Energy- and Spectral-Efficiency Trade-Off in OFDMA-Based Cooperative Cognitive Radio Networks

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We study the trade-off between energy efficiency (EE) and spectral efficiency (SE) in cooperative cognitive radio networks (CCRN); joint power and subcarrier allocation scheme is proposed. Resource is assigned to each user in a way which ensures maximizing energy efficiency, maintaining primary and second user quality of service (QoS) requirements. Optimum transmit power of user is got by analysis; validity of theory is verified by simulation, and the proposed algorithm can adaptively allocate resource for CCRN.

1. Introduction

In consequence of wireless communications exponential increase, frequency spectrum becomes one of the scarcest resources. Cognitive radio (CR) networks have been seen as a promising solution to improve the current spectrum efficiency. Wireless devices can access radio spectrum without causing harmful interference to licensed users [1]. Orthogonal frequency division multiplexing access (OFDMA), which offers a high flexibility in adaptation of subcarriers to fast changing conditions in radio spectrum, is deemed as an appropriate air interface of a CR system [2]. The OFDMA-based systems can flexibly incorporate dynamic resource allocations in cognitive radio networks. Different subcarriers can be allocated to different users to take advantage of the varying nature of channel quality across users in a given subcarrier, which is known as multiuser diversity [3].

Spectrum efficiency (SE) has been widely studied from the perspective of spectrum allocation and management in the past decades. Green radio emphasizes energy efficiency (EE) besides spectral efficiency (SE); the energy efficiency (EE) has been considered more and more important in future wireless systems. It is reported [4] that a large electricity bill results from the huge energy consumption of a wireless base station (BS). From [5–7], more than 80% of the total energy is consumed by the radio access part, where 50–80% is used for the power amplifier (PA). Therefore, from the operators’ perspective, energy efficiency (EE) not only has great ecological benefits and represents social responsibility in fighting climate change but also has significant economic benefits.

From the users’ perspective, energy-efficient wireless communication is also imperative. The latest report [8] in China also reflects the same problem. Based on the data in [8], up to 60% of the users complained that battery endurance was the greatest burden when using 3G services. The authors in [9–12] studied the allocation of subcarrier and power in OFDMA networks so that EE is maximized. A risk-return model was introduced to incorporate channel reliability by defining an average rate loss function in [9]. The advantage of this model is that it takes into account not only channel reliability for power allocation but also the interference constraint limits. The researchers [10] set up a general EE-SE trade-off framework, where the overall EE, SE, and per-user quality of service (QoS) are all considered, and prove that, under this framework, EE is strictly quasiconcave in SE. The energy-efficient power allocation problem of OFDM-based CR systems is studied under the total power constraint, the
interference power constraint, and the rate constraint [11]. A time-sharing method was employed to transform resource allocation into a nonlinear fractional programming problem [12], which can be further converted into an equivalent convex optimization problem. It can be solved by standard optimization technique.

Power and/or subcarrier allocation in OFDM/OFDMA-based CR systems have received much attention. For conventional OFDMA-based systems, subcarrier allocation and power allocation have been studied extensively [13]. Most of the existing works aforementioned regard the secondary transmission as a harmful interference and hence the CR users do not participate in the primary transmission. However, a cooperative orthogonal frequency division multiple access- (OFDMA-) based cognitive radio network is proposed, where the primary system leases some of its subchannels to the secondary system for a fraction of time in exchange for the secondary users (SUs) assisting the transmission of primary users (PUs) as relays [14]. The energy-efficient resource allocation in OFDMA systems with relay strategies also needs to be addressed [15]. When relay strategies are used in OFDMA systems, energy-efficient resource allocation may become more complicated. However, both relay systems and OFDMA are among the key technologies in LTE-Advanced; thus this issue warrants further study. Efficient and reliable subcarrier power allocation in cooperative cognitive radio networks is still a challenging problem.

In this paper, we address optimal energy-efficient resource allocation in cooperative cognitive radio networks with the consideration of spectral efficiency. We model the problem as maximizing EE under each user peak power constraint. We then solve the problems by the Lagrange dual decomposition (LDD) and continuous relaxation, respectively.

