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Optimization of hard fusion based spectrum sensing for energy-constrained cognitive radio networks

Sina Maleki *, Sundeep Prabhakar Chepuri, Geert Leus

Faculty of Electrical Engineering, Mathematics, and Computer Science, Delft University of Technology, Delft, The Netherlands

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ABSTRACT

The detection reliability of a cognitive radio network improves by employing a cooperative spectrum sensing scheme. However, increasing the number of cognitive radios entails a growth in the cooperation overhead of the system. Such an overhead leads to a throughput degradation of the cognitive radio network. Since current cognitive radio networks consist of low-power radios, the energy consumption is another critical issue. In this paper, throughput optimization of the hard fusion based sensing using the k-out-of-N rule is considered. We maximize the throughput of the cognitive radio network subject to a constraint on the probability of detection and energy consumption per cognitive radio in order to derive the optimal number of users, the optimal k and the best probability of false alarm. The simulation results based on the IEEE 802.15.4/ZigBee standard, show that the majority rule is either optimal or almost optimal in terms of the network throughput.

1. Introduction

Spectrum sensing is a key functionality of a cognitive radio system. It is shown that single radio sensing is prone to the hidden terminal problem and its detection performance degrades with fading and shadowing effects. Cooperative spectrum sensing is considered as a solution for the low detection reliability of a single radio detection scheme [1]. In this paper, we consider a cognitive radio network where each cognitive user senses a specific frequency band in a fixed sample size detection period and makes a local decision about the primary user's presence. The results are then sent to a fusion center (FC) in consecutive time slots by employing a time-division-multiple-access (TDMA) approach. The final decision is made at the FC. Although, several fusion schemes have been proposed in literature [2,3], we consider a hard fusion scheme due to its improved energy and bandwidth efficiency. Among them, the OR and AND rules have been studied extensively in literature. The OR and AND rules are special cases of the more general k-out-of-N rule with $k = 1$ and $k = N$, respectively. In a k-out-of-N rule, the FC decides the target's presence, if at least k out of N sensors report to the FC that a target is present [2].

Optimization of the k-out-of-N rule based spectrum sensing is considered in this paper. The optimal k and optimal N is derived for a throughput optimization setup. The sensing time of each cognitive radio is given but the reporting time which is directly related to the number of cognitive users is unknown.

The throughput of the cognitive radio network is maximized subject to a constraint on the global probability of detection and energy consumption per cognitive radio in order to determine the optimal number of cognitive users N and k. It is shown that the underlying problem can be solved by a bounded two-dimensional search. As we will discuss later, the reporting time of the cognitive radio system is directly proportional to N and thus by deriving the optimal N, the reporting time is also optimized.

Cooperative spectrum sensing optimization is studied extensively in the literature. The sensing-throughput trade-off is studied in [4,5]. The optimal sensing time is determined by maximizing the cognitive radio throughput

* Corresponding author.
E-mail addresses: s.maleki@tudelft.nl (S. Maleki), s.p.chepuri@tudelft.nl (S.P. Chepuri), g.j.t.leus@tudelft.nl (G. Leus).

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subject to the probability of detection constraint in [4]. An extended version of [4] including k as an argument of optimization is discussed in [5]. Our work is different from [5], in the sense that in the proposed throughput optimization setup for a given sensing time, the combined optimization of the reporting time and k is discussed, and further the energy consumption per cognitive radio is included as an additional constraint in our work. Lee and Akyildiz [6] propose an optimal spectrum sensing scheme where the sensing efficiency of a cognitive radio network is maximized subject to an interference constraint. The sensing efficiency is defined as the transmission time divided by the total cognitive radio time frame. However, this work also ignored the effect of the reporting time on the sensing efficiency of the cognitive radio network.

