Energy-Efficient Resource Allocation for Wireless Powered Massive MIMO System with Imperfect CSI

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***Abstract*—In this paper, we propose an energy-efficient resource allocation scheme for a wireless power transfer (WPT) enabled multi-user massive MIMO system with imperfect channel estimation. In the considered system, the users who have data to transmit in the uplink only can be empowered by the WPT in the downlink from a base station (BS) with large scale multiple antennas. The problem of optimizing the energy efficiency of the considered system is formulated with consideration of beamforming design, antenna selection, power allocation and time division protocol based on the practical consideration, i.e., imperfect channel state information (CSI) at the BS. In particular, the proposed antenna selection scheme is intended to find the optimal number of antennas and then employ the energy beamforming. Moreover, In order to find the optimal power and time allocation, a scheme based on nonlinear fractional programming is utilized. Extensive simulation studies are conducted to demonstrate the effectiveness of the proposed schemes and their superior performance over other existing schemes.**

***Index Terms*—wireless power transfer; antenna selection; energy efficiency; resource allocation; massive MIMO, imperfect CSI**

I. Introduction

A. Background and Motivation

Many types of wireless networks, such as wireless sensor networks, are energy constrained, in the sense that the network elements are empowered by noncontinuous energy supplements (such as batteries, etc.). While the lifetime of these devices can be extended by replacing or recharging the battery, sometimes it may be inconvenient and expensive. Another way to prolong the lifetime of devices is to realize the energy-harvesting (EH) capabilities and to design energy-efficient schemes to improve their energy efficiency (EE). The EH techniques enable the elements in wireless networks to harvest energy from the surrounding environment. Meanwhile, it is worth mentioning that most of the EH sources are location-dependent or weather-dependent (solar, wind, etc). However, for wireless elements that cannot easily access these sources, provision of energy supply is problematic. Recently, apart from the techniques that harvest energy from sun, wind, or other physical phenomena, scavenging from electromagnetic signal offers an interesting idea for addressing the problem of energy supply. So called simultaneous wireless information and power transfer (SWIPT) is attracting increasing interests from the research and industrial communities [1].

Meanwhile, it is widely acknowledged that the current cellular structure has immense difficulties in satisfying the increasing demand for data traffic as well as the spectrum crunch. To further improve the spectrum utilization, massive multiple-input multiple-output (MIMO) systems make a clean break with the current practice through the use of a large number of antennas. When compared to the current MIMO system, a large number of extra antennas helps bringing significant improvements in throughput by focusing transmit energy into smaller regions of space. However, one of the main disadvantages of employing large scale multiple antennas is the associated complexity of employing a separate RF chain for every employed antenna, which also brings a significant increase in the hardware and energy consumption cost. When the number of transmit and receive antennas is getting large, the aggregate power needed to support the corresponding RF chains can be significant [2]. Currently, most of the energy-efficient communication techniques typically focus on minimizing the transmit power only, which is reasonable when the transmit power is large enough and the number of RF chains used is small. However, when the transmit power is relatively small, especially in the system with large scale multiple antennas where the circuit power consumption can be comparable to or even dominates the transmit power, it would be worthwhile and of significant research interest to investigate whether the massive MIMO systems can outperform the systems with fewer antennas in terms of the EE [3][4]. In addition, it is also interesting to find the optimal number of antennas to further investigate the optimal use of RF chains and to explore the resource allocation scheme for improving the system EE performance.

B. Contribution

In this paper, our aim is to investigate an energy-efficient resource allocation algorithm for a wireless power transfer (WPT) enabled multi-user massive MIMO system. It is considered that the users who have data to transmit to the BS can only

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be empowered by WPT in the downlink. In particular, a joint optimization of antenna selection, power allocation and time allocation are studied with the objective to maximize system EE. Moreover, we also assume only the imperfect channel state information (CSI) is available, which is rather a practical case in the wireless networks. Taking into consideration of imperfect CSI can also enhance the robustness of the proposed resource allocation algorithm. Specifically, our contributions on the existing literature can be summered as follows,

- This paper studies the EE optimization for a multi-user massive MIMO system empowered by WPT with imperfect CSI. After presenting the theoretical analysis of throughput of the system, a novel antenna selection scheme is presented to find the optimal number of transmit antennas at the BS to obtain the optimal EE performance. The introduced antenna selection scheme is based on a binary searching algorithm to find the optimal solution. Moreover, the energy beamforming scheme is applied for the selected antennas to maximize energy transfer.
- In the system considered, the whole time slot, T, is divided into energy transfer time and data transmission time. If more time is allocated to energy transfer, higher transmit power is available at the user. However, less time remains then for data transmission, which leads to a lower system throughput. Therefore, we also propose a time allocation scheme to determine the optimal time allocation. A power allocation algorithm is thus presented to find the optimal transmit power at the BS.
- We also present the impact of imperfect channel estimation on the proposed schemes in the considered system. To address the formulated problem, a nonlinear fractional programming scheme is introduced. The proposed schemes are illustrated and verified through extensive simulations. The performance evaluation demonstrates the effectiveness and superior performance compared with the recent proposed scheme.

C. *Organization*

The rest of the paper is organized as follows. In Section II, we briefly overview the recent development in the related research area. Section III introduces the system model and problem formulation. Section IV presents the antenna selection algorithm and resource allocation optimization. Simulation results are discussed in Section V. Finally, we conclude this study in Section VI.

II. Related Work

Recently, the resource allocation problems of wireless powered communications system have been widely investigated [5]-[8]. In [5] and [6], when considering single-user and multi-user cases, the problems of maximizing the throughput of MIMO WPT systems are studied, respectively. In [7], with the objective to optimize the EE of a point-to-point MIMO system with large scale multiple antennas and SWIPT, the authors present a joint optimization of power and time allocation. The authors of [8] also propose an energy-efficient resource allocation scheme for a multi-user MISO system. In order to improve the energy transfer efficiency of multiple antenna system with SWIPT, various beamforming methods are adopted [9]-[12]. In [9], a beamforming strategy for a secure wireless information and power transmission system is proposed. In [10], the authors study a multiuser MISO beamforming scheme for wireless information and power transmission with the objective to maximize the weighted sum-power under a series of constraints. [11] and [12] also propose different robust beamforming schemes to maximize the WPT in a multiuser MISO SWIPT system. In [13], the authors focus on the throughput optimization problem for a multi-user massive MIMO system, the main objective being to maximize the achievable data rate of the system by optimizing the time and power allocation. In [14], the authors examine the feasibility of wireless energy transfer with multiple antennas array over fading channels. The authors of [15] focus on the beamforming design and power allocation method to improve EH gain in a point-to-point (P2P) MISO system where a receiver harvests energy from a transmitter. In [16], the authors concentrate on the design of an efficient CSI acquisition method for a P2P MIMO WPT system, i.e., the energy transmitter can estimate the CSI via dedicated reverse-link training from the energy receiver.

