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Power Allocation for OFDM-based Cognitive Radio Systems under Outage Constraints

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***Abstract*—This paper investigates power allocation algorithms for OFDM-based cognitive radio systems, where the intra-system channel state information (CSI) of the secondary user (SU) is perfectly known. However, due to loose cooperation between the SU and the primary user (PU), the inter-system CSI is only partially available to the SU transmitter. Two types of PUs are considered to have different capabilities. One is a dumb (Peak Interference-Power tolerable) system that can tolerate a certain amount of peak interference at each subchannel. The other is a more sophisticated (Average Interference-Power tolerable) system that can tolerate the interference from the SU as long as the average interference over all subchannels is within a certain threshold. Accordingly, we introduce an interference power outage constraint, with which the outage is maintained within a target level. The outage is here defined as the probability that peak or average interference power to the PU is greater than a given threshold. With both this interference-power outage constraint along with a transmit-power constraint, we propose optimal and suboptimal algorithms to maximize the capacity of the SU. We evaluate the spectral efficiency through extensive simulations and show that the SU can achieve higher performance (up to two times) with the more sophisticated PU than with the dumb PU.**

I. Introduction

Cognitive radio (CR) is a highly promising technology to solve the spectrum insufficiency problem [1]. In spectrum sharing based CR networks, where a secondary (unlicensed) system coexists with a primary (licensed) system, a fundamental design problem is how to maximize the throughput of the secondary user (SU) while ensuring the quality of service (QoS) of the primary user (PU). Based on how not to harm the primary system, transmission modes are classified into three types: *interweaved*, *overlay* and *underlay modes* [2].

In the interweaved mode, the secondary system can utilize the unused license band, i.e., a spectrum hole, when the spectrum is typically under-utilized. The secondary transmitter in this mode needs to have the real-time functionality for monitoring spectrum and detecting the spectrum hole that changes with time and geographic location. The overlay mode enables the secondary system to utilize a license band when the primary system is using the band. The secondary transmitter is assumed to have perfect knowledge of the primary message. Therefore, the secondary transmitter may use this knowledge to mitigate the interference seen by its receiver using dirty paper coding and/or to relay the primary signal to compensate for the SNR (signal-to-noise ratio) at the primary receiver.

In the underlay mode, simultaneous transmissions of primary and secondary systems are also allowed under the condition that the secondary system interferes lower than a certain threshold with the primary system. Accordingly, the concept of interference-temperature has been introduced to determine a tolerable interference level at the primary receiver. By the way, recently, the Federal Communications Commission (FCC) has ruled out the possibility of using the underlay mode based on interference-temperature in dynamic spectrum sharing environments due to several disadvantages [3]. However, we still believe that the interference-temperature mode is a promising strategy to improve spectral efficiency in spite of several practical obstacles and intensive academic research is needed to eliminate the obstacles. In this paper, we concentrate on the underlay mode in multi-carrier CR systems and investigate the system capacity gain obtained by this underlay transmission mode.

A. Related Work

In the underlay CR setting, optimal power allocation algorithms have been developed for orthogonal frequency-division multiplexing (OFDM) systems [4] and for multiple input multiple output (MIMO) systems [5]. In order to keep the interference at the PU receiver (PU-Rx) below a desired level, these papers [4], [5] assumed that the SU transmitter (SU-Tx) is fully aware of the channel from the SU-Tx to the PU-Rx. However, compared to the intra-system channel state information (CSI) between the SU-Tx and the SU receiver (SU-Rx), which is relatively easy to obtain, it would be difficult or even infeasible for the SU-Tx to obtain the perfect inter-system CSI because the primary and secondary systems are usually loosely coupled. Even if they are tightly coupled, obtaining the perfect inter-system CSI may be a big burden for the SU due to a large amount of feedback overhead. Therefore, assuming only partial CSI between the SU and the PU seems to be a reasonable approach.

The impact of imperfect channel knowledge and capacity maximization problems with partial CSI have been extensively investigated in the non-CR setting (see [6], [7] and references

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therein). However, these studies are not directly applicable to our CR setting which has two-dimensional channels: SU-Tx→SU-Rx and SU-Tx→PU-Rx. Zhang *et al.* [8], [9] investigated a robust cognitive beamforming problem with partial CSI in MISO and MIMO environments.

