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A Fair Energy Allocation Algorithm for IRS-Assisted Cognitive MISO Wireless-Powered Networks

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Abstract: With the rapid development of wireless communication networks and Internet of Things technology (IoT), higher requirements have been put forward for spectrum resource utilization and system performance. In order to further improve the utilization of spectrum resources and system performance, this paper proposes an intelligent reflecting surface (IRS)-assisted fair energy allocation algorithm for cognitive multiple-input single-output (MISO) wireless-powered networks. The goal of this paper is to maximize the minimum energy receiving power in the energy receiver, which is constrained by the signal-to-interference-plus-noise ratio (SINR) threshold of the information receiver in the secondary network, the maximum transmission power at the cognitive base station (CBS), and the interference power threshold of the secondary network on the main network. Due to the coupling between variables, this paper uses iterative optimization algorithms to optimize and solve different variables. That is, when solving the active beamforming variables, the passive beamforming variables are fixed; then, the obtained active beamforming variables are fixed, and the passive beamforming variables are solved. Through continuous iterative optimization, the system converges. The simulation results have verified the effectiveness of the proposed algorithm.

Keywords: intelligent reflecting surface; wireless-powered networks; cognitive radio; iterative optimization

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1. Introduction

With the increasing integration of future wireless communication and intelligent applications, wireless networks require higher spectral efficiency and lower communication costs to meet the growing demands of wireless communication networks and traffic [1]. Although direct sequence ultra-wideband and random cooperative beamforming technologies can reduce the cost of long-distance communication in wireless sensor networks [2,3], in reality, most of the spectrum is not fully utilized. Therefore, addressing the issues of scarce radio frequency spectrum resources and improving utilization is of utmost importance [4]. Cognitive radio (CR) technology, as an important means to enhance spectrum utilization, has been widely applied to alleviate spectrum scarcity [5,6]. In recent years, the development of artificial intelligence and software-defined radio technologies has provided a theoretical basis and implementation means for cognitive radio technology. In CR networks, primary users (PUs) possess higher spectrum access rights. Secondary users (SUs) communicate by sharing the spectrum, keeping their interference power below a threshold to ensure the PU's communication performance, effectively increasing spectrum efficiency [7].

Currently, research in CR networks mainly focuses on spectrum sensing [8], dynamic spectrum resource allocation [9], interference suppression [10], etc. Reference [8] primarily investigated perception-enhanced spectrum-sharing CR networks. The proposed method has an important improvement effect on the perceptual performance and spectral efficiency of CR networks. Reference [9] proposes a system dynamic spectrum allocation scheme based on a central heterogeneous network architecture, considering the efficiency and fairness of different CR systems. Reference [10] mainly studies interference suppression techniques in CR communication systems from the perspective of dynamic spectrum management and proposes a cell-based dynamic spectrum management scheme. The above-mentioned literature primarily focuses on the effective management and utilization of limited resources without considering their integration with new technologies.

As a new technique, IRS can further improve spectral efficiency. IRS consists of numerous small reflecting units, each of which can adjust its reflection coefficient and phase to modify the amplitude and direction of incident signals. They can be arranged in various geometric patterns on a reflecting surface to achieve more intricate signal manipulation. By intelligently controlling the parameters of the reflecting surface, IRS can optimize signal coverage, reduce interference, enhance the effective utilization of spectrum resources, and improve signal quality in multi-user communication scenarios. This technology holds the potential to offer better performance and efficiency for future wireless communication systems.

