Deep Multi-User Reinforcement Learning for Distributed Dynamic Spectrum Access

Oshri Naparstek and Kobi Cohen

Abstract

We consider the problem of dynamic spectrum access for network utility maximization in multichannel wireless networks. The shared bandwidth is divided into K orthogonal channels. In the beginning of each time slot, each user selects a channel and transmits a packet with a certain attempt probability. After each time slot, each user that has transmitted a packet receives a local observation indicating whether its packet was successfully delivered or not (i.e., ACK signal). The objective is a multi-user strategy for accessing the spectrum that maximizes a certain network utility in a distributed manner without online coordination or message exchanges between users. Obtaining an optimal solution for the spectrum access problem is computationally expensive in general due to the large state space and partial observability of the states. To tackle this problem, we develop a novel distributed dynamic spectrum access algorithm based on deep multi-user reinforcement leaning. Specifically, at each time slot, each user maps its current state to spectrum access actions based on a trained deep-Q network used to maximize the objective function. Game theoretic analysis of the system dynamic is developed for establishing design principles for the implementation of the algorithm. Experimental results demonstrate strong performance of the algorithm.

Index Terms**—** Wireless networks, dynamic spectrum access, medium access control (MAC) protocols, multi-agent learning, deep reinforcement learning.

I. Introduction

The increasing demand for wireless communication, along with spectrum scarcity, have triggered the development of efficient dynamic spectrum access (DSA) schemes for emerging

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wireless network technologies. A good overview of the various DSA models for medium access control (MAC) design can be found in [2]. In this paper we focus on DSA in the open sharing model among users that acts as the basis for enabling a large number of users to access and share the same limited frequency band. We consider a wireless network with N users sharing K orthogonal channels (e.g., OFDMA). In the beginning of each time slot, each user selects a channel and transmits its data with a certain attempt probability (i.e., Aloha-type narrowband transmission). After each time slot, each user that has transmitted a packet receives a local binary observation indicating whether its packet was successfully delivered or not (i.e., ACK signal). The goal of the users is to maximize a certain network utility in a distributed manner without online coordination or exchanging messages used for managing the spectrum access.

A. Learning Algorithms for Dynamic Spectrum Access

Developing distributed optimization and learning algorithms for managing efficient spectrum access among users has attracted much attention in past and recent years (see Section I-D for a detailed discussion on related work). Complete information about the network state is typically not available online for the users, which makes the computation of optimal policies intractable in general [3]. While optimal structured solutions have been developed for some special cases (e.g., [4]–[6] and references therein), most of the existing studies have been focused on designing spectrum access protocols for specific models so that efficient (though not optimal) and structured solutions can be obtained. However, model-dependent solutions cannot be effectively adapted in general for handling more complex real-world models. Model-free Q-learning has been used in [7] for Aloha-based protocol in cognitive radio networks. Handling large state space and partial observability, however, becomes inefficient under Q-learning (see Section II-A for details on Q-learning).

B. Deep Multi-User Reinforcement Learning for Dynamic Spectrum Access

Our goal is to develop a distributed learning algorithm for dynamic spectrum access that can effectively adapt for general complex real-world settings, while overcoming the expensive computational requirements due to the large state space and partial observability of the problem. We adopt a deep multi-user reinforcement learning approach to achieve this goal.

Deep reinforcement learning (DRL) (or deep Q-learning) has attracted much attention in recent years due to its capability to provide a good approximation of the objective value (referred to as Q-value) while dealing with a very large state and action spaces. In contrast to Q-learning methods that perform well for small-size models but perform poorly for large-scale models, DRL combines deep neural network with Q-learning, referred to as Deep Q-Network (DQN), for overcoming this issue. The DQN is used to map from states to actions in large-scale models so as to maximize the Q-value (for more details on DRL and related work see Sections I-D and II-A). In DeepMind's recently published Nature paper [8], a DRL algorithm has been developed to teach computers how to play Atari games directly from the on-screen pixels, and strong performance has been demonstrated in many tested games. In [9], the authors developed DRL algorithms for teaching multiple players how to communicate so as to maximize a shared utility. Strong performance has been demonstrated for several players in MNIST games and the switch riddle. In recent years, there is a growing attention on using DRL methods for other various fields. A survey on very recent studies can be found in [10].

Due to the large state space and the partially observed nature of spectral region management among wireless connected devices, we postulate that incorporating DRL methods in the design of DSA algorithms has a great potential for providing effective solutions to real-world complex spectrum access settings, which motivates the research in this paper.

C. Main Results

Using DRL methods in the design of spectrum access protocols is a new research direction, motivated by recent developments of DRL in various other fields, and very little has been done in this direction so far (for details see I-D). In Section III, we develop a novel deep multi-user reinforcement learning-based algorithm that allows each user to adaptively adjust its transmission parameters (i.e., which channel to access, and which attempt probability to use) with the goal of maximizing a certain network utility. The algorithm can effectively adapt to topology changes, different objectives, and different finite time-horizons (in which solving dynamic programming is intractable). The algorithm is executed without online coordination or message exchanges between users used for managing the spectrum access. The proposed algorithm works as follows. While offline, we train the multi-user DQN at a central unit for maximizing the objective function. Since the network state is partially observable for each user, and the dynamic is non-Markovian and determined by the multi-user actions, we use Long Short Term Memory (LSTM) layer that maintains an internal state and aggregate observations over time. This gives the network the ability to estimate the true state using the past partial observations. Furthermore, we incorporate the dueling DQN method used to improve the estimated Q-value due to the occurrence of bad states regardless of the taken action [11]. Note that the experience replay method, suggested in [12], [8] for handling a single-agent learning from past observations, is undesirable when handling a multi-user learning for DSA due to interactions among users. Hence, instead of using experience replay, we collect M episodes at each iteration and create target values for all the episodes used for multi-user learning.

After completion of the training phase, the users only need to update their DQN weights by communicating with the central unit. In real-time, at each time slot, each user maps its local observation to spectrum access actions (i.e., which channel to select next and which attempt probability to set) based on the trained DQN. The design of the DQN enables each user to learn a good policy in online and fully distributed manners, while dealing with the large state space without online coordination or message exchanges between users. A detailed description of the algorithm is provided in Section III.

Note that the proposed algorithm is very simple for implementation using simple software defined radios (SDRs). The expensive computations at the training phase is done offline by a centralized powerful unit (e.g., cloud, or network edge located with wireless access point as in mobile edge computing (MEC) setting). Since an extensive training over many experiences with dynamic environment and topology changes can be done offline, then updating the DQN is rarely required (e.g., once per weeks, months, only when the environment characteristics have been significantly changed and no longer reflects the training experiences).

Training the DQN with different objective functions might lead to significantly different operating points of the system. Therefore, in Section IV we analyze the system dynamic from a game-theoretic perspective for establishing design principles for the implementation of the proposed algorithm. We investigate both non-cooperative and cooperative utilities of the system. For a non-cooperative utility, we show that distributed training leads to inefficient subgame perfect equilibriums (which extend the concept of Nash equilibrium for dynamic games). Thus, we develop a mechanism that restricts the strategy space for all users when training the DQN, referred to as common training, so that it avoids convergence to those inefficient operating points (see Section IV for details). For a cooperative utility, we show that the Pareto optimal operating points are stable (in terms of Nash equlibrium), where the specific resource sharing among users depends on the parameter setting of the objective function.

