Spectrum Allocation Based on Simultaneous Wireless Information and Power Transfer in Cognitive Radio Networks

Qiuju Shi, Jianbin Li
School of Information Science and Engineering, Central South University, Changsha 410083, China
1006589486@qq.com

Abstract. This paper proposes an incentive simultaneous wireless information and power transfer (SWIPT) scheme for cognitive radio networks, wherein the secondary user (SU) provides wireless power transfer for the primary user (PU) in the exchange for partial bandwidth of the latter. To enable the proposed scheme, both the secondary transmitter (ST) and the primary receiver (PR) are equipped with multiple antennas. Specifically, SU helps to charge PU via adjusting its beamforming vector and PR harvests energy with a subset of its antennas; as a reward, PU allocates part of its bandwidth to SU. Our goal is to jointly optimize the beamforming vector of SU, the bandwidth allocation and covariance matrix of PU, such that the transmission rate of SU is maximized and meanwhile PU’s requirements in transmission rate and energy are satisfied. This optimization problem is non-convex. To handle this non-convex problem, we decompose it into two independent subproblems. One is to optimize the covariance matrix, the other is to optimize the beamforming vector of SU as well as the bandwidth allocation of PU, which is divided into a two-layer optimization problem. In the inner subproblem, we obtain the optimal beamforming vector for any given fixed bandwidth allocation, while in the outer subproblem we propose a gradient based algorithm and obtain the optimum bandwidth allocation. Numerical results are given to show the achievable system performance with varying parameters and also the convergence of the proposed algorithm.

1. Introduction
Due to the ever-increasing wireless data services, spectrum resource becomes unprecedented scarce. To improve the spectrum efficiency, in cognitive radio networks unlicensed user (SU) and authorized user (PU) are allowed to share spectrum resources. The key idea is to enable SU make full use of the spectrum without degrading PU’s performance[1]. Another issue with the rapid expansion of wireless services is the large amount of energy needed. By energy harvesting techniques[2], communication nodes can get energy from the surrounding environment, such as solar energy, wind energy. However, the harvesting of those energy depends on the location, weather, climate, etc, which is out of the control of our human beings. An alternative method in control is to harvest energy from radio frequency (RF) signals. RF signals can carry both information and energy simultaneously[3], which, in existing relevant works referred to as SWIPT, is considered as a promising technique to solve the energy scarcity problem and ensure the sustainable operation in wireless communication systems[4].

Inspired by the above discussions, we consider a scenario that combines SWIPT with cognitive radio networks. In cognitive radio networks PU has rich spectrum resources but limited energy. As
such, the research on the performance of SWIPT based cognitive radio networks has attracted a lot of attention recently. In [5], Zheng et al. propose a cooperative cognitive radio network, in which SU acts as a relay of PU’s information transmission, and PU provides SU with energy via wireless power transfer. In [6], the authors consider maximizing the data rate of SU, subject to a given data rate requirement of PU. The work of [7] extends the SWIPT results to the scenario of imperfect channel state information. In [8], Wang et al. analyze the network outage probability and the tradeoff between the achievable transmission data rate and harvested energy. In [9] and [10], the authors investigate the secure communication problems in presence of eavesdropping. In [9], the transmission covariance matrix and the artificial noise covariance matrix are designed to maximize the secure transmission data rate of SU. The work of [10] considers the secondary transmitter transmitting artificial noise signals to ensure the secure communication of PU; it minimizes the total transmission power of PU and SU, such that the constraints on secure transmission data rate and harvested energy are satisfied.

All the existing relevant works study the achievable spectrum/energy efficiency under the assumption that the spectrum allocation is fixed. In this paper, we propose a novel incentive scheme for motivating SWIPT in cognitive radio networks, wherein SU provides wireless power transfer for PU in the exchange for partial bandwidth of the latter. This is a win-win strategy as it charges PU with wireless power transfer and allows SU to use unlicensed spectrum.

The main contributions of this paper are summarized as follows:

• We propose an incentive SWIPT scheme for cognitive radio networks, wherein SU provides wireless power transfer for PU in the exchange for partial bandwidth of the latter.
• We formulate an optimization problem in order to improve the spectrum utilization as well as energy efficiency. In particular, we aim to maximize SU’s transmission rate with respect to the beamforming vector of SU, the bandwidth allocation and covariance matrix of PU, under certain constraints on PU’s transmission rate and harvested energy.
• Although the formulated problem is a non-convex, we decompose it into two independent subproblems. One is to optimize the covariance matrix, the other is to optimize the beamforming vector of SU as well as the bandwidth allocation of PU, which is divided into a two-layer optimization problem. In the inner subproblem, we obtain the optimal beamforming vector for any given fixed bandwidth allocation; in the outer subproblem we give a gradient based algorithm and solve for the optimum bandwidth allocation.