Today, IRS technology is more widely applied, and numerous studies have made new advancements with IRS assistance. Reference [11] studied the use of passive beamforming and information transmission technology in IRS for multi-input multi-output (MIMO) systems and proposed a turbo message-passing algorithm to generate near optimal, low-complexity solutions. Reference [12] studied a MIMO secure simultaneous wireless information and power transfer (SWIPT) system assisted by IRS, proposed an imprecise block coordinate descent (BCD) method, and verified the effectiveness of IRS in enhancing security. Reference [13] proposes an unmanned aerial vehicle (UAV) CR system based on IRS, which contributes to rebuilding a dependable chain in UAV-assisted CR networks. In the past few years, research combining CR and IRS technologies has also made significant progress. Reference [14] investigates the maximization of the SUs rate in downlink MISO CR communication with IRS assistance. Considering that half-duplex communication may not fully exploit radio frequency spectrum resources, Reference [15] explores the maximization of spectrum efficiency in IRS-assisted full-duplex CR systems, aiming to improve the behavior of secondary networks while effectively reducing interference to PUs. Reference [16] further investigated the rate maximization problem of SUs in symmetric and asymmetric cross interference links. Reference [17] studied channel-aware binary decision fusion on a shared flat fading channel with multiple antennas with the assistance of IRS. While proposing the optimal rule, the (suboptimal) joint fusion rule and IRS design were derived as an alternative solution to reduce complexity and system knowledge requirements.

With the advancement of IoT technology, the increasing need for ubiquitous device-to-device communication, and the widespread adoption of low-power devices [18], in order to better utilize wireless spectrum resources, SWIPT technology is a good solution for a large number of low-power devices to simultaneously decode information and transmit energy [19–22]. Currently, IRS-assisted SWIPT technology is gaining widespread attention. Reference [23] uses power allocation at the user's location and introduces artificial noise at the access point, which further improves user security while collecting energy and decoding information. Reference [24] used an IRS model with physical properties and researched the resource allocation algorithm for IRS-assisted SWIPT systems. Reference [25] designed an active IRS-assisted SWIPT system to address the inherent path loss attenuation problem in IRS-assisted communication channels, which significantly improved system performance. Reference [26] studied the problem of simultaneously optimizing the information rate and harvesting power in IRS-assisted MISO downlink multi-user wireless networks. However, it did not consider cognitive scenarios, and spectrum resource utilization was still limited. Moreover, only two models with and without IRS were considered, without considering the situation with and without energy beams. The system performance still has great room for improvement. Reference [27] studied a simultaneously transmitting and reflecting reconfigurable intelligent surface assisted SWIPT system, but it also did not consider the situation with and without energy beams.

However, the fairness-aware resource allocation for a large number of low-power devices in IRS-assisted cognitive scenarios has been less explored in the literature mentioned above. In addressing this issue, this article studies the IRS-assisted MISO wireless portable communication system in CR scenarios, which can provide energy for a large number of low-power devices in the IoT and fully utilize idle spectrum resources. Due to potential obstacles between the CBS and SUs leading to degraded communication quality, this article optimizes signal transmission by adjusting the IRS reflection coefficient and phase. The objective of this article is to maximize the minimum energy received power in the energy receiver, while satisfying SINR thresholds for information decoders, the maximum interference at the primary users, and the transmit power constraints of the CBS, to balance energy reception and information decoding fairness.

The main contributions of this article are as follows:

- This article focuses on the simultaneous transmission of information and energy storage between numerous single-antenna devices at the receiving end in a cognitive network. With the assistance of IRS and SWIPT technologies, a system model is constructed to study the beamforming of cognitive networks assisted by IRS. The research objective of this article is to achieve an optimal state of the system under certain physical constraints, in order to achieve a balance between energy reception and information exchange. While ensuring the minimum SINR threshold requirement for all information receivers and maximizing the energy power received by the smallest energy receiver, the energy receiver has the optimal energy transmission performance while fully utilizing the spectrum resources of the entire communication network.
- This article proposes an iterative algorithm based on BCD to alternately optimize active and passive beamforming variables. First, fix the passive beamforming variables, optimize the active beamforming variables, apply the semi-definite relaxation (SDR) techniques to non-convex objective and constraint functions to relax the rank one condition constraints, and use Gaussian randomization schemes to ensure the rank one condition. Then, fix the active beamforming variables and optimize the passive beamforming variables. Replace the rank one constraint with a relaxed convex constraint using the sequential rank one constraint relaxation algorithm, and then, use a convex optimization method to solve the problem.
- The simulation results indicate that the joint iterative optimization algorithm proposed in this article can quickly converge and obtain high-quality solutions. At the same time, the system settings in this article can significantly improve system performance and produce a significant improvement in spectral efficiency. Comparing the four system models with energy beam and IRS, with energy beam and no IRS, without energy beam and IRS, and without energy beam and no IRS, the SINR threshold, the number of transmitting antennas of the AP, the horizontal distance between the energy receiver and the AP, and the AP transmission power are used as variables. While the rest remain unchanged, the system model with energy beam and IRS established in this paper has the highest energy power received by the minimum energy receiver and the best performance compared to the other three models. This is because IRS can increase the signal coverage range of the AP, and even energy receivers in poor channel environments can receive signals reflected from the IRS. On the other hand, interference signals can also be coherently cancelled through the superposition of reflection and direct paths, reducing the energy dependence of the information beam and giving AP more freedom to allocate more energy to the energy beam for energy transmission. It can be observed that, regardless of whether there is an IRS or not, the system performance with an energy beam is always better than that without an energy beam. This is because in systems with energy beams, energy beams can be designed specifically for the channel of the energy receiver, while in systems without energy beams, the channel of the energy receiver can only be considered simultaneously

