Towards the Incorporation of Learning and Adaptation Functionality in Cognitive Radio Systems

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Abstract—**This paper addresses the problem of effectively encompassing learning functionality in a cognitive radio system. It provides a brief overview of the main principles of cognitive radio and discusses on ways to meet the emerging engineering challenges. It proposes Bayesian Networks as a valuable tool for modeling the stated problem and elaborates on the deployment of an effective learning and adaptation strategy. Finally, indicative results are presented and useful conclusions are reached.**

Index Terms— **Bayesian networks, Cognitive radio, Machine learning**

1 INTRODUCTION

An increasingly important engineering challenge is the proper management of the electromagnetic radio spectrum, a valuable yet limited natural resource. The current fragmentation of the radiofrequency (RF) spectrum leads to its significant underutilization [1]-[2]. Thus, there is need for the development of a robust spectrum management scheme, capable of exploiting available frequency bands as efficiently as possible.

Cognitive radio [3]-[5] appears as an attractive, highly promising answer to the abovementioned challenge. Its basic principle lies in the ability to sense the RF environment and properly adjust to current network characteristics. This adjustment can be realized through appropriate *reconfiguration* of network elements (network transceivers), i.e. through suitable switching among different configurations. The term *configuration* refers to a combination of Radio Access Technology (RAT), spectrum, transmission power, as well as algorithms and parameters for modulation, coding and error control.

A typical cognitive radio operation can be divided into three, tightly interconnected, phases [5]: (a) radio-scene analysis, i.e. selecting a configuration and measuring the interference levels perceived; (b) channel identification, i.e. configuration capabilities estimation, based on (a); (c) transmit-power control and dynamic spectrum management.

Although the term cognitive directly dictates the need for encompassing (machine) learning functionality in the selection process, this necessity has not yet been adequately addressed in the literature. The need for learning, based on knowledge (data and experience), is amplified, especially in phase (b), by the stochastic nature of a configuration's capabilities (e.g., maximum achievable bit-rate, maximum achievable coverage), since the latter are influenced by external RF stimuli.

Hence, the primary problem that needs to be tackled is the following: "*Given a candidate configuration, which are the anticipated capabilities, especially in terms of achievable bit-rate and coverage values? Which learning and adaptation mechanisms guarantee a high degree of assurance in the estimation process?*"

The contribution of this paper lies exactly in the provision of such a machine learning technique for addressing the aforementioned problem. This paper aims at solving the specified problem by deploying a simple Bayesian Network [6]-[8] (Section 3), in combination with a learning and adaptation strategy (Section 4). The goal is to maintain a certain level of simplicity

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	$CFG = c_1$	...	$CFG = c_n$
abr_1	$\Pr\left[ABR = abr_1 \middle| CFG = c_1\right]$	...	$\Pr\left[ABR = abr_1 \middle| CFG = c_n\right]$
abr_2	$\Pr\left[ABR = abr_2 \middle| CFG = c_1\right]$	...	$\Pr\left[ABR = abr_2 \middle| CFG = c_n\right]$
...	...	...	...
abr_m	$\Pr\left[ABR = abr_m \middle| CFG = c_1\right]$	...	$\Pr\left[ABR = abr_m \middle| CFG = c_n\right]$

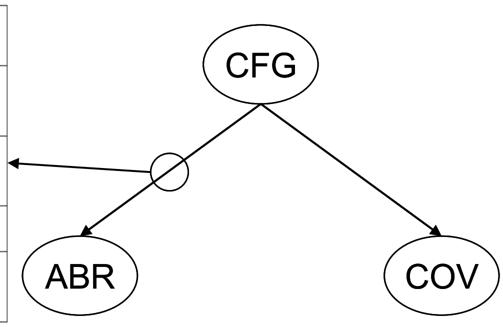

Figure 1: Bayesian Network for the estimation of configuration capabilities

(computationally intensive operations are undesirable in a real-time optimization system), without however compromising the effectiveness and extendibility of the proposed solution. Finally, comprehensive results are presented (Section 5), and conclusive remarks are reached (Section 6).

2 BACKGROUND

In today's literature, the 'learning' aspect of cognitive radio has been underestimated. So far, this trend has fueled much research into policy-based cognitive radios. These are radios whose operation is governed by a reasoning engine that examines the current state of the environment and makes decisions on how the radio should operate [9]. An example of this is an IEEE 802.11 modulation controller that switches from 16-QAM to QPSK to BPSK, as the Signal-to-Noise Ratio (SNR) decreases [9]-[10].

