Energy-Efficient Resource Allocation in Energy Harvesting Communication Systems: A Heuristic Algorithm

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Abstract. Harvesting energy from the environment is a method to improve the energy utilization efficiency. However, most renewable energy has a poor stability due to the weather and the climate. The reliability of the communication systems will be influenced to a large extent. In this paper, an energy-efficient downlink resource allocation problem is investigated in the energy harvesting communication systems by exploiting wireless power transfer technology. The resource allocation problem is formulated as a mixed-integer nonlinear programming problem. The objective is to maximize the energy efficiency while satisfying the energy causality and the data rate requirement of each user. In order to reduce the computational complexity, a suboptimal solution to the optimization problem is obtained by employing a quantum-behaved particle swarm optimization (QPSO) algorithm. Simulation results show that the QPSO algorithm has a higher energy efficiency than the traditional particle swarm optimization (PSO) algorithm.

Keywords: Energy harvesting communication · Resource allocation · Heuristic algorithm

1 Introduction

Green communication is an attractive solution to improve the energy utilization efficiency of communication systems. Resource management strategies such as power control and resource allocation are effective measures to save energy, which can minimize the total transmission power and maximize the system throughput, respectively. In addition, energy harvesting communication is an emerging trend of green communication [1]. It can provide electrical energy for communication equipments by collecting renewable energy such as solar energy and wind energy from the surroundings, which can significantly reduce energy consumption.

Energy harvesting communication has recently attracted extensive research attention. The stochastic characteristic of energy harvesting was taken into account in [2]. An optimal power policy was proposed, which can maximize the average throughput under additive white Gaussian noise channel. The authors of

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[3] presented an optimum transmission policy under the constraints of the energy storage and the energy causality. It was shown that the proposed transmission policy could maximize the short-term throughput of an energy harvesting node. The optimal packet scheduling problem in a single-user communication scenario with an energy harvesting transmitter was investigated in [4]. The goal was minimize the transmission time by adaptively changing the transmission rate according to the traffic load and available energy. In [5], for single-user Gaussian channel and two-user Gaussian multiple access channel, two online algorithms for minimizing packet transmission time were developed, respectively. In two-hop communication systems with an energy harvesting source and a non-energy harvesting relay, the joint time scheduling and power allocation problem was discussed in [6]. The objectives of short-term throughput maximization and transmission time minimization were both taken into consideration. An optimal power allocation strategy was explored in energy harvesting and power grid coexisting wireless communication systems [7]. The optimization problem was formulated as minimizing the grid power consumption with random energy and data arrival. The optimal solution was obtained by the Lagrangian multiplier method.

However, there still exist a series of challenges for energy harvesting communication. Most renewable energy has a poor stability due to the weather and the climate, which will bring about serious effect on the communication system performance. Moreover, because the capacity of the existing energy storage device is limited, the restriction of limited energy should be taken into account. Wireless power transfer technology [8,9] can provide electrical power for communication equipments by harvesting energy from the electromagnetic wave. It is able to overcome the disadvantage of the renewable energy that is easily affected by the climate change, which is a promising solution to energy harvesting communication. Therefore, there is a strong motivation to investigate the resource allocation problem in the energy harvesting communication systems using wireless power transfer technology.

In this paper, we propose an energy-efficient resource allocation strategy in the energy harvesting communication systems. Specifically, an energy-efficient downlink resource allocation problem is investigated in the wireless power transfer systems. The objective is to maximize the energy efficiency under the constraints of the energy causality and the data rate requirement of each user. The formulated optimization problem is a mixed-integer nonlinear programming problem, which is difficult to derive the optimal solution. In order to degrade the computational complexity, a quantum-behaved particle swarm optimization (QPSO) algorithm is exploited to solve the optimization problem. A suboptimal solution is obtained with an acceptable complexity.

2 System Model and Problem Formulation

The network architecture of wireless power transfer systems is shown in Fig. 1. The scenario of one base station and multiple users are taken into account. The base station is provided with electrical energy by the traditional power grid.

Each user is equipped with an energy harvesting equipment, which can harvest energy from the eletromagnetic wave in the surrounding environment. When the base station sends data to an active user, other idle users can harvest energy from the received eletromagnetic wave. The collected energy is stored in the energy storage device, which is used to communicate with the base station at a certain time in the future.

