Robust Discovery of Reconfiguration Capabilities for Cognitive Radio

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Abstract—**Beyond 3G wireless connectivity can efficiently be realized by exploiting cognitive networking concepts. Cognitive systems dynamically reconfigure the Radio Access Technologies and the spectrum they use, based on experience, in order to adapt to the changing environment conditions. However, dynamic reconfiguration decisions call for robust 'discovery' processes, i.e. stable and reliable schemes targeted for radio-scene analysis and channel identification. This paper aims at contributing in the areas of discovery: firstly, by explaining how a cognitive radio system can acquire interference and capacity estimations; and, secondly, by enhancing the above with a learning system, which is essential for obtaining a truly cognitive process. The proposed approach introduces a robust probabilistic model for optimal prediction of the capabilities of alternative configurations, in terms of capacity.**

Index Terms—**B3G wireless infrastructures, Bayesian networks, Capacity estimation, Cognitive radio, Interference estimation, Learning and adaptation**

1 INTRODUCTION

THE evolution of wireless communication systems over the past years demonstrates a clear trend towards architectures that will support multiple access technologies, and multimode mobile terminal devices, i.e. capable of alternately operating in the diverse radio segments available in the infrastructure. This trend is often referred to as 'systems beyond 3G' (B3G), and its main notion is that a network operator can rely on multiple Radio Access Technologies (RATs) for achieving the desired capacity and Quality of Service (QoS), in a cost efficient manner [1]-[2].

The need for this stems from the fact that each RAT is best suited for handling certain – but not all – situations, in terms of desirable capacity, coverage, mobility support and cost. Thus, in order to be competitive and raise customer satisfaction, a network operator will need to combine the benefits offered by different RATs.

Reconfigurability is an effective response to tackle the complexity of operating within a heterogeneous environment. According to this notion, the network infrastructure consists of hardware elements (transceivers) capable of changing the RATs and spectrum they use, in order to better meet current requirements.

However, in this context, a significant management issue arises: how to manage the reconfigurable elements in such a way so as to reach optimal configuration decisions. Therefore, a hardware element needs to be not only *reconfigurable* but also *cognitive*, i.e. aware of its RF environment and capable of adapting to the current needs and conditions.

The need for cognition can also be materialized in a way that conforms to the *autonomic* computing paradigm [3]-[4]. In this sense, each element should be able of *self*-adapting to its environment, without the need of being instructed by a central management entity with higher rationality. This approach results in greater scalability and lower complexity.

As outlined in [5]-[6], three fundamental cognitive tasks, tightly interconnected, are identified within the framework of cognitive radio: *(a) Radio-scene analysis*, which involves tuning to a frequency and measuring the interference levels perceived; *(b) Channel identification*, which encompasses channel capacity estimation, based on the levels of interference measured in (a); and *(c) Transmit-power control and dynamic spectrum management*.

This paper adopts the general term '*discovery*' to refer to cognitive tasks (a) and (b). Discovery is targeted to the identification of the capabilities, e.g. capacity and coverage, of the alternative configurations of a reconfigurable element. These capabilities change over time, since they are influenced by the element's environment, including the behaviour of 'near-by' elements. Therefore, a reconfigurable element needs to monitor (sense) its environment and extract proper conclusions.

This paper aims at contributing in the areas of discovery by: *(a) explaining how a cognitive radio system can acquire interference and capacity estimations*; and *(b) enhancing the above with a learning system*, which is essential for obtaining a truly cognitive process. The proposed approach lies in the introduction of a robust (stable and reliable) probabilistic model for optimal prediction of the capabilities of alternative configurations, in terms of capacity. The latter can then serve as input for reaching optimal configuration decisions. The overall idea is depicted in Figure 1.

The remainder of this paper is structured as follows: Section 2 presents the channel quality metrics that can be used for radio-scene analysis, namely the signal-to-

Manuscript received Oct. 20, 2007, accepted Jan. 21, 2008. The work presented herein is conducted in the framework of Ph.D. research performed by E. Adamopoulou and K. Demestichas, under the supervision of Prof. M. Theologou. The work was also supported in part by the General Secretariat of Research and Technology (GSRT) of the Greek Ministry of Development, in the context of the ARIADNE project (03EΔ235).

interference-plus-noise ratio and the interference temperature, and then explains how interference estimations can be derived. Section 3 identifies how to obtain capacity estimations from the measured interference levels. Section 4 describes the message exchange sequence for the radio-scene analysis process of a cognitive radio system. Section 5 introduces the proposed probabilistic model for achieving robust capacity estimation. Section 6 provides results that demonstrate the efficiency of the proposed model, and finally section 7 concludes the paper.

