Energy Efficiency Optimization for Energy-Harvesting Massive MIMO Systems (Postprint)

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Abstract

This paper investigates the energy efficiency optimization problem for energy harvesting-based massive multiple-input multiple-output (MIMO) systems. Subject to constraints of guaranteeing user quality of service, power beacon transmit power limitations, and energy harvesting time, we jointly optimize the power beacon transmit power and energy harvesting time to maximize the energy efficiency of uplink massive MIMO systems. This problem is a non-convex optimization problem. First, the original optimization problem is equivalently transformed through fractional programming theory. Then, adopting the block coordinate descent (BCD) method, we iteratively solve for the power beacon transmit power, energy harvesting time, and system energy efficiency, and propose a joint optimization energy efficiency algorithm for energy harvesting-based massive MIMO systems (energy-efficient power and time allocation algorithm, EPTA). Simulation results show that, while guaranteeing user quality of service, compared with the time-averaged minimum QoS guaranteed algorithm (TA-QoSA) and the throughput maximization based power and time algorithm (TPTA), this algorithm improves system energy efficiency.

Full Text

Energy-Efficient Optimization of Massive MIMO Systems with Energy Harvesting

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Abstract

This paper investigates the energy efficiency optimization problem for massive multiple-input multiple-output (MIMO) systems with energy harvesting. Under constraints of user quality of service (QoS), power beacon transmit power limitations, and energy harvesting time, we jointly optimize the power beacon' s transmit power and energy harvesting time to maximize the energy efficiency of uplink massive MIMO systems. This problem is a non-convex optimization problem. First, we transform the original optimization problem into an equivalent form using fractional programming theory. Then, we propose an energy-efficient power and time allocation algorithm (EPTA) based on the block coordinate descent (BCD) method to iteratively solve for the power beacon' s transmit power, energy harvesting time, and system energy efficiency. Simulation results show that, compared with the time-averaged minimum QoS guaranteed algorithm (TA-QoSA) and the throughput maximization based power and time algorithm (TPTA), the proposed algorithm improves system energy efficiency while guaranteeing user QoS.

Key Words: massive Multiple-Input Multiple-Output; energy harvesting; energy efficiency; fractional programming; convex optimization

0 Introduction

In recent years, with the rapid development of human society and severe resource scarcity, wireless power transfer (WPT) has attracted significant attention in wireless research. Unlike traditional wired power sources, sensor nodes harvest energy from electromagnetic radiation to extend the lifetime of energy-constrained networks or devices. WPT can be applied in many extreme conditions, such as underwater environments, deserts, and body area networks. In medical applications, implanted devices can conveniently harvest energy from external sources through WPT technology. In wireless sensor nodes for intelligent transportation, aircraft, and Internet of Things applications, WPT extends battery life. Recently, applying WPT to cellular systems has eliminated the need for power cords and chargers for mobile devices, and radio frequency (RF) signal-based wireless power transfer has generated considerable interest in the scientific community. Information and energy can be transmitted simultaneously via RF signals, and transmission power can be flexibly increased to improve reception quality.

However, several challenges must be addressed to implement WPT. Compared with traditional wireless information transmission, WPT exhibits both similarities and differences. First, both suffer performance degradation due to channel fading and path loss. Second, the received power levels suitable for wireless information transmission are not applicable for energy transfer, and energy harvesting is more sensitive than information decoding. Furthermore, energy transfer distance is shorter than wireless information transmission distance. Recently, in conventional wireless information transmission, massive multiple-input multiple-output (MIMO) technology with hundreds of antennas at the base station can improve fading channel performance. Multi-antenna technology uses spatial beamforming to adapt transmitted signals to channel states and leverages channel fading to enhance performance. Similarly, in wireless power transfer, multi-antenna technology can align RF signals with power receivers to improve energy efficiency. Multi-antenna technology has become a leading 5G wireless communication technology that can simultaneously support multiple information streams and energy transfer, providing better data rates and energy efficiency than current systems, and can significantly enhance WPT performance.

