A UNIFYING VIEW ON ENERGY-EFFICIENCY METRICS IN COGNITIVE RADIO CHANNELS

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ABSTRACT

The objective of this paper is to provide a unifying framework of the most popular energy-efficiency metrics proposed in the wireless communications literature. The target application is a cognitive radio system composed of a secondary user whose goal is to transmit in an optimal energy-efficient manner over several available bands under the interference constraints imposed by the presence of the primary network. It turns out that, the optimal allocation policies maximizing these energy-efficiency metrics can be interpreted as Pareto-optimal points lying on the optimal tradeoff curve between the rate maximization and power minimization bi-criteria joint problem. Using this unifying framework, we provide several interesting parallels and differences between these metrics and the implications w.r.t. the optimal tradeoffs between achievable rates and consumed power.

Index Terms— Energy-efficiency metrics, Cognitive radio, Multi-criteria optimization, Pareto optimality, Tradeoffs.

1. INTRODUCTION

The radio spectrum scarcity and its inefficient usage have led to new communication paradigms such as cognitive radio (CR). A CR system relies on opportunistic communications between unlicensed or secondary users (SUs) over unused spectral bands that are licensed to primary users (PUs) or over used spectral bands provided that their resulted signal power levels at the primary receivers are kept below some predefined interference threshold. In this context, the resource allocation problem at the SUs has mainly been studied from a data rate maximization point of view (e.g., [1], [2]). This view may not always be suitable, especially in ad-hoc networks and applications in which the major bottleneck is the power consumption efficiency (e.g., sensor networks, limited battery-life device systems). Our scenarios of interest are home-automation ones in which several technologies (WiFi, PLC, Femto) are able to operate simultaneously and different appliances may have different hierarchical priorities [3], but also CR systems with several orthogonal sub-channels available for communication such as OFDM systems.

In this paper, we investigate energy-efficiency metrics with a focus on those which capture the benefit of the transmission by the Shannon achievable rate and its cost by the power consumption (consumption for data transmission and the circuit power consumption). Several such metrics have been proposed in the literature, the most popular ones being: a) weighted difference between overall achievable rate and power consumption [4], [5]; b) overall consumed power under minimum rate constraint [6], [7]; c) the ratio between the overall rate and consumed power [8], [9], [10], [11]. Our contributions are multi-fold: i) we propose a unifying framework to analyze all these energy-efficiency metrics based on multi-criteria convex optimization tools; ii) we underline the major similarities and differences between these metrics; iii) we illustrate our claims using numerical results. Even though we consider a simplified CR model for the illustrative purpose, our analysis and main results are generic and carry over many other scenarios of interest (i.e., interference channels, multiple SUs CR models).

The paper is organized as follows. Sec. 2 describes the system model. In Sec. 3, we discuss the general power minimization versus rate maximization problem and, in Sec. 4, we show how the three types of energy-efficiency metrics fit in this framework. We conclude the paper in Sec. 5.

2. SYSTEM MODEL

We focus on the CR channel model in Fig. 1 composed of one SU and several ($K \geq 1$) PUs. Each primary/secondary user consists of a Primary/Secondary Transmitter (PT/ST) and a Primary/Secondary Receiver (PR/SR) respectively. Each device is equipped with only one antenna. The transmission is performed over N orthogonal frequency bands. The transmit power of ST in the frequency band $n \in \{1, \dots, N\}$ is denoted by p_n and the overall power allocation profile is denoted by $\underline{p} = (p_1, p_2, \dots, p_N)$, $\underline{p} \in \mathbb{R}_+^N$. The received signal

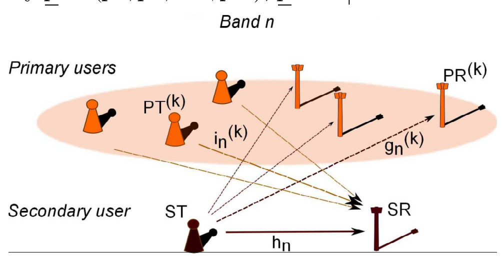

Fig. 1. Model of the system in band n.

