Research Article

Optimization of Energy Efficiency for Uplink Wireless Information and Downlink Power Transfer System with Imperfect CSI

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As an emerging paradigm, supplying power by radio frequency signal has been a key technology for the wireless powered communication network (WPCN) to prolong the lifetime. This paper considers a multiple input multiple output (MIMO) system where users are charged only by one source. The source is equipped with multiple antennas while each user with one antenna. Besides receiving information as the traditional way, the source has the capacity to transfer energy with beamforming, which can be harvested by users to store for information transmission in the later. However, the unknown channel state information (CSI), low energy efficiency, and various demands of transmitting volume jointly raise inaccurate, wasteful, and flexible conditions in transmitting design. On the other hand, energy and spectrum efficient solutions are indispensable to the success of Internet of Things (IoT). In this case, we put forward a novel design of downlink energy transfer, uplink information transmission, and channel estimation to achieve a practical efficient transmission. By jointly optimizing the source antenna number, power allocation, energy beamforming vectors, and each phase time of channel estimation, information transmission, we aim to achieve the optimized system energy efficiency with constraints of signal-to-noise ratio (SNR), data transmission volume, and transmitting power. Based on fractional programming and Lagrangian dual functions, we also put forward a distributed iterative algorithm to solve the formulated problem optimally. Simulation results verify the convergence of our proposed algorithm and illustrate the relationship between variables of antenna number, data volume requirement, pathloss factor and system performance of sum-throughput, energy efficiency, and user fairness. Our proposed transmitting design can achieve the optimized energy efficiency, whose upper bound is improved by appropriate massive antenna employment.

1. Introduction

In recent years, the Internet of Things (IoT) is emerging as an important networking paradigm which enables communication among physical objects [1–3]. It is indicated that in the future, devices in offices and houses will have the ability to sense, communicate, and process the information. Artificial intelligence (AI) management technologies adopting dynamic methods to control for IoT in smart cities are needed more and more. In the meanwhile, long distance wireless energy transfer (WET) has been studied as a potential technology to solve the lifetime problem of the wireless powered communication system [4]. Users can be supplied by radio frequency (RF) signal to prolong the lifetime. It has been proved that a user equipped with proper circuit can receive signal and convert it into energy to store. When transmission frequency is 915 Hz, it is reported that 3.5 mW and 1uW can be harvested from RF signal with distances of 0.6 m and 1.1 m, respectively [5].

1.1. Motivation and Related Work. As RF signal decays largely with transmission distance, it demands energy transfer more concentrated by narrow beam to achieve a higher transmission efficiency. Multiple input multiple output (MIMO) technology is considered as a crucial way for the fifth generation (5G) of wireless communication [6, 7].
helps beamforming design to transmit energy directionally, which solves the problem above. Wireless power transfer with massive MIMO technology enables energy harvesting users to be supplied efficiently in the future IoT network [8–12].

Wireless information and power transfer are widely studied as its character of supplying power when transmitting information. [13, 14] study the trade-off between receiving information and harvesting energy in the orthogonal frequency division multiplexing (OFDM) system and broadcasting system, respectively. [15] takes a research on relay system while [16] concentrates on the interference channel environment. Furthermore, in [17], authors investigate the secondary users harvesting energy from nearby primary users in the cognitive radio network. [18] proposes a transmission design to maximize the harvesting energy with data constraints, [19] achieves optimal transmission rate with energy constraints, and [20] optimizes system outage probability.

Users in WPCN harvest energy by wireless RF signal to transmit information [21]. The advent of commercial products has proved the feasibility of this mode [22]. In WPCN, the transmission is mainly divided into two parts, the downlink energy transfer and uplink information transmission. Researchers have studied this kind of network with perfect channel state information (CSI). Time allocation of one user uplink transmission and source downlink transfer phase is optimized to achieve the maximal transmission rate in [23]. With multiple users, [24] jointly optimizes the power allocation and time for each phase to achieve the optimal system sum-throughput. Authors in [25] consider source beamforming and power allocation to minimize the transmission rate, which is seen as the fairness of users. As for imperfect CSI, [19] adds a channel estimation phase behind the two phases in traditional WPCN. System sum-throughput is optimized by balancing the time length of channel estimation, downlink energy transfer, and uplink data transmission. However, the objective of maximizing sum-throughput raises unbalanced throughput between users, which is inapplicable for wireless sensors network or IoT because their flexible data requirements for users. Meanwhile, the objective of fairness optimization makes the result that each user transmits the same data volume. Since users may have different functions and the data requirements of them is not the same, fairness optimization cannot satisfy the variability. In this paper, we take maximizing energy efficiency as the objective to design a novel transmission scheme.

Energy efficiency is a crucial system indicator, defined as the ratio of total transmission data volume to the whole consumption of system [26]. It indicates the amount of data transmitted by per unit of energy consumed, the optimization of which meets the requirement of green generation. In the information transmission system, transmission efficiency is improved by the help of massive antennas employment [27]. And it increases all the time with the increasing number of antennas when ignoring antenna circle consumption. However, in the practical system, this part of consumption is so large that it is worthy to consider especially for energy efficiency. In [28], authors study downlink information transmission efficiency in the massive MIMO system with a spatial correlated channel. It is shown that with a saturated signal-to-interference-plus-noise ratio (SINR), the optimal transmission power is independent of the number of antennas. [29] investigates an energy and information transfer system including a massive antenna equipped source and one single antenna user. With delay constraints, energy efficiency is maximized by jointly optimizing power allocation and time allocation. With perfect CSI, [30] studies energy efficiency of a multiuser WPCN. It indicates that the number of antennas and time allocation has deep effects on the objective indicator. [19, 31] both concentrate on a system where users are supplied only by wireless energy transfer. The energy efficiency of such system can be written as the ratio of total uplink data transmission volume to the source power consumption. However, the literatures above work little on the whole system energy efficiency in the multiuser WPCN system with imperfect CSI. We generally consider the number of antennas, source beamforming, and resources allocation of power, time, and reserved energy portion factor to achieve the optimal energy efficiency. To be noted, [31] designs a kind of transmission scheme for energy efficiency with imperfect CSI, which can achieve the asymptotic maximal power transfer efficiency and corresponding energy efficiency. Although our work has similar transmission phases with [31], we focus on the optimal energy efficiency by jointly considering various of factors, instead of the relationship between number of antennas and downlink power transfer efficiency. We aim to achieve the maximal energy efficiency of the system. Furthermore, in this paper, we consider the information transmission volume as constraints and the optimization of channel estimation time.