The study of spectral efficiency (SE) in MIMO systems has received great interests during last decades [17]. Among these works, [17] has studied the mutual information quantity optimization problem of the MIMO system, showing that increasing number of antennas leads to the increment in spectral efficiency. As a matter of fact, although the use of MIMO can improve the system's spectral efficiency, the use of a large number of antennas brings a significant problem to the EE design. Therefore, the question of how to improve EE in a multiple antenna system has received increasing attentions [4],[19]-[20]. For a massive MIMO system, the number of selected antennas should be decided in an optimized manner. In [4], the EE of a large multiple antenna system with transmit antenna selection is studied, and two antenna selection algorithms are presented based on the sequential search and the binary search algorithms. In [18], by elaborating on the performance of crossing-layer design with antenna selection under imperfect feedback information in a MIMO system, the SE and the bit error rate of a closed form are obtained. In [19], the authors investigate the trade-off between the SE and EE for massive MIMO systems with linear precoding and transmit antenna selection. The weighted-sum particle swarm optimization algorithm and the normal-boundary intersection particle swarm optimization algorithm are applied to address the formulated multiobjective optimization problem. The authors of [20] also focus on a similar problem and propose user association and power coordination schemes to ensure user fairness.

It can be well observed that most of the aforementioned works assume that the CSI can be perfectly obtained. However, in practical wireless communication systems, the CSI cannot be perfectly obtained due to the imperfection of channel estimation and feedback. Such imperfection of the CSI can typically induce system performance degradation. In [21], the

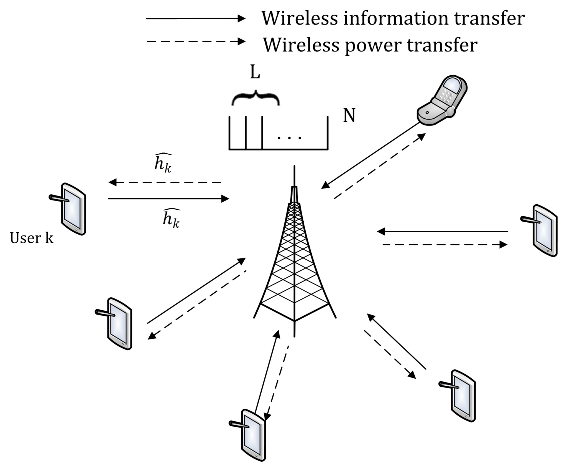

Fig. 1. A multi-user wireless powered communications system with transmit antenna selection.

Downlink: Wireless power transfer	Uplink: Wireless information transfer
τ_k	$T-\tau_k$

Fig. 2. Time protocol for wireless information and power transfer.

authors focus on the resource allocation for OFDMA-based networks with imperfect CSI and multiple classes of services with diverse QoS requirements. In [22], an energy-efficient resource allocation for OFDMA relay systems with imperfect CSI is presented, and a proportional fairness design for the EE maximization problem is considered. In [23], the authors formulate a non-convex optimization problem for determining the training interval of channel estimation, user scheduling, and power allocation strategies to maximize the EE, and transform the problem into a tractable convex one. The authors of [24] investigate the performance of an OFDMA relay system with imperfect CSI and propose a resource allocation algorithm to obtain throughput maximization.

III. System Model and Problem Formulation

A. System Model

As shown in Fig. 1, we consider a multi-user massive MIMO system with WPT. In the system, there is one BS, K mobile users and the set of users is denoted by $\mathcal{K}$. The BS is equipped with $N \gg 1$ antennas and each user is equipped with one antenna. In this model, the role of the BS is to charge the users via downlink WPT, while the users have the functionality of storing the energy transmitted by the BS and use the received energy to deliver data to the BS in the uplink. The users can also deliver the channel state information (CSI) through a feedback channel to the BS. For the channel estimation, the BS first sends preambles, and the user performs channel estimation in an interval of symbol periods. Then, the MT feeds the CSI back to the BS. Such a process can be handled in a standardlized way. Since the usually CSI feedback is general small comparing with the transmit data, we mainly focus on the energy and data transmission [15].

We assume that the whole transmission process including WPT in the downlink and data transmission in the uplink is within a time block T. In the downlink, BS will use a power P_t transfer energy to all the users and the duration of WPT time τ_k will depend on the individual user k, which should be further optimized. As shown in Fig. 2, in the first time slot τ_k, the BS charges user k via WPT and the user stores the harvested energy in a rechargeable battery. Then, in the time duration $T-\tau_k$, user k sends its own data to the BS.

We consider a quasi-static block fading channel model where the channel between the BS and user is constant for a given transmission block T, and can vary independently from one block to another. In each transmission block, user k uses a minimum mean square error (MMSE) channel estimator to estimate the channel. The estimated channel is denoted by $\hat{\mathbf{h}}_k$ and the estimation error is $\hat{\mathbf{e}}_k$. Thus, we have the expression of imperfect CSI as

$$\hat{\mathbf{h}}_k = \mathbf{h}_k + \hat{\mathbf{e}}_k, \tag{1}$$

where $\mathbf{h_k}$ is the channel coefficient and we assume $\hat{\mathbf{e}}_k \sim \mathcal{CN}(0, \sigma_{e_k}^2 I_{e_k})$, where I_{e_k} is the identity matrix. The BS is equipped with N antennas, where N is very large. Meanwhile, each antenna of BS requires a separate RF chain, which increases the energy consumption and cost of the massive MIMO system. In order to reduce the energy consumption and improve the system EE, we propose an antenna selection algorithm at the BS, that is, L antennas are selected from the N antennas with the objective to maximize the EE of the considered system. Meanwhile, we also propose to design the energy beamforming vector for the selected antennas to improve the efficiency of WPT. According to the law of conservation of energy, user k can obtain the received energy from the BS as follows [6],