The reporting time optimization is studied in [7,8]. Choi et al. [7] optimized the cognitive radio network throughput subject to a detection probability constraint in order to find the optimal sensing and reporting time. An extension of [7] to a general k-out-of-N rule based spectrum sensing is considered in our earlier work [8]. The difference is that in [8] and our paper the sensing time is assumed to be given. In the current work, a combined optimization of N and k is given while optimization of k is ignored in [7,8]. In contrast to [8], we include an additional constraint on the energy consumption per cognitive radio in this paper. As shown in Section 3, this additional constraint requires new algorithms to solve the problem. Peh et al. [9] consider the optimization of the cognitive radio network energy efficiency. Energy efficiency is defined as the ratio of the average network throughput over the average network energy consumption. Optimization of the energy efficiency is considered for two cases. In the former case, energy efficiency is optimized in order to find k and in the latter case, the sensing threshold at the energy detector is derived by optimizing the energy efficiency. However, the combined optimization of k, N as well as the sensing threshold is not considered. Further, no typical performance constraint is considered for the optimization problem such as the probability of detection which is inherent in a cognitive radio design technique.

The remainder of the paper is organized as follows. The considered cooperative sensing configuration and its underlying system model are presented in Section 2. The problem formulation is discussed and analyzed in Section 3. We provide some numerical results based on the IEEE 802.15.4/ZigBee standard in Section 4 and draw our conclusions in Section 5.

2. System model

We consider a network with N identical cognitive radios under a cooperative spectrum sensing scheme. Each cognitive radio senses the spectrum periodically and makes a local decision about the presence of the primary user based on its own observations. To avoid any false detections of the secondary users instead of a primary user, the secondary users are silent during the sensing period. The local decisions are to be sent to the FC in consecutive time slots based on a TDMA scheme. The FC employs a hard decision fusion scheme over a soft fusion scheme due to its higher energy and bandwidth efficiency along with a reliable detection performance that is asymptotically similar to that of a soft fusion scheme [1].

To make local decisions about the presence or absence of a primary user, each cognitive radio solves a binary hypothesis testing problem, by choosing hypothesis H_1 in case the primary user is present and hypothesis H_0 when the primary user is absent. Denoting $y[n]$ as the n-th sample received by the cognitive radio, $w[n]$ as the noise and $x[n]$ as the primary user signal, the hypothesis testing problem can be represented by the following model

$$\begin{aligned} H_0 &: y[n] = w[n], \quad n = 1, \ldots, M \\ H_1 &: y[n] = x[n] + w[n], \quad n = 1, \ldots, M \end{aligned} \tag{1}$$

where the noise and the signal are assumed to be i.i.d. Gaussian random processes with zero mean and variance σ_w^2 and σ_x^2, respectively, and the received signal-to-noise-ratio (SNR) is denoted by $\gamma = \frac{\sigma_x^2}{\sigma_w^2}$.

Each cognitive radio employs an energy detector in which the accumulated energy of M observation samples is compared with a predetermined threshold denoted by λ as follows

$$E = \sum_{n=1}^{M} y^2[n] \underset{H_0}{\overset{H_1}{\gtrless}} \lambda. \tag{2}$$

For a large number of samples, we can employ the central limit theorem, and the decision statistic is given by [1]

$$\begin{aligned} H_0 &: E \sim \mathcal{N}(M\sigma_w^2, 2M\sigma_w^4), \\ H_1 &: E \sim \mathcal{N}(M(\sigma_w^2 + \sigma_x^2), 2M(\sigma_w^2 + \sigma_x^2)^2). \end{aligned} \tag{3}$$

Denoting P_f and P_d as the respective local probabilities of false alarm and detection, $P_f = \Pr(E \geq \lambda | H_0)$ and $P_d = \Pr(E \geq \lambda | H_1)$ are given by

$$\begin{aligned} P_f &= Q\left(\frac{\lambda - M\sigma_w^2}{\sqrt{2M\sigma_w^4}}\right), \\ P_d &= Q\left(\frac{\lambda - M(\sigma_w^2 + \sigma_x^2)}{\sqrt{2M(\sigma_w^2 + \sigma_x^2)^2}}\right). \end{aligned} \tag{4}$$

