Short Paper: Intelligent Secondary LTE Spectrum Sharing in High Capacity Cognitive Cellular Systems

Nils Morozs, Tim Clarke and David Grace
Department of Electronics, University of York
Heslington, York YO10 5DD, United Kingdom
E-mail: {nm553, tim.clarke, david.grace}@york.ac.uk

***Abstract*—This paper investigates the distributed Q-learning approach to secondary LTE spectrum sharing, its autonomously emerging spectrum usage patterns, and their impact on the primary and secondary user quality of service (QoS). Large scale simulations of a stadium temporary event scenario show that it is capable of servicing a dramatic 51-fold increase in offered traffic, but with no need for additional spectrum and with no perceived degradation in the primary user QoS.**

***Keywords*—Distributed Q-Learning; Dynamic Spectrum Access**

I. Introduction

One of the fundamental tasks of a cellular system is spectrum management, concerned with dividing the available spectrum into a set of resource blocks or subchannels and assigning them to voice calls and data transmissions in a way which provides a good quality of service (QoS) to the users. Flexible dynamic spectrum access (DSA) techniques play a key role in utilising the given spectrum efficiently. For example, cognitive cellular systems employ intelligent opportunistic DSA techniques that allow them to access licensed spectrum underutilized by the incumbent users [1]. An emerging state-of-the-art technique for intelligent DSA is reinforcement learning (RL); a machine learning technique aimed at building up solutions to decision problems only through trial-and-error.

This paper investigates a high capacity density secondary spectrum sharing problem currently considered in the EU FP7 ABSOLUTE project. It is designed for a stadium event scenario and involves a temporary cognitive cellular infrastructure that is deployed in a stadium to provide extra capacity and coverage to the users and event organizers involved in a temporary event, e.g. a football match or a concert. The small cell eNodeBs (eNBs) inside the densely populated stadium depicted in Figure 1 have secondary access to a 20 MHz LTE channel, also used by a network of 3 primary eNBs (PeNBs) in the local suburban area.

The purpose of this paper is to investigate dynamic spectrum sharing patterns that emerge autonomously using a distributed Q-learning approach, and to assess their impact on the spatial distribution of the primary and secondary user quality of service (QoS). These results bring a new insight into the dynamics of distributed Q-learning based secondary LTE spectrum sharing. The rest of the paper is organised as follows: Section II briefly introduces distributed Q-learning based DSA. The novel simulation results are discussed in Section III, and the conclusions are given in Section IV.

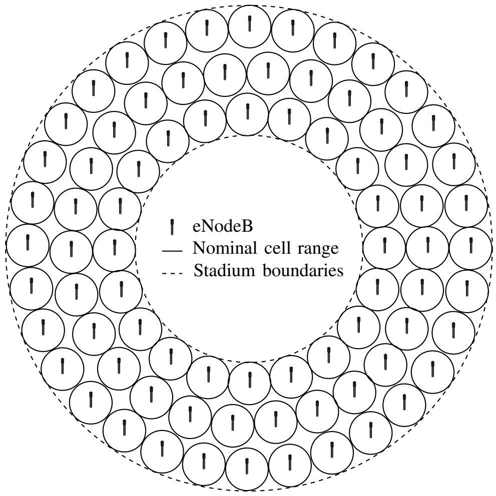


Figure 1. Stadium small cell network architecture [2]

II. Distributed Q-Learning Based Dynamic Spectrum Access

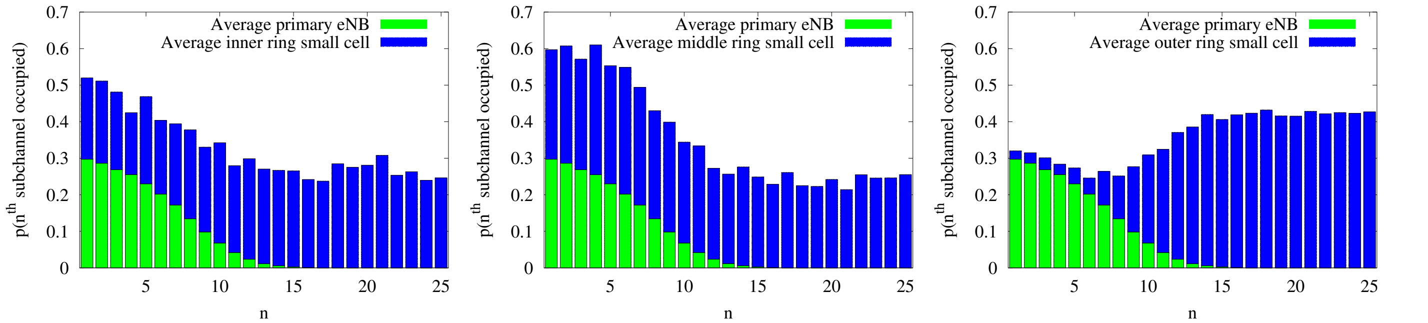
One of the most successful and widely used RL algorithms is Q-learning. In particular, a simple stateless variant of this algorithm, as formulated in [3], has been shown to be effective for distributed DSA problems, e.g. [2]. Each eNB maintains a Q-table $Q(a)$ such that every subchannel a has an expected reward or Q-value associated with it. Upon each file arrival, the eNB either assigns a subchannel to its transmission or blocks it if all subchannels are occupied. It decides which subchannel to assign based on the current Q-table and the greedy action selection strategy described by the following equation:

$$\hat{a} = \underset{a}{\operatorname{argmax}}(Q(a)), \; a \in A', A' \subset A \tag{1}$$

where $\hat{a}$ is the subchannel chosen for assignment out of the set of currently unoccupied subchannels A', $Q(a)$ is the Q-value of subchannel a, and A is the full set of subchannels. The values in the Q-tables are initialised to zero, so all eNBs start learning with equal choice among all available subchannels. A Q-table is updated by an eNB each time it attempts to assign a subchannel to a transmission. The recursive update equation for stateless Q-learning, as defined in [3], is given below:

$$Q(a) \leftarrow (1 - \alpha)Q(a) + \alpha r \tag{2}$$

where r is the reward associated with the most recent trial and is determined by a reward function, and $\alpha \in [0, 1]$ is the learning rate parameter which weights recent experience with



(a) Inner ring of eNBs (b) Middle ring of eNBs (c) Outer ring of eNBs

Figure 2. Subchannel occupancy of primary eNBs, and three rings of stadium small cell eNBs

respect to previous estimates of the Q-values. The choice of these parameters is discussed in [2].

III. Simulation Results and Discussion

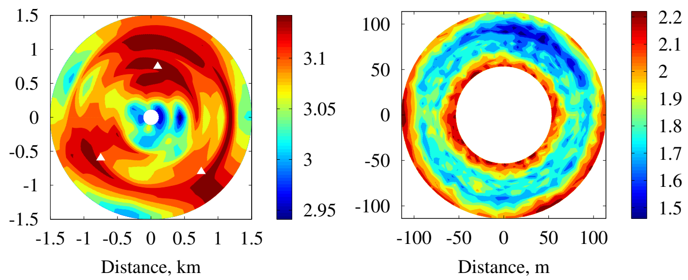
The spectrum sharing problem investigated in this paper involves a network of small cell eNBs that share spectrum among themselves and with a primary system of three local eNBs operating in the area. The stadium network architecture is shown in Figure 1. The offered traffic is 20 Mb/s outside of the stadium and 1 Gb/s inside. All other parameters and assumptions of the simulation model are described in detail in [2]. The primary system employs a heuristic inter-cell interference coordination (ICIC) scheme for spectrum management introduced in [2]. The secondary stadium network employs the distributed Q-learning DSA scheme described in Section II.

A. Spectrum Occupancy Patterns

Figure 2 shows the spectrum occupancy patterns that emerge autonomously in the stadium small cell network through distributed machine intelligence, in response to a specific spectrum occupancy pattern used by the local primary LTE network. It demonstrates that the outer ring of small cell eNBs from Figure 1, which is most vulnerable to interference from the external primary system, has learnt to largely avoid parts of the spectrum most heavily used by the PeNBs. In contrast, the inner and the middle ring of stadium eNBs have not suffered from the primary system interference on those subchannels, and thus learned to fully reuse them without many negative reinforcements, i.e. blocked/interrupted transmissions. These results demonstrate the remarkable effectiveness of such an autonomous RL approach, where no coordination or spectrum planning is required.

B. Primary and Secondary User Quality of Service

An essential requirement for secondary cognitive cellular systems is to ensure that they do not have a harmful effect on the QoS in the primary system. The contour plots in Figure 3 show the spatial distribution of user throughput (UT), i.e. data rates, experienced by the primary and the secondary users. Figure 3a shows that the primary user UT varies insignificantly, 2.95-3.15 Mb/s, whilst Figure 3b shows that at the same time an adequate QoS (≈1.5-2.2 Mb/s UT) is provided to the ultra-dense population of secondary users. These simulation results emphatically demonstrate that it is possible to develop a temporary cognitive network that is capable of servicing a dramatic increase in the offered traffic (1 Gb/s in addition to the original 20 Mb/s, i.e. by a factor of 51), but with no need for additional spectrum and with no notable degradation in the primary user QoS.



(a) Primary user UT, Mb/s (b) Secondary user UT, Mb/s

Figure 3. Spatial distribution of user throughput (UT) outside (primary users) and inside the stadium (secondary users)

IV. Conclusion

The distributed Q-learning approach to DSA is capable of facilitating autonomous emergence of efficient secondary spectrum sharing patterns. Large scale simulations of a stadium temporary event scenario show that it is capable of servicing a dramatic 51-fold increase in the offered traffic, but with no need for additional spectrum and with no perceived degradation in the primary user QoS.

Acknowledgment

This work has been funded by the ABSOLUTE Project (FP7-ICT-2011-8-318632), which receives funding from the 7th Framework Programme of the European Commission.

References

[1] M. Guizani, B. Khalfi, M. Ghorbel, and B. Hamdaoui, "Large-scale cognitive cellular systems: resource management overview," *Communications Magazine, IEEE*, vol. 53, pp. 44–51, 2015.

[2] N. Morozs, D. Grace, and T. Clarke, "Distributed Q-learning based dynamic spectrum access in high capacity density cognitive cellular systems using secondary LTE spectrum sharing," in *International Symposium on Wireless Personal Multimedia Communications (WPMC)*, 2014.

[3] C. Claus and C. Boutilier, "The dynamics of reinforcement learning in cooperative multiagent systems," in *Proceedings of the fifteenth national/tenth conference on Artificial intelligence/Innovative applications of artificial intelligence*, 1998.