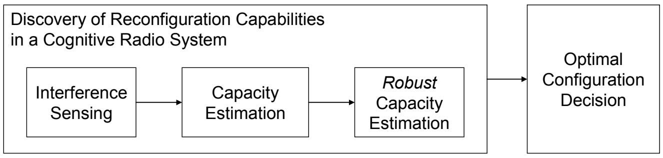


Figure 1: The process of discovering reconfiguration capabilities in a cognitive radio system

2 INTERFERENCE ESTIMATION METHODOLOGY

Channel quality metrics

Interference is inherent to all radio communications, hence there is need to utilize appropriate metrics reflecting its effect in signal transmission. The most widely used is the signal-to-interference-plus-noise ratio (SINR), represented by the ratio between the received wanted carrier signal power and the total received interference power.

An alternative, recently proposed and highly promising, metric is the interference temperature (IT) [14]-[16], which is defined as:

$$T_I = \frac{I}{kB} \quad (1)$$

where B represents a bandwidth in Hertz, I denotes interference power in Watts, and k is the Boltzmann's constant. According to the Federal Communications Commission's (FCC) model, for a given frequency band in a given geographic location, an 'interference temperature limit' is defined by some regulatory agency. A transmitter should then ensure that by transmitting it does not raise the current IT above the specified IT limit [6].

SINR estimation

Over the years, the SINR estimation problem has been discussed, in the literature, in some detail (e.g., [7]-[12]). It has been studied both for analog communication systems (e.g., AMPS) and, more recently, for digital Time Division Multiple Access (TDMA), Code Division Multiple Access (CDMA), and Orthogonal Frequency-Division Multiplexing (OFDM) based systems.

In general, two strategies can be employed for achieving SINR estimations. The first is based on the transmission of pilot symbols (training sequences), whereas the second tries to derive the channel characteristics directly from the data symbols, i.e. the received signal, without the use of training sequences. The two strategies are often referred to in the literature as 'non-blind' and 'blind', respectively.

A training sequence is a priori known to the receiver, thus the task of SINR calculation is made easier, since the receiver knows which symbols it is supposed to receive. Consequently, the use of training sequences allows for greater accuracy, but also introduces a significant overhead, which could be used instead for the transmission of additional data sequences [13]. *In the cognitive radio context*, *the interference estimation part of the discovery procedure can be based solely on pilot transmission*, since we are interested in the potential capabilities of alternate configurations. On the other hand, of course, interference estimation in the frequency band that is currently used for service delivery can follow either of the two strategies.

Interference temperature estimation

IT estimation is rather straightforward, compared to SINR estimation, as it only involves tuning to the frequency of interest and calculating the received signal energy. However, a significant issue related to the estimation of the current IT is that an IT measurement taken at the transmitter might be different from one taken at the receiver. Thus, in a worst case scenario, the current IT at the receiver's location might be near the IT limit, whereas the current IT at the transmitter's location might be significantly lower, leading the transmitter to wrongly declare the frequency band as usable. Although this unintentional interference is rather rare and small, yet future work will probably need to be conducted, in order to quantify it [15].

As can be deduced from this, a reliable estimation of the current IT can be a challenging task. A more systematic approach is framed in [6], according to which a reliable spectral estimate of the IT can be achieved by: *(a)* using the 'multitaper' spectral estimation procedure to estimate the power spectrum of the IT; and *(b)* using a large number of sensors to take measurements from the RF environment.

3 CAPACITY ESTIMATION

Throughout the paper, the term capacity refers to the achievable transmission capacity (i.e., achievable bit rate), and not the traffic load (active sessions) within a cell. As a general rule, if the measured SINR is high or, equivalently, the measured IT is low, this allows for the employment of a more efficient (in terms of achievable capacity) modulation strategy (i.e., larger number of bits per symbol) and probably less redundancy (i.e., smaller number of parity bits). However, capacity estimation, on the basis of SINR measurement, is not a trivial matter. Nonetheless, reliable results can be reached by employing any of the following strategies: *(a)* the Shannon-Hartley theorem; *(b)* the attainable data rate formula; or *(c)* the bit error probability diagrams of the candidate modulation schemes. Method (a) derives information-theoretic bounds on capacity, for given bandwidth and power constraints. Method (b) goes one step further, by taking into account the constraints of a physically realizable system. Method (c) illustrates how to select the most appropriate and efficient modulation scheme, depending on the circumstances. The aforementioned methods are described concisely in what follows.