1.2. Contributions. In this paper, we study energy efficiency of a downlink energy transfer and uplink information transmission in the multiuser MIMO system with imperfect CSI. Considering practical accuracy, the source estimates channel firstly. We have a deep research on the effects of antenna number, source transmitting power, channel estimation time, downlink transfer time, uplink transmission time, and energy beamforming vectors on the system optimal energy efficiency. The contributions of our work are mainly summarized below:

(1) We first jointly optimize the three phases: channel estimation, downlink energy transfer, and uplink information transmission to achieve the optimal energy efficiency, for the practical problem of inaccurate CSI. Users have to harvest sufficient power to transmit not only information data but also pilot sequence for estimation. At the same time, power consumption increases largely with the increasing number of antennas. For which we put forward a consumption model extended with the number of antennas to get a more practical power consumption, leading to a more accurate energy efficiency calculation

(2) We design a novel scheme to achieve the maximal energy efficiency to satisfy flexible data requirements and avoid wastage of energy, under constraints of
minimum data transmission volume and transmitting power limitation. We firstly formulate the maximizing problem by jointly considering antenna number, source transmitting power, channel estimation time, downlink transfer time, uplink transmission time, and energy beamforming vectors. Then, we transfer the multiple factor coupled objective function from fractional form into equality and prove the existing of optimal solution in the feasible region.

(3) For multiple constraints especially when the number of users is large, using the internal point method to solve the optimization problem undoubtedly brings high computational complexity. We put forward a distributed iterative algorithm based on fractional programming and Lagrangian dual functions to solve the formulated problem optimally. For the Lagrangian duality problem, we firstly prove the convexity of the transformed function and constraints, respectively, which indicates the strong duality of the problem. Then, we solve it with tight condition equations.

(4) Simulation results corroborate the analysis. It is numerically indicated the performance of our proposed scheme and factors’ effects on energy efficiency, throughput, and fairness between users. It is also known that appropriate massive antennas employment helps achieve optimal energy efficiency.

The rest of this paper is organized as follows. Section 2 describes and analyzes the system model. Section 3 and Section 4 formulate the proposed problem then solve it optimally to achieve the maximal energy efficiency. Simulation results are shown in Section 5. Finally, Section 6 concludes the paper. Variables and their corresponding meanings are described in Table 1.

## 2. System Model

We consider a time division wireless information and power transfer system as shown in Figure 1, including one source node equipped with $M$ antennas, described as $S$ and $K$ single antenna users, $U_k$, $k = 1, \cdots, K$. Equipped with rectifier to harvest energy and store, users are supplied only by wireless energy transfer from the source and utilize the harvested power to transmit information in the uplink.

As shown in Figure 2, the length of one period time is expressed as $T$. And it is divided into three phases: phase one: channel estimation; phase two: downlink energy transfer; and phase three: uplink information transmission. In phase one $\alpha_{Te}, T, 0 < \alpha_{Te} \leq 1$, users transmit orthogonal training sequences to the source, utilizing the conserve power in the last period. The source receives and estimates the downlink CSI by channel reciprocity. Then, in phase two time $\alpha_{Wet} T, 0 < \alpha_{Wet} \leq 1$, the source supplies power to users by exploiting energy beamforming. And receivers harvest then store the power for the phase three and the next phase one. In phase three $\alpha_{Wit} T, 0 < \alpha_{Wit} \leq 1$, users transmit independent data by time division multiple access (TDMA). It is known that time of three phases satisfies $\alpha_{Te} + \alpha_{Wet} + \alpha_{Wit} \leq 1$. Assuming $H = [h_1, h_2, \cdots, h_K]$ presents uplink channel $M \times K$ matrix between the source and users, $[H_{mk}] = h_{mk}$ denotes the channel from the $m$th antenna to the $k$th user. Then, channel matrix $H$ can be written as

$$H = H^T W^{1/2},$$

where $H^T$ represents the $M \times K$ independent Rayleigh fading coefficient matrix between the source and users, and $[H^T_{mk}] = h^T_{mk} \sim \mathcal{CN}(0, 1)$, where $\mathcal{CN}(0, 1)$ means the distribution of a circularly symmetric complex Gaussian (CSCG) random

| Table 1: Variables and their corresponding meanings. |
|---------------------------------------------------|
| Variable | Meaning |
|----------|---------|
| $M$      | Number of antennas |
| $K$      | Number of users |
| $U_k$    | The $k$th user |
| $T$      | Length of one period time |
| $\alpha_{Te}$ | Channel estimation time portion |
| $\alpha_{Wet}$ | Energy transfer time portion |
| $\alpha_{Wit}$ | Information transmission time portion |
| $H$      | Channel matrix |
| $V$      | Source beamforming vector |
| $\beta$  | Pathloss factor |
| $P_E$    | Source transmitting power |
| $Q_k$    | Harvested power at the $k$th user |
| $\eta$   | Receiving storage conversion ratio |
| $\xi_k$  | Reserving energy portion for user $k$ |
| $I_{lk}$ | The $k$th user information transmitting power |
| $I_k$    | The $k$th user information transmission time |
| $I_k$    | The $k$th order identity matrix |
| $A^T$    | Transpose of matrix $A$ |
| $E[]$    | Mathematical expectation |

Figure 1: The system model with downlink energy transfer and uplink information transmission.
vector with mean 0 and covariance 1. \( W \) is a \( K \times K \) diagonal matrix, where \( [W_{kk}] = w_k \) denotes long distance path fading. It is further supposed the channel remains constant in one period of time, called quasistatic flat fading. We analyze the three phases, respectively, in the following.

