Goodput Maximization in Opportunistic Spectrum Access Radio Links with Imperfect Spectrum Sensing and FEC-based Packet Protection

Maurizio A. Bonuccelli
Dipartimento di Informatica
University of Pisa
Largo Bruno Pontecorvo 3, I-56127 Pisa, Italy
Email: bonucce@di.unipi.it

Donatella Ermini, Loreto Pescosolido, Chiara Petrioli
Computer Science Department
University of Rome "La Sapienza"
Via Salaria 113, I-00198 Rome, Italy
Email: loreto.pescosolido@uniroma1.it,
{ermini,petrioli}@di.uniroma1.it

***Abstract*—We consider a cognitive radio scenario where the communication between two secondary users (SUs) exploits opportunistic spectrum access (OSA) over a wireless channel licensed to primary users (PUs). Assuming a slotted MAC over a single frequency channel and imperfect spectrum sensing, we address the problem of determining the packet size and Forward Error Correction (FEC) coding rate that maximize the SU communication goodput, i.e., the amount of *payload* bits correctly received in the unit time. Assuming a Markovian model for the PU activity, a saturation regime for the SU, and periodic channel sensing, we find out the mean time between two consecutive packet transmissions and derive approximate analytical expressions, in closed form, which provide upper and lower bounds on the SUs goodput. Such expressions show the dependence of the SU goodput on packet size, FEC coding rate, signal to noise plus interference ratio, amount of resources allocated to sensing, packet overhead, and primary traffic statistics. We provide simulation results showing that the derived analytical expressions are very close to the actual system performance. We also evaluate the sensitivity of the optimal packet size and FEC coding rate pair to the operational conditions represented by the received power and the PU traffic load, showing that the optimal pair is very sensitive to the former, and only moderately affected by the latter.**

***Index Terms*—Cognitive radio, Opportunistic Spectrum Access (OSA), spectrum sensing, packet size, FEC, Markov processes, recurrent events, throughput maximization.**

I. Introduction

The cognitive radio paradigm, [1]–[3], has emerged as a promising approach to increase the efficiency in using the available radio spectrum. In cognitive radio networks (CRNs), wireless terminals learn about the radio environment and exploit this knowledge to adapt their behavior to possibly varying conditions. In the Opportunistic Spectrum Access (OSA) implementation of the cognitive radio paradigm, the "cognition" process is enabled at the physical layer by means of spectrum sensing, [4]–[6]. The so called secondary users (SUs) acquire knowledge about the status of the channel licensed to primary users (PUs), and opportunistically use the channel if they detect it as currently idle. This channel reuse principle is applicable both in time and space. In the former case, the SU communication happens during time intervals in which the channel is idle; in the latter, it is enabled in spatial regions in which the spectrum is unused [7].

A central issue in any OSA system design is the maximization of the SU performance under a constraint on the performance degradation caused to PUs. In our work, we focus on maximizing the system goodput, defined as the amount of payload bits that a node can correctly receive in the unit time. Specifically, we consider a single-user scenario, where a SU and a PU communication coexist. SU and PU share the same slotted MAC structure. We assume a traffic saturation regime for the SU (i.e., the SU always has data to transmit) and that the PU activity can be modeled by a discrete-time Markov chain (DTMC). Under these assumptions, we investigate how to maximize the goodput experienced by the secondary system, while fulfilling a constraint on the maximum tolerable performance loss of the primary system.

We formulate the SU performance optimization problem taking into account, as a key aspect of the problem, the overhead and redundancy introduced at the different levels of the protocol stack (application, transport, routing, data link control, MAC, and physical layers).

The system parameters we consider for optimizing the SU performance are the packet size and the Forward Error Correction (FEC) coding rate applied to each packet. We show that, to achieve optimal goodput, this pair of parameters should be optimized jointly, on the basis of the conditions in which the SU operates. The operating conditions relevant to our optimization are the Signal to Noise plus Interference Ratio (SNIR) experienced by the SU receiver and the PU traffic statistics.

With respect to previous works, our paper provides the following contributions:

- The computation of the average time between two successive packet transmissions by the SU. We do this by approximating the sequence of the PU traffic *as observed* by the SU with a Markov chain, and using results from the theory of recurrent events [8].
- The computation of upper and lower bounds on the SU packet error probability, including the effect of using different FEC codes.
- The derivation of analytical expressions for upper and lower bounds on the achievable goodput, which show that the best performance can be obtained combining packet

978-1-4673-2433-5/12/$31.00 ©2012 IEEE

size (i.e., payload percentage) and FEC coding rate.

- Simulation results are provided to validate our analytical findings and to explore the impact of different relevant parameters on the packet size and FEC code optimization.

Summarizing, taking into account the throughput penalty due to spectrum sensing, the sensing performance, and different types of packet overhead, we show that the selection of the SU packet size and the FEC coding rate should be done in a joint manner, in order to maximize the SU goodput.

The paper is organized as follows: Section II discusses works in the literature that are relevant to our problem and clarifies the novelty of our paper. Section III introduces our system model for PU and SU operations, including spectrum sensing and PU traffic modeling assumptions. In Section IV we derive our analytic results in terms of characterization of the average time between two consecutive packet transmissions and average system goodput. In Section V we describe the results of our performance evaluation. Finally, Section VI concludes the paper.

II. Related work

Designing MAC and scheduling protocols is an important challenge for an effective implementation of CRNs based on DSA. The research in this area has considered a variety of network architecture and system assumptions. An overall overview of the state of the art in this vast field can be found, for instance, in [9]–[12]. Despite this impressive amount of research, it is hard to find works that take into account, at the same time, realistic (i.e. imperfect) spectrum sensing performance, MAC and data link aspects such as the selection of the payload size and the best FEC coding rate, optimizing goodput instead of throughput. We show that, indeed, the above mentioned aspects should be taken into account jointly, to maximize the amount of payload bits transferred through an OSA radio link.

Computing the throughput-optimal sensing time while taking into account realistic sensing performance is the objective of [13]–[15]. In [13], under an unslotted PU channel access and a continuous-time Markovian modeling of the PU activity, optimal channel search times and sensing times are derived which maximise SU throughput. A framework for the optimal scheduling of spectrum sensing and transmission is presented in [14], which also considers adaptive scheduling and cooperative sensing, under an unslotted PU MAC assumption. In [15], Liang et al. assume a slotted PU MAC, with SUs able to synchronize to the PU slot structure. They show that the problem has an optimal sensing time, which yields the highest throughput SUs, under the constraint that primary users are sufficiently protected. A similar analysis is carried out by Wang et al. in [16]. In this paper, we use the same SU MAC and spectrum sensing assumptions of [15], [16].

In [17], the authors consider a time varying traffic-load and channel quality. They show the sub-optimality of performing spectrum sensing at fixed intervals, under such varying conditions. They then propose to adaptively schedule spectrum sensing and data transmissions to channel and traffic conditions, so as to minimize throughput loss and transmission delay. Our contribution differs from [13]–[17] in that these works do not consider the payload/overhead distinction and the presence of FEC, both in terms of overhead bits and the impact on the packet error probability.

