Energy Efficiency Maximization In Cognitive Radio Channels Using Modified Water Filling Algorithm

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***Abstract*— In this paper, we present a novel and computationally efficient water filling algorithm for multiuser in cognitive radio network (CRN). This algorithm is based on the multiuser water filling theorem and persuades the subcarrier allocation for a multiple access system. This approach exaggerates the total bit rate under the constraints of user-individual power budgets. Acquiring Energy Efficiency (EE) is very troublesome for wireless communication systems exclusively for CRN. The analysis here is with the mean EE maximization problem for secondary user (SU) with both primary user (PU) and SUs. The solution to the problem starts by examining both the peak and mean transmit power constraints for the SUs and outage probability constraint for the PUs. The problem here is nontrivial. The results attest that the efficiency of the system is enhanced with the proposed water filling algorithm and also it has been observed that the outage probability is reduced. Further, there is enhancement in the capacity of a MIMO system.**

***Index Terms*— Cognitive radio networks, energy efficiency, outage constraint, power budget, water filling algorithm**

I. INTRODUCTION

Cognitive Radio (CR) is an adaptive, intelligent radio and network technology that can automatically detect available channels in a wireless spectrum and change transmission parameters enabling more communications to run concurrently and also improve radio operating behavior. It is a form of wireless communication in which a transceiver can intelligently detect which communication channels are in use and which are not, and instantly move into vacant channels while avoiding occupied ones. This optimizes the use of available radio-frequency (RF) spectrum while minimizing interference to other users. This technology obviously promotes the spectrum efficiency (SE) among primary user (PU) and secondary user (SU) by spectrum sharing. With the condition that SUs interference to PUs is restricted so that the licensed user's performance depravation is in tolerable range[1] and so the transmission between PUs and SUs occurs simultaneously. The EE grew as a matter of point for future wireless networks since the cost of energy is promulgated on both financial and ecological burden on its development[2] beyond the SE unfortunately. Increase in EE is a fundamental necessity for SUs in order to accomplish improved utilization of limited power transmission which consumes to maximum SE and spectrum sensing.

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Some more works are designed for a near optimal algorithm with low complexity to maximize the SUs EE under some practical constraints [3],[4]. As it is known that Multiple-Input Multiple-Output (MIMO) systems are used to get higher data rate as compared to a normal SISO system, the same power budget and signal to noise (SNR) is considered. A comparison of MIMO system with a SIMO reveals that the MIMO system need lesser transmit power than the SISO system in order to achieve the same capacity. As we need to minimize the energy consumed by the circuit and want to maximize the capacity of a system and that is possible only if we use multiple MIMO system.

Water filling algorithm is proposed to maximize the SUs EE. The EE design for slow fading scenarios is suitable to perform static optimization depending upon the instantaneous channel state information (CSI). It is impossible to provide some performance for each state in fast fading channels to employ statistical metrics such as SU's mean EE and PUs outage probability constraint. The capacity of a MIMO system can further be increased if we know the channel parameters both at the transmitter and at the receiver and assign extra power at the transmitter by allocating the power according to the water filling algorithms to all the channels.

The concentration is on SE with SU's capacity in fast fading channels. Maximizing SU's capacity and outage probability of PU's with statistical CSI do not help in increasing EE directly[5]. Here, we maximize SU's mean EE in fast fading channels where SUs and PUs are involved and also we propose a water filling algorithm to address the optimal power allocation problem and to achieve the parameters like bandwidth, delay, jitter and throughput of Quality of Service (QoS)[6]. To safeguard the QoS of PU's transmission, we consider PUs outage probability constraint. Also we consider peak and mean transmit power constraints of SUs. The problem identified here is formulated in fractional programming initially. It is observed to be nontrivial since the objective function is non convex[7].

To solve it, we initiate transformation of problem to a parameterized convex optimization problem based on fractional programming. And by using Lagrangian duality theory, the problem is decomposed into multiple sub problems in parallel. Then an efficient water filling algorithm has been proposed to derive optimal power allocation strategy for SUs in order to maximize its mean EE. This maximizes the total bit rate under the constraint of a maximum transmit power per user. An algorithm which computes the power spectral density for each user has been presented recently [14].

