Energy Efficiency Optimization for Heterogeneous Small Cell Networks Based on Simultaneous Wireless Information and Power Transfer (Postprint)

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Abstract

This paper investigates the energy efficiency optimization problem for simultaneous wireless information and power transfer (SWIPT) in heterogeneous small cell networks. To maximize the downlink energy efficiency of the small cell system under constraints guaranteeing the communication quality of small cell users and macro users, energy harvesting of small cell users, and transmission power of small cell base stations, joint optimization of the transmit power of small cell base stations and the power splitting coefficient at small cell user ends is conducted. This problem is a non-convex optimization problem, which is equivalently transformed through variable substitution and then solved using a subgradient algorithm based on Lagrange multipliers. Computer simulation results demonstrate that the joint optimization algorithm is simple and effective.

Full Text

Energy Efficiency Optimization of Heterogeneous Small Cellular Networks with Simultaneous Wireless Information and Power Transfer

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Abstract: This paper investigates the energy efficiency optimization problem in heterogeneous small cellular networks with simultaneous wireless information and power transfer (SWIPT). Under constraints guaranteeing the communication quality of small cell users and macro users, energy harvesting requirements at small cell users, and transmission power limits at small cell base stations, we jointly optimize the transmit power at small cell base stations and the power splitting coefficients at user terminals to maximize the downlink energy efficiency of the small cell system. This problem belongs to the class of non-convex optimization problems. We first perform an equivalent transformation through variable substitution, then solve it using a subgradient algorithm based on Lagrange multipliers. Computer simulation results demonstrate that the proposed joint optimization algorithm is simple and effective.

Keywords: simultaneous wireless information and power transfer; heterogeneous small cellular network; energy efficiency; power splitting; convex optimization

0 Introduction

With the rapid development of mobile Internet and Internet of Things, communication network energy consumption is escalating dramatically. To address the energy limitation of mobile terminals, SWIPT has attracted widespread attention from academia and industry. Currently, SWIPT typically utilizes electromagnetic radiation, which can serve as both an information carrier for wireless information transmission and an energy carrier for wireless power transfer, with minimal interference from external conditions.

Since a single receiver cannot simultaneously perform energy harvesting and information reception in SWIPT systems, two receiver architectures have emerged: a separated structure where information receivers and energy receivers use different antennas, and a co-located receiver structure employing time-switching (TS) and power-splitting (PS) with a shared antenna. The latter can be implemented with smaller physical dimensions, making it more practical for mobile devices. This study adopts the power-splitting-based shared antenna receiver architecture, where the received signal is split into two independent streams for energy harvesting and information decoding respectively.

Extensive research has been conducted on SWIPT, evolving from initial studies on point-to-point single-antenna systems to current investigations of multi-antenna systems. However, the core challenge remains balancing information decoding and energy harvesting, with most work focusing on throughput, transmission power, and terminal energy harvesting. Studies on SWIPT system energy efficiency remain limited. Ng et al. investigated energy efficiency based on resource allocation in point-to-point single-antenna OFDM SWIPT systems, proposing an effective resource allocation iterative algorithm using the Dinkelbach method to handle the coupling between carrier power allocation and power splitting coefficients. Sudha et al. studied downlink resource allocation in SWIPT-enabled two-tier heterogeneous small cellular networks, considering both time-switching and power-splitting schemes, and jointly optimized throughput and energy harvesting rates for small cell users while guaranteeing macro user communication quality. Building upon this, Sheng et al. considered a two-tier multiple-input single-output (MISO) heterogeneous model with multiple small cells attached to a macro cell, where information receivers and energy receivers obtain information and harvest energy through separate information and energy channels.

Unlike previous works, this paper studies downlink resource allocation in MISO SWIPT heterogeneous small cellular networks. Under constraints ensuring communication quality for both small cell and macro users, energy harvesting at small cell users, and transmission power limits at small cell base stations, we jointly optimize the transmit beamforming vectors at small cell base stations and the power splitting coefficients at user terminals to maximize downlink energy efficiency. To make the problem mathematically tractable, we first perform an equivalent transformation through variable substitution, then solve it using a subgradient algorithm based on Lagrange multipliers.

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1 System Model

We investigate downlink data and energy transmission in a large-scale multiple-input single-output small cell system co-channel deployed on a conventional macrocell, as illustrated in [Figure 1: see original paper]. In the figure, solid lines represent desired signals while dashed lines represent interference signals. The small cell base station is equipped with N antennas serving K single-antenna small cell users and one single-antenna macro user, all with passive antennas. The downlink channel from the small cell base station to small cell users is modeled as Rician fading and operates in time-division duplex (TDD) mode.