(a) Shannon-Hartley theorem: The concept of capacity estimation may be clarified by utilizing the Shannon-Hartley theorem, as implied in [6] and demonstrated in [16]. According to the celebrated theorem, given the bandwidth B in Hz, and the measured value of *SINR*, capacity C (in bits/s) is related as follows:

$$C = B\log_2(1+SINR) \quad (2)$$

Alternatively, given the measured value T_I of IT, (2) becomes:

$$C = B\log_2\left(1+\frac{S}{I}\right) = B\log_2\left(1+\frac{LP_S}{kBT_I}\right) \quad (3)$$

where P_S is the transmit power in Watts and $S = LP_S$ is the power at the receiver's location, with $L \in (0,1)$ representing the signal attenuation due to path loss and shadowing.

(b) Attainable data rate formula: In practice, a physically realizable encoding system must transmit data at a rate R (in bits/s) less than the maximum possible rate C (as given by (2) and (3)) for it to be reliable. Thus, for an implementable system operating at low enough probability of symbol error, a measure called 'signal-to-noise ratio gap', or just 'gap', is utilized [17]. The gap is denoted by Γ and is a function of the permissible probability of symbol error P_e and the encoding system of interest. It provides a measure of the efficiency of an encoding system with respect to the ideal transmission system of equation (2) or (3). The gap is defined as follows:

$$\Gamma = \frac{2^{C/B}-1}{2^{R/B}-1} = \frac{SINR}{2^{R/B}-1} \quad (4)$$

Hence, equivalently it holds that:

$$R = B\log_2\left(1+\frac{SINR}{\Gamma}\right) \quad (5)$$

As an example, for encoded Pulse Amplitude Modulation (PAM) or Quadrature Amplitude Modulation (QAM) operating at $P_e = 10^{-6}$, the gap Γ is fixed to 8.8 dB. Through the use of codes (e.g., trellis codes or turbo codes), nonetheless, the gap Γ may be reduced to as low as 1 dB.

However, through the use of codes, the actual data rate R_I (in bits/s), i.e. the data rate of the information source, is lower than that given by (5), due to the presence of redundant bits. For a code that uses n-bit code words consisting of k message bits and n-k redundant bits, R_I is given by:

$$R_I = r \cdot R = \frac{k}{n}R \quad (6)$$

where r represents the dimensionless ratio k/n and is known as the 'code rate'.

(c) Bit error probability diagrams: The goal of this method is to determine the most appropriate modulation scheme among the candidates. The proposed method to accomplish this stands as follows:

Step (i): Based on the measured SINR, the E_b/N_0 ratio, i.e. the energy per bit to noise power spectral density ratio, is determined as follows:

$$\frac{E_b}{N_0} = \begin{cases} \dfrac{1}{\log_2 M} SINR, & \text{M-ary PSK, M-ary QAM} \\ \dfrac{M}{\log_2 M} SINR, & \text{M-ary FSK} \end{cases} \quad (7)$$

Step (ii): Based on the value of E_b/N_0, the bit error probability P_b of each candidate modulation scheme is computed. Figure 2 is a plot of P_b vs. E_b/N_0 for uncoded M-ary Frequency Shift Keying (FSK), Phase Shift Keying (PSK) and QAM signals, in the case of coherent demodulation. Similar curves can be found in the literature for non-coherent demodulation. Similar curves should be utilized, if error control codes are in use, depending on the actual encoding scheme and code rate.