The reported local decisions are combined at the FC and the final decision regarding the presence or absence of the primary user is made according to a certain fusion rule. Several fusion schemes have been discussed in literature [3]. Due to its simplicity in implementation, lower overhead and energy consumption, we employ a k-out-of-N rule to combine the local binary decisions sent to the FC. Thus, the resulting binary hypothesis testing problem at the FC is given by, $I = \sum_{i=1}^{N} D_i < k$ for H_0 and $I = \sum_{i=1}^{N} D_i \geq k$ for H_1, where D_i is the binary local decision of the i-th cognitive radio which takes the binary value '0' if the local decision supports the absence of the primary user and '1' for the presence of the primary user. For the sake of analytical simplicity, we assume that all the cognitive radios experience the same SNR and each cognitive radio employs an identical threshold λ to make the decision. Such an assumption on the SNR is a valid assumption when the SNR difference is less than 1 dB [10].

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This way, the global probability of false alarm (Q_f) and detection (Q_d) at the FC are given by

$$Q_d = \sum_{i=k}^{N} \binom{N}{i} P_d^i (1-P_d)^{N-i},$$
$$Q_f = \sum_{i=k}^{N} \binom{N}{i} P_f^i (1-P_f)^{N-i}. \tag{5}$$

We can rewrite (5) using the binomial theorem as follows

$$Q_f = 1 - \psi(k-1, P_f, N),$$
$$Q_d = 1 - \psi(k-1, P_d, N) \tag{6}$$

where ψ is the regularized incomplete beta function as follows

$$\psi(k,p,n) = I_{1-p}(n-k, k+1) = (n-k)\binom{n}{k}\int_0^{1-p} t^{n-k-1}(1-t)^k\, dt.$$

Denoting P_x as the local probability of detection or false alarm and Q_x as the global probability of detection or false alarm, we can define $P_x = \psi^{-1}(k, 1-Q_x, N)$ as the inverse function of ψ in the second variable.

Each cognitive radio employs periodic time frames of length T for sensing and transmission. The time frame for each cognitive radio is shown in Fig. 1. Each frame comprises two parts namely a sensing time required for sensing and decision making and a transmission time denoted by T_x for transmission in case the primary user is absent. The sensing time can be further divided into a time required for energy accumulation and local decision making denoted by T_s and a reporting time where cognitive radios send their local decisions to the FC. Here, we employ a TDMA based approach for reporting the local decision to the FC, i.e., the first user reports its decision in the first time slot, the second user in the second time slot and so on. This way, we avoid collisions among the reported data from the cognitive radios. Hence, denoting T_r as the required time for each cognitive radio to report its result, the total reporting time for a network with N cognitive radios is NT_r.

Considering the above structure of a cognitive radio time frame, we define the throughput of the cognitive radio network, R_{CR}, by

$$R_{\mathrm{CR}} = \pi_0\left(\frac{T-T_s-NT_r}{T}\right)(1-Q_f)\Pr(success|H_0) + \pi_1\left(\frac{T-T_s-NT_r}{T}\right)(1-Q_d)\Pr(success|H_1) \tag{7}$$

where $\pi_0 = \Pr(H_0)$, $\pi_1 = \Pr(H_1)$ and $\Pr(success|H_i)$, $i = 0, 1$ is the probability that the cognitive radio can successfully send its data to the cognitive receiver upon the detection of a spectrum hole or miss detection of a primary user. Upon the correct detection of a spectrum hole, since the whole bandwidth is free for the cognitive radio, $\Pr(success|H_0) \to 1$. On the other hand, in case of miss detection of a primary user, since the bandwidth is almost occupied completely by the primary user, $\Pr(success|H_0) \to 0$. This way, the second part of R_{CR} is negligible. Therefore, in this paper, after normalizing with π_0, the first part of R_{CR} denoted by R is considered as the throughput of the cognitive radio network and is given by

