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JOINT CHANNEL AND POWER ALLOCATION SCHEME FOR OFDM BASED COGNITIVE RADIO SYSTEMS

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Abstract– In this paper, we consider cognitive radio network in which two cognitive radio sources communicate with two cognitive destinations via a relay node. The decode and forward (DF) relay node employs physical layer network coding (PLNC) to improve the data rate. Based on the availability of the spectrum bands at the source, relay and destination, the network employs three different diversity schemes namely source to relay diversity, relay to destination diversity and combination of earlier two diversity schemes with overall source to destination diversity schemes. Optimal power loading algorithms under the Zero Mean Circularly Symmetric Complex Gaussian (ZMCSCG) constraint in OFDM based CR systems. The capacity of the Secondary User (SU) is maximized while keeping the interference introduced to the Primary User (PU) band remains within tolerable range. However the drawback of such an approach is that channel capacity increases with increasing Signal to Noise Ratio (SNR), which is not applicable to a practical scenario. Therefore, we propose an optimal power loading scheme under the Finite Symbol Alphabet (FSA) constraint, (i.e., QPSK, 8-PSK, 16-QAM and 64-QAM, etc.)to achieve realistic system performance especially under the high SNR region. Subsequently, Mutual Information (MI) is derived and compared against channel capacity which reveals that in the low SNR region, they are closely related.

Keywords– Cognitive radio, OFDM, SNR, QPSK, QAM

I.Introduction

Cognitive radio (CR) aims to have more adaptive and aware communication devices that can make betteruse of available natural resources [1]-[2]. It is expected to perform a more significant role in view ofefficient utilization of the spectrum resources in the future communication networks. It can adjust itstransmission parameters, such as spectrum bands, transmission power, coding rates and modulation levelsopportunistically to access the available spectrum bands without interfering with the primary users. Withthe Federal Communication Commission (FCC's) spectrum policy reform, secondary users can access the

licensed spectrum as long as the created interference to the primary users does not affect their Quality ofService (QoS) [3].

The energy-efficiency of wireless sensor devices and the scarcity of wireless bands are two major design parameters in any wireless sensor network (WSN), due to limited battery power of these devices and the fixed natural wireless spectrum. Intelligent and optimal use of electrical energy is also of paramount importance in order to reduce green house gas emissions. Recent studies show that wireless communication and sensor networks will be responsible for a significant portion of the total green house gas emissions, due to their predicted exponential growth in the near future [1]. Therefore, energy-efficient design is indispensable for future WSNs. The problem of wireless bands is even more exacerbated, because of the static spectrum allocation policy. As a result, some spectra are heavily used, and some, on the other hand, are heavily under-utilized in time, frequency or space. This fact has given birth to opportunistic spectrum access techniques in cognitive radio networks, where the cognitive user can sense and access the licensed spectrum dynamically while it is not in use. However, the secondary sensor nodes (SSNs) need to make sure that at any time, they do not exceed the total interference limit that they inherently generate on the primary users. Cognitive radio is seen as an effective approach for higher spectral and energy efficiency in wireless communication systems for two reasons. Firstly, the energy efficiency related functionalities can be embedded into the cognitive operational cycle. Secondly, from the green perspective, the spectrum is a natural resource, which should not be wasted on idle licensed channels, but be shared efficiently [2]. Wireless sensors play a very important role in many applications, such as industrial monitoring [3], environmental (air/water quality) monitoring [4], health monitoring [5], seismic vibration sensing, *etc*. They have found applications in many *ad hoc*, military and commercial wireless systems.

