Energy Efficiency Optimization for Subcarrier Allocation-Based SWIPT in OFDM Communications

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Abstract. Simultaneous wireless information and power transfer (SWIPT) is a promising technology to realize simultaneous information and energy transfer by utilizing radio frequency signals. It extends the life of wireless networks and is conducive to the realization of green communications. In this paper, a subcarrier allocation-based SWIPT is studied to transfer information and energy in different subcarriers of an Orthogonal Frequency Division Multiplexing (OFDM) communication system. To improve the SWIPT performance, we maximize the energy efficiency of OFDM communication system while satisfying the constraints including minimum harvested energy, target rate and transmit power budget. To obtain the optimal solution, we investigate a dual-layer iterative optimization algorithm from Lagrange dual function to solve the energy efficiency optimization problem. The simulation results show that the energy efficiency of the proposed scheme can be effectively improved.

Keywords: SWIPT · Subcarrier allocation · Power allocation · Energy efficiency

1 Introduction

For the past few years, simultaneous wireless information and power transfer (SWIPT) has been proposed as a promising method to realize green communications, due to that it can continuously provide energy to those devices supplied by finite batteries. Thus, SWIPT can lengthen the working time of energy-constrained wireless networks to some extent [1]. Since wireless signals carrying radio frequency (RF) energy can be used for transmitting information, SWIPT have the capability of performing both energy acquisition and information transmission at the same time. In [2], Varshney first proposed the notion of SWIPT and characterized the fundamental tradeoff between information and energy transfer with a proposed capacity-energy function. And the work in [2] is extended to frequency-selective channels in [3]. However, these studies are based

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on the assumption that the circuits at the receiver for energy harvesting are ideally thought to be capable of simultaneously decoding information directly from the same received signal.

In order to implement SWIPT within practical circuit constraints, two traditional practical SWIPT schemes including power splitting (PS) [4] and time switching (TS) [5] are proposed. In the TS scheme, the receiver can switch between decoding mode and energy harvesting mode in the time domain according to the instantaneous channel condition, so it is not strictly simultaneous. And in the PS scheme, the received signals are divided into two streams at the receiver through the power splitter in a certain proportion, which can be utilized to decode information and harvest energy separately.

Orthogonal Frequency Division Multiplexing (OFDM), a popular multicarrier transmission technique, can effectively achieve high rate transmission and has been widely adopted in various standards [6]. Therefore, the strengths of SWIPT can be fully used to achieve efficient wireless transmission by combining OFDM with SWIPT [7]. The multiuser OFDM system, based on two SWIPT transmission scheme including power splitting and time switching, is studied to achieve maximum sum of information rate in [8]. However, in the SWIPT OFDM system applied with power splitting scheme or time switching scheme, a power splitter or time switcher is required at the receiver, which increases the complexity of the circuits. Thus, the study in [9] proposed a resources allocation algorithm to obtain maximum energy at the receiver which does not require a splitter.

Since saving energy has been considered a matter of great urgency. In this paper, an algorithm for obtaining energy efficiency maximization will be studied to realize the effective utilization of resources. All received subcarriers will be split into two sets, and the subcarriers in the two sets will be used for energy harvesting or information decoding respectively. The receiver knows the subcarrier distribution and carries on the information transmission.

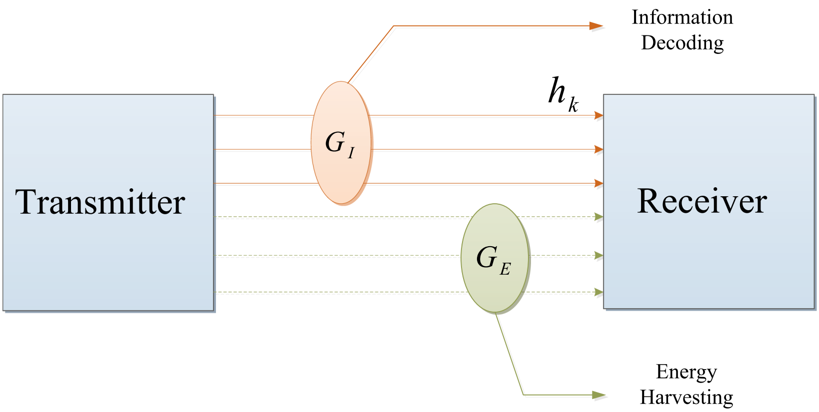

Fig. 1. System model.