Finally, in Section V we performed extensive numerical experiments for demonstrating the capability of the proposed algorithm to effectively adapt to different problem settings. Under both cooperative and non-cooperative network utilities, we observed that users effectively learn in online and fully distributed manners only from their ACK signals how to access the channel so as to increase the channel throughput by reducing the number of idle time slots (i.e., when no user transmits) and collisions (i.e., when two or more users transmit). Specifically, the proposed algorithm achieves up to twice the channel throughput as compared to slotted-Aloha with optimal attempt probabilities (which requires complete knowledge about the number of users). Second, in terms of rate allocation among users, we observed that users can learn (again, only from their ACK signals) effective policies depending on the objective network utility. When the network utility is the user sum rate we observed that in about 80% of the Mont-Carlo experiments some users are willing to get zero rate (to reduce interferences to other users) in order to increase the network utility. On the other hand, when the network utility is competitive in the sense that each user aims to maximize its own rate, we observed that in about 80% of the Mont-Carlo experiments users converge to a Pareto-optimal sharing policy under a competitive setting. This result presents a tremendous improvement as compared to the Nash equilibrium points of competitive Aloha games which are highly inefficient [13]. Then, we tested the algorithm using a proportional fairness criterion (i.e., the objective function is the sum log-rate). Interestingly, we observed that the algorithm tends to share the spectrum equally among users, which is Pareto optimal under this objective function (with a somewhat inferior channel throughput, however, due to losses during the learning process). The observed operating points support the analysis provided in Section IV.

D. Related work

Developing DRL-based methods for solving DSA problems is a new research direction, motivated by recent developments of DRL in various other fields, and few works have been done in this direction recently. We discuss next the very recent studies on this topic which are relevant to the problem considered in this paper. In [14], the authors have developed a spectrum sensing policy based on DRL for a single user who interacts with an external environment. The multi-user setting considered here, however, is fundamentally different in environment dynamics, network utility, and algorithm design. In [15], the authors studied a non-cooperative spectrum access problem in a different setting, in which multiple agents (i.e., base-stations in their model) compete for channels and aim at predicting the future system state using LSTM layer with REINFORCE algorithm. The neural network is trained at each agent. The problem formulation in [15] is non-cooperative in the sense that each agent aims at maximizing its own utility, while using the predicted state to reach a certain fair equilibrium point. Our algorithm and problem setting are fundamentally different. First, our algorithm uses LSTM with DQN which is different from the algorithm in [15]. Second, in our algorithm, the DQN is trained for all users at a single unit (e.g., cloud), which is more suitable to various cognitive radio networks and Internet of Things (IoT)-based applications, in which cheap SDRs only need to rarely update their DQN weights by communicating with the central unit. Third, we are interested in both cooperative and non-cooperative settings, where fundamentally different operating points are reached depending on the network utility function. Furthermore, in [15] the focus is on matching channels to BSs, where in our setting we focus on sharing the limited spectrum by a large number of users (i.e., matching might be infeasible).

Other related works on learning algorithms for DSA have been mainly focused on model-dependent settings or myopic objectives so that tractable and structured solutions can be obtained. The problem has been widely studied under multi-armed bandit (and variants) formulations, in which the channels are represented as arms that the user aims to explore to receive a high reward (e.g., rate). A main goal in these problems is to find a balance between exploration (i.e., searching for better channels) and exploitation (i.e., selecting the best channels based on the current knowledge). Related works can be found in [4]–[6], [16] (and references therein) under the Bayesian setting and in [17]–[19] (and references therein) under the non-Bayesian settings. Another set of related work on the multi-user case has been studied from game theoretic and congestion control ([20]–[28] and references therein), matching theory ([29]–[33] and references therein), and graph coloring ([34]–[37] and references therein) perspectives. Game theoretic aspects of the problem have been investigated from both non-cooperative (i.e., each user aims at maximizing an individual utility) [21], [22], [26], [27], and cooperative (i.e., each user aims at maximizing a system-wide global utility) [20], [28], [38] settings. Matching algorithms have been focused on allocating channels to users so that a certain utility is maximized (e.g., user sum rate) [29], [30], [32]. Graph coloring formulations are concerned with modeling the spectrum access problem as a graph coloring problem, in which users and channels are represented by vertices and colors, respectively. Thus, coloring vertices such that two adjacent vertices do not share the same color is equivalent to allocating channels such that interference between neighbors is being avoided (see [34]–[37] and references therein for related works). However, the problem considered in this paper is fundamentally different since the number of users might be much larger than the number of channels (thus, coloring the graph might be infeasible). Furthermore, the control aspect in our problem (by updating the transmission parameters) is absent in the graph coloring formulation. Finally, all these studies mainly focus on model and objective-dependent problem settings, and often require more involved implementations (e.g., carrier sensing, wideband monitoring), which make them fundamentally different from the problem setting considered in this paper.

E. Organization

In Section II, we describe the network model and problem statement. A background on Q-learning and DRL is also provided. In Section III we develop the proposed algorithm, referred to as Deep Q-learning for Spectrum Access (DQSA), that uses a deep reinforcement learning approach in the design of the multi-user dynamic spectrum access. In Section IV, we establish game theoretic analysis of the operating points of the system and develop design principles for the setting of DQSA algorithm. In section V, we provide experimental results that present very good performance of the algorithm under various problem settings and support the analysis in Section IV. Section VI concludes the paper.

II. Network Model and Problem Statement

We consider a wireless network consisting of a set $\mathcal{N} = \{1, 2, ..., N\}$ of users and a set $\mathcal{K} = \{1, 2, ..., K\}$ of shared orthogonal channels (i.e., subbands). The users transmit over the shared channels using a random access protocol. At each time slot, each user is allowed to choose a single channel for transmission with a certain attempt probability (i.e., Aloha-type narrowband transmission). We assume that users are backlogged, i.e., all users always have packets to transmit. Transmission on channel k is successful if only a single user transmits over channel k in a given time slot. After each time slot (say t), in which each user (say n) has attempted to transmit a packet, it receives a binary observation $o_n(t)$, indicating whether its packet was successfully delivered or not (i.e., ACK signal). If the packet has been successfully delivered, then $o_n(t) = 1$. Otherwise, if the transmission has failed (i.e., a collision occurred), then $o_n(t) = 0$.

Let

$$a_n(t) \in \{0, 1, ..., K\} \tag{1}$$

be the action of user n at time slot t, where $a_n(t) = 0$ refers to the case in which user n chooses not to transmit a packet at time slot t (to reduce the congestion level for instance), and $a_n(t) = k$, where $1 \leq k \leq K$, refers to the case in which user n chooses to transmit a packet on channel k at time slot t. We define

$$a_{-n}(t) = \{a_i(t)\}_{i \neq n} \tag{2}$$

as the action profile for all users except user n at time slot t. We consider a distributed setting without online coordination or message exchanges between users used to managing the spectrum access. As a result, the network state at time t (i.e., $a_{-n}(t)$) is only partially observed by user n through the local signal $o_n(t)$. The history $\mathcal{H}_n(t)$ of user n at time t is defined by the set of all actions and observations up to time t:

$$\mathcal{H}_n(t) = \left(\{a_n(i)\}_{i=1}^{t}, \{o_n(i)\}_{i=1}^{t}\right). \tag{3}$$

Definition 1: A strategy $\sigma_n(t)$ of user n at time t is a mapping from history $\mathcal{H}_n(t-1)$ to a probability mass function over actions $\{0, 1, ..., K\}$. The time series vector of strategies (or *policy*) for user n is denoted by $\boldsymbol{\sigma}_n = (\sigma_n(t), t = 1, 2, ...)$. A strategy profile of all users except user n is denoted by $\boldsymbol{\sigma}_{-n} = \{\boldsymbol{\sigma}_i\}_{i \neq n}$. A strategy profile of all users is denoted by $\boldsymbol{\sigma} = \{\boldsymbol{\sigma}_i\}_{i=1}^{n}$.

