Beamforming and Resource Allocation for Charging Power Minimization in Multiuser Wireless-Powered Networks

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ABSTRACT In this paper, a multi-antenna base station (BS) concurrently serves uplink users with harvested energy in wireless-powered communication networks (WPCNs). We minimize the average power consumption of the BS due to wirelessly charging under the quality-of-service (QoS) requirements for uplink users. Based on this, the downlink/uplink beamforming, downlink/uplink time allocation, and uplink multiuser power control are jointly designed. The non-convex problem is first solved with fixed time allocation and uplink receive beamforming via a semi-definite relaxation (SDR) approach, based on which an iterative algorithm is proposed for updating the optimal time allocation and the receive beamforming. The feasibility condition and the equivalence condition between the original and relaxed problems are analyzed. Simulation results show that the average charging power consumption of the BS is significantly reduced compared with a heuristic scheme that adopts the average user channel gain as energy beamforming in the downlink and exhausts the harvested energy for multiuser power control with zero-forcing (ZF) receive beamforming in the uplink.

INDEX TERMS Energy beamforming, multiple users, power consumption minimization, resource allocation, wirelessly charging, wireless-powered communications

I. INTRODUCTION Energy harvesting has recently received significant attention due to its capability of providing untethered power supplies to wireless devices by scavenging energy from ambient environments. The common ambient energy sources include solar energy, wind, radio-frequency (RF) radiation, piezoelectric effect, and so on. While most of the ambient energy sources can offer an inexhaustible supply of energy, they are usually intermittent and unstable [1]. Among a wide variety of ambient energy sources, a RF signal emitted by a dedicated base station (BS) has been recognized as a promising solution to wirelessly charge devices on demand, thereby facilitating wireless applications with guaranteed quality-of-service (QoS) [2] [3].

The conventional battery-powered devices suffer from two fundamental problems: short battery life and high maintenance cost [3]. Recently, wireless energy transfer has been proposed to offer an alternative way to energize wireless devices, especially for low-power devices, in wireless communications. In this context, the wireless devices are capable of harvesting energy from dedicated wireless signals within some specific areas, and this provides an "efficient" means to overcome the hassle of battery recharging with physical connections or the difficulty of frequent battery replacement when the batteries are depleted. Wireless-powered communication networks (WPCNs) have been advocated in the recent research works to support uplink wireless communications [4]. It refers to a wireless network of wireless-powered devices which harvest energy from RF signals by the BS in the downlink and utilize the harvested energy for transmitting data in the uplink. Since more and more wireless nodes are being deployed to monitor the surrounding environments, it is impractical to change the batteries of wireless devices over a wide deployment area or complicated environments. Although the major limitation on the wireless energy transfer is the attenuation of RF signals over distance, with the continuous decrease in the operation power of devices and the recent advance of multi-input multi-output (MIMO) tech-
nology to improve the efficiency of wireless energy transfer, one can envision the combination of wireless energy transfer and communication such as WPCNs in many emerging applications, e.g., Internet of Things (IoT), in the future [5]. However, it possesses design challenges to jointly optimize downlink energy beamforming and uplink power control for WPCNs, while minimizing the BS wireless charging power consumption and satisfying users’ QoS requirement under doubly (downlink and uplink) fading channel environments. The design problems are particularly challenging in interference channels because the BS downlink power charging, multiuser uplink power control, and received signal quality closely interact to affect the network performance.

The design of WPCNs has been investigated in recent works [6]–[11]. In [6], time allocation for downlink and uplink was studied to maximize the sum-throughput of a WPCN, where the BS is equipped with a single antenna, and users send data to the BS in the uplink by time-division multiple access with the harvested energy from BS in the downlink. In [7], a resource allocation problem, in terms of time and power allocation, was cast to maximize the users’ weighted sum rate for a full-duplex WPCN. A WPCN BS with two antennas, one for transferring energy in the downlink and one for receiving information in the uplink, was studied in [8], and the time allocation problem was tackled to maximize the throughput. Some works addressed the energy efficiency issues in WPCNs [9]–[11]. The authors in [9] maximized the energy efficiency of a WPCN while ensuring users’ QoS via the joint design of power and time allocation. In [10], the authors developed an iterative resource allocation method to maximize the energy efficiency in WPCNs with dynamic time division duplex configurations. As an extension of [9], time allocation and power control were jointly studied in [11] to maximize the weighted sum of user energy efficiencies in WPCNs, and the tradeoff of energy efficiency among users was further characterized.

Multiple antennas were also utilized to improve the performance of energy harvesting networks by focusing transmission signals on specific directions through the idea of beamforming [12]–[17]. In [12], a multi-antenna BS was deployed to enable energy beamforming in WPCNs, and the minimum throughput among all users was maximized in order to achieve user rate fairness. In [13], energy beamforming at an energy transmitter and information beamforming at a wireless device were jointly optimized to maximize the achievable data rate in WPCNs with co-channel interference. In [14], the author studied the average throughput of energy beamforming for a WPCN with a multi-antenna BS and a single-antenna user, and the asymptotic downlink energy harvesting time was further optimized at a high signal-to-noise ratio (SNR). The work in [15] jointly designed energy beamforming and time allocation for time division multiple access users in WPCNs by maximizing the system sum throughput. The authors in [16] studied the cooperation of two communication groups via wireless power transfer and time sharing to fulfill the information delivery. In [17], a spectrum and energy cooperation strategy was proposed for hierarchical cognitive radio cellular networks, and multiple antenna beamforming was utilized at the secondary base station for not only transmitting data to its receiver and but also charging the primary receiver. In [18], the secrecy energy efficiency was considered for multiple-input single-output underlay cognitive radio networks in the presence of an energy harvesting receiver, and the transmit beamforming was optimized under different assumptions of perfect, statistical and imperfect channel state information (CSI). The authors in [19] maximized the sum of users’ energy efficiencies under two multiple access schemes by jointly optimizing the energy beamforming, users’ transmit power and time allocation. The work in [20] considered a more complicated multi-cell interference network and designed the downlink energy beamforming and uplink power control by maximizing the minimum signal-to-interference plus noise ratios (SINRs) among users. These existing works, however, mainly focus on the maximization of data throughput or energy efficiency, instead of addressing the design problems from the perspective of minimum average BS charging power consumption.

RF energy harvesting is a kind of far-field RF transmission technology. Generally, the signal strength is attenuated by at least 20 dB when the distance is increased ten times on the wireless channel. Due to the round-trip channel loss in the WPCN, the BS needs to boost the emitted power to compensate for the downlink path loss effect, so that the wireless nodes can obtain sufficient energy for uplink data transmission. On the other hand, minimum RF harvested power is required in the circuitry implementation to achieve better RF-to-DC conversion efficiency. For example, the minimum RF harvested power is around $-20$ dBm and $40$ dBm for $1$ V and $30$ V DC output, respectively [3]. Under these two considerations, the charging power level of the BS in the WPCN should be increased by several dozens of decibels, as compared with the transmit power of a traditional BS without supporting energy harvesting. Therefore, the charging power becomes an important issue toward the green design of WPCNs, which has not been undertaken in the existing works and prompts us to minimize the charging power of the BS through the joint design of beamforming and resource management. This raises an interesting question of how much BS charging power can be saved with the joint design of beamforming and resource management.