by sacrificing the optimality of the information beam, which leads to a decrease in system performance.

The rest of the paper is organized as follows. In Section 2, we show the cognitive MISO wireless portable communication system model and formulate the problem of maximizing the received power of the minimum energy receiver in the secondary network. Section 3 uses iterative optimization algorithms to optimize active beamforming variables and passive beamforming variables, respectively. Simulations are provided for demonstrating the performance of proposed algorithms in Section 4. Section 5 is used to conclude the paper.

Notations: $\mathbb{C}^{M\times 1}$ denotes the space of $M\times 1$ complex valued vectors, diag(x) denotes a diagonal matrix whose diagonal elements correspond to vector x, and X^H denote the conjugate transpose of vector x and matrix X, respectively. The notations Tr(X) and rank(X) denote the trace and rank of matrix X, respectively. $CN(0,\sigma^2)$ represents the distribution of a circularly symmetric complex Gaussian variable with zero mean and σ^2 variance. All acronyms and full names in the paper are shown in Table 1.

Table 1. Acronyms and full names.

Acronyms	Full Names
IoT	Internet of Things
MISO	Multiple-Input Single-Output
SINR	Signal-to-Interference-plus-Noise Ratio
CBS	Cognitive Base Station
SDR	Semi-Definite Relaxation
CR	Cognitive Radio
PUs	Primary Users
SUs	Secondary Users
IRS	Intelligent Reflecting Surface
MIMO	Multi-Input Multi-Output
SWIPT	Simultaneous Wireless Information and Power Transfer
BCD	Block Coordinate Descent
UAV	Unmanned Aerial Vehicle
SDP	Semi Definite Programming
KKT	Karush–Kuhn–Tucker
LOS	Line-Of-Sight

2. System Model and Problem Statement

2.1. System Model

Consider the cognitive portable communication system assisted by IRS, as shown in Figure 1. It contains two parts: the main network and the secondary network assisted by the IRS. The main network includes multiple information receivers, while the secondary network includes multiple information receivers, multiple energy receivers, a CBS, and an IRS. Adopting a cushion-based spectrum-sharing method to ensure that the interference power received by the PUs is lower than the pre-set threshold, minimizing the impact of SUs' access to the network on system communication performance. Specifically, the CBS equipped with M transmitting antennas, assisted by IRS with N reflection units, simultaneously sends corresponding signals to the single antenna information receiver of the main network, the single antenna information receiver of the secondary network, and the single-antenna energy receiver. Here, the set of transmit antennas is $\overline{M} \triangleq \{1,\ldots,M\}$, the set of reflecting elements is $\overline{N} \triangleq \{1,\ldots,N\}$, the set of information receivers for the PUs is $\overline{K}_{ipu} \triangleq \{1,\ldots,K_{ipu}\}$, the set of information receivers for the SUs is $\overline{K}_{isu} \triangleq \{1,\ldots,K_{isu}\}$, and the collection of energy receivers is $\overline{K}_{esu} \triangleq \{1,\ldots,K_{esu}\}$. Regarding the channel, let the channel from the CBS to IRS be expressed by a matrix $T\in\mathbb{C}^{N\times M}$, the channel from the CBS to the $k\in\overline{K}_{ipu}$ information receiver of the PUs be represented by vector $h_{d,k}$, the channel to the $i\in\overline{K}_{isu}$ information receiver of the SUs be represented by vector $p_{d,i}$ the channel for the $j\in\overline{K}_{esu}$ energy receiver be represented by a vector $g_{d,j}$, the channel from IRS to the $k \in \overline{K}_{ipu}$ information receiver of the PUs be represented by vector $h_{r,k}$, the channel to the $i \in \overline{K}_{isu}$ information receiver of the SUs be represented by vector $p_{r,i}$ and the channel to the $j \in \overline{K}_{esu}$ energy receiver be represented by vector $g_{r,j}$. In order to better focus on the design of active beamforming and passive beamforming, while also obtaining the system performance upper bound brought by spectrum sharing, this article assumes that all channel state information can be constantly obtained at the CBS.