II. SYSTEM MODEL

In underlay CRN, the secondary transmission link coexists with primary transmission link is considered. Here, PT stands for PU transmitter, PR for PU receiver, ST and SR for SU transmitter and SU receiver respectively. Because of its spatial reuse property, we consider underlay CRNs. The links are ergodic, stationary and mutually independent in fast fading channels between the transmitters and receivers of PUs and SUs.

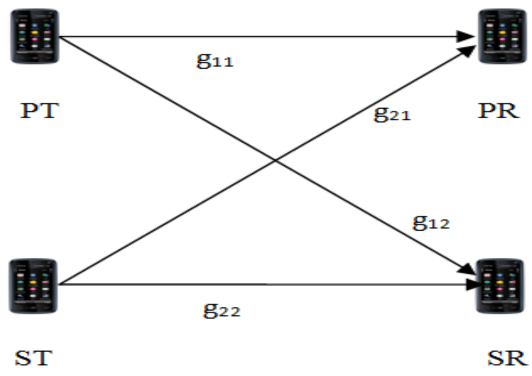

Fig.1 System model of cognitive radio channels

In between the link from primary to SUs the instantaneous channel power gains are represented as $g_{11}(v)$, $g_{12}(v)$, $g_{21}(v)$ and $g_{22}(v)$ where v denotes the fading index. By using standard signal processing techniques, cooperation of PUs, estimation of data or reference signals the CSI of ST-PR, PT-PR, PT-SR can be obtained. It is obvious in realistic scenarios, that all CSI would contain errors related to quantization error, estimation error, out-dated error. We assume perfect CSI[8],[9].

A. Transmit Power Constraints & Qos Requirement

Two kinds of constraints such as the peak transmit power limit and mean transmit power limit has been used for ST to model the power limit for SU's transmission as

$$TP_2(v) \leq P_{max}, \forall v \geq 0 \quad (1)$$

$$E\{TP_2(v)\} \leq P_{av}, \forall v \geq 0 \quad (2)$$

Where P_{max} and P_{av} represents the peak and mean transmit power limits for SU, $E\{.\}$ denote expectation. Then the signal-to-interference plus noise ratio (SINR) outage probability constraint for PUs has been adopted

$$\varepsilon_p = \Pr\left\{\frac{P_1 g_{11}(v)}{TP_2(v) g_{21}(v)+\sigma_p^2} < \gamma_p\right\} \leq \varepsilon_0 \quad (3)$$

Where ε_p and γ_p refers the outage probability for PR and target SINR, ε_0 and σ_p^2 represents the outage probability threshold for PR and white Gaussian noise power at PR respectively. The PU outage probability when the SU link is inactive is expressed as

$$\varepsilon_p^0 = \Pr\{TP_1 g_{11}(v)/\sigma_p^2 < \gamma_p\} \quad (4)$$

Here TP_1 refers to the constant transmit power for PT.

B. Mean Energy Efficiency Maximization

In this section, the investigation is on the optimal transmission strategy for SU to maximize its mean EE. Here, the ratio of SU's mean data rate to its mean power consumption is said to be mean EE so as to determine the EE of SU averaged over different fading states. The formulation on the SU's mean EE maximization problem as

$$\mathbf{P1}: \max_{TP_2(v)} h(TP_2(v)) = \frac{E\left\{B\log_2\left(1+\frac{TP_2(v)g_{22}(v)}{TP_1 g_{12}(v)+\sigma_s^2}\right)\right\}}{E\{\zeta TP_2(v)+P_C\}} \quad (5)$$

Where P_C refers the constant circuit power consumption. In **P1** the numerator of $h(TP_2(v))$ is a concave function[11] and its denominator is an affine function[12]. Therefore, $h(TP_2(v))$is quasi-concave for $TP_2(v)$ and **P1** belongs to the quasi-concave programming.

$$\mathbf{P2}: \max_{P_2(v)} T(q) = E\left\{B\log_2\left(1+\frac{TP_2(v)g_{22}(v)}{TP_1 g_{12}(v)+\sigma_s^2}\right)\right\} - q.E\{\zeta TP_2(v)+P_C\} \quad (6)$$

Where *q* is a positive parameter and can be interpreted as a pricing factor for SU's power consumption. As for the optimal values of **P1** and **P2**, the result is as

Theorem 1: The optimal mean EE value of **P1** is obtained only if there exists an optimal parameter q* in **P2** such that *T(q*)=0* holds. However, the optimal EE equals *q**.

