DISCRETE RATE AND VARIABLE POWER ADAPTATION FOR UNDERLAY COGNITIVE NETWORKS*

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ABSTRACT

We consider the problem of maximizing the average spectral efficiency of a secondary link in underlay cognitive networks. In particular, we consider the network setting whereby the secondary transmitter employs discrete rate and variable power adaptation under the constraints of maximum average transmit power and maximum average interference power allowed at the primary receiver due to the existence of an interference link between the secondary transmitter and the primary receiver. We first find the optimal discrete rates assuming a predetermined partitioning of the signal-to-noise ratio (SNR) of both the secondary and interference links. We then present an iterative algorithm for finding a suboptimal partitioning of the SNR of the interference link assuming a fixed partitioning of the SNR of secondary link selected for the case where no interference link exists. Our numerical results show that the average spectral efficiency attained by using the iterative algorithm is close to that achieved by the computationally extensive exhaustive search method for the case of Rayleigh fading channels. In addition, our simulations show that selecting the optimal partitioning of the SNR of the secondary link assuming no interference link exists still achieves the maximum average spectral efficiency for the case where the average interference constraint is considered.

1. INTRODUCTION

The concept of cognitive networks was first introduced by Mitola [1] as an efficient means for utilizing the scarce spectrum by allowing spectrum sharing between a licensed primary network and a secondary network. Cognitive networks can be divided into three different types; namely, interweave, underlay, and overlay. For the interweave type the secondary users are only allowed to use the spectrum of the primary network whenever it is idle, which requires continuous sensing of the primary spectrum by the secondary network. For the underlay network simultaneous transmissions are allowed by letting the secondary network share the spectrum with the primary network under the condition of maximum interference power level allowed at the primary receiver. Finally, for the overlay type, the secondary network is aware of the signal characteristics of the primary network which is exploited to achieve an enhanced performance for the secondary network by minimizing the interference incurred by the primary transmissions. In this paper, we focus on the underlay cognitive network model whereby a secondary user is communicating over a secondary link to a certain destination under the constraints of maximum average transmit power and maximum average interference level at the primary receiver.

Adaptive transmission has been introduced as a power-efficient technique for improving the performance of wireless networks [2, 3]. In particular, the problem of discrete rate adaptation has been addressed in [4, 5, 6] for the case of a single slowly fading wireless link where it was shown that by carefully selecting the optimal discrete rates, the achievable spectral efficiency is close to the Shannon capacity [6]. Recently, adaptive transmission has been applied to cognitive networks. For instance, from an information-theoretic view, the problem of finding the optimal power allocation schemes for fading channels in underlay cognitive networks assuming continuous rate adaptation have been addressed in [7, 8, 9, 10] under different constraints such as peak/average transmit power and peak/average interference power. From a practical view, an adaptive QAM modulation has been proposed in [11] where it was assumed that the cognitive user first estimates its channel, during a training phase, and this estimate is then utilized to find the optimal QAM modulation. In this paper, we deal with the problem of adaptive transmission in underlay cognitive network using an information-theoretic approach. In particular, we employ discrete-rate variable power adaptive system to maximize the average spectral efficiency under average transmit power constraint and average interference power constraint. We first consider the problem of finding the optimal discrete rates assuming fixed partitioning of the secondary and interference link SNRs. Then we develop techniques to determine the partitioning of the secondary and interference link SNRs that provide almost close-to-optimal performance in terms of maximizing the average spectral efficiency for Rayleigh fading channels.

The paper is organized as follows; in Sec. 2 and Sec. 3, we present the system model as well as the problem formulation. In Sec. 4, we present methods for finding the optimal discrete rates. In Sec. 5, we present computationally-efficient suboptimal techniques for selecting the partitioning both the secondary and interference link SNRs. In Sec. 6, we present numerical results to assess the performance of the developed techniques for finding the optimal discrete rates as well as the partitioning of the SNR of the secondary and interference links for Rayleigh fading channels. Finally, we conclude the paper in Sec. 7.