$$E_k = \eta\tau_k(\alpha_k^2|\mathbf{b}_k^H\mathbf{h}_k|^2 P_t), \tag{2}$$

where α_k is the path loss from the BS to user k, $\mathbf{b}_k^H$ is a energy beamforming vector for user k at the BS and $\mathbf{s}$ is the transmitted signal. In the system, when L antennas are selected, we have $\hat{\mathbf{h}}_k \in \mathbb{C}^{1\times L}$. The transmit power of the BS is P_t. $\eta(0<\eta\leq 1)$ is the conversion efficiency which transfers the harvested energy into electric energy stored by the user. In order to maximize the harvested energy, we design the energy beamforming policy as $\mathbf{b}_k = \frac{\hat{\mathbf{h}}_k}{\|\hat{\mathbf{h}}_k\|}$ [15], which is named as maximum ratio transmission (MRT) [12]. According to the estimated CSI and beamforming strategy, the energy transfer direction can be adjusted properly to maximize the received energy at the user. Denoting $Q_k = \frac{\sigma_{e_k}^2}{1+\sigma_{e_k}^2} + \frac{\|\hat{\mathbf{h}}_k\|^2}{(1+\sigma_{e_k}^2)^2}$, the obtained energy of user k can be reformed as follows [15]:

$$E_k = \eta\tau_k(\alpha_k^2 Q_k P_t). \tag{3}$$

B. Throughput Analysis

During the second time slot $T-\tau_k$, user k can use the harvested energy to send its data to the BS, and the received signal at the BS is can be expressed as,

$$y_k^{ID} = \sqrt{\frac{E_k}{T-\tau_k}}\alpha_k \hat{\mathbf{h}}_k^H x_k + \mathbf{n}_{u,k}, \tag{4}$$

where y_k^{ID} is the received signal at the BS, x_k is the transmitted signal at user k, and $\mathbf{n_{u,k}} \sim \mathcal{CN}(0,\sigma^2)$ is the channel noise. It is also worth noticing that $\frac{E_k}{T-\tau_k}$ is the transmit power of user k.

In a massive MIMO system, with the increase of the number of antennas, the channel hardening effect emerges [17]. Therefore, in order to obtain the expected data rate of the considered system with imperfect CSI, we first study the mutual information distributions with/without antenna selection. To this end, we first arrive at **Theorem 1** about the mutual information distribution of the considered system without antenna selection.

Theorem 1. *Given the imperfect CSI and $N \gg 1$ antennas, a numerical approximation of the mutual information in UL of the considered system is given as,*

$$I \sim \mathcal{N}\left(\log_2(1+N\rho_k), \frac{(\log_2 e)^2}{N}\right), \tag{5}$$

where $\mathcal{N}$ represents standard normal distribution. The signal to interference plus noise ratio (SINR) ρ_k of user k in the uplink can be expressed as:

$$\rho_k = \frac{\frac{E_k\alpha_k^2}{T-\tau_k}}{\sigma^2 + \frac{E_k\alpha_k^2}{T-\tau_k}\sigma_{e_k}^2 + \sum\limits_{j\neq k}\frac{E_j\alpha_j^2}{T-\tau_j}}, \tag{6}$$

where σ^2 is noise variance and $\sigma_{e_k}^2$ is the variance of estimation error.

Proof. The proof of **Theorem 1** is shown in Appendix A. □

Theorem 1 presents the distribution of mutual information when considering N antennas. Similarly, we can obtain the expression of mutual information when L antennas are selected out of N in **Theorem 2**.

Theorem 2. *In the considered system, when L antennas are selected, the mutual information distribution is given as follows:*

$$\begin{aligned} I_{sel} \sim \mathcal{FN}\Big(&\log_2\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right), \\ &\frac{(\log_2 e)^2\rho_k^2 L(2-\frac{L}{N})}{(1+(1+\ln\frac{N}{L})\rho_k L)^2}\Big), \end{aligned} \tag{7}$$

where $\mathcal{FN}$ represents the folded normal distribution.

Proof. The proof of **Theorem 2** is shown in Appendix B. □

Obviously, if $L = N$ (N is sufficiently large), the expected value of the distribution is the same as that of the system without antenna selection, and the variance is approximately the same as well. Therefore, adding antenna selection does not affect the channel hardening phenomenon. Thus, in each time block, the expected channel capacity under imperfect CSI is denoted by $E[I]_{im}$:

$$E[I]_{im} = \log_2\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right). \tag{8}$$

Correspondingly, when L antennas are selected, the throughput is

$$C(P_t,\tau_k,L) = \sum_{k=1}^{K}(T-\tau_k)\log_2\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right). \tag{9}$$

C. Energy Consumption Model

Meanwhile, the total energy consumption of the system can be expressed as:

$$U(P_t,\tau_k,L) = P_c\cdot T + P_t \max_{k\in\mathcal{K}}\tau_k, \tag{10}$$

where P_c is the constant circuit power consumption, which can be expressed as [25]

$$\begin{aligned} P_c \approx\ & L(P_{DAC}+P_{mix}+P_{filt}) \\ &+ K(2P_{syn}+P_{LNA}+P_{mix}+P_{IFA}+P_{filr}+P_{ADC}), \end{aligned} \tag{11}$$

where $P_{DAC}, P_{mix}, P_{filt}, P_{syn}, P_{LNA}, P_{IFA}, P_{filr}, P_{ADC}$ denotes the power consumption of the DAC, the mixer, the transmit filter, the frequency synthesizer, the low noise amplifier, the frequency amplifier, the receiver filter and ADC, respectively. We denote P_{user} as the power consumption of the each user, i.e., $P_{user} = 2P_{syn}+P_{LNA}+P_{mix}+P_{IFA}+P_{filr}+P_{ADC}$. P_{bs} is expressed as the power consumption for each antenna on the BS, i.e., $P_{bs} = P_{DAC}+P_{mix}+P_{filt}$. Then we have $P_c = KP_{user}+LP_{bs}$. Since the BS and users have to be active for the whole time and the transmit power only exists in the first time slot, in (10), the denominator of EE is rewritten as:

$$U(P_t,\tau_k,L) = (KP_{user}+LP_{bs})T + P_t\max_{k\in\mathcal{K}}\tau_k. \tag{12}$$