Proof: $h(TP_2(v))$ in **P1** is a concave function over an affine function[12]. According to this, we can solve **P2** to obtain the optimal power allocation policy for **P1**. To facilitate the analysis, an indicator function is introduced for PU's outage event at the fading state v:

$$\chi_p(v) = \begin{cases} 0, & \frac{TP_1 g_{11}(v)}{TP_2(v)g_{21}(v)+\sigma_p^2} \geq \gamma_p \\ 1, & otherwise \end{cases} \quad (7)$$

(3) can be rewritten as

$$E\{\chi_p(v)\} \leq \varepsilon_0 \quad (8)$$

Since *T*(*q*) is a concave function for, the optimal power can be derived since for $TP_2(v)$, T(q) is concave by forming the Lagrangian of **P2** as

$$L(TP_2(v),\lambda,\mu) = E\left\{B\log_2\left(1+\frac{TP_2(v)g_{22}(v)}{TP_1 g_{12}(v)+\sigma_s^2}\right)\right\} - q.E\{\zeta TP_2(v)+P_C\} - \lambda\left(E\{TP_2(v)\}-P_{av}\right) - \mu\left(E\left\{\chi_p(v)\right\}-\varepsilon_0\right) \quad (9)$$

Where λ and μ are the positive Lagrangian multipliers with (2) and (8). Then, **P2** can be expressed using the Lagrangian dual function as

$$g(\lambda,\mu) = \max_{TP_2(v)\geq 0, TP_2(v)\leq P_{max}, \forall v} L(TP_2(v),\lambda,\mu) \quad (10)$$

Thus, the P2 dual problem is defined as

$$\mathbf{P3}: \min_{\lambda\geq 0,\mu\geq 0} g(\lambda,\mu) \quad (11)$$

With a feasible point **P2**, the condition is satisfied and the dual gap is 0, that is, *d** = *r** for the convex optimization problem. This assures that we can solve **P3** to obtain the optimal solution to **P2**. To start with, we consider the problem *g*(λ,*μ*) in (10) for some given λ and *μ*. It can be written as

$$g(\lambda,\mu) = E\{g'(v)\} + qP_C + \lambda P_{av} + \mu\varepsilon_0 \quad (12)$$

Where,

$$g'(v) = \max_{TP_2(v)\geq 0, TP_2\leq P_{max}, \forall v} B\log_2\left(1+\frac{TP_2(v)g_{22}(v)}{TP_1 g_{12}(v)+\sigma_s^2}\right) - (q\zeta+\lambda)TP_2(v) - \mu\chi_p(v) \quad (13)$$

Therefore, *g*(λ,*μ*) is derived by solving the sub problem $g'(v)$ for each v. For various values of v, maximization problems (13) have similar structure. For brevity, we eliminate the fading state index v and the indicator function as a function of TP_2

$$max\ f(TP_2) = Blog_2\left(1 + \frac{TP_2 g_{22}}{TP_1 g_{12} + \sigma_s^2}\right) - (q\zeta + \lambda)TP_2 \quad (14)$$

$f(TP_2)$ is concave of TP_2. Depending upon KKT conditions, the optimal transmit power is derived from (14) as

$$x = min\left\{\left[\frac{B}{(q\zeta+\lambda)\ln 2} - \frac{TP_1 g_{12} + \sigma_s^2}{g_{22}}\right], P_{max}\right\} \quad (15)$$

With a turning point y, indicator function is a step function of TP_2

$$y = \frac{1}{g_{21}}\left(\frac{TP_1 g_{11}}{\gamma_p} - \sigma_p^2\right) \quad (16)$$

$\chi_p(TP_2)$=1 if y<0 for any $TP_2 \geq 0$. $TP_2{*}$ is denoted as the optimal solution to the problem. The values of $TP_2{*}$ are derived based on the values of x and y in various cases.