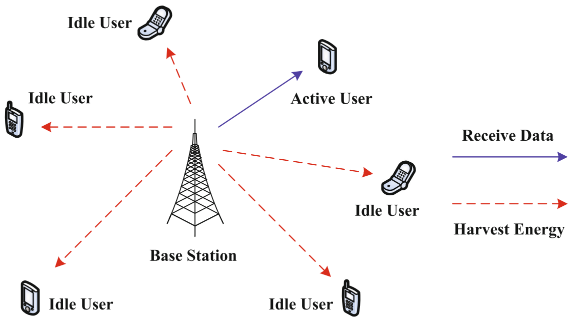

Fig. 1. Network architecture of wireless power transfer systems.

Energy-efficient downlink resource allocation problem is investigated in the above wireless power transfer systems. It is assumed that the base station sends data to K users by N sub-carriers during T time slots. Meanwhile, only one user can communicate with the base station at the t-th time slot, which is denoted by a binary variable $\delta_{t,k} \in \{0, 1\}$. Moreover, $p_{t,n,k}$ indicates the transmission power for the k-th user on the n-th sub-carrier at the t-th time slot. The system capacity can be obtained by the following expression:

$$C_{total} = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=1}^{K} \delta_{t,k} W \log_2 \left(1 + \frac{p_{t,n,k} h_{t,n,k}^2}{N_0 W} \right), \tag{1}$$

where W is the sub-carrier bandwidth, $h_{t,n,k}$ denotes the channel gain for the k-th user on the n-th sub-carrier at the t-th time slot, and N_0 represents the power spectral density of additive white Gaussian noise. At the same time, system energy consumption per second is shown as:

$$E_{total} = P_C + \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=1}^{K} \delta_{t,k} p_{t,n,k} - P_H, \tag{2}$$

where P_C denotes the circuit energy consumption per second and P_H indicates the energy harvested by idle users per second. The specific expression of P_H is denoted as:

$$P_H = \sum_{t=1}^{T} \sum_{n=1}^{N} \sum_{k=1}^{K} \delta_{t,k} p_{t,n,k} \left(\sum_{j \neq k} \eta h_{t,n,j}^2 \right), \tag{3}$$

where η indicates the energy harvesting efficiency of the idle user. Here, for simplicity, we assume that each idle user has the equal energy harvesting efficiency. Moreover, $h_{t,n,j}$ represents the channel gain for the j-th idle user on the n-th sub-carrier at the t-th time slot.

The objective of resource allocation problem is to maximize the energy efficiency while satisfying several constraint conditions. This is an optimization problem, which can be formulated as follows:

$$\underset{\delta_{t,k},p_{t,n,k}}{\text{maximize}} \frac{C_{total}}{E_{total}}, \tag{4a}$$

$$\text{C1}: \sum_{n=1}^{N}\sum_{k=1}^{K}\delta_{t,k}p_{t,n,k} \leq P_{\max}, \forall t, \tag{4b}$$

$$\text{C2}: \sum_{n=1}^{N}\sum_{j=1}^{K}\delta_{t,j}p_{t,n,j}\left(\eta h_{t,n,k}^{2}\right) \geq \left(1-\delta_{t,k}\right)P_{k}^{\min}, \forall t, k, \tag{4c}$$

$$\text{C3}: \sum_{t=1}^{T}\sum_{n=1}^{N}\delta_{t,k}W\log_2\left(1+\frac{p_{t,n,k}h_{t,n,k}^{2}}{N_0 W}\right) \geq R_{k}^{\min}, \forall k, \tag{4d}$$

$$\text{C4}: \delta_{t,k} \in \{0,1\}, \forall t, k, \tag{4e}$$

$$\text{C5}: \sum_{k=1}^{K}\delta_{t,k} \leq 1, \forall t, \tag{4f}$$

$$\text{C6}: p_{t,n,k} \geq 0, \forall t, n, k, \tag{4g}$$

where the objective function is the energy efficiency and its unit is bits per Joule (bits/J). The first constraint indicates that the total transmission power in the base station is limited to the maximum power $P_{\max}$. The second constraint ensures that the energy harvested by the k-th idle user at the t-th time slot is no less than the minimum value $P_k^{\min}$, which is called the energy causality. The third constraint guarantees that the data rate of the k-th user is greater than or equal to the minimum value $R_k^{\min}$. The fourth and fifth constraints show that the base station only sends data to one user at the t-th time slot. The sixth constraint reveals that the transmission power in the base station is non-negative. It is noted that the objective function is nonlinear. Besides, the values of $\delta_{t,k}$ and $p_{t,n,k}$ are discrete and continuous, respectively. As a consequence, the above optimization problem is a mixed-integer nonlinear programming problem.