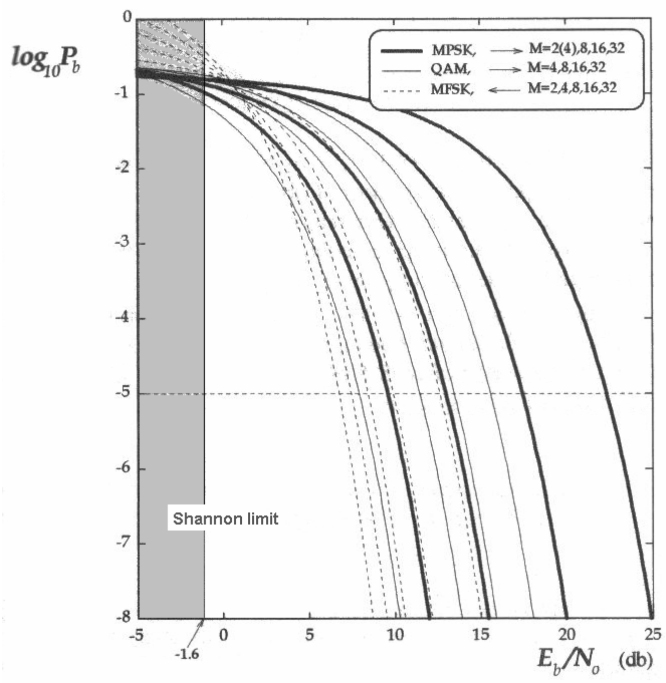


Figure 2: Bit error probabilities for uncoded M-ary FSK, PSK and QAM, coherent demodulation - Adapted from [18]

Step (iii): The bit error probability P_b of each candidate modulation scheme is compared to the value of the bit error probability threshold $P_{b,thres}$, i.e. the maximum permissible bit error probability (e.g., $P_{b,thres} = 10^{-5}$). For a candidate modulation scheme, if $P_b > P_{b,thres}$, then the modulation scheme is rejected.

Step (iv): Among the acceptable modulation schemes, the one that provides the maximum bit rate R, given the bandwidth B in Hz, is selected, according to:

$$R = \begin{cases} B\log_2 M, & \text{M-ary PSK, M-ary QAM} \\ B\dfrac{\log_2 M}{M}, & \text{M-ary FSK} \end{cases} \quad (8)$$

In case that error control codes are in use, relation (6) should consecutively be used, in order to determine the bit rate of the information source.

4 INTERFERENCE SENSING PROCESS IN COGNITIVE RADIO

In the cognitive radio context, a reconfigurable transceiver of a B3G service area needs to be able to sense the capabilities of alternative configurations. For this reason, a few timeslots during its operation should be devoted to the execution of sensing procedures. Thus, a realistic proposal is to break up a transceiver's operational time into 'service provision timeslots' (during which the transceiver *serves* the network traffic) and 'sensing timeslots' (during which the transceiver *senses* the interference levels of an alternative configuration), as depicted in Figure 3(a).

Assume that a reconfigurable transceiver is currently operating under RAT r_0 and is tuned to carrier frequency f_0. This configuration will be denoted henceforth as (r_0, f_0). In addition, let us assume that the transceiver needs to sense the interference level of an alternative configuration (r, f), where $(r, f) \neq (r_0, f_0)$. Figure 3(b) and Figure 3(c) illustrate the interference sensing process on the uplink and downlink, respectively. The estimation of the SINR has to be carried out at the receiver, i.e. the transceiver on the uplink and the terminals on the downlink.

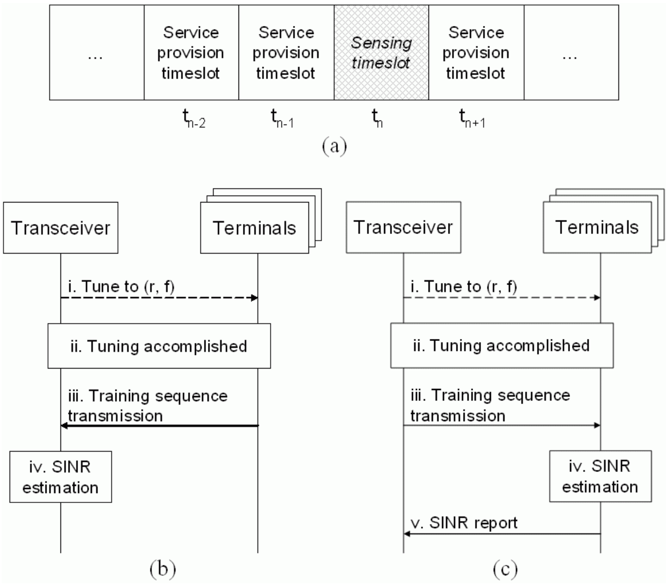


Figure 3: Interference sensing process in a cognitive radio system: (a) notion of service provision timeslots and sensing timeslots; (b) process for the uplink; (c) process for the downlink

In the first case, the transceiver instructs a group of terminals within its service area to temporarily change their configuration *(i)*, and tune to (r, f). The transceiver itself also changes its configuration. Once the tuning has been accomplished *(ii)*, each of the terminals transmits a training sequence back to the transceiver *(iii)*, in order for the latter to estimate the SINR *(iv)*. Once the sensing procedure is complete, both the terminals and the transceiver tune back to their previous configuration (r_0, f_0). Message *(i)* is transmitted under the configuration (r_0, f_0), while all other messages are exchanged under the configuration (r, f).