2.1. Channel Estimation Model. In the channel estimation part, each user transmits its pilot sequence of length \( L \) to the source. Generally, \( L \geq K \) and tacitly the time for transmitting \( L \) symbols is less than \( a_e T \). The power required by \( U_k \) for transmitting sequence is expressed as \( \rho_k^{\text{Tr}} \), corresponding to different users’ transmission distances. The signal can be given by \( x_{\text{Tr}} = \Phi B^{1/2} \), where \( B = \text{diag} \{ Lp_1^{\text{Tr}}, Lp_2^{\text{Tr}}, \ldots, Lp_K^{\text{Tr}} \} \), and \( L \times K \) matrix \( \Phi \) satisfies \( \Phi \Phi^H = I_K \), denoting the orthogonality with each other. So, the received signal by the source is described as

\[
y_{\text{Tr}} = H(\Phi B^{1/2})^T + n_{\text{Tr}},
\]

where the noise \( n_{\text{Tr}} \sim CN(0, \sigma_{{n}_{\text{Tr}}}^2) \). Given the received signal, we estimate channel matrix \( \tilde{H} \) by the minimum mean-square-error (MMSE) principle. The estimation result \( \tilde{H} = [\tilde{h}_1, \tilde{h}_2, \ldots, \tilde{h}_K] \) is shown as [32]

\[
\tilde{H} = y_{\text{Tr}} \Phi^T (WB + \sigma_{{n}_{\text{Tr}}}^2 I_K)^{-1} B^{1/2} W.
\]

Estimation error matrix is denoted as \( E = \tilde{H} - H \), independent of estimation matrix \( H \). By (3), we know the \( k \)th column of matrix \( E \) has the mean 0, and the variance is represented as

\[
\sigma_{{e}_{k,k}}^2 = \frac{w_k}{1 + w_k Lp_k^{\text{Tr}} / \sigma_{{n}_{\text{Tr}}}^2}.
\]

It can be seen that the estimation result is up to the path fading factor and transmitting power, which is derived by reserving energy scheme in phase three of the last period.

2.2. Energy Transfer Model. After phase one, the source has known the estimated CSI \( \tilde{h}_k \). For the convenience in the following, we express it as \( \tilde{h}_k = \sqrt{\beta_k} g_k \), where \( \beta_k \) means path-loss factor between the source and the \( k \)th user, and \( g_k \) is the direction vector. In phase two, the source supplies power to users by energy beamforming, and the receivers harvest and store. We put forward a consumption model extended with the number of antennas to satisfy the practical environment. It is shown that by beamforming is the best way to transfer energy [33]. Defining \( V = [v_1, v_2, \ldots, v_K] \) as energy beamforming vector, \( F_W \) as transmitting power, the received signal at the \( k \)th user is expressed as

\[
y_{\text{Wet},k} = P_E \tilde{h}_k^H v_k x_{\text{Wet},k} + z_k,
\]

where \( x_{\text{Wet},k} \) is the baseband signal, \( E[|x_{\text{Wet},k}|^2] = 1 \). Receiver noise \( z_k \) is ignored in this paper as its few effects. We know that the nonlinear energy harvesting models have been discussed, where the practical harvested energy is related to maximum power that a receiver can harvest and physical hardware in terms of its circuit sensitively, limitations, and leakage currents, besides the input power considered in the linear model. We observe that the differences are determined by receivers themselves. And we mainly focus on beamforming, power splitting, time allocation, etc. Thus, in this paper, we assume that users have the same parameters and adopt the linear energy harvesting model, which uses a linear factor to represent the nonlinear result. Hence, expressing the receiving storage conversion ratio with \( \eta_k, 0 < \eta_k < 1 \), we get the received energy

\[
Q_k = \eta_k a_{\text{Wet}} T E[|y_{\text{Wet}}|^2].
\]

As the periodic transmission, sometimes, the source can know the CSI in conditions of little changes, for example, in no man environment with short range line-of-sight transmission. So, we firstly focus on the harvested energy in
perfect CSI, then on the imperfect. As for perfect CSI, \( \tilde{g}_k \sim \text{CN}(0, 1) \).

**Lemma 1.** When the source is equipped with \( M \) antenna, and the number of single antenna user is \( K \), with perfect CSI, the received energy can be expressed as

\[
Q_k = \eta_k P_k \alpha_{\text{wet}} T \beta_k \left( \frac{M + K - 1}{K} \right) |g_k^h v_k|^2. \tag{7}
\]

**Proof.** [31] has proved that when downlink average transmitting power is \( P_{\text{dl}} \) beamforming vector \( \mathbf{w}_{\text{dl}} = \sum_{i=1}^{K} \sqrt{\frac{1}{\xi}} (g_i || g_i) \), and defining \( S = TB \), where \( T \) is the time length of period and \( B \) is the bandwidth, received power is \( \overline{y}_i = \tilde{g}_{i} \alpha_{i} (\xi M + (1 - \xi)) \), where \( \alpha_i \) denotes pathloss factor. In practical, users store the harvested energy with receiving storage conversion factor \( \eta \), and beamforming optimization effects the energy consumption. Hence, in this paper, \( Q_k = \eta_k P_k \alpha_{\text{wet}} T \beta_k (M + K - 1/K) |g_k^h v_k|^2 \).

It is observed that the harvested energy is closely related to antenna number and number user. Our proposed statement is more consistent with the actual system, beneficial to accurate energy harvested calculation for extended number of antennas and users. Visually, given user number, the harvested energy grows up with the increase of antenna numbers, satisfying the advantage of massive antennas. In the following, we investigate the imperfect CSI condition.

**Lemma 2.** With imperfect CSI, channel estimation by MMSE, the \( k \)th user’s harvested energy is expressed as

\[
\tilde{Q}_{E,k} = \eta_k T \left| g_k^h v_k \right|^2 \frac{A + \sqrt{A^2 + 4 \alpha_{\text{wet}} P_k \sigma_{\text{f}}^2 l/(\xi_k M)}}{2}, \tag{8}
\]

where \( A = \alpha_{\text{wet}} P_k \beta_k ((1/K) + (1 - 1/K/M)) - \sigma_{\text{f}}^2 \xi_k P_k \eta T \).