To the best of our knowledge, the joint design of downlink/uplink beamforming and resource allocation for WPCNs has not been investigated in the literature from a green perspective to minimize the average charging power consumption of the BS with guaranteed QoS for users. In this paper, we study the WPCN with a multi-antenna BS to simultaneously serve multiple uplink users that harvest energy from the BS in the downlink and then transmit data to the BS in the uplink using their harvested energy. The main contributions of this paper are summarized in the following:

- A joint design problem of downlink/uplink beamform-
ing, downlink/uplink time allocation, and uplink multiuser power control is tackled to minimize the average charging power consumption of the BS while meeting a specified QoS requirement for all users. The motivation of the context lies in that the antenna techniques are capable of enhancing downlink wireless power transfer efficiency and mitigating uplink multiuser interference. Further, minimizing the BS downlink charging power consumption is a crucial issue toward realizing green wireless communications.

- Since the joint design problem is non-convex, we resort to the semi-definite relaxation (SDR) and alternative optimization approaches to transform the problem into convex, and develop an algorithm to jointly optimize downlink/uplink beamforming, downlink/uplink time allocation, and uplink multiuser power control.
- A feasibility condition of the joint design problem is derived to capture the impact of the design variables on the time allocation. In addition, the equivalence condition between the original and relaxed optimization problems is provided based on rank analysis. It is proved that the solution obtained from the SDR problem is exactly the same as the original problem when the number of served users in the WPCN is less than or equal to three.
- The proposed algorithm is proposed based on the convex optimization skills and SDR approach, and we theoretically analyze the convergence of the proposed algorithm to justify the convergence of the obtained solutions to locally optimal ones. Hence, the proposed algorithm is not heuristic.
- Computer simulation is conducted to evaluate the performance of the proposed joint design scheme. Simulation results show the promising performance of the proposed iterative algorithm, as compared with a conventional heuristic scheme without considering the joint design.

The rest of this paper is organized as follows. The mathematical notations used in this paper are introduced in Section II. Section III presents the system model of the WPCN with a multi-antenna BS and multiple single-antenna users. In Section IV, the joint design optimization problem is formulated and the flexibility analysis is provided. The joint design algorithm, based on the SDR approach, is then proposed in Section V. The convergence analysis and computational complexity of the proposed algorithm are discussed in Section VI. The simulation results are demonstrated and discussed in Section VII. Finally, conclusions are drawn in Section VIII.

II. NOTATIONS

The following notations are used throughout the paper. The uppercase and lowercase boldface letters denote matrices and vectors, respectively. The notations $(\cdot)^*$ and $(\cdot)^{-1}$ stand for conjugate transpose and matrix inversion, and $\text{Diag}\{x\}$ is a diagonal matrix with $x$ as its diagonal entries. The matrices $I_N$ and $O_N$ are used to express $N \times N$ identity and zero matrices. The operators $E[]$ and $\text{Rank}\{(\cdot)\}$ take expectation and rank values, while $\|x\|_2$ finds the Euclidean norm of a vector $x$. $X \succeq O$ and $x \succeq \mathbf{0}$ denote that $X$ is a positive semi-definite matrix and $x$ is a non-negative real vector. The notation $x \sim \text{CN}(m, C)$ stands for a complex Gaussian random vector with mean $m$ and covariance $C$.

III. SYSTEM MODEL

In this work, we address the beamforming and resource allocation design problems for multiple users (e.g., low-power wireless sensor nodes) in WPCNs to improve the efficiency of energy usage by minimizing the BS charging power. For this WPCN, a BS can power multiple wireless nodes in the downlink phase and simultaneously receive their own information in the uplink phase. The system model can be practically applicable to wireless sensor networks for environmental sensing, smart home applications, in which the wireless nodes do not require electric wire for power supply or frequent battery replacement in complicated environments.

A. SIGNAL MODEL

In Fig. 1, the WPCN consists of one BS and $K$ users, where the BS is equipped with $M$ antennas, and each user only has a single antenna. A time-division duplex protocol is applied, and the BS wirelessly charges the $K$ users during the downlink time duration $\tau T$, while the users utilize the harvested energy to simultaneously transmit their data to the BS during the rest of the time duration $(1 - \tau) T$, where $T$ is the entire time duration. The variable $\tau$ is served as a parameter for adjusting the downlink and uplink time allocation and takes a value between zero and one. In the downlink, the transmitted signal of the BS is given as $x = \mathbf{v}s_0$, where $\mathbf{v} \in \mathbb{C}^{M \times 1}$ is a downlink beamforming vector, and $s_0$ is a reference signal with unit power, i.e., $E[|s_0|^2] = 1$. Hence, the received signal at the $k$th user $y_k$ can be expressed as

$$
y_k = g_k^*x + n_k = g_k^*\mathbf{v}s_0 + n_k, \quad k = 1, \ldots, K, \tag{1}
$$

where $g_k \in \mathbb{C}^{M \times 1}$ is a channel gain from the BS to the $k$th user, and $n_k$ is complex white Gaussian noise with zero mean and variance $\sigma^2$. Accordingly, the amount of the harvested energy at the $k$th user $E_k$ is calculated as

$$
E_k = \varepsilon \tau T \left( |g_k^*\mathbf{v}|^2 + \sigma^2 \right), \quad k = 1, \ldots, K, \tag{2}
$$

where $\varepsilon$ is the energy conversion efficiency of the receiver. In the uplink, the received signal at the BS $r$ is given by

$$
r = \sum_{k=1}^{K} h_k \sqrt{p_k}s_k + z, \quad k = 1, \ldots, K, \tag{3}
$$

where $p_k$ and $s_k$ are the transmit power and the uplink data symbol of the $k$th user, respectively. $h_k \in \mathbb{C}^{M \times 1}$ is a channel from the $k$th user to the BS, and $z \in \mathbb{C}^{M \times 1}$ denotes a zero-mean complex Gaussian noise vector with covariance $\sigma^2 \mathbf{I}$. We further assume that $E[|s_k|^2] = 1$ and $E[s_j s_k^*] = 0$, if $j \neq k$. By applying the receive beamforming $\mathbf{w}_k \in \mathbb{C}^{M \times 1}$ to (3), where $\|\mathbf{w}_k\|_2^2 = 1$, the SINR of the $k$th user $\Gamma_k$ can be
and it can be decomposed as \( Q = M 37 6 \).