2. System Model and Problem Formulation

In Fig.1, we consider a cognitive radio network with SWIPT, which consists of one pair of primary transmitter (PT) and primary receiver (PR), and one pair of secondary transmitter (ST) and secondary receiver (SR). Here, SR is equipped with a single antenna, while ST, PT and PR are equipped with \( L \geq 1, M \geq 1 \) and \( N \geq 2 \) antennas, respectively. To enable SWIPT, one of PR’s antennas is used to harvest energy and the remaining antennas are used to receive data. Moreover, PU divides its bandwidth \( B \) into two parts, one \((\alpha B)\) for its own data transmission and the remaining \(((1 - \alpha)B)\) for SU’s transmission. EH indicates energy harvesting circuit, which uses the transmission signal of SU to harvest energy. ID indicates information decoding circuit, which is used to decode the data of PU.
2.1. The secondary user model

The wireless channel of SU is modeled as MISO (Multiple Input Single Output), and the channel gain from ST to SR is $h \in \mathbb{C}^{L \times 1}$. The received signal of SR is then expressed as

$$ y_s = h^t x_s + z_s $$

(1)

where $z_s \sim \mathcal{CN}(0, 1)$ refers to the additive white Gaussian noise (AWGN) caused by receiving antenna at SR, and $x_s \in \mathbb{C}^{L \times 1}$ is the transmission signal of ST. Let $\bar{x}_s$ be the original transmission signal before beamforming, satisfying $\mathbb{E}[||\bar{x}_s||^2] = 1$. The transmission signal of ST is then expressed as $x_s = v \bar{x}_s$, where $v \in \mathbb{C}^{L \times 1}$ is the beamforming vector of ST.

Since SU works on a different frequency band from PU, it suffers no interference from PU. On the other hand, the bandwidth used by SU is $(1-\alpha)B$, so the data rate of SU can be written as

$$ R_s = (1-\alpha)B \log(1 + ||h^t v||^2) $$

(2)

2.2. The primary user model

PR adopts an antenna switching scheme to harvest energy, i.e., one antenna is selected to harvest energy, and $N-1$ antennas to receive data signal. Since PU and SU work in different frequency bands, the ID circuit suffers no interference from the energy harvesting signal. Therefore, the received signal at the ID receiver can be written as

$$ y_{ID} = H x_p + z_p $$

(3)

where $H \in \mathbb{C}^{(N-1) \times M}$ denotes the channel gain from PT to PR, and $z_p \in \mathbb{C}^{(N-1) \times 1}$ refers to the AWGN with the distribution following $z_p \sim \mathcal{CN}(0, I)$. $x_p \in \mathbb{C}^{M \times 1}$ is the transmitted signal by PT. We use $S = \mathbb{E}[x_p x_p^H]$ to represent the covariance matrix of $x_p$. So, the data rate of PU can be given by

$$ R_p = \alpha B \log |I + H S H^t| $$

(4)

2.3. Energy harvesting model

PU uses an antenna to harvest energy, which indicates the energy harvesting channel as a MISO channel, denoted by $g \in \mathbb{C}^{L \times 1}$. Therefore, the received signal at EH receiver can be written as

$$ y_{EH} = g^t x_s + z_{EH} $$

(5)

where $z_{EH} \sim \mathcal{CN}(0, 1)$ denotes the AWGN noise. Based on (5), the energy received of PU as follows

$$ Q_{EH} = \eta (1-\alpha)B \mathbb{E}[||g^t x_s + z_{EH}||^2] $$

where $\eta$ is a constant that accounts for the conversion efficiency for converting the harvested energy to the electrical energy stored. Since the energy generated by the additive noise of the EH receiver is much smaller than the average power of the received signal, it almost has no effect on EH receiver[11]. Therefore, the additive noise can be omitted for the purpose of simplifying the calculation. The received energy can then be rewritten as

$$ Q_{EH} = \eta (1-\alpha)B \mathbb{E}[||g^t x_s||^2] = \eta (1-\alpha)B ||g^t v||^2 $$

(7)