In opportunistic spectrum access where PU and SU co-exist side by side, mutual interference is the imiting factor forperformance of both networks. The amount of

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interferenceintroduced by the SU ubcarriers into the PU's band dependson (i) power allocated in that subcarrier (ii) spectral distancebetween that particular subcarrier and the PU's band. In theliterature, different power allocation schemes in OFDM basedCR systems have been introduced in order to maximize theSU data rate while keeping the interference introduced tothe PU band within limits. However, authors have assumedZMCSCG constraint to evaluate optimal power allocationalgorithms in OFDM based CR systems which maximize thechannel capacity of the SU. The derived capacity is alwaystoo optimistic for practical systems especially for high SNRand interference threshold values. It remains of interest andof practical importance to evaluate optimal power loadingschemes under the FSA constraint, e.g., QPSK, 8-PSK, 16-QAM & 64-QAM. This loading scheme saturates the achievabledata rate of the SU at high SNR and values. To address theproblem, in this paper we propose an optimal power loadingscheme under the FSA constraint using Lagrange formulationin SISO-OFDM based CR systems.

II. Related Work

In conventional OFDM systems, power allocation depends mainly on the channel gain of the subcarriers. If the channel condition is good, more power is allocated to that subcarrier and vice versa. However, the same power allocation scheme cannot be applied in OFDM based CR systems due to mutual interference. The amount of interference introduced to the PU's band not only depends on the power allocated in that subcarrier, but also on the spectral distance between that particular subcarrier and the PU's band. Therefore, in the interference limited scenario, allocation of power is based on the location of the subcarrier with respect to the PU's spectrum, i.e., more power should be allocated to distant subcarriers and vice versa. Therefore in the OFDM based CR system, a judicious power loading scheme is required which should take into consideration the fading gain of the subcarrier as well as spectral distance between the subcarrier and the PU's band. An optimal and ladder based suboptimal powerprofile is proposed in [10], [11] based on the position of the SU with respect to PU. Another important aspect of power allocation in OFDM based CR networks is the reliability of the subcarriers, i.e.,subcarriers that are more frequently available for SU transmissionas compared to those which are always busy due to PUactivity. Previously, it was assumed that after sensing spectrumholes are available to secondary usage up to a certain time untilthe SU completes its task. However, in the real time scenario,the PU being the spectrum owner may return at any time andretrieve its spectrum which is currently available for secondaryaccess. Therefore, power allocated by the SU is wasted due tothe unaccomplished task by the SU. In view of this fact, morepower should be allocated to more reliable subcarriers in orderto guarantee the SU's QoS requirements [12] and [13]. In [14]& [15], optimal power allocation scheme has been analyzed formultiuser scenario where more subcarriers are given to thoseSUs which not only increase the capacity but also introducelow interference to the PU. For a given subcarrier allocation,optimal power allocation has been proposed to maximizethe capacity of the SU. In [16], authors considered fairnessconstraint among multiple SUs and proposed algorithms whichfirst ensure fairness that each user has received and then usea greedy approach for power allocation.In [17], author has investigated MI of wireless systemsunder the FSA constraint whereas an expression has beenderived for the achievable data rate between the input andthe output of the system. In this paper, we propose to analyzean MI based optimal power loading scheme under the FSAconstraint for SISO-OFDM based CR system and compareit with channel capacity. Our simulation results reveal thatthe capacity of the OFDM based CR system is unachievableespecially in the high SNR region. This motivates us to analyzeMI, resulting in an achievable data rate over the entire SNRregion. It also holds true especially in the case of the highSNR region where it achieves a saturation level and remainsconstant with increasing SNR value in contrast to channelcapacity.

III.System Model

Although energy-efficient techniques for WSNs exist in the literature, according to the best knowledgeof the authors, there is no power allocation scheme that deals with the analysis and optimization of theEE metric in a cognitive radio-based WSN. The motivation of this work is to fill the gap, especiallyimportant for future green radio communication, with the aim of analyzing the power allocation problemthat maximizes the EE (bits/Joule/Hz).The main contributions of this paper are summarized as follows:

1. We propose a constrained optimization problem that maximizes the EE for an uplink wirelesssensor network utilizing cognitive radio techniques. First, we show that the proposedoptimization problem is a fractional programming problem. We use Charnes-Coopertransformation to transform the formulated concave fractional program (CFP) into an equivalentconcave optimization problem that has a water-filling type power allocation rule.