at the SR in band n can be written as:

$$y_n = \sqrt{p_n h_n} s_n + \sum_{k=1}^{K} i_n^{(k)} + b_n, \tag{1}$$

where s_n denotes the transmitted signal at the ST. The instantaneous power gain of the ST-SR direct link and the interfering ST-PR of the k^{th} PU link are denoted by h_n and $g_n^{(k)}$

respectively, $k \in \mathcal{K} \triangleq \{1, \ldots, K\}$. All links are assumed to be stationary, ergodic and independent from noises. The noise in band n, $b_n \backsim \mathcal{CN}(0, \sigma_n^2)$ is a zero-mean circularly symmetric complex Gaussian variable and the interfering signal from PU k is denoted by $i_n^{(k)} \backsim \mathcal{CN}(0, (\tau_n^{(k)})^2)$. The Gaussian assumptions are quite standard in efficient resource allocation in CR channels related works [1], [12], [7]. Although this model is simple, it allows us to compare and unify existing energy-efficiency metrics. In this scenario, the Shannon achievable rate of the SU transmission is given by:

$$R(\underline{p}) = \sum_{n=1}^{N} \log_2(1 + c_n p_n) \qquad (2)$$

where c_n is related to the Signal to Interference Noise Ratio (SINR) of the direct link ST-SR and is given by $c_n = h_n/(\sigma_n^2 + \sum_{k=1}^{K} (\tau_n^{(k)})^2)$ where $\sum_k (\tau_n^{(k)})^2$ is the overall interference power from the PU and σ_n^2 is the variance of the thermal noise in band n.

The SU is allowed to opportunistically use the spectrum held by the PUs provided the interference it creates to the primary transmissions is below the tolerated levels. Otherwise, the SU is not scheduled in the network and, thus, it cannot transmit at all. Typically, two types of constraints are considered in the literature [1]: peak and average maximum interference constraints which are discussed below.

Maximum average interference constraint:

$$\forall k \in \mathcal{K}, \quad \sum_{n=1}^{N} g_n^{(k)} p_n \leq \overline{P}^{(k)} \qquad (3)$$

where $\overline{P}^{(k)}$ represents the maximum average interference level that can be tolerated by the k^{th} PR.

Maximum peak interference constraints:

$$\forall\ k \in \mathcal{K},\ \forall\ m \in \mathcal{N}, \quad 0 \leq g_m^{(k)} p_m \leq P_m^{peak(k)} \qquad (4)$$

where $P_m^{peak(k)}$ represents the maximum peak interference level that can be tolerated at k^{th} PR in band m. These constraints limit the transmission possibilities at the SU level and shape the feasible set of power allocations, denoted by $\mathcal{P}$, as follows:

$$\mathcal{P} = \left\{ \begin{array}{l|l} \underline{p} \in \mathbb{R}_+^N & \sum_{n=1}^{N} g_n^{(k)} p_n \leq \overline{P}^{(k)}, \quad \forall\ k \in \mathcal{K}, \\ \multicolumn{2}{l}{0 \leq g_m^{(k)} p_m \leq P_m^{peak(k)},\ \forall\ k \in \mathcal{K},\ \forall m \in \mathcal{N}} \end{array} \right\} \qquad (5)$$

To avoid the trivial case in which the SU is not allowed to transmit, we assume that $\mathcal{P}$ is non-void (see [7] for details).

3. POWER MINIMIZATION VS. RATE MAXIMIZATION TRADEOFF

Multi-criteria optimization techniques are becoming popular in wireless communications [13], [14] as they capture the tradeoff between opposing performance criteria. Here, exploiting these tools shows that the different existing energy-efficiency metrics can be unified under the same umbrella. This allows us to compare them and to give insights on choosing the most pertinent metric in a specific scenario.