D. Problem Formulation

With the above analysis, we can obtain the expressions of $C(P_t,\tau_k,L)$ in [bits/s/Hz] and $U(P_t,\tau_k,L)$ in [W]. Correspondingly, the objective of EE in [bits/J/Hz] can be defined as follows,

$$\Pi(P_t,\tau_k,L) = \frac{C(P_t,\tau_k,L)}{U(P_t,\tau_k,L)}. \tag{13}$$

From (3), (9) and (13), $\Pi(P_t,\tau_k,L)$ can be given as follows:

$$\begin{aligned} &\Pi(P_t,\tau_k,L) \\ &= \frac{\sum\limits_{k=1}^{K}(T-\tau_k)\log_2(1+(1+\ln\frac{N}{L})\rho_k L)}{(KP_{user}+LP_{bs})T+P_t\max_{k\in\mathcal{K}}\tau_k}. \end{aligned} \tag{14}$$

With the defined objective, the optimization problem $\mathbf{P_1}$ can be formulated as follows,

$$\max_{P_t,\tau_k,L} \Pi(P_t,\tau_k,L), \tag{15}$$

s.t.

$$\begin{aligned}
&\mathbf{C1}: \quad 0 \le P_t \le P_{bs,max},\\
&\mathbf{C2}: \quad \frac{E_k}{T-\tau_k} \le P_{user,max},\\
&\mathbf{C3}: \quad 0 \le \tau_k \le T,\\
&\mathbf{C4}: \quad \frac{C_k}{T-\tau_k} \ge R_{min},\\
&\mathbf{C5}: \quad L \le N.
\end{aligned} \tag{16}$$

In $\mathbf{P_1}$, the objective is to maximize the overall system EE. In (16), **C1** is the BS transmit power constraint, which shows that the transmit power of the BS cannot be larger than the maximum transmit power $P_{bs,max}$. **C2** is the transmit power constraint for user k. **C3** means that τ_k cannot be larger than T and **C4** can ensure that Quality of Service (QoS) R_{min} can be meet. Because the channel hardening phenomenon after antenna selection still exists, we can bring (3) into **C2**, to arrive at

$$P_t \le \frac{P_{user,max}(T-\tau_k)}{\eta\tau_k Q_k \alpha_k^2}. \tag{17}$$

Combining **C1** and (17), we can obtain

$$\tau_k \le \frac{P_{user,max}T}{(\eta\alpha_k^2 P_{bs,max}Q + P_{user,max})} = \tau_{max}. \tag{18}$$

IV. Antenna Selection and Resource Allocation

In this section, antenna selection and resource allocation schemes are introduced to address the formulated problem $\mathbf{P_1}$. At first, we propose an antenna selection scheme to find the optimal number of antennas that the BS can use to obtain EE maximization. Then, power and time allocation schemes are presented to find the optimal transmit power and time duration of WPT.

A. Proposed Antenna Selection Algorithm

The proposed scheme is based on an improved bisection method to find the solution for antenna selection. The antenna selection scheme is presented in Algorithm 1. First, we initialize three variables: the lower bound of the number of antennas, the upper value and the intermediate value, denoted as ω_l, ω_h and ω_m, respectively. Among them, the initial values of ω_l and ω_h are 1 and N, respectively, and the intermediate values are calculated as $\omega_m = \frac{\omega_l+\omega_h}{2}$. In each cycle, we need to compare the two values of $\Pi(\omega_m)$ and $\Pi(\omega_m+1)$, and determine which subset of the maximum value is located. If $\Pi(\omega_m)$ is less than $\Pi(\omega_m+1)$, ω_m+1 is assigned to ω_l; if $\Pi(\omega_m)$ is bigger than $\Pi(\omega_m+1)$, ω_m is assigned to ω_h. Thus, the maximum value of EE is found by selecting the optimal number of antennas. At the end of each cycle, the ω_m value is updated to the new ω_l or ω_h. When $\omega_h-\omega_l=1$, the search is ended. Finally, the corresponding L can be obtained.

Algorithm 1 Antenna Selection Algorithm

Initialize N, $\Pi(N)$, $\omega_l=1$, $\omega_h=N$,$\omega_m=\frac{\omega_l+\omega_h}{2}$.
while $(\omega_h-\omega_l)>1$ **do**
  if $\Pi(\omega_m)<\Pi(\omega_m+1)$ **then**
    set $\omega_l=\omega_m+1$;
  else if $\Pi(\omega_m)>\Pi(\omega_m+1)$ **then**
    set $\omega_h=\omega_m$;
  else
    break;
  end if
end while
if $\omega_h-\omega_l=1$ **then**
  $\Pi(L)=max\{\Pi(\omega_l),\Pi(\omega_h)\}$;
else
  $\Pi(L)=\Pi(\omega_m)$;
end if

B. Power and Time Allocation Schemes

The formulated problem with objective in (15) is a non-convex fractional programming problem. Based on the Dinkelbach's method [26], we are able to transform it into a subtractive form. First, given L is obtained, we consider q^* as the global optimal solution of EE, i.e.,

$$q^* = \frac{C(P_t,\tau_k)}{U(P_t,\tau_k)}\Big|_{P_t=P_t^*,\tau_k=\tau_k^*}, \tag{19}$$

where P_t^* is the optimal transmit power and τ_k^* is the optimal WPT time. Then, we can obtain the following **Theorem 3**,

Theorem 3. *q can reach its optimal value if and only if*

$$\max_{P_t,\tau_k} C(P_t,\tau_k) - qU(P_t,\tau_k) = 0. \tag{20}$$

The proof can be found in [26]. Consequently, problem $\mathbf{P_1}$ can be transformed into a problem $\mathbf{P_2}$:

$$\max_{P_t,\tau_k} \Gamma(P_t,\tau_k), \tag{21}$$

s.t.