2. Then, we present an iterative ε-optimal solution for the CFP. The proposed algorithms are basedon the Dinkelbach method for CFP.We show that it converges to the ε-optimal solution point. Theproposed ε-optimal algorithm provides a practical solution for power allocation in energy-efficientcognitive radio networks.

3. We present performance analysis of a ε-optimal algorithm with the simulation results.

Therefore, power allocated by the SU is wasted due to the unaccomplished task by the SU. In view of this fact, more power should be allocated to more reliable subcarriers.

A one-cell wireless system is assumed, where the PU and SU transceivers coexist in the same geographical location as shown in Fig. 1. The scenario is investigated for one SU in the downlink path. There are three instantaneous fading gains: (i) gss, between the SU transmitter and SU receiver; (ii) gsp, between the SU transmitter and PU receiver; and (iii) gps, between PU transmitter and SU receiver. We assume

these instantaneous fading gains are perfectly known at the SU transmitter. The SU network has an individual base-station that

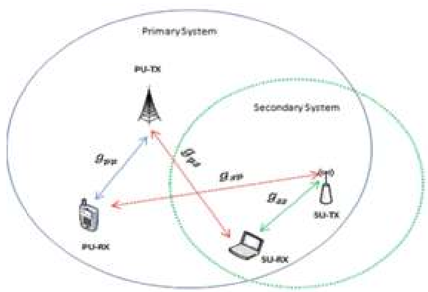

Fig. 1. Distribution of PU &SU

identifies the spectrum holes on the basis of the information collected about the spectrum; then deactivates the PUs' subcarriers and transmits its users information via the remaining sub-carriers as shown in Fig. 2. We consider adjacent co-existence of primary and secondary users in a frequency localised way, i.e., the Discrete FourierTransform (DFT) outputs are mapped to consecutive subcarriers as shown in Fig. 2. The OFDM modulation scheme is employed for SUs and the available bandwidth for SU transmission is divided into N subcarriers each having abandwidth of σ_f. This implies that the bandwidth of the transmitted signal is very small and can be assumed frequency flat. It is assumed that subcarriers are orthogonal to each other, therefore no Inter-Symbol Interference (ISI) occurs. The transmit power is adaptively loaded in each secondary user's subcarrier.

In the OFDM based CR system, the interference limited scenario limits the transmit power and accordingly achievable data rate of the SU. Therefore, we propose to calculate an optimal power under the FSA constraint based on Lagrange. This optimal power will be allocated to each OFDM subcarrier for a given channel fading gain such that the total transmission rate of the SU is maximized while keeping the interference introduced into the PU band within thresholdlevel. The mutual information is given by[17].

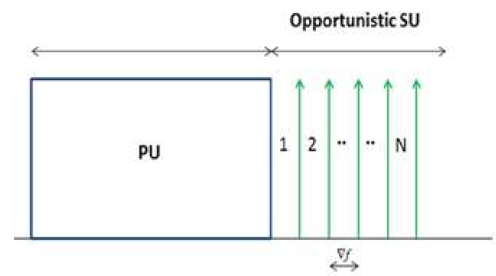

Fig. 2. Co-existence of PU & SU in Opportunistic Scheme

The unit for Eq. (1) is rate in bits per channel use. In Eq. (1) nT&nR are the number of transmit and receive antennas, Mc is the number of bits per symbol, Pi & Hi are the transmit power and channel response of the ith subcarrier, σ^2_N denotes AWGN noise variance, y is received signal and si is the transmitted symbols of the ith subcarrier. sεFnT and y ε FnT are finite symbols alphabet input and output

$$I_i(S_i(y, H_i)) =$$

$$-E\left\{E\left\{\sum_{i=1}^{N}\log_2\left\{X\sum_{a\in S}\exp\left[\frac{-\| y-H_iP_iS_i\|^2}{2\sigma_N^{\ 2}}\right]\right\}\right\}\right\}-B$$