2 System Model and Problem Formulation

2.1 System Model

The SWIPT enabled OFDM system, as shown in Fig. 1, is composed of a transmitter (Tx) and a receiver (Rx); each device is assumed to be equipped with one single antenna. During transmission, the entire bandwidth of the link Tx → Rx is split into K subcarriers. Then all these subcarriers are combined into a set and denoted as $K = \{1, ..., k\}$. We denote the channel power gain on the subcarrier k as h_k and assume that the transmitter knows about h_k. P is considered as the total transmission power of transmitter, and the power allocated to subcarrier k is set to p_k. At Rx, on each subcarrier noise n_k will destroy the received signal. The noise n_k is considered as an additive Gaussian white noise (AWGN) and follows a $n_k \sim CN(0, \sigma_k^2)$ distribution. Moreover, slow fading is considered in this paper that all coefficients associated with the channel conditions are assumed to be constant during one transmission period. In the transmission process, Rx uses subcarriers in G_I to decode information and subcarriers in G_E to collect energy, where $G_I \in K$, $G_E \in K$ and $G_I + G_E = K$.

2.2 Problem Formulation

For the transmission link Tx → Rx, achievable rate can express as

$$R = \sum_{k \in G_I} \ln(1 + \frac{p_k h_k}{\sigma_k^2}) \tag{1}$$

The energy harvested by Rx can be written as

$$Q = \xi \sum_{k \in G_E} (p_k h_k + \sigma_k^2) \tag{2}$$

where the energy conversion efficiency is denoted by ξ.

The total power consumed by the system can be given by

$$U_{total} = \sum_{k \in G_I} p_k + \sum_{k \in G_E} p_k + P_c - \xi \sum_{k \in G_E} (p_k h_k) \tag{3}$$

where P_c denotes the fixed power consumption of entire system hardware. Therefore, the energy efficiency of the proposed system can be expressed as a ratio of the achievable total rate to the total consumed power, which can be given by

$$E_{eff}(p, G) = \frac{R_{total}(p, G)}{U_{total}(p, G)} \tag{4}$$

where $G = \{G_I, G_E\}$, $p = \{p_k\}$. In order to achieve maximum energy efficiency of the system within the constraints of the total transmitted power, the target rate and the minimum harvested energy. Then optimization problem can be expressed as

$$\max \frac{\sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2})}{\sum_{k\in G_I} p_k + \sum_{k\in G_E} p_k + P_c - \xi \sum_{k\in G_E} (p_k h_k)} \tag{5a}$$

$$\text{s.t. } \xi \sum_{k\in G_E} (p_k h_k) \geq E_{min} \tag{5b}$$

$$\sum_{k\in G_I} p_k + \sum_{k\in G_E} p_k \leq P \tag{5c}$$

$$\sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2}) \geq R_T \tag{5d}$$

where R_T and E_{min} respectively represent target rate and minimum harvested energy requirement that need to be met. And σ_k^2 is not considered in the energy collection. It can be observed from the formulated equation that the objective function is fractional form, which is hard to be solved directly. Therefore, we can convert the fraction into a new objective function in subtractive form. The maximum achievable energy efficiency is denoted as q^*, which can be written as

$$q^* = \frac{R_{total}(p^*, G^*)}{U_{total}(p^*, G^*)} = \max \frac{R_{total}(p, G)}{U_{total}(p, G)} \tag{6}$$

We can obtain maximum achievable energy efficiency only when $\max R_{total}(p, G) - q^* U_{total}(p, G) = R_{total}(p^*, G^*) - q^* U_{total}(p^*, G^*){=}0$ is satisfied. By utilizing q, the original optimization problem is then transformed into the following form

$$\max \sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2}) - q(\sum_{k\in G_I} p_k + \sum_{k\in G_E} p_k + P_c - \xi \sum_{k\in G_E} (p_k h_k)) \tag{7a}$$

$$\text{s.t. } \xi \sum_{k\in G_E} (p_k h_k) \geq E_{min} \tag{7b}$$

$$\sum_{k\in G_I} p_k + \sum_{k\in G_E} p_k \leq P \tag{7c}$$

$$\sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2}) \geq R_T \tag{7d}$$

3 Optimal Solution

We can observe that our optimization problem is nonconvex. If subcarriers number is sufficient enough and the "time-sharing" condition can be satisfied, Lagrangian dual function and Dinkelbach method can be utilized to figure out the proposed problem. The associated Lagrangian dual function of (7a) can be written as

$$g(\beta) = \max_{\{p,G\}} L(p, G) \tag{8}$$

$$\begin{aligned} L(p,G) = &\sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2}) - q(\sum_{k\in G_I} p_k + \sum_{k\in G_E} p_k + P_c - \xi \sum_{k\in G_E} (p_k h_k)) \\ &+ \beta_1(\xi \sum_{k\in G_E} (p_k h_k) - E_{\min}) + \beta_2(P - \sum_{k\in G_I} p_k - \sum_{k\in G_E} p_k) \\ &+ \beta_3(\sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2}) - R_T) \end{aligned} \tag{9}$$

where $L(p, G)$ is shown in (9) and $\beta = (\beta_1, \beta_2, \beta_3)$ represents the dual variables vector. Then, we can give the dual optimization problem