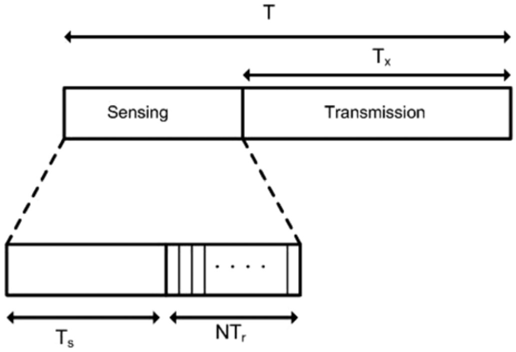

Fig. 1. Cognitive radio time frame.

$$R = \left(\frac{T-T_s-NT_r}{T}\right)(1-Q_f). \tag{8}$$

The energy consumption of each cognitive radio is another critical element in a low-power cognitive radio network. Denoting P_s and P_t to be the sensing and transmission power respectively, the average energy consumption at each cognitive radio, E, is defined as follows

$$E = P_sT_s + P_tT_r + \pi_0(1-Q_f)P_t(T-T_s-NT_r) + \pi_1(1-Q_d)P_t(T-T_s-NT_r). \tag{9}$$

In the following section, a throughput optimization setup is considered to optimize the k-out-of-N rule based spectrum sensing subject to a constraint on the probability of detection and average energy consumption per cognitive radio.

3. Analysis and problem formulation

The cooperative sensing performance improves with the number of cognitive users. However, a larger number of cooperating users lead to a higher reporting time and hence a lower network throughput. Further, in a low-power cognitive radio network, the energy consumption of each cognitive radio is constrained. Therefore, it is desirable to find the optimal number of users and fusion rule that satisfies a certain detection performance and energy consumption by optimizing the cognitive radio network throughput. The cognitive radio throughput depends on the specific choice of the k-out-of-N rule. In this section, we consider a setup where the network throughput is maximized subject to a constraint on the probability of detection and energy consumption per cognitive radio to find the system parameters including the number of users, the optimal k-out-of-N rule and the probability of false alarm.

The sensing-throughput trade-off has been extensively studied in literature, e.g. [4–6]. However, the combined reporting time and k-out-of-N rule optimization attracted less attention while it is a critical factor in the cognitive radio throughput. Reducing the reporting time leads to an increase in the throughput of the cognitive radio network.

In a TDMA based scheme, the reporting time directly corresponds to the number of cognitive radios. As such, N becomes an argument of the optimization in the following discussions. Here, we fix the sensing time, T_s, and focus on optimizing the reporting time NT_r where $T_r = \frac{1}{R_b}$, with R_b the cognitive radio transmission bit rate. The other important factor is the parameter k in the k-out-of-N rule. For a given N, it is shown that different values of k lead to different throughputs. Thus, the optimization of k along with N is an important issue in cognitive network design. Naturally, also the local sensing threshold, λ, which is related to the local probability of false alarm, P_f, is part of the optimization problem. Avoiding harmful interference to the primary user is one of the requirements of a cognitive radio network. Cognitive radios interfere with the primary user if they miss the detection of the primary user. Therefore, it is desirable that the probability of detection is lower bounded. Finally, most cognitive radio networks consist of low-power radios. Hence, the energy consumption of each cognitive radio should also be constrained. To summarize, we define our problem as an optimization of the network throughput over k, N and P_f (or λ) subject to the constraint on the probability of detection and average energy consumption per cognitive radio as follows:

$$\begin{aligned} \max_{N,k,P_f} \quad & \left(\frac{T - T_s - NT_r}{T}\right)(1 - Q_f) \\ & \text{s.t. } Q_d \geq \alpha \\ & 1 \leq N \leq \left\lfloor \frac{T - T_s}{T_r} \right\rfloor \\ & 1 \leq k \leq N \\ & E \leq E_{\max} \end{aligned} \tag{10}$$

where E is defined in (9).