3 Suboptimal Solution to Resource Allocation Optimization Problem

The optimization problem in (4) is quite difficult to obtain a globally optimal solution with a low computational complexity. Therefore, a heuristic algorithm is used to derive a suboptimal solution with an acceptable complexity.

The QPSO algorithm [10,11] is adopted to solve the optimization problem in (4). The QPSO algorithm is an improved version of the traditional PSO algorithm [12]. Compared with the PSO algorithm, it can achieve a globally suboptimal solution. The PSO algorithm is easy to fall into a locally optimal solution. The original constrained optimization problem needs to be transformed to an unconstrained form, which can be done by the penalty function method. Thus, a fitness function that consists of one objective function and one penalty function is constructed as follows:

$$F\left(\delta_{t,k}, p_{t,n,k}\right) = f\left(\delta_{t,k}, p_{t,n,k}\right) - \alpha P_f\left(\delta_{t,k}, p_{t,n,k}\right), \tag{5}$$

where $f\left(\delta_{t,k}, p_{t,n,k}\right)$ is the objective function, α denotes the penalty factor, and $P_f\left(\delta_{t,k}, p_{t,n,k}\right)$ indicates the penalty function that includes six items:

$$P_f\left(\delta_{t,k}, p_{t,n,k}\right) = P_f^1 + P_f^2 + P_f^3 + P_f^4 + P_f^5 + P_f^6. \tag{6}$$

They are corresponding to six constraints of the optimization problem in (4), which are shown as:

$$P_f^1 = \sum_{t=1}^{T}\left[\max\left(0, \sum_{n=1}^{N}\sum_{k=1}^{K}\delta_{t,k}p_{t,n,k} - P_{\max}\right)\right]^2, \tag{7a}$$

$$P_f^2 = \sum_{t=1}^{T}\sum_{k=1}^{K}\left[\max\left(0, A\right)\right]^2, \tag{7b}$$

$$P_f^3 = \sum_{k=1}^{K}\left[\max\left(0, B\right)\right]^2, \tag{7c}$$

$$P_f^4 = \sum_{t=1}^{T}\sum_{k=1}^{K}\left(\delta_{t,k}^2 - \delta_{t,k}\right)^2, \tag{7d}$$

$$P_f^5 = \sum_{t=1}^{T}\left[\max\left(0, \sum_{k=1}^{K}\delta_{t,k} - 1\right)\right]^2, \tag{7e}$$

$$P_f^6 = \sum_{t=1}^{T}\sum_{n=1}^{N}\sum_{k=1}^{K}\left[\max\left(0, -p_{t,n,k}\right)\right]^2, \tag{7f}$$

where $\max\left(\cdot,\cdot\right)$ returns a greater number between two numbers. Moreover, for the A and B in P_f^2 and P_f^3, their expressions are given as:

$$A = \left(1 - \delta_{t,k}\right)P_k^{\min} - \sum_{n=1}^{N}\sum_{j=1}^{K}\delta_{t,j}p_{t,n,j}\left(\eta h_{t,n,k}^2\right), \tag{8}$$

$$B = R_k^{\min} - \sum_{t=1}^{T}\sum_{n=1}^{N}\delta_{t,k}W\log_2\left(1 + \frac{p_{t,n,k}h_{t,n,k}^2}{N_0 W}\right). \tag{9}$$

In order to apply the QPSO algorithm to the formulated optimization problem, resource allocation results of K users are defined as the particle position. We assume that there are M particles in the multi-dimensional space. For the m-th particle, its position vector $\mathbf{X}_m$ can be expressed as:

$$\mathbf{X}_m = \left(\mathbf{X}_m^1, \mathbf{X}_m^2, ..., \mathbf{X}_m^k, ..., \mathbf{X}_m^K\right), \tag{10}$$

where $\mathbf{X}_m^k$ denotes the resource allocation result of the k-th user. The specific expression of $\mathbf{X}_m^k$ is shown as:

$$\mathbf{X}_m^k = \left(\delta_{1,k}, \delta_{2,k}, ..., \delta_{T,k}, p_{1,1,k}, p_{1,2,k}, ..., p_{T,N,k}\right). \tag{11}$$

It can be seen that $\mathbf{X}_m^k$ is a multi-dimensional vector. The first T elements indicate the time slot allocation result. The rest TN elements denote power allocation result on different sub-carriers at different time slots.