2.4. Problem formulation

When PU does not require a high data rate, it can split a part of the bandwidth for SU with meeting the basic requirements in order to exchange for the energy provided by SU and avoid the degradation of communication quality caused by insufficient energy. The optimization problem is formulated as

$$ \max \limits_{(x,s)} R_s $$

subject to

$$ \beta Q_{EH} + R_p \geq \tau $$

$$ ||v||^2 \leq P_s $$

$$ \text{tr}(S) \leq P_p $$

$$ 0 \leq \alpha \leq 1 $$

(8) (9) (10) (11)

where $\beta$ is a parameter used to ensure that $Q_{EH}$ and $R_p$ are on the same order of magnitude, and $\tau$ is the basic requirements for PU. $P_s$ and $P_p$ are the maximum transmission power of ST and PT, respectively.
By solving this optimization problem, we are able to find the beamforming vector of SU, the bandwidth allocation and covariance matrix of PU. Consequently, the transmission rate of SU is maximized and meanwhile PU’s requirements in transmission rate and energy are satisfied.

3. Optimisation Solution

The problem P formulated in the last section is a non-convex optimization problem. To handle it, in this section we decompose it into two independent subproblems. One is to optimize the covariance matrix, the other is to optimize the beamforming vector of SU as well as the bandwidth allocation of PU, which is divided into a two-layer optimization problem.

3.1. The optimal covariance matrix of PU

From the description of problem P, it is easy to see that in order to maximize $R_\text{Su}$ and satisfy the constraints, PU’s data rate $R_\text{Pu}$ should be maximized. That is, the optimization of $S$ can be formulated as follows:

$$P_1: \max_S R_\text{Su} \quad \text{s.t.} \quad \text{tr}(S) \leq P_\text{Pu}$$ (12)

It is not difficult to find that problem $P_1$ is a classical rate maximization for MIMO communication. Therefore, its solution can be easily obtained. Let the SVD decomposition of $H$ be $U_H \Sigma_H V_H^T$, where $V_H \in \mathbb{C}^{M \times T}$, $U_H \in \mathbb{C}^{N \times N}$, and $\Sigma_H = \text{diag}(\sigma_1, ..., \sigma_T)$ with $\sigma_1 \geq \sigma_2 \geq \cdots \geq \sigma_T \geq 0$. According to the water-filling power allocation scheme[12], the optimal covariance matrix can be written as $S^* = V_H \Lambda V_H^T$. Here, $\Lambda = \text{diag}(p_1, ..., p_T)$, and $p_i = \left( \mu - \frac{1}{\sigma_i} \right)^+$, $i = 1, ..., T$, where $\mu$ is a constant water-level, and it satisfies that $\sum_{i=1}^T p_i = p_\text{Pu}$.

3.2. Design of the optimal beamforming vector

In this subsection, we obtain the optimal beamforming vector $v$ by fixing the bandwidth splitting ratio $\alpha$ and PU’s data rate $R_\text{Pu}$. Therefore, the problem P can be written as

$$P_2: \max_{v_h, v_\text{Pu}} R_\text{Su} \quad \text{s.t.} \quad \beta Q_\text{EH} + R_\text{Pu} \geq \tau$$

$$\|v\|^2 \leq P_\text{Su}$$ (13) (14)

According to the problem $P_2$, $v$ is related to $g$ and $h$, so it can be expressed by

$$v^* = \omega_h g^\perp + \theta_h h^\perp$$ (15)

where $g^\perp = g / \|g\|$ and $h^\perp = h / \|h\|$, $h^\perp = h - (g^\perp h) g^\perp$, and $\omega_h$ and $\theta_h$ are the weights in the direction of $g^\perp$ and $h^\perp$, respectively.

We substitute (15) into $P_2$ and let $h = \omega_h g^\perp + \theta_h h^\perp$, where $\omega_h = g^H h$, $\theta_h = h^H h$, we can obtain that $R_\text{Su} = (1 - \alpha) B \log(1 + \| \omega_h g + \theta_h h^\perp \|^2)$. Since $\alpha$ is fixed, it can be seen a constant. Moreover, $R_\text{Su}$ is proportion to $\| h^\perp v \|^2$, and $\hat{g} \cdot \hat{h} = 0$, so $\| (\omega_h \hat{g} + \theta_h \hat{h}^\perp) (\omega_h g + \theta_h h^\perp) \|^2 = \| \omega_h g + \theta_h h^\perp \|^2 = \| \omega_h \mathbf{v} + \theta_h \mathbf{v} \|^2$. Therefore, $P_2$ is equivalent to the $P_3$ which is given by

$$P_3: \max_{(\omega_h, \theta_h)} \| \omega_h \mathbf{v} + \theta_h \mathbf{v} \|^2$$

$$\text{s.t.} \quad \beta \eta (1 - \alpha) B \|g\|^2 \|\mathbf{v}\|^2 + R_\text{Pu} \geq \tau$$ (16)

$$\|\omega_h \mathbf{v}\|^2 + \|\theta_h \mathbf{v}\|^2 \leq P_\text{Su}$$ (17)