**Proof.** The source estimates channel by MMSE, and then the harvested energy is shown as (9)

\[
\tilde{Q} = \eta_k T \left| g_k^h v_k \right|^2 \left\{ \alpha_{\text{wet}} T P_k \beta_k \left[ \frac{1}{M - 1 - \frac{1}{M}} - \frac{1}{1 + \omega_k L_p \sigma_{\text{f}}^2} \right] \right. \\
+ \alpha_{\text{wet}} P_k \beta_k \left( 1 - \frac{1}{M} \right) \right\}. \tag{9}
\]

Similar to [5], this result takes advantage of independent channel randomness, which has mean 0 and variance \( \sigma_{\text{f}}^2 = \omega_k + 1 + \omega_k L_p \sigma_{\text{f}}^2 / \xi_k^2 \), as shown in Section 2(a). Defining a reserving energy portion \( \xi_k \), denoting the portion of harvested energy reserved for the channel estimation phase in the next period for the user \( k \), we have

\[
L_p \beta_k^r = \xi_k \tilde{Q}. \tag{10}
\]

Hence, the solution is shown as

\[
\tilde{Q}_{E,k} = \eta_k T \left| g_k^h v_k \right|^2 \frac{A + \sqrt{A^2 + 4 \alpha_{\text{wet}} P_k \sigma_{\text{f}}^2 l/(\xi_k M)}}{2}. \tag{11}
\]

We learn that multiple factors, time length of the period, energy beamforming vector, antennas number, user number, and energy transmitting power are coupled in the expression of the harvested power. And the employment of massive antennas helps energy transfer directly.

2.3. Information Transmission Model. In phase three, users transmit information to the source by time division. It is assumed that time length \( r_k \) is for user \( k \) to transmit, so \( \sum_{k=1}^{K} r_k = \alpha_{\text{wet}} T \). It is also supposed the \( k \)th user’s transmitting signal is expressed as \( y_k = P_k x_k \), where \( P_k \) denotes information transmitting power and \( x_k \sim \text{CN}(0, 1) \). We know in the former that \( \xi_k \) portion of harvested energy has to be reserved for the channel estimation phase in the next period, which means \( 1 - \xi_k \) portion is for information transmitting. Hence, average transmitting power satisfies

\[
P_k \leq \frac{\eta_{\text{wet}} k (1 - \xi_k) \tilde{Q}_{E,k}}{r_k}, \tag{12}
\]

where \( \eta_{\text{wet}} \) means efficiency for utilizing the stored energy to transmit. For convenience, we assume \( \eta_{\text{wet}} = 1 \) in the following as it is a constant factor. Then, the received signal \( y_{S,k} \) is shown as

\[
y_{S,k} = \sqrt{\beta_k x_k} + z_{S,k}, k = 1, \ldots, K, \tag{13}
\]

where \( z_{S,k} \sim \text{CN}(0, \sigma_{S,k}^2) \) denotes transmission noise. \( \Gamma \) denoting the difference of signal-to-noise ratio caused by modulation and demodulation strategy in the actual system, we can get the transmission rate in bits/second/Hz (bps/Hz)

\[
R_k = \log_2 \left( 1 + \frac{\beta_k P_k}{\Gamma \sigma_{S,k}^2} \right) = \log_2 \left( \frac{1 + \beta_k (1 - \xi_k) \tilde{Q}_{E,k}}{\Gamma \sigma_{S,k}^2 \tau_k} \right). \tag{14}
\]

It is seen that the rate is not only derived by the factors included in the harvested power \( \tilde{Q}_{E,k} \), but also by the corresponding reserving energy portion \( \xi_k \) and allocated time \( r_k \). It is hard for our optimization.

3. Problem Formulation

The crucial point of wireless information and energy transmission lies in the rational use of power. As we known, the source has power supply. With sufficiently large transmitting power, users must be well supplied to satisfy information transmission in phase three. However, such condition results in the waste of energy. Hence, it is energy efficiency, a crucial factor to system we focus on in this paper. We aim to achieve the optimized energy efficiency by allocation of time and
power, as well as energy beamforming. The energy efficiency of our system is defined as the ratio of all users’ sum information transmission volume in phase three to power consumption in the whole period. The numerator is expressed by the sum of each user’s transmission rate multiplied by allocated time, while the denominator includes energy transmitting power in phase two, as well as the basic operation and calculation consumption of other phases. We write the average power of latter consumption as $P_{F}$ as

$$P_{F} = P_{o} + MP_{Tr} + \alpha_{Tr}P_{ES} + (\alpha_{Wet} + \alpha_{Wet})P_{BF} - 0.1$$  (15)

$P_{o}$ means fixed working consumption of the source, while $P_{Tr}$ denotes the power of sending and receiving RF signals for one single antenna, and both processes last in the whole period of time. $P_{ES}$ is calculating power for estimating channel in phase one, and $P_{BF}$ means beamforming and decoding consumption in phases two and three. We learn that there is no extra power supply from outside of the system, and the consumption at each user is all supported by the source. Thus, the whole power consumption we calculate occurs at the source. Notably, consider one condition that there remains some energy at users after phase three, which breaks the scheme of the next phase. We aim to optimize the energy efficiency and contrast to the condition above because remaining energy raises a smaller transmission volume per power in current period. Hence, it is an unreasonable condition. Besides, if there is remaining energy at users, the source can know it in phase one. We do not investigate it for the reason in the following. Our design confirms a constant working for the system, while remaining energy represents initial thing in the next period, which can be calculated to improve the objective function of this time. However, after several periods, the initial energy will drain. Above all, we consider no remaining energy condition. Then, the energy efficiency can be expressed as

$$U_{eff} = \frac{\sum_{k=1}^{K} R_{k} \tau_{k}}{TP_{F} + \alpha_{Wet} TP_{E}}.$$  (16)