$$\begin{aligned}
&\mathbf{C1}, \mathbf{C3}, \mathbf{C4},\\
&\tau_k < \tau_{max},
\end{aligned} \tag{22}$$

where $\Gamma(P_t,\tau_k) = C(P_t,\tau_k) - q^*U(P_t,\tau_k)$. We can see that $\Gamma(P_t,\tau_k)$ is a concave function with respect to P_t and τ_k as its Hessian matrix is negative semi-define. Therefore, $\mathbf{P_2}$ is now a convex optimization problem and we are able to address it in dual domain to obtain a closed-form solution. The Lagrange dual function corresponding to $\mathbf{P_2}$ is

$$\begin{aligned}
&\mathcal{L}(P_t,\tau_k,\alpha,\beta,\mu,\varphi) = C(P_t,\tau_k) - q^*U(P_t,\tau_k)\\
&-\lambda(P_t-P_{bs,max}) - \beta(\tau_k-\tau_{max}) - \mu(\tau_k-T)\\
&-\varphi(R_{min}-\frac{C_k}{T-\tau_k}),
\end{aligned} \tag{23}$$

where $\{\lambda,\beta,\mu,\varphi\}$ are the positive Lagrange multipliers associated with the constraint in (22), respectively. Correspondingly, the dual problem of (23) can be expressed as

$$\mathbf{P_3}: \min_{\alpha,\beta,\mu,\varphi} \max_{P_t,\tau_k} \mathcal{L}(P_t,\tau_k,\alpha,\beta,\mu,\varphi). \tag{24}$$

Optimal transmit power P_t^* and the optimal time for WPT τ_k^* can be obtained by solving the Karush-Kuhn-Tucker(KKT) condition:

$$\frac{\partial \mathcal{L}(P_t, \tau_k, \lambda, \beta, \mu, \varphi)}{\partial P_t} = 0, \tag{25}$$

and

$$\frac{\partial \mathcal{L}(P_t, \tau_k, \lambda, \beta, \mu, \varphi)}{\partial \tau_k} = 0. \tag{26}$$

From (25), we can obtain

$$P_t^* = \frac{-(\Omega_4 + \Omega_3)\Omega_2 + \sqrt{(\Omega_3 - \Omega_4)^2 \Omega_2^2 + 4\prod_{i=1}^{5} \Omega_i}}{2\Omega_3 \Omega_4}, \tag{27}$$

where $\Omega_1 \sim \Omega_5$ are given as

$$\begin{aligned}
&\Omega_1 = \eta \tau_k (\alpha_k^4 Q)(L + L\ln(N/L)),\\
&\Omega_2 = (T - \tau_K)\sigma^2,\\
&\Omega_3 = \eta \tau_k (\alpha_k^2 Q)(\sigma_{e_k}^2 + K - 1),\\
&\Omega_3 = \Omega_1 + \Omega_3,\\
&\Omega_5 = \frac{(T - \tau_k + \varphi)K}{(\lambda + q^* \max_{k \in \mathcal{K}} \tau_k)(\ln 2)}.
\end{aligned} \tag{28}$$

Next, τ_k^* can be obtained by addressing (26) numerically. To obtain the lagrangian multipliers $\lambda, \beta, \mu, \varphi$, the subgradient method with guaranteed convergence [27] can be applied,

$$\begin{aligned}
&\lambda(n+1) = [\lambda(n) - \triangle\lambda(P_{bs,max} - P_t)]^+,\\
&\beta(n+1) = [\beta(n) - \triangle\beta(\tau_{max} - \tau_k)]^+,\\
&\mu(n+1) = [\mu(n) - \triangle\mu(T - \tau_k)]^+,\\
&\varphi(n+1) = [\varphi(n) - \triangle\varphi(\frac{C_k}{T - \tau_k} - R_{min})]^+,
\end{aligned} \tag{29}$$

where n is iteration index, $[x]^+ = max\{0, x\}$, $\triangle\lambda$, $\triangle\beta$, $\triangle\mu$, and $\triangle\varphi$ are the step sizes. Based on the optimal value q^* and the iterative update of the time allocation and power allocation parameter, the convergence can be obtained by satisfying the following relations: $|C(P_t, \tau_k, L) - q^* U(P_t, \tau_k)| < \varepsilon$, where ε is a sufficiently small positive number. If this condition cannot be meet, $q^* = \frac{C(P_t, \tau_k)}{U(P_t, \tau_k)}$ will be updated until the convergence condition is satisfied. The proposed power and time allocation scheme is summarized in Algorithm 2.

Algorithm 2 Energy Efficient Resource Allocation

```
Initialization:
  N, L, K, η, α_k, P_bs, P_user, P_bs,max, P_user,max, R_min,
  △λ, △β, △μ, and △φ.
Define ε as a sufficiently small positive real number.
while (!Convergence) do
  Update λ, β, μ, φ according to (29).
  Obtaining the P_t' and τ_k' by solving the equations (27)
  and (26).
  if |C(P_t', τ_k') − qU(P_t', τ_k')| ≤ ε, then
    Convergence = true,
    return P_t* = P_t', τ_k* = τ_k', and obtain optimal q*
  else
    Convergence = false,
    return q = C(P_t', τ_k')/U(P_t', τ_k'),
  end if
end while
return Obtain P_t* and τ_k*.
```

TABLE I
SIMULATION PARAMETERS

Parameter	Value
N	100
K	10
$P_{bs,max}$	$46dBm$
$P_{user,max}$	$23dBm$
R_{min}	$0.1bit/s/Hz$
$\triangle\alpha, \triangle\beta, \triangle\mu, \triangle\varphi$	0.001
C	2
η	0.35
ε	0.001
P_{DAC}, P_{ADC}	$10mW$
P_{filt}, P_{filr}	$2.5mW$
P_{mix}	$30.3mW$
P_{syn}	$50mW$
P_{LNA}	$20mW$
P_{IFA}	$3mW$

V. Simulation Results

In this section, the performance of the proposed scheme is presented and illustrated. Some simulation parameters are given in Table I [25].