2. SYSTEM MODEL

We consider an underlay cognitive system model whereby a secondary cognitive user is allowed to share the spectrum with a primary link under the constraint of the maximum av-

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erage interference power set under a predetermined threshold. We assume that the secondary link between the secondary transmitter and receiver is not affected by the primary transmissions. Furthermore, we assume that the channels involved in communication are discrete-time fading channels where the secondary SNR and the interference SNR are denoted by γ_s and γ_p, respectively, with average values $\bar{\gamma}_s$ and $\bar{\gamma}_p$. We also assume that the secondary transmitter has a perfect knowledge of the secondary and interference link SNRs.

We partition the SNR ranges of the secondary and the interference links into $(N+1)\times(M+1)$ two dimensional intervals, $I_{i,j}$, defined as follows,

$$I_{i,j}=\left([\gamma_{s,i},\gamma_{s,i+1}),[\gamma_{p,j},\gamma_{p,j+1})\right),0\leq i\leq N,0\leq j\leq M, \quad (1)$$

where $\gamma_{s,i}$ and $\gamma_{p,j}$ are the thresholds used for partitioning the secondary and interference links, respectively. We assume that $\gamma_{s,0}=\gamma_{p,0}=0$ and $\gamma_{s,N+1}=\gamma_{p,M+1}=\infty$. We also adopt the scenario of zero information outage where the secondary user is not allowed to transmit below $\gamma_{s,1}$ given any value of γ_p. In addition we assume, without loss of generality, no transmission is allowed above $\gamma_{p,M}$. Such setting results in having $N\times M$ rates for the $(N+1)\times(M+1)$ two dimensional intervals.

3. PROBLEM FORMULATION

In this paper, our objective is to find the discrete rate, $R_{i,j}$, used at the $I_{i,j}$ th interval and the associated thresholds that maximize the average spectral efficiency R_s. Assuming employing continuous power adaptation $p_{i,j}(\gamma_s)$ and capacity-achieving codes, the fixed rate used at each interval is given by $R_{i,j}=\log_2(1+\zeta_{i,j})$ where $\zeta_{i,j}=\gamma_s p_{i,j}(\gamma_s)$. Hence, the average spectral efficiency is defined as follows,

$$R_s=\sum_{i=1}^{N}\sum_{j=0}^{M-1}R_{i,j}\alpha_{s,i}\alpha_{p,j} \quad (2)$$

subject to the following constraints

$$\mathrm{C1}: P_s=\sum_i\sum_j\zeta_{i,j}\mu_{s,i}\alpha_{p,j}\leq P, \quad (3)$$

$$\mathrm{C2}: P_I=\sum_i\sum_j\zeta_{i,j}\mu_{s,i}q_{p,j}\leq Q, \quad (4)$$

where $\alpha_{s,i}=\int_{\gamma_{s,i}}^{\gamma_{s,i+1}}f_{\gamma_s}(\gamma_s)\mathrm{d}\gamma_s$, $\alpha_{p,j}=\int_{\gamma_{p,j}}^{\gamma_{p,j+1}}f_{\gamma_p}(\gamma_p)\mathrm{d}\gamma_p$, $\mu_{s,i}=\int_{\gamma_{s,i}}^{\gamma_{s,i+1}}\frac{1}{\gamma_s}f_{\gamma_s}(\gamma_s)\mathrm{d}\gamma_s$, $q_{p,j}=\int_{\gamma_{p,j}}^{\gamma_{p,j+1}}\gamma_p f_{\gamma_p}(\gamma_p)\mathrm{d}\gamma_p$, and $f_{\gamma_s}(\gamma_s)$ and $f_{\gamma_p}(\gamma_p)$ are the probability density functions (pdf) of the secondary SNR and interference SNR, respectively. While P_s, P_I, P, and Q denote the average transmit power, average interference power, maximum average transmit power, and maximum interference level required at the primary receiver.