With energy transfer, the harvested power in phase two should satisfy the requirement of information transmission consumption in phase three, as well as the conserved part for sequence transmission in the next period. With the information, each user’s transmission volume has to meet its scheduled demand. Therefore, this paper is aimed at achieving the maximal energy efficiency by jointly optimizing estimation time $\alpha_{Tr}$, energy transfer time $\alpha_{Wet}$, information transmission time $\alpha_{Wet}$, reserved energy portion $\xi_{k}$, energy transmitting power $P_{E}$, beamforming vector $V$, and information transmission time. The problem can be described as

$$\max U_{eff}(\alpha_{Tr}, \alpha_{Wet}, \tau_{k}, \xi_{k}, P_{E}, V).$$  (17a)

subject to $P_{E} \leq P_{S,max}$.  (17b)

$$\frac{Q_{k}}{\tau_{k}} \leq P_{U_{k,max}}, \forall k, \quad (17c)$$

$$\frac{\beta_{k}(1 - \xi_{k}) Q_{k}}{\sigma_{S_{k},x_{k}}^{2} \tau_{k}} \geq y_{k_{min}}, \forall k, \quad (17d)$$

$$R_{k} \tau_{k} \geq \phi_{min}, \forall k, \quad (17e)$$

$$0 \leq \alpha_{Tr} + \alpha_{Wet} + \sum_{k=1}^{K} \tau_{k} \leq 1, \forall k, \quad (17f)$$

$$\tau_{k} \geq 0, \forall k, \quad (17g)$$

$$\alpha_{Tr} \geq 0, \alpha_{Wet} \geq 0, \quad (17h)$$

where (17b) is due to the source beamforming transmitting power constraint in phase two, and (17c) is due to the user transmitting power limitation. (17d) confirms SNR of the system, meaning that the information transmitted can be received by the source, while meets the communication service quality such as time delay. (17e) also focuses on the information transmission in the uplink. Not only its rate satisfies (17d) but also the volume should meet system requirement of user’s collection. In the traditional system, SNR can represent the volume and quality as its transmitting information all the time. However, in the information and energy transfer system, only a part of time is allocated to transmit information. So, it is necessary for this constraint of transmission volume. As well, (17f) and (17h) denote that the sum time of three phases should be within time length of one period, and each time is greater than or equal to zero. Notably, when $\alpha_{Tr} = 0$, there is no channel estimation, while $\tau_{k} = 0$ represents the kth user that does not transmit information to the source.

The problem formulated in (17) is full of challenge even if antenna number $M$ is given. The difficulties mainly come from the fractional structure of objective function and nonlinear relationship between transmission rate $R_{k}$, time for three phases $\alpha_{Tr}$, $\alpha_{Wet}$, and $\alpha_{Wet}$ and energy harvesting, energy transmitting power $P_{E}$, beamforming vector $V$, and information transmission time. The problem can be described as follows. Channel estimation time $\alpha_{Tr}$, and reserved energy portion $\xi_{k}$ have deep effects on the accuracy of estimation. It influences the transmitting power in phase two, which has a further impact on energy harvesting. Besides, the volume of information transmission and energy transfer are mainly determined by energy transfer time $\alpha_{Wet}$ and energy beamforming vector. As a constraint, multiplying transmission rate and time $\alpha_{Wet}$ makes all the variables coupled together. We solve the problem in the following section.

4. The Proposed Transmission Design

In this section, we solve the formulated energy efficiency problem optimally. The process mainly includes three steps. The first is to transform the objective function from fractional form into equation, and then the second step is to propose an iterative algorithm to transfer the problem again into multiple one-step optimal problems. Finally, we propose an
inner iteration algorithm based on the Lagrange dual function to get the optimal solution.

4.1. Transform of the Objective Function. Firstly, we transform the fractional objective function into the subtraction form which is easier to calculate. Assuming the optimal energy efficiency is expressed by $q^*$, we can rewrite it as

$$q^* = \max_{\alpha} \frac{\sum_{k=1}^{K} R_k \tau_k}{TP_E + a_{Wet} TP_E} \cdot R(P_E, \alpha, \xi_k, V, \tau_k, P_E)$$

where $R = \sum_{k=1}^{K} R_k \tau_k$ and $Q = a_{Wet} TP_E$, both of which are positive as the definition. [34] has proved that the solution \( \{ \alpha, \xi_k, \alpha_{Wet}, V, \tau_k, P_E \} \) achieves the maximal energy efficiency if and only if

$$\max_{\alpha, \xi_k, \alpha_{Wet}, V, \tau_k} (R - q^* Q) = R^* - q^* Q^* = 0.$$ (19)

This conclusion fully illustrates that for any maximum optimization problem with fractional form as the objective function, and there exists an equivalent problem in the subtraction form, where both objectives can achieve the maximization simultaneously by one optimal solution.

Secondly, we propose an iterative algorithm based on the Dinkelbach method [35] to solve the transformed problem with objective function $\max (R - q^* Q)$, and the details are described in Algorithm 1.

Algorithm 1 is mainly described as follows. In every iteration, we solve the problem (20), getting a set of allocation policy solution \( \{ P_E, \alpha, \xi_k, \alpha_{Wet}, V, \tau_k \} \) and an energy efficiency result $q$, which is given as a new initial factor in the next iteration. $q$ will be updated in every iteration until it satisfies that $R(P_E, \alpha, \xi_k, \alpha_{Wet}, V - q Q(\alpha, \xi_k, \alpha_{Wet}, P_E, \alpha_{Wet}) < \varepsilon$. So far, we obtain the optimal solution \( \{ \alpha, \xi_k, \alpha_{Wet}, V, \tau_k, P_E \} \) and the corresponding energy efficiency $q^*$. Hence, the initial problem can be transformed equally into

$$\max_{\alpha, \xi_k, \alpha_{Wet}, V, \tau_k} (R - q Q),$$

s.t. \( P_E \leq P_{S, \text{max}} \).

[35] has proved the convergence character of the transformed subtraction function, and we will also confirm it in the simulation part. To be concluded, we achieve the optimal energy efficiency by solving (20) in every iteration.

4.2. Lagrangian Dual Function-Based Distributed Iterative Algorithm. In this part, we propose a distributed iterative algorithm to solve the problem (20) optimally. We prove convexity of the objective function and all constraints. Then, utilizing the tight conditions, we put forward a distributed iterative algorithm based on Lagrangian dual functions.