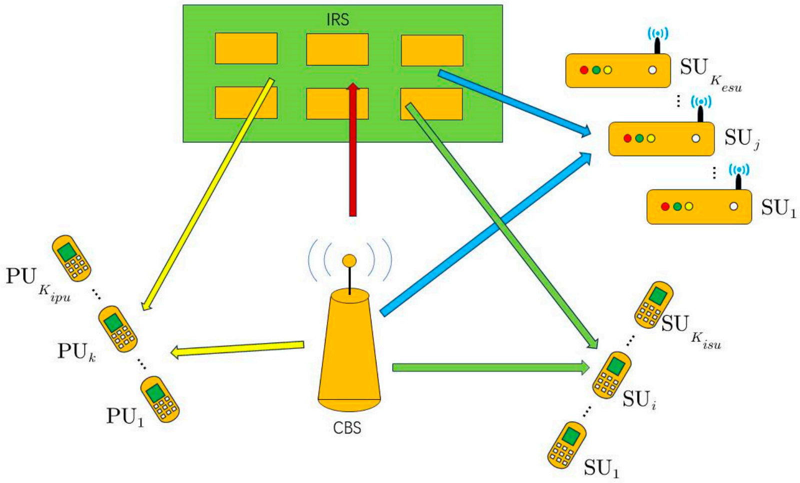

Figure 1. Cognitive MISO Wireless Portable Communication System Model.

2.2. Problem Statement

First, this article considers the scenario of CR, and for active beamforming, in addition to setting up traditional beamforming for information receivers in cognitive networks, energy beamforming for energy receivers is also specifically added. Since the information is random, let the information to be sent to the $i \in \overline{K}_{isu}$ cognitive information receiver be denoted as variable $s_i \sim CN(0,1)$. Then, the corresponding information beamforming is represented by vector $w_i \in \mathbb{C}^{M\times 1}$. For energy receivers in the cognitive network, they only need to receive energy without the need for information decoding. Therefore, the transmitted energy signal can be generated by the CBS using a pseudo-random sequence. Its beamforming is represented by variable $s_E \in \mathbb{C}^{M\times 1}$, with a mean of 0, and its covariance matrix is defined as $S_E \triangleq E\left(s_E s_E^H\right)\succeq 0$. The matrix S_E can be a high-dimensional matrix. Where $A\succeq 0$ represents that matrix A is positive semidefinite, combining the above definitions, we can obtain the transmission signal at the CBS as $\sum_{i\in\overline{K}_i} w_i s_i + s_E$. Suppose the maximum transmission power of the CBS is, then the power constraint at the CBS is $E\left(\|\sum_{i\in\overline{K}_i} w_i s_i + s_E\|\right) = \sum_{i\in\overline{K}_i}\|w_i\|^2 + tr(S_E) \leqslant P$.

