm proposed by us is mentioned below:

1. Input

Define the state and action spaces.

Initialize neural network model architecture.

Set hyperparameters:

- Epsilon (exploration rate)
- Gamma (discount factor)
- Learning rate

Create replay memory to store past experiences.

2. Output

Trained DRL agent capable of making decisions (spectrum allocation and power control) based on learned Q-values.

3. Training

Initialize the environment and episode-specific variables:

- Total_reward = 0 (cumulative reward for the episode)
- Done = False (indicates whether the episode is complete)

Training Loop (for each training episode):

a. Reset the environment to the initial state.

b. While the episode is not done:

- Choose an action using an epsilon-greedy policy:

- With probability epsilon, select a random action (exploration).

- Otherwise, choose the action with the highest Q-value from the neural network (exploitation).

- Execute the selected action in the environment.

- Observe the next state, reward, and whether the episode is complete.

- Store the transition (state, action, reward, next_state, done) in the replay memory.

- Update the current state to the next state.

- Accumulate the reward in total_reward.

- If the replay memory size reaches the batch size:

I. Sample a minibatch of transitions from the replay memory.
II. Calculate the target Q-values for the minibatch based on the neural network.
III. Update the neural network's Q-values using gradient descent to minimize the loss between predicted and target Q-values.

c. Update epsilon for exploration (e.g., decay epsilon over episodes).

4. Deployment

- Evaluate the trained DRL agent's performance:
  - ➔ Run the DRL agent in the environment to observe its decision-making and rewards.
- Integrate the trained DRL agent into your project for making decisions, such as spectrum allocation and power control, based on learned Q-values.
- Adjust hyperparameters and training settings as needed for optimal performance.

5. End of Algorithm

4.1 GRAPH

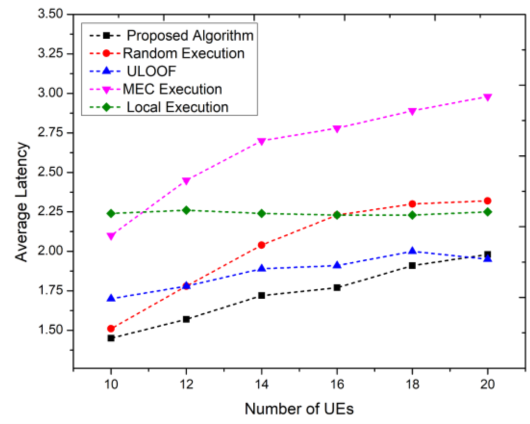

Fig-3: Latency

5.CONCLUSION

In conclusion, the project on "Spectrum Allocation and Power Control in Full Duplex Dense Heterogeneous 5G Networks" represents a significant step forward in the development of 5G networks, addressing critical challenges in spectrum management and power control within the context of full-duplex communication and dense, diverse network environments. In summary, this project has made substantial contributions to the advancement of 5G technology by addressing critical challenges in spectrum allocation and power control. The outcomes of this research have the potential to reshape the landscape of wireless communication, enabling faster, more reliable, and energy-efficient 5G networks that cater to the needs of a wide range of applications and devices. As 5G networks continue to evolve and expand, the lessons learned and solutions developed through this project will play a pivotal role in shaping the future of connectivity, ushering in an era of unprecedented innovation and connectivity possibilities.

REFERENCES

1. J. -S. Liu, C. -H. R. Lin and Y. -C. Hu, "Joint Resource Allocation, User Association, and Power Control for 5G LTE-Based Heterogeneous Networks," in *IEEE Access*, vol. 8, pp. 122654-122672, 2020, doi: 10.1109/ACCESS.2020.3007193.