Huang et al. investigate in [18], [19], the data capacity, defined as the percentage of time in which SUs can transmit on the channel under stringent constraints on collision probability and overlapping collision time. The assumption on the slotted MAC/PHY organization is similar to our one. Both analytical tools and simulations are used to validate the results, which shed further light into the fundamental trade-off between sensing performance and throughput. This work is relevant to ours as it considers imperfect sensing and focuses on payload bits. However, differently from our work, it does not incorporate the use of FEC to protect SU packets. Indeed, FEC plays an important role and has an interesting interplay with the other system parameters.

The proper dimensioning of payload and overhead in packets is a classical problem in MAC protocol design. Although this problem has been well studied in conventional systems (e.g., WiFi, sensor networks, etc. [20]–[25]), it is hard to find works which address it in new paradigms such as CRNs, DSA and OSA, in conjunction with a realistic modeling of the spectrum sensing activity and other low-level issues which play a key role to obtain an effective, integrated, protocol design. For instance, works such as [26]–[29] address the packet size and payload issues, but do not take accurately into account the effect of imperfect spectrum sensing. In [26], Borgonovo et al. propose a modeling framework to evaluate the performance of SUs in CRNs. Leveraging queuing theory they derive closed form expressions for the throughput and delay of secondary users. The impact of several traffic characteristics (e.g., packet size, primary traffic load, traffic statistics, etc.) is considered on the derived bounds, and they show how the proposed throughput model can be used to optimize the payload length of secondary transmissions. However, their model is based on perfect spectrum sensing (i.e., miss-detection and false alarms are not considered), meaning that secondary users leave/access the channel as soon as the primary presence/absence is detected, without causing any interference or resource waste. In [27], [28], the authors compute the SU goodput. In [28], they compare the impact on goodput of having SU packets with either exponentially distributed payloads or with fixed size. The authors show that, the exponentially distributed payload leads to lower throughput than a fixed-size SU packet stream, even if it has lower *blocking* and *forced termination* probabilities. These works assume perfect, and instantaneous, detection of the channel status, as well as the ability to vacate the channel immediately as the PU is back on the channel. In [29], a discrete-time queuing system is used to describe the behavior of a secondary network. The model captures the discontinuous nature of SU transmissions as SUs alternate spectrum sensing and data transmission on the same channel. A slot-by-slot transmission structure and a sense-then-transmit strategy is adopted, where each slot is fragmented in several periods: a sensing and decision period, a transmission period, and an acknowledgement period. By means of simulations, it is shown that longer packets might increase SUs' throughput, but lead to a higher number of collisions. In contrast, smaller packets might decrease the probability of collisions, while increasing the overhead of sensing and decision making. Notice that, although [29] considers that sensing inhibits the SU from transmitting in dedicated periods, assuming the alternation of sensing and transmission as in [15], [16] and in our work, it neither accounts for sensing errors, nor for the impact of using different FEC codes.

To the best of our knowledge, our work is the first one to target goodput instead of throughput as the SU performance metric, while combining PHY layer aspects such as spectrum sensing performance with MAC layer issues such as packet size and the choice of the best FEC code.

III. System Model

We consider a scenario where primary, licensed users, coexist with SUs operating in the same wireless frequency band. Primary Transmitters (PTx) use the licensed frequency band to send packets to Primary Receivers (PRx). They operate according to a protocol stack that, in general, is designed without considering the presence of SUs and the possibility to cooperate with them. Secondary Transmitters (STx) can "opportunistically" access the same channel to send their own packets to Secondary Receivers (SRx). The opportunistic channel access protocol should ensure that:

1) When a STx has a packet to transmit, it is able to check if the channel is currently in use by a PTx. In case the channel is busy, the STx refrains from accessing the channel.

2) If the PTx starts using the channel to transmit its own data during a STx packet transmission, the STx will immediately stop transmitting, thus loosing the current packet.

We assume that there cannot be any control information exchange between primary and secondary systems to coordinate transmissions, and that the two requirements described above are fulfilled through the so called *"spectrum sensing functionality"* of the secondary system. Spectrum sensing enables the STx to detect the primary presence on the channel, inhibiting a packet transmission in case the channel is already in use, or vacating the channel during a SU packet transmission in case new PU transmission begins.

Our objective is the maximization of the goodput experienced by the secondary system, while fulfilling a constraint on the maximum tolerable performance loss of the primary system. The goodput is defined as the amount of payload bits, successfully received per unit time. Particularly, we will show that the selection of the packet size and FEC code pair deeply affects the SU goodput, suggesting that these two parameters should be jointly optimized as a function of received power and PU traffic load. We explicitly account for different types of overhead, which we classify in the following three categories:

a) Redundancy bits for error correction: required to implement the data link layer functionalities. Specifically, we

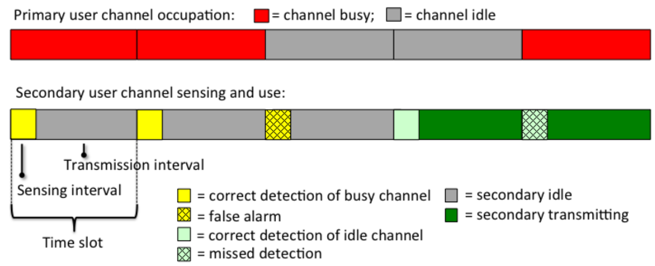

Figure 1. Channel use of primary and secondary users

consider the use of FEC codes, which encode bits at a coding rate

$$K \triangleq b_m / b_c, \tag{1}$$

where b_m is the number of uncoded bits and b_c is the length of the codeword. For the sake of simplicity, we assume that the whole packet is encoded at the same rate although, in practical schemes, different portions of a packet may be encoded at different rates.

b) Overhead due to the packet header and trailer: consisting of all the control information that, in any practical communication system, allows the implementation of application, transport, routing, data link control, and MAC protocols. Typical information that may be included in such packet fields are the IP addresses of source and destination, the packet flow identifier, the required QoS indicators, MAC addresses, packet identifiers in PDU MAC fragments, and so on. In this category, we also include a constant (non-depending on the packet size) number of bits, needed for FEC implementation[1]. Additionally, several cyclic redundancy check (CRC) bits may be envisioned to increase the reliability of the data link layer by deciding whether or not to accept a packet. We denote with b_h the number of bits required in each secondary packet to implement all the above mentioned functionalities *and* that are independent of the number of payload bits.

c) Overhead due to spectrum sensing: although not consisting of actual transmitted bits, this overhead expresses the percentage of transmission resources that the STx is prevented from using to be able to perform the primary signal detection[2]. This overhead reduces STx transmission efficiency. However, the higher the percentage of transmission resources left for primary user detection, the better its performance are in terms of miss-detection and false alarm probabilities. From the allocation of these resources to the PTx detection or to the STx transmission, it arises the fundamental trade-off described in [15]. We assume that a constant percentage α_s of transmission resources is not available to SUs due to the implementation of the spectrum sensing functionality.