For convenience, we often write strategy $\sigma_n(t)$ as a $1 \times K$ raw vector:

$$\sigma_n(t) = \left(p_{n,0}(t), p_{n,1}(t), ..., p_{n,K}(t)\right), \tag{4}$$

where

$$p_{n,k}(t) = \Pr\left(a_n(t) = k\right), \tag{5}$$

is the probability that user n takes action $a_n(t) = k$ at time t.

Let $r_n(t)$ be a reward that user n obtains at the beginning of time slot t. The reward depends on user n's action $a_n(t-1)$ and other users' actions $a_{-n}(t-1)$ (i.e., the unknown network stat that user n aims to learn). Let

$$R_n = \sum_{t=1}^{T} \gamma^{t-1} r_n(t) \tag{6}$$

be the accumulated discounted reward, where $0 \leq \gamma \leq 1$ is a discounted factor, and T is the time-horizon of the game. We often set $\gamma = 1$, or $\gamma < 1$ when T is bounded or unbounded, respectively. The objective of each user (say n) is to find a strategy $\boldsymbol{\sigma}_n$ that maximizes its expected accumulated discounted reward:

$$\max_{\boldsymbol{\sigma}_n} \quad \mathbf{E}\left[R_n(\boldsymbol{\sigma}_n, \boldsymbol{\sigma}_{-n})\right], \tag{7}$$

where $\mathbf{E}\left[R_n(\boldsymbol{\sigma}_n, \boldsymbol{\sigma}_{-n})\right]$ denotes the expected accumulated discounted reward when user n performs strategy $\boldsymbol{\sigma}_n$ and the rest of the users perform strategy profile $\boldsymbol{\sigma}_{-n}$.

We are interested in developing a model-free distributed learning algorithm to solve (7) that can effectively adapt to topology changes, different objectives, different finite time-horizons (in which solving dynamic programming becomes very challenging, or often impossible for large T), etc. Computing optimal solution, however, is a combinatorial optimization problem with partial state observations which is mathematically intractable as the network size increases [3]. Thus, we apply deep reinforcement learning approach due to its capability to provide good approximate solutions while dealing with a very large state and action spaces. In the next section we first describe the basic idea of Q-learning and deep reinforcement learning. We then develop the proposed algorithm that uses a deep reinforcement learning approach for DSA design in Section III.

A. Background on Q-learning and Deep Reinforcement Learning (DRL)

Q-learning is a reinforcement learning method that aims at finding good policies for dynamic programming problems. It has been widely applied in various decision making problems, primarily because its ability to evaluate the expected utility among available actions without requiring prior knowledge about the system model, and its ability to adapt when stochastic transitions occur [39]. The algorithm was originally designed for a single agent who interacts with a fully observable Markovian environment (in which convergence to the optimal solution is guaranteed under some regularity conditions in this case). It has been widely applied for more involved settings as well (e.g., multi-agent, non-Markovian environment) and demonstrated strong performance, although convergence to optimal solution is open in general under these settings. Assume first that the network state $s_n(t) = a_{-n}(t)$ is fully observable by user n. By applying Q-learning to our setting, the algorithm updates a Q-value at each time t for each action-state pair as follows:

$$\begin{aligned} Q\left(s_n(t), a_n(t)\right) \leftarrow\; & Q\left(s_n(t), a_n(t)\right) \\ & +\alpha \Big[r_n(t+1) + \gamma \max_{a_n(t+1)} Q\left(s_n(t+1), a_n(t+1)\right) \\ & \qquad\qquad - Q\left(s_n(t), a_n(t)\right) \Big], \end{aligned} \tag{8}$$

where

$$r_n(t+1) + \gamma \max_{a_n(t+1)} Q\left(s_n(t+1), a_n(t+1)\right) \tag{9}$$

is the learned value obtained by getting reward $r_n(t+1)$ after taking action $a_n(t)$ in state $s_n(t)$, moving to next state $s_n(t+1)$, and then taking action $a_n(t+1)$ that maximizes the future Q-value seen at time $t+1$. The term $Q\left(s_n(t), a_n(t)\right)$ is the old learned value. Thus, the algorithm aims at minimizing the Time Difference (TD) error between the learned value and the current estimate value. The learning rate α is set to $0 \leq \alpha \leq 1$, where typically is set close to zero. When the problem is partially observable, the state is set to the history, i.e., $s_n(t) = \mathcal{H}_n(t)$ in our case (or a sliding window history when the problem size is too large). While Q-learning performs well when dealing with small action and state spaces, it becomes impractical when the problem size increases for mainly two reasons: (i) A stored lookup table of Q-values for all possible state-action pairs is required which makes the storage complexity intolerable for large-scale problems; (ii) As the state space increases, many states are rarely visited, which significantly decreases performance.

In recent years, a great potential was demonstrated by DRL methods that combine deep neural network with Q-learning, referred to as Deep Q-Network (DQN), for overcoming these issues. Using DQN, the deep neural network maps from the (partially) observed state to an action, instead of storing a lookup table of Q-values. Furthermore, large-scale models can be represented well by the deep neural network so that the algorithm has the ability to preserve good performance for very large-scale models. Although convergence to optimal solution of DRL is an open question (even for a single agent), great improvements have been demonstrated by training DQN for learning algorithms in various fields that significantly overcome existing methods. A well known single-player DRL-based algorithm has been developed in DeepMind's recently published Nature paper [8], for teaching computers how to play Atari games directly from the on-screen pixels, in which strong performance has been demonstrated in many tested games. For other recent developments see Section I-D.

Due to the large state space and the partially observed nature of the DSA problem at hand, we aim to develop a DRL-based algorithm for solving the multi-user DSA problem in this paper. In the next section, we develop the Deep Q-learning for Spectrum Access (DQSA) algorithm that uses a DRL approach in the design of the multi-user dynamic spectrum random access.

III. The Proposed Deep Q-Learning for Spectrum Access (DQSA) Algorithm

Direct computation of the optimal channel allocation and attempt probabilities for the multi-channel spectrum access problem (7) is a combinatorial optimization problem with partial state observations which is mathematically intractable as the network size increases [3]. Furthermore, it requires online centralized computation. Iterative algorithms that approximate (7) have been mainly developed for specific problem settings, where obtaining global network utility generally requires message exchanges between users (e.g., [28]). In this section, we develop the proposed DQSA algorithm based on deep multi-user reinforcement learning, for solving (7). The DQSA algorithm applies for general large and complicated settings and does not require online coordination or message exchanges between users.