The subgradient method is adopted to derive the optimal Lagrange multipliers λ*and μ*, that is, we iteratively update λ and μ.

$$\lambda^{(k+1)} = \left[\lambda^k - s^k(P_{av} - E\{TP_2(v)\})\right] \quad (17)$$

$$\mu^{(k+1)} = \left[\mu^k - s^k\left(\varepsilon_0 - E\left\{\chi_p(v)\right\}\right)\right] \quad (18)$$

where k denotes the iteration index and s^k refers to a small positive step size for the k-th iteration. When the step size is constant, the sub gradient method is ensures to converge to the optimal value.

C. Algorithm Steps

1. We do not need to reorder the MIMO sub channel gain realization in a descending order
2. Take the inverse of the channel gains
3. Water filling has non uniform step structure due to the inverse of the channel gain
4. Initially take the sum of the Total Power and the Inverse of the channel gain .It gives the complete area in the water filling and inverse power gain
5. The initial water level by the formula given below is decided by taking the average power allocated (average water Level)
6. The power values of each sub channel are calculated by subtracting the inverse channel gain of each channel
7. In case the Power allocated value becomes negative stop the iteration process

III. SIMULATION RESULTS

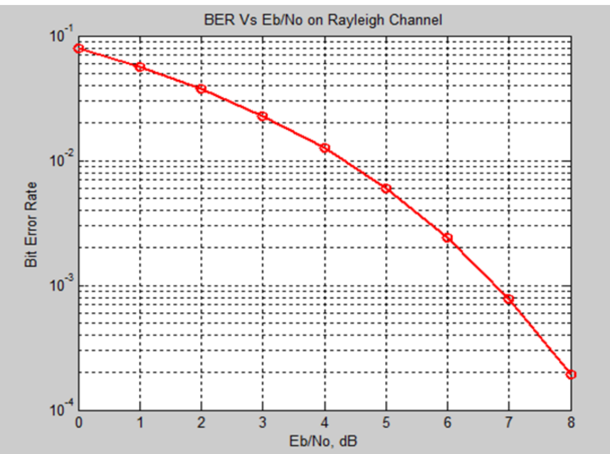

Fig.2 BER Vs E_b/N_0

Fig.2 shows BER Vs E_b/N_0 where BER represents Bit Error Rate which defines the number of bits per unit time and E_b/N_0 defines energy per bit to noise power spectral density ratio. It is a normalized signal-to-noise ratio (SNR) measure, also known as the "SNR per bit". It is especially useful when comparing the BER performance of different digital modulation schemes without taking bandwidth into account. As the description implies, E_b is the signal energy associated with each user data bit.

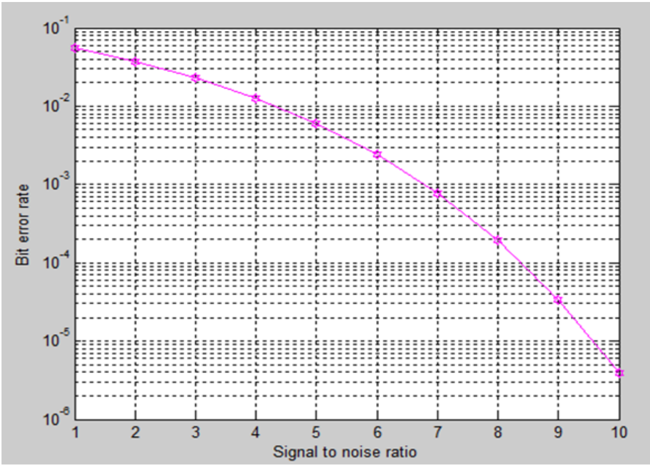

Fig.3 BER Vs SNR

Fig. 3 depicts the relationship curve between Bit error rate and signal to noise ratio. As the SNR increase, BER constantly decreases proving the system to be efficient.