The rest of the paper is organized as follows. In Section 2, we describe the system model and formulate the optimization problem. The optimal power and subcarrier allocation for spectrum-efficiency and energy-efficiency trade-off relation is investigated in Section 3. We search for optimal cognitive radio energy efficiency by bisection method and update the Lagrangian dual variables through subgradient method. In Section 4, we present numerical results and conclude the paper in Section 5.

2. System Model and Problem Formulation

In this section, we describe the architecture of CCRN and frame structure. The primary system coexists with the OFDMA-based CCRN as shown in Figure 1. The primary system is an ad hoc network, consisting of multiple user pairs with each user pair conducting bidirectional communications. Primary user may select several secondary users from the secondary network to behave as the cooperative relays and, in return, give them the chance to access the channel which is assumed to be occupied only by primary system.

There are totally \( K \) users, with the first \( K_p \) being the primary user pairs and the remaining \( K_s = 1 - K_p \) being the secondary user pairs. The traffic demand of user is assumed to be \( R_k \). It is assumed that the secondary users do their best to improve the whole energy efficiency. The users work in direct transmission mode or cooperative transmission mode. In the former mode, each user occupies the entire subcarrier to transmit data for itself. While in the latter mode, primary user selects a secondary user, as the cooperative relay to help in forwarding data, and further divides its transmission time into two equal slots. By taking advantage of the parallel OFDMA-based relaying architecture, each PU pair can conduct the bidirectional communication through two transmission modes, namely, direct transmission and relay transmission, on different sets of subcarriers. We assume that the two-hop transmission uses the same subcarrier for both links, that is, the source \( \rightarrow \) relay link and the relay \( \rightarrow \) destination link. The time slot allocation between a PU and a SU on a cooperative subcarrier is the same and assumes that the two hops of the cooperative transmission use equal time slots. This is true for amplify-and-forward relaying strategy because AF needs equal time allocation.

The source node sends data to the destination node through relay transmission with direct link as in Figure 2.
The broadband wireless channel is assumed to be frequency-selective Rayleigh slow fading; all the channel state information is perfectly known at the BS. Let \( N = \{1, 2, \ldots, N\} \) denote the set of subcarriers and denote \( \sigma^2 \) as the variance for the additive white Gaussian noise on each subcarrier, and \( h_{k,n} \) is the complex fading experienced by user \( k \) on subcarrier \( n \); then the channel-to-noise ratio (CNR) and the corresponding instantaneous transmission capacity can be written as
\[
\text{CNR}_{k,n} = \frac{|h_{k,n}|^2}{\sigma^2}, \quad (1)
\]
\[
R_{k,n} = \tau_{k,n} \log_2 \left( 1 + p_{k,n} \text{CNR}_{k,n} \right), \quad (2)
\]
where \( p_{k,n} \) is the transmission power allocated on subcarrier \( n \) for user \( k \) and \( \tau_{k,n} \) is a binary variable representing whether the subcarrier \( n \) is used to serve user \( k \) or not. The power consumption model of the BS can be formulated in the linear fashion:
\[
P_{\text{BS}} = \varepsilon_0 P_{tx} + P_0. \quad (3)
\]
The coefficient \( \varepsilon_0 \) includes the power which scales with the radiated power \( P_{tx} \), such as amplifier inefficiency and feeder losses. \( P_0 \) is a power offset that is independent with radiated power, derived from signal processing, battery backup, and so forth.

The most popular is “bits-per-Joule,” which is defined as the system throughput for unit-energy consumption [15]. The optimization problem is mathematically formulated as the following problem (4):
\[
\begin{align*}
\max & \quad \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} \tau_{k,n} R_{k,n} \\
\text{subject to} & \quad \sum_{n=1}^{N} \tau_{k,n} R_{k,n} (n) \geq R_k \quad \forall k, \quad (5) \\
& \quad \sum_{k=1}^{K} \tau_{k,n} \leq 1, \quad \tau_{k,n} \in \{0, 1\} \quad \forall n \in N \quad \forall k \in K, \quad (6) \\
& \quad \sum_{n=1}^{N} P_{k,n} (n) \leq P_{k}^{\text{max}} \quad \forall k. \quad (7)
\end{align*}
\]

Here, (5) is the minimum rate requirement for the service requested by each user. Constraint (6) represents that each subcarrier can be assigned to only one user, following the essential principle of OFDMA to avoid cochannel interference (CCI). Constraint (7) denotes the transmission power upper bound for the user.