In the second case, the process is initially similar *(i)-(ii)*. Then, a training sequence is transmitted by the transceiver to the temporarily reconfigured terminals *(iii)*. Next, the estimation of the SINR takes place at the terminal side *(iv)*, and the results are relayed back to the network side *(v)*.

The number of terminals instructed to temporarily reconfigure may vary. In the simplest case, the sensing process may have to be confined to a single terminal. Moreover, instead of SINR estimation, an interference temperature measurement process may take place. In this case, the transmission of a training sequence is not needed. This leads to a considerable simplification of the overall process, especially for measurements on the uplink.

5 THE PROBLEM OF ROBUST CAPACITY ESTIMATION

The need for robustness

Capacity estimation, on the basis of SINR and/or IT measurement, is a prerequisite for optimal configuration selection. However, the most recently measured (estimated) value of capacity is not necessarily the most accurate one. In practice, the estimated values can fluctuate (oscillate) due to *measurement errors*, as well as *temporary changes* in the environment. This yields the need for a more robust capacity estimation scheme.

An essential requirement for such a scheme is to favour the *autonomic* computing paradigm [3]-[4], which is of high importance for cognitive radio systems. According to this paradigm, each B3G service area (i.e., cell) decides autonomously about the most appropriate configuration of its transceivers. This notion of 'self-configuration' is an efficient means for tackling complexity and scalability.

Within this framework, the capabilities of candidate configurations, in terms of capacity, can change over time, as they are influenced by the varying conditions in the environment, *especially* the behaviour of 'near-by' reconfigurable elements. The goal of 'self-configuration' is to enable all elements to act in a completely distributed and autonomous manner. This poses a significant engineering challenge: *how to increase the degree of assurance* that, by assigning a certain configuration (r, f) to a reconfigurable transceiver, the resulting capacity will be the expected one (e.g., x Mbps). A probabilistic model, as well as a learning and adaptation strategy, should be adopted. The resulting problem is: Given a specific candidate configuration (r, f), how can the most probable value of the random variable "capacity" be predicted?

In the following, this problem is solved through a robust learning and adaptation strategy, based on Bayesian networks [19], which are valuable tools for learning and reasoning through probabilistic relationships [20]-[21]. The solution does not violate the autonomy of network elements. In fact, no cooperation (e.g., no message exchange) between the different network elements is needed.

Formulation as a Bayesian network

Figure 4(a) depicts a basic Bayesian model that can be employed for modelling the specified problem. *CAP* is a random variable representing capacity. *CFG* is another random variable, representing a configuration, e.g. configuration (r, f) may be an instance of *CFG*. *CFG* is the Bayesian network's predictive attribute (node), while *CAP* is the target attribute.

The goal is the determination of the maximum value of the conditional probability $\Pr[CAP \mid CFG]$. Therefore, a conditional probability table *(CPT)* is organized, the structure of which is depicted in Figure 4(b). Each CPT refers to a particular RAT. Consequently, if R is the set of possible RATs, then $|R|$ CPTs in total are required for the full information. Each column of the CPT refers to a specific configuration (i.e., RAT and carrier frequency). Each line of the CPT corresponds to a capacity value. In this sense, a discrete set of potential capacity values is defined. Each cell (intersection of line and column) provides the probability (likelihood) that the configuration (corresponding to the column) will achieve the potential capacity value (corresponding to the line). Given a configuration, the most probable value of capacity is the value that corresponds to the maximum conditional probability.

Figure 4(b) is an example for an arbitrary RAT r_1. With F_{r1} denoting the set of spectrum carriers with which RAT r_1 may operate, the CPT consists of $|F_{r1}|$ columns, corresponding to configurations $c_1=(r_1, f_1)$, …, $c_{|Fr1|}=(r_1, f_{|Fr1|})$, and m lines, corresponding to capacity values cap_1, cap_2, …, cap_m. Without loss of generality, enumeration is done in ascending order, i.e. $cap_1 < cap_2 < \ldots < cap_m$. In other words, cap_m is the maximum value. The cell at the intersection of line i and column j is a probability value. It expresses the likelihood that capacity cap_i will be achieved, given the fact that configuration c_j has been selected. Formally, this is denoted as $\Pr[CAP = cap_i \mid CFG = c_j]$.