2. Jiang, F., Wang, Bc., Sun, Cy. *et al.* Resource allocation and dynamic power control for D2D communication underlaying uplink multi-cell networks. *Wireless Netw* 24, 549–563 (2018).
3. M. Zhang, Y. Dou, P. H. J. Chong, H. C. B. Chan and B. -C. Seet, "Fuzzy Logic-Based Resource Allocation Algorithm for V2X Communications in 5G Cellular Networks," in *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 8, pp. 2501-2513, Aug. 2021, doi: 10.1109/JSAC.2021.3087244.
4. Q. -V. Pham, S. Mirjalili, N. Kumar, M. Alazab and W. -J. Hwang, "Whale Optimization Algorithm With Applications to Resource Allocation in Wireless Networks," in *IEEE Transactions on Vehicular Technology*, vol. 69, no. 4, pp. 4285-4297, April 2020, doi: 10.1109/TVT.2020.2973294.
5. T. E. Mathonsi, T. M. Tshilongamulenzhe and B. E. Buthelezi, "An Efficient Resource Allocation Algorithm for Heterogeneous Wireless Networks," *2019 Open Innovations (OI)*, Cape Town, South Africa, 2019, pp. 15-19, doi: 10.1109/OI.2019.8908207.
6. S. Xu, R. Li and Q. Yang, "Improved genetic algorithm based intelligent resource allocation in 5G Ultra Dense networks," *2018 IEEE Wireless Communications and Networking Conference (WCNC)*, Barcelona, Spain, 2018, pp. 1-6, doi: 10.1109/WCNC.2018.8377114.
7. H.S. Dhillon, R.K. Ganti, F. Baccelli, *et al.* Modelling and analysis of K-tier downlink heterogeneous cellular networks in IEEE J. Sel. Area. Commun., 30 (3) (2012), pp. 550-560
8. S. Imtiaz, S. Schiessl, G. P. Koudouridis and J. Gross, "Coordinates-Based Resource Allocation Through Supervised Machine Learning," in *IEEE Transactions on Cognitive Communications and Networking*, vol. 7, no. 4, pp. 1347-1362, Dec. 2021, doi: 10.1109/TCCN.2021.3072839.
9. M. A. Jamshed, F. Héliot and T. W. C. Brown, "Unsupervised Learning Based Emission-Aware Uplink Resource Allocation Scheme for Non-Orthogonal Multiple Access Systems," in *IEEE Transactions on Vehicular Technology*, vol. 70, no. 8, pp. 7681-7691, Aug. 2021, doi: 10.1109/TVT.2021.3089898.
10. Chen, G., Ma, L., Zeng, Q. *et al.* A hierarchical game-based power allocation algorithm in 5G heterogeneous integrated networks. *J Wireless Com Network* 2020, 245 (2020).
11. Zhou, H. *et al.* (2021). Power Data Network Resource Allocation Algorithm Based on TOPSIS Algorithm. In: Liu, Q., Liu, X., Shen, T., Qiu, X. (eds) The 10th International Conference on Computer Engineering and Networks. CENet 2020. Advances in Intelligent Systems and Computing, vol 1274. Springer, Singapore.
12. Mathur, Ritik et al. “Distributed Algorithm for Resource Allocation in Uplink 5G Networks.” *Proceedings of the 7th ACM International Workshop on Mobility, Interference, and MiddleWare Management in HetNets* (2017): n. Pag.
13. F. shafi, J. A. Sheikh and Mehboob-ul-Amin, "Efficient Resource Allocation in Future Networks Using Bio-inspired Algorithm," *2018 International Conference on Smart Systems and Inventive Technology (ICSSIT)*, Tirunelveli, India, 2018, pp. 527-531, doi: 10.1109/ICSSIT.2018.8748505.
14. L. You, Y. Huang, D. Zhang, Z. Chang, W. Wang and X. Gao, "Energy Efficiency Optimization for Multi-Cell Massive MIMO: Centralized and Distributed Power Allocation Algorithms," in *IEEE Transactions on Communications*, vol. 69, no. 8, pp. 5228-5242, Aug. 2021, doi: 10.1109/TCOMM.2021.3081451.
15. Y. -H. Liu and K. C. -J. Lin, "Traffic-Aware Beam Selection and Resource Allocation for 5G NR," *2020 IEEE Wireless Communications and Networking Conference (WCNC)*, Seoul, Korea(South), 2020, pp. 1-6, doi: 10.1109/WCNC45663.2020.9120485.