The complex baseband signal transmitted by the base station is expressed as

$$\mathbf{x} = \sum_{k=1}^{K} \mathbf{v}_k s_k$$

where $\mathbf{v}_k \in \mathbb{C}^{N\times 1}$ denotes the transmit beamforming vector for small cell user k, and s_k represents the corresponding data symbol. Assuming flat fading channels between the small cell base station and users, the channel is denoted as $\mathbf{h}_k \in \mathbb{C}^{N\times 1}$. Under ideal conditions, s_k are independent and identically distributed circularly symmetric complex Gaussian random variables satisfying $s_k \sim \mathcal{CN}(0, 1)$. The signal received by small cell user k before power splitting is

$$y_k = \mathbf{h}_k^H \mathbf{x} + \varepsilon_k + n_k$$

where $\varepsilon_k \sim \mathcal{CN}(0, \sigma_{\varepsilon,k}^2)$ represents interference from the macro base station, and $n_k \sim \mathcal{CN}(0, \sigma_{n,k}^2)$ denotes receiver antenna noise. The receiver employs a power splitter to divide the received signal, with a fraction ρ_k $(0 < \rho_k < 1)$ used for information decoding and the remaining portion for energy harvesting.

The signal for information decoding at user k can be expressed as

$$y_k^{ID} = \sqrt{\rho_k}\left(\mathbf{h}_k^H\mathbf{v}_k s_k + \sum_{j\neq k}\mathbf{h}_k^H\mathbf{v}_j s_j + \varepsilon_k + n_k\right) + z_k$$

where $z_k \sim \mathcal{CN}(0, \delta_k^2)$ represents additional noise introduced by information decoding. The signal-to-interference-plus-noise ratio (SINR) is

$$\mathrm{SINR}_k = \frac{\rho_k|\mathbf{h}_k^H\mathbf{v}_k|^2}{\rho_k\left(\sum_{j\neq k}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2\right) + \delta_k^2}$$

The signal for energy harvesting at small cell user k is

$$y_k^{EH} = \sqrt{1-\rho_k}\left(\mathbf{h}_k^H\mathbf{v}_k s_k + \sum_{j\neq k}\mathbf{h}_k^H\mathbf{v}_j s_j + \varepsilon_k + n_k\right)$$

Notably, the noise introduced during energy harvesting is uncontrollable and negligible due to its small magnitude. The harvested energy at small cell user k can be expressed as

$$E_k = \zeta_k(1-\rho_k)\left(\sum_{j=1}^{K}|\mathbf{h}_k^H\mathbf{v}_j|^2 + \sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2\right)$$

where $\zeta_k \in (0,1]$ denotes the conversion efficiency from RF signals to DC power.

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2 Optimization Problem Formulation

This study aims to maximize the energy efficiency of the downlink MISO SWIPT heterogeneous small cell system. Energy efficiency is defined as the ratio of the downlink sum rate to the total energy consumption at the small cell base station, representing the number of bits transmitted per unit energy. From the SINR expression, the rate of small cell user k is

$$R_k = \log_2(1 + \mathrm{SINR}_k)$$

The downlink sum rate of the small cell system is

$$R = \sum_{k=1}^{K} R_k$$

The total energy consumption at the small cell base station comprises transmit power consumption and static power consumption. Transmit power consumption represents the energy consumed for transmitting baseband signals, while static power consumption accounts for energy consumed by various components during signal transmission. The total system energy consumption is defined as

$$P_{\text{total}} = P_c + \sum_{k=1}^{K} \|\mathbf{v}_k\|^2$$

where P_c denotes static power consumption and the second term represents signal transmission power consumption.