For a given N and k, the optimization problem reduces to

$$\begin{aligned} & \max_{P_f} \ (1 - Q_f) \\ & \text{s.t. } Q_d \geq \alpha \\ & E \leq E_{\max} \end{aligned} \tag{11}$$

which can be further simplified to

$$\begin{aligned} & \min_{P_f} \ Q_f \\ & \text{s.t. } P_d \geq \psi^{-1}(k-1, 1-\alpha, N) \\ & E \leq E_{\max} \end{aligned}$$

and is equivalent to finding the minimum P_f in the feasible set of the problem. Since the probability of false alarm grows with the probability of detection, the minimum P_f considering the probability of detection constraint is the P_f that satisfies $P_d = \psi^{-1}(k-1, 1-\alpha, N)$. In this case, P_f is given by

$$P_f = Q\left(\frac{M\sigma_x^2 + Q^{-1}(\psi^{-1}(k-1, 1-\alpha, N))\sqrt{2M(\sigma_x^2 + \sigma_w^2)^2}}{\sqrt{2M\sigma_w^4}}\right). \tag{12}$$

Since both Q_f and Q_d increase as P_f increases, E decreases with P_f. Therefore, from the energy viewpoint, the probability of false alarm is desired to be as high as possible. The minimum P_f in this case is the one that satisfies $E = E_{\max}$. Denoting $P_f(\alpha)$ as the P_f that satisfies $P_d = \psi^{-1}(k-1, 1-\alpha, N)$ and $P_f(E_{\max})$ as the P_f that satisfies $E = E_{\max}$, the optimal P_f denoted by $\tilde{P}_f$ is $\tilde{P}_f = \max\{P_f(\alpha), P_f(E_{\max})\}$.

Inserting $\tilde{P}_f$ in (10) for a given k, we obtain a line search optimization problem as follows

$$\begin{aligned} \max_{N} \quad & \left(\frac{T - T_s - NT_r}{T}\right)(1 - \tilde{Q}_f) \\ & \text{s.t. } 1 \leq N \leq \left\lfloor \frac{T - T_s}{T_r} \right\rfloor \end{aligned} \tag{13}$$

where $\tilde{Q}_f = 1 - \psi(k-1, \tilde{P}_f, N)$. Similarly inserting $\tilde{P}_f$ in (10) for a given N, we obtain a line search optimization problem as follows

$$\begin{aligned} \max_{k} \quad & \left(\frac{T - T_s - NT_r}{T}\right)(1 - \tilde{Q}_f) \\ & \text{s.t. } 1 \leq k \leq N. \end{aligned} \tag{14}$$

Since both N and k are bounded, a two-dimensional search utilizing (10) can be carried out if both N and k are unknown. Further, employing (13) and (14), an alternating optimization algorithm is possible that in general converges faster than a two-dimensional search, but is suboptimal.

4. Numerical results

A cognitive radio network with a number of secondary users is considered for the simulations. A Chipcon CC2420 transceiver based on the IEEE 802.15.4/ZigBee standard is considered to compute the sensing and transmission power as well as the data rate [11]. Our cognitive radio network comprises of such radios arranged in a circular field with a radius of 70 m. This way, the data rate is $R_b = 250$ Kbps, the sensing power is $P_s = 2.1$ V $\times$ 17.4 mA and the transmission power is $P_t = 20$ mW [11]. Each cognitive radio accumulates $M = 275$ observation samples in the energy detector to make a local decision. The received SNR at each cognitive user is assumed to be $\gamma = -7$ dB. Unless mentioned otherwise, we take $T = 105$ μs, $T_s = 45$ μs and $T_r = 1/R_b = 4$ μs. The constraints are defined so as to satisfy the current cognitive radio standard requirements [12].