The average charging power consumption of the BS is based on a 3GPP path loss model and given by

\[
\text{loss and small-scale Rayleigh fading. The channel path loss}
\]

For the channel model, the downlink channel is modeled as

\[
\theta \text{ exponential correlation and uniform correlation} [22]. \text{ Define}
\]

Here, two widely known spatial correlation models can be

\[
\text{g is the distance in meters} [21]. \text{ Let}
\]

\[
\text{power of the Rayleigh fading component is equal to one.}
\]

\[
\text{vector with independent and identically distributed entries}
\]

Thus, the average transmission rate for the \( k \)th user \( B_k \) during the entire time duration \( T \) is given as

\[
B_k = (1 - \tau) \log_2 (1 + \Gamma_k), \quad k = 1, \ldots, K. \tag{5}
\]

The average charging power consumption of the BS \( P_{bs} \) during the entire time duration \( T \) can be calculated as

\[
P_{bs} = \tau \|v\|_2^2. \tag{6}
\]

### B. CHANNEL MODEL

For the channel model, the downlink channel \( g_k \) and uplink channel \( h_k \) both consist of the features of the large-scale path loss and small-scale Rayleigh fading. The channel path loss is based on a 3GPP path loss model and given by \( 15.3 + 37.6 \times \log_{10}d \), where \( d \) is the distance in meters [21]. Let \( Q \) be an \( M \times M \) spatial correlation matrix for the BS antennas, and it can be decomposed as \( Q = UU^H \). The Rayleigh fading component of the channels \( g_k \) (or \( h_k \)) is modeled as a vector \( \frac{1}{\sqrt{M}} U \xi \), where \( \xi \) is a complex Gaussian random vector with independent and identically distributed entries \( \sim \text{CN} (0_M, I_M) \), and \( \frac{1}{\sqrt{M}} \) is a normalization factor such that the power of the Rayleigh fading component is equal to one. Here, two widely known spatial correlation models can be used to examine the impact of antenna correlations, namely, exponential correlation and uniform correlation [22]. Define \( \theta \) as a spatial correlation coefficient, where \( 0 \leq \theta \leq 1 \). For the exponential correlation case, the \((i,j)\)th element of the correlation matrix \( Q \) is given by

\[
Q(i,j) = \theta^{|i-j|}. \tag{7}
\]

For the uniform correlation, the \((i,j)\)th element of the correlation matrix \( Q \) is

\[
Q(i,j) = \begin{cases} 1, & i = j; \\ \theta, & i \neq j. \end{cases} \tag{8}
\]

Note that in these two spatial correlation models, the complex channel gains among the different antennas of the BS are uncorrelated, if \( \theta = 0 \), e.g., \( Q = I_M \).

### IV. JOINT DESIGN PROBLEM OF BEAMFORMING AND RESOURCE ALLOCATION

Our goal is to minimize the average charging power consumption of the BS \( P_{bs} \), while ensuring the uplink QoS of the users by jointly optimizing the time allocation \( \tau \), downlink/uplink beamforming \( v \) and \( w_k \), and uplink power control \( p_k \). From (2) and (5), the problem can be formulated as

\[
\begin{align*}
\text{(P1)} : & \quad \min_{1 \geq \tau \geq 0, v, p_1, \ldots, p_K} \tau \|v\|_2^2 \\
\text{s.t.} & \quad (C.1) \quad p_k (1 - \tau) T \leq E_k, \quad k = 1, \ldots, K; \\
& \quad (C.2) \quad B_k \geq B_{th}, \quad k = 1, \ldots, K. \tag{9}
\end{align*}
\]

where we define \( p = [p_1, \ldots, p_K]^T \) and \( W = [w_1, \ldots, w_K] \). In (9), the first constraint indicates that for each user, the energy spending in the uplink \( p_k (1 - \tau) T \) should not exceed its downlink harvested energy \( E_k \), while the second constraint shows that the average transmission rate for each user \( B_k \) is required to be larger than or equal to a preset QoS threshold \( B_{th} \). Define \( D_{j,k} = w_k^t h_j h_j^t w_k \), for \( j, k = 1, \ldots, K \). Notice that it can be proven in the following lemma (Lemma 1) that all users can achieve the same average transmission rate \( B_{th} \) due to the imposed QoS constraint, no matter what optimal time allocation value of \( \tau \) is obtained. Thus, the energy consumption of the BS for processing the received information bits in the uplink can be treated as a constant value, and we only focus on the downlink charging power consumption of the BS \( P_{bs} \) in our design problem. In addition, the optimization requires the CSI which can be estimated at the BS by periodically sending pilot signals. The CSI estimation can be very accurate if the training period is sufficiently long. Hence, we will only concentrate on the joint design of beamforming and resource allocation in the perfect CSI case, but the design in the imperfect CSI case will be an interesting problem for future research.

Below we show that all users can achieve the same average transmission rate \( B_{th} \). After that, the feasibility condition of the problem (P1) is analyzed.

Lemma 1: For the optimal solution of (P1), all users can achieve the same average transmission rate \( B_{th} \), i.e., \( B_k = B_{th} \), for \( k = 1, \ldots, K \).

Proof: Let \( (W^*, \tau^*, p^*, v^*) \) denote the optimal solution to the problem (P1), and suppose that \( B_j > B_{th} \) for some \( j \). Another feasible solution \( (W^*, \tau^*, \tilde{p}, \tilde{v}) \) can be constructed as follows. First, we decrease the power control value of \( p_j^* \) to get \( \tilde{p}_j \) without violating the uplink QoS constraint (C2) in (9). Since the interference power from the \( j \)th user to
each user is reduced, it also allows us to lower the transmit power of all the other users $p_{k}$, for all $k \neq j$. Hence, there exists another feasible solution for the uplink transmit power $\bar{p}$ that satisfies the uplink QoS constraint (C.2) in (9), where $\bar{p}_{k} < p_{k}$, for all $k$. Then we decrease the value of harvested energy $E_k$ by scaling down the amplitude of the downlink energy beamforming $\nu^*$ to obtain $\bar{v}$, where $||\bar{v}||^2_2 < ||\nu^*||^2_2$. The solution $(\bar{W}^*, \tau^*, \bar{\nu}, \bar{\nu})$ can achieve a smaller objective value of $P_{v\gamma}$, which contradicts to the optimality of $(\bar{W}^*, \tau^*, \bar{p}^*, \nu^*)$, and the proof is completed.

Theorem 1: The problem (P1) is feasible if and only if

$$
\tau < 1 - \frac{B_{th}}{\log_2 \left(1 + \frac{1}{\rho(D^{-1}\Phi^T)}\right)} \triangleq \tau_{U},
$$

where $D_{j,k} = w^j_1 h^j_1 w^j_k$, $D = \text{Diag} \{D_{1,1}, \ldots, D_{K,K}\}$, $\Phi$ is a zero-diagonal matrix and its $(j,k)^{th}$ off-diagonal entry is $D_{j,k}$, and $\rho(\cdot)$ denotes the spectral radius.