We first present in Section III-A the proposed architecture of the DQN used in the DQSA algorithm. In Section III-B we present the offline algorithm used for training the DQN, and in Section III-C we describe the online learning algorithm for the distributed random access, in which every user operates in a fully distributed manner by using the trained DQN. The specific setting of the objective function used for training the DQN depends on the desired performance as will be discussed in Section IV. Specifically, in Section IV we establish design principles for implementing DQSA based on a game theoretic analysis of the operating points of (7) under both cooperative and competitive utility functions.

A. Architecture of the Proposed Multi-User DQN Used in DQSA Algorithm

In this section, we describe the proposed architecture for the multi-user DQN used in DQSA algorithm for solving the DSA problem. An illustration of the DQN is presented in Fig. 1.

1) Input Layer: The input $\mathbf{x}_n(t)$ to the DQN is a vector of size $2K+2$. The first $K+1$ input entries indicate the action (i.e., selected channel) taken at time $t-1$. Specifically, if the user has not transmitted at time slot $t-1$, the first entry is set to 1 and the next K entries are set to 0. If the user has chosen channel k for transmission at time $t-1$ (where $1 \leq k \leq K$), then the $(k+1)^{th}$ entry is set to 1 and the rest K entries are set to 0. The following K input entries are the capacity of each channel (i.e., the packet transmission rate over a channel conditioned on the event that the channel is free, which is proportional to the bandwidth of the channel). In the experiments presented in Section V, we simulated equal channels (i.e., we set 1 at all K entries). The last input is 1 if ACK signal has been received. Otherwise, if transmission has failed or no transmission has been executed, it is set to 0.

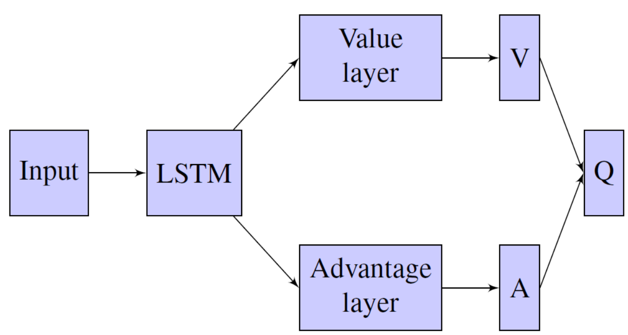

Fig. 1. An illustration of the architecture of the proposed multi-user DQN used in DQSA algorithm.

2) LSTM Layer: Since the network state is partially observable for each user, and the dynamic is non-Markovian and determined by the multi-user actions, classical DQNs do not perform well in this setting. Thus, we add an LSTM layer ([40]) to the DQN that maintains an internal state and aggregate observations over time. This gives the network the ability to estimate the true state using the history of the process. This layer is responsible of learning how to aggregate experiences over time.

3) Value and Advantage Layers: Another improvement that we incorporate is the use of dueling DQN, as suggested in [11]. The intuition behind this architecture lies in the fact that there is an observability problem in DQN. There are states which are good or bad regardless of the taken action. Hence, it is desirable to estimate the average Q-value of the state which is called the value of the state $V(s_n(t))$ independently from the advantage of each action. Thus, when we input $\mathbf{x}_n(t)$ to the DQN with dueling, the Q-value for selecting action $a_n(t)$ at time t is updated by:

$$Q(a_n(t)) \leftarrow V + A(a_n(t)) \tag{10}$$

where V is the value of the state and A is the advantage of each action. Note that both V and $A(a_n(t))$ depend on the state $s_n(t)$ (which is hidden and mapped by the DQN from the history).

4) Block output layer: The output of the DQN is a vector of size $K+1$. The first entry is the estimated Q-value if the user will choose not to transmit at time t. The $(k+1)^{th}$ entry, where $1 \leq k \leq K$, is the estimated Q-value for transmitting on channel k at time t.

5) Double Q-learning: The max operator in standard Q-learning and DQN (see (8)) uses the same values to both selecting and evaluating an action. Thus, it tends to select overestimated values which degrades performance. Hence, when training the DQN, we use double Q-learning [41] used to decouple the selection of actions from the evaluation of Q-values. Specifically, we use two neural networks, referred to as DQN$_1$ and DQN$_2$. DQN$_1$ is used for choosing actions and DQN$_2$ is used to estimate the Q-value associated with the selected action.

B. Training the DQN:

The DQN is trained for all users at a central unit in an offline manner. We train the DQN as follows:

1) Repeat:
2) In each iteration, repeat the following for M episodes to form a mini batch of M training examples:

3) In each episode, repeat the following for T time-slots:
4) In each time-slot, repeat the following for all $n \in \mathcal{N}$ users:
5) Observe an input $\mathbf{x}_n(t)$ and feed it into the neural network DQN$_1$. The neural network generates an estimation of the Q-values $Q(a)$ for all available actions $a \in \{0, 1, ..., K\}$.
6) Take action $a_n(t) \in \{0, 1, ..., K\}$ (according to (12) that will be discussed later) and obtain a reward $r_n(t+1)$.
7) Observe an input $\mathbf{x}_n(t+1)$ and feed it into both neural networks DQN$_1$ and DQN$_2$. The neural networks generate estimations of the Q-values $\widetilde{Q}_1(a)$ and $\widetilde{Q}_2(a)$, respectively, for all actions $a \in \{0, 1, ..., K\}$.
8) Form a target vector for the training by replacing the $a_n(t)$ entry by:

$$Q(a_n(t)) \leftarrow r_n(t+1) + \widetilde{Q}_2\left(\arg\max_a \left(\widetilde{Q}_1(a)\right)\right). \tag{11}$$

9) End loop for $n \in \mathcal{N}$ users (line 4).
10) End loop for T time-slots (line 3).
11) End loop for M episodes (line 2).
12) Train DQN$_1$ with inputs $\mathbf{x}$s and outputs Qs.
13) Every ℓ iterations set $Q_2 \leftarrow Q_1$.
14) End outer loop (line 1).

In our experiments, we repeated the outer loop for several thousands iterations until convergence, and ℓ was set to 5. Note that unlike [8], [12], in which experience replay is used in the single-agent case to learn from past observations, in the multi-user case considered here such learning is undesirable due to interactions among users. Hence, we collect the M episodes at each iteration and create target values for all the episodes.

C. Online Learning: Distributed Random Access using DQN:

The training phase is rarely required to be updated by the central unit (e.g., once per weeks, months, only when the environment characteristics have been significantly changed and no longer reflects the training experiences). Users' SDRs only need to update their DQN weights by communicating with the central unit. In real-time, each user (say n) makes autonomous decisions in online and distributed manners using the trained DQN, so as to learn efficient spectrum access policies from its ACK signals only:

1) At each time slot t, obtain observation $o_n(t)$ and feed input $\mathbf{x}_n(t)$ to the trained DQN$_1$. Output Q-values $Q(a)$ are generated by DQN$_1$ for all available actions $a \in \{0, 1, ..., K\}$.

2) Play strategy $\sigma_n(t)$ as follows: Draw action $a_n(t)$ according to the following distribution:

$$\Pr\left(a_n(t) = a\right) = \frac{(1-\alpha)\, e^{\beta Q(a)}}{\sum\limits_{\tilde{a}\in\{0,1,\ldots,K\}} e^{\beta Q(\tilde{a})}} + \frac{\alpha}{K+1} \qquad \forall a \in \{0, 1, ..., K\}\,, \tag{12}$$

for small $\alpha > 0$, and β is the temperature. The game is played over a time-horizon of T time slots.