3. QoS Aware Energy-Efficient Resource Scheduling

This section considers resource allocation adaptive schemes that will result in maximum energy efficiency. The problem (4) is nonconvex for power and it is a mixed integer programming problem. It is shown in [16] that the duality gap for a nonconvex optimization problem is zero if the optimization problem satisfies a time-sharing condition. Further, the time-sharing condition is always satisfied for the multiuser spectrum optimization problem in multicarrier systems when the number of frequency carriers goes to infinity and for most practical systems with a finite number of frequency carriers the duality gap is still nearly zero [17].

The fractional programming in (4) can be associated with the following parametric problem:
\[
F(\eta) = \max \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} R_{k,n} - \eta \left( \varepsilon_0 \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} P_{k,n} + P_0 \right). \quad (8)
\]

With \( \eta^* \) as the optimal value of (4), the following equivalence is obtained:
\[
\eta = \eta^* \iff F(\eta) = 0. \quad (9)
\]

It is clear that \( F(\eta) \) is strictly decreasing function with respect to \( \eta \). We also see that \( \eta \to -\infty F(\eta) > 0 \) and \( \eta \to \infty F(\eta) < 0 \). With these properties, the bisection method can locate the root of (9).

The value of \( h \) plays an important role in solving \( F(h) \). From (8), it is clear that \( \eta \leq 0 \) yields \( F(\eta) > 0 \), because \( \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} R_{k,n} \) and \( \varepsilon_0 \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} P_{k,n} + P_0 \) are, respectively, sum rate and total power consumption in (4) which are definitely positive. Therefore, \( F(\eta) = 0 \) happens at \( \eta > 0 \) and only the case \( \eta > 0 \) needs analyzing in particular. We propose to solve \( F(\eta) \) in problem (9) by the Lagrangian duality and always remember that \( \eta > 0 \) is the case concerned below:
\[
L(\Gamma, \Pi, \lambda, \beta) = \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} \tau_{k,n} R_{k,n}
- \eta \left( \varepsilon_0 \sum_{k=K_p+1}^{K} \sum_{n=1}^{N} \tau_{k,n} P_{k,n} + P_0 \right)
+ \sum_{k=1}^{K} \lambda_k \sum_{n=1}^{N} \tau_{k,n} R_{k,n} - R_k
+ \sum_{k=1}^{K} \beta_k \left( P_{k}^{\text{max}} \sum_{n=1}^{N} \tau_{k,n} P_{k,n} \right). \quad (10)
\]

The Lagrangian dual function is given by
\[
g(\lambda, \beta) = \max L(\Gamma, \Pi, \lambda, \beta). \quad (11)
\]
And the dual problem can be expressed as
\[
\min \quad g(\lambda, \beta)
\quad \text{s.t.} \quad \lambda \geq 0, \quad \beta \geq 0. \quad (12)
\]

The dual function can be rewritten as
\[
g(\lambda, \beta) = \sum_{n=1}^{N} g_n(\lambda, \beta) + \sum_{k=1}^{K} \beta_k P_{k}^{\text{max}} - \sum_{k=1}^{K} \lambda_k R_k - \eta \varepsilon_0 P_0, \quad (13)
\]
Initialize \( \eta_d = 0 \), \( \eta_u \gg 0 \)
Solve \( F(\eta) \) at each bi-section iteration
Update \( \eta_{temp} = (\eta_d + \eta_u)/2 \)
Initialize \( \lambda, \beta \)
For each subcarrier \( n \), solve subproblem (14) with \( \eta_{temp} \)
Obtain the optimal \( p_k \) via (17)
End
Update \( \lambda, \beta \) using subgradient method until converges
Update \( \eta_d \leftarrow \eta_{temp} \) if \( F(\eta_{temp}) > 0 \), else \( \eta_u \leftarrow \eta_{temp} \)
Repeat until \( |F(\eta_{temp})| < \delta \)

Algorithm 1

where

\[
g_n(\lambda, \beta) = \max \left[ \sum_{k=k_{p_1}}^{K} \tau_{k,n} R_{k,n} + \sum_{k=1}^{K} \lambda_k \tau_{k,n} R_{k,n} \right. \\
\left. - \sum_{k=k_{p_1}}^{K} \beta_k \tau_{k,n} P_{k,n} - \sum_{k=k_{p_1}}^{K} \eta \epsilon_0 \tau_{k,n} P_{k,n} \right].
\] (14)