Fig. 2 depicts the optimal throughput versus $E_{\max}$ for $\alpha = 0.9, 0.95$ and $\pi_0 = \pi_1 = 0.5$. We can see that as $E_{\max}$ increases, the optimal throughput increases up to a certain point. After this point the optimal throughput becomes saturated. The reason is that as $E_{\max}$ increases, for a given N and k, $P_f(E_{\max})$ decreases up to a point after which $\max\{P_f(\alpha), P_f(E_{\max})\} = P_f(\alpha)$ and the optimal point becomes independent from $E_{\max}$. As α increases, $P_f(\alpha)$ also increases, thus the point where $\max\{P_f(\alpha), P_f(E_{\max})\}$ changes from $P_f(E_{\max})$ to $P_f(\alpha)$ occurs for a lower $E_{\max}$.

In Fig. 3, the optimal throughput versus the probability of detection constraint, α, is considered for different values of π_0 and $E_{\max}$. In this figure, $E_{l,\max}$ and $E_{u,\max}$ denote the lower and upper bounds on the $E_{\max}$ for the considered range of α. For example, in case $\pi_0 = 0.2$, for $E_{\max}$ less than 1970 nJ, the feasible set of (10) is empty and for $E_{\max}$ more

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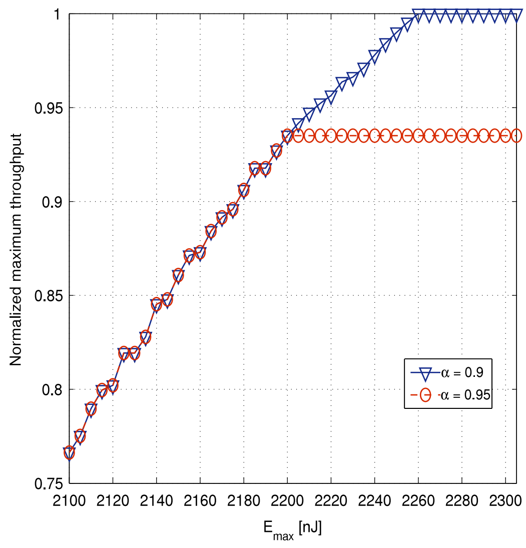

Fig. 2. Optimal throughput versus E_{max}.

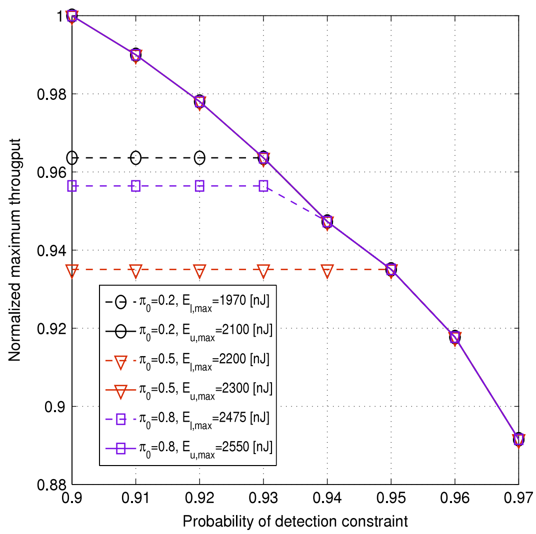

Fig. 3. Optimal throughput versus the probability of detection constraint.

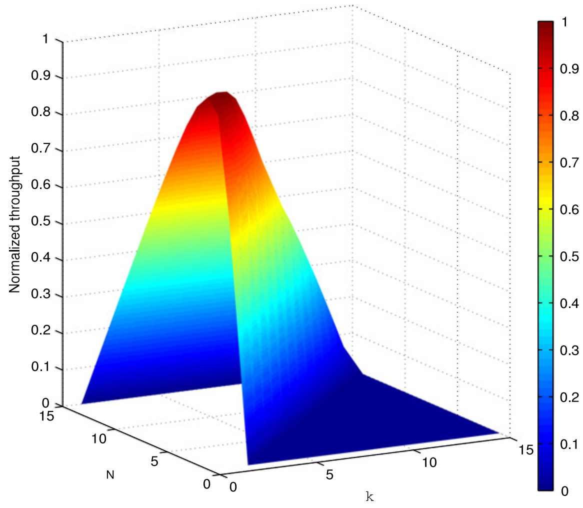

Fig. 4. Throughput versus N and k.