IV. Analysis of the System Dynamic with Different Utility Functions

Training the DQN with different objective functions might lead to significantly different operating points of the system. Therefore, in this section we analyze the system dynamic from a game-theoretic perspective for establishing design principles for the implementation of DQSA algorithm. Since users take autonomous actions when operating the spectrum access, it is convenient to model the network dynamic from a game theoretic perspective. We investigate both non-cooperative and cooperative utilities of the system. We first define the Nash equilibrium point as a strategy profile for all users, in which there is no incentive for any user to unilaterally deviate from it. The users dynamic in this section is referred to as a multichannel random access game.

Definition 2: A Nash equilibrium (NE) for the multichannel random access game is a strategy profile $\boldsymbol{\sigma}^* = (\boldsymbol{\sigma}_n^*, \boldsymbol{\sigma}_{-n}^*)$, such that

$$R_n\left(\boldsymbol{\sigma}_n^*, \boldsymbol{\sigma}_{-n}^*\right) \geq R_n(\tilde{\boldsymbol{\sigma}}_n, \boldsymbol{\sigma}_{-n}^*)\,, \quad \forall n\,, \forall \tilde{\boldsymbol{\sigma}}_n. \tag{13}$$

A refinement of a NE is a subgame perfect equilibrium (SPE), which is a strategy profile that obeys a NE for each subgame.

Definition 3: A subgame perfect equilibrium (SPE) for the multichannel random access game is a strategy profile $\boldsymbol{\sigma}^*$, if for any history $\{\mathcal{H}_n(t-1)\}_{n=1}^N$ for all t, the induced continuation strategy at times $t, t+1, ..., T$ is a NE of the continuation game that starts at time t following history $\{\mathcal{H}_n(t-1)\}_{n=1}^N$.

NEs and SPEs describe operating points which are stable in terms of local efficiency. Specifically, no user has an incentive to unilaterally deviate from its current strategy given the current system state. However, these operating points might be highly inefficient in terms of the reward that users can obtain by cooperating. Thus, we next define efficient operating points in terms of Pareto optimality.

Definition 4: A NE $\boldsymbol{\sigma}^*$ is Pareto-optimal if no strategy profile can improve the reward of one user without decreasing the reward of at least one other user.

Next, we analyze the operating points of the system under different utility functions. We will use this analysis for establishing design principles for the setting of DQSA algorithm used to bring the system to operate in efficient operating points.

A. Competitive Reward Maximization

The first optimization problem that we investigate is concerned with the case in which each user aims at maximizing its own rate. Specifically, let $\mathbf{1}_n(t)$ be the indicator function, where $\mathbf{1}_n(t) = 1$ if user n has successfully transmitted a packet at time slot t, and $\mathbf{1}_n(t) = 0$ otherwise. Let

$$r_n(t) = \mathbf{1}_n(t-1). \tag{14}$$

As a result, by substituting (14) in (6) each user (say n) aims to maximize the total number of its own successful transmissions (i.e., *individual rate*). Next, we show that equilibrium points of competitive rate maximization are efficient when $N \leq K$, but might be highly inefficient when $N > K$.

Theorem 1: Set $r_n(t)$ as in (14). Then , the following statements hold:

1) Assume that $N \leq K$. Then, the following strategy profile is a SPE: (i) $p_{n,0}(t) = 0 \ \forall n, t$, (ii) $\sum_{k=1}^{K} p_{n,k}(t) = 1 \ \forall n, t$, and (iii) for all t, if $p_{n,k}(t) > 0$ for any k, then $p_{n',k}(t) = 0$ for $n' \neq n$.

2) Assume that $N > K$, and assign channel k_n for any user n, such that $k_n \in \{1, 2, ..., K\}$, and $\{1, 2, ..., K\} \subseteq \bigcup_{n=1}^{N} k_n$. Then, for any such assignment the following strategy profile is a SPE: (i) $p_{n,0}(t) = 0 \;\forall n, t$, (ii) $p_{n,k_n}(t) = 1 \;\forall n, t$.

Proof: We start with proving the first statement. Note that the strategy profile described in the statement avoids collisions among users by transmitting on orthogonal channels at each time slot (condition (iii)). The strategy is feasible since $N \leq K$. By conditions (i) and (ii), each user surely receives $r_n(t) = 1$ at each time slot. As a result, no user has an incentive to switch to a different channel or reduce its attempt probability since its individual rate will not increase. Since this argument holds for all t independent of the history, the strategy profile described in Statement 1 is a SPE.

Next, we prove the second statement. Since $N > K$, then there exists at least one channel $k \in \{1, ..., K\}$ which is assigned to at least two users (pigeonhole principle) under the strategy profile described in the statement. Let $\mathcal{K}_c$ be the set of all channels that are assigned to at least two users. Since $p_{n,k_n}(t) = 1 \;\forall n, t$, then:

$$R_n = 0, \text{ for all } n \text{ such that } k_n \in \mathcal{K}_c. \tag{15}$$

On the other hand,

$$R_n = \sum_{t=1}^{T} \gamma^{t-1} \text{ for all } n \text{ such that } k_n \notin \mathcal{K}_c. \tag{16}$$

Next, we show that no user has an incentive to switch to a different channel or reduce its attempt probability. Consider first user n such that $k_n \in \mathcal{K}_c$. Since $\{1, 2, ..., K\} \subseteq \bigcup_{n=1}^{N} k_n$ by the condition (i.e., every channel is assigned to at least one user), and $p_{n,k_n}(t) = 1 \;\forall n, t$, then switching to a different channel or reducing its attempt probability, still result in getting $r_n(t) = 0$ for all t. Next, consider user n such that $k_n \notin \mathcal{K}_c$. Under the current strategy profile its individual reward is maximized, and it has no incentive to deviate from it. As a result, the strategy profile described in Statement 2 is a SPE. ■

Theorem 1 implies that when $N > K$, the equilibrium points of the system might be highly inefficient. In fact, any learning dynamic among users in which users can update sequentially their attempt probability to increase their individual rate, will result in increasing the attempt probability close to 1 (since every user has an incentive to increase its rate by increasing the attempt probability as long as the channel yields a positive capacity). To avoid the situation in which users keep increasing their attempt probability to increase their rates, we develop a mechanism that restricts their strategy space when training the DQN, as described below.

Definition 5: We say that DQSA algorithm is implemented using a common training, when the Q values in the training phase (see Section III-B) are estimated under the implicit assumption that all users use the same protocol rules, i.e., $\sigma_n(t) = \sigma_{n'}(t)$ for all n, n', for all t.

The next proposition shows that implementing DQSA algorithm using a common training avoids convergence to competitive SPEs as described in Theorem 1 Statement 2. To avoid trivial solutions, it is assumed that users are allowed to transmit with probability $1-\epsilon$ for small $\epsilon > 0$ (otherwise if users always transmit with probability 1, the reward equals zero on all channels).

Proposition 1: Fix K, and assume that DQSA algorithm is implemented using a common training. Then, the probability that the algorithm will converge to competitive SPEs approaches zero as N approaches infinity.

