Researches on Resource Allocation with Reinforcement Learning in Cell-Free Networks

Yunseong Lee
School of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
yslee@uclab.re.kr

Donghyun Lee
School of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
dhlee@uclab.ac.kr

Junsuk Oh
School of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
jsoh@uclab.ac.kr

Chihyun Song
School of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
chsong@uclab.re.kr

Wonjong Noh
School of Software
Hallym University
Chuncheon, Republic of Korea
wonjong.noh@hallym.ac.kr

Sungrae Cho
School of Computer Science and Engineering
Chung-Ang University
Seoul, Republic of Korea
srcho@cau.ac.kr

***Abstract*—This paper explores reinforcement learning (RL) based on resource allocation in cell-free networks, a promising alternative to traditional cellular architectures. Cell-free networks eliminate cell boundaries by using distributed access points (APs) to collaboratively serve users, improving spectral efficiency and service uniformity. However, managing power allocation, beamforming, and AP clustering in such decentralized environments presents new challenges. We present several RL-based algorithms aimed at optimizing key network functions. Specifically, the study explores dynamic power control, advanced beamforming techniques, and multi-agent RL frameworks for clustering access points. The proposed methods leverage the adaptability of RL to optimize network performance in real-time under varying conditions.**

***Index Terms*—Cell-free networks, reinforcement learning, resource allocation, massive MIMO**

I. Introduction

The rapid evolution of wireless communication systems has led to increasing demands for higher data rates, lower latency, and more reliable connections. Traditional cellular networks, which rely on well-defined cell boundaries and centralized management, are facing significant challenges in meeting these demands, especially with the rise of applications like the Internet of Things (IoT), augmented reality, and autonomous vehicles. To address these challenges, cell-free networks have emerged as a promising alternative. Cell-free networks eliminate the concept of cell boundaries by deploying numerous distributed access points (APs) that work together to serve users in a coordinated manner. This architecture improves spectral efficiency, reduces interference, and provides a more uniform quality of service across the network. However, the decentralized nature of cell-free networks introduces new complexities in resource management, particularly in the areas of power allocation, beamforming, and access point clustering. Reinforcement learning (RL), a subset of machine learning, has shown great potential in solving complex optimization problems in dynamic and uncertain environments. In the context of cell-free networks, RL offers a powerful tool for optimizing resource allocation, enabling the network to adapt to varying conditions and user demands in real-time. By leveraging RL, we can develop intelligent algorithms that enhance the performance of cell-free networks, making them more efficient and scalable.

This paper investigates the application of reinforcement learning to resource allocation in cell-free networks. We explore various RL-based techniques for optimizing power allocation, beamforming, and access point clustering, and demonstrate their effectiveness through simulations. The results highlight the potential of RL to improve network performance, paving the way for more adaptive and efficient wireless communication systems.

II. Beamforming with Reinforcement Learning

In [1], the authors explore dynamic power allocation for uplink communication in a cell-free network that supports device-to-device (D2D) communication. The authors propose a deep reinforcement learning (DRL) approach to optimize power allocation to maximize the worst-case user rate, ensuring fairness among users. They compare the performance of their DRL scheme under zero-forcing and conjugate beamforming methods. The results demonstrate that the proposed DRL method effectively guarantees user fairness by maximizing the worst-case user rate. In [2], this paper presents a study on power control in cell-free massive multiple-input and multiple-output (MIMO) systems with a focus on achieving a balance between sum rate and fairness. The authors propose a TD3-based algorithm for dynamic power control, which outperforms traditional approaches in terms of both sum rate and fairness. The paper also introduces a sequential convex approximation (SCA) method as a benchmark. Simulation results highlight the TD3 algorithm's ability to optimize conflicting objectives efficiently while maintaining high convergence speed and low computational complexity. In [3], The paper investigates distributed beamforming in cell-free wireless networks using DRL. The authors propose centralized and distributed DRL-based methods to optimize beamforming. The centralized approach utilizes deep deterministic policy gradient (DDPG), while the distributed method employs a distributed distributional deterministic policy gradient (D4PG) approach. The results indicate that the D4PG method achieves the best performance, particularly in large networks, by efficiently handling the beamforming tasks in a distributed manner. [4] focuses on downlink power control in cell-free massive MIMO networks using a deep reinforcement learning approach. The authors propose a DDPG-based method to solve power control problems with different objectives, including max-min, max-sum, and max-product strategies. The results show that the DDPG algorithm can approximate optimal solutions significantly faster than traditional methods while providing better performance in terms of user data rate and computational efficiency. In [5], the authors propose an intelligent scheduling scheme for downlink resources in mmWave cell-free urban vehicle networks. The authors formulate the scheduling problem as a Markov decision process and propose a Hybrid Action Multi-Agent Reinforcement Learning (HA-MARL) algorithm to minimize power consumption while meeting latency constraints. The simulation results demonstrate that the proposed scheme effectively reduces energy consumption and adapts well to varying channel conditions, outperforming conventional DRL algorithms in low-latency scenarios. [6] addresses dynamic power allocation in cell-free massive MIMO systems using deep reinforcement learning methods. The authors implement a DDPG-based algorithm to optimize power allocation with the goal of maximizing the worst-case user rate. The proposed method is shown to significantly improve user fairness and system performance, particularly in environments with diverse user demands and channel conditions. In [7], the authors present a novel cell-free network architecture for mmWave MIMO systems that self-organizes into independent subnetworks using deep reinforcement learning. The authors propose a hybrid beamforming approach that combines DRL-based analog beamsteering with convex optimization-based digital beamforming. The results show that this hybrid approach significantly enhances network performance, especially as the number of partitions increases, while the hierarchical DRL design ensures efficient and scalable network operation.