(1)

respectively, where F denotes the symbol alphabet (like QAM or PSK [17]). In Eq. (1) expectations are taken over variables Pi & Hi. The total MI is the sum of the MI of N number of available subcarriers is as follows.

s.t

$$X=\frac{1}{2^{M_c n_T}(2\pi\varepsilon\sigma_N^{\ 2})^{n_R}} \quad \text{………………….(2)}$$

Due to adjacent co-existence of PU & SU, there are two types of interference in the system (i) interference introduced from the PU into the SU band (ii) interference introduced from the SU into the PU band. Our objective is to protect the PU from an unacceptable interference, therefore, in this paper we will consider interference introduced by the SU into PU band.

A. Interference introduced by the seconday user's signal The power density spectrum of the ith subcarrier in the SU user band can be written as [11].

$$\phi_i(f)=P_iT_s\left(\frac{\sin \pi_f T_s}{\pi_f T_s}\right)^2 \quad (3)$$

where Pi is the total transmit power emitted by the ith subcarrier in the secondary user's band and Ts is the symbol duration. The interference introduced by the ith subcarrier to the PU band is the integration of the power density spectrum

of the ith subcarrier across the PU band and can be written as

$$J_i(d_i.p_i) = P_{i.}.T_s \int_{d_n-\frac{n}{2}}^{d_i+\frac{n}{2}} \left(\frac{\sin \pi.f.T_s}{\pi.f.T_s}\right)^2 .df \qquad (4)$$

where B is the bandwidth in Hz occupied by the PU, di represents the spectral distance between the ith subcarrier of SU and the PU band. Ji(di; Pi) represents the interference introduced by the ith subcarrier of SU into the PU band. The interference Eq. (4) should also take into account channel gain from the SU base station to the PU receiver. We use a normalized channel gain of 1.

IV. Optimal Power Allocation Under The FSA Constraint

Our purpose is to analyze an optimal power allocation scheme that maximizes the achievable data rate of the SU provided that the interference introduced into the PUs' bands does not exceed to a certain level. This problem can be dened

as an optimization problem as follows

$$I_{Total} = \max_{p,i} \sum_{i=1}^{N} I_i \qquad (5)$$

$$\sum_{i=1}^{N} J_i(d_i, p_i) \le \tau_{th} \qquad (6)$$

$$p_i \ge 0 \_ \forall_i = 1,2,3 \_\_\_ N \qquad (7)$$

where Ii denotes the mutual information, N denotes the total number of available subcarriers and σth denotes the interference threshold prescribed by the PU. Using Lagrange

formulation we can write

$$L(P_i,\lambda) = \left[-E\left\{E\left\{\sum_{i=1}^{N}\log_2\left\{X\sum_{a\in S}\exp\left[\frac{-\|y-HP_iS_i\|^2}{2\sigma_N^2}\right]\right\}\right\}-B\right]-\lambda\left(\sum_{i=1}^{N}J_i(d_i,P_i)-\tau_{th}\right) \qquad (8)$$

V. Evaluation Of OFDM Based CR System

In this section, we compute optimal power for ZMCSCGand FSA constraints in CR networks and accordingly calculateand compare capacity and MI in both cases. The simulationsare performed for a SISO-OFDM based CR network in anopportunistic scheme as given in Fig. 2. It is assumed thatthe SU base station has the information about PU activesubcarriers and accordingly disables them. Consider that thereare 64 subcarriers of which 32 subcarriers are used by the PUand the remaining are used by the SU in frequency localizedtransmission. The values of Ts, B & _th are 4_s, 1MHzand 1mW , respectively. We further assume the IEEE 802.11multipath channel model with RMS delay spread of 50ns. Theresults are averaged over 1000 MATLAB simulations.In Fig. 3,. From this figure we observe that theachievable data rate indicated by MI (Eq. 1) closely follow thechannel capacity (Eq. 4) under low SNR region, oppositelyMI saturates in the high SNR region. The reason for thissaturation is that in the high SNR region, the achievable data