Generic learning-based cognitive radio is a relatively untapped research area. State-of-the-art research activities include the employment of genetic algorithms [11] to evolve a radio defined by a chromosome, with a view to optimizing performance [12]-[13]. Specifically, the chromosome's genes represent the adjustable parameters in a given radio, and by genetically manipulating the chromosomes, the genetic algorithm can find a set of parameters that optimize the radio for the user's current needs. In addition to these efforts, Clancy et al. [9] examine the fundamentals of learning (learning-based approach) and reasoning (policy-based approach) and propose an architecture to jointly utilize them. The resulting framework is then used to address two common problems in cognitive radio, namely capacity maximization and dynamic spectrum access.

The present paper intends to extend the existing literature with regards to learning-based cognitive radio, by providing a Bayesian Network based technique targeted for the effective discovery of configuration capabilities.

3 FORMULATION AS A BAYESIAN NETWORK

Figure 1 depicts the Bayesian network that is proposed for modelling the problem specified in Section 1. *ABR* and *COV* are random variables representing achievable bit-rate and coverage, respectively. Since *ABR* represents the configuration's achievable bit-rate and not the traffic load (active sessions), variables *ABR* and *COV* are conditionally independent, even for CDMA-based systems. *CFG* is another random variable, representing a configuration. *CFG* is the Bayesian network's predictive attribute (node), while *ABR* and *COV* are the target attributes.

The goal is the determination of the maximum value of the conditional probability $\Pr[ABR, COV \mid CFG]$. Using the joint probability formula and the Bayesian chain rule formula, it can easily be shown that:

$$\Pr\left[ABR, COV \middle| CFG\right] = \Pr\left[ABR \middle| CFG\right] \cdot \Pr\left[COV \middle| CFG\right] \quad (1)$$

Relation (1) means that *ABR* and *COV* can be decoupled. Two independent conditional probability tables (CPTs) can, therefore, be organized. The analysis that follows refers to achievable bit-rate estimation. Exactly the same approach can be used for coverage, therefore it is omitted.

Figure 1 depicts the structure of a CPT for achievable bit-rate. Each column of the CPT refers to a specific configuration. Assuming there are n possible configurations, the CPT includes n columns. Each line of the CPT corresponds to an achievable bit-rate value.