In this paper, we consider OFDM-based CR systems in the problem setting, which makes our paper different from theirs. Huang *et al.* [11] studied the resource allocation problem in OFDM-based CR systems with partial CSI, where the authors assumed partial intra-system CSI (between SU-TX and SU-RX) and perfect inter-system CSI (between SU-TX and PU-RX). However, this is not a good assumption because as we mentioned above, the inter-system partial CSI assumption is more reasonable rather than the intra-system partial CSI due to loose cooperation between the SU and the PU. In this paper, we focus on a problem of maximizing capacity in OFDM-based CR systems, where the SU-Tx has *perfect intra-system CSI* and *partial inter-system CSI*. The partial CSI means that we have knowledge only about the average channel gain over all the subchannels instead of individual channel gain for each subchannel. In particular, we deal with a little considered problem so far: what are the ramifications of different capabilities in the PU and how much more capacity could be obtained if the SU is operating in band with a more sophisticated PU instead of a dumb PU.

The remainder of this paper is organized as follows. In Section II, we first present our system model and describe our partial CSI assumption. We formulate capacity maximization problems subject to the transmit-power constraint and peak or average interference-power outage constraint. In order to solve these problems, in Section III, we propose an optimal power allocation algorithm and a suboptimal power allocation algorithm. In Section IV, we demonstrate our power allocation algorithms through extensive simulations. Finally, in Section V, we draw conclusions.

II. System Model and Problem Formulation

A. System Model

We consider an OFDM-based CR network where both PU and SU share the same spectrum resource with N subchannels in bandwidth B. We denote by $\mathcal{N}=\{1,2,\cdots,N\}$ the set of all subchannels. The signal model of an SU can be represented as $\mathbf{y}=\mathbf{D_{h_2}x}+\mathbf{z}$, where $N\times 1$ vectors $\mathbf{y}$ and $\mathbf{x}$ are the received and transmitted signals, respectively; $\mathbf{D_{h_2}}$ is a diagonal matrix with diagonal elements $\mathbf{h_2}=[h_{21},\cdots,h_{2N}]^T$, which is a channel response from the SU-Tx to the SU-Rx; and $\mathbf{z}$ is the noise vector. Furthermore, the channel response from the SU-Tx to the PU-Rx is denoted by a vector $\mathbf{h_1}=[h_{11},\cdots,h_{1N}]^T$.

Suppose that the SU-Tx has perfect CSI for its own link $\mathbf{h_2}$. In other words, it knows instantaneous channel gains $g_{2n}=|h_{2n}|^2$ for all subchannels $\forall n\in\mathcal{N}$. However, due to the lack of inter-system cooperation, the PU intermittently informs the SU-Tx of only partial CSI about $\mathbf{h_1}$. Based on the assumption that a subchannelization with sufficient interleaving depth is applied, we use an uncorrelated fading channel model [12]. Therefore, in this case, the $\mathbf{h_1}$ is a zero-mean complex Gaussian random vector and the channel gains $g_{1n}=|h_{1n}|^2,\forall n\in\mathcal{N}$ are independent and identically distributed (i.i.d.) exponential random variables with mean λ_1. The partial CSI includes this average channel gain λ_1, and we further assume that the channel is time-varying and frequency-selective but the mean remains unchanged until the next feedback.

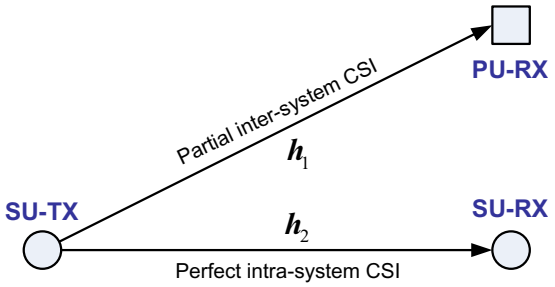

Fig. 1. The system model for OFDM-based CR systems with perfect intra-system CSI and partial inter-system CSI

B. Problem Formulation

Our objective is to determine the optimal transmit power allocation vector $\mathbf{p}=[p_1,\cdots,p_N]^T$ of SU-Tx such that the capacity of the SU is maximized while the QoS of the PU is guaranteed by keeping an outage probability within a target level ϵ. We define the outage probability $P_{out}(\cdot)$ as the probability that the interference power to the PU is greater than a threshold, i.e., interference-temperature $I_{max,n}$ or I_{max}. Motivated by these considerations, we mathematically formulate two types of optimization problems.