In the following, we refer to a specific implementation of the physical layer, although most of our results, at least from a qualitative point of view, could be easily extended

[1] Convolutional FEC codes as those we consider in this paper require a constant number of trailing bits, independent of the packet size, to bring the decoder in a regime state.

[2] Secondary systems in which it is possible to opearate the spectrum sensing functionality on the same set of resources used for transmission are covered by our framework. In this case, the spectrum sensing functionality has no impact in terms of overhead.

to scenarios with different PHY characteristics. Similarly to [15], we consider a system in which PUs and SUs share the same slotted MAC structure, leaving the study of the case with absence of synchronization between SU and PU, or with an unslotted PU MAC, to our future work. PUs transmit packets of variable length, starting at the beginning of a slot, and corresponding to an integer number of slots (See Subsection III-A for our assumption on the PU traffic statistics). We assume that SUs are equipped with a half-duplex radio transceiver, which cannot transmit and receive (and therefore, sense) at the same time on the same frequency band. A *sense-then-transmit* strategy is hence employed by the SU in each slot. The percentage of resources made unavailable for transmission due to the implementation of spectrum sensing consists of small sensing intervals placed at the beginning of each slot[3] (see Fig. 1). SUs transmit packets with size corresponding to a fixed integer number of slots. In our set-up, the interruption of an SU packet transmission due to the detection of the PU presence determines the loss of the whole SU packet. On one hand, the risk of losing the whole packet due to a PU return can be reduced through a decrease of the packet size. On the other hand, increasing the packet size yields a reduction of the overhead percentage. Finding the best compromise between these two effects allows to achieve goodput-optimal performance. In this paper, we consider the single user case, for both primary and secondary systems, leaving the analysis of the multi-user case to a future work.

As showed in Fig. 1, if the channel is detected as idle during the sensing interval, the rest of the slot is used for transmission; otherwise, if a primary signal is detected, the transmission is interrupted, causing a loss of the current packet. We point out that SU transmissions are periodically suspended (in the initial portion of each slot) for a pre-determined amount of time in order to perform spectrum sensing; we are implicitly assuming that the receiver is able to recover the signal tracking at the end of the sensing interval at the physical layer. The assumption is justified in a scenario in which the sensing interval lasts for a very short time, sufficiently short to let the receiver keep the synchronization, even in phase, with the signal. On the other hand, interruptions occurring upon detection of the PU signal do cause the loss of the whole packet, because the time interval after which the SU will have access again to the channel is unknown to the SU receiver and much longer (several time-slots) than the sensing intervals. We remark that the slot duration is not, for us, a parameter to optimize, since this issue has been considered in other works, e.g. [17].

We denote with M the SU packet length, in number of slots. The goal of our analysis is to find out the values for M and K which maximize the *goodput* of the secondary system, i.e. the number of payload bits *correctly received*, on average, per unit time.

We define the transmission rate B of the secondary system as the number of bits that can be transmitted per second by the STx and denote with b_m the number of payload bits contained in a secondary packet. In general, given the (bit) transmission rate B, the percentage of transmission resources α_s unavailable due to the need to perform spectrum sensing, the overhead length b_h, and the coding rate K, the time required to transmit a packet with b_m payload bits is

$$\tau_p = \left(b_h + b_m/K\right)\Big/\left(B\left(1-\alpha_s\right)\right). \tag{2}$$

We complete our model giving the expressions of the net amount of bits in a SU packet, i.e. b_m, tailored to the particular MAC-PHY structure we have assumed. If either PU or SU were allowed to use the whole slot, the number of bits transmitted in a slot would be $b = \tau_s B$, where τ_s is the slot duration. Due to the presence of sensing intervals at the beginning of each slot, SUs can effectively transmit b' bits per slot, with

$$b' = \left(1-\alpha_s\right)\tau_s B = \left(1-\alpha_s\right) b\,. \tag{3}$$

With an overhead of b_h bits, we obtain the following expression for b_m:

$$b_m = K\cdot\left(Mb' - b_h\right) = K\cdot\left(Mb\left(1-\alpha_s\right) - b_h\right). \tag{4}$$

In the following, we describe our assumptions for modeling the primary activity on the channel and the spectrum sensing performance in the SUs.

A. Primary system model

The primary user activity is represented by an alternating pattern of periods during which either the primary uses the channel to transmit (busy periods) or the channel is unused (idle periods). We denote with $x[k]$ the state of the channel during slot k. Specifically, $x[k] = 1$ means that the channel is in use by the PU, and $x[k] = 0$ that the primary is not transmitting. We model $x[k]$ as a two state DTMC, with steady-state probabilities defined as $p_0 \triangleq P(x[k] = 0)$ and $p_1 \triangleq P(x[k] = 1)$, and transition probabilities

$$\begin{aligned} p_{00} &\triangleq P(x[k] = 0/x[k-1] = 0)\\ p_{01} &\triangleq P(x[k] = 1/x[k-1] = 0)\\ p_{10} &\triangleq P(x[k] = 0/x[k-1] = 1)\\ p_{11} &\triangleq P(x[k] = 1/x[k-1] = 1). \end{aligned} \tag{5}$$

According to this assumption, the busy and idle periods follow a geometric distribution, with average sojourn times μ_0 and μ_1 (measured in number of steps) in the idle or busy state respectively given by (see e.g. [30]) $\mu_0 = 1/\left(1-p_{00}\right)$ and $\mu_1 = 1/\left(1-p_{11}\right)$.

B. Spectrum sensing model

The periodic sensing activity of the primary presence on the channel enables the STx to avoid interfering with primary transmissions. In our model, we consider the case of imperfect sensing, which means that the primary activity detection may fail. Specifically, we may incur a *miss-detection*, when the detector does not reveal the primary transmission on the channel, or a *false alarm*, when the detector reveals a primary signal on the channel, although the PTx is not transmitting.

[3]Alternative formulations are possible. For instance, keeping the "half duplex" assumption, the sensing could be done continuously over a limited frequency portion of the primary channel.

Imperfect sensing of the channel affects both primary and secondary system performance. In this work, we assume that the constraint on the impairments caused to the primary system is in the form of a prescribed miss-detection probability. This key constraint could be imposed in the form of alternative metrics like PU packet error rate (PER), PU bit error rate (BER), amount of interference (AOF), and so on. The reason to use the miss-detection probability is that all these performance metrics depend on it, but it also has the advantage of an immediate and simple functional relation with the SU performance. In the following, we indicate with $y[k]$ the decision of the primary signal detector in the k-th slot. Each element of the sequence $y[k]$ can be either "0", if the STx has decided that the channel is idle, or "1", if it appears to be busy. The performance of the detector are expressed in terms of false alarm and miss-detection probability, defined as:

$$\begin{aligned} p_{fa} &= P(y[k]=1/x[k]=0) \\ p_{md} &= P(y[k]=0/x[k]=1). \end{aligned} \tag{6}$$

We are not interested in writing explicit equations for the detector since this equations are implementation specific[4]. The important aspects, at least for the class of hard detectors which is of interest for us, are that *i):* A detector compares a suitable test statistic, which is a function of a set of signal readings, with a threshold; *ii):* For a given technology, setting the threshold determines the false alarm and miss-detection probabilities: increasing the threshold lowers p_{fa} but increases p_{md}; *iii):* Since increasing the sensing interval allows to take more signal samples[5], the sensing performance p_{fa} and p_{md} are also function of the length of the time interval $\alpha_s\tau_s$, besides the primary signal strength.