We now analyze details of the problem (20). Firstly, the objective function can be divided into two parts, information transmission volume and energy consumption. The former is related with multiple variables, where energy beamforming...
vector is mainly desired by channels. As the investigation in [29], it is optimal to transfer energy by the maximum ratio transmission (MRT) scheme with equal transmitting power, which helps achieve the optimal energy efficiency. By the scheme, the optimal beamforming vector is denoted as \( V = \frac{H}{\|H\|} \). Then, we can obtain the second derivative of the information transmission volume part with respect to each variable, \( \partial^2 R(P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) / P_E \leq 0 \), \( \partial^2 R(P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) / \partial^2 \alpha_T \leq 0 \), \( \partial^2 R(P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) / \partial^2 \alpha_W \leq 0 \), \( \partial^2 R(P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) / \partial^2 \tau_k \leq 0 \), and \( \partial^2 R(P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) / \partial^2 \xi_k \leq 0 \). At the same time, the energy consumption part is linear, illustrating its concavity. Above all, the objective function is concave, and the maximum of a concave function is a convex function. Then, we discuss the convexity of constraints.

In the following, we put forward an iteration algorithm to solve the dual problem (22). In each iteration, given the initial multipliers \( \mu, v, \nu, \phi, \theta \), we solve the problem by Karush-Kuhn-Tucker (KKT) conditions [36], getting a solution \( \{ P_E, \alpha_T, \alpha_W, \tau_k, \xi_k \} \), which is utilized to update, obtaining a new set of Lagrangian multipliers. The solving process of energy beamforming power, channel estimation time, energy transfer time, information transmission time, and the maximum is written as the following equations.

\[
\begin{align*}
\partial L(\mu, v, \nu, \phi, \theta, P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) &= \frac{\partial R_k}{\partial \tau_k} \tau_k + \nu \frac{\partial Q_{E,k}}{\partial \tau_k} + \frac{1}{\tau_k} + \nu Q_{E,k} \frac{1}{\tau_k} + \nu \left( \frac{\beta_k(1 - \xi_k)}{\Gamma \sigma^2_k \tau_k} \right) + \phi \frac{\partial R_k}{\partial \tau_k} \tau_k + R_k = 0, \\
\partial L(\mu, v, \nu, \phi, \theta, P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) &= \frac{\partial P_E}{\partial \mu_k} = \alpha_T = 1 - \alpha_W - \sum_{k=1}^{K} \tau_k, \\
\partial L(\mu, v, \nu, \phi, \theta, P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) &= \frac{\partial \alpha_W}{\partial \alpha_W} = v, \\
\partial L(\mu, v, \nu, \phi, \theta, P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) &= \frac{\partial \xi_k}{\partial \xi_k} = \theta, \\
\partial L(\mu, v, \nu, \phi, \theta, P_E, \alpha_T, \alpha_W, \tau_k, \xi_k) &= \frac{\partial \tau_k}{\partial \tau_k} = \frac{\partial R_k}{\partial \tau_k} \tau_k = 0.
\end{align*}
\]

(23)-(27), it is known the expression of parameters \( P_E, \alpha_T, \alpha_W, \tau_k, \xi_k \) with respect to \( \mu, v, \nu, \phi, \theta \), respectively. Next, we update the Lagrangian multipliers.

\[
\mu_k(n + 1) = [\mu_k(n) + \delta(n)(P_E - P_{S,max})],
\]

(28)
\[ u_k(n+1) = \left[ u_k(n) + \delta(n) \left( \frac{Q^N_{\text{E},k}}{r_k} - P_{U_k,\text{max}} \right) \right]^+, \quad (29) \]
\[ v_k(n+1) = \left[ v_k(n) - \delta(n) \left( \frac{\beta_k(1 - \xi_k)Q^N_{\text{E},k}}{\Gamma r_k} - y_{k,min} \right) \right]^+, \quad (30) \]
\[ \phi_k(n+1) = \left[ \phi_k(n) - \delta(n)(R_kr_k - \phi_{\min}) \right]^+, \quad (31) \]
\[ \theta(n+1) = \left[ \theta(n) + \delta(n) \left( \alpha_{\text{T}} + \alpha_{\text{W}} + \sum_{k=1}^{K} r_k - 1 \right) \right]^+, \quad (32) \]

where index factor \( n \geq 0 \) and \( \delta(n) \) denotes the diminishing positive step size. From (28)-(32), we obtain the updated \( \mu, \nu, \varphi, \theta \) in each iteration. Then, we can calculate a new set of \( P_E, \alpha_{\text{T}}, \alpha_{\text{W}}, r_k, \xi_k \). Eventually, this process of iteration stops when the convergence is achieved, assuming the number of iterations \( I_{\text{max}} \) we set is sufficient large for the main function in Algorithm 1.

5. Implementation and Performance Analysis

In this section, the research theory above is simulated, and aspects of performance are analyzed. We verify the convergence of our proposed algorithm and investigate the effects of variates and threshold to system performance such as energy efficiency and sum-throughput. We further compare our design with sum-throughput optimization (Sum-opt) transmission scheme in [24] and average fairness optimization (Ave-opt) design in [19], whose transmission policies are described detailedly in the later.

5.1. Environment Setup. We set the carrier frequency that is 1.8GHz, the bandwidth is 10 MHz, and the length of period time \( T \) is 180 ms. The upper limit of transmitting power is \( P_{\text{S,max}} = 20W \), and the noise power is \( \sigma_E^2 = -120dBm \). As for source consumption, we set the fixed circuit power spent on the source as \( P_h = 18W \), and the power spent by one antenna is denoted as \( P_{\text{T}} = 1W \) [31]. \( P_{\text{ES}} = 200MK^2/\alpha r_k T_k \) models power consumption in the channel estimation phase, and \( P_{\text{BF}} = 300MK/(1 - \alpha r_k) T_k \) represents the power consumption for linear processing, where \( \kappa = 20 \times 10^9 \) in flops/W denoting the BS computational efficiency. While we assume pathloss factor as \( \beta_k = 10^{-3}d^{-3} \), receiving storage conversion ratio as \( \eta_k = 0.4 \), iteration factor is \( \epsilon = 5 \), and information transmission volume threshold is \( \phi_{\min} = 5 \times 10^6 \) bits.