III. Clustering with Reinforcement Learning

In [8], a method for AP clustering in cell-free massive MIMO systems using MARL is proposed. Cell-free massive MIMO networks enhance network performance by eliminating traditional cell boundaries and allowing multiple distributed APs to cooperate in serving a smaller number of users. However, these networks face challenges in scalability and energy efficiency. The paper suggests forming AP clusters based on user groups to improve network efficiency, thereby reducing computational complexity and power consumption. The results show that the proposed MARL-based clustering method significantly reduces power consumption and computational costs while maintaining high network performance. In [9], the authors propose a machine learning-based approach for optimizing AP selection in cell-free massive MIMO systems. The proposed method uses a trained model that predicts the optimal set of APs for each user in large-scale network scenarios, thereby enhancing user throughput and overall network efficiency. The study demonstrates that the machine learning-based AP selection method outperforms traditional AP selection methods in terms of performance. [10] introduces a method that combines cooperative clustering with power control in cell-free XL-MIMO systems using MARL to achieve energy-efficient network operation. The MARL framework dynamically adjusts both clustering and power levels to minimize energy consumption while meeting user demands. The results show that the proposed framework can significantly reduce energy consumption and enhance the network's ability to handle large-scale user demands without compromising service quality. [11] proposes a multi-agent DRL (MADRL) approach to optimize AP activation strategy in cell-free massive MIMO networks. The distributed solution enables each AP to independently decide whether to activate or deactivate based on the current network state. This approach effectively addresses the scalability issue and outperforms centralized approaches by reducing power consumption while maintaining high service quality. The study demonstrates the effectiveness of distributed learning in solving the AP activation problem in cell-free massive MIMO networks. [12] investigates multiple access strategies in cell-free networks, focusing on optimizing outage performance through dynamic clustering and DRL. The proposed DRL-based framework dynamically adjusts the clustering of APs based on real-time network conditions to minimize the outage probability for users, thus enhancing overall system performance, especially in dense user environments. In [13], a method using DRL to optimize user-centric clustering in cell-free MIMO networks is proposed. The proposed DRL framework adjusts the cluster size according to user demand and propagation conditions to optimize network performance while reducing fronthaul load and power consumption. The study shows that the DRL-based clustering approach can achieve performance similar to traditional setups while significantly reducing fronthaul requirements, demonstrating its scalability and efficiency in real-world scenarios.

IV. Computing Resource and Trajectory with Reinforcement Learning

In [14] the resource-constrained users offloading computation to edge servers is addressed in cell-free massive MIMO networks. The proposed approach uses MARL to optimize communication and computing resource allocation, aiming to minimize energy consumption while meeting user-specific latency requirements. [15] proposes using unmanned aerial vehicles (UAVs) to enhance coverage in cell-free vehicular networks. It introduces the DRL approach to dynamically position UAVs in real-time, maximizing coverage and minimizing interference, outperforming traditional fixed UAV deployment strategies. [16] suggests using MARL to optimize distributed resource allocation in cell-free massive MIMO networks. Each user autonomously allocates resources, aiming to minimize energy consumption while meeting latency requirements, achieving similar performance to centralized approaches with reduced overhead.

V. Conclusion

This paper explored the RL-based resource allocation in cell-free networks, a promising alternative to traditional cellular architectures. We highlighted the potential of RL-based approaches to optimize key network functions such as power allocation, beamforming, and access point clustering. These methods allow for more efficient and adaptive management of network resources, enhancing overall performance and ensuring consistent service quality across the network. These researches suggest that RL can effectively address the complexities of managing decentralized and dynamic networks, making it a valuable tool for the future of wireless communication. Future research should focus on further refining these techniques and addressing practical challenges to fully realize the potential of RL in real-world cell-free networks.