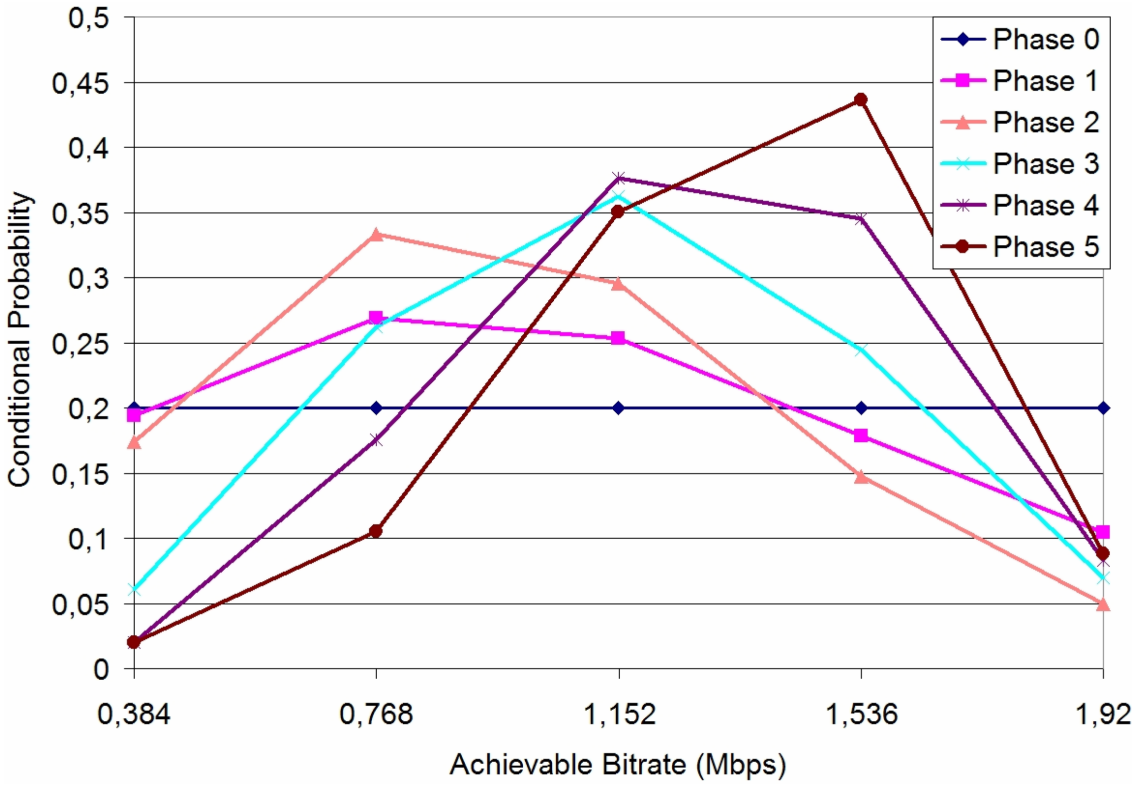

Figure 2: Scenario 1 – Probability distribution through scenario phases

Notice that a discrete set of m potential achievable bit-rate values has been defined. Without loss of generality, enumeration is done in ascending order (i.e., $abr_1 < abr_2 < \ldots < abr_m$). The cell at the intersection of line i and column j is a probability value. It expresses the probability that bit-rate abr_i will be achieved, given the fact that configuration c_j has been selected. Formally, this is denoted as $\Pr\left[ABR = abr_i \middle| CFG = c_j\right]$. Given a configuration, the most probable value of the achievable bit-rate is the value that corresponds to the maximum conditional probability.

4 LEARNING AND ADAPTATION STRATEGY

In Section 3, it was explained that the capabilities of potential configurations are modelled through the CPTs. The next step will be to describe how to update the CPTs. This learning and adaptation process takes into account the measurements (initial estimations) of the cognitive radio system and, more specifically, the "distance" (absolute difference) between each candidate value and the measured value.

Let us assume that an initial estimation shows that a specific configuration can achieve bit-rate abr_{meas}. This measurement can be exploited, in order to fine-tune (enhance or decrease) the values of the CPTs, so as to increase the degree of assurance of future predictions. Let Δa be the maximum difference between the candidate achievable bit-rate values, i.e. $\Delta a = abr_m - abr_1$.

Then, the following correction factor, cor_i, can be computed for each candidate achievable bit-rate value abr_i:

$$cor_i = 1 - \frac{|abr_i - abr_{meas}|}{\Delta a} \qquad (2)$$

It holds that $0 \le cor_i \le 1$. A value close to 1 reflects that the corresponding candidate value abr_i is close to the measured value abr_{meas}, thus it should be reinforced accordingly. The opposite stands for a value that is close to 0.

Given a candidate configuration c_j, the correction of the CPT values $\Pr[ABR = abr_i \mid CFG = c_j]$ can then be done as follows, for each candidate value abr_i:

$$\begin{aligned} &\Pr[ABR = abr_i \mid CFG = c_j]_{new} = \\ &L \cdot cor_i \cdot \Pr[ABR = abr_i \mid CFG = c_j]_{old} \end{aligned} \qquad (3)$$

Parameter L is a normalizing factor whose value is computed by requiring all the "new" probabilities to sum up to 1.