Proof: For given $W$, $\tau$, and $p$, there always exists a feasible solution of energy beamforming $\nu$ such that the energy harvesting constraint (C.1) is satisfied; for instance, we can set $\nu = \alpha \sum_{k=1}^{K} g_k$, where $\alpha$ is a sufficiently large constant to ensure $p_k (1 - \tau) \leq E_k$. Hence, the feasibility of the problem (P1) only depends on the QoS constraint (C.2). Since the constraint (C.2) is always active according to Lemma 1, the problem (P1) is feasible if and only if there exists an uplink transmit power value of $p$ such that $B_k = B_{th}$, for $k = 1, \ldots, K$, or equivalently, $(1 - \gamma_{th} D^{-1} \Phi^T) p = D^{-1} \gamma_{th} \sigma^2 1$, where $\gamma_{th} = 2B_{th} - 1$, and 1 is an all-one vector. By using (23), the above equation has solutions if and only if the spectral radius condition $\rho \left(\gamma_{th} D^{-1} \Phi^T\right) < 1$ holds. By substituting the definition of $\gamma_{th}$ into this spectral radius condition and after some manipulation, we can get the feasibility condition as shown in (10).

Theorem 1 implicitly shows that if zero-forcing (ZF) receive beamforming is applied, i.e., $w^j_1 h^j_1 = 0$, for $j \neq k$, the corresponding spectral radius is zero and the problem (P1) is always feasible because of the downlink charging time allocation $\tau < 1$. If the receive beamforming is simply chosen as $w^j_j = h^j_j$, the feasibility region of the downlink charging time allocation $\tau$ becomes smaller. Moreover, if the QoS threshold $B_{th}$ increases, the feasibility region of the downlink charging time allocation $\tau$ also becomes smaller, i.e., the feasibility region of the uplink time allocation for data transmission $(1 - \tau)$ tends to be increased in order to meet the QoS requirement.

V. PROPOSED JOINT DESIGN ALGORITHM

Since the problem (P1) is non-convex in its current form, we resort to SDR techniques to deal with the problem as follows. Define an energy beamforming-related matrix $V = \nu \nu^T \succeq O$, which implicitly indicates that $\text{Rank}(V) = 1$. By ignoring the rank-one constraint for the matrix $V$, the problem (P1) can be rewritten as

$$
(P2) : \min_{\substack{1 \geq \tau \geq 0, p \succeq 0, V \succeq O, W}} \tau \text{Tr}(V)
$$

s.t. (C.1) $\left(1 - \frac{1}{\tau}\right) p_k \leq \text{Tr}(G_k V) + \sigma^2$, $k = 1, \ldots, K$;

(C.2) $B_k \geq B_{th}$, $k = 1, \ldots, K$,

where we define a channel matrix $G_k = g_k h^j_1 \succeq O$. The constraint (C.2) can be further rewritten as

$$
\left(\frac{2B_{th}}{\tau} - 1\right) \left(\sum_{j=1}^{K} p_j \left(w^j_1 h^j_1 h^j_1 w^j_k + \sigma^2\right) - p_k \left(w^j_1 h^j_1 w^j_k\right)^2\right) \leq 0,
$$

which is an affine constraint in terms of the variables $p = [p_1, \ldots, p_K]^T$. Note that for the fixed values of the uplink receive beamforming $W$ and the downlink charging time allocation $\tau$, the problem (P2) is semi-definite convex programming in terms of the uplink power control $p$, and the downlink energy beamforming-related matrix $V$, since the objective and the constraints are all affine. By fixing $W$ and $\tau$, the optimization problem can be efficiently solved by using off-the-shelf solvers such as CVX [24]. Let $(p^*, V^*)$ be the optimal solution of the problem (P2) for given $W$ and $\tau$, and the following theorem is then provided.

Theorem 2: The optimal solution of the problem (P2) satisfies $\text{Rank}(V^*) \leq \sqrt{K}$.

Proof: From (11), the optimal solution of the downlink energy beamforming-related matrix $V^*$ must satisfy

$$
(P3) : \min_{V \succeq O} \text{Tr}(V)
$$

s.t. (C.1) $\text{Tr}(G_k V) \geq \eta_k$, $k = 1, \ldots, K$,

where we define $\eta_k = \left(1 - \frac{1}{\tau}\right) p^*_k - \sigma^2$. From [24], the Karush-Kuhn-Tucker (K.K.T.) conditions for the problem (P3) can be written as

$$
\text{Tr}(G_k V^*) \geq \eta_k, k = 1, \ldots, K;
$$

(14)

$$
\text{Tr}(Z^* V^*) = 0;
$$

(15)

$$
V^* \succeq O,
$$

(16)

where $Z \succeq O$ represents the optimal value of the Lagrangian multiplier with respect to the constraint $V \succeq O$. Let $L = \text{Rank}(V^*)$. By decomposing $V^* = \Psi \Psi^T$, where $\Psi \in \mathbb{C}^{M \times L}$, we can rewrite (14) as

$$
\text{Tr}(G_k V^*) = \text{Tr}(\Psi^T G_k \Psi) \geq \eta_k, k = 1, \ldots, K.
$$

(17)

Consider the following linear equation:

$$
\text{Tr}(\Psi^T G_k \Psi \Delta) = 0, k = 1, \ldots, K,
$$

(18)

where $\Delta$ is a Hermitian matrix of size $L \times L$, including $L^2$ unknown real values. As such, the linear equation (18) has $K$ equations and $L^2$ unknown variables. If $L^2 > K$, there exists a non-zero solution to (18). Let $\delta_l$ be the eigenvalues of $\Delta$, for $l = 1, \ldots, L$, and without loss of generality, it is...
assumed that $|\delta_i| \geq |\delta_j|$ if $l < j$. We can then construct another solution for the energy beamforming-related matrix $\tilde{V} = \Psi \left( I_L - \frac{1}{\delta_1} \Delta \right) \Psi$. It is straightforward to verify that $\tilde{V} \succeq O$ and $\text{Rank}(\tilde{V}) \leq L - 1$, i.e., the rank is reduced by at least one. In addition, the relationship of $V \Psi \Psi^T = O$, since $Z^* \succeq O$. Thus, it can be shown from (17) and (18) that this obtained solution $\tilde{V}$ also satisfies the optimality conditions (14) and (15) for $V$ as follows:

$$\begin{align*}
\text{Tr} \left( G_K \tilde{V} \right) &= \text{Tr} \left( G_K \Psi \left( I_L - \frac{1}{\delta_1} \Delta \right) \Psi \right) \geq \eta_k; \quad (19) \\
\text{Tr} \left( Z^* \tilde{V} \right) &= \text{Tr} \left( \Psi^T Z^* \Psi \left( I_L - \frac{1}{\delta_1} \Delta \right) \right) = 0. \quad (20)
\end{align*}$$

Hence, the new constructed matrix $\tilde{V}$ is also the optimal solution for the problem (P2). The above rank reduction procedure can be repeated until $L^2 \leq K$, and the proof is completed.