The above constrained problem is a multidimensional optimization problem that involves several parameters including finding the optimal fixed rates and the associated thresholds. In solving such problem, we first find the optimum rates assuming a specific set of thresholds. Then, we turn our attention to finding the thresholds that maximize the average spectral efficiency. By fixing the set of thresholds, the problem of finding the optimal rates turns out to be a convex optimization problem that can be solved using the Lagrangian method where the Lagrangian function is given as follows,

$$L=R_s-\lambda_1\Big(\sum_i\sum_j\zeta_{i,j}\mu_{s,i}\alpha_{p,j}-P\Big)-\lambda_2\Big(\sum_i\sum_j\zeta_{i,j}\mu_{s,i}q_{p,j}-Q\Big), \quad (5)$$

where λ_1 and λ_2 are positive constants. The optimal rates can then be obtained by finding the values that maximize the Lagrangian function. By taking this approach, the optimal rates can be easily obtained in terms of λ_1, λ_2 and the other parameters $\{\alpha_{s,i},\alpha_{p,j},\mu_{s,i},q_{p,j}\}$. However, finding the values of λ_1 and λ_2 that satisfy the power constraints can be only performed using numerical techniques. This approach of computing λ_1 and λ_2 is not desirable as it complicates the problem of finding the optimal thresholds. In the next section, based on similar approaches proposed in [8, 9], we find the optimal rates assuming predetermined values of the thresholds.

4. DISCRETE-RATE DESIGN FOR A FIXED SET OF THRESHOLDS

In our approach for finding the discrete rates, we consider decoupling the optimization problem into two separate problems as follows,

- (Prob1): we find the discrete values, $\zeta^1_{i,j}$, that maximize the average spectral efficiency assuming only the average transmit power constraint (C1).
- (Prob2): we find the discrete values, $\zeta^2_{i,j}$, that maximize the average spectral efficiency assuming only the interference power constraint (C2).

We then select the discrete rates that satisfy both constraints. We first derive the values, $\zeta^1_{i,j}$, that maximize the average spectral efficiency under the average transmit power control. By formulating the Lagrangian function

$$L_1=R_s-\lambda_1\Big(\sum_{i=1}^{N}\sum_{j=0}^{M-1}\zeta^1_{i,j}\mu_{s,i}\alpha_{p,j}-P\Big) \quad (6)$$

and applying the KKT optimality conditions, the optimal rates, $\zeta^1_{i,j}$, are given by,

$$\zeta^1_{i,j}=\frac{\alpha_{s,i}}{\mu_{s,i}}\left(\frac{1}{\lambda_1}-\frac{\mu_{s,i}}{\alpha_{s,i}}\right)^+, \quad (7)$$

where $(a)^+=\max(0,a)$. The value of λ_1 can be obtained by substituting the values of $\zeta^1_{i,j}$ in the average transmit power constraint (C1) defined in Eq.(3). By defining the set of values of the index i, denoted by $\mathcal{I}$, where $\zeta^1_{i,j}$ is strictly positive, the value of λ_1 is given by

$$\lambda_1=\frac{\sum_{i\in\mathcal{I}}\alpha_{s,i}}{\left(\sum_{i\in\mathcal{I}}\mu_{s,i}+\frac{P}{1-\alpha_{p,M}}\right)}. \quad (8)$$

By substituting equation (8) in equation (7), the optimal value $\zeta^1_{i,j}$ is given by,

$$\zeta^1_{i,j}=\frac{\alpha_{s,i}}{\mu_{s,i}}\left(\frac{\sum_{i\in\mathcal{I}}\mu_{s,i}+\frac{P}{1-\alpha_{p,M}}}{\sum_{i\in\mathcal{I}}\alpha_{s,i}}-\frac{\mu_{s,i}}{\alpha_{s,i}}\right)^+. \quad (9)$$