The first problem **[P-peak]** assumes that the PU is a dumb (peak interference-power tolerable) system that can tolerate a certain amount of peak interference at each subchannel. Thus, in this problem, we attempt to find an optimal power allocation vector $\mathbf{p}$ for maximizing the capacity under a total transmit-power constraint and a *peak* interference-power outage constraint.

[P-peak]:

$$\max_{\mathbf{p}\geq 0} \sum_{n\in\mathcal{N}} B\log_2\left(1+\frac{1}{\Gamma}\frac{g_{2n}p_n}{N_0B}\right) \quad (1)$$

$$\text{subject to} \sum_{n\in\mathcal{N}} p_n \leq P_{max}, \quad (2)$$

$$P_{out}(\mathbf{p})=Pr[g_{1n}p_n>I_{max,n}]\leq\epsilon,\forall n\in\mathcal{N}, \quad (3)$$

where N_0 is the noise power spectral density and P_{max} is the maximal transmit power of the SU; $I_{max,n}$ is the peak interference temperature threshold that the PU can tolerate at subchannel n, which may differ from subchannel to subchannel. Here, Γ denotes the SNR-gap to capacity, which is a function of the desired BER (bit error rate), coding gain and noise margin [13]. For notational simplicity, we will absorb Γ into the definition of N_0.

In the second problem **[P-average]**, we assume that the PU operates in a more sophisticated system rather than the dumb

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system. The PU has an average interference-power tolerable capability so that it can tolerate the interference from the SU as long as the average of interference over all subchannels is within a certain threshold. The rationale behind this averaging assumption is that even though there is large interference in some subchannels, small interference in the other subchannels can compensate for the performance of PU in an average sense. Thus, in this problem, we try to find an optimal power allocation vector $\mathbf{p}$ for maximizing the capacity under a total transmit-power constraint and an *average* interference-power outage constraint.

[P-average] :

$$\max_{\mathbf{p}\geq 0} \sum_{n\in\mathcal{N}} B\log_2\left(1+\frac{1}{\Gamma}\frac{g_{2n}p_n}{N_0B}\right) \tag{4}$$

$$\text{subject to} \sum_{n\in\mathcal{N}} p_n \leq P_{max}, \tag{5}$$

$$P_{out}(\mathbf{p}) = Pr\Big[\frac{1}{N}\sum_{n\in\mathcal{N}} g_{1n}p_n > I_{max}\Big] \leq \epsilon, \tag{6}$$

where I_{max} is the average interference temperature threshold that the PU can tolerate over all subchannels.

III. Power allocation algorithm with Partial CSI

A. Capacity maximization of SU with Peak Interference-Power tolerable PU: [P-peak]

The problem **[P-peak]** is the same as the classical water-filling problem [14] except the peak interference-power outage constraint (3). Since g_{1n} is assumed to follow an exponential distribution, we can rewrite this constraint (3) as follows:

$$p_n \leq \frac{I_{max,n}}{F_E^{-1}(1-\epsilon)}, \quad \forall n \in \mathcal{N}, \tag{7}$$

where $F_E^{-1}(\cdot)$ is the inverse cumulative density function (CDF) of an exponential distribution with the mean λ_1.

It is worthwhile to mention that $F_E^{-1}(1-\epsilon)$ can be interpreted as an *effective channel gain*. The constraint (7), which limits the maximum allowable transmit power on each subchannel n, is additionally introduced into the classical water-filling problem. Therefore, we can easily obtain the following optimal power allocation algorithm for **[P-peak]**, so called *capped water-filling* [1].

$$p_n = \left[\frac{1}{\mu} - \frac{N_0B}{g_{2n}}\right]_0^{I_{max,n}/F_E^{-1}(1-\epsilon)}, \quad \forall n \in \mathcal{N}, \tag{8}$$

where $[z]_a^b \doteq \min[\max[a,z],b]$; μ is a non-negative Lagrange multiplier associated with the total transmit-power constraint (2) and is chosen such that

$$\sum_n p_n = \min\left[P_{max}, \sum_n \frac{I_{max,n}}{F_E^{-1}(1-\epsilon)}\right]. \tag{9}$$

[1]This terminology is borrowed from [5] where the authors obtained a similar form of solution in a different problem setting.