$P_3$ can be solved by geometric method[13]. The optimal values of $\omega_h$ and $\theta_h$ are as follows:

Case I: If $\tau \leq \Omega_h$,

$$\omega_h = \frac{P_\text{Su}}{\sqrt{\|\omega_h \mathbf{v}\|^2 + \|\theta_h \mathbf{v}\|^2}}$$ (18)
\[ \theta_v = \frac{P_v}{\|w_h\|^2 + \|\theta_h\|^2} \theta_h \]  

(19)

where \( \Omega_h = \beta \eta (1 - \alpha) B P_s \|g\| \omega_h \|g\| (\|\omega_h\|^2 + \|\theta_h\|^2) + R_p \). In this case, (16) is a loose constraint, (17) is a tight constraint, and \( v \) is in the same direction with \( h \), i.e., \( v = \sqrt{P_s} h/\|h\| \). Therefore, \( \omega_v = \sqrt{P_s} \omega_h/\|h\|, \theta_v = \sqrt{P_s} \theta_h/\|h\| \), we can obtain (18) and (19).

Case I: If \( \Omega_h < \tau \leq \Omega_g \),

\[ \omega_v = \frac{P_v}{\eta(1-\alpha)B\|g\|^2} \quad \theta_v = \frac{P_v - \frac{Q}{\eta(1-\alpha)B\|g\|^2}}{\sqrt{P_v}} \]  

(20) \hspace{1cm} (21)

where \( \Omega_g = \beta \eta (1 - \alpha) B P_s \|g\|^2 + R_p \) and \( Q = \frac{\tau - R_p}{\beta} \). In this situation, (16) and (17) are both tight constraints, and the transmission power \( \|\omega_v\|^2 \) allocated in the direction of \( \hat{g} \) needs to be regulated by \( \tau \). According to (16) and (17), we can obtain (20) and (21).

Case III: If \( \tau > \Omega_g \),

\[ \omega_v = 0, \theta_v = 0 \]  

(22)

Then SU cannot meet the requirements of PU. As such, PU refuses to allocate bandwidth to SU. As a result, we have \( v = 0 \).

3.3. The optimal bandwidth splitting ratio

From what derived in the last subsection, one can see that \( v \) only depends on \( \alpha \). Substituting the optimum \( v \) into the problem P2, we obtain an optimization problem which only involves \( \alpha \), i.e., the data rate \( R_s = R_s(\alpha) \). Theoretically, \( R_s \) should be differentiated with respect to \( \alpha \), and the optimal \( \alpha \) can be obtained at the point when the derivative is zero. However, the exact expression of this derivative is difficult to obtain. As such, in this subsection we will give a gradient-based iterative algorithm to search for the optimum value of \( \alpha \) [13].

Also, from Subsection 3.2, one can see that PU and SU will cooperate only when \( \tau \leq \Omega_g \), i.e., \( \frac{\tau - \varphi}{\psi - \varphi} \leq \alpha \leq 1 \), where \( \varphi = \beta \eta B P_s \|g\|^2 \), \( \psi = B \log(1 + HSH^H) \). And so, we can adjust \( \alpha \) iteratively.

The iterative formula for \( \alpha \) is:

\[ \alpha(t + 1) = \alpha(t) + \delta \nabla(R_s(\alpha)) \]  

(23)

That is, \( \alpha \) is adjusted in the direction of increasing \( R_s(\alpha) \), and \( \delta \) is the step size used to control the speed of the adjustment for \( \alpha \). \( \nabla(R_s(\alpha)) \) is an approximation of the derivative of \( R_s(\alpha) \) and is expressed as follows:

\[ \nabla(R_s(\alpha)) = \frac{R_s(\alpha + \varepsilon) - R_s(\alpha - \varepsilon)}{2\varepsilon} \]  

(24)

where \( \varepsilon \) is a constant indicating the approximate accuracy.

In summary, Algorithm 1 describes the detailed steps for solving the original optimization problem \( P \).