The objective of the SU is to find its most energy-efficient power allocation over the available spectrum while complying with the PUs constraints. As mentioned in Sec. 2, several energy-efficiency metrics have been proposed in the literature. The main objective, in this work, is to investigate the connections between the most common energy-efficiency metrics and to identify their main advantages and drawbacks. It turns out that these measures can be unified and interpreted under a common umbrella: multi-criteria convex optimization [15]. The SU has two different desiderata when choosing its best power allocation policy: rate maximization and power consumption minimization. This translates into the following multi-objective optimization problem:

$$\underset{\underline{p} \in \mathcal{P}}{\text{maximize}} \qquad f_0(\underline{p}) = \big(\ -P_T(\underline{p});\quad R(\underline{p})\ \big) \qquad (6)$$

where $f_0 : \mathbb{R}^N \to \mathbb{R}_+^2$ is the objective function, $P_T(\underline{p})$ denotes the average transmit power given by $P_T(\underline{p}) = \sum_{n=1}^{N} p_n$, $R(\underline{p})$ is the achievable rate in (2) and $\mathcal{P}$ is the feasible set shaped by the constraints imposed by the PUs. It can be easily checked that this problem is a convex optimization problem since the objectives are affine and concave and the feasible set is defined by affine inequality constraints.

Remark 3.1 *There is an inherent conflict among these objectives : a) Minimizing the power consumption implies a minimum rate equal to zero, i.e., the SU is not transmitting; b) Maximizing the rate under the constraints in $\mathcal{P}$ implies a maximum overall power consumption P_T (the rate is a logarithmic non-decreasing function of the transmit powers). Therefore, there is no power allocation policy which optimizes both objectives simultaneously. A tradeoff between them has to be made.*

3.1. The set of feasible power-rate pairs

To study the possible *optimal* tradeoffs between the power-rate objectives, we introduce the set of all feasible values of the power-rate pair:

$$\mathcal{F} = \big\{ \big(\ P_T(\underline{p});\ R(\underline{p})\ \big) \,\big|\, \underline{p} \in \mathcal{P} \big\}. \qquad (7)$$

To further investigate this set, we visualise it in several scenarios. In Fig. 2, the set $\mathcal{F}$ is illustrated in the following scenario[1] : $N = 3$ orthogonal frequency bands, $K = 1$

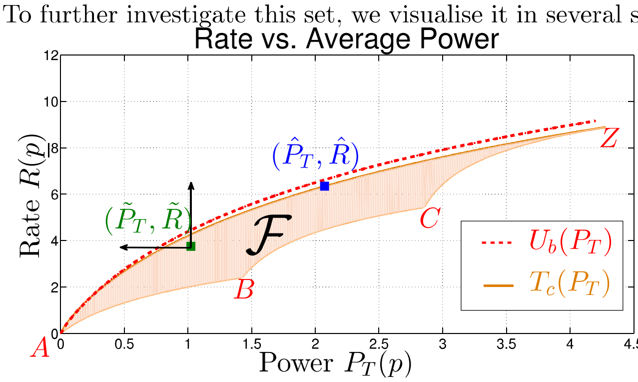

Fig. 2. The set $\mathcal{F}$ in the case of $N = 3$ orthogonal frequency bands and the corner points A, B,C and Z

[1] We denote by $\underline{\underline{x}}$ the $N \times K$ dimensional matrix containing the quantities $x_n^{(k)}$ in all bands $n \in \mathcal{N}$ and for all PUs $k \in \mathcal{K}$; $\underline{x}$ is the N

only one PU, power channel gain ordered in decreasing order $\underline{c} = [7,\ 5,\ 3]$ and $\underline{g} = [7,\ 7,\ 7]$, maximum average interference power constraint $\overline{P} = 40$ and maximum peak interference power constraint $\underline{P}^{peak} = [10,\ 10,\ 10]$.