B. Capacity maximization of SU with Average Interference-Power tolerable PU: [P-average]

To deal with the problem **[P-average]**, let us introduce random variables $X_n = p_n g_{1n}$ for all $n \in \mathcal{N}$, which are independently exponential distributed with mean $p_n\lambda_1$, and X denotes the sum of these random variables. Then, the average interference-power outage constraint (6) in the problem **[P-average]** can be rewritten as

$$Pr\left[X = \sum_n X_n > N \cdot I_{max}\right] \leq \epsilon. \tag{10}$$

To further examine this constraint (10), it is necessary to know the distribution of X. If the transmit power is equally allocated to all the subchannels, i.e., $p_n = p$ for all $n \in \mathcal{N}$, then X follows an Erlang distribution (the sum of several i.i.d. exponential variables), $X \sim Erlang(N, 1/(p\lambda_1))$. Therefore, we can find the upper bound of power p to satisfy this outage constraint.

However, in general, the power allocation at the SU-Tx is not even in order to exploit the frequency-selectivity of the channel. Since it is hard to explicitly determine the distribution of X for the general power allocation, we use the Gaussian approximation based on the *Lyapunov's central limit theorem (CLT)* [15]. In order to apply the Lyapunov's CLT, the following *Lyapunov condition* should be satisfied:

$$\lim_{N\to\infty} \frac{\left(\sum_{n=1}^N r_n^3\right)^{\frac{1}{3}}}{\left(\sum_{n=1}^N \sigma_n^2\right)^{\frac{1}{2}}} = 0, \tag{11}$$

where r_n is defined as the third central moment of the random variable X_n, i.e., $E\left[(X_n - m_n)^3\right]$; m_n and σ_n^2 represent the finite mean and variance of the exponential distributed random variable X_n, respectively. We can easily check this condition, but omit the proof due to the paper length limitation.

Thus, for a large number of subchannels, X can be approximated as a normally distributed random variable with mean m and variance σ^2:

$$\begin{aligned} m &\simeq \sum_n p_n\lambda_1 \quad \text{and} \\ \sigma^2 &\simeq \sum_n (p_n\lambda_1)^2. \end{aligned} \tag{12}$$

Thus, we can rewrite the constraint (10) as:

$$P_{out}(\mathbf{p}) = 1 - F_N(NI_{max}) \tag{13}$$

$$= \frac{1}{2}erfc\left(\frac{NI_{max}-m}{\sqrt{2}\sigma}\right) \leq \epsilon, \tag{14}$$

where $F_N(\cdot)$ is the CDF of a normal distribution with mean m and variance σ^2, and $erfc(z) = \frac{2}{\sqrt{\pi}}\int_z^\infty e^{-t^2}dt$.

If a power allocation is given, then we can check whether it satisfies the outage constraint (14) or not. Unfortunately, however, it is difficult to solve the problem **[P-average]** simultaneously considering both constraints (5) and (14) because (14) has a very complicated form.

Alternatively, we develop a suboptimal power allocation algorithm, which repeatedly (however, it is very fast because

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we require only a few iterations based on binary search.) solves a subproblem having only a transmit-power constraint using the classical water-filling algorithm and then adjusts the available transmit power $\overline{P}$ until the desired outage probability is achieved. The following Lemma 1 tells us that the outage probability is a strictly increasing function of the available transmit power $\overline{P}$, and thus we can determine a unique $\overline{P}$ using the *binary search*.

Lemma 1: The $P_{out}(\mathbf{p})$ is a *strictly increasing* function of the available transmit power $\overline{P}$ if the conventional WATERFILLING($\overline{P}$) is applied, i.e., $p_n = [1/\mu - N_0 B/g_{2n}]^+$ for all $n \in \mathcal{N}$, where μ satisfies $\sum_n p_n = \overline{P}$.