IV. Secondary User Goodput Maximization

A. The "perceived" primary traffic

For the evaluation of the SU goodput, it is important to properly take into account that the STx decides to access the channel on the basis of its perception of the channel idle/busy states. Since we assume that the SU has always information to transmit, it performs spectrum sensing at any time slot. We indicate with $y[k]$ the sequence of decisions made by the detector. The statistical properties of the sequence of sensing outcomes $y[k]$ are determined by the transition probabilities of the DTMC $x[k]$ and the false alarm and miss-detection probabilities of the detector. For the sequence $y[k]$, due to the sensing performed at each step, it can be showed that, in general, the Markov property does not hold. For small values of p_{md} and p_{fa}, however, the dependence of the state in the current step from the past history *beyond* the previous step is negligible. In such a case, the modified DTC retains, approximately, a Markovian behavior. In practical terms, this means that the distribution of the length of runs of consecutive "0" or "1" states is very well approximated by a geometric distribution. In the following, we will treat $y[k]$ as a DTMC. To indicate its steady-states and transition probabilities, we will use the following notation:

$$\begin{aligned} q_0 &\triangleq P(y[k]=0) \quad & q_{00} &\triangleq P(y[k]=0/y[k-1]=0) \\ q_1 &\triangleq P(y[k]=1) \quad & q_{01} &\triangleq P(y[k]=1/y[k-1]=0) \\ & & q_{10} &\triangleq P(y[k]=0/y[k-1]=1) \\ & & q_{11} &\triangleq P(y[k]=1/y[k-1]=1). \end{aligned} \tag{7}$$

Using standard Bayesian analysis arguments, we can derive the following expressions of the steady states and transition probabilities of the chain $y[k]$, which are function of the corresponding probabilities for the actual channel use sequence $x[k]$, and the miss-detection and false alarm probabilities of the detector:

$$\begin{aligned} q_0 &= p_0(1-p_{fa}) + p_1 p_{md} \\ q_1 &= p_0 p_{fa} + p_1(1-p_{md}) \end{aligned} \tag{8}$$

and

$$q_{00} = \frac{p_0\,(1-p_{fa})\,(p_{01}p_{md} + p_{00}\,(1-p_{fa}))}{p_0\,(1-p_{fa}) + p_1 p_{md}} + \frac{p_1 p_{md}\,(p_{11}p_{md} + p_{10}\,(1-p_{fa}))}{p_0\,(1-p_{fa}) + p_1 p_{md}} \tag{9a}$$

$$q_{01} = \frac{p_0\,(1-p_{fa})\,(p_{00}p_{fa} + p_{01}\,(1-p_{md}))}{p_0\,(1-p_{fa}) + p_1 p_{md}} + \frac{p_1 p_{md}\,(p_{10}p_{fa} + p_{11}\,(1-p_{md}))}{p_0\,(1-p_{fa}) + p_1 p_{md}} \tag{9b}$$

$$q_{10} = \frac{p_0 p_{fa}\,(p_{00}\,(1-p_{fa}) + p_{01}p_{md})}{p_0 p_{fa} + p_1\,(1-p_{md})} + \frac{p_1\,(1-p_{md})\,(p_{10}\,(1-p_{fa}) + p_{11}p_{md})}{p_0 p_{fa} + p_1\,(1-p_{md})} \tag{9c}$$

$$q_{11} = \frac{p_0 p_{fa}\,(p_{00}p_{fa} + p_{01}\,(1-p_{md}))}{p_0 p_{fa} + p_1\,(1-p_{md})} + \frac{p_1\,(1-p_{md})\,(p_{10}p_{fa} + p_{11}\,(1-p_{md}))}{p_0 p_{fa} + p_1\,(1-p_{md})}. \tag{9d}$$

B. Packet transmission rate

In the following, we restrict our attention to the case of a SU working in a saturation regime. From the description of our system model, it is clear that the transmission of a SU packet can be completed *if and only if* the STx detects a sequence of M consecutive idle slots on the channel.

We define the *packet transmission rate* R_{Tx}, as the number of packets transmitted in a given time interval by the SU, divided by the duration of that interval. R_{Tx} represents "how often" the STx manages to complete the transmission of a packet, given that each PU signal detection stops its transmissions. To find R_{Tx}, we resort to the theory of recurrent events [8]. A known result of this theory characterizes the behavior of the waiting time (i.e. the number of trials or, in our case, time slots) required to observe a run of a given length of consecutive steps in the same state, of a two-state DTMC with known transition probabilities. Such number of trials is a

[4]In our simulations, similarly to the majority of the works considering spectrum sensing in the context of a broader optimization framework, we have assumed the expressions for p_{md} and p_{fa} corresponding to the use of the popular energy detector [31], with the further assumption that the primary signal can be approximated with a zero mean white Gaussian signal. Suitable expression of p_{md} and p_{fa} can be found e.g. in [19].

[5]To be precise, it allows to take independent (conditionally on the presence or absence of the PU signal), noise corrupted, samples.

random variable that has been studied in [32]. To determine the average time interval between the transmission of consecutive packets, let us consider the last slot of a packet transmission and denote it, without loss of generality, with the step index 0. The fact that the slot has been used for transmission from the SU yields that we should consider the state of the chain in step zero as idle, i.e. $y[0] = 0$. Now, the time one has to wait to transmit another packet is exactly the waiting time to observe (for the first time) a new run of M consecutive zero states. We remark that it is important to specify from which state "we are starting to wait for the new run". In fact, the statistics of the waiting time when starting to wait from a "0" are different from those of the waiting time when starting from a "1". Clearly, we are interested in the former of the two. In particular, from [32], eq. (2.17), we can express the mean waiting time, measured in number of time slots, as

$$\bar{t}_M = \frac{1-(1-q_{01})^M}{q_{01}q_{10}(1-q_{01})^{M-1}}(q_{01}+q_{10}). \tag{10}$$

This expression gives the average time the SU has to wait for managing to transmit a packet with the duration of M slots. The inverse of this average waiting time tells us how many packets the SU manages to transmit per unit time, i.e. the SU packet transmission rate R_{Tx}. In packets per time slot, we have

$$R_{Tx} = \frac{1}{\bar{t}_M} = \frac{q_{01}q_{10}(1-q_{01})^{M-1}}{1-(1-q_{01})^M}\frac{1}{(q_{01}+q_{10})}. \tag{11}$$

Notice that (11) depends both on the primary traffic statistics *and* on the detector performance, since q_{01} and q_{10} are parameters of the DTMC representing the perceived traffic, which depend on the primary traffic and the detector by (9b) and (9c). In the following subsection we model the performance at the receiver, which allow us to compute the average packet *correct reception* rate.