First, we remark that $\mathcal{F}$ is a non-convex set and has four pikes denoted by $\{A, B, C, Z\}$. It is easy to see that the lower-right boundary of $\mathcal{F}$ illustrates the "worst" power allocation strategies in terms of both objectives, whereas the upper-left boundary gives the best tradeoff points. More precisely, the four pikes can be explained as follows:

- The point $A = (0, 0)$ represents the trivial SU no-transmission case and which minimizes the power consumption providing zero transmission rate.
- All the points (P_T, R) on the low-right border of $\mathcal{F}$ between A and B represent the power-rate pairs when transmitting in the "worst" band (highest in SU SINR c_n). Obviously no other points than the extremes of the segment $[A, B]$ are contained in $\mathcal{F}$ and, thus, the non-convexity property follows. The peak at point B is caused by the maximum interference constraint in the first band by the PUs which cannot be violated.
- The points (P_T, R) between the pikes B and C are given by sharing the transmit power P_T among the two "worst" channels. At point C, the maximum peak interference constraint in the second "worst" channel is also saturated.
- The point $Z = (P_{max}, R_{max})$ is the point which is limited by all the constraints in $\mathcal{P}$ and represents the maximum achievable rate $R_{max} = \max\{R(\underline{p}) \mid \underline{p} \in \mathcal{P}\}$ but requiring maximum power consumption as well.

Similar observations are made in many other scenarios. The only difference is the number of pikes on the low-left boundary which equals $N + 1$. However, our main interest will be on the upper-left boundary of $\mathcal{F}$ which contains the best tradeoff points which will be studied next.

3.2. The optimal power-rate tradeoff curve

Since there exist no power allocation policies optimizing both objectives simultaneously, we are now interested in the Pareto-optimal power allocation policies achieving the optimal compromise points between these objectives. Indeed, these optimal compromise points are the power-rate pairs that lie on the upper-left boundary of $\mathcal{F}$, also called the Pareto-boundary or the optimal tradeoff curve [15]. Intuitively, a Pareto-optimal point is a feasible power allocation such that there is no other feasible point achieving a strictly better objective with respect to both power and rate objectives.

In Fig. 2, we can easily see that an interior point such as $(\tilde{P_T}, \tilde{R})$ is not on the Pareto-boundary since strictly higher objectives can be achieved (in the upper-left corner starting at $(\tilde{P_T}, \tilde{R})$). For the boundary point $(\hat{P_T}, \hat{R})$, there doesn't exist any other feasible point achieving strictly better objectives (lower power than $\hat{P_T}$ and higher rate than $\hat{R}$). The optimal tradeoff curve, denoted by the function $R = T_c(P_T)$, is given by the maximum achievable rate when the power equals to P_T:

$$T_c(P_T) = \max\left\{ R(\underline{p}) |\ \underline{p} \in \mathcal{P},\ \sum_{n=1}^{N} p_n \leq P_T \right\} \tag{8}$$

Therefore, a simple upper-bound on the optimal tradeoff curve is given by the classical water-filling problem, i.e., rate maximization under overall power constraint P_T [Ex.5.2 [15]] and is defined as follows:

$$U_b(P_T) = \max\left\{ R(\underline{p}) |\ p_n \geq 0,\ \forall n,\ \sum_{n=1}^{N} p_n \leq P_T \right\} \tag{9}$$

Indeed, $U_b(P_T) \geq T_c(P_T),\ \forall P_T$, since the feasible set in (8) is included in the feasible set of (9). This upper-bound is interesting not only for its simplicity but also for the fact that, for small values of P_T it coincides with the optimal tradeoff curve.

In Fig. 2, we also represent this upper bound $U_b(P_T)$. Intuitively, for a fixed set of PU constraints, when P_T is relatively small, the allocations satisfying $\sum_n p_n \leq P_T$ also satisfy the PU constraints $\underline{p} \in \mathcal{P}$. Thus, the two optimal values in (8) and (9) are identical. Indeed, we observe a threshold on the power P_T below which $U_b(P_T) \equiv T_c(P_T)$ and above $U_b(P_T) > T_c(P_T)$.

In the following section, we will see that all the energy-efficiency scalar objectives provide optimal power-rate tradeoffs which lie on this optimal tradeoff curve.

