

# Benchmarking Multi-agent Reinforcement Learning-based Access Control using Real-world IoT Traffic

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## I. INTRODUCTION

In recent years, the proliferation of Internet of Things (IoT) devices and applications has given rise to massive Machine-Type Communication (mMTC), a critical domain within next-generation wireless communication. mMTC is characterized by a massive number of low-power devices generating data sporadically, posing a formidable challenge in efficiently allocating the limited physical wireless channel resources among them. Conventional centralized allocation methods prove infeasible in mMTC scenarios due to the overwhelming volume of control messages relative to the actual data transmissions required by mMTC devices. To address this challenge, there has been a notable upsurge in research endeavors dedicated to enhancing fully distributed channel access protocols for mMTC, leveraging the power of cooperative multi-agent reinforcement learning. However, an existing research gap becomes evident when we observe that prior studies predominantly tested their algorithms under conditions of either saturated traffic or simulated traffic models. This limited scope fails to accurately capture the dynamics of real-world mMTC networks. In this study, we bridge this gap by utilizing real-world IoT traffic data from a network operator in Vietnam.

## II. SYSTEM MODEL

We adopt the multiple-access problem formulation from Polyanskiy et al. (2017) [1], commonly referred to as un-sourced multiple access (UMA), where users share a common codebook and the receiver decodes messages up to a permutation. Specifically, we consider a slotted-time multiple access network with a total of  $K_{\text{tot}}$  ( $\approx 1$  million) IoT devices participating. In each time slot, a few devices ( $K_a$  less than 1,000) send data to the base station (BS). Assume that each device only have one packet in the buffer, and new packet preempt the stale packet. Let  $x_i \in \mathbb{C}^n$  be the signal from device  $i$  over  $n$  available wireless resource units. The BS receives  $y = \sum_{i=1}^{K_a} x_i + z$ , where  $z$  is Gaussian noise. The BS decodes  $y$  to a permutation of the messages  $x_i$ . Following [2], with the current  $K_a$  and UMA codebook configuration, we obtain achievability bounds on the minimum probability of BS misdetecting messages  $\epsilon_{MD}$  and probability of false alarm

$\epsilon_{FA}$ . To ensure reliable delivery to the BS, mMTC devices can resend messages until the probability of misdetecting multiple resent messages is negligible (i.e., less than  $10^{-5}$ ).

## III. PROBLEM FORMULATION

Let the action of device  $i$  at time slot  $t$  among  $T$  slots be  $a_i(t)$ . In each slot, devices choose either (1) to wait or (2) to transmit the uplink packet. Each packet can be sent up to  $r$  times until the joint probability of all  $r$  copies being misdetected by the BS is negligible. The channel access strategies aim to cooperatively minimize the maximum delay:

$$\min_{a_i(t)} \max_{i,t} d_i(t) \quad (1)$$

for all  $i \in [K_a]$  and  $\forall t \in [T]$ . If all devices aggressively send packets in congested channels,  $K_a$  increases, leading to higher  $\epsilon_{MD}$  and eventually requiring more transmissions. However, if devices wait too long, their delay  $d_i(t) \forall i \in [K_a]$  becomes large. Thus, devices need to intelligently trade-off between waiting and transmitting to jointly minimize the maximum delay.

## IV. EXPERIMENTAL STUDY

### A. Experimental Setup

This study addresses a gap by using real-world IoT traffic data from a central Vietnamese network operator [3]. The data include 24-hour timestamps for packets generated by IoT devices, spanning applications like industrial and environmental sensors.

### B. Channel Access Strategies for Benchmarking

We perform a comparative analysis on channel access delay and fairness, evaluating four distributed and dynamic strategies: (1) classical multi-channel ALOHA, (2) a heuristic enhancement of multi-channel ALOHA to improve fairness, and (3) the centralized training decentralized execution multi-agent deep reinforcement learning (MADRL) algorithms adapted from [4]. This research aims to provide insights into the practicality and effectiveness of these strategies in addressing challenges unique to mMTC scenarios in real-world wireless communication environments.

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