4. Simulation results

In this section, the performance of above described scheme is evaluated by numerical results. The parameters are set as follows. ST and PT are equipped with \( L=M=4 \) antennas, SR is equipped with single antenna, and PR is equipped with 5 antennas. The distance from ST to PR is set to \( d_e=4m \). The distance from ST to SR and PT to PR are set to \( d_s=d_p=10m \). And it is assumed that all channel models are randomly generated independent and identically distributed Rayleigh channel models. The transmission power of ST and PT are \( P_s=P_p=10W \). The noise power is assumed to be 1W. The bandwidth of PU is \( B = 1 \) MHz, and the energy conversion efficiency is \( \eta = 0.3 \).

Fig.2 plots the achievable transmission data of SU with respect to the bandwidth splitting ratio \( \alpha \). In Fig.2, when \( \alpha \) is small, the data rate of SU is zero. This is because the bandwidth used by PU is too
small to meet the basic requirement of the PU. In this case, PU does not cooperate with SU. Otherwise, the data rate of SU is a concave function with respect to the bandwidth splitting ratio.

Fig. 2 The relationship between $R_s$ and $\alpha$

Fig. 3 The relationship between $\tau$ and $R_s$

**Algorithm 1** Optimal solution to problem P

Initialize $\frac{\tau - \varphi}{\varphi - \varphi} \leq \alpha \leq 1$, step size $\delta$ and precision $\varepsilon$;

Compute $S^* = V_H A V_H^H$

repeat
   if $\Omega_h \geq \tau$ then
      $v = \sqrt{P_s h / \|h\|}$;
   else
      $v = \omega_v \hat{g} + \theta_v \hat{h}_\perp$;
   end if

end repeat
if $\alpha < \frac{\tau-\varphi}{\psi-\varphi}$ then
    update $\alpha$ using $\alpha(t+1) = \alpha(t) + \mu$,
    where $\mu$ is a small value;
    $t = t+1$;
else if $\alpha > 1$ then
    update $\alpha$ using $\alpha(t+1) = \alpha(t) - \mu$;
    $t = t+1$;
else
    Update $\alpha$ using (23) and (24);
end if
Until $\alpha$ keeps unchanged;
return $(\alpha, v)$;

Fig.3 plots the achievable data rate of SU with respect to the requirement of PU $\tau$. It can be seen that as $\tau$ increases, the data rate of SU gradually decreases. And when $\tau$ reaches to a certain point, the data rate of SU drops to zero. In this case, SU cannot transmit its own data, and so PU and SU will not cooperate. On the other hand, when $\tau$ is small, the data rate of SU remains unchanged first. This is because PU only needs a small amount of energy, and so SU can fully send its own data while satisfying the energy demand of PU. Moreover, Fig.3 shows the data rate of SU with varying distance from ST to PR. It shows that SU can obtain a higher data rate when this distance is small. This is because the PR can harvest more energy when ST is closer to PR, which indicates that SU can sacrifice less data rate while meeting the energy requirement of PU.

Fig.4 shows the impact of the system parameter $\beta$ on the optimal data rate of SU. It shows that as $\beta$ increases, the optimal data rate of SU gradually increases first, and then remains unchanged. This can be explained as follows. An increasing value of $\beta$ means that PU requires more energy and smaller data transmission rate. Therefore, more bandwidth of PU could be allocated to SU. As such, the achievable transmission data rate of SU increases. Further, when PU’s requirement for the data rate decreases to zero, that is, PU does not need to send data, PU allocates the entire bandwidth to SU. In this case, the data rate of SU achieves its maximum and does not increase anymore.

5. Conclusion
This paper has proposed a scheme for cooperation between primary and secondary users in a cognitive radio network, including the covariance matrix design, bandwidth allocation and beamforming design. Specifically, we have jointly optimized the covariance matrix and bandwidth allocation of PU, and beamforming vector of SU, such that the transmission rate of SU is maximized and meanwhile PU’s requirements in transmission rate and energy are satisfied. This is a non-convex optimization problem.
To handle this problem, we decompose it into two independent subproblems. One is to optimize the covariance matrix, the other is to optimize the beamforming vector of SU as well as the bandwidth allocation of PU, which is divided into a two-layer optimization problem. In the inner subproblem, we obtain the optimal beamforming vector for any given fixed bandwidth allocation, while in the outer subproblem we propose a gradient based algorithm and obtain the optimum bandwidth allocation. Numerical results have been given to validate the performance of the proposed algorithm.

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