In Fig. 3, we present the EE performance of our proposed schemes and prove the effectiveness of the proposed antenna selection and time allocation schemes. To illustrate the advances of the proposed antenna selection scheme, we compare our proposed scheme with the one without antenna selection, which is modified from [7]. It can be clearly seen that the proposed antenna selection scheme can improve system EE by selecting the optimal number of antennas from Fig. 3. Such observation reveals that the antenna selection has great influence on the EE performance, especially when the BS is close to users. At the same time, we also compare our proposed scheme with the one with equal time allocation, i.e., $\tau_k = 0.5T$ and we assume $T = 1$ for simplicity. Obviously, the proposed algorithm also has the superior performance over the equal time allocation algorithm, which indicates that proper design of time allocation is needed for the SWIPT system. Moreover, It can also be found that as the distance between the BS and users becomes larger, the EE performance decreases.

In Fig. 4, we present the impact of CSI imperfection on the system EE performance by varying the variance of channel estimation error $\sigma_{e_k}^2$ and the distance between the BS and the user k. The EE performance of the system with perfect CSI is compared with the EE performance with estimation errors $\sigma_{e_k}^2 = 0.3$ and $\sigma_{e_k}^2 = 0.5$. As we can observe,

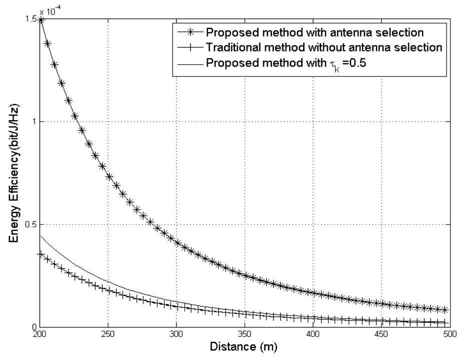

Fig. 3. EE w/wo antenna selection and time allocation

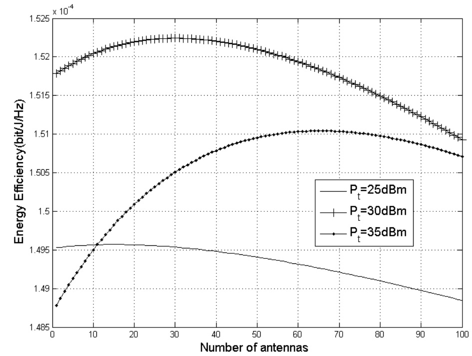

Fig. 5. EE vs. number of antennas

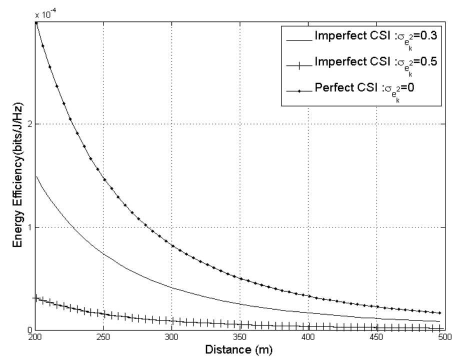

Fig. 4. Effect of imperfect CSI and BS-user distance

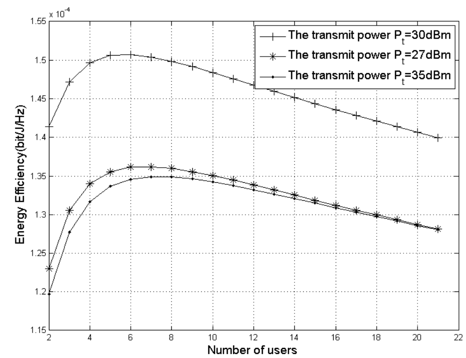

Fig. 6. EE vs. number of users

the system performance with perfect CSI is higher than that with imperfect CSI. When the variance of estimation error increases, the system performance degrades. Also, when the average distance between the BS and users is longer, the performance gap between the one with perfect CSI and the system with the imperfect CSI becomes smaller. For example, when the distance between the BS and the user is 200m, the system with the perfect CSI has about 4 times higher EE than the one with $\sigma_{e_k}^2 = 0.5$. However, when the distance becomes 450m, the system with perfect CSI has only 2 times better performance. From Fig. 4, the EE of the system when $\sigma_{e_k}^2 = 0.3$ is higher than the one when $\sigma_{e_k}^2 = 0.5$, which confirms that the imperfect CSI has significant impact on the system performance. At the same time, we can also observe that the EE decreases with the increase of the distance between the BS and the users, which is similar to the observation in Fig. 3.

Fig. 5 describes the EE performance when considering a different transmit power with the change of the number of antennas. It can be seen that with the increase of the number of antennas, the EE performance generally first increases and then decreases after reaching the maximum. For the considered system, different transmit power allocation leads to a different optimal number of antennas. For example, when the transmit power is $30dBm$, optimal $L = 30$ and when the transmit power is $35dBm$, $L = 50$. In addition, from the comparison of the EE performance of a different transmit power allocation, we can clearly find that increasing transmit power can not guarantee any increment of EE. Fig. 5, where the EE of $P_t = 30dBm$ is higher than the other two curves of the EE, also illustrates the effectiveness of the optimized transmit power allocation.

The EE performance for different transmit powers with the change of the number of users K is presented in Fig. 6. It can be seen that with the increase of the number of users, the EE performance first increases and then decreases after reaching the maximum. In addition, by comparing the curves, we can clearly see that proper increase of transmit power can improve the EE. The EE with $P_t = 30dBm$ is higher than the other two cases, which also illustrates the effectiveness of the proposed transmit power allocation scheme.

VI. Conclusion

In the future wireless network, massive antennas will be explored to improve the system capacity. Meanwhile, as an emerging technique, wireless power transfer offers a potential solution to prolong the lifetime of mobile devices. This paper studies the energy efficiency of a wireless power transfer enabled multi-user massive MIMO system under imperfect channel estimation. A joint optimization of beamforming design, antenna selection, power and time allocation is studied. In particularly, the antenna selection algorithm is based on an improved bisection scheme to find the optimal number of transmit antennas at the BS. Moreover, a scheme based on nonlinear fractional programming is utilized to address the resource allocation problem and find the optimal power and time allocation. Extensive simulation results can demonstrate the effectiveness of the proposed schemes.