5.2. Simulation Results. In this part, we simulate our proposed transmission design and analyze results of each phase, respectively. Firstly, we consider the energy transfer results, reserving energy portion vs harvested power. It is assumed that transmitting power \( P_E = 20W \) and users are located randomly at an annular resign with \( r_{\text{min}} = 5m, r_{\text{max}} = 30m \). Figure 3 illustrates the relationship between the \( \xi_k \) and each user’s average harvested power when the user number is 1, 2, and 4.

According to the definition of reserving energy portion, it is the energy portion of harvested power allocated for the channel estimation in the next period. It is shown that, in the general trend, the less energy is reserved for the test phase in three cases, the more power is obtained by users in the energy harvesting phase. Since the reserving energy portion of zero means no channel estimation phase, we figure the harvested power as zero. Furthermore, we recall that if the portion is too large, it takes the time for harvesting energy and transmitting information, while a too small portion raises the inaccuracy channel estimation. It is simulated that some amount of time allocated to phase one balances the accuracy of the channel estimation with the energy transfer, and the optimal reserving energy portion is smaller than 0.02 in all three conditions.

Figure 4 shows the relationship between antenna number and energy efficiency (EE) with perfect and imperfect CSI when there are 2 or 40 users. As the application of beamforming technology requires more antennas than the number of users, we simulate the case of 40 users from number of antennas 50. It is illustrated that, no matter 2 or 40 users, the optimal efficiency increases until reaching a peak and then decreases as the rising of antennas number. It is because as the increasing amount of antennas utilized for energy transfer beamforming, the transmitting beam directional accuracy is getting better, resulting in a high-energy transfer efficiency, which decreases the loss of transmission and makes users harvest more power. In this case, the system transmits more information data with the same amount of power consumption. However, as the number of antennas is too large, though the transmission rate is accordingly growing up, it leads to a low energy efficiency because not worth making the excessive antenna circuit consumption. We also learn that, as the number of users increases, the amount of antenna to achieve the optimal energy efficiency rises, which confirms the transmission advantage of multiple antenna cooperation. When the number increased indefinitely, system energy efficiency diminishes asymptotically to zero eventually. It is a waste of energy, not satisfying the demand of green communication.
Then, we focus on the information transmission phase, where the basis of our proposed iterative algorithms is its convergence. Figure 5 confirms the variation tendency of energy efficiency with the number of iterations with imperfect and perfect CSI, when antenna number is 203 and 40 users. It is recalled in Algorithm 1 that we calculate transmission scheme \((\alpha_T, \alpha_{\text{Wet}}, \xi_k, V, \tau_k, P_E)\) with a given energy efficiency \(q\), then use the calculation result to obtain a new energy efficiency for the next iteration. We can learn that no matter with perfect or imperfect CSI, as the number of iterations increases, energy efficiency decreases and finally tends to be stable. This proves the feasibility of Algorithm 1 under two channel conditions. Notably, the number of iterations indicates only the main loop iterations for the Dinkelbach method, but not that for the gradient method. We also know that the energy efficiency is directly proportional to \(P_{\text{max}}\). This is justifiable since a higher transmit power allowance leads to the larger transmit power and data rate. Actually, the energy efficiency increases not linearly with the number of the iterations, and the growth trend of the curve first rises then descends.

Finally, we compare our proposed energy efficiency optimization (EE-opt) scheme with design of Sum-opt and Ave-opt in multiple aspects. In the Sum-opt design, authors maximize the sum-throughput of all users by jointly optimizing the time allocation in the downlink energy transfer phase.

**Figure 4:** Number of antenna vs maximal EE for users number is 2 or 40 with perfect and imperfect CSI. Optimization of antennas number helps achieve maximal energy efficiency.

**Figure 5:** Number of iterations vs energy efficiency with perfect and imperfect CSI. The convergence results prove the feasibility of our iteration algorithm.

**Figure 6:** Pathloss distance index vs information volume fairless for 2 users, \(d_1 = 6\) m and \(d_2 = 12\) m. The proposed design achieves a compromise between other two schemes, which satisfies flexible demands of system.
and the uplink information transmission phase, with constraints of a total time and transmitting power. While in Ave-opt scheme, the so-called common-throughput is optimized. The objective is to maximize the minimum user transmission rate.

With 2 users, Figure 6 considers the fairness of users, that is ratio of their information transmission volume, when they are at distance of $d_1 = 6\text{m}$ and $d_2 = 12\text{m}$, respectively. The horizontal axis denotes the pathloss distance index caused by the transmission distance, which is 3 in the former simulation when the pathloss factor is expressed by $\beta_k = 10^{-3}d^{-3}$.

It is shown that the ratio result of Ave-opt scheme is 1 and keeps all the time. This is because as the amount of data transferred is monotonically increasing relative to the allocated information transfer time, and [19] has shown that in the Ave-opt design, the optimal allocation strategy needs to satisfy the equal amount of data transmission between users.

Under the strategy of Sum-opt, the ratio grows up with increase of the pathloss factor, and the growth rate also increases lightly. This is because as the factor rises, the decay caused by the transmission distance increases exponentially. On the other hand, the ratio of user transmission volume under the Sum-opt strategy is the largest. The reason is that in order to obtain the maximum transmission volume, a large part of system resources is allocated to users with small fading, so that the power distribution obtained by remote users is far less than that obtained by close users, which is completely unfair. The performance in this paper lies between the unfairness and the fairness strategy. When the remote user reaches the threshold of data transmission, the remaining resources are allocated to the close user to maximize the energy efficiency of the system.