C. Packet reception rate

The SU communication goodput is determined by the percentage of the transmitted packets that the receiver manages to correctly decode. The packet error rate, in general, depends on the particular FEC code with which packets are protected and on the SNIR experienced by the receiver during the reception of the packet. In the following, we restrict our attention to convolutional codes[6]. The reason is their high flexibility in terms of the encoded message length, which allows us to "scan" the packet size domain with an arbitrary granularity and range, while leaving unchanged the ratio between message and codeword length (except for the trailing bits, which do not depend on the message length). More details on the chosen codes will be given in Section V. For a given convolutional encoder of rate K (whose structure does not depend on the encoded message length), assuming that the SNR at the SRx remains constant during the whole packet reception, the packet error probability, which we denote as $\bar{P}_e$, is uniquely determined by the SNR value and by the packet length M.

$$\bar{P}_e = \bar{P}_e(K, M, \mathcal{P}_{rx}/\sigma^2), \tag{12}$$

[6]All our analytical results can be applied also to block codes.

where $\mathcal{P}_{rx}$ is the power received by the SRx and σ^2 is the noise power. In our scenario, we must take into account that there is a non-zero probability that in one, or more, of the M time-slots used by the SU to transmit the packet, the PU does, in fact, use the channel, while the SU doesn't detect its transmission due to sensing errors (miss-detections). Therefore, the SU packet error probability depends on the pattern of such actual channel uses. Depending on the specific code, (12) may or may not be available in closed form, but can always be found by numerical simulations and tabulated for each value of interest of the SNR. In other words, it can safely be assumed as a known characteristic of the code that only depends on the values of K and M.

We now indicate with $\mathcal{S} = \{\boldsymbol{s}_0, ..., \boldsymbol{s}_{2^M-1}\}$, the set of 2^M possible sequences of states of the PU during the M time slots, where $\boldsymbol{s}_i$ is (without loss of generality) the binary representation of the number i, $\forall i \in \{0, \dots, 2^M-1\}$. We observe that, while receiving a packet transmitted by the STx, the SRx could experience an interfering signal coming from the PTx which may follow any of the distinct patterns represented by the sequences introduced above, although with different probabilities. The PTx-vs-PRx interference, $\mathcal{P}_{int}$, generated by the (undetected) primary transmission in a subset of the SU packet time-slots, is summed to the noise term, thus increasing (in those time slots) the noise plus interference power term. It is clear that each of the possible interference patterns corresponds to a distinct SU packet error probability. We denote the packet error probabilities for the patterns in $\mathcal{S}$ with $P_e(\boldsymbol{s}_i)$, $\forall i \in \{0, \dots, 2^M-1\}$, where the dependency on K, M, $\mathcal{P}_{rx}$, σ^2, and $\mathcal{P}_{int}$ has been dropped, since they are intended to be fixed parameters in the following derivations.

We now define $\tilde{p}(\boldsymbol{s}_i)$ as the *posterior conditional probability* of the sequence of states $\boldsymbol{s}_i$, i.e. the probability that, given that the SU has succeeded in transmitting over a sequence of M slots (i.e., it has transmitted a packet), the interference from the PU, in those M slots, has followed the pattern $\boldsymbol{s}_i$. The average packet error probability, for a given packet size M and error correction coding rate K, is given by

$$P_e(K, M) = \sum\nolimits_{i=0}^{2^M-1} P_e(\boldsymbol{s}_i)\,\tilde{p}(\boldsymbol{s}_i). \tag{13}$$

We remark that the $\tilde{p}(\boldsymbol{s}_i)$ are *conditional* probabilities, with the conditioning event being a sequence of M idle state detections in the chain $x[k]$.

The problem with (13) is that, except for the case of M consecutive channel idle states $\boldsymbol{s}_0 = [0, \dots, 0]$, corresponding to M consecutive correct decisions, expressions for the terms $P_e(\boldsymbol{s}_i)$ are not available. $P_e(\boldsymbol{s}_0)$ coincides with (12), i.e. the performance of the code in the presence of a constant SNR, and is hence available, whereas the remaining $2^M - 1$ terms are too many (even with moderately large values of M) to be computed for all the desired SNR values. To proceed with our analysis, we resort to lower and upper bounds for the packet error probability. We can readily say that the packet error probability (13) is lower bounded by $P_e(\boldsymbol{s}_0)$, which corresponds to the performance in the absence of PU signal in all the M time-slots, since it represents the characteristic of the chosen code, i.e. (12).On the other hand, an upper bound on the PER can be obtained bounding the probabilities $P_e(\boldsymbol{s}_i)$, $i = \{1, \ldots, 2^M - 1\}$, with the value[7] 1, i.e. $P_e(\boldsymbol{s}_i) < 1$. We have hence

$$\begin{aligned}P_e(\boldsymbol{s}_0) \leqslant P_e(K, M) =& P_e(\boldsymbol{s}_0)\,\tilde{p}(\boldsymbol{s}_0) + \sum\nolimits_{i=1}^{2^M-1} P_e(\boldsymbol{s}_i)\,\tilde{p}(\boldsymbol{s}_i)\\ <& P_e(\boldsymbol{s}_0)\,\tilde{p}(\boldsymbol{s}_0) + 1 \cdot \sum\nolimits_{i=1}^{2^M-1} \tilde{p}(\boldsymbol{s}_i)\\ =& P_e(\boldsymbol{s}_0)\,\tilde{p}(\boldsymbol{s}_0) + (1 - \tilde{p}(\boldsymbol{s}_0)). \qquad (14)\end{aligned}$$

To derive a suitable expression for $\tilde{p}(\boldsymbol{s}_0)$, let us denote with $\boldsymbol{x} \triangleq [x_1, \ldots, x_M]$ and $\boldsymbol{y} \triangleq [y_1, \ldots, y_M]$ the vectors composed by the sequences of states of the PU channel use and perceived channel use, respectively, during the transmission of a SU packet of length M time slots. Notice that, without loss of generality, we have use the time indexes $1, \ldots, M$ to identify such time slots. The posterior conditional probability of the sequence $\boldsymbol{s}_0$ is given by

$$\tilde{p}(\boldsymbol{s}_0) = \frac{p(\boldsymbol{x} = \boldsymbol{s}_0,\, \boldsymbol{y} = \boldsymbol{s}_0)}{p(\boldsymbol{y} = \boldsymbol{s}_0)}. \qquad (15)$$

We now indicate the generic sequence $\boldsymbol{s}_i \in \{0,1\}^M$ defined above with $\boldsymbol{s}_i \triangleq \left[s_1^{(i)}, \ldots, s_M^{(i)}\right]$, and define the function ϕ of the generic state $s \in \{0,1\}$ as

$$\phi(s) = \begin{cases} (1 - p_{fa}) & \text{if } s = 0 \\ p_{md} & \text{if } s = 1 \end{cases}.$$