Learning and adaptation process

In the previous subsection, it was defined that the capabilities of configurations, in terms of capacity, are modelled through the CPTs. The next step is to describe how to update the CPTs. Figure 4(c) is the general representation of the process. This learning and adaptation process yields the robust methods for discovering the performance capabilities of candidate configurations. The update process takes into account the measurements (estimations) of the cognitive radio system and, more specifically, the "distance" (absolute difference) between each probable value and the measured value.

Let us assume that measurements *(obtained through the basic discovery-sensing functionality described in sections 2, 3 and 4)* show that a specific configuration can achieve capacity cap_{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 Δc be the maximum difference between the probable capacity values, i.e. $\Delta c = cap_m - cap_1$.

Then, the following correction factor, cor_i, can be computed for each candidate capacity value cap_i:

$$cor_i = 1 - \frac{|cap_i - cap_{meas}|}{\Delta c} \quad (9)$$

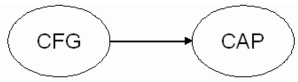
It holds that $0 \le cor_i \le 1$. A value close to 1 reflects that the corresponding candidate value cap_i is close to the measured value cap_{meas}, thus it should be reinforced accordingly. The opposite stands for a value that is close to 0. The correction of the CPT values $\Pr[CAP = cap_i \mid CFG]$ can then be done as follows, for each candidate capacity value cap_i:

$$\begin{aligned} &\Pr[CAP = cap_i \mid CFG]_{new} = \\ &c \cdot cor_i \cdot \Pr[CAP = cap_i \mid CFG]_{old} \end{aligned} \quad (10)$$

where parameter c is a normalizing factor whose value is computed by requiring all 'new' probabilities to sum up to 1.

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

(a)



(b)

CAP	$RAT = r_1$		
	$FRQ = f_1$ ($CFG = c_1 = (r_1, f_1)$)	…	$FRQ = f_{\lvert F_{r_1}\rvert}$ ($CFG = c_{\lvert F_{r_1}\rvert} = (r_1, f_{\lvert F_{r_1}\rvert})$)
cap_1	$\Pr[CAP = cap_1 \mid CFG = c_1]$	…	$\Pr[CAP = cap_1 \mid CFG = c_{\lvert F_{r_1}\rvert}]$
cap_2	$\Pr[CAP = cap_2 \mid CFG = c_1]$	…	$\Pr[CAP = cap_2 \mid CFG = c_{\lvert F_{r_1}\rvert}]$
…	…	…	…
cap_m	$\Pr[CAP = cap_m \mid CFG = c_1]$	…	$\Pr[CAP = cap_m \mid CFG = c_{\lvert F_{r_1}\rvert}]$

(c)

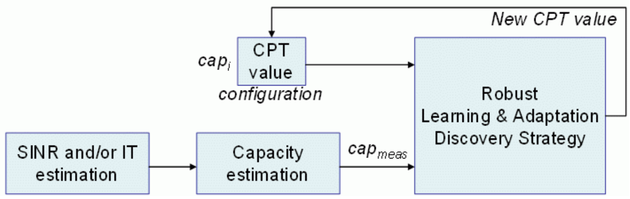


Figure 4: (a) Basic Bayesian network for robust capacity estimation; (b) Sample of the conditional probability table for capacity; (c) Process for updating the CPT values

6 RESULTS

This section exhibits results on the efficiency of the robust discovery method. Two scenarios are presented. The first one aids in the comprehension of the proposed technique. The second one focuses on the evaluation of the scheme's performance, in terms of adaptation speed, when dealing with severe and permanent changes in the values of the measurements taken. In all scenarios, parameter a has been set equal to 0.1.

Scenario 1: Simple example

This scenario helps the in-depth understanding of the proposed technique. Our focus is on an arbitrary configuration $c_1=(r_1, f_1)$, with m=5 candidate capacity values (in Mbps): cap_1=0.5, cap_2=1.0, cap_3=1.5, cap_4=2.0, cap_5=2.5. Hence, Δc=2 Mbps. Also, only three consecutive reinforcements are allowed, after convergence.