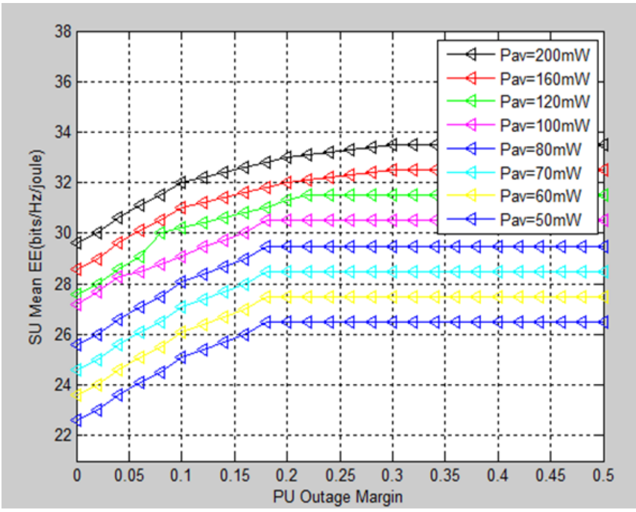

Fig.4 EE under different P_{av} using Dinkelbach's algorithm

Fig.4 represents mean EE vs. ΔE under various P_{av} with known P_{max} = 0.5 W. The EE starts getting increased with P_{av} . But, when P_{av} = 200 mW, it remains stable in consideration with SU attaining its maximal mean EE when P_{av}^* = 167 mW. When ΔE decreases below a particular value, there exist the tradeoff between SU's mean EE and ΔE. All others are consistent with more increase of ΔE, since SU achieves its maximal mean EE for the line with P_{av} = 200 mW.

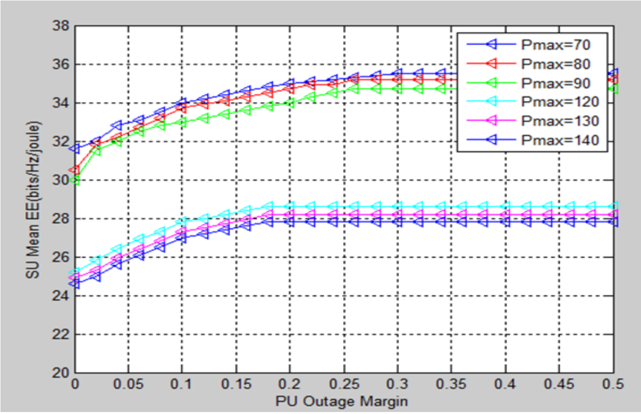

Fig.5 EE under different P_{max}

Fig.5 shows the mean EE vs. ΔE under different P_{max}. Similarly, the EE also increases with ΔE. However, it also keeps unaltered with the further increase of ΔE. Besides, increase in P_{max} can increase SU's mean EE given $P_{av} \leq P_{av}^{*}$ where P_{av}^{*} is the optimal value. Since the EE has an abating margin, the increasing amount of EE decreases when P_{max} increases further.