The position of each particle is updated according to the following iterative equation:

$$\begin{cases} \mathbf{X}_m(s+1) = \mathbf{P} + \beta \left|\mathbf{C}(s) - \mathbf{X}_m(s)\right| \cdot \ln\left(1/u\right), \ r \geq 0.5 \\ \mathbf{X}_m(s+1) = \mathbf{P} - \beta \left|\mathbf{C}(s) - \mathbf{X}_m(s)\right| \cdot \ln\left(1/u\right), \ r < 0.5 \end{cases}, \tag{12}$$

where s denotes the iteration number and the maximum iteration number is S, β is the contraction-expansion coefficient, u and r are both random numbers between 0 and 1, and $\mathbf{C}(s)$ is the mean best position. The value of β in the s-th iteration can be calculated by:

$$\beta = 0.5\frac{S-s}{S} + 0.5. \tag{13}$$

In addition, $\mathbf{C}(s)$ can be obtained by:

$$\mathbf{C}(s) = \frac{1}{M}\sum_{m=1}^{M} \mathbf{P}_m(s), \tag{14}$$

where $\mathbf{P}_m(s)$ is the best position of the m-th particle in the s-th iteration. Based on the fitness function in (5), $\mathbf{P}_m(s)$ can be derived by:

$$\mathbf{P}_m(s) = \begin{cases} \mathbf{X}_m(s), F\left[\mathbf{X}_m(s)\right] > F\left[\mathbf{P}_m(s-1)\right] \\ \mathbf{P}_m(s-1), F\left[\mathbf{X}_m(s)\right] \leq F\left[\mathbf{P}_m(s-1)\right] \end{cases}. \tag{15}$$

Moreover, the vector $\mathbf{P}$ in (12) is given by the following expression:

$$\mathbf{P} = \varphi \cdot \mathbf{P}_m(s) + (1-\varphi) \cdot \mathbf{G}(s), \tag{16}$$

where φ is a random number between 0 and 1, and $\mathbf{G}(s)$ denotes the global best position of all the particles in the s-th iteration. $\mathbf{G}(s)$ can be obtained by:

$$\begin{cases} \xi = \arg \max\limits_{1 \leq m \leq M} \left\{F\left[\mathbf{P}_m(s)\right]\right\} \\ \mathbf{G}(s) = \mathbf{P}_\xi(s) \end{cases}. \tag{17}$$

4 Simulation Results and Analysis

In this section, the performance of the proposed resource allocation strategy is evaluated by simulation. The related parameters are set as $T = 5$, $N = 32$, $W =$ 15 kHz, $N_0 = 2 \times 10^{-8}$ W/Hz, $P_C = 5$ W, $\alpha = 1.5$, and $S = 10$. Without loss of generality, we assume that the values of $P_k^{\min}$ and $R_k^{\min}$ are 0.1 W and 1 Mbps, respectively. Moreover, the values of different $h_{t,n,k}$ are generated by random numbers with uniform distribution between 0 and 1. In addition, an existing resource allocation algorithm based on particle swarm optimization (PSO) [12] is used for comparison.

Figure 2 presents the relationship between the energy efficiency and the number of particles for different numbers of users under QPSO and PSO algorithms. It can be observed that the energy efficiency increases gradually as the number of particles increases. The reason is that more accurate suboptimal solution can be obtained under more particles. Moreover, for the QPSO algorithm, the energy efficiency increases with the growth of the number of users. This is because more idle users can harvest the energy from the received electromagnetic wave. In addition, the QPSO algorithm has a higher energy efficiency than the PSO algorithm under the same number of users. It can be explained that the QPSO algorithm can obtain a globally suboptimal solution while the PSO algorithm is easy to fall into a locally optimal solution.

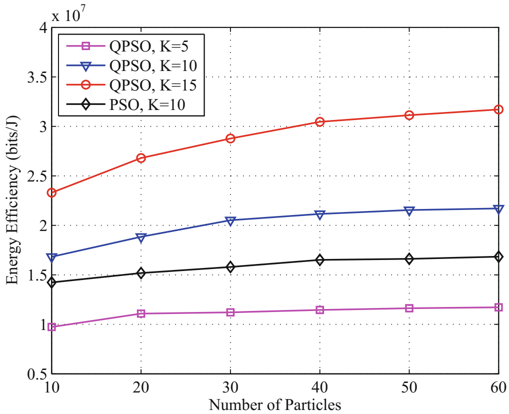

Fig. 2. Energy efficiency versus number of particles with $\eta = 0.1$ and $P_{\max} = 10$ W.