4. ENERGY-EFFICIENCY METRICS COMPARISON

In this section, we show that the most popular energy-efficiency metrics proposed in the communication literature can be interpreted under the multi-criteria optimization analysis provided in the previous section.

4.1. Weighted sum of objectives

Scalarization, via optimizing the weighted sum of objectives, is a standard technique for finding the Pareto optimal points in multi-criteria problems [sec.2.6.3 [15]]. This approach has been studied by [4] in interference channels and by [5] in a radio cognitive model similar to ours. In our CR model, this problem becomes:

$$\underset{\underline{p} \in \mathcal{P}}{\text{maximize}} \qquad \sum_{n=1}^{N} \log_2(1 + c_n p_n) - \alpha \sum_{n=1}^{N} p_n \tag{10}$$

where $\alpha \in \mathbb{R}_+$ represents the penalty or pricing factor for the power consumption (and, thus, for the interference created). By using the KKT optimality conditions, the solution of (10) is a water-filling solution in which the optimal water level depends on the penalty factor α and the primary network interference constraints. In Fig. 3, we represent the rate R versus the total power consumption P_T for different values of the penalty factor $\alpha \in \{1000,\ 6,\ 3,\ 1.8,\ 1.5,\ 1.25,\ 0\}$ in the following scenario[2]: $N = 4$ orthogonal frequency bands, $K = 3$ PUs, power channel gain $\underline{c} = [3,\ 5,\ 7,\ 10]$ and $\overrightarrow{\underline{g}} = 7\ \mathbb{1}_{N,K}$, maximum average interference power $\overrightarrow{\overline{P}} = 40\ \mathbb{1}_K$ and maximum peak interference power $\overrightarrow{\underline{P}}^{peak} = 10\ \mathbb{1}_{N,K}$.

dimensional vector containing quantities x_n in all bands; $\overrightarrow{x}$ is the K dimensional vector containing quantities $x^{(k)}$ for all PUs.

[2] We denote by $\mathbb{1}_{N,K}$ the $N \times K$ dimensional matrix containing all the components equal to one

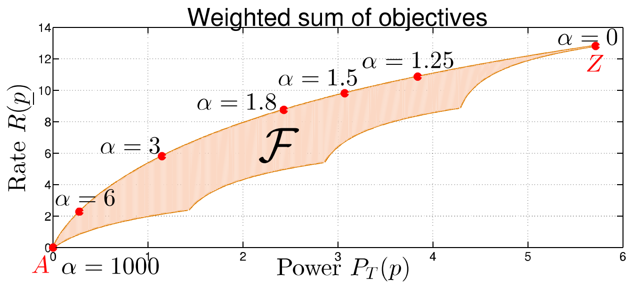

Fig. 3. Optimal power-rate tradeoffs for the weighted sum of objectives problem for different values of α

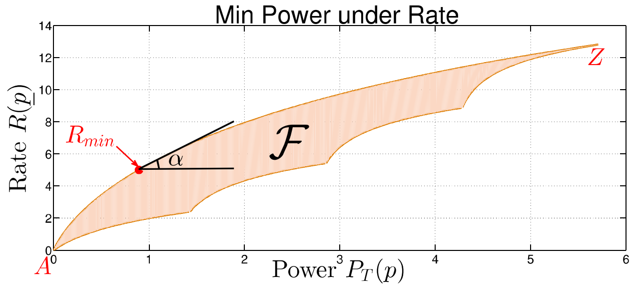

Fig. 4. Optimal power-rate tradeoffs for the power minimization problem under rate constraint for R_{min}

The extreme cases in terms of α are quite intuitive: i) when $\alpha \to \infty$, minimizing the power is the dominant objective and, thus, the optimal strategy is not to transmit, corresponding to $A = (0, 0)$; ii) when $\alpha = 0$, problem (10) is a classical rate maximization problem under primary network constraints [1] optimized by point $Z = (P_{max}, R_{max})$. By tuning the penalty factor α in between these two extremes, all points on the optimal tradeoff curve can be achieved. Indeed, the geometric interpretation is that, by choosing a certain value of α, the solution of (10) achieves the power-rate pair $(\hat{P}_{T,\alpha}, \hat{R}_\alpha)$ lying on the optimal tradeoff curve such that α is the slope of the tradeoff curve at this point:

$$\alpha = \frac{\partial T_c}{\partial P_T}\left(\hat{P}_{T,\alpha}\right). \tag{11}$$