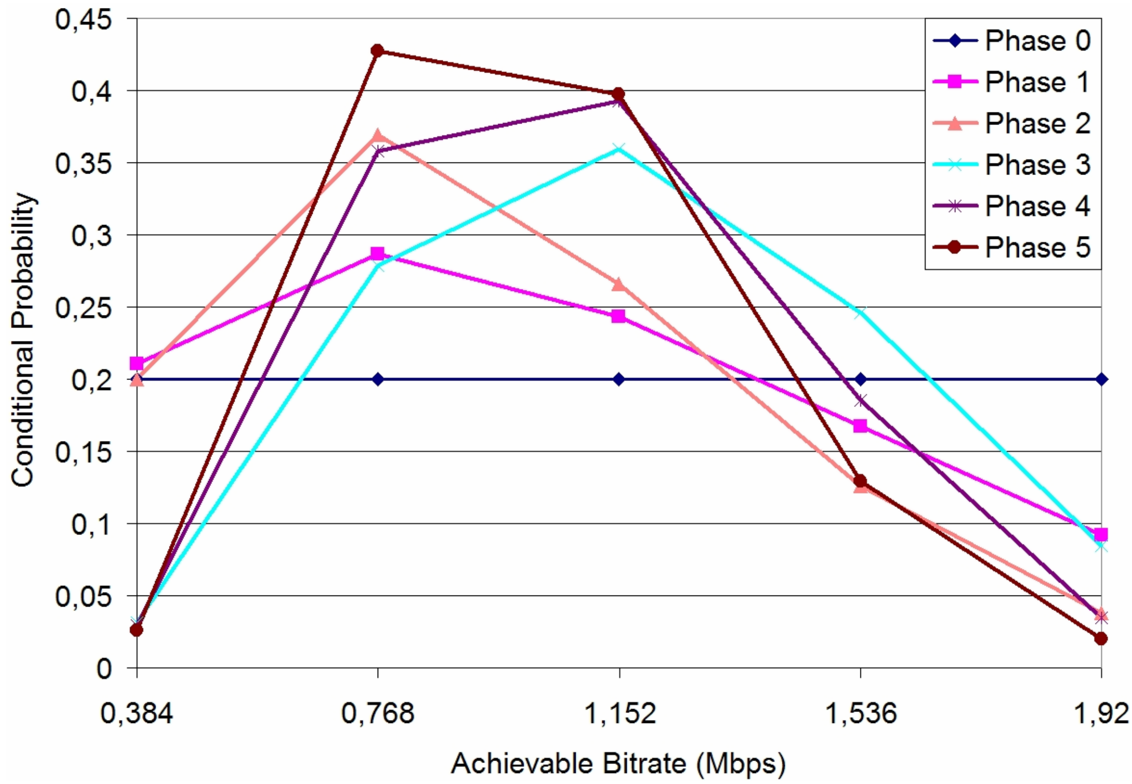

Figure 3: Scenario 2 – Probability distribution through scenario phases

The system *converges* when the most probable candidate value (i.e., the one with the maximum probability) is being reinforced, while the probabilities of the other candidate values are either being reduced or reinforced less. After convergence, we limit the number of consecutive updates that can be applied on the probability associated with each candidate achievable bit-rate value. This is done for assisting fast adaptation to new conditions. For the same reason, we do not allow that a probability falls under a certain threshold, r/m, where $0<r<1$ (m is the number of potential achievable bit-rate values). In such cases, the normalization factor, L, is computed by requiring all the other "new" probabilities to sum up to $1-(k \cdot r/m)$, where k is the number of probabilities that are assigned equal to the threshold.

5 RESULTS

Two comprehensive scenarios demonstrating the functionality of the proposed method are presented in this section. Our focus is on an arbitrary configuration c_j. It is assumed that there are m=5 candidate achievable bit-rate values (in Mbps): abr_1=0.384, abr_2=0.768, abr_3=1.152, abr_4=1.536, abr_5=1.920. Hence, Δa=1.536 Mbps. Let it be noted that a denser grid of candidate values could have been selected, and also that the distance between two subsequent candidate values needs not be the same. Parameter r has been set equal to 0.1.

Figure 2 depicts the distribution of the conditional probabilities in the framework of the *first scenario*. Initially, i.e. in *phase 0* (time epoch 0), all candidate values are considered equally probable, thus the distribution is uniform and any value can be considered as the most probable one. Subsequently, the value of abr_{meas} in *phase 0*, denoted henceforth as $abr_{meas,0}$, together with the probability distribution of this phase, are taken into account in order to compute the probability distribution of *phase 1*, using relations (2) and (3). The same procedure is followed for all phases. The values of abr_{meas} per phase are: 0) $abr_{meas,0}$ = 0.920; 1) $abr_{meas,1}$ = 0.920; 2) $abr_{meas,2}$ = 1.612; 3) $abr_{meas,3}$ = 1.612; 4) $abr_{meas,4}$ = 1.612. I.e., in this scenario the value of abr_{meas} changes at a certain point from 0.920 to 1.612.

As may be observed from Figure 2, abr_2 is correctly selected in *phase 1* as the most probable value. As was expected, there are high values for abr_2 and abr_3, a slight diminishment for abr_1 and abr_4, and a severe degradation for abr_5. In *phase 2*, the scheme is further applied, and since $abr_{meas,1} = abr_{meas,0}$, the most probable value does not change and is actually further reinforced. In *phase 3*, however, $abr_{meas,2}$ is 1.612, and abr_3 is selected as the most probable value. It is important to notice that, although abr_4 is closer to $abr_{meas,2}$, abr_3 (instead of abr_4) is chosen as the most probable value. This constitutes the desired behaviour, i.e. to adapt gradually and not immediately, in order to avoid oscillations and smooth out temporary fluctuations. In the next phase, abr_3 remains the most probable value, but abr_4 is also reinforced considerably. Finally, in *phase 5*, the system converges to abr_4, since the value of abr_{meas} has remained the same. We may also note from Figure 2 that, in the last two phases, the probability of abr_1 has been set equal to the threshold's value, i.e. $\Pr[ABR = abr_1 \mid CFG = c_j] = 0.1 \cdot 0.2 = 0.02$.