The optimization problem is formulated as

$$\begin{aligned}
\max_{\{\mathbf{v}_k, \rho_k\}} \quad & \frac{\sum_{k=1}^{K} \log_2(1 + \text{SINR}_k)}{P_c + \sum_{k=1}^{K} \|\mathbf{v}_k\|^2} \\
\text{s.t.} \quad & C_1 : \sum_{k=1}^{K} \|\mathbf{v}_k\|^2 \le P_{\max} \\
& C_2 : \text{SINR}_k \ge \gamma_k, \quad \forall k \\
& C_3 : E_k \ge e_k, \quad \forall k \\
& C_4 : \text{SINR}_c \ge \eta \\
& C_5 : 0 < \rho_k \le 1, \quad \forall k
\end{aligned}$$

where C_1 represents the small cell base station transmit power constraint, C_2 and C_4 denote communication quality constraints for small cell users and the macro user respectively, C_3 and C_5 represent energy harvesting and power splitting coefficient constraints for small cell users, and $\mathbf{g}$ denotes the channel gain from the small cell base station to the macro user. This problem belongs to the class of non-convex nonlinear fractional programming, making it difficult to solve directly.

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3 Problem Transformation and Solution

Considering that heterogeneous small cell networks employ low-power transmission nodes and signals experience significant attenuation during propagation, energy harvesting at mobile terminals becomes challenging. Therefore, while ensuring normal communication for mobile terminals, the base station should minimize algorithmic overhead to enable more energy harvesting at mobile devices. Consequently, this study adopts zero-forcing beamforming (ZFBF) to process transmitted signals, which eliminates inter-user interference and simplifies transmitter design.

3.1 Problem Transformation

This subsection performs equivalent transformation of the original problem through mathematical construction to simplify mathematical processing. Let $\mathbf{H} = [\mathbf{h}_1, \dots, \mathbf{h}_K]$, and let $\mathbf{U}_k$ be an orthogonal basis for the null space of $[\mathbf{h}_1, \dots, \mathbf{h}_{k-1}, \mathbf{h}_{k+1}, \dots, \mathbf{h}_K]^H$. Further define $\mathbf{v}_k = \mathbf{U}_k \mathbf{f}_k$, where $\mathbf{f}_k$ represents the effective beamforming vector. Then problem (10) can be transformed into

$$\max_{\{p_k, \rho_k\}} \quad \frac{\sum_{k=1}^{K} \log_2(1 + \frac{p_k \rho_k}{\rho_k(\sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2) + \delta_k^2})}{P_c + \sum_{k=1}^{K} p_k}$$

subject to the constraints C_1 through C_5, where $p_k = \|\mathbf{v}_k\|^2$.

Clearly, the optimization variables p_k and ρ_k are coupled in the objective function, which appears as a fraction. Therefore, problem (11) remains a non-convex optimization problem. We first convert the fractional objective function into a subtractive form using fractional programming, then transform problem (11) into an unconstrained optimization problem using a subgradient algorithm based on Lagrange multipliers.

Lemma 1: Assume $f(x)$ and $g(x)$ are continuously differentiable functions, and the constraint set S is compact. If $g(x) > 0$, then $\max_{x \in S} \frac{f(x)}{g(x)}$ can be solved by addressing $\max_{x \in S}\{f(x) - \lambda g(x)\}$, where λ is chosen such that $\max_{x \in S}\{f(x) - \lambda g(x)\} = 0$.

Applying Lemma 1, we transform the objective function into a subtractive form. Then, we process constraints C_2 and C_3 by introducing auxiliary variables. Let $l_k(p_k, \rho_k) = \rho_k p_k - \gamma_k(\rho_k(\sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2) + \delta_k^2)$ and $e_k(p_k, \rho_k) = \zeta_k(1 - \rho_k)(p_k + \sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2) - e_k$. The problem becomes

$$\max_{\{p_k, \rho_k\}} \quad \sum_{k=1}^{K} \log_2(1 + \frac{p_k \rho_k}{\rho_k(\sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2) + \delta_k^2}) - \lambda \left(P_c + \sum_{k=1}^{K} p_k \right)$$

subject to constraints C_1, C_4, and C_5.

The Lagrangian dual function of the transformed problem is

$$\mathcal{L}(\{p_k, \rho_k\}, \{\alpha_k, \beta_k, \nu_k\}) = \sum_{k=1}^{K} \log_2(1 + \frac{p_k \rho_k}{\rho_k(\sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2) + \delta_k^2}) - \lambda \left(P_c + \sum_{k=1}^{K} p_k \right) - \sum_{k=1}^{K} \alpha_k l_k(p_k, \rho_k) - \sum_{k=1}^{K} \beta_k e_k(p_k, \rho$$

where α_k, β_k, and ν are Lagrange multipliers corresponding to the constraints. The unconstrained optimization problem equivalent to the original can be defined as $\min_{\{\alpha_k, \beta_k, \nu \geq 0\}} \max_{\{p_k, \rho_k\}} \mathcal{L}(\cdot)$.