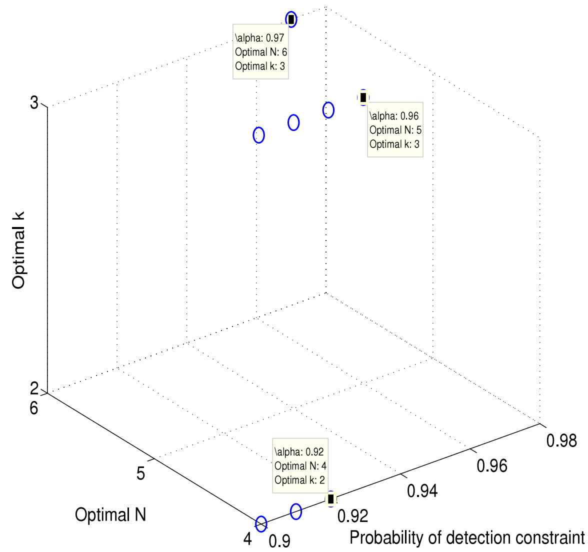

Fig. 5. Optimal N and k versus the probability of detection constraint.

than 2100 nJ, the optimal throughput does not increase anymore. It is depicted that as π_0 increases, $E_{l,\max}$ increases as well. Assume that for a certain π_0, $E_{\max}$, N and k, we define $\beta = P_f(E_{\max})$ and we choose β as the probability of false alarm of the system. We keep all the parameters the same and only increase the π_0. Since in a cognitive radio system, $Q_f \ll Q_d$, we obtain $(1-Q_f)P_t(T-T_s-T_r) \gg (1-Q_d)P_t(T-T_s-T_r)$. Therefore, by increasing π_0, we increase the larger term more than that we decrease the smaller term and so E increases and passes $E_{\max}$. That is why we need to increase $E_{l,\max}$ in order to make (10) feasible for a higher π_0. Furthermore, we can see that as α decreases, the optimal throughput increases up to a certain point after which the optimal throughput saturates to a certain level. With a similar explanation as given for Fig. 2, for the highest feasible α in the range $E_{l,\max} \le E_{\max} \le E_{u,\max}$, we have $\max\{P_f(\alpha), \; P_f(E_{\max})\} = P_f(\alpha)$. As α decreases, $P_f(\alpha)$ also decreases and thus the optimal throughput increases up to the point where $\max\{P_f(\alpha), P_f(E_{\max})\}$ becomes $P_f(E_{\max})$. After that point, the optimal throughput becomes independent from α.

Fig. 4 depicts the throughput versus the number of cognitive users and k for a detection constraint equal to $\alpha = 0.97$, $E_{\max} = 2300$ nJ and $\pi_0 = 0.5$. It is shown that the optimal throughput is a quasi-concave function of N and k, and thus there is a unique optimal point. The mathematical investigation of quasi-concavity is subject of future work. Further, it is evident that the choice of N and k has a significant impact on the cognitive network throughput.

In Fig. 5, the optimal N and k are depicted versus the probability of detection constraint. In this figure, $T = 0.5$ ms and $E_{\max} = 6500$ nJ. It is shown that for the desired range of the detection rate constraint, the majority rule is either optimal or nearly optimal.