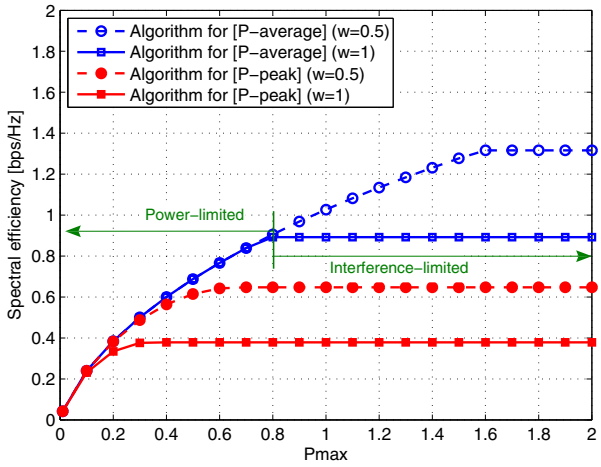
Proof: Due to the property of the water-filling algorithm, if the available transmit power $\overline{P}$ increases, then p_n does not decrease for any n and at least more than one p_n increase. Accordingly, both m and σ^2 in (12) increase as well. Since the $erfc(\cdot)$ is a decreasing function, $P_{out}(\mathbf{p}) = \frac{1}{2} erfc\left(\frac{NI_{max}-m}{\sqrt{2}\sigma}\right)$ is a strictly increasing function of $\overline{P}$. This completes the proof. ■

The following algorithm describes the detailed procedure for **[P-average]** with the help of Lemma 1.

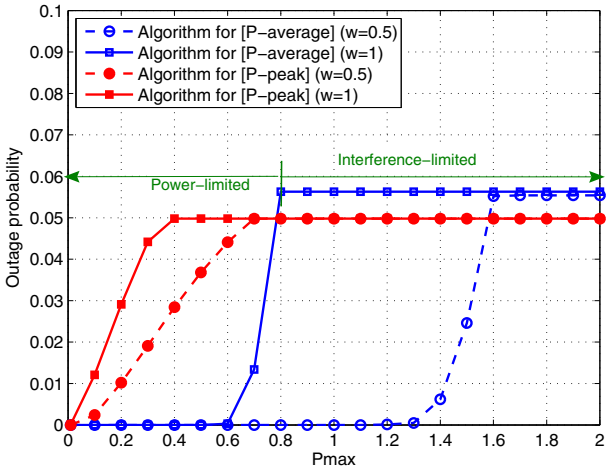
1: Initialization:
$\overline{P} = P_{max}$ and $\mathbf{p} =$ WATERFILLING(P_{max}).
if $P_{out}(\mathbf{p}) > \epsilon + \delta$,
then $[a, b] \leftarrow [0, P_{max}]$,
else,
go to Finish.

2: Repeat (binary search):
$\overline{P} = (a+b)/2$ and $\mathbf{p} =$ WATERFILLING$(\overline{P})$.
if $P_{out}(\mathbf{p}) > \epsilon + \delta$,
then $[a, b] \leftarrow [a, \overline{P}]$,
else if $P_{out}(\mathbf{p}) < \epsilon - \delta$,
then $[a, b] \leftarrow [\overline{P}, b]$,
else,
go to Finish.

3: Finish:
$\mathbf{p}$ is a suboptimal power allocation.



(a) Spectral efficiency for the secondary system



(b) Outage probability for the primary system

Fig. 2. The performance of proposed algorithms: N=128 and ϵ=0.05.

IV. NUMERICAL RESULTS

A. Simulation Setup

In simulations, without loss of generality, the total noise power over the spectrum $(N_0 B) \cdot N$ is set to be one and the interference-temperature thresholds are adapted to the level of noise power, i.e., $I_{max,n} = I_{max} = 1/N$ for all $n \in \mathcal{N}$. The channel gains $[g_{1n}, \forall n \in \mathcal{N}]$ and $[g_{2n}, \forall n \in \mathcal{N}]$ are i.i.d. exponential random variables with mean λ_1 and λ_2, respectively. We obtain numerical results based on 10^5 randomly generated channel realizations.

B. Performance of the proposed algorithms

We examine the performance of our power allocation algorithms by choosing $N = 128$ and $\epsilon = 0.05$. The error tolerance δ for the algorithm for **[P-average]** is chosen to be a small value of 10^{-5} (much smaller than ϵ). For your information, the number of iterations until the convergence of binary search is 15 times on average.