Appendix A

First, we consider a MIMO system with the dimension of $N \times M$. Let $\lambda_1, \lambda_2, \lambda_3, \cdots, \lambda_M$ be the eigenvalues of $\frac{\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}}{N}$. Then in a MIMO system, the mutual information is given by

$$\begin{aligned}\mathcal{I} &= \log_2 \det \left(\mathbf{I_M} + \frac{\rho}{M}\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}\right)\\ &= \log_2 |\mathbf{I_M} + \frac{\rho N}{M}\frac{\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}}{N}|\\ &= \log_2 \left(1 + \frac{\rho N}{M}\lambda_1)(1 + \frac{\rho N}{M}\lambda_2)\cdots(1 + \frac{\rho N}{M}\lambda_M\right)\\ &= \sum_{m=1}^{M}\log_2\left(1 + \frac{\rho N}{M}\lambda_m\right),\end{aligned} \tag{30}$$

where ρ is the SINR in the UL SIMO channel, and $\mathbf{I_M}$ is a unit array. As for massive MIMO system, $N \to \infty$, we have that $\frac{\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}}{N} \to \mathbf{I_M}$(strong law of large numbers [28]. Since $\lambda_1, \lambda_2, \lambda_3, \cdots, \lambda_M$ are continuous functions of $\frac{\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}}{N}$, it follows that $\lambda_m \to 1$ for $m = 1, 2, 3, \cdots, M$. Thus, we let $\lambda_m = 1 + \tilde{\lambda}_m$, with the understanding that $N \to \infty$, $\tilde{\lambda}_m \to 0$. Then we have

$$\begin{aligned}&\sum_{m=1}^{M}\log_2\left(1 + \frac{\rho N}{M}\lambda_m\right)\\ &= \log_2\left(1 + \frac{\rho N}{M}\lambda_1\right)\left(1 + \frac{\rho N}{M}\lambda_2\right)\cdots\left(1 + \frac{\rho N}{M}\lambda_M\right)\\ &= \log_2\left(1 + \frac{\rho N}{M}\right)^M \frac{\left(1 + \frac{\rho N}{M}\lambda_1\right)\left(1 + \frac{\rho N}{M}\lambda_2\right)\cdots\left(1 + \frac{\rho N}{M}\lambda_M\right)}{\left(1 + \frac{\rho N}{M}\right)^M}\\ &= \log_2\left(1 + \frac{\rho N}{M}\right)^M + \log_2\left(\frac{1 + \frac{\rho N}{M}\lambda_1}{1 + \frac{\rho N}{M}}\right) +\\ &\log_2\left(\frac{1 + \frac{\rho N}{M}\lambda_2}{1 + \frac{\rho N}{M}}\right) + \cdots + \log_2\left(\frac{1 + \frac{\rho N}{M}\lambda_M}{1 + \frac{\rho N}{M}}\right)\\ &= M\log_2\left(1 + \frac{\rho N}{M}\right) + \sum_{m=1}^{M}\log_2\left(\frac{1 + \frac{\rho N}{M}\lambda_m}{1 + \frac{\rho N}{M}}\right)\\ &= M\log_2\left(1 + \frac{\rho N}{M}\right) + \sum_{m=1}^{M}\log_2\left(\frac{1 + \frac{\rho N}{M} + \frac{\rho N}{M}\tilde{\lambda}_m}{1 + \frac{\rho N}{M}}\right)\\ &= M\log_2\left(1 + \frac{\rho N}{M}\right) + \sum_{m=1}^{M}\log_2\left(1 + \frac{\frac{\rho N}{M}\tilde{\lambda}_m}{1 + \frac{\rho N}{M}}\right)\\ &= M\log_2\left(1 + \frac{\rho N}{M}\right) + \frac{\frac{\rho N}{M}log_2 e}{1 + \frac{\rho N}{M}}\sum_{m=1}^{M}\tilde{\lambda}_m + O\left(\sum_{m=1}^{M}\tilde{\lambda}_m^2\right).\end{aligned} \tag{31}$$

As $N \to \infty$, we can see that $x_N = O(y_N)$ if $|x_N| \le cy_N$ for some $c > 0$ and N sufficiently large. Note that the sum of all eigenvalues $\sum_m^M \lambda_m$ is the trace of matrix $\frac{\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}}{N}$, and

$$\begin{aligned}\sum_{m=1}^{M}\tilde{\lambda}_m &= \sum_{m=1}^{M}(\lambda_m - 1)\\ &= \lambda_1 + \lambda_2 + \cdots + \lambda_M - M = tr\left(\frac{\hat{\mathbf{H}}^{\mathbf{H}}\hat{\mathbf{H}}}{N}\right) - M,\end{aligned} \tag{32}$$

$\sum_{m=1}^{M}\tilde{\lambda}_m$ has a zero mean. From Lemma A in [17], we can see that $E[\sum_{m=1}^{M}\tilde{\lambda}_m^2] = \frac{M^2}{N}$. Therefore, $O(\sum_{m=1}^{M}\tilde{\lambda}_m^2)$ in (31) has an expected value μ_N, which is $O(\frac{1}{N})$ as $N \to \infty$. Thus, the expected value of (31) is $M\log_2(1 + \frac{\rho N}{M}) + O(\frac{1}{N})$.

By Lemma A in [17], $\sum_{m=1}^{M}\tilde{\lambda}_m$ has variance $\frac{M}{N}$, and the fourth-order moment calculations of Wishart matrix show that the variance of $\sum_{m=1}^{M}\tilde{\lambda}_m^2$ is $O(\frac{1}{N^2})$. Therefore, $\sum_{m=1}^{M}\tilde{\lambda}_m^2 - \mu_N$ is $O_p(\frac{1}{N^2})$, which is a probabilistic statement. We have $x_N = O_p(y_N)$ if for any $\xi > 0$, we can find a $c > 0$ such that $P[|x_N| > cy_N] < \xi$ for a sufficiently large N [30]. From Lemma B in [17], $\sqrt{\frac{N}{M}}\sum_{m=1}^{M}\tilde{\lambda}_m \longrightarrow \mathcal{N}(0, 1)$ as $N \to \infty$. Thus, $\sum_{m=1}^{M}\tilde{\lambda}_m$ is $O_p(\frac{1}{N})$ and is the dominant random term in (31). The asymptotic distribution of (31) is therefore also similarly normal [30], too. Using $\frac{\frac{\rho N}{M}}{1+\frac{\rho N}{M}} = 1 + O(\frac{1}{N})$, we can see that