Corollary 1: When the number of users is less than or equal to three, i.e., $K \leq 3$, the optimal solution of the problem (P2) is exactly the same as that of the original problem (P1), for any fixed $W$ and $\tau$.

Proof: The difference between these two problems is that the rank-one constraint of the energy beamforming-related matrix $V$ is neglected in the problem (P2) after change of variables. Hence, if the optimal solution $V^*$ in the problem (P2) is rank-one, the problems (P1) and (P2) are equivalent. From Theorem 2, it implies that the rank of $V^*$ must be equal to one, if $K \leq 3$. This is because $V^* = O$ contradicts to the optimality of the solution.

Let $\xi$ and $\nu$ be the principal eigenvector and the maximum eigenvalue of the obtained solution $V^*$, respectively. From Corollary 1, it is known that the obtained optimal solution of (P2) is the globally optimal solution of (P1), if the number of users in the WPCN is less than or equal to three. In this case, the optimal beamforming $v^*$ in the problem (P1) can be found by extracting the principal eigenvector of the matrix $V^*$, where $V^* = \nu v^* \nu^T$. On the other hand, if $K > 3$ and $\text{Rank}(V^*) \neq 1$, we can apply a rank-one approximation on the matrix $V^*$ to extract a feasible, but not optimal, solution $v^* = \sqrt{\beta} \xi$, where $\beta$ is a power factor to be determined. By substituting this solution into the problem (P1), we can adjust the power factor $\beta$ to minimize the BS transmit power, while meeting the energy harvesting constraint for all users $(C.1)$ in (P1):

$$\beta = \max_{k=1, \ldots, K} \frac{1}{g_k \xi^2} \left( \frac{1 - \tau^*}{\varepsilon \tau^*} p_k^* - \sigma^2 \right). \quad (21)$$

Now we proceed to find the optimal solution for the downlink charging time allocation $\tau$ by incorporating the semi-definite programming in (P2) into the golden section search method [25]. An iterative algorithm is proposed and summarized in Table 1. The joint design variables are divided into two sets and alternatively optimized, where one is the set of the uplink receive beamforming $W$ and the other set includes the time allocation, downlink energy beamforming and uplink power control $\{\tau, v, p\}$.

For the proposed algorithm, we first initialize the uplink transmit power $p_k = c$. Then, the receive beamforming is updated based on the given uplink multiuser power control values and a minimum mean square error (MMSE) criterion for maximizing the SINR of each user, given as $W = (HPH^T + \sigma^2 I_N)^{-1} H$, where $P = \text{Diag} \{p_1, \ldots, p_K\}$ and $H = [h_1, \ldots, h_K]$. For the given receive beamforming $W$, the convex problem (P2) is solved for two selected time allocation values of $\tau_1$ and $\tau_2$, ranging between a lower bound $\tau_L = 0$ and an upper bound $\tau_U$, where the corresponding objective values are denoted as $\tau_1 \cdot \text{Tr} (V^* (\tau_1))$ and $\tau_2 \cdot \text{Tr} (V^* (\tau_2))$. According to these two reference objective values, the search interval is then narrowed by updating the values of $\tau_L$ and $\tau_U$ until the interval $\tau_U - \tau_L$ is smaller than a preset threshold $\mu$. That is, we update the lower bound $\tau_L$ as $\tau_1$, if $\tau_2 \cdot \text{Tr} (V^* (\tau_2)) < \tau_1 \cdot \text{Tr} (V^* (\tau_1))$. Otherwise, we update the upper bound $\tau_U$ as $\tau_2$. From [25], the number of iterations can be minimized by choosing $\delta = \frac{1 + \sqrt{5}}{2}$, and the minimum required number of inner loop iterations (the iterative procedure from step 5 to step 11) for convergence in finding the time allocation $\tau$ is no more than \left[ \frac{\log \mu}{\log(1 - \delta)} \right]$, where \left[ \cdot \right]$ is a ceiling function. The above procedures are repeated until the maximum number of outer loop iterations $N_I$ is reached.

### VI. CONVERGENCE ANALYSIS AND COMPUTATIONAL COMPLEXITY OF THE PROPOSED ALGORITHM

In this section, we in turn analyze the convergence behavior and computational complexity of the proposed algorithm.

#### A. CONVERGENCE ANALYSIS

Assume that $W^{(i)}$ is the MMSE receive beamforming at the $i^{th}$ outer loop, which is calculated according to the optimal uplink power control solution $p^{(i-1)*}$ obtained from

| Step | Description |
|------|-------------|
| 1    | Initialize $p_k = c$ |
| 2    | For $i = 1 : N_I$ (outer loop) |
| 3    | Compute the receive beamforming $W = (HPH^T + \sigma^2 I_M)^{-1} H$ |
| 4    | Initialize $\tau_L = 0$, $\tau_U$ using (10), and $\delta = \frac{1 + \sqrt{5}}{2}$ |
| 5    | Repeat (inner loop) |
| 6    | Update $\tau_1 = \tau_U - \kappa (\tau_U - \tau_L)$ and $\tau_2 = \tau_L + \kappa (\tau_U - \tau_L)$ |
| 7    | Solve the problem (P2) for given values of $\tau_1$ and $\tau_2$ via CVX |
| 8    | Calculate the corresponding optimal objective values $\tau_1 \cdot \text{Tr} (V^* (\tau_1))$ and $\tau_2 \cdot \text{Tr} (V^* (\tau_2))$ |
| 9    | If $\tau_2 \cdot \text{Tr} (V^* (\tau_2)) < \tau_1 \cdot \text{Tr} (V^* (\tau_1))$, set $\tau_L = \tau_1$ |
| 10   | Else set $\tau_U = \tau_2$ |
| 11   | Until $\tau_U - \tau_L < \mu$ |
| 12   | Update power control $p_k = p_k^{*}$ |
| 13   | End |
| 14   | Compute time allocation $\tau^* = (\tau_U + \tau_L) / 2$ |
| 15   | Compute eigenvector $\xi$ from $V^*$ and power factor $\beta$ using (21) |
| 16   | Compute energy beamforming $v^* = \sqrt{\beta} \xi$. |

| Table 1: A Proposed Iterative Algorithm. |

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the \((i - 1)^{th}\) outer iteration. In each inner loop, the uplink power control and downlink energy beamforming are jointly optimized by the SDR approach under the given time allocation \(\tau\) and uplink receive beamforming \(W^{(i)}\). Moreover, the time allocation \(\tau\) is optimized with the golden section search method. Since it has been proved in Corollary 1 that the relaxation imposed by the SDR approach does not affect the optimality of the solutions of the uplink power control \(p\) and downlink energy beamforming \(v\), if the number of users is less than or equal to three, i.e., \(K \leq 3\). As a result, when \(K \leq 3\), we can find the globally optimal solution of \(\tau\), \(p\) and \(v\) for a joint design subproblem which is obtained from the original problem (P2) under the given \(W^{(i)}\) at each outer loop. For \(K > 3\), although the globally optimal solution of \(v\) is unnecessarily guaranteed by the SDR approach, the resultant solution is still acceptable according to our simulation results.