The amount of average interference power observed at the primary receiver, as a result of using the values of $\zeta^1_{i,j}$, is given by substituting these values in the average interference constraint and is given by $P_I = \frac{P(\bar{\gamma}_p - q_{p,M})}{1-\alpha_{p,M}}$. If this value is less than Q then the solution for (5) is given by $\zeta^1_{i,j}$. In the case that P_I is greater than Q, then we turn our attention to solve the problem under the average interference power constraint which can be obtained, similarly, by using the Lagrangian method and is given by,

$$\zeta^2_{i,j} = \frac{\alpha_{s,i}}{\mu_{s,i}}\left[\left(\frac{\alpha_{p,j}}{q_{p,j}}\right)\left(\frac{\sum_{j\in\mathcal{J}} q_{p,j}}{\sum_{j\in\mathcal{J}}\alpha_{p,j}}\right)\left(\frac{\sum_{i\in\mathcal{I}}\mu_{s,i} + \frac{Q}{\sum_{j\in\mathcal{J}} q_{p,j}}}{\sum_{i\in\mathcal{I}}\alpha_{s,i}}\right) - \frac{\mu_{s,i}}{\alpha_{s,i}}\right]^+, \quad (10)$$

where $\mathcal{J}$ denotes the set of values of the index j for which the values of $\zeta^2_{i,j}$ is strictly positive. The average transmit power achieved by these rates is then computed and compared to the maximum average transmit power P. In case that the average transmit power is not satisfied then we need to solve the original Lagrangian problem in (5). However, based on our observations from the numerical results, the optimal solution of (5) is either equal to $\zeta^1_{i,j}$ or $\zeta^2_{i,j}$.

We finally consider the question of whether to start finding the rates for (Prob1) or (Prob2). This question can be answered by considering the case where the interference thresholds are set to infinity where in this case $\alpha_{p_0} = 1$, $\alpha_{p,i} = 0, i > 0$, $q_{p,0} = \bar{\gamma}_p$ and $q_{p,i} = 0, i > 0$. For such case, the values of $\zeta^1_{i,j}$ are given by substituting $M = 1$, $\alpha_{p,0} = 1$ and $q_{p,0} = \bar{\gamma}_p$ in equation (9) which is considered optimal if the average interference power satisfies the following condition

$$P\,\bar{\gamma}_p \le Q. \quad (11)$$

We note that the above condition depends solely on the design parameters of the problem which are known in advance; namely, P, $\bar{\gamma}_p$ and Q. Therefore, we can use equation (11) to suggest whether we should start solving (Prob1) or (Prob2) depending on whether the the relation in (11) is satisfied or not.

5. SUBOPTIMAL ITERATIVE-BASED THRESHOLD DESIGN ALGORITHM

In this section, we consider the problem of finding the optimal SNR thresholds for the secondary and interference link that maximize the average spectral efficiency. Finding the optimal thresholds can be conducted using exhaustive search which is computationally extensive problem. We first consider finding the thresholds for the secondary SNR then we turn our attention to finding the thresholds of the interference SNR.

To find the secondary SNR thresholds, we consider the case where we assume that the average maximum interference constraint is not considered. This case is equivalent to setting all the interference SNR thresholds to infinity where in this case $\alpha_{p_0} = 1$, $\alpha_{p,i} = 0, i > 0$, $q_{p,0} = \bar{\gamma}_p$ and $q_{p,i} = 0, i > 0$. In this scenario, the problem reduces to the discrete-rate adaptation problem considered in [4, 6] where the optimal rates are given by $\zeta^1_{i,j}$ where $\alpha_{p,M} = 0$ and the secondary SNR thresholds can be obtained using techniques shown in [4, 6]. As will be shown later by simulations in Sec. 6, the obtained secondary SNR thresholds can still be considered optimal for the case where the constraint on the maximum interference is considered.

Next, we turn our attention to finding the optimal interference thresholds. We devise a suboptimal iterative-based threshold selection algorithm where we first find the threshold for $M = 1$, then we use this threshold to find the thresholds for $M = 2$ and subsequently for higher values of M.