4.2. Power minimization under minimum rate

Another energy-efficient allocation policy is the one minimizing the power consumption under a minimum target rate constraint introduced by [2] in interference channels. In [7], we have studied this approach in a CR scenario:

$$\begin{array}{ll} \underset{\underline{p}\in\mathcal{P}}{\text{minimize}} & \displaystyle\sum_{n=1}^{N} p_n \\ \text{subject to} & R(\underline{p}) = \displaystyle\sum_{n=1}^{N} \log_2(1 + c_n p_n) \geq R_{min} \end{array} \tag{12}$$

where R_{min} is the minimum rate constraint required to ensure a certain level of QoS for the SU transmission. When R_{min} is achievable, the optimal solution is obtained using the KKT optimality conditions. Similarly to the problem (10), the optimal power allocation is also a water-filling solution parametrized by R_{min} instead of α. We remark that by choosing the target $R_{min} \in [0, R_{max}]$, where $R_{max} = \max\{R(\underline{p}), \underline{p} \in \mathcal{P}\}$ we can choose any power-rate pair on the optimal tradeoff curve from A (when $R_{min} = 0$) to Z (when $R_{min} = R_{max}$).

The relation between the penalty factor α in problem (10) and the target rate R_{min} follows directly from the geometric interpretation provided in the previous subsection. If α is equal to the slope of the optimal tradeoff curve T_c at the point achieving the rate R_{min}:

$$\alpha = \frac{\partial T_c}{\partial P_T}\left(T_c^{-1}(R_{min})\right), \tag{13}$$

then both problems are equivalent in the sense that at the optimal allocation policies they provide the same optimal tradeoff between the overall consumed power and achievable rate (see Fig. 4 for the same scenario as in Fig. 3).

4.3. Overall rate to power ratio

Another relevant energy-efficiency metric which measures the number of reliably transmitted bits per unit of consumed energy is given by the ratio between the achievable rate and the total consumption including circuit and radio. This metric was introduced in [8] (see [16], for an extended discussion and comparison between this information-theoretic and other practical efficiency metrics [17], [18]). In our scenario of interest, this energy-efficiency metric writes as:

$$EE(\underline{p}) \triangleq \frac{R(\underline{p})}{P_T(\underline{p}) + P_c} = \frac{\displaystyle\sum_{n=1}^{N} \log_2(1 + c_n p_n)}{\displaystyle\sum_{n=1}^{N} p_n + P_c} \tag{14}$$

where P_c is the circuit power consumption of the SU devices. The objective function $EE(\underline{p})$ is maximized subject to the constraints on the SU transmit powers $\underline{p} \in \mathcal{P}$ and the resulting optimization problem writes as:

$$\underset{\underline{p}\in\mathcal{P}}{\text{maximize}} \quad EE(\underline{p}) \tag{15}$$

This problem is similar to the one in [9]. The difference lies in the additional constraints (3) and (4) imposed by the primary network. As opposed to the previous energy-efficiency metrics, this optimization problem is no longer a convex optimization one and belongs to the class of fractional programs [11]. Indeed, the objective function is not concave in $\underline{p}$. Nevertheless, given that the achievable rate $R(\underline{p})$ is strictly concave in $\underline{p}$ and the total power $P_T(\underline{p}) + P_c$ is affine in $\underline{p}$ it is easy to prove that the objective function is strictly quasi-concave and has a unique maximum point: if $P_c = 0$, $EE(\underline{p})$ is decreasing in each p_n and, if $P_c > 0$, it is increasing and then decreasing. Thus, when $P_c = 0$, the optimal solution is trivial (no transmission)[3]. Otherwise, such quasi-convex optimization problems can be solved quite efficiently [15] by solving not one but a sequence of carefully chosen convex optimization problems. In our case, following [11], the precise sequence of optimization problems are:

$$\underset{\underline{p}\in\mathcal{P}}{\text{maximize}} \quad R(\underline{p}) - \alpha(P_T(\underline{p}) + P_c) \tag{16}$$

parametrized by α. The major difference with (10) is that, α is no longer a tunning parameter but an additional variable