Figure 7 studies the relationship between the number of antennas and sum information transmission volume when there are 2 or 4 users. With 2 users, the deployment is $d_1 = 6\text{m}$ and $d_2 = 12\text{m}$, respectively. While as for 4 users, they are located at distance of $d_1 = 3\text{m}$, $d_2 = 6\text{m}$, $d_3 = 9\text{m}$, and $d_4 = 12\text{m}$. We learn that when the number of antennas is too small (less than 40) or too large (more than 300), the sum of system transmission volume under the strategy of Sum-opt and our scheme is basically the same, while Sum-opt design outperforms our EE-opt design when the number of antennas is in the middle value. This is because the transmitting power is optimized in the whole optimization process in this paper. When the number of antenna is within the range of middle value, the transmitting power under our strategy is less than the upper limit of the source node. While in Sum-opt scheme, the transmitting power keeps at the value of upper limit for the maximal sum-throughput. On the other hand, when the number of antennas is too small or too large, the optimal transmitting power obtained by the strategy in this paper also reaches the upper limit of the limiting condition, which makes the same total power consumption of the system between two schemes under the same number of antennas. According to the definition of energy efficiency, with the same energy consumption, the maximum transmission volume leads to the optimal energy efficiency.

The Ave-optimal strategy always has the lowest total transmission volume because it improves the minimum user’s transmission volume while reduces the overall amount of data. Furthermore, it can be seen from Figure 7 that when the number of users is 2 and the number of antennas is between 55 and 80, the Sum-opt scheme exceeds most, which is consistent with the results in Figure 4. The system achieves

![Figure 7: Number of antennas vs sum-throughput for 2 users, $d_1 = 6\text{m}$, $d_2 = 12\text{m}$, and 4 users, $d_1 = 3\text{m}$, $d_2 = 6\text{m}$, $d_3 = 9\text{m}$, and $d_4 = 12\text{m}$. The performance of our proposed design is slightly worse than Sum-opt scheme and outperforms Ave-opt scheme obviously.](image-url)
great energy efficiency under the region of antenna number, and the corresponding transmitting power is small.

Data transmission volume threshold is also very important for system quality, especially in IoT, and intelligent devices network. Users need to collect their corresponding variety of data to the source for summary and analysis. Different from the traditional transmission rate threshold, the information volume threshold in this paper is the product results of the optimized data transmission time and optimal rate. Transmission rate constraints here mainly ensure that the receiver can normally receive data, system delay, and other requirements. No special simulation demonstration is done here. In Figure 8, the relationship between energy efficiency and information transmission threshold under three schemes is given, where 2 users are at the distance of $d_1 = 6$ m and $d_2 = 12$ m, respectively. As for EE-opt scheme, it can be seen

![Figure 8: Transmission volume threshold vs energy efficiency for $M = 63$, 2 users. Different data volume threshold result in different performance advantages of energy efficiency between three transmission designs.](image1.png)

![Figure 9: Channel estimation time vs energy efficiency for $M = 63$, 2 users. System can maximize the energy efficiency by allocating the right amount of estimating time portion.](image2.png)
that when the threshold is small, energy efficiency grows up with its increasing. This is because small data volume results in small amount of antennas and short time to send energy. In this case, hardware consumption takes mainly part of the whole consumption, leading to a low energy efficiency. When the threshold of data volume is too large, the source node can meet the requirements of it only by increasing the number of antennas due to transmitting power limitation of the source. And the corresponding increased power consumption is not worth the growing date volume as for energy efficiency. With Sum-opt scheme in [18], energy efficiency diminishes all the time, and the reason is that the optimal policy requires it spends the minimum source to satisfy the threshold of the remote user, the rest to the near one. So, with the increasing of volume threshold, more part of the resource is allocated to the remote user, resulting in a low energy efficiency as discussion in the former. While in the Ave-opt strategy, its energy efficiency keeps all the time. It is due to the fairness that no matter the threshold is, the two users transmit the same volume. It is further learned that our proposed scheme outperforms obviously Sum-opt strategy when the threshold is in the middle value. The reason is that when the data volume threshold is high, the system resource allocation of the Sum-opt design will be more fair, which is similar to the EE-opt scheme proposed in this paper. And when the threshold is too small, the optimal transmitting power does not reach the upper limitation. When the threshold is sufficiently high, Sum-opt and Ave-opt designs have similar energy efficiency.

Finally, Figure 9 studies the channel estimating time with energy efficiency. Compared to Figure 3, reserving energy portion is the energy portion of harvested power allocated for the channel estimation in the next period, while means the channel estimation time portion. Generally, a bigger portion of energy leads to more portion of estimation time. However, the two factors do not have linear relationship. It is shown that as the increasing of the channel estimation time portion, energy efficiency in three designs all grows up until a peak, then decreases. This is because an increasing short time leads to a more accurate channel estimation, which results in a more efficient data transmission and energy transfer, while too much time for channel estimation takes up the time for phases two and three. Besides, in Figure 9, we learn that our proposed scheme outperforms Sum-opt and Ave-opt in the portion from 0.2% to 2%. Above all, as for the three designs, we know that in the Sum-opt design, it aims to achieve the maximal sum-throughput by allocating the most resource to the nearest user who can provide the most efficient transmission, making an unfairness between users, and the transmitting power is in upper limitation all the time. While in the Ave-opt design, fairness is considered, and all users transfer the same amount of data. It raises another problem, and much resource is applied for the remote user obstructive to high efficiency. Our schemes balance the two transmission designs, achieving the optimal energy efficiency.

6. Conclusion

In this paper, we study the wireless information and energy transfer in multi-user MIMO system under imperfect CSI, and put forward a novel transmission strategy to achieve the maximal energy efficiency. In the system, the source node equipped with multiple antennas supplies energy to multiple single antenna users, which only utilize the collected energy to transmit data to the source node. We first divide the transmission process into three phases, channel estimation, energy transfer, and information transmission. And we raise an extensible computing model to calculate energy consumption. Then, we formulate a maximizing problem for energy efficiency by jointly optimizing antenna number, channel estimation time, energy transfer time, information transmission time, energy transmitting power, energy beamforming vector, and reserving energy portion. We also present a distributed iteration algorithm to solve the formulated problem. Finally, we carry on the simulation and analysis to the proposed strategy in all aspects. Results illustrate that it is huge that the effect of antenna number on the system and the optimal number depends on the number of users, hardware power consumption, and other factors. By comparison with two other mainstream transmission strategies, our proposed design presents the highest energy efficiency and achieves balance between sum-throughput and data transmission volume fairness.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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