Based on the above analysis, our system model differs from existing literature. We consider both single-antenna power beacons and multi-antenna base stations in a typical uplink multi-user wireless communication system with multiple sensor nodes, assuming perfect channel state information (CSI). The sensor network and power beacon share the same deployment authority. During system operation, multiple sensor nodes harvest energy from the power beacon, then use the harvested energy to communicate with the multi-antenna base station. Unlike previous work that employs zero-forcing (ZF) reception and ignores large-scale fading effects, this paper adopts ZF reception while considering large-scale fading impacts. Under constraints of user QoS and power beacon transmit power, we establish an optimization model to maximize system energy efficiency. According to fractional programming properties, we transform the original fractional optimization problem into a subtractive form and then convert it into a convex optimization problem. By jointly adjusting the power beacon’ s transmit power and sensors’ energy harvesting time, we optimize the energy efficiency function. Since closed-form expressions for optimal power allocation and energy harvesting time cannot be obtained, we employ the bisection method and convex optimization interior-point method to find feasible numerical solutions for the optimization problem, deriving the power beacon’ s transmit power and sensors’ energy harvesting time that maximize energy efficiency. Simulation results demonstrate that the proposed algorithm improves system energy efficiency while guaranteeing user QoS and maintains good throughput performance for the entire system.

1 System Model and Problem Description

We consider a typical uplink multi-user wireless communication system consisting of a multi-antenna base station, a power beacon, and K geographically distributed sensor nodes, as shown in [Figure 1: see original paper]. The base station is equipped with M antennas, while the power beacon and sensors each have a single antenna. All sensor nodes can communicate directly with the base station. In a Rayleigh fading channel, we assume the base station has perfect CSI and employs ZF reception.

We adopt the harvest-then-transmit protocol. Without loss of generality, we assume each time slot has unit length, divided into two parts: (a) in the first portion of duration τ, the power beacon transmits energy to sensor nodes for harvesting; (b) in the second portion of duration $1-\tau$, sensor nodes use all harvested energy to transmit information to the base station. The total power transmitted by the power beacon through broadcasting is P.

During the energy harvesting time τ in the first part, the energy harvested by the k-th sensor node is

$$E_k = \xi_k g_k P \tau, \quad k = 1, 2, \dots, K$$

where g_k is the channel gain from the power beacon to the k-th sensor node, and we assume the base station has complete information about all g_k (which can be obtained using pilot training signals). ξ_k is the energy conversion efficiency of the k-th sensor node ($0 < \xi_k < 1$). The second part is divided into $(1-\tau)$, and each sensor node fully consumes the energy harvested during the first part when transmitting data to the base station in the second part of its time slot. Therefore, the transmission power of the k-th sensor in the second part $(1-\tau)$ is

$$P_k = \frac{E_k}{1-\tau} = \frac{\xi_k g_k P \tau}{1-\tau}, \quad k = 1, 2, \dots, K$$

Since the data throughput of the k-th sensor node at the base station is

$$D_k(P,\tau) = (1-\tau)\log_2\left(1 + \frac{\beta_k (M-K) P_k}{\sigma^2}\right), \quad k = 1, 2, \dots, K$$

where β_k is the large-scale fading factor of the k-th sensor. In the throughput expression, we assume Gaussian noise has zero mean and variance σ^2. Substituting equation (1) into equation (3), the total throughput of K sensors is

$$D(P,\tau) = \sum_{k=1}^{K} D_k(P,\tau) = (1-\tau)\sum_{k=1}^{K}\log_2\left(1 + \frac{\xi_k \beta_k g_k (M-K) P \tau}{(1-\tau)\sigma^2}\right)$$

The energy efficiency of the uplink multi-user massive MIMO system is

$$\eta(P,\tau) = \frac{D(P,\tau)}{P_c + P}$$

where P_c represents the total circuit power consumption of the entire system, including all circuit modules along the signal transmission path such as A/D converters, D/A converters, frequency synthesizers, mixers, power amplifiers, etc.