Let \(f^{(i)}(W^{(i)}) \triangleq \tau^{(i)} \cdot \text{tr} \left( V^{(i)^*} \right) \) denote the obtained objective value of the \(i^{th}\) outer iteration with respect to the fixed receive beamforming \(W^{(i)}\), where \(\tau^{(i)}\) and \(V^{(i)^*}\) are the solutions after carrying out the inner loop. By calculating the receive beamforming \(W^{(i+1)}\) at the \((i + 1)^{th}\) outer iteration according to the uplink transmit power \(p^{(i)^*}\) (obtained from the previous outer iteration), the objective value at the \((i + 1)^{th}\) outer iteration is given by \(f^{(i+1)}(W^{(i+1)})\). From (5), we define \(B_k(W,p)\) as the average transmission rate function of \(W\) and \(p\). Since the MMSE receive beamforming \(W^{(i+1)}\) can maximize the users’ SINRs with respect to \(p^{(i)^*}\), it implies that the average transmission rate \(B_k(W^{(i+1)}; p^{(i)^*})\) is larger than \(B_k(W^{(i)}; p^{(i)^*})\) for any fixed time allocation \(\tau\), where \(B_k(W^{(i)}; p^{(i)^*}) \geq B_{kh}\).

Therefore, at the \((i + 1)^{th}\) outer iteration and for any fixed \(\tau\), one can easily find a feasible power control solution of \(p\) by reducing the transmit power values of \(p^{(i)^*}\), while keeping the QoS constraint (C.2) in (11) satisfied, thereby lowering the requirement of harvested energy and the objective value. That is, we can get \(f^{(i+1)}(W^{(i+1)}) \leq f^{(i)}(W^{(i)})\). Because the objective \(f^{(i+1)}(W^{(i+1)})\) is always larger than zero and bounded, the proposed algorithm can finally get converged when the iteration number \(N_j\) is sufficiently large. Moreover, since the original joint design problem (P2) is non-convex, the proposed iterative algorithm, which alternatively optimizes the two sets of variables \(W\) and \((\tau, p, v)\), can provide locally optimal solutions when it gets converged.

### B. COMPLEXITY ANALYSIS

The complexity of the proposed algorithm is mainly dominated by the operation of calculating the MMSE receive beamforming \(W\), executing the semi-definite programming (P2) with golden search, and finding the principal eigenvector of the matrix \(V^*\) and the power factor \(\beta\) in (21). The complexity of the MMSE receive beamforming is given as \(\mathcal{O}(M^4 + 2M^2K + MK)\). We apply the results of [26] to evaluate the complexity of the semi-definite programming in the inner loop of golden search, where the complexity order is obtained by counting the arithmetic operations of the primal-dual path following method [27]. Accordingly, the worst-case complexity of solving (P2) is given by \(\mathcal{O}((M + K)^4 \log(1/\epsilon))\), where \(\zeta > 0\) is a solution accuracy. Note that the inner loop of golden search requires no more than \(\left\lceil \frac{\log\mu}{\log(1 - \tau)} \right\rceil\) iterations. The complexity of finding the principal eigenvector and power factor is given by \(\mathcal{O}(M^3)\) and \(\mathcal{O}(MK)\), respectively. Hence, the total complexity of the proposed algorithm for each outer iteration can be summarized in Table 2.

### VII. COMPUTER SIMULATION AND DISCUSSIONS

#### A. PARAMETER SETTINGS

The performance is evaluated by computer simulations. We assume that users are uniformly located within a semicircle of radius \(\chi\) to the BS. The downlink and uplink channels are reciprocal, and a 3GPP path-loss model 15.3 + 37.6 × \(\log_{10} d\) dB and the Rayleigh fading ~ \(\mathcal{CN}(0_M, \frac{1}{\chi} I_M)\) are applied, where \(d\) is the distance in meters [21]. The noise power and the energy conversion efficiency are set as \(\sigma^2 = -114\) dBm and \(\epsilon = 0.8\), respectively. In the proposed algorithm, the stopping threshold \(\mu\) is given as 10^{-4}, and we set the transmit initial power allocation \(c = 15.3 + 37.6 \times \log_{10}\chi\) dBm and \(N_I = 3\). The spatial correlation coefficient of the exponential and uniform correlation models is set as \(\theta = 0\), except as otherwise stated.

#### B. HEURISTIC SCHEME

To demonstrate the effectiveness of the proposed algorithm, a heuristic scheme is also included for performance comparison as follows. The downlink energy beamforming \(v\) is calculated according to the average channel gain of users \(g_k\) and given as

\[v = \sqrt{\alpha} \tilde{v},\]

where \(\tilde{v} = \sum_{k=1}^{K} g_k / \|g_k \|^2\) is the energy beam direction vector, and the variable \(\alpha\) is a scaling power factor to be determined. Notice that the energy beam direction vector is set by considering the doubly near-far problem among users so that the user with a worse channel power gain can harvest more energy for uplink data transmission. For each user, the harvested energy \(E_k\) is fully utilized to perform the uplink power control, i.e., \(p_k = \frac{\epsilon \tau}{1 - \tau} \left( \|g_k v\|^2 + \sigma^2 \right)\). Furthermore, the ZF receive beamforming is simply adopted for completely eliminating the multiuser interference without requiring the knowledge of the uplink transmit power \(p_k\) and downlink harvested energy \(E_k\). Accordingly, by substituting (22) into the QoS constraint (C.2) in the problem (P1), it results in

\[
\frac{\epsilon \tau}{1 - \tau} \left( \|g_k v\|^2 + \sigma^2 \right) \|w_k h_k\|^2 \geq \gamma_{\text{th}}, \quad k = 1, \ldots, K.
\]
TABLE 2: Complexity of the proposed and heuristic schemes

| Operation                                      | Complexity                                      |
|------------------------------------------------|------------------------------------------------|
| Proposed scheme                                |                                                |
| MMSE receive beamforming $W$                   | $\mathcal{O}(M^3 + 2M^2K + MK)$                |
| Solving (P2)                                   | $\mathcal{O}((M + K)^{4.5}\log(1/\zeta))$     |
| Principal eigenvector $\xi$                    | $\mathcal{O}(M^3)$                             |
| Power factor $\beta$                           | $\mathcal{O}(MK)$                              |
| Total (per inner iteration)                    | $\mathcal{O}(2M^3 + 2M^2K + 2MK + \left\lfloor \frac{\log \mu}{\log(1-\tau)} \right\rfloor \times (M + K)^{4.5}\log(1/\zeta))$ |

| Heuristic scheme                               |                                                |
| Energy beamforming and power control           | $\mathcal{O}(2MK)$                             |
| ZF receive beamforming                         | $\mathcal{O}(2MK^2 + K^3)$                    |
| Power factor $\alpha$                          | $\mathcal{O}(3MK)$                             |
| Total                                          | $\mathcal{O}(5MK + 2MK^2 + K^3)$              |