5.1 Optimal Threshold Design for $M = 1$

Using equations (7), (8) and (10), the optimal values of $\zeta_{i,j}$ is either equal to $\zeta^1_{i,j}$ if $Pq_{p,0} \le Q\alpha_{p,0}$ or $\zeta^2_{i,j}$ otherwise, which is equivalently can be written as follows,

$$\zeta^1_{i,j} = \frac{\alpha_{s,i}}{\mu_{s,i}}\left(\frac{\sum_{i\in\mathcal{I}}\mu_{s,i} + \min(\frac{1}{\alpha_{p,0}}, \frac{Q}{q_{p,0}})}{\sum_{i\in\mathcal{I}}\alpha_{s,i}} - \frac{\mu_{s,i}}{\alpha_{s,i}}\right)^+. \quad (12)$$

Hence, the value of optimal threshold $\gamma_{p,1}$ can be obtained by maximizing the following equation

$$R^*_s = \max_{\gamma_{p,1}} \sum_{i\in\mathcal{I}} \log_2\left[\frac{\alpha_{s,i}}{\mu_{s,i}}\left(\frac{\sum\mu_{s,i} + \min(\frac{1}{\alpha_{p,0}}, \frac{Q}{q_{p,0}})}{\sum\alpha_{s,i}}\right)\right]\alpha_{p,0}\alpha_{s,i}. \quad (13)$$

By careful investigation of the above relation, we can observe the following

- If the value of the term $\frac{1}{\alpha_{p,0}}$ is less than the value of the term $\frac{Q}{q_{p,0}}$ for all values of $\gamma_{p,1}$, then the interference constraint condition is satisfied for all values of $\gamma_{p,1}$. Hence, we can set $\gamma_{p,1}$ to infinity and the problem reduces to the well known capped inversion channel capacity problem [2].
- In case that there exists an intersection point $\gamma^0_{p,1}$ between the relations $\frac{1}{\alpha_{p,0}}$ and $\frac{Q}{q_{p,0}}$ then for $\gamma^0_{p,1} \le \gamma_{p,1}$, the value of $\gamma_{p,1}$ can be increased while still the maximum interference constraint is satisfied. Therefore, we can deduce that the capacity is increasing with $\gamma_{p,1}$ within the average transmit power constraint region. For the interference constraint region where $\gamma^o_{p,1} > \gamma_{p,1}$, we note that there must exists a value for the threshold $\gamma_{p,0}$ where the capacity is maximized. Therefore, we deduce that we can limit the search for the $\gamma_{p,1}$ in the interference constraint region and the capacity optimization problem can be reduced to the following

$$R^*_s = \max_{\gamma_{p,1}\ge\gamma^0_{p,1}} \sum \log 2\left[\frac{\alpha_{s,i}}{\mu_{s,i}}\left(\frac{\sum\mu_{s,i} + \frac{Q}{q_{p,0}}}{\sum\alpha_{s,i}}\right)\right]\alpha_{p,0}\alpha_{s,i} \quad (14)$$

5.2 Threshold Design for $M > 1$

For higher values of M, the problem of finding the optimal thresholds is computationally intensive and therefore we outline an iterative-based algorithm for selecting the thresholds. In particular, for the case of $M = 2$, we can initially select the value of the first threshold as follows. Assume that the obtained threshold at $M = 1$ is $\gamma_{p,1}^{*,1}$, we can select the first threshold, $\gamma_{p,1}^{*,2}$ for the case of $M = 2$ according to the following relation,

$$\gamma_{p,1}^{*,2} = \frac{1}{2}\gamma_{p,1}^{*,1}. \quad (15)$$

By setting the value of the first threshold according to the above relation, the problem reduces to a one dimensional problem where the second threshold can be easily obtained. Then, at the next iteration, we can fix the second threshold to the one obtained in the first iteration and then search for the first threshold that maximizes the average spectral efficiency. This process can be repeated until the values of thresholds converge to the optimal values. However, as observed by our simulation, that using the second threshold obtained by selecting the first threshold according to Eq. (15) attains average spectral efficiency values close to that achieved by the exhaustive search technique for the case of Rayleigh fading channels. The proposed iterative technique can be extended to find the thresholds for higher values of M. However, we can show that the achieved spectral efficiency at $M = 2$ is almost equal to that achieved assuming perfect knowledge of the interference SNR (details are omitted due to space limitation).

