머신러닝 기반 셀룰라 임의접속 연구 동향

Ashleigh T. Manjoro[1], 이영묵 [1], 박천음 [1], 방인규[*2], 김태훈[*1]
[1]국립한밭대학교 컴퓨터공학과, [2]국립한밭대학교 지능미디어공학과

Research Trends of Machine Learning based Cellular Random Access

Ashleigh T. Manjoro[1], YeongMuk Lee[1], Cheoneum Park[1], Inkyu Bang[*2], Taehoon Kim[*1]
[1]Dept. of Computer Engineering, Hanbat National University
[2]Dept. of Intelligence Media Engineering, Hanbat National University
{ashleighmanjoro, 20191746}@edu.hanbat.ac.kr, {parkce, ikbang, thkim}@hanbat.ac.kr

Abstract

The nature and number of devices that access cellular networks have increased exponentially over the years, challenging the conventional random-access procedure (RAP). To support these diverse devices, the application of machine learning (ML) to the RAP has improved its efficiency, reliability, robustness, and effectiveness. Various models and algorithms have been proposed to handle preamble collision, resource allocation, and manage backoff of devices reducing latency and signaling overhead.

Ⅰ. Introduction

Several ML-enabled enhancements demonstrate improvements in the conventional 4-step RAP and 2-step RAP. Developments in machine-machine communication aided the need for a more robust RAP for the diverse use cases and requirements. In 5G and beyond, managing low latency in a high-traffic environment is the pursuit of cellular networks. This study seeks to reveal the application of ML techniques such as supervised learning, deep learning (DL), and Reinforcement Learning (RL) in RAP and how they have improved the procedure.

Ⅱ. Machine Learning Techniques in Cellular Random Access

The conventional RAP can't entirely fulfill the diverse requirements of numerous devices, from cellular devices to IoT, machine-type communication (MTC) devices, and satellites.

* Corresponding Authors: Inkyu Bang and Taehoon Kim

This abrupt increase in devices continue to outweigh the fixed resources at the base station (BS) causing network congestion due to the RAP overload. Supervised learning facilitates training of the system using an available dataset. Magrin et al. proposed a ML-based model for preamble detection and calculating the collision multiplicity on devices that selected the same preamble in LTE [1]. Jang *et al.* proposed a DL-based RAP framework that can detect and resolve preamble collision [2].Preamble collision detection occurs at step 3 and affected devices are to re-transmit the preamble using various backoff algorithms. Back-off algorithms ensure devices wait for a set time before re-transmitting a preamble after a collision. Jadoon *et al.* proposed a deep reinforcement learning (DRL) based RAP transmission policy that adapts to different traffic arrival rates [3]. Reinforcement learning enables the system to learn through trial and error by getting a reward for a valuable action and a penalty for a wrong action. da Silva et al. proposed an algorithm to dynamically allocate RAP slots to MTC devices using Non-Orthogonal Multiple Access (NOMA) and Q-learning [4]. Neural networks resemble the function of the human brain, they can learn from experiences or previous actions or steps. Almahjoub and Qiu proposed deep neural networks (DNN) that predict devices likely to have successful transmission by considering channel conditions as input [5]. Swain and Subudhi proposed using Deep Learning to improve 5G NR 2-step RAP using Recurrent Neural Networks (RNN) and Long Short-term Memory (LSTM) to predict UE that will participate in RAP within a timeslot [6]. 5G New Radio (NR) has low latency tolerance which makes 2-step RAP better compared to 4-step RAP but there's no time alignment (TA) between the device and BS. Kim et al proposed using a deep neural network model to determine the TA value [7].

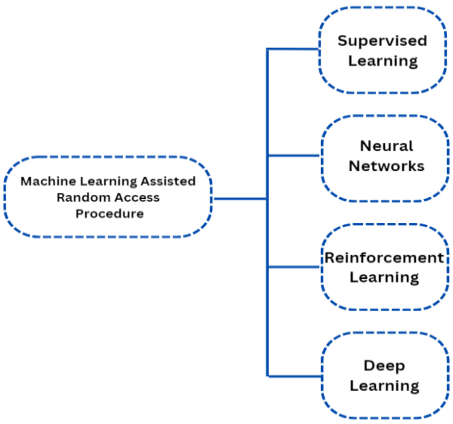

Fig 1. ML-assisted RAP

Ⅲ. Conclusion

The advances in cellular networks require agile RAP models that quickly adapt to the dynamic environment. Various ML models and algorithms continue to improve the RAP, and network performance, reduce collision and improve user experience. RL continues to inspire most research since the devices and BS learn from interacting with the environment. While much research focuses on the 4-step RAP, we will apply machine learning to enhance the performance of the 2-step RAP.

ACKNOWLEDGMENT

"This research was supported by the MSIT(Ministry of Science, ICT), Korea, under the National Program for Excellence in SW), supervised by the IITP(Institute of Information & communications Technology Planning & Evaluation) in 2024"(2022-0-01068)

REFERENCES

[1] D. Magrin *et al.* "Enabling LTE RACH collision multiplicity detection via machine learning." 2019 International Symposium on Modeling and Optimization in Mobile, Ad Hoc, and Wireless Networks. IEEE, 2019.

[2] H. S. Jang, *et al.* "Deep learning-based cellular random access framework." IEEE Transactions on Wireless Communications 20.11 (2021): 7503-7518.

[3] M. A. Jadoon, *et al.* "Deep reinforcement learning for random access in machine-type communication." 2022 IEEE Wireless Communications and Networking Conference (WCNC). IEEE, 2022.

[4] MV da Silva, *et al.* "A NOMA-based Q-learning random access method for machine type communications." IEEE Wireless Communications Letters 9.10 (2020): 1720-1724.

[5] A. Almahjoub and D. Qiu. "A Grant-Free Random Access Process for Low-End Distribution System Using Deep Neural Network," Applied Sciences 12.14 (2022): 7070.

[6] S. N. Swain and A. Subudhi, "On employing deep learning to enhance the performance of 5G NR two step RACH procedure." 2023 Joint European Conference on Networks and Communications & 6G Summit (EuCNC/6G Summit). IEEE, 2023.

[7] J. Kim, *et al.* "Two-step random access for 5G system: Latest trends and challenges." IEEE Network 35.1 (2020): 273-279.