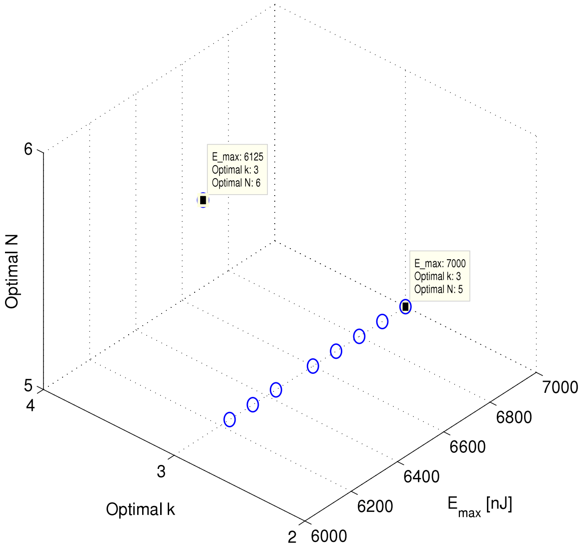

Fig. 6. Optimal N and k versus the maximum average energy consumption per cognitive radio.

Fig. 6 illustrates the optimal N and k versus E_{max}. In this figure, $T = 0.5$ ms and $\alpha = 0.95$. We can see that similar to the previous scenario, the majority rule is optimal.

5. Conclusions

In this paper, the network throughput is maximized subject to a detection rate and energy constraint in order to find the optimal reporting time, k and probability of false alarm. We have shown that the problem can be solved by a bounded two-dimensional search. It is also shown that as the energy constraint reduces, the optimal throughput also reduces while reducing the probability of detection constraint for the same energy constraint leads to a higher throughput. Furthermore, we have shown that in the desired range of the probability of detection constraint, the majority rule is either optimal or nearly optimal in terms of the cognitive network throughput.

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Sina Maleki received his B.Sc. degree in electrical engineering from Iran University of Science and Technology, Tehran, Iran, in 2006, and his M.S. degree in electrical and telecommunication engineering from Delft University of Technology, Delft, The Netherlands, in 2009. From July 2008 to April 2009, he was an intern student at the Philips Research Center, Eindhoven, The Netherlands, working on spectrum sensing for cognitive radio networks. He then joined the Circuits and Systems Group at the Delft University of Technology, where he is currently a Ph.D. student. He has served as a reviewer for several journals and conferences.

Sundeep Prabhakar Chepuri received his B.E. (Distinction) degree in electrical engineering from the Visveswaraiah Technological University, India in 2007, and his M.Sc. (Cum Laude) degree in electrical engineering from the Delft University of Technology in 2011. He has held positions at Robert Bosch Ltd., India, and Holst Centre/imec-nl, The Netherlands. Since September 2011, he is with the Circuits and Systems group at the Faculty of Electrical Engineering, Mathematics and Computer Science of the Delft University of Technology, The Netherlands, pursuing his Ph.D. degree. His research interest lies in the field of signal processing for communications.

Geert Leus was born in Leuven, Belgium, in 1973. He received his electrical engineering degree and Ph.D. degree in applied sciences from the Katholieke Universiteit Leuven, Belgium, in June 1996 and May 2000, respectively. He has been a Research Assistant and a Postdoctoral Fellow of the Fund for Scientific Research — Flanders, Belgium, from October 1996 till September 2003. During that period, Geert Leus was affiliated with the Electrical Engineering Department of the Katholieke Universiteit Leuven, Belgium. Currently, Geert Leus is an Associate Professor at the Faculty of Electrical Engineering, Mathematics and Computer Science of the Delft University of Technology, The Netherlands. During the summer of 1998, he visited Stanford University, and from March 2001 till May 2002 he was a Visiting Researcher and Lecturer at the University of Minnesota. His research interests are in the area of signal processing for communications. Geert Leus received a 2002 IEEE Signal Processing Society Young Author Best Paper Award and a 2005 IEEE Signal Processing Society Best Paper Award. He was the Chair of the IEEE Signal Processing for Communications and Networking Technical Committee, and an Associate Editor for the IEEE Transactions on Signal Processing, the IEEE Transactions on Wireless Communications, and the IEEE Signal Processing Letters. Currently, he serves on the Editorial Board of the EURASIP Journal on Advances in Signal Processing. Geert Leus has recently been elevated to IEEE Fellow.

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