Figure 5(a)-(d) depicts the distribution of conditional probabilities in four cases. In each case cap_{meas} is (in Mbps) 1.2, 1.5, 2.1 and 0.75, respectively. The algorithm is applied in five phases of runs (i.e., five time epochs). Initially, the conditional probabilities are uniformly distributed, i.e. equal to 0.2, in all four cases (phase 1). Figure 5(a) shows that the model correctly and quickly adapts to the situation, by selecting cap_2 as the most probable value, in phase 2 (phase 1 represents the initial phase). The model accurately adapts to the second case also (Figure 5(b)), in which cap_{meas}=1.5.

The peak is at cap_3, whereas cap_2 and cap_4 remain practically the same, and, finally, cap_1 and cap_5 suffer significant diminishment. Figure 5(c) shows the results from the third case (in which cap_{meas}=1.8), where the model quickly adapts to cap_4. Finally, the model is also robust in the last, rather unlikely case, in which cap_{meas}=0.75 (Figure 5(d)), suggesting cap_1 and cap_2 as the most likely values.

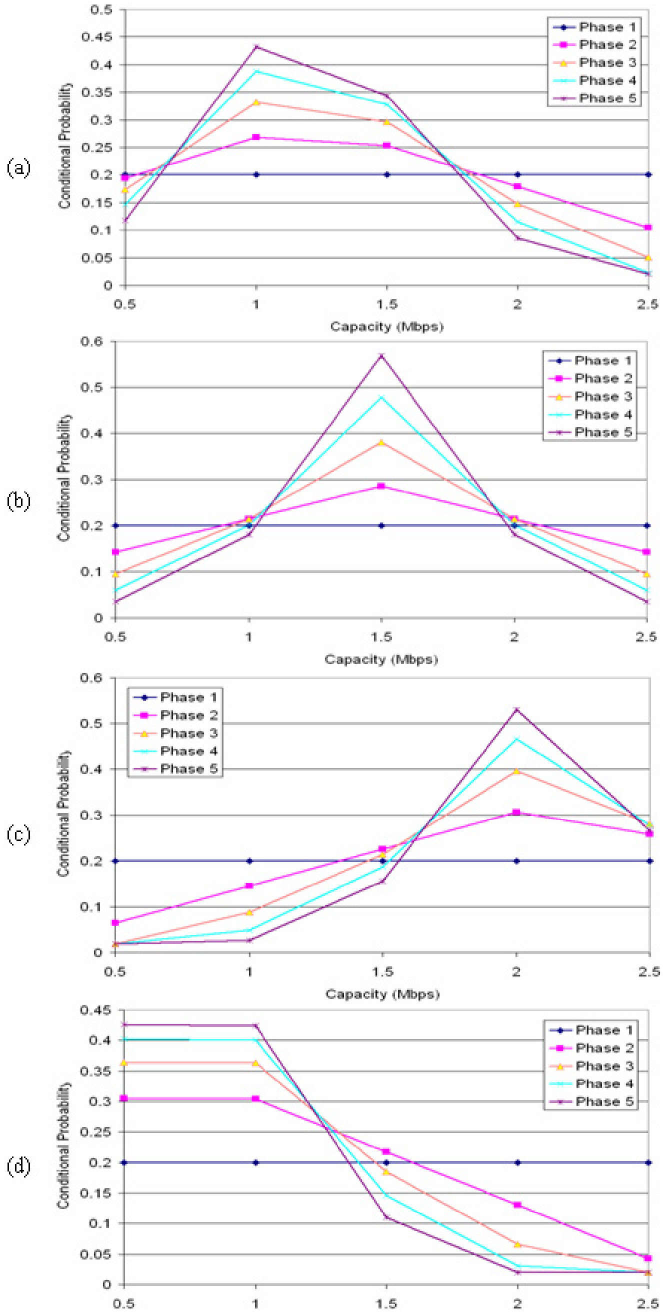


Figure 5: Scenario 1 - Arbitrary configuration c_1. Conditional probabilities corresponding to candidate capacity values, when cap_{meas} is (in Mbps): (a) 1.2; (b) 1.5; (c) 2.1; (d) 0.75

Scenario 2: Adaptation speed vs. number of consecutive reinforcements

The main goal of this scenario is to examine how many steps it takes for the scheme to adapt to a sudden and significant change in the environment conditions. Figure 6(a)-(b) shows the speed of the adaptation when there is a sudden degradation of the measured capacity. In Figure 6(a), we allow three consecutive reinforcements of the most probable value, after convergence. In Figure 6(b), only one reinforcement is allowed.