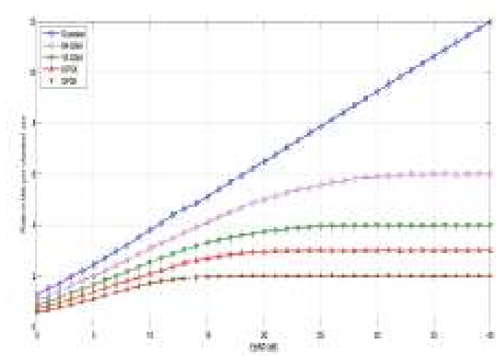

Fig. 3. Mutual information curves under FSA compared to channel capacity under ZMCSCG for 32 subcarriers at 10mW

Table I Saturation Value And Achievable Data Rate Of Su Under The Fsa Constraint

Finite symbol Alphabets	τ_{th}=1 mW& N=32		τ_{th}=10 mW& N=32	
	Saturation Value (dB)	Achievable data rate for FSA input (bits PCU)	Saturation Value (dB)	Achievable data rate for FSA input (bits PCU)
QPSK	*20*	*2*	*15*	*2*
8-PSK	*25*	*3*	*20*	*3*
16-QAM	*0*	*4*	*24*	*4*
64-QAM	*35*	*6*	*32*	*6*

rate is limited by the signal constellation. Thus after saturation, the data rate remains constant no matter how high the SNR value is. It is clearly evident from the Fig. 3 that the saturationvalue for QPSK, 8-PSK, 16-QAM & 64-QAM are 20dB, 25dB, 30dB & 35dB and the maximum achievable data rate is 2, 3, 4 & 6 bits per channel use respectively. In contrast to that, channel capacity increases with increasing SNR value. Fig. 3 clearly indicates that the channel capacity as derived in Section V is unrealistic for the practical systems. On the other hand analysis of MI calculated in Section IV provides a realistic prediction of achievable data rate in real systems as shown in Table 1.

In the opportunistic scheme, the achievable data rate of the SU is dependent on the available bandwidth and interference threshold level of the PU. In Fig. 4, we vary interference threshold from 1mW to 10mW for 32 available subcarriers.

The capacity changes from 11 to 12 bits per channel use, however, MI remains unchanged except that it achieves a saturation value earlier for the 1mW case, i.e., 15dB instead of 20dB for QPSK as shown in Table 1. So we can concludethat, varying the interference threshold value only affects the saturation value but the maximum achievable data rate remains the same for FSA constraint. Table 1 presents the overall summary of obtained results.

VI. Conclusion

In this paper, we have evaluated an optimal power loading schemes under both FSA and ZMCSCG constraints for SISOOFDM based CR networks. Results have revealed that the

derived power loading scheme under ZMCSCG constraint maximizes the capacity by keeping the interference introduced to the PU band within a given limit. The capacity increases with increasing SNR and cannot be achieved in practical systems. On the contrary, the proposed power loading scheme under the FSA constraint results in a saturated MI at high SNR value and provides a realistic prediction of achievabledata rate in real systems, e.g., saturation values for QPSK, 8-PSK, 16-QAM & 64-QAM are 20dB, 25dB, 30dB & 35dB and maximum achievable data rate is 2, 3, 4 & 6 bits per channel use respectively. We have further investigated channel capacity and MI by varying the interference threshold i.e., from 1mW to

10mW and observed that the saturation value of MI changes accordingly e.g., 15dB instead of 20dB for QPSK but total achievable data rate remains the same. On the other hand, the

capacity increases with increasing interference threshold i.e., 11 to 12 bits per channel use. In future work we will evaluate optimal power allocation algorithm under the FSA constraintin MIMO-OFDM based CR system.

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