The energy efficiency optimization problem can be formulated as

$$\begin{aligned}\max_{P,\tau}\quad & \eta(P,\tau)=\frac{(1-\tau)\sum_{k=1}^{K}\log_2\left(1+\frac{\xi_k\beta_k g_k(M-K)P\tau}{(1-\tau)\sigma^2}\right)}{P_c+P}\\ \text{s.t.}\quad & \gamma_k(P,\tau)\geq\gamma_k^{\min},\quad k=1,2,\dots,K\\ & 0\leq P\leq P_{\max}\\ & 0\leq\tau\leq 1\end{aligned}$$

where $P_{\max}$ is the maximum transmit power of the power beacon, and $\gamma_k^{\min}$ is the minimum signal-to-interference-plus-noise ratio (SINR) required for the QoS guarantee of the k-th sensor.

2 Energy-Efficient Resource Allocation for Massive MIMO Systems with Energy Harvesting

Equation (8) presents the system energy efficiency optimization problem. The objective of this section is to design an effective algorithm to find the power beacon transmission power value P and sensor energy harvesting time value τ that maximize energy efficiency. Substituting equation (7) into equation (8) yields

$$\max_{P,\tau}\quad \eta(P,\tau)=\frac{(1-\tau)\sum_{k=1}^{K}\log_2\left(1+\frac{\xi_k\beta_k g_k(M-K)P\tau}{(1-\tau)\sigma^2}\right)}{P_c+P}$$

The objective function in equation (9) is in the form of a ratio of two functions, which can be regarded as a standard fractional programming problem. According to literature [13], fractional programming problems can be equivalently transformed into a set of subtractive-form optimization problems containing an energy efficiency parameter, where the optimal energy efficiency of the original fractional programming problem is the zero point of the transformed optimization problem. First, for the subtractive-form optimization problem with fixed energy efficiency, we adopt the Block Coordinate Descent (BCD) method [14] and convex optimization methods to jointly optimize transmit power and energy harvesting time. Then, based on the Dinkelbach method [14], we update the energy efficiency parameter until the algorithm converges. Thus, we propose a joint optimization energy efficiency algorithm for transmit power and energy harvesting time.

Let η^* denote the optimal energy efficiency of the system, and P^* and τ^* denote the transmit power and energy harvesting time that achieve maximum energy efficiency. Therefore, the objective function (9) can be transformed into

$$F(q)=\max_{P,\tau}\left[D(P,\tau)-q(P_c+P)\right]$$

where q is the energy efficiency parameter. The optimal solution (P^*,τ^*) satisfies

$$F(q^*) = D(P^*, \tau^*) - q^*(P_c + P^*) = 0$$

Thus, the original problem can be converted to

$$\begin{aligned} \max_{P,\tau} \quad & D(P,\tau) - q(P_c + P) \\ \text{s.t.} \quad & \gamma_k(P,\tau) \geq \gamma_k^{\min}, \quad k = 1, 2, \dots, K \\ & 0 \leq P \leq P_{\max} \\ & 0 \leq \tau \leq 1 \end{aligned}$$

The objective function has two optimization variables. We adopt the BCD method. For a given initial variable τ, we first fix the time τ and iteratively optimize power P to obtain a suboptimal solution for P. Then, with fixed power P, we iteratively optimize time τ to obtain a suboptimal solution for τ. This process is repeated until convergence, which is known as the BCD method.

a) Fix τ, solve for P. For a given τ, the optimal power beacon transmit power can be expressed as

$$P^* = \arg \max_{0 \leq P \leq P_{\max}} \left[D(P,\tau) - q(P_c + P)\right]$$

Taking the first derivative with respect to P:

$$\frac{\partial \Psi(P,q,\tau)}{\partial P} = \frac{(1-\tau)}{\ln 2} \sum_{k=1}^{K} \frac{\xi_k \beta_k g_k (M-K)\tau}{(1-\tau)\sigma^2 + \xi_k \beta_k g_k (M-K) P \tau} - q$$

Setting the derivative to zero yields the stationary point. Taking the second derivative with respect to P:

$$\frac{\partial^2 \Psi(P,q,\tau)}{\partial P^2} = -\frac{(1-\tau)}{\ln 2} \sum_{k=1}^{K} \frac{(\xi_k \beta_k g_k (M-K)\tau)^2}{[(1-\tau)\sigma^2 + \xi_k \beta_k g_k (M-K) P \tau]^2} < 0$$

