Multichannel Random Access Optimization Via Evolutionary Algorithm

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***Abstract*—Recently, researchers have applied multi-agent deep reinforcement learning to improve throughput of multichannel random access systems. However, optimizing hyperparameters of deep neural networks (DNNs) remains challenging. This paper proposes utilizing evolutionary computation to optimize such hyperparameters. Numerical results show that the proposed optimization method improves the convergence speed of DNNs compared to the existing manual tuning methods.**

***Index Terms*—Random access, hyperparameter optimization, genetic algorithm, deep learning, reinforcement learning.**

I. Introduction

To support massive connectivity to various Internet of Things (IoT) devices with limited wireless resource, multichannel random access systems have been actively investigated [1], [2]. Recently, multi-agent deep reinforcement learning (DRL) techniques have been proposed to enhance throughput of such systems [3], [4]. However, optimizing hyperparameters for deep neural networks (DNNs) is quite challenging and complicated. In this paper, we utilize an evolutionary algorithm (EC) to automate the configuration of DNNs by optimizing their hyperparameters for multi-channel random access systems.

II. System model

We investigate a multichannel random access system consisting of N users and a single access point (AP). We assume a time-slotted system and each user sends its packets through one of K distinct orthogonal resource blocks (RBs) in each time slot. For each user $n \in [1:N]$, let $\eta_n(t) \in [0:K]$ be the binary decision variable representing the RB selected by user n at time slot t. Here $\eta_n(t) = 0$ signifies that no RB is chosen for transmission at time slot t. If $\sum_{i=1}^{N} \mathbb{1}\big((\eta_i(t) = k) = 1\big)$, a successful transmission occurs for RB k at time slot t. Otherwise, no transmission or collision occurs.

At the end of each time slot t, the AP broadcasts acknowledgment (ACK) or negative acknowledgment (NAK) information of all RBs to the users. Let $\delta^{[k]}(t)$ denotes the feedback message for RB k at time slot t, which is set as

$$\delta^{[k]}(t) = \begin{cases} \text{ACK, if } \sum_{i=1}^{N} \mathbb{1}\big((\eta_i(t) = k) = 1\big), \\ \text{NAK, otherwise.} \end{cases} \tag{1}$$

III. Numerical Evaluation

In order to evaluate the schemes, we compare the throughput obtained from the DRL agent's manually optimized DQN and EC-optimized DQN. The DQN architecture utilized in our algorithm is a fully connected feed-forward neural network.

Fig. 1 (a) and (b) show the evolution of the throughput over time slots for both the manually optimized DQN and the EC-optimized DQN. From the figures, we can observe that the EC-optimized DQN achieves faster convergence compared to the manually optimized DQN.

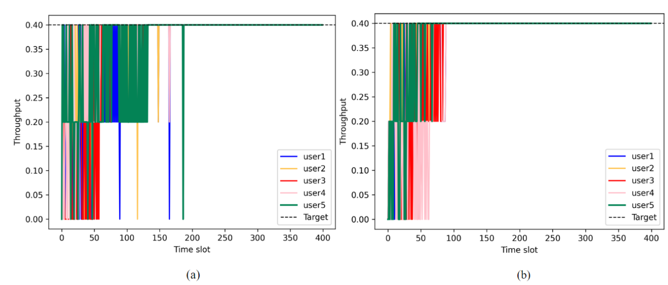

Fig. 1: Throughput obtained by the manually optimized DQN (a) and the EC-optimized DQN (b).

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