It is independently solved at each subcarrier given \( \lambda, \beta \). Subgradient method can be used to minimize \( g(\lambda, \beta) \) by updating \( \lambda, \beta \), and it is to design a step-size sequence to guarantee convergence to the optimal \((\lambda^*, \beta^*)\). The subgradients of \( g(\lambda, \beta) \) are

\[
d(\lambda) = \sum_{n=1}^{N} \tau_{k,n} R_{k,n} - R_k,
\] (15)

\[
d(\beta) = P_k - \sum_{n=1}^{N} \tau_{k,n} P_{k,n}.
\]

The per-subcarrier optimization in (14) can be expressed as

\[
J^p(p_k) = \max R_k + \lambda_k R_k - \lambda_k \beta_k P_k - \eta \epsilon_0 P_k.
\] (16)

By substituting (2) into \( J^p(p_k) \) and taking derivative with respect to \( p_k \), we get the optimal power allocation on subcarrier \( n \):

\[
p_k = \begin{cases} 
\left( \frac{\lambda_k}{\beta_k \ln 2 - \frac{1}{\text{CNR}_k}} \right)^+, & 1 \leq k \leq k_p, \ k = k^*, \\
\left( \frac{1+\lambda_k}{(\beta_k + \eta \epsilon_0) \ln 2 - \frac{1}{\text{CNR}_k}} \right)^+, & 1+k_p \leq k \leq K, \ k = k^*, \\
0, & \text{otherwise}.
\end{cases}
\] (17)

If relaying is required on a given subcarrier, in case of DF one-way relaying, the per-subcarrier problem in (16) can be rewritten as

\[
J^p(p_k) = \max R_k + \lambda_k R_k - \beta_k P_k - \eta \epsilon_0 P_k.
\]

In order to minimize power, the equality \( R_{k_1} = R_{k_2} \) must hold, which leads to

\[
P_r = \frac{h - h'}{g} P_r.
\] (19)

The above is a convex problem. By applying the KKT conditions, the optimal power allocation is given by

\[
P_r = \left( \frac{\lambda_k}{2 (\beta_k + \eta \epsilon_0) / (h - h') \ln 2 - \frac{1}{h}} \right)^+.
\] (20)

The function \( F(\eta) \) is obtained by the analysis at certain \( \eta \) and the equation \( F(\eta) = 0 \) can be solved by bisection method above. The proposed algorithm is summarized in Algorithm 1.

4. Simulation Result

In order to assess the performance of the proposed algorithm, a single-base-station cognitive radio system with rate constraints is set beforehand. Let us concentrate on the simulated system, consisting of \( K = 2 \) users utilizing \( N = 8 \) subcarriers equispaced on a bandwidth of \( B = 1.5 \) MHz around the central frequency \( f_c = 2.1 \) GHz. We set \( \epsilon_0 = 1/0.38 \), which stands for the amplifier inefficiency; the total power of the single base station is set to 1 W, whereas the OFDMA symbol time is fixed to 66.67 \( \mu \)s. The Extended Vehicular A ITU Channel Model (ITU-R Recommendation M.1225, 1997) has been selected, which specifies a Doppler frequency of 70 Hz (corresponding to a relative speed of 36 Km/h) and an r.m.s delay spread of 357 ns. The noise spectral density \( N_0 \) is kept fixed to \( -30 \) dBm.
Figure 3 shows the energy efficiency versus spectrum efficiency for noncooperation transmission strategy. From this figure, it can be seen that energy efficiency first increases and then decreases. There is a maximum energy efficiency satisfying the rate requirement. The proposed scheme outperforms WSPmin scheme in [17], because our algorithm looks for the optimal energy efficiency over the whole domain, while the other yields energy efficiency, respectively, on the boundary of (5) and (7).

5. Conclusion

In this paper, we study a QoS-based RA algorithm, in order to improve the energy efficiency and simultaneously fulfill the requirement of the primary and cognitive users. It is a network-level scheme for cognitive OFDMA radio systems. Prior frequency planning is not required and simulation results show that the proposed scheme is able to offer optimal solution.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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