Since $\Psi(P,q,\tau)$ is a convex function of P, to guarantee user QoS, the solution can be expressed as

$$P^* = \max\left\{P_{\min}, \min\left\{P_{\max}, \tilde{P}\right\}\right\}$$

where $\tilde{P}$ is the solution to $\frac{\partial \Psi(P,q,\tau)}{\partial P} = 0$, and $P_{\min} = \max_k \frac{\gamma_k^{\min} \sigma^2 (1-\tau)}{\xi_k \beta_k g_k (M-K)\tau}$.

b) Fix P, solve for τ. For a given P, the optimal sensor energy harvesting time can be expressed as

$$\tau^* = \arg\max_{0\le\tau\le1} [D(P,\tau) - q(P_c + P)]$$

Taking the first derivative with respect to τ:

$$\frac{\partial\Psi(P,q,\tau)}{\partial\tau} = -\sum_{k=1}^{K}\log_2\left(1+\frac{\xi_k\beta_k g_k(M-K)P\tau}{(1-\tau)\sigma^2}\right)+\frac{(1-\tau)}{\ln 2}\sum_{k=1}^{K}\frac{\xi_k\beta_k g_k(M-K)P}{(1-\tau)\sigma^2+\xi_k\beta_k g_k(M-K)P\tau}$$

Taking the second derivative with respect to τ:

$$\frac{\partial^2\Psi(P,q,\tau)}{\partial\tau^2} = -\frac{2}{\ln 2}\sum_{k=1}^{K}\frac{\xi_k\beta_k g_k(M-K)P\sigma^2}{[(1-\tau)\sigma^2+\xi_k\beta_k g_k(M-K)P\tau]^2} < 0$$

Since $\Psi(P,q,\tau)$ is a convex function of τ, to guarantee user QoS, we consider two cases:

Case 1: When $\tau = 0$ or $\tau = 1$, the objective function value is zero, which is discarded.

Case 2: When $0 < \tau < 1$. We use the bisection method to find τ^*.

Using the Dinkelbach method from literature [14], we propose a novel iterative approach to maximize function F by jointly optimizing P and τ.

Algorithm: Energy-Efficient Power and Time Allocation Algorithm (EPTA)

1. **Initialization:** Set maximum iteration number $T_{\max}$ and maximum tolerance factor ε, initial energy efficiency value q, power beacon transmit power P, sensor energy harvesting time τ, and other system parameters. Set iteration counter $T = 0$.
2. **Repeat:**
3. For a given q and P, use the bisection method to solve equation (15) to obtain the sensor energy harvesting time τ.
4. For the obtained τ, substitute into P and use convex optimization interior-point method to solve equation (12) to obtain the power beacon transmit power P.
5. **Check termination condition:**
    - If $|F(q^{(T)})| \le \varepsilon$, set convergence = true and return.
    - Otherwise, set convergence = false.
6. **Until** convergence = true or $T = T_{\max}$.

3 Simulation Results and Analysis

This chapter presents simulations of the proposed EPTA algorithm and compares it with the time-averaged minimum QoS guaranteed algorithm (TA-QoSA) [15] and the throughput maximization based power and time algorithm (TPTA) [16]. TA-QoSA equally divides energy harvesting time and information transmission time while guaranteeing minimum QoS, minimizing total transmit power. TPTA jointly optimizes power beacon transmit power P and sensor energy harvesting time τ to maximize system throughput. The simulation environment was built on a Windows 10 computer using MATLAB 2015a (32-bit) software. Relevant system parameters are set as follows: base station and power beacon coordinates are located at $(-20, 0)$ m and $(20, 0)$ m, respectively. Sensors are randomly distributed in a $[-10, 10] \times [-10, 10]$ m rectangular area. Channel gains from the power beacon to the k-th sensor node and from the k-th sensor node to the base station are modeled as $g_k = d_k^{-3}$ and $\beta_k = d_k^{-3}$, where d_k represents the distance from the k-th sensor to the power beacon and base station, respectively. Background noise variance is $\sigma^2 = 10^{-10}$ W, energy conversion efficiency is $\xi = 0.6$, circuit power consumption is $P_c = 0.5$ dBm, and the number of base station antennas is $M = 100$. Simulation results are obtained by averaging over 10^3 independent channel realizations. The number of sensors is set to 9 for Figures 2-4, and $P_{\max}$ is set to 30 dBm for Figures 5 and 6.