Figure 6(a) depicts the probability distributions when cap_{meas} suddenly becomes 1.1 Mbps and constantly remains the *same* for all next series of measurements. Our starting point is the case depicted in Figure 5(c) (i.e., our model evolved as depicted in Figure 5(c), before the sudden change in cap_{meas}). The goal is to examine how quickly the system can adapt and converge to cap_2, which is the value that is nearest to cap_{meas}. As can be observed, in 4 steps (phases 2-5) the most probable value drops from cap_4 to cap_3. In another 6 steps (phases 6-11), candidate values cap_2 and cap_3 are suggested as the most likely ones. Finally, in the next step (phase 12), cap_2 becomes the most probable one.

Pertaining to Figure 6(b), in just 2 steps (phases 2-3), the most probable value drops from cap_4 to cap_3. In another 3 steps (phases 4-6), cap_2 almost reaches cap_3, and in the next step (phase 7) cap_2 becomes the most probable value.

Thus, another useful conclusion that can be deduced from the simulations described in this subsection is that the number of consecutive reinforcements, after convergence, clearly affects the model's adaptation speed. High number of consecutive reinforcements reduces the adaptation speed.

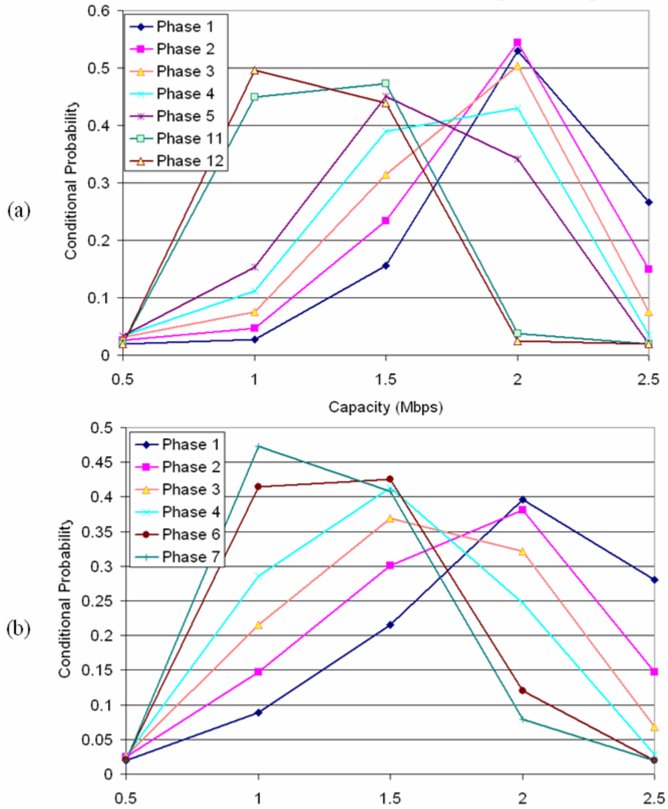


Figure 6: Scenario 2 - Arbitrary configuration c_1. Learning and adaptation process when cap_{meas} suddenly degrades from 2.1 to 1.1 Mbps. Speed of adaptation when the number of consecutive updates, after convergence, is: (a) three; (b) one

7 CONCLUSIONS

In the B3G wireless scenery, cognitive systems will dynamically reconfigure the RATs and the spectrum they use, in order to adapt to the changing environment conditions. However, dynamic reconfiguration decisions call for robust discovery (i.e., radio-scene analysis and channel identification) schemes. This paper's goal was to contribute in the areas of radio-scene analysis and channel identification: firstly, by explaining how a cognitive radio system can acquire interference and capacity estimations; and, secondly, by enhancing the above with a learning system, which is essential for obtaining a truly cognitive process. The proposed approach was to develop a simple yet robust Bayesian probabilistic model for optimal prediction of the capabilities of alternative configurations, in terms of transmission capacity.

The short-term future plan is to enrich the basic Bayesian model that has been described, by adding more nodes (random variables), including 'coverage' and 'context' (i.e., 'traffic' and 'user mobility'). The overall future plan is to further employ probabilistic relationships and autonomic computing principles in the direction of realizing cognitive, wireless access, infrastructures. The goal is to develop an autonomic manager which will encompass the robust estimation scheme. The manager will consist of policies, context perception capabilities, reasoning algorithms, learning functionality and knowledge engineering, technologies for the representation of ontologies and semantics. All these will yield a system that *hypothesises* on causes to a situation, and subsequently validates or falsifies the hypothesis.

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