$$\min_{\beta} g(\beta) \tag{10a}$$

$$\text{s.t.}\, \beta \geq 0 \tag{10b}$$

Since the dual function is convex, we can obtain the optimal variables $\beta = (\beta_1, \beta_2, \beta_3)$ through the subgradient-based iterative method. The subgradient can be formulated as follows

$$\begin{aligned} \Delta\beta_1 &= \eta \sum_{k\in G_E} (p_k h_k) - E_{\min} \\ \Delta\beta_2 &= P - \sum_{k\in G_I} p_k - \sum_{k\in G_E} p_k \\ \Delta\beta_3 &= \sum_{k\in G_I} \ln(1+\frac{p_k h_k}{\sigma_k^2}) - R_T \end{aligned} \tag{11}$$

The optimal β can be obtained by $\beta^{t+1} = \beta^t + v^t \Delta\beta$, where v_t denotes the step size, t is iteration times and $\Delta\beta = (\Delta\beta_1, \Delta\beta_2, \Delta\beta_3)$. During the iteration, we can find out the optimal dual variables when convergence is reached. With the following two steps, we can finally achieve the optimal $\{p, G\}$ on a given β.

3.1 Optimizing p with Fixed G

When the set G is fixed, we can calculate the partial derivative of Lagrange function (9) with $p_k, k \in G_I$ and $p_k, k \in G_E$, which can be given by

$$\frac{\partial L(p,G)}{\partial p_k} = \frac{(1+\beta_3)h_k}{\sigma_k^2 + p_k h_k} - q - \beta_2, k \in G_I \tag{12}$$

$$\frac{\partial L(p,G)}{\partial p_k} = -q + q\xi h_k + \beta_1 \xi h_k - \beta_2, k \in G_E \tag{13}$$

According to KKT condition, we can obtain the optimized p by making the partial derivative equal to zero, which is $\frac{\partial L(p,G)}{\partial p_{k,k\in G_I}} = 0$ and $\frac{\partial L(p,G)}{\partial p_{k,k\in G_E}} = 0$. Thus, the power allocated to decode information can be optimized through the following formula

$$p_k{}^* = \left(\frac{1+\beta_3}{\beta_2+q} - \frac{\sigma_k^2}{h_k}\right)^+ \tag{14}$$

where $()^+$ denotes that all negative numbers calculated by (14) will be changed to zero, while positive numbers will remain the same. And the power allocation of energy collection can also be optimized as

$$p_k* = \begin{cases} p_{\max} & \xi h_k(q+\beta_1) > q+\beta_2 \\ p_{\min} & \xi h_k(q+\beta_1) \le q+\beta_2 \end{cases} \tag{15}$$

where $p_{\min}$ is the minimum power constraint for each subcarrier while $p_{\max}$ denotes the maximum power constraint.

3.2 Obtaining the Optimal *G*

Substituting (14) and (15) into (9), the Lagrangian in (9) can be rewritten as (17) through algebraic transformation.

$$L(G) = \sum_{k\in GI} F_K{}^* + \sum_{k=1}^{K} (\eta p_k{}^* h_k(q+\beta_1) - p_k{}^*(q+\beta_2)) \tag{16}$$

$$- \beta_1 E_{\min} + \beta_2 P - qP_c - \beta_3 R_T \tag{17}$$

where

$$F_k^* = (1+\beta_3)\ln(1+\frac{p_k{}^* h_k}{\sigma_k^2}) - \xi p_k{}^* h_k(q+\beta_1) \tag{18}$$

We can observe from (17) that on the right hand side only the first part, F_k^*, is related to subcarrier set G_I. Therefore, the subcarrier set G_E can be optimized by finding the set which maximizes the Lagrangian function. And the optimal G_I can be written as

$$G_I^* = \arg\max_{G_I} \sum_{k\in G_I} F_k^* \tag{19}$$

It can be easy to obtain optimal G_I^*, since we can find all $k(k \in k)$ that make F_k^* positive. Then we can get optimal G_E^* which is written as

$$G_E^* = K - G_I^* \tag{20}$$

We can solve the optimization problem of subcarrier and power distribution through the above Algorithm 1, and find out the maximum optimal energy efficiency by utilizing the Dinkelbach Iterative Algorithm, which can be summarized in Algorithm 2.