[Figure 2: see original paper] shows the convergence performance of the proposed EPTA algorithm under three different values of power beacon maximum transmit power. The results demonstrate that the algorithm converges quickly within a few iterations. In all three considered scenarios, the algorithm converges to the optimal value within 5 iterations, and the fast convergence speed meets the requirements of real-time communication.

[Figure 3: see original paper] compares the energy efficiency performance of the three algorithms under different maximum transmit power $P_{\max}$ values. When $P_{\max} \leq 20$ dBm, the energy efficiency of both the proposed EPTA algorithm and TPTA algorithm improves significantly with increasing $P_{\max}$, and their performance is relatively close. However, when $P_{\max} \geq 20$ dBm, the gap between EPTA and TPTA gradually widens because EPTA optimizes energy efficiency while TPTA optimizes system throughput. When $P_{\max} \geq 35$ dBm, the EPTA algorithm gradually converges, indicating that the optimal transmit power of the power beacon is $P^* = P_{\max} = 35$ dBm. At this point, the transmit power P has reached its optimal value P^*, and further increasing the maximum transmit power will not improve energy efficiency. Conversely, if $P_{\max}$ continues to increase, the power beacon using $P_{\max}$ as the transmit power will actually decrease energy efficiency. When $P_{\max} = 25$ dBm, TPTA' s energy efficiency reaches its optimum and then gradually declines because TPTA' s optimization target is system throughput, not energy efficiency. For TA-QoSA, with a fixed number of sensors and under minimum QoS guarantees, all parameters remain constant, so system energy efficiency stays unchanged. When $P_{\max} = 35$ dBm, the energy efficiency of EPTA is 2.6 times that of TA-QoSA and 66% higher than TPTA.

[Figure 4: see original paper] compares the throughput performance of the three algorithms under different maximum transmit power $P_{\max}$ values. When $P_{\max} \leq 20$ dBm, the performance of EPTA and TPTA is relatively close. When $P_{\max} \geq 20$ dBm, the throughput of EPTA gradually converges to a constant value. Throughout the process, TPTA's throughput continues to increase, while TA-QoSA' s throughput remains constant for the same reasons as explained in Figure 3.

[Figure 5: see original paper] and [Figure 6: see original paper] compare the energy efficiency and throughput performance of the three algorithms under different numbers of sensors. As the number of sensors increases, the system energy efficiency and throughput of all three algorithms gradually improve. In terms of energy efficiency: EPTA > TPTA > TA-QoSA. In terms of throughput: TPTA > EPTA > TA-QoSA. When the number of sensors is 20, EPTA' s energy efficiency is twice that of TA-QoSA and 51% higher than TPTA. Although EPTA optimizes system energy efficiency and TPTA optimizes system throughput, EPTA achieves good energy efficiency performance while maintaining satisfactory system throughput.

4 Conclusion

This paper studied the energy-efficient resource allocation for uplink multi-user massive MIMO systems with energy harvesting. With perfect CSI at the transmitter and ZF reception, and under constraints of power beacon transmit power and user QoS guarantees, we maximized system energy efficiency by optimizing the power beacon' s transmit power and sensor energy harvesting time. Using fractional programming properties, we transformed the original fractional optimization problem into subtractive form and converted it into a convex optimization problem. We then proposed an effective iterative algorithm using the bisection method and convex optimization interior-point method. Simulation results demonstrate that the proposed algorithm achieves superior energy efficiency performance. Since this work considers energy-efficient resource allocation under perfect CSI, future work will focus on proposing resource allocation algorithms based on imperfect CSI.

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Note: Figure translations are in progress. See original paper for figures.