3.2 Solution Approach

Given the Lagrange multipliers, the optimal p_k and ρ_k can be obtained through Karush-Kuhn-Tucker (KKT) conditions.

a) Fixed ρ_k, solve for p_k:

Setting $\frac{\partial \mathcal{L}}{\partial p_k} = 0$ yields the closed-form expression

$$p_k^* = \left[\frac{1}{\ln 2 \cdot (\lambda + \nu + \alpha_k + \beta_k \zeta_k (1 - \rho_k))} - \frac{\rho_k (\sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2) + \delta_k^2}{\rho_k} \right]^+$$

where $[x]^+ = \max(0, x)$. Notably, λ represents the value within the optimal energy efficiency interval, which will be determined later. Since the second partial derivative of the problem with respect to p_k is negative, the solution obtained from the KKT conditions is indeed optimal.

The Lagrange multipliers are updated using subgradient iterations:

$$\alpha_k^{(t+1)} = \left[\alpha_k^{(t)} - \tau_\alpha^{(t)} \nabla_{\alpha_k} \mathcal{L} \right]^+$$
$$\beta_k^{(t+1)} = \left[\beta_k^{(t)} - \tau_\beta^{(t)} \nabla_{\beta_k} \mathcal{L} \right]^+$$
$$\nu^{(t+1)} = \left[\nu^{(t)} - \tau_\nu^{(t)} \nabla_{\nu} \mathcal{L} \right]^+$$

where $\tau^{(t)}$ denotes the step size at iteration t, which must be positive to ensure convergence. The convergence condition for dual variable updates can be set according to complexity and performance requirements.

b) Substitute p_k^*, solve for ρ_k:

Substituting the optimal p_k^* into the Lagrangian and setting $\frac{\partial \mathcal{L}}{\partial \rho_k} = 0$ yields an expression for ρ_k. Multiple solutions may be obtained, and the optimal ρ_k^* is selected as the one satisfying $0 < \rho_k \leq 1$.

c) Determine optimal energy efficiency:

Substituting the optimal p_k^* and ρ_k^* into the objective function, we employ the bisection method to find the optimal energy efficiency value λ^* that satisfies $F(\lambda) = 0$, where $F(\lambda) = \max_{\{p_k, \rho_k\}} \{\sum_{k=1}^{K} R_k - \lambda P_{\text{total}}\}$. The function $F(\lambda)$ is monotonically decreasing in λ, and $F(0) > 0$. Therefore, a zero point must exist within the optimal energy efficiency interval.

The computational complexity of the joint optimization algorithm is analyzed as follows. The inner loop updates Lagrange multipliers via subgradient iterations with complexity $\mathcal{O}(N \log(1/\epsilon_p))$, where ϵ_p is the power convergence threshold. The outer loop employs bisection search for optimal energy efficiency with complexity $\mathcal{O}(\log(1/\epsilon_\lambda))$, where ϵ_λ is the energy efficiency convergence threshold. The overall algorithm complexity is $\mathcal{O}(N \log(1/\epsilon_p) \log(1/\epsilon_\lambda))$.

The bisection method requires determination of the interval endpoints. We obtain the upper bound of the optimal energy efficiency interval through scaling. Assuming all small cell base stations transmit at maximum power under identical channel conditions ($p_k = P_{\max}$), the upper bound is given by

$$\lambda_{\max} = \frac{\sum_{k=1}^{K} \log_2(1 + \frac{P_{\max}}{\sigma_{\varepsilon,k}^2 + \sigma_{n,k}^2 + \delta_k^2})}{P_c + P_{\max}}$$

Thus, the optimal energy efficiency λ^* lies in the interval $[0, \lambda_{\max}]$.

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4 Algorithm Simulation

This section presents simulation results to validate the proposed joint optimization algorithm through comparison with the Lagrange Relaxation (LR) method from reference [16]. Key simulation parameters are: number of small cell users $K = 4$, small cell base station antennas $N = 10$ unless otherwise specified, total transmit power $P_{\max} = 40$ dBm, and bandwidth $W = 15$ kHz. The path loss model assumes 30 dB attenuation per 5m. All users share identical parameter sets: $\sigma_{\varepsilon,k}^2 = -30$ dBm, $\sigma_{n,k}^2 = -50$ dBm, $\sigma_{\delta,k}^2 = -70$ dBm, $\gamma_k = \gamma$, $e_k = e$, and $\zeta_k = 0.65$. Due to the short propagation distances in heterogeneous cellular networks with low-power nodes, line-of-sight (LOS) signals dominate. The channel adopts a Rician fading model:

$$\mathbf{h}_k = \sqrt{\frac{K_R}{K_R + 1}} \mathbf{h}_k^{LOS} + \sqrt{\frac{1}{K_R + 1}} \mathbf{h}_k^{NLOS}$$

where $\mathbf{h}_k^{LOS}$ represents the LOS component, $\mathbf{h}_k^{NLOS}$ represents the non-LOS component following Rayleigh distribution with zero mean and variance σ_h^2, and K_R is the Rician factor. The LOS component uses a far-field uniform linear antenna array model: $\mathbf{h}_k^{LOS} = [1, e^{-j2\pi d \sin(\phi_k)/\lambda}, \ldots, e^{-j2\pi(N-1)d \sin(\phi_k)/\lambda}]^T$, where d is antenna spacing, λ is carrier wavelength, and ϕ_k is the direction angle. We assume $d = \lambda/2$ and $\{\phi_1, \phi_2, \phi_3, \phi_4\} = \{-30^\circ, 60^\circ, 60^\circ, -30^\circ\}$.

The outer loop updates $\lambda^{(t)}$ via bisection to find the optimal system energy efficiency, while the inner loop updates $\{p_k, \rho_k\}$ through dual decomposition and subgradient iterations to obtain the optimal power allocation strategy.

Algorithm 1: Bisection Method - Input: Interval $[0, \lambda_{\max}]$, precision ϵ_λ - **Output:** Zero point λ^* 1. Initialize $\lambda_{\text{low}} = 0$, $\lambda_{\text{high}} = \lambda_{\max}$ 2. Compute midpoint $\lambda_{\text{mid}} = (\lambda_{\text{low}} + \lambda_{\text{high}})/2$ 3. If $F(\lambda_{\text{mid}}) = 0$ or $|\lambda_{\text{high}} - \lambda_{\text{low}}| < \epsilon_\lambda$, return λ_{mid} 4. If $F(\lambda_{\text{mid}}) > 0$, set $\lambda_{\text{low}} = \lambda_{\text{mid}}$; else set $\lambda_{\text{high}} = \lambda_{\text{mid}}$ 5. Repeat from step 2

Algorithm 2: Joint Optimization Algorithm - Input: System parameters, initial multipliers, convergence thresholds ϵ_p, ϵ_λ - **Output:** Optimal power allocation $\{p_k^*\}$, optimal power splitting coefficients $\{\rho_k^*\}$, optimal energy efficiency λ^* 1. Initialize Lagrange multipliers $\{\alpha_k^{(0)}, \beta_k^{(0)}, \nu^{(0)}\}$ 2. For fixed λ, compute optimal p_k^* using (21) and ρ_k^* using KKT conditions 3. Update multipliers via subgradient iterations (22) 4. If $\|\nabla\mathcal{L}\| > \epsilon_p$, return to step 2; otherwise proceed 5. Update λ using bisection method 6. If $|F(\lambda)| > \epsilon_\lambda$, return to step 2; otherwise output results

[Figure 2: see original paper] demonstrates the convergence performance of the proposed algorithm, showing rapid convergence while maintaining high system energy efficiency. [Figure 3: see original paper] illustrates the relationship between the number of base station antennas and average system energy efficiency. The efficiency initially increases then decreases with more antennas, peaking at $N = 10$ due to the rapid growth in static power consumption.

[Figure 4: see original paper] and [Figure 5: see original paper] show the relationship between total transmit power and average system energy efficiency under different QoS and energy harvesting thresholds. The average energy efficiency increases with transmit power, saturating at $P_{\max} = 40$ dBm for given γ and e. Lower QoS and energy harvesting requirements achieve higher energy efficiency, revealing a trade-off between system efficiency and user requirements.

5 Conclusion

This paper studied energy efficiency optimization in MISO SWIPT heterogeneous small cellular networks. Under constraints ensuring normal communication and energy harvesting for small cell users, we proposed a low-complexity multi-objective joint optimization algorithm. Compared with existing work, the proposed algorithm effectively improves system energy efficiency with low computational complexity, facilitating energy harvesting at mobile terminals and providing a theoretical foundation for addressing energy limitations in mobile devices. Future work will further investigate the relationship between antenna selection in large-scale antenna arrays and system energy efficiency.

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