Fig. 2(a) shows the spectral efficiency for the SU with respect to the maximal transmit power for different combinations of the ratio $w = \lambda_1/\lambda_2$ (we fix $\lambda_2 = 1$ and vary λ_1). In the low P_{max} regime, the spectral efficiency increases as the available power increases. On the other hand, when P_{max} is greater than a certain turning point, the spectral efficiency does not further increase because the interference-power outage constraints becomes dominant. We indicate the boundary of power-limited and interference-limited regimes in the case of **[P-average]** and $w = 1$ in the middle of figures.

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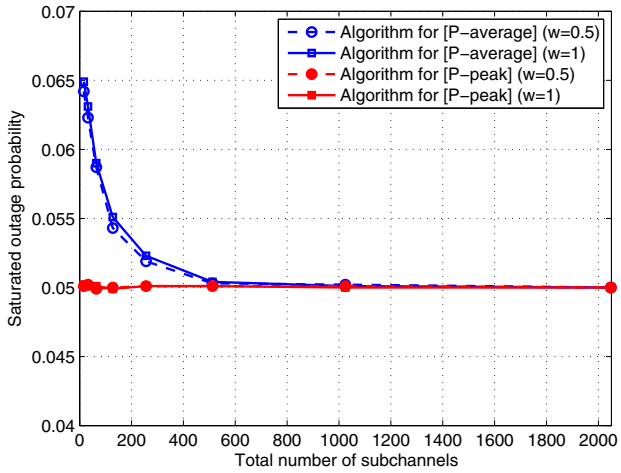

Fig. 3. Saturated outage probability versus the total number of subchannels.

Reducing the ratio w increases the spectral efficiency due to loose interference-power outage constraints because the PU goes far away from the SU. It is important to highlight that the SU can always obtain the higher spectral efficiency in **[P-average]** than **[P-peak]**, e.g., more than two times in terms of the saturated performance. This is because the more sophisticated PU instead of the dumb one gives additional freedom in power allocation to the SU. We may confirm this argument by comparing the interference-power outage constraint of **[P-average]** with that of **[P-peak]**. Since the average interference-power outage constraint (6) is looser than the peak interference-power outage constraint (3) at the same interference-temperature $I_{max,n} = I_{max}, \forall n \in \mathcal{N}$, more flexible power allocation is possible.

Fig. 2(b) shows the outage probability for the PU. In the power-limited regime, the outage probability is much lower than the target $\epsilon = 0.05$. If we keep increasing P_{max} until the interference-limited regime, then the outage probability is saturated to the target. The optimal algorithm for **[P-peak]** always achieves the exact target requirement, while the suboptimal algorithm for **[P-average]** exhibits a small deviation from the target value due to Gaussian approximation error.

C. Effect of the number of subchannels on Gaussian approximation error

We investigate the relationship between the total number of subchannels available and Gaussian approximation error. As you can see in Fig. 3, the saturated outage probability sticks to the target outage level as the number of subchannels N increases. In other words, the approximation error asymptotically goes to zero. However, if the system does not have the sufficient number of subchannels, a suitable margin on the target error probability will be necessary to make the system robust.

V. Conclusion

In this paper, we considered OFDM-based CR systems with perfect intra-system CSI and partial inter-system CSI and investigated how much capacity can be achieved if the SU is operating in a band with a more sophisticated PU instead of a dumb PU. Accordingly, we formulated two problems, **[P-peak]** and **[P-average]** that maximize the capacity of SU while ensuring the outage probability below the target level under outage constraint jointly with a classical transmit-power constraint. To solve these problems, we proposed an optimal power allocation algorithm for **[P-peak]** and a suboptimal power allocation algorithm for **[P-average]**. Our suboptimal algorithm may result in a small deviation from the target outage level due to Gaussian approximation error, however, this gap asymptotically goes to zero as the number of subchannels increases. We evaluated the spectral efficiency performance through extensive simulations and concluded that the SU can achieve higher performance with the more sophisticated PUin **[P-average]** than with the dumb PU in **[P-peak]**. In terms of saturated spectral efficiency, the performance gain obtained with the more sophisticated PU is two times higher. Extension to more general channel models that include correlation or feedback delay might be a subject for future work.

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