[3] This is precisely the information theoretic result of [8] for Gaussian channels, extended to the MIMO case in [10].

of the problem at hand which has to be chosen numerically in such a way that the maximum value of the objective function in (15) is reached. An important remark is that, the optimal

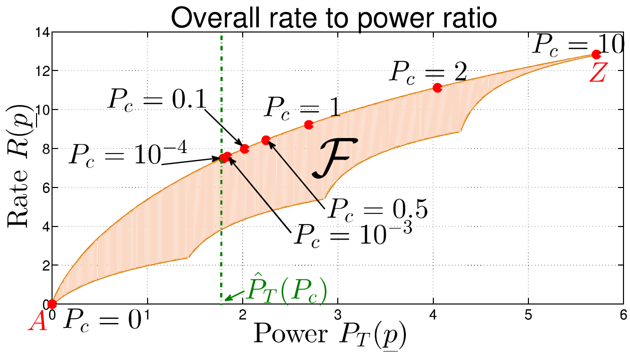

Fig. 5. Optimal power-rate tradeoffs for the rate to power ratio problem for different values of P_c

power allocation and the optimal penalty are both functions of the circuit power P_c ($\underline{p}^* = \underline{p}^*(P_c)$, $\alpha^* = \alpha^*(P_c)$). This represents a major difference between this energy-efficiency metric and the previous ones. Therefore, a rising question is whether all optimal power-rate points on the optimal tradeoff curve can still be achieved, by tunning the circuit power P_c. In Fig. 5, we represent the overall achievable rate as function of the overall power P_T for different values of the power circuit $P_c = [0,\ 10^{-4},\ 10^{-3},\ 0.1,\ 0.5,\ 1,\ 2,\ 5]$ in the same scenario as in Sec. 4.1. The extremes A and Z are achieved when: i)$P_c = 0$, the optimal solution is trivial; ii)$P_c \to \infty$ the overall consumed power at the nominator is dominated by P_c and, thus, the optimal strategy is to maximize the achievable rate. However, as opposed to the previous cases, not all the pairs overall power-rate on the tradeoff curve in between these extremes are achievable. Actually, there is a threshold on the optimal tradeoff curve below which no points other than A are achieved by tunning P_c. This means that, for the energy-efficiency metric defined by the ratio (14), for a very small but non-zero circuit power consumption $P_c > 0$, there is a minimum level of achievable rate $\hat{R}(P_c)$ (and, thus, a minimum level of power consumption $\hat{P}_T(P_c)$) required for the communication to be energy-efficient. This shows that the energy-efficiency metric is more conservative than the previous ones. By maximizing the logarithm of $EE(\underline{p})$, an equivalent problem to (15) is obtained which is viewed [19] as a more conservative variation of the rate maximization with power pricing in (10).

5. CONCLUSIONS

In this paper, we have provided a unifying view on the most common energy-efficiency metrics in cognitive radio systems: i) weighted sum between rate and consumed power; ii) power consumption under minimum rate constraints; iii) ratio between rate and power consumption. We have shown that all these metrics can be interpreted under a joint power vs. rate optimization framework. All three energy efficient allocation policies achieve Pareto optimal power-rate tradeoffs. Using the first two metrics, all optimal tradeoff pairs can be achieved and a neat geometric relationship between them is provided. This is not the case with the third metric. Indeed, while the circuit power consumption does not influence the achieved power-rate tradeoff for the first two metrics, this consumption becomes critical for the third one and imposes a minimum level on both rate and data power consumption for the communication to operate at an optimally energy-efficient point.

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