Acknowledgment

This work was supported in part by the National Research Foundation of Korea (NRF), South Korea grant funded by the Korea government (MSIT) (No. 2022R1A4A5034130), in part by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2024-RS-2022-00156353) supervised by the IITP (Institute for Information and Communications Technology Planning and Evaluation), South Korea.

References

[1] G. Xia, Y. Zhang, L. Ge, and H. Zhou, "Deep reinforcement learning based dynamic power allocation for uplink device-to-device enabled cell-free network," in *2022 IEEE International Symposium on Broadband Multimedia Systems and Broadcasting (BMSB)*. IEEE, 2022, pp. 01–06.

[2] M. Rahmani, M. Bashar, M. J. Dehghani, A. Akbari, P. Xiao, R. Tafazolli, and M. Debbah, "Deep reinforcement learning-based sum rate fairness trade-off for cell-free mmimo," *IEEE Transactions on Vehicular Technology*, vol. 72, no. 5, pp. 6039–6055, 2022.

[3] F. Fredj, Y. Al-Eryani, S. Maghsudi, M. Akrout, and E. Hossain, "Distributed beamforming techniques for cell-free wireless networks using deep reinforcement learning," *IEEE Transactions on Cognitive Communications and Networking*, vol. 8, no. 2, pp. 1186–1201, 2022.

[4] L. Luo, J. Zhang, S. Chen, X. Zhang, B. Ai, and D. W. K. Ng, "Downlink power control for cell-free massive mimo with deep reinforcement learning," *IEEE Transactions on Vehicular Technology*, vol. 71, no. 6, pp. 6772–6777, 2022.

[5] J. Zhao, F. Hu, Y. Gong, and D. Wang, "Downlink resource intelligent scheduling in mmwave cell-free urban vehicle network," *IEEE Transactions on Vehicular Technology*, 2024.

[6] Y. Zhao, I. G. Niemegeers, and S. M. H. De Groot, "Dynamic power allocation for cell-free massive mimo: Deep reinforcement learning methods," *IEEE Access*, vol. 9, pp. 102 953–102 965, 2021.

[7] Y. Al-Eryani and E. Hossain, "Self-organizing mmwave mimo cell-free networks with hybrid beamforming: A hierarchical drl-based design," *IEEE Transactions on Communications*, vol. 70, no. 5, pp. 3169–3185, 2022.

[8] B. Banerjee, R. C. Elliott, W. A. Krzymień, and H. Farmanbar, "Access point clustering in cell-free massive mimo using multi-agent reinforcement learning," in *2022 IEEE 33rd Annual International Symposium on Personal, Indoor and Mobile Radio Communications (PIMRC)*. IEEE, 2022, pp. 1086–1092.

[9] S. Biswas and P. Vijayakumar, "Ap selection in cell-free massive mimo system using machine learning algorithm," in *2021 Sixth International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*. IEEE, 2021, pp. 158–161.

[10] Z. Liu, J. Zhang, Z. Liu, D. W. K. Ng, and B. Ai, "Joint cooperative clustering and power control for energy-efficient cell-free xl-mimo with multi-agent reinforcement learning," *IEEE Transactions on Communications*, 2024.

[11] L. Sun, J. Hou, and R. Chapman, "Multi-agent deep reinforcement learning for access point activation strategy in cell-free massive mimo networks," in *IEEE INFOCOM 2023-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*. IEEE, 2023, pp. 1–6.

[12] Y. Al-Eryani, M. Akrout, and E. Hossain, "Multiple access in cell-free networks: Outage performance, dynamic clustering, and deep reinforcement learning-based design," *IEEE Journal on Selected Areas in Communications*, vol. 39, no. 4, pp. 1028–1042, 2020.

[13] C. F. Mendoza, S. Schwarz, and M. Rupp, "User-centric clustering in cell-free mimo networks using deep reinforcement learning," in *ICC 2023-IEEE International Conference on Communications*. IEEE, 2023, pp. 1036–1041.

[14] F. D. Tilahun, A. T. Abebe, and C. G. Kang, "Drl-based distributed resource allocation for edge computing in cell-free massive mimo network," in *GLOBECOM 2022-2022 IEEE Global Communications Conference*. IEEE, 2022, pp. 3845–3850.

[15] M. Samir, D. Ebrahimi, C. Assi, S. Sharafeddine, and A. Ghrayeb, "Leveraging uavs for coverage in cell-free vehicular networks: A deep reinforcement learning approach," *IEEE Transactions on Mobile Computing*, vol. 20, no. 9, pp. 2835–2847, 2020.

[16] F. D. Tilahun, A. T. Abebe, and C. G. Kang, "Multi-agent reinforcement learning for distributed resource allocation in cell-free massive mimo-enabled mobile edge computing network," *IEEE Transactions on Vehicular Technology*, 2023.