Proof: Under any competitive SPE in Theorem 1 Statement 2 (when users are allowed to transmit with probability $1-\epsilon$ for small $\epsilon > 0$), every user transmits on a single channel with probability $1-\epsilon$ at each given time. Let $N_k(t)$ be the number of users that transmit on channel k at time t. As N approaches infinity, $N_k(t)$ approaches N/K. Otherwise, users have an incentive to switch channels. As a result, the reward for each user approaches $(1-\epsilon)\epsilon^{N/K-1}$ for all t which approaches zero exponentially fast with N. On the other hand, the reward for each user when applying a simple strategy in which every user transmits over a randomly selected channel with probability K/N approaches Ke^{-1}/N. Thus, when applying a common training the Q values increase when decreasing the transmission probabilities as N increases, which avoids convergence to competitive SPEs. ■

Proposition 1 establishes an important design principle. It implies that implementing DQSA algorithm using a common training avoids the algorithm to reach highly inefficient operating points. Next, we characterize the Pareto optimal operating points of the system when $N > K$ (i.e., when SPEs are inefficient).

Theorem 2: Assume that $N > K$ and set $r_n(t)$ as in (14). Then , the following strategy profile is Pareto optimal: for each time t, for every channel $k \in \{1, ..., K\}$ there exists a user $n_k(t)$, such that $p_{n_k(t),k}(t) = 1$ and $p_{n',k}(t) = 0$ for all $n' \neq n_k(t)$.

Proof: Let $\boldsymbol{\sigma}^*$ be the strategy profile defined by the theorem. Let $\boldsymbol{\sigma'}$ be a strategy profile in which user n gets higher reward: $R_n(\boldsymbol{\sigma'}) > R_n(\boldsymbol{\sigma}^*)$. We define the total reward for all users under any strategy profile $\boldsymbol{\sigma}$ by $S_R(\boldsymbol{\sigma}) = \sum_{n=1}^{N} R_n(\boldsymbol{\sigma})$. Since there are no collisions under $\boldsymbol{\sigma}^*$, then the total reward for all users under $\boldsymbol{\sigma}^*$ is given by:

$$S_R(\boldsymbol{\sigma}^*) = K \sum_{t=1}^{T} \gamma^{t-1}. \tag{17}$$

Next, since $S_R(\boldsymbol{\sigma}^*) \geq S_R(\boldsymbol{\sigma'})$ and $R_n(\boldsymbol{\sigma'}) > R_n(\boldsymbol{\sigma}^*)$, the total rewards for all users except user n under $\boldsymbol{\sigma}^*$, and $\boldsymbol{\sigma'}$ satisfy:

$$S_R(\boldsymbol{\sigma}^*) - R_n(\boldsymbol{\sigma}^*) > S_R(\boldsymbol{\sigma'}) - R_n(\boldsymbol{\sigma'}). \tag{18}$$

Hence, there exists a user n' that receives a smaller reward when the system switches from $\boldsymbol{\sigma}^*$ to $\boldsymbol{\sigma'}$, $R_{n'}(\boldsymbol{\sigma'}) < R_{n'}(\boldsymbol{\sigma}^*)$. Hence, $\boldsymbol{\sigma}^*$ is Pareto optimal. ■

Theorem 2 implies that any strategy profile that shares resources without collisions among users is Pareto optimal. In Section V, we implemented DQSA algorithm using a common training, and it is shown that users indeed avoid inefficient SPEs (as stated in Proposition 1). Interestingly, it is shown that the users often reach (in about 80% of the Monte-Carlo experiments) Pareto optimal strategies as characterized by Theorem 2 using only ACK signals. Although convergence of DRL to optimal strategies is an open question, the intuition for reaching Pareto optimal strategies can be explained as follows. Assume that a user has succeeded to learn well the system state from its history using the DQN (which occurs often since large-scale partially observed models can be represented well by the DQN). Since users use common training when updating their strategy, they tend to strategies that avoid collisions to increase the reward. Which one of the operating points is reached depends on the initial conditions and randomness of the algorithm.

B. *Cooperative Reward Maximization*

In this section, we investigate the case in which every user in the system aims at maximizing the same global system-wide reward. Specifically, let

$$r_n(t) = 0, \text{ for all } 1 \leq t \leq T-1, \tag{19}$$

and

$$r_n(T) = \sum_{n=1}^{N} f\left(\sum_{t=1}^{T} \mathbf{1}_n(t-1)\right). \tag{20}$$

The function $f(x)$ can be designed so as to achieve a certain network utility. We focus here on the unified system-wide α-fair utility function which is given by [42]:

$$f(x) = \frac{x^{1-\alpha}}{1-\alpha}, \tag{21}$$

for $\alpha \geq 0$.

It should be noted that various well-known system-wide utility functions are special cases of the unified α-fair utility function. For example, setting $\alpha = 0$ results in maximizing the user sum-rate (since $f(x) = x$). Setting $\alpha = 1$ results in maximizing the user sum log-rate, which is known as proportional fairness [43] (since differentiating $f(x) - Const$, where $Const = 1/(1-\alpha)$ and taking the limit as $\alpha \to 1$ yields $f(x) = \log(x)$).

Next, we characterize the operating points of the system under the cooperative utility function, which are fundamentally different from the operating points under the competitive reward setting.

Theorem 3: Set $r_n(t)$ as in (19), (20), (21). Then , the following statements hold:

1) Assume that $\alpha = 0$ in (21). Then, the following strategy profile is SPE and Pareto optimal: for each time t, for every channel $k \in \{1, ..., K\}$ there exists a user $n_k(t)$, such that $p_{n_k(t),k}(t) = 1$ and $p_{n',k}(t) = 0$ for all $n' \neq n_k(t)$.

2) Assume that $\alpha > 0$ in (21) and $KT/N \in \mathbb{N}$. Then, the following strategy profile is SPE and Pareto optimal: (i) for each time t, for every channel $k \in \{1, ..., K\}$ there exists a user $n_k(t)$, such that $p_{n_k(t),k}(t) = 1$ and $p_{n',k}(t) = 0$ for all $n' \neq n_k(t)$. (ii) Each user transmits during KT/N time slots, i.e., $\sum_{t=1}^{T} \mathbf{1}_n(t) = KT/N$ for all n.

Proof: Let $x_n \triangleq \sum_{t=1}^{T} \mathbf{1}_n(t-1)$. For proving both statements we first solve the following optimization problem:

$$\begin{aligned} \max \quad & \sum_{n=1}^{N} \gamma^{T-1} \frac{x_n^{1-\alpha}}{1-\alpha} \\ \text{s.t.} \quad & \sum_{n=1}^{N} x_n \leq KT. \end{aligned} \tag{22}$$

Note that (22) maximizes the total reward that each user can get subject to constraint on the total number of transmissions in the network, which equals KT. The Lagrangian for the problem is given by:

$$L(\mathbf{x},\lambda)=\sum_{n=1}^{N}\gamma^{T-1}\frac{x_n^{1-\alpha}}{1-\alpha}-\lambda\left(\sum_{n=1}^{N}x_n-KT\right), \tag{23}$$

for $\lambda \geq 0$. Differentiating with respect to x_n yields $x_n^{-\alpha}=\lambda$ for all n. As a result, when $\alpha > 0$, we have $x_1 = x_2 = \cdots = x_N = KT/N$. When $\alpha = 0$, we have $\sum_{n=1}^{N} x_n = KT$, so that any partition of KT among users solves (22).