6. NUMERICAL RESULTS

In this section, we present the simulation results conducted according to the system model shown in Sec. 2. We assume a slowly varying and frequency-flat Rayleigh fading channel. We also assume, without loss of generality, that the maximum average transmit power, P is set to one. For the secondary channel, we use only four thresholds (N = 4) corresponding to four fixed-rate regions. We use the values of secondary SNR thresholds based on the results shown in [6] which are given by $[1.4, 5.5, 8.9, 12.3]$ in dB.

First, we consider the case that we only have one threshold used for the interference link (M=1). In Fig.1, we depict the optimum threshold $\gamma_{p,1}$ as a function of the average interference SNR ($\bar{\gamma}_p$) for different levels of maximum interference power level (Q). It is obvious that $\gamma_{p,1}$ increases as $\bar{\gamma}_p$ increases, but for relatively high values of Q (the case of $Q = 1$ is shown in Fig.1), the optimum threshold reaches a minimum below which the threshold starts increasing until it reaches infinity as the average interference SNR $\bar{\gamma}_p$ reaches absolute zero. This is due to the fact that the power constraint is the dominant condition for all values of γ_p.

In Fig.2, we present the average spectral efficiency of in case of ($M = 1$) for different values of average interference power level Q, and average interference SNR $\bar{\gamma}_p$. As shown in Fig.2, at low values of Q, the interference constraint is relatively dominant and hence results in highly affecting the optimum spectral efficiency as it increases with Q. On the other hand, as the values of Q increases, the power constraint is more dominant and the effect of increasing Q will be of minimal effect on the spectral efficiency, especially at large values of $\bar{\gamma}_p$

In Fig.3, we present the average spectral efficiency as a function of the average interference SNR for different values of M which shows as Q increases, the effect of having more discrete levels for interference SNR results in less improvement of achieved optimal rate. This result shows that it is sufficient to have ($M = 1$) or (at most $M = 2$) especially at values of Q equivalent to a strong interference constraint ($Q \leq 1$).

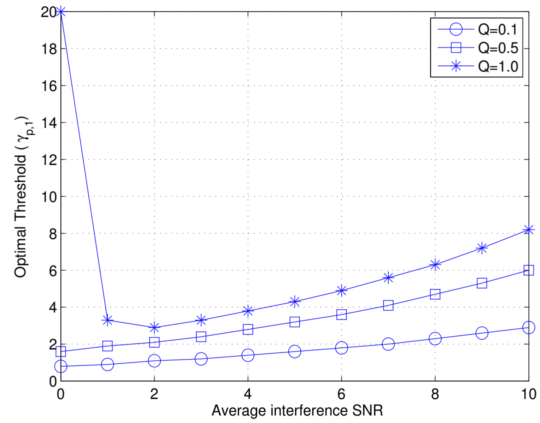

Figure 1: Optimal threshold $\gamma_{p,1}$ for ($M = 1$) versus $\bar{\gamma}_p$ (in dB) for different levels Q.

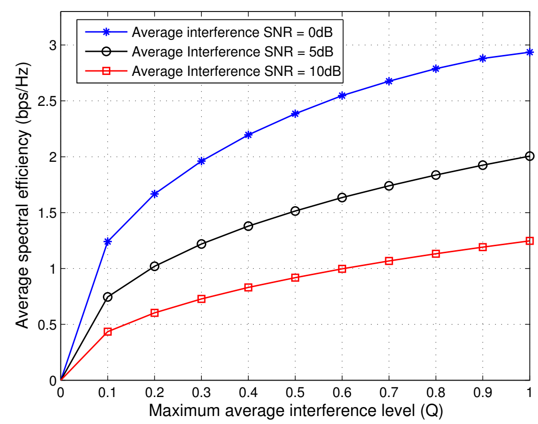

Figure 2: Average spectral efficiency (bps/Hz) for ($M = 1$) versus Q for different values of $\bar{\gamma}_p$.

In Fig.4, we present the rates obtained by the optimal algorithm (exhaustive search) compared to the iterative suboptimal one for the values of $M = 1$ and $M = 2$. It is obvious that the average spectral efficiency attained by using the iterative suboptimal algorithm is close to those achieved by using the optimal algorithm (exhaustive search).

