Reinforcement Learning based Adaptive Access Class Barring for Cellular Networks

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***Abstract*—The Access Class Barring (ACB) mechanism enhances network performance by selectively allowing certain devices to access the network while barring others. In this paper, we investigate a Deep Q-Network (DQN) model that dynamically adjusts the ACB factor set by the base station based on network conditions to ensure robust performance.**

***Index Terms*—Cellular Networks, Two-Step Random Access, Reinforcement Learning, Access Class Barring**

I. Introduction

Cellular networks continue to evolve sustaining an expansive range of devices, applications, and services prompting for efficient algorithms. Optimizing performance and managing network traffic is crucial for creating robust networks that adapt to changes and efficiently manage resources. When the number of devices requesting network access simultaneously exceeds the available resources, it leads to increased collisions, access delays, and a decline in Quality of Service [1]. The current conditions and available resources determine the number of devices that can access the network with minimal collisions. The Access Control Barring (ACB) technique uses a static barring factor [2], which negatively impacts network performance in dynamic environments by increasing collisions and lowering the likelihood of successful access [3].

In this paper, we investigate a Deep Q-Network (DQN) model that dynamically adjusts the ACB factor set by the base station based on network conditions to ensure robust performance.

II. ACB Factor Optimization with RL

Given the dynamic nature of network traffic, we applied RL to determine the optimal ACB factor that avoids excessive or insufficient traffic barring. The RL model's states include the number of devices, available preambles, and a randomly set ACB factor, which the agent takes as observations. The environment provides feedback on the number of devices that can optimally access the network and those completing the random access procedure on the first attempt. The agent is rewarded for selecting an ACB factor that minimizes collisions and penalized for causing more collisions. The adaptive ACB factor adjusts as traffic increase of decrease. In Fig 1. the reward converges with more training, performance of 1,000 episodes is better than 100 episode in training the data. As the model gets better at setting the optimal ACB factor, the reward increases.

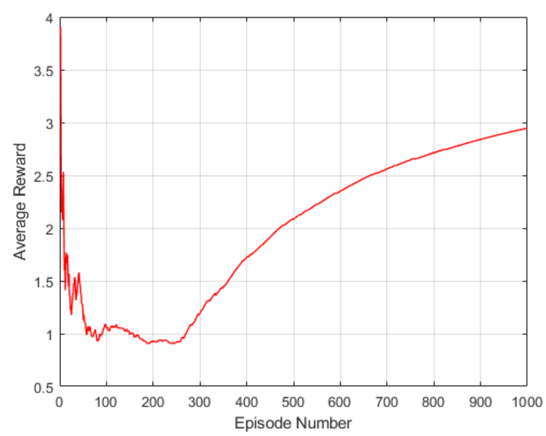

Fig. 1. Reward graph for RL model

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References

[1] J. Park and Y. Lim, "Adaptive Access Class Barring Method for Machine Generated Communications," Mobile Information Systems, 2016 (1): 6923542

[2] 3GPP, TS 22.011, V13.1.0, Service Accessibility, Sep 2017

[3] L. Tello-Oquendo, J. Vidal, V. Pla, L. Guijjaro " Dynamic access class barring parameter tuning in LTE-A networks with massive M2M traffic", In 2018 17th annual mediterranean ad hoc networking workshop (Med-Hoc-Net) (pp. 1-8). IEEE.

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