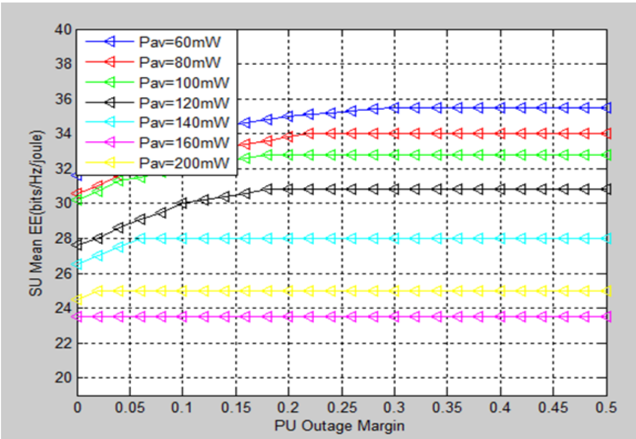

Fig.6 EE under different P_{av} using water filling algorithm

Fig. 6 shows mean EE vs. ΔE under various P_{av} using water filling algorithm with known P_{max} = 0.5 W. The EE increases with P_{av}. But, it remains stable when P_{av} = 200 mW, since SUs attain its maximal mean EE when P_{av}^{*} = 167 mW. When ΔE falls below a particular value, there exist the tradeoff between SU's mean EE and ΔE. All others are consistent PU achieves its maximal mean EE for the line with P_{av} = 200 mW. It is observed that the energy is more efficient when compared to Fig.4.

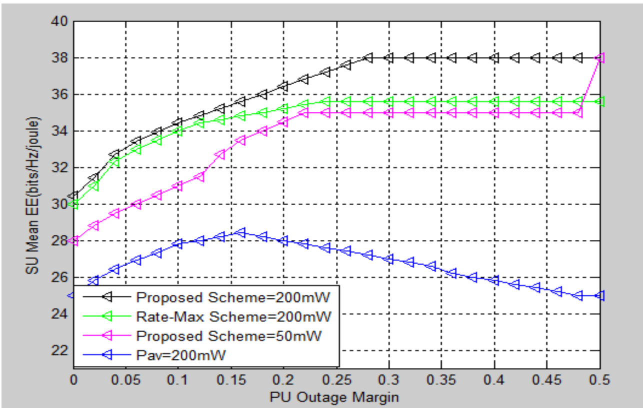

Fig.7 EE comparison

Fig.7 illustrates SU's EE scheme and Rate-Max scheme with P_{max} = 0.5 W. The Rate-Max scheme maximizes SU's mean SE and corresponds to P_1 when q = 0 in particular. As well, the mean EE under Rate-Max scheme first gets increased, but with constant P_{av} = 200 mW and drops quickly with P_{av} = 500 mW owing to pursuing SE maximization.

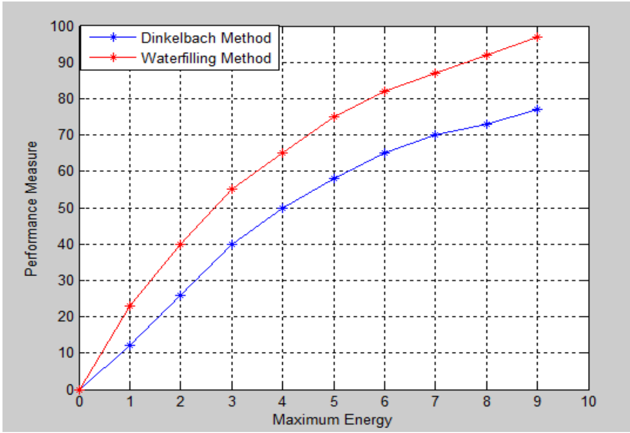

Fig.8 Comparison between Dinkelbach's and water filling algorithm

Fig.8 depicts that the energy is much more efficient in water filling algorithm than Dinkelbach's algorithm. The range for the intervene between mean EE and Δε diminishes, since SU can be limited by (2) or reaches its paramount EE. Finally, the mean EE remains constant when ε_0 further increases because it is either restricted by (2) with small $P1$ or reaches its maximal value with a greater $P1$. All channel gains chase the exponential distribution since they are observed to be Rayleigh fading and the simulation outcome judge the performance.

IV. CONCLUSION

In case of successive power allocation the number of iterations is more, but in proposed water filling Algorithm the number of iterations are less. Initial level of the power allocated is close to the ideal value, so the results of proposed algorithm are better. In case of equal power allocation, power is distributed equally among all the sub channels but experiences degradation in performance due to the bad channels having low value of SNR. In successive water filling, the maximum gain can be achieved, if step size is close to Zero (very small) but then the iterations would be infinite and time taken to allocate the power would be large. The results indicate that the proposed water-filling scheme has better capacity. Further, the variation of the outage probability is given for the system.

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