Finally, we conduct simulations to show that the optimal secondary SNR thresholds obtained for the case where the average interference SNR constraint is not considered can be also used for the case when the average interference SNR constraint is taken into consideration. In particular, we define the variable Δ which denotes the difference between the secondary thresholds selected for our simulations and the optimal secondary SNR thresholds. We assume that all thresholds are either increased or decreased by a factor of Δ from the optimal secondary SNR thresholds. For example, when $\Delta = 0$, this reduces to the values of the SNR secondary thresholds used in the previous figures. In Fig. 5, we depict the average spectral efficiency as a function of the drift (Δ in dB) for different values of the average interference link SNR ($\bar{\gamma}_p$). it is obvious that the average spectral efficiency is achieved at Δ equal to zero.

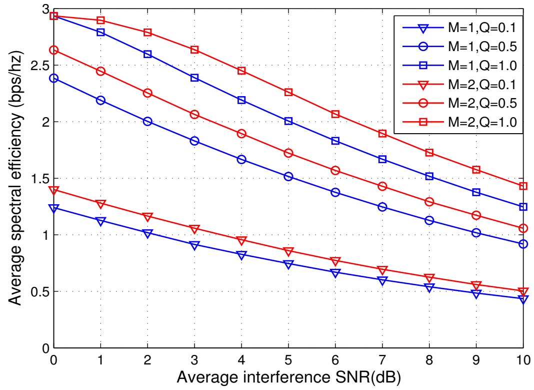

Figure 3: Average spectral efficiency (bps/Hz) (for $M = 1$ and $M = 2$) versus average interference SNR(dB) for different levels of Q.

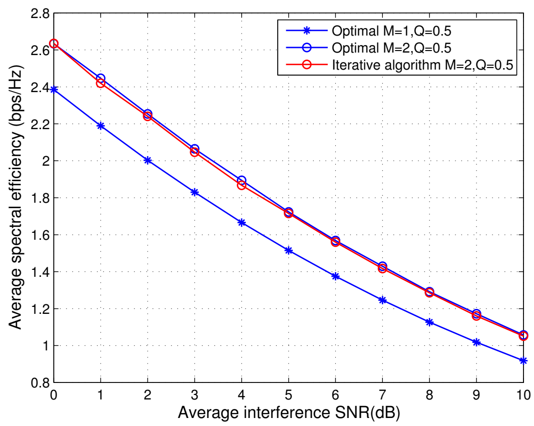

Figure 4: Average spectral efficiency (bps/Hz) (for $M = 1$ and $M = 2$) versus average interference SNR(dB) using optimal and iterative techniques for $Q = 0.5$.

7. CONCLUSION

In this paper, we present the problem of maximizing the average spectral efficiency for a secondary user in an underlay cognitive network under the constraints of average transmit power and average interference power. We develop algorithms for finding the optimal average spectral efficiency for predetermined values of the thresholds. Then, we present a suboptimal iterative-based algorithm for finding the thresholds for the secondary and interference SNR links. Our simulation results indicate that the values of the average spectral efficiency achieved using the iterative algorithm is close to that attained by the computationally extensive exhaustive search optimal methods.

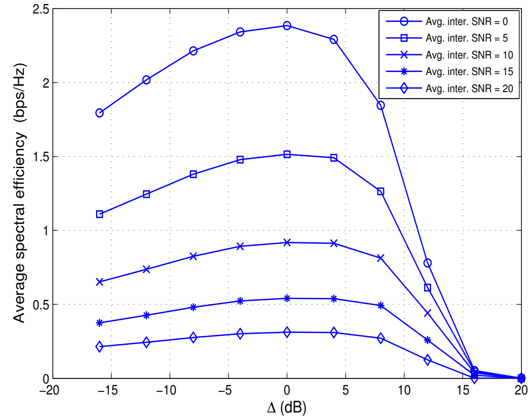

Figure 5: Average spectral efficiency (bps/Hz) as a function of the drift (Δ in dB) for different values of $\bar{\gamma}_p$ at $Q = 0.5$.

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