It then implies that

$$\alpha \geq \frac{\sigma^2}{\left\| g_k^\dagger \hat{b} \right\|^2} \left( \gamma_{th} \frac{(1 - \tau)}{\varepsilon \tau} \| w_k \|^2 + 1 \right), \quad k = 1, \ldots, K. \tag{24}$$

As a result, the optimal value of the scaling power factor $\alpha$ which minimizes the average charging power consumption of the BS and also ensures the QoS constraint (C.2) in (9) is given by

$$\alpha^* = \max_{k = 1, \ldots, K} \left\{ \frac{\sigma^2}{\left\| g_k^\dagger \hat{b} \right\|^2} \left( \gamma_{th} \frac{(1 - \tau)}{\varepsilon \tau} \| w_k \|^2 + 1 \right) \right\}. \tag{25}$$

Finally, the entire time duration $T$ is equally allocated to the downlink charging and uplink transmission in this heuristic scheme, i.e., we set $\tau = 0.5$.

For the heuristic scheme, the complexity of calculating the energy beamforming and uplink transmit power is given by $\mathcal{O}(2MK)$. The calculation of the ZF receive beamforming needs the complexity of $\mathcal{O}(2MK^2 + K^3)$. Finally, the complexity of determining the scaling power factor $\alpha$ is $\mathcal{O}(3MK)$. The total complexity of the heuristic scheme is summarized in Table 2.

The maximum ratio combining (MRC) is another possible way for designing the receive beamforming of the heuristic scheme, i.e., $w_k = h_k/\| h_k \|$. As compared with the ZF receive beamforming which could cause a noise enhancement problem, the MRC receive beamforming can enhance the desired signal strength without noise enhancement at the expense of poorer interference suppression capability. For the heuristic scheme with the MRC receive beamforming, the scaling power factor $\alpha$ of the energy beamforming can be determined by substituting $w_k = h_k/\| h_k \|$ and $v = \sqrt{\varepsilon \tau \hat{b}}$ into the QoS constraint (C.2) of the problem (P1), yielding the following condition:

$$\alpha \left( \left\| g_j^\dagger \hat{b} \right\|^2 \| h_k \|^4 - \gamma_{th} \sum_{j = 1, j \neq k}^K \left\| g_j^\dagger \hat{b} \right\|^2 \left\| h_k \right\|^2 \right) \geq \gamma_{th} \sigma^2 \left( \sum_{j = 1, j \neq k}^K \left\| h_k \right\|^2 \left\| h_j \right\|^2 + \frac{1 - \tau}{\varepsilon \tau} \| h_k \|^2 \right) - \sigma^2 \left\| h_k \right\|^4, \quad k = 1, \ldots, K. \tag{26}$$

Due to the severe multiuser interference, the term $\left( \left\| g_j^\dagger \hat{b} \right\|^2 \| h_k \|^4 - \gamma_{th} \sum_{j = 1, j \neq k}^K \left\| g_j^\dagger \hat{b} \right\|^2 \left\| h_k \right\|^2 \right)$ has a high probability to be a negative value, resulting in a fact that no feasible solution of the scaling power factor $\alpha$ can be found to meet the QoS constraints of all users. If the feasible solution is available, the factor $\alpha$ can be derived in (27), as shown on the top of the next page.

C. SIMULATION RESULTS

Fig. 2 compares the two heuristic schemes with the ZF and MRC receive beamforming, in terms of the average BS charging power consumption and the probability of feasibility. The computer simulations are run over $10^6$ channel realizations. The number of antennas, cell size, and QoS requirement are given as $M = 16$, $\chi = 20$ m, $B_{th} = 1$ bps/Hz, respectively. It can be found that the average BS charging power consumption of the heuristic scheme with the MRC receive beamforming is significantly lower than that with the ZF only when the number of users $K$ is smaller than or equal to 2. However, we can observe that the heuristic scheme with the MRC receive beamforming has a very low probability of feasibility (lower than 0.6) even under the case of two uplink users, and the feasibility probability becomes extremely low and almost approaches to zero when $K \geq 4$. As a result, the QoS requirement cannot be easily met with the MRC receive beamforming due to the multiuser interference. On the contrary, the heuristic scheme with the ZF receive beamforming is always feasible and can satisfy the QoS requirement, since the multiuser interference is completely removed. Hence, we will only adopt the ZF
receive beamforming in the heuristic scheme for performance comparisons in the subsequent figures.

The convergence behavior of the proposed algorithm is shown in Figure 3, where the number of antennas, cell size, and QoS threshold are set as \( M = 16 \), \( \chi = 20 \) m, and \( B_{th} = 1 \) bps/Hz, respectively. The number of users could be \( K = 2 \) or \( K = 5 \). For a single channel realization, it demonstrates that the objective value \( \tau Tr(V) \) is monotonically decreased with the iterations of the outer loop and finally gets converged, which validates the result of the convergence analysis in Section VI.A. By averaging over 500 channel realizations, it can be observed that the performance converges, on average, in three iterations, i.e., \( N_I = 3 \).

Fig. 4 compares the average BS charging power consumption \( P_{bs} \) of the proposed scheme and the heuristic scheme, where the number of antennas and the cell size are set to \( M = 16 \) and \( \chi = 20 \) m, respectively. It exhibits that the average BS charging power \( P_{bs} \) increases with the number of users \( K \). Interestingly, it can be found that when the number of users \( K \) is increased from two to seven, the proposed scheme has less increase on the average BS power charging consumption \( P_{bs} \) than the heuristic scheme. For example, the BS using the heuristic scheme requires extra power consumption of \( 15 \) dB for the case of \( B_{th} = 4 \) bps/Hz, while the value with the proposed scheme is only \( 6.5 \) dB. Furthermore, the proposed scheme requires much less average BS charging power consumption \( P_{bs} \) than the heuristic scheme. Taking an example of \( K = 6 \) and \( B_{th} = 4 \) bps/Hz, the proposed joint design can save about \( 20 \) dB charging power consumption, as compared with the heuristic scheme.

Fig. 5 shows the average value of the optimal downlink charging time allocation \( \tau \) for various QoS requirements \( B_{th} \). The cell size is \( \chi = 10 \) m. We can see that the time ratio \( \tau \) allocated for the downlink wireless charging decreases when the QoS \( B_{th} \) becomes stringent or the number of users \( K \) is enlarged. This is because more uplink transmission time is necessary for achieving the QoS requirement under more severe multuser interference. Furthermore, when the number of antennas \( M \) increases, the average value of the optimal downlink charging time \( \tau \) is decreased, since the BS is capable of providing better beamforming gains and focusing the charging energy on the users.