$$\begin{aligned}&\sum_{m=1}^{M}\log_2\left(1 + \frac{\rho N}{M}\lambda_m\right) - M\log_2\left(1 + \frac{\rho N}{M}\right)\\ &= [1 + O\left(\frac{1}{N}\right)]\log_2 e\sum_{m=1}^{M}\tilde{\lambda}_m + O\left(\sum_{m=1}^{M}\tilde{\lambda}_m^2\right)\\ &= \log_2 e\sum_{m=1}^{M}\tilde{\lambda}_m,\end{aligned} \tag{33}$$

which equals to

$$\begin{aligned}&\sqrt{\frac{N}{M}}\frac{\sum_{m=1}^{M}\log_2\left(1 + \frac{\rho N}{M}\lambda_m\right) - M\log_2\left(1 + \frac{\rho N}{M}\right)}{\log_2 e}\\ &= \sqrt{\frac{N}{M}}\sum_{m=1}^{M}\tilde{\lambda}_m \sim \mathcal{N}(0, 1).\end{aligned} \tag{34}$$

Therefore,

$$\begin{aligned}&\sqrt{N}[\sum_{m=1}^{M}\log_2\left(1 + \frac{\rho N}{M}\lambda_m\right) - M\log_2\left(1 + \frac{\rho N}{M}\right)]\\ &\longrightarrow \mathcal{N}(0, M\log_2^2 e),\end{aligned} \tag{35}$$

namely, $\sqrt{N}[I - M\log_2(1 + \frac{\rho N}{M})] \longrightarrow \mathcal{N}(0, M\log_2^2 e)$, and correspondingly, $I \sim \mathcal{N}(M\log_2(1 + \frac{\rho N}{M}), \frac{M\log_2^2 e}{N})$.

For the considered system, when $M = 1$, we have

$$I \sim \mathcal{N}\left(\log_2(1 + N\rho_k), \frac{(\log_2 e)^2}{N}\right), \tag{36}$$

Appendix B

According to [31], We use $x_1 > x_2 > \cdots > x_N$ as the ordered random variables, as $N \to \infty$ and $1 \leq L \leq N$. The distribution of the trimmed sum $\sum_{i=1}^{L} x_i$ is asymptotically normal. [32] gives the mean and variance when x_i is a chi-square random variable with two degrees of freedom. Thus, we get the following observation

$$\sum_{i=1}^{L} |\hat{h}_i|^2 \sim \mathcal{N}\left(L\left(1+\ln\frac{N}{L}\right), L\left(2-\frac{L}{N}\right)\right), \tag{37}$$

where $\hat{h}_i$ denotes the subchannel of SIMO channel matrix $\hat{\mathbf{H}}$. Note that the left hand side in (37) is approximated as a random variable of normal distribution which can take negative values. However, the left hand side in (37) is positive for sure. This is because the normal distribution is just an approximation. The approximation is accurate around the mean but not very precise in the tails of the distribution. However, in a massive MIMO system with large N, the mean of the normal distribution increases while the variance almost remains constant. Therefore, the probability of taking negative values becomes smaller and the approximation gets more accurate.

We have the following derivations of antenna selection,

$$\begin{aligned} I_{sel} &= \log_2 |1 + \rho_k \sum_{i=1}^{L} |\hat{h}_i|^2| \\ &= \log_2 \left| \left(1 + \left(1 + \ln\frac{N}{L}\right)\rho_k L\right) x \right|, \end{aligned} \tag{38}$$

where $|\cdot|$ denotes the absolute value, and x is given by:

$$x = 1 + \frac{\rho_k \left(\sum_{i=1}^{L} |\hat{h}_i|^2 - L\left(1+\ln\frac{N}{L}\right)\right)}{1 + \left(1+\ln\frac{N}{L}\right)\rho_k L}. \tag{39}$$

According to (37), it is very easy to obtain that

$$x \sim \mathcal{N}\left(1, \frac{\rho_k^2 L\left(2-\frac{L}{N}\right)}{\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right)^2}\right). \tag{40}$$

Given a normally distributed random variable x with mean μ and variance σ^2, the random variable $y = |x|$ has a folded normal distribution, i.e. , $\mathcal{FN}(\mu, \sigma^2)$, the PDF is given by

$$f(y) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y-\mu)^2}{2\sigma^2}} + \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(y+\mu)^2}{2\sigma^2}}, y > 0, \tag{41}$$

where $\mu = 1$, $\sigma^2 = \frac{\rho_k^2 L\left(2-\frac{L}{N}\right)}{\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right)^2}$. Then, (38) becomes

$$I_{sel} = \log_2\left(1 + \left(1+\ln\frac{N}{L}\right)\rho_k L\right) + \log_2\left(1 + (y-1)\right). \tag{42}$$

The mean of $(y-1)$ is zero, and the variance of $(y-1)$ is

$$\sigma_{y-1}^2 = \frac{\rho_k^2 L\left(2-\frac{L}{N}\right)}{\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right)^2} < \frac{2-L}{\left(1+\ln\frac{N}{L}\right)^2 L}. \tag{43}$$

Note that $\sigma^2 \to 0$ is almost surely for large N. Then,

$$\begin{aligned} I_{sel} &= \log_2\left(1 + \left(1+\ln\frac{N}{L}\right)\rho_k L\right) \\ &\quad + (y-1)\log_2 e + O\left((y-1)^2\right), \end{aligned} \tag{44}$$

where $O\left((y-1)^2\right)$ can be asymptotically negligible [4]. Thus, the distribution of I_{sel} is given by

$$\begin{aligned} I_{sel} \sim \mathcal{FN}\Bigg(&\log_2\left(1 + \left(1+\ln\frac{N}{L}\right)\rho L\right), \\ &\frac{(\log_2 e)^2 \rho_k^2 L\left(2-\frac{L}{N}\right)}{\left(1+\left(1+\ln\frac{N}{L}\right)\rho_k L\right)^2}\Bigg). \end{aligned} \tag{45}$$

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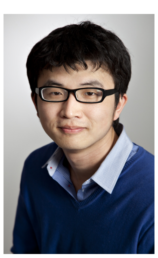

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