Figure 3 depicts the distribution of the conditional probabilities in the framework of the *second scenario*. In this scenario, the values of abr_{meas} per phase are: 0) $abr_{meas,0} = 0.86$; 1) $abr_{meas,1} = 0.84$; 2) $abr_{meas,2} = 1.82$; 3) $abr_{meas,3} = 0.85$; 4) $abr_{meas,4} = 0.85$. I.e., in this scenario the value of abr_{meas} features a temporary fluctuation in *phase 2*.

As may be observed from Figure 3, abr_2 is correctly selected in *phase 1* as the most probable value. In *phase 2*, the scheme is further applied, and the probability of abr_2 is reinforced. In *phase 3*, the measurement of *phase 2*, i.e. $abr_{meas,2}$, is taken into account, which results in selecting abr_3 as the most probable value. Instead of selecting abr_5, which is the closest to the measured value, abr_3 is chosen, since this abrupt fluctuation may be due to a temporary situation (e.g., temporary reconfigurations of near-by reconfigurable network transceivers) or some measurement error. Hence, it is preferable to make gradual adaptations, instead of immediate ones. In the next phase (*phase 4*), the system gradually tends to adapt back to abr_2. In *phase 5*, abr_2 is further reinforced and becomes again the most probable one.

6 CONCLUSIONS

Cognitive radios seem a highly promising way towards handling the complexity of the B3G wireless landscape. Cognitive systems dynamically reconfigure the algorithms and parameters they use, in order to adapt to the changing environment conditions. However, making proper reconfiguration decisions presupposes a way of knowing, with high enough assurance, the capabilities of the alternative configurations, especially in terms of achievable bit-rate and coverage.

This paper addresses this problem by incorporating the use of Bayesian Networks, in combination with an effective learning and adaptation strategy. Moreover, indicative results have been presented, demonstrating the method's functionality.

7 REFERENCES

[1] M. McHenry, "Frequency agile spectrum access technologies", in FCC Workshop Cognitive Radio, May 2003.

[2] G. Staple and K. Werbach, "The end of spectrum scarcity", *IEEE Spectrum*, Vol. 41, No. 3, pp. 48–52, 2004.

[3] J. Mitola, "Cognitive radio: An integrated agent architecture for software defined radio", Doctor of Technology, Royal Institute of Technology (KTH), Stockholm, Sweden, 2000.

[4] J. Mitola and G. Maguire Jr., "Cognitive Radio: Making Software Radios More Personal", *IEEE Personal Communications Magazine*, Vol. 6, No. 6, pp. 13-18, August 1999.

[5] S. Haykin, "Cognitive Radio: Brain-Empowered Wireless Communications", *IEEE Journal on Selected Areas In Communications*, Vol. 23, No. 2, pp. 201-220, Feb. 2005.

[6] T. Mitchell, "Machine Learning", *McGraw-Hill*, ISBN 0070428077, 1997.

[7] E. Adamopoulou, K. Demestichas, A. Koutsorodi, and M. E. Theologou, "Access Selection and User Profiling in Reconfigurable Terminals", presented at the 15th Wireless World Research Forum (WWRF), Paris, December 2005.

[8] R. E. Neapolitan, "Learning Bayesian Networks – Series in Artificial Intelligence", *Prentice Hall*, 2002.

[9] T. Clancy, J. Hecker, E. Stuntebeck, and T. O'Shea, "Applications of machine learning to cognitive radio networks", *to appear in IEEE Wireless Communications Magazine*, 2007.

[10] IEEE 802.11, "Working group on wireless local area networks.", http://www.ieee802.org/11/

[11] D. Goldberg, "Genetic Algorithms in Search, Optimization, and Machine Learning", *Addison Wesley*, 1989.

[12] C. Rieser, "Biologically Inspired Cognitive Radio Engine Model Utilizing Distributed Genetic Algorithms for Secure and Robust Wireless Communications and Networking", Ph.D. thesis, Virginia Polytechnic Institute and State University, August 2004.

[13] T. Rondeau, C. Rieser, B. Le, and C. Bostian, "Cognitive radios with genetic algorithms: Intelligent control of software defined radios", SDR Forum Conference 2004.