In Fig. 6, for the proposed joint design, we further demonstrate the impact of the time allocation parameter \( \tau \) on the average BS charging power consumption \( P_{bs} \) with different QoS requirement \( B_{th} = 1 \) bps/Hz or 3 bps/Hz. The number of antennas, the number of users and the cell size are set as \( M = 6 \), \( K = 3 \) and \( \chi = 60 \) m respectively. As can be seen, there exists an optimal downlink charging time allocation \( \tau \). For the cases of \( B_{th} = 1 \) bps/Hz and 3 bps/Hz, the optimal downlink charging time allocation values that can achieve the minimum BS charging power consumption are around at \( \tau = 0.3 \) and 0.1, respectively. This indicates that the downlink charging time portion \( \tau T \) is reduced to ensure that the increased QoS value \( B_{th} \) can be met. In addition, when the QoS requirements of \( B_{th} \) become stricter, the BS consumes more average charging power \( P_{bs} \). In addition, it can be found that under a given QoS \( B_{th} \), when the time allocation value \( \tau \) is set to be greater than the optimal value, the average charging power consumption of the BS \( P_{bs} \) will increase. This is because users need more collected energy \( E_k \) for uplink transmission in less uplink time, so that the QoS can be met. On the contrary, when the time allocation \( \tau \) is set to be less than the optimal value, the average charging power consumption of the BS \( P_{bs} \) will also increase. The reason is that under the QoS requirements, the BS needs to transmit more charging power to provide users with enough collected energy \( E_k \) in less downlink time.

Fig. 7 compares the average BS charging power consumption \( P_{bs} \) of the proposed and heuristic schemes for various cell sizes \( \chi \), where the number of users \( K \) could be two, three or five, and the number of BS antennas \( M \) is six. It
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\[
\alpha^* = \max_{k=1,...,K} \left\{ \frac{\gamma_l \sigma^2}{\| h_k \|^2} \left( \sum_{j=1,j\neq k}^{K} \| h_k h_j \|^2 + \frac{1-\epsilon}{\sigma^2} \| h_k \|^2 - \sigma^2 \| h_k \|^4 \right) - \gamma_l \sum_{j=1,j\neq k}^{K} \| g_j v \|^2 \| h_k h_j \|^2 \right\},
\]

(27)

is shown that the average charging power consumption of the BS \( P_{bs} \) is increased with the cell size \( \chi \), since more severe channel path loss is introduced in the wireless environment with a larger cell size. For various cell sizes, one can also find that the proposed scheme can achieve less average BS charging power consumption \( P_{bs} \) than the heuristic scheme. In particular, it can be observed that the performance gap between the proposed and heuristic schemes becomes wider when the number of BS antennas \( M = 6 \) is increased and gets close to the number of users \( K \). For example, at \( \chi = 110 \text{ m} \), the performance gap for \((M,K) = (6,2)\) is around 5 dB, while the performance gap becomes 10 dB for \((M,K) = (6,5)\). Another observation is that under a fixed setting of \((M,K)\), the performance gap becomes larger when the cell size \( \chi \) is increased.

Fig. 8 shows the average BS charging power consumption \( P_{bs} \) of the proposed and heuristic schemes under a larger antenna array configuration, where the QoS requirement is \( B_{th} = 1 \text{ bps/Hz} \) and the cell size is \( \chi = 60 \text{ m} \). As expected, the average charging power consumption of the BS
$P_{bs}$ can be effectively reduced by enlarging the number of antennas $M$ at the BS. For $K = 5$, the average charging power consumption of the BS $P_{bs}$ for the proposed scheme with $M = 6$ is around 54 dBm, whereas the average power consumption $P_{bs}$ with $M = 15$ can be reduced to 50 dBm. This performance improvement mainly comes from the spatial degree-of-freedom of a larger antenna array to enhance the downlink energy harvesting capability and uplink interference suppression. From this figure, it can be also observed that the performance gap of the average BS charging power consumption $P_{bs}$ between the proposed and heuristic schemes become wider under a larger antenna array configuration when the number of served users $K$ increases.

![FIGURE 8: Average BS charging power consumption under a larger antenna array configuration ($B_{th} = 1$ bps/Hz and $\chi = 60$ m).](image)

![FIGURE 9: The impact of antenna correlation on the average BS charging power consumption in the two spatial correlation models ($B_{th} = 1$ bps/Hz, $\chi = 60$ m and $K = 2$).](image)

Fig. 9 shows the impact of antenna correlation on the average BS charging power consumption in the two spatial correlation models. The antenna correlation coefficient is $\theta = 0.1$ or $\theta = 0.3$. The number of users, the cell size, and the QoS threshold are set as $K = 2$, $\chi = 60$ m, and $B_{th} = 1$ bps/Hz, respectively. When the antenna correlation becomes large, the BS consumes more charging power to achieve the required QoS. However, the proposed joint design scheme has less power consumption boost than the heuristic scheme under the same spatial correlation model and coefficient. Moreover, one can observe that the uniform correlation model causes more influence on the boost of BS charging power consumption than the exponential correlation model. For example, when the correlation is increased from $\theta = 0.1$ to $\theta = 0.3$, the power consumption of the proposed scheme at $M = 9$ is boosted by 0.2 dB and 1 dB for the exponential and uniform models, respectively.

**VIII. CONCLUSION**

We jointly designed downlink/uplink beamforming, downlink/uplink time allocation and uplink multiuser power control to minimize the BS charging power consumption under the QoS requirement and the uplink power control constraint when multiple users are concurrently served in the WPCN with energy harvesting. An effective algorithm was proposed to deal with this non-convex problem based on the SDR and alternative optimization approaches. The feasibility condition was theoretically analyzed to understand the impact of channels, beamforming weights and QoS on the feasibility region of time allocation. In addition, the rank value of the SDR problem was theoretically analyzed, showing the equivalence between the original and SDR problems when the number of users are less than or equal to three. Computer simulations were adopted to capture the impact of various design parameters, including the cell size, number of users, number of antennas, and QoS rate requirement, time allocation, on the BS charging power consumption. Extensive simulation results showed that superior performance can be achieved by the proposed joint design scheme, as compared with the heuristic scheme in which conventional maximum ratio transmission (using the average channel gain of users) and ZF schemes are used as the downlink energy beamforming and uplink receive beamforming, respectively. As compared with the heuristic method, the average BS charging power consumption for various numbers of users (from two to seven) can be reduced by about $7 \sim 21$ dB, and the improvement becomes large as the number of users or the QoS threshold increase. The average optimal downlink charging time allocation is reduced as a function of the QoS threshold, the number of users, and the number of antennas. The average BS charging power consumption increases with the cell size, but our proposed scheme has been able to reduce it up to 17 dB (for a cell size of 200 meters, six antennas, and five users) when compared with the heuristic method.

As a future research direction, it will be interesting to investigate the charging power minimization of WPCNs under the imperfect CSI scenario, since the joint design of beamforming and resource management relies on the CSI.
Moreover, due to the mobility and flexibility of unmanned aerial vehicles (UAVs), it is also attractive to consider UAV-assisted WPCNs to further improve the network performance and minimize the overall power consumption.

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