Next, we prove the statements. We first prove Statement 1. Since the strategy profile defined in Statement 1 avoids collisions, then it satisfies the solution to (22) under $\alpha = 0$. Since any unilaterally deviation by a single user results in collisions, no user has an incentive to deviate at each subgame. Thus, the strategy profle is SPE. Also, we cannot increase the reward of any user by switching to another strategy profile (since it solves (22)). Thus, the strategy profle is also Pareto optimal.

Next, we prove Statement 2. Since the strategy profile defined in Statement 2 avoids collisions and also partitions the time slots equally among users, then it satisfies the solution to (22) under $\alpha > 0$. Since any unilaterally deviation by a single user results in collisions, no user has an incentive to deviate at each subgame (although the total reward at each subgame (say at the remaining time slots $t_s + 1, ..., T$) might not be optimal for the subgame since $\sum_{t=t_s+1}^{T} \mathbf{1}_n(t)$ does not necessarily equal $K(T - t_s)/N$). Thus, the strategy profle is SPE. Also, we cannot increase the reward of any user by switching to another strategy profile under the total game (played at time solts $t = 1, 2, ..., T$) since it solves (22). Hence, the strategy profile is also Pareto optimal. ■

Remark 1: Theorem 3 implies that when $\alpha = 0$, any strategy profile that avoids collisions and idle time slots is Pareto optimal and SPE. In Section V, we trained the DQN with $\alpha = 0$ (i.e., for maximizing the user sum rate). We observed that the proposed DQSA algorithm often reaches these strategies by learning from ACK signals only. Interestingly, the algorithm often converges to the simplest form of these strategies, in which the same K users always transmit, and the rest $N - K$ users do not transmit for all $t = 1, ..., T$. On the other hand, when $\alpha > 0$, Theorem 3 implies that any strategy profile that avoids collisions and idle time slots, and also equally shares the time slots among users is Pareto optimal and SPE[1]. In Section V, we trained the DQN with $\alpha = 1$ (i.e., for maximizing the user sum log-rate). We observed that the proposed DQSA algorithm often reaches these strategies as well by learning from ACK signals only. The learning process, however, is more involved since users need to learn from ACK signals only how to equally share the time slots. Thus, we observed higher losses during the learning process. Although convergence of DRL to optimal strategies is an open question, the intuition for often reaching the desired strategies can be explained as follows. Assume that a user has succeeded to learn well the system state from its history using the DQN (which occurs often since large-scale partially observed models can be represented well by the DQN). Since all users receive the same global reward, they aim at maximizing the same global function (or potential function). Thus, selecting actions with high temperature in (12) converges to an operating point that maximizes the reward, resulting in Pareto optimal strategies according to Theorem 3.

Remark 2: For purposes of analysis in this section, we focused on well-known representative utility functions. Nevertheless, it should be noted that in addition to the settings that were analyzed analytically in this section, the utility function can be adjusted to handle more general settings as well when implementing the proposed DQSA algorithm. For instance, we can set $r_n(t) = x_n$ at each time slot under the competitive setting instead of a unit reward given in (14) to model situations with channel diversity. We can also set a weighted sum utility $r_n(T) = \sum_{n=1}^{N} \omega_n f\left(\sum_{t=1}^{T} x_n\right)$ in the cooperative utility (20) to give different priorities to users in the system.

V. Experiments

In this section, we present numerical experiments to illustrate the performance of the proposed algorithm. The network model follows the description in Section II.

A. Learning to Increase the Channel Throughput

Since there is no coordination between users, inefficient channel utilization occurs when no user accesses the channel (referred to as idle time slots) or whether two or more users access

[1]Note that if more complex scenarios are considered as discussed in Remark 2, then different operating points are expected for different values of α.

the channel at the same time slot (i.e., collisions). The channel throughput is the fraction of time that packets are successfully delivered over the channel, i.e., no collisions or idle time slots occur. We first examine the throughput of a single channel that the proposed algorithm can achieve under topology uncertainty. We simulated a large-scale network with disconnected cliques with a random number of users distributed uniformly between 3 and 11. At each clique, transmission is successful if only a single user in the clique transmits over a shared channel in a given time slot. There is no interference between users located at different cliques (e.g., uplink communication with scattered hotspots). We compared the following schemes: (i) *The slotted Aloha protocol with optimal attempt probability:* In this scheme each user at clique j transmits with probability p_j at each time slot. ALOHA-based protocols are widely used in wireless communication primarily because of their ease of implementation and their random nature. Setting $p_j = 1/n_j$ is known to be optimal from both fairness (proportional fairness [43], max-min fairness) and Nash bargaining [27] perspectives. We assume that users set their attempt probability to the optimal value $p_j = 1/n_j$ and computed the expected performance analytically as a benchmark for comparison. (ii) *The proposed DQSA algorithm:* We implemented the proposed algorithm, in which each user has the freedom to choose any attempt probability at each time slot.

We are interested to address the following question: Under slotted-Aloha, the expected channel throughput (conditioned on n_j) is given by $n_j p_j (1-p_j)^{n_j-1} = (1-1/n_j)^{n_j-1} \in (0.385, 0.45)$ for $3 \leq n_j \leq 11$ and decreases to $e^{-1} \approx 0.37$ as n_j increases. *We are thus interested to examine whether the users can effectively learn in a fully distributed manner only from their ACK signals how to access the channel so as to increase the channel throughput by reducing the number of idle time slots and collisions.* To make this question more challenging, the actual number of users at each clique was unknown to the users when implementing the proposed algorithm (in contrast to the implementation of slotted-Aloha).

Figure 2 provides a positive answer to this question for the experiments that we did. The blue line shows the average channel throughput achieved by the proposed algorithm when each user aims at maximizing its own rate (i.e., competitive setting as described in Section IV-A). The red line shows the average channel throughput achieved by the proposed algorithm when each user aims at maximizing the total number of successful packet transmissions (i.e., user sum rate, by setting $\alpha = 0$ in (21)). The yellow line is the well known channel throughput achieved by slotted-Aloha with optimal attempt probability and it serves as a benchmark for comparison. It can be seen that the proposed algorithm significantly outperforms the slotted-Aloha protocol very quickly under both utility functions. *The algorithm was able to deliver packets successfully almost* 80% *of the time, about twice the channel throughput as compared to slotted-Aloha with optimal attempt probability. This is achieved when each user learns only from its ACK signals, without online coordination, message exchanges between users, or carrier sensing.*

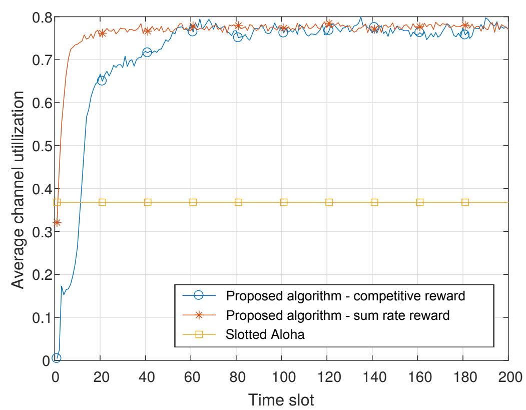

Fig. 2. Channel throughput for the experiments conducted in Section V-A.