It can be showed that the probability $p(\boldsymbol{y} = \boldsymbol{s}_0)$ is given by

$$\begin{aligned}p(\boldsymbol{y} = \boldsymbol{s}_0) =& p_0(1 - p_{fa}) \sum_{i=0}^{(2^{M-1}-1)} \prod_{k=2}^{M} p_{s_{k-1}^{(i)} s_k^{(i)}}\, \phi\left(s_k^{(i)}\right)\\ &+ p_1 p_{md} \sum_{i=2^{M-1}}^{(2^M-1)} \prod_{k=2}^{M} p_{s_{k-1}^{(i)} s_k^{(i)}}\, \phi\left(s_k^{(i)}\right), \qquad (16)\end{aligned}$$

where we have used the index the number i as an index into the set $\{0,1\}^M$ according to the definition of $\boldsymbol{s}_i$ given above, and used the couples of states $s_{k-1}^{(i)} s_k^{(i)}$ as indices into the set of the transition probabilities $\{p_{00}, p_{01}, p_{10}, p_{11}\}$.

The joint probability $p(\boldsymbol{x} = \boldsymbol{s}_0,\, \boldsymbol{y} = \boldsymbol{s}_0)$ is the probability that a sequence of M idle states occurs in the PU channel uses, and each of them is correctly identified by the SU. Hence

$$p(\boldsymbol{x} = \boldsymbol{s}_0,\, \boldsymbol{y} = \boldsymbol{s}_0) = p_0 p_{00}^{M-1} (1 - p_{fa})^M. \qquad (17)$$

Combining (17) and (16) into (15), one can compute a suitable expression for the upper bound in (14).

We now define the packet *reception* rate R_{Rx}, as the average number of packets *received* (i.e. correctly decoded) by the SRx per unit time. Combining the packet error probability with (11), we obtain the following expression of R_{Rx} in packets per time-slot:

$$\begin{aligned}R_{Rx} =& R_{Tx}(1 - P_e(K, M)) = \qquad (18)\\ & \frac{q_{01} q_{10} (1 - q_{01})^{M-1}}{1 - (1 - q_{01})^M} \frac{(1 - P_e(K, M))}{(q_{01} + q_{10})}.\end{aligned}$$

[7]A tighter bound could be obtained using, in place of 1, the PER value corresponding to (12), with signal to noise ratio $\mathcal{P}_{rx}/(\sigma^2 + \mathcal{P}_{int})$. The simpler bound obtained with 1 fits, however, to our purposes.

Notice that, in (18), the packet throughput depends on the sensing performance and the primary traffic activity through λ and β (respectively given by (9b) and (9c)).

To compute the goodput, in terms of information bits per time slot, we combine (18) with (4), which expresses how many payload bits are contained in each packet, obtaining

$$\begin{aligned}G_{bits} = R_{Rx} b_m =& \frac{q_{01} q_{10} (1 - q_{01})^{M-1}}{1 - (1 - q_{01})^M} \frac{1}{(q_{01} + q_{10})} \qquad (19)\\ & \cdot (1 - P_e(K, M))\, K \cdot (M b (1 - \alpha_s) - b_h).\end{aligned}$$

We remark that the two terms of this expression, R_{Rx} and b_m, are not independent of each other, since a variation in the redundancy introduced for error protection, whose amount is part of b_h, and/or of the percentage of time reserved for spectrum sensing, α_s, has an effect on the packet error probability contained in the expression of R_{Rx}.

Replacing $P_e(K, M)$ in (19) with the lower and upper bounds for the PER in (14), we obtain upper and lower bounds, respectively, for the goodput:

$$R_{Tx}\left(1 - \hat{P}_e(K, M)\right) b_m < G_{bits} < R_{Tx}(1 - P_e(\boldsymbol{s}_0))\, b_m, \qquad (20)$$

where $\hat{P}_e(K, M)$ represents the term in the last row of (14). In the next section we show an excellent match between this expression, although in the form of upper and lower bounds, and the results obtained via simulation. This is due to the fact that such bounds are very close to each other. The reason for such a short gap is that we have assumed small values for p_{fa} and p_{md} which, in turn, lead to a value of the posterior conditional probability $\tilde{p}(\boldsymbol{s}_0)$ close to one. The analytical expressions for the bounds can hence be used to compute the optimal packet length and FEC coding rate: for a fixed K, it is required to evaluate (19) (using the appropriate available values of $P_e(K, M)$) and select the value of M which maximizes it. This is simple since (19) presents a single maximum with respect to M, see Section V. The optimal K is then chosen, among the limited number of available choices, as the one providing the overall maximum goodput.

V. Performance evaluation and optimal choices

We evaluated the behavior of the primary and secondary systems performing Matlab simulations. Our metric of interest is goodput, as defined in Section III. We considered the scenario depicted in Fig. 2, where a PTx and a STx send their own traffic to a PRx and SRx, respectively. For both primary and secondary communications, the distance between transmitter and receiver was set to 100m in fixed scenarios (Figures 3 and 4), whereas for the plots in Fig. 5 we have considered different positions for the SU receiver. The distance between a STx and PRx was 120m.

For the signal power attenuation, we used the simple path loss model $\mathcal{P}_{rx} = \mathcal{P}_{tx}/d_{tr}^{\eta}$, where $\mathcal{P}_{tx}$ is the transmit power, d_{tr} is the distance between transmitter and receiver, and η is the path loss exponent, which was set to 4.
Table I shows the values or the ranges we set in our simulations for the key system parameters. Additional parameters, which

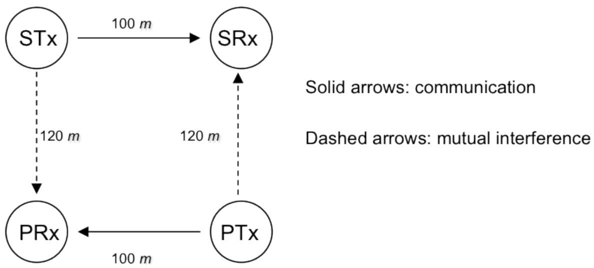

Figure 2. Simulation scenario.

Table I
SYSTEM PARAMETERS VALUES

Parameter	value/range
normalized transmit power $\mathcal{P}_{tx}$	70 - 90 dB
noise power σ^2	1
time slot size b	128 bits
sensing time $\alpha_s b$	40 (equivalent) bits
false alarm probability p_{fa}	10^{-5}
miss-detection probability	0,0034
primary channel use: average *busy* states sojourn time	10-50 time slots
primary channel use: average *idle* states sojourn time	50-10 time slots
convolutional code constraint length	8 bits
convolutional code trailing bits for each packet	40 bits
secondary packet header	64 bits
secondary packet length	1 - 20 time-slots
coding rate	$K \in \{\frac{4}{5}, \frac{3}{4}, \frac{2}{3}, \frac{1}{2}, \frac{1}{3}, \frac{1}{4}, \frac{1}{5}\}$
CRC bits	4

can be derived from those listed in Table I are the normalized power of the (respective) received signal for primary and secondary receivers $\mathcal{P}_{rx}$, which ranges from -10 dB to 10 dB, and the (normalized) interference power $\mathcal{P}_{int}$ in the range from -13.2 to 6.9 dB.