Algorithm 1. The Algorithm for Optimization Problem

```
initialize the non-negative variables {β1, β2, β3}.
repeat
Update power allocation p*_k defined in (14) and (15).
Update subcarrier sets G*_I and G*_E according to (19) and (20).
Update {β1, β2, β3} according to (11).
until {β1, β2, β3} converge.
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Algorithm 2. The Algorithm for Energy Effciency Optimization

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initialize the stopping error ϵ and the maximum iteration times N.
Set n = 0 and q = 0.
repeat
Obtain the optimal {p, G} according to Algorithm 1.
if
R_total(p, G) − q U_total(p, G) ≤ ϵ.
return {p*, G*} = {p, G} and q* = R_total(p,G) / U_total(p,G).
else
Update n = n + 1 and q = R_total(p,G) / U_total(p,G).
end
until R_total(p, G) − q U_total(p, G) ≤ ϵ.
```

4 Simulations Result

The performance of our proposed energy efficiency algorithm is finally demonstrated by the simulation results in terms of energy efficiency and achievable rate.

We set the number of subcarriers to 32, and the fixed power consumption P_c of the system hardware is assumed to be 0.7 mW. The channel conforms to the Rayleigh distribution, and the channel noise is considered as an additive white Gaussian noise (AWGN) random variable, which can be denoted as $n_k \sim CN(0, \sigma_k^2)$,$\sigma_k^2 = -50\,\text{dBm}$. In addition, the energy conversion efficiency ξ is set to 1 for simplicity.

Figure 4 shows the allocation of power and subcarriers when $P = 3\text{mW}$, $R_T = 2\,\text{bps/Hz}$ and $E_{min} = 0.002\,\mu\text{W}$. Figure 2 and Fig. 3 illustrate the performance of our proposed algorithm and other algorithms.

Algorithm 1: The total transmitted power is divided into M components on average. In a fixed ratio, the power allocated on each subcarrier is split into two parts, respectively for harvesting the energy and decoding the information.

Algorithm 2: All subcarriers are randomly divided into two sets, and each set has the same number of subcarriers. The subcarrier sets are fixed and the water-filling method is utilized for power allocating. Subcarriers in different sets will be respectively used to decode information and harvest energy.

It can be clearly observed from Fig. 2 and Fig. 3 that our proposed algorithm performs better than Algorithm 1 and Algorithm 2, and Algorithm 2 is superior to Algorithm 1. We can know that in Algorithm 1, all subcarriers, regardless

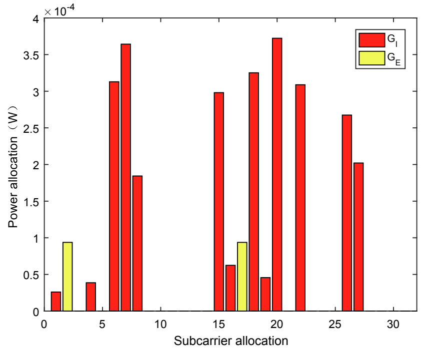

Fig. 2. Power and subcarriers allocation

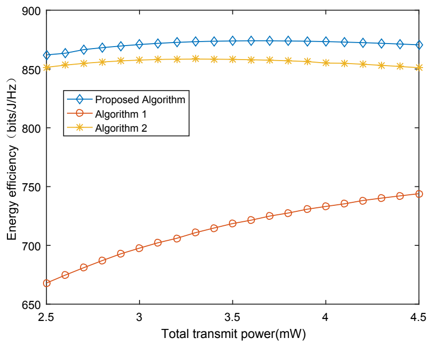

Fig. 3. Comparison of energy efficiency versus P of different algorithms

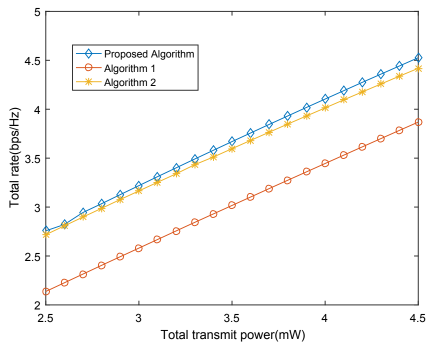

Fig. 4. Comparison of achievable rate versus P of different algorithms

of channel gain, are used for transmission, so that the power will be wasted on some poor subcarriers. In Algorithm 2, the subcarrier set is not optimal, which will inevitably cause power waste even if the power is allocated by water-filling algorithm. And since the condition of subcarries will be judged before power allocation, the subcarriers with poor channel condition will not be used for transmission. Therefore Algorithm 2 wastes less power than Algorithm 1 and performs better. Our proposed algorithm optimizes both subcarrier and power allocation and thus performs best among the three algorithms.

5 Conclusions

In this paper, to achieve green communication, we study an energy efficiency optimization scheme based on the OFDM SWIPT system where no power splitter or time switcher is required at the receiver. In this system, all received subcarriers will be split into two sets, and the subcarriers in the two sets will be utilized for energy harvesting or information decoding respectively. In order to achieve maximum energy efficiency while satisfying certain constrains, a dual-layer iterative joint allocation algorithm is proposed. Simulation results show that our proposed algorithm achieves superior energy efficiency compared with the other two algorithms.

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