B. Achieving Efficient Rate Allocations Using Different Utility Functions

Channel throughput is an important measure for communication efficiency, but it does not provide an indication about the rate allocation among users. For example, if user 1 transmits 100% of the time and all other users receive rate zero, then the channel throughput is 1, but the solution might be undesirable. Hence, in this section we are interested to address the following question: *Can we train the DQN by different utilities so that the users can learn policies that result in good rate allocations depending on the desired performance?*

In what follows, we provide a positive answer to this question for the experiments that we did. We first simulated a network with 4 users and 2 channels. The DQN was trained when the users aim at maximizing the total number of successful packet transmissions (i.e., user sum rate). In Fig. 3 we show a representative example of the channel selection behavior among users. The presented policy after convergence (convergence was slightly slower occasionally than presented in the figure) is such that a single user transmits on each channel 100% of the time while the other users always do not transmit on that channel. In the figure, users $1, 4$ always transmit over channels $1, 2$, respectively, and users $2, 3$ do not transmit. This policy achieves a very good channel throughput (above 0.9). We observed such type of rate allocations in about 80% of the Monte-Carlo experiments. In terms of user sum rate, such type of rate allocations performs very well. Since each user contributes equally to the user sum rate, the users have learned a simple and efficient policy that achieves this goal.

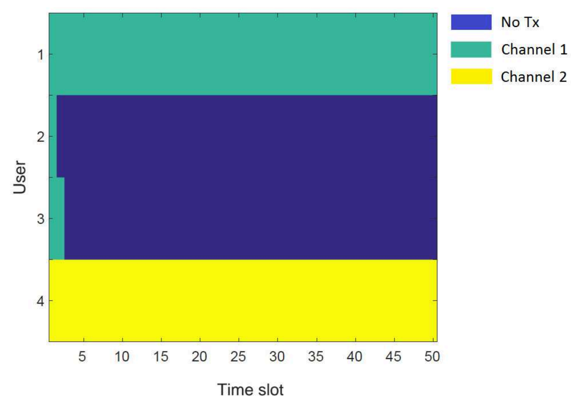

Fig. 3. A representative channel selection (observed in about 80% of the time) when maximizing the user sum rate.

It is well known that user sum rate is not a good choice when seeking for fair rate allocations. Indeed, from a fairness perspective the simple policy presented in Fig. 3 performs poorly, since 2 users receives rate zero. Hence, in the next simulation we examine the performance of the proposed algorithm when each user aims at maximizing its own individual rate (i.e., competitive reward). In Fig. 4 we show a representative example of the channel selection behavior among users observed in about 80% of the Monte-Carlo experiments. We simulated the case of 3 users and 2 channels. It can be seen that in this competitive reward case the users have learned a more complex protocol. Specifically, after convergence, a single user (user 3 in the figure) transmits on a single channel (channel 2 in the figure) 100% of the time, while the two other users (users $1, 2$ in the figure) share a channel (channel 1 in the figure) using TDMA, where each one of them transmits 50% of the time.

Next, we examined whether setting $\alpha = 1$ in (21) (i.e., aiming to maximize the user sum log-rate, known as proportional fair rates) when training the DQN can lead to equally sharing the channels among users. In Fig. 5 we show a representative example of the channel selection behavior among users observed in more than 95% of the Monte-Carlo experiments. We simulated the case of 4 users and 2 channels. It can be seen that in this case users learn a much more involved strategy in order to equally share the channels. Users transmit over channels during a batch of time slots (with a random size) and then stop transmitting (whether collisions have been observed or not). Such strategies enable the users to equally share (approximately) the number of time-slots. However, the algorithm was able to deliver packets successfully only 60% of the time, which is much better than slotted Aloha, but not as good as the channel throughput that we obtained under the competitive utility maximization and the user sum-rate maximization (in which the algorithm was able to deliver packets successfully almost 80% of the time).

In summary, the experimental results are supported by the following insights:

- The rate allocation presented in Figures 4, 5 are clearly better than the rate allocation presented in Fig. 3 from a fairness perspective. This result is reasonable since in Fig. 4 each user tries to reach a good operating point so as to maximize its own rate. Which one of the users succeeds better is affected by the initial conditions and randomness of the algorithm. In Fig. 5 the users aim to equally share the channels for maximizing the objective function, as supported by Theorem 3.
- From a game theoretic perspective, the SPE of the competitive game (i.e., when each user aims at maximizing its own rate) is reached when each user transmits with probability 1 at each time slot, as shown by Theorem 1. As discussed in Section IV-A, the SPEs result in an inefficient rate allocation, in which a single user receives 100% utility, and the two users that transmit over the same channel receive zero rate due to persistent collisions. Thus, implementing the DQSA algorithm using a common training yields a tremendous improvement in this respect.
- Finally, note that the policies observed in Figs. 3, 4 converge to Pareto optimal operating points, as analyzed in Section IV. The policy observed in Fig. 5 learns to equally share the channels among users, which is Pareto optimal as well (though collisions and idle time slots still occur since the learning process is more involved), as analyzed in Section IV. These results further demonstrate the strong performance of the DQSA algorithm and its capability to adapt to different problem settings.

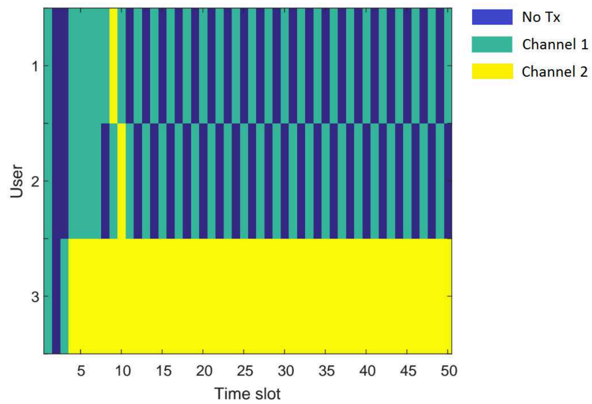

Fig. 4. A representative channel selection (observed in about 80% of the time) under individual utility maximization.

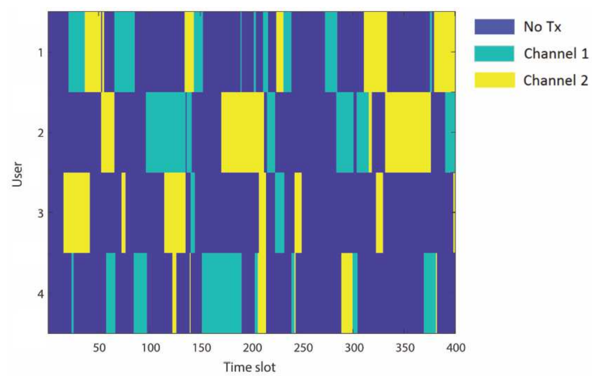

Fig. 5. A representative channel selection (observed in more than 95% of the time) under user sum log-rate maximization.

VI. Conclusion

The problem of dynamic spectrum access for network utility maximization in multichannel wireless networks was considered. We developed a novel distributed dynamic spectrum access algorithm based on deep multi-user reinforcement leaning, referred to as Deep Q-learning for Spectrum Access (DQSA). The proposed algorithm enables each user to learn good policies in online and distributed manners, while dealing with the large state space without online coordination or message exchanges between users. Analysis of the system dynamic is developed for establishing design principles for the implementation of the DQSA algorithm. Experimental results demonstrated strong performance of the algorithm in complex multi-user scenarios.

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