We have selected a class of convolutional codes from [33] with a structure similar to each other and good error correcting coding performance as well as decoding complexity. The parameters of such codes, constraint length, trailing bits field length, and coding rate, are given in Table I. We remark that this choice does not entail any loss of generality, i.e. our results hold, in general, for any class of convolutional or block codes.

Figures 3–5 show that the upper and lower bounds on the goodput in (20) are very close to the actual behavior of the system obtained through simulations, thus validating our analytical approach. Furthermore, they allow us to discuss the impact of system parameters such as PU traffic load and STx distance from the SRx (i.e. received power) on optimal FEC code selection and packet size. In these plots we show on the vertical axis the goodput expressed in bit per unit time, where the unit time is the time required to transmit a single bit.

Fig. 3 shows the achievable goodput utilizing different convolutional FEC coding rates. The normalized transmit power was set to 86 dB, corresponding to a normalized received SU signal power (i.e. the SNR in the absence of PU interference) of 6 dB. The results show that, for a sufficiently high SNR (6 dB), a safe choice is to choose a packet size in the range 10–14 time-slots, which yields close-to-optimal performance for all

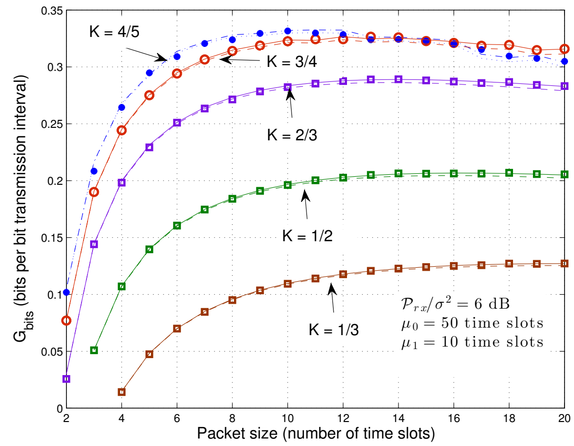

Figure 3. Goodput for different coding rates. Solid lines represent the upper bound, dashed lines represent the lower bound, markers represent the values obtained through simulations.

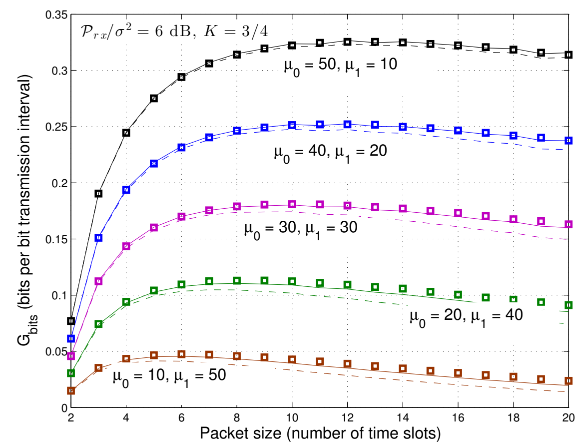

Figure 4. Goodput for different PU traffic load. Solid lines represent the upper bound, dashed lines represent the lower bound, markers represent the values obtained through simulations.

the coding rates. Fig. 4 shows the dependence of the optimal packet size on the PU traffic load. It is clear that a good choice for M lies in the interval 8–12: with such a choice, the SU could avoid adapting the packet size to varying PU traffic load, since the goodput is close to the highest achievable one for any PU traffic. Fig. 5 reproduces the effect of a STx positioned at different distances, e.g. because it is moving, from the SRx. Assuming that the STx cannot adjust the transmit power, for instance because it is already transmitting at maximum power, this figure shows that the SU MAC protocol should adapt the packet size to the received power, otherwise incurring a considerable loss with respect to the maximum value.

Our findings suggest that the (K, M) pair should be tuned to the operating condition in terms of SNR, and adapted to it, in case there is a change due to, e.g., user mobility. The parameters may be left unchanged, to some extent, although within a "safety region", with respect to the PU traffic load.

VI. CONCLUSION

We have analysed the goodput performance of an OSA-based cognitive radio system over a single frequency channel. The SU access is controlled by a periodic sense-then-transmit

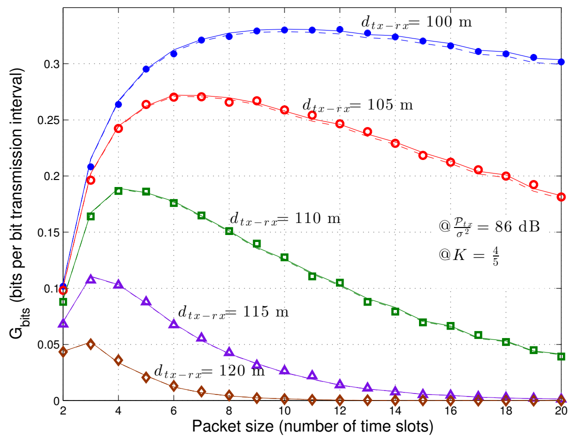

Figure 5. Goodput for different SU Tx-Rx distances (with constant $\mathcal{P}_{tx}$). Solid lines represent the upper bound, dashed lines represent the lower bound, markers represent the values obtained through simulations.

strategy, with periods coinciding with the slots of a PU slotted MAC, allowing for channel release in case a PU starts using the channel during a SU packet transmission. Our analysis considered the presence of sensing errors and overhead, including FEC redundancy. Under a Markovian PU activity model and a SU traffic saturation regime, we have obtained expressions of the average time between successive SU packets transmissions, of upper and lower bounds on the packet error probability in the presence of miss-detections, and, finally, of upper and lower bounds on the average goodput. Our results suggest that FEC codes and packet size should be chosen taking into account the received power, interference power, and PU traffic statistics.

Acknowledgment

This work was partially funded by the "Regione Lazio" regional project "A cognitive approach to radio resource management in new generation wireless systems".

References

[1] J. Mitola, III and G. Q. Maguire, Jr, "Cognitive radio: Making software radios more personal," *IEEE Personal Commun. Mag.*, vol. 6, no. 4, pp. 13–18, Aug. 1999.

[2] J. Mitola, III, "Cognitive Radio, An Integrated Agent Architecture for Software Defined Radio," Ph.D. Dissertation, School of Information and Communication Technology (ICT) - Royal Institute of Technology (KTH), SE-164 40 Kista, Sweden, May 2000. [Online]. Available: www.it.kth.se/~maguire/jmitola/Mitola_Dissertation8_Integrated.pdf

[3] S. Haykin, "Cognitive radio: Brain empowered wireless communications," *IEEE J. Sel. Areas Commun.*, vol. 23, no. 2, pp. 201–220, Feb. 2005.

[4] Q. Zhao and B. Sadler, "A survey of dynamic spectrum access," *IEEE Signal Process. Mag.*, vol. 24, no. 3, pp. 79–89, May 2007.