Figure 3 depicts the relationship between the energy efficiency and the number of particles for different energy harvesting efficiency under QPSO and PSO algorithms. For the QPSO algorithm, we can see that the energy efficiency grows with the increase of the energy harvesting efficiency from 0.1 to 0.5. That is because idle users can harvest more energy from the received eletromagnetic wave. Additionally, the QPSO algorithm with $\eta = 0.1$ outperforms the PSO algorithm with $\eta = 0.3$. The reason is that the QPSO algorithm can effectively avoid searching the solution in a local area to a great degree.

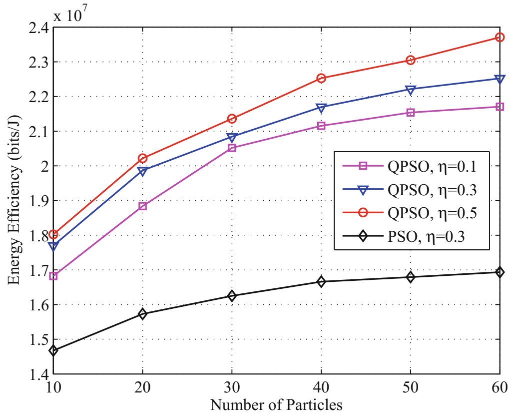

Fig. 3. Energy efficiency versus number of particles with $K = 10$ and $P_{\max} = 10$ W.

Figure 4 illustrates the relationship between the energy efficiency and the number of users for different energy harvesting efficiency under QPSO and PSO algorithms. We can find that the energy efficiency rises up as the number of users increases. That is because more idle users can harvest the energy from the received electromagnetic wave. Furthermore, although $\eta = 0.1$, the QPSO algorithm has a better performance in terms of the energy efficiency than the PSO algorithm with $\eta = 0.3$. The reason is that the PSO algorithm cannot obtain a globally suboptimal solution.

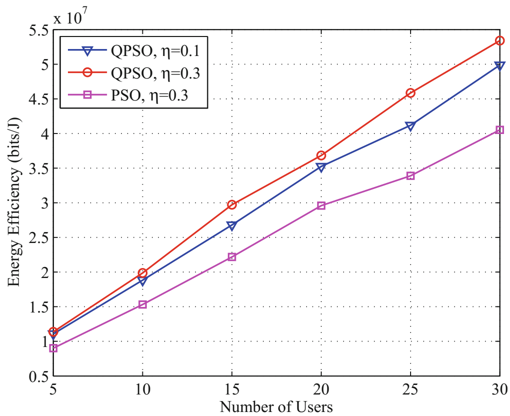

Fig. 4. Energy efficiency versus number of users with $M = 20$ and $P_{\max} = 10$ W.

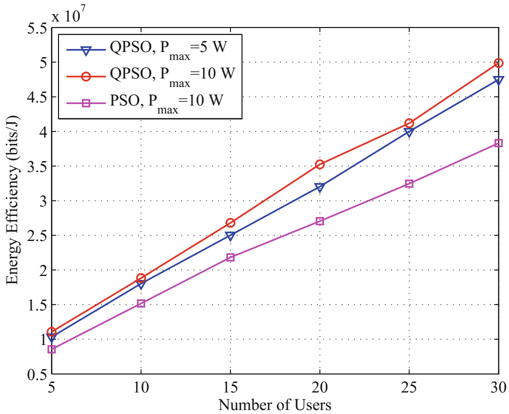

Fig. 5. Energy efficiency versus number of users with $\eta = 0.1$ and $M = 20$.

Figure 5 shows the relationship between the energy efficiency and the number of users for different the maximum power under QPSO and PSO algorithms. It can be seen that the energy efficiency increases with the growth of the maximum power under the QPSO algorithm. It can be explained that the active user can send signal with a higher power. Thus, a higher system capacity can be obtained. At the same time, all the idle users can harvest more energy. In addition, the QPSO algorithm with $P_{\max} = 5$ W has a better performance than the PSO algorithm with $P_{\max} = 10$ W. This is because the QPSO algorithm can overcome the disadvantage of the PSO algorithm to a large extent.

5 Conclusion

In this paper, an energy-efficient resource allocation problem based on QPSO algorithm was presented in the wireless power transfer systems. The resource allocation problem was formulated as a mixed-integer nonlinear programming problem. The objective was to maximize the energy efficiency under the constraints of the energy causality and the data rate requirement of each user. Moreover, the suboptimal solution to the formulated optimization problem was derived by introducing the QPSO algorithm. The proposed resource allocation strategy has a higher energy efficiency by the simulation evaluation. For simplicity, we assume that the base station only sends data to one user at one time slot. Multiple users can be provided service at the same time in the practical communication systems, which will be taken into account in future work.

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