[5] S. Srinivasa and S. Jafar, "Cognitive Radios for Dynamic Spectrum Access - The Throughput Potential of Cognitive Radio: A Theoretical Perspective," *IEEE Commun. Mag.*, vol. 45, no. 5, pp. 73–79, 2007.

[6] A. Ghasemi and E. S. Sousa, "Spectrum Sensing in Cognitive Radio Networks: Requirements, Challenges and Design Trade-offs," *IEEE Commun. Mag.*, vol. 46, no. 4, pp. 32–39, Apr. 2008.

[7] R. Tandra, S. M. Mishra, and A. Sahai, "What is a spectrum hole and what does it take to recognize one?" *Proc. IEEE*, vol. 97, no. 5, pp. 824–848, May 2009.

[8] W. Feller, *An Introduction to Probability Theory and its Applications (Second ed.)*. Wiley, 1966, vol. 2.

[9] I. F. Akyildiz, W.-Y. Lee, and K. R. Chowdhury, "CRAHNs: Cognitive Radio Ad Hoc Networks," *Ad Hoc Networks*, vol. 7, no. 5, pp. 810–836, Jul. 2009.

[10] C. Cormio and K. R. Chowdhury, "A Survey on MAC Protocols for Cognitive Radio Networks," *Ad Hoc Networks*, vol. 7, no. 7, pp. 1315–1329, 2009.

[11] Y.-C. Liang, K. Chen, G. Li, and P. Mahonen, "Cognitive Radio Networking and Communications: An Overview," *IEEE Trans. Veh. Technol.*, vol. 60, no. 7, pp. 3386–3407, Sep. 2011.

[12] A. De Domenico, E. Calvanese Strinati, and M.-G. Di Benedetto, "A survey on mac strategies for cognitive radio networks," *IEEE Commun. Surveys Tuts.*, vol. 14, no. 1, pp. 21–44, 2012.

[13] A. Ghasemi and E. S. Sousa, "Optimization of Spectrum Sensing for Opportunistic Spectrum Access in Cognitive Radio Networks," in *4th Annual IEEE Consumer Communications and Networking Conference (CCNC 2007)*, Las Vegas, NV, USA, Jan. 11-13, 2007.

[14] I. F. Akyildiz and W.-Y. Lee, "Optimal Spectrum Sensing Framework for Cognitive Radio Networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 10, pp. 3845–3857,, Oct. 2008.

[15] Y.-C. Liang, Y. Zeng, E. C. Y. Peh, and A. T. Hoang, "Sensing-Throughput Tradeoff for Cognitive Radio Networks," *IEEE Trans. Wireless Commun.*, vol. 7, no. 4, pp. 1326 – 1337, Apr. 2008.

[16] P. Wang, L. Xiao, S. Zhou, and J. Wang, "Optimization of Detection Time for Channel Efficiency in Cognitive Radio Systems," in *Proc. IEEE Wireless Communications and Networking Conference, WCNC 2007*, Mar. 11-15, 2007.

[17] A. T. Hoang, Y.-C. Liang, and Y. Zeng, "Adaptive Joint Scheduling of Spectrum Sensing and Data Transmission in Cognitive Radio Networks," *IEEE Trans. Commun.*, vol. 58, no. 1, pp. 235 – 246, Jan. 2010.

[18] S. Huang, X. Liu, and Z. Ding, "Opportunistic Spectrum Access in Cognitive Radio Networks," in *Proc. IEEE 27th Conference on Computer Communications, INFOCOM 2008*, Apr. 13-18, 2008.

[19] ——, "Optimal Transmission Strategies for Dynamic Spectrum Access in Cognitive Radio Networks," *IEEE Trans. Mobile Comput.*, vol. 8, no. 12, pp. 1636–1648, Dec. 2009.

[20] J. Yin, X. Wang, and D. Agrawal, "Optimal packet size in error-prone channel for IEEE 802.11 distributed coordination function," in *Proc. IEEE Wireless Communications and Networking Conference, WCNC 2004*, Mar. 21-25, 2004.

[21] J. Korhonen and Y. Wang, "Effect of packet size on loss rate and delay in wireless links," in *Proc. IEEE Wireless Communications and Networking Conference, WCNC 2005*, Mar. 13-17, 2005.

[22] T. Yoo, R. Lavery, A. Goldsmith, and D. Goodman, "Throughput Optimization Using Adaptive Techniques," *IEEE Commun. Letters*, 2006.

[23] M. Vuran and I. Akyildiz, "Cross-Layer Packet Size Optimization for Wireless Terrestrial, Underwater, and Underground Sensor Networks," in *Proc. IEEE 27th Conference on Computer Communications, INFOCOM 2008*, Apr. 13-18, 2008.

[24] W. Dong, X. Liu, C. Chen, Y. He, G. Chen, Y. Liu, and J. Bu, "DPLC: Dynamic Packet Length Control in Wireless Sensor Networks," in *Proc. IEEE INFOCOM, 2010*, Mar. 14-19, 2010.

[25] M. Holland, T. Wang, B. Tavli, A. Seyedi, and W. Heinzelman, "Optimizing physical-layer parameters for wireless sensor networks," *ACM Transactions on Sensor Networks (TOSN)*, vol. 7, no. 4, Feb. 2011.

[26] F. Borgonovo, M. Cesana, and L. Fratta, "Throughput and Delay Bounds for Cognitive Transmissions," *IFIP Advances in Ad Hoc Networking*, vol. 265, pp. 179–190, 2008.

[27] W. Ahmed, J. Gao, H. Zhou, and M. Faulkner, "Goodput and Channel Allocation in Opportunistic Spectrum Access Networks," in *Proc. IEEE 20th International Symposium Personal, Indoor and Mobile Radio Communications*, Sep.13-16, 2009.

[28] J. Gao, W. Ahmed, and M. F. J. Yang, "Throughput Comaparison in Cognitive Radio Networks," in *Proc. Int. Conf. Electrical Engineering/Electronics Computer Telecommunications and Information Technology (ECTI-CON)*, May 19-21, 2010.

[29] Y. Xu, J. Wang, and Q. Wu, "A Discrete-time Model for Multichannel Opportunistic Spectrum Access Based on Preempted Queuing," in *Proc. Int. Conf. Wireless Communications and Signal Processing (WCSP)*, Suzhou, Oct. 21-23, 2010.

[30] O. C. Ibe, *Markov Processes for Stochastic Modeling*. Elsevier Academic Press, 2009.

[31] S. Kay, *Fundamentals of Statistical Signal Processing, Volume II: Detection Theory*. Upper Saddle River, NJ, USA: Prentice Hall, 1998.

[32] S. G. Mohanty, "Success Runs of Length k in Markov Dependent Trials," *Ann. Inst. Statist. Math.*, vol. 46, no. 4, pp. 777–796, 1994.

[33] Y. Jiang, *A Practical Guide to Error-Control Coding Using MATLAB*. Artech House, 2010.