Next, consider passive beamforming in CR networks assisted by IRS and define the reflection parameters of the reflection array units on the IRS. Define the reflection phase of the nth reflecting units as $\theta_n \in [0, 2\pi)$, where $n \in N$. Define the reflection phase vector as $\theta = [\theta_1, \ldots \theta_N]$ and the reflection phase matrix for passive beamforming as $\Theta \triangleq \mathrm{diag}\left(e^{j\theta_1}, \ldots, e^{j\theta_N}\right)$, where $\mathrm{diag}(a_1, \ldots, a_N)$ is represented as a diagonal matrix with $a_1, \ldots, a_N$ as its diagonal elements. Here, $j = \sqrt{-1}$ represents the imaginary unit.

In summary, the receivers can respectively receive direct signals from the CBS and reflected signals from IRS. The received signal at the $k \in \overline{K}_{ipu}$ primary network information receiver and the $i \in \overline{K}_{isu}$ secondary network information receiver are as follows:

$$y_{kpu} = \left(p_{r,k}^H \Theta T + p_{d,k}^H\right)\left(\sum_{m\in\overline{K}_{ipu}} w_m s_m + s_E\right) + n_{kpu} \quad (1)$$

$$y_{isu} = \left(h_{r,i}^{H}\Theta T + h_{d,i}^{H}\right)\left(\sum_{n\in\overline{K}_{isu}} w_n s_n + s_E\right) + n_{isu} \tag{2}$$

where $n_{kpu} \sim CN\left(0, \sigma_{kpu}^2\right)$ and $n_{ksu} \sim CN\left(0, \sigma_{ksu}^2\right)$ are additive white Gaussian noise at the k-th primary network information receiver and the i-th secondary network information receiver, with noise powers σ_{kpu}^2 and σ_{ksu}^2, respectively. For the primary network, the energy receivers do not consider the form of energy signal they carry; only the received signal power is considered. Therefore, energy signals can be generated at the CBS using pseudo-random sequences. It can be assumed that each information receiver has prior knowledge of the pseudo-random sequence of the energy signal and can perfectly eliminate the interference from the energy signal. After interference cancellation from the energy signal, the SINR for the $i \in \overline{K}_{isu}$ information receiver can be expressed as:

$$\gamma_i(\{w_i\},\theta) = \frac{\left|\left(p_{r,j}^{H}\Theta T + p_{d,i}^{H}\right)w_i\right|^2}{\sum\limits_{k\neq i,k\in\overline{K}_i}\left|\left(p_{r,i}^{H}\Theta T + p_{d,i}^{H}\right)w_k\right|^2 + \sigma_i^2} \tag{3}$$

The interference power generated by the secondary network on the i-th information receiver in the primary network can be expressed as:

$$\begin{aligned} &P_k(\{w_i\}, S_E, \theta) \\ &= E\left(\left|\left(p_{r,i}^{H}\Theta T + p_{d,i}\right)\left(\sum_{m\in\overline{K}_{isu}} w_m s_m + s_E\right)\right|^2\right) \\ &= \left(p_{r,i}^{H}\Theta T + p_{d,i}\right)S_E\left(p_{r,i}^{H}\Theta T + p_{d,i}\right)^H + \sum_{i\in\overline{K}_{isu}}\left|\left(p_{r,i}^{H}\Theta T + p_{d,i}\right)w_i\right|^2 \end{aligned} \tag{4}$$

For energy receivers, they aim to collect all radio frequency signals to charge the battery. Therefore, the energy received at the $j \in \overline{K}_{epu}$ energy receiver in the secondary network is:

$$\begin{aligned} &Q_j(\{w_i\}, S_E, \theta) \\ &= E\left(\left|\left(g_{r,j}^{H}\Theta T + g_{d,j}^{H}\right)\left(\sum_{n\in\overline{K}_{isu}} w_n s_n + s_E\right)\right|^2\right) \\ &= \left(g_{r,j}^{H}\Theta T + g_{d,j}^{H}\right)S_E\left(g_{r,j}^{H}\Theta T + g_{d,j}^{H}\right)^H + \sum_{i\in\overline{K}_{isu}}\left|\left(g_{r,j}^{H}\Theta T + g_{d,j}^{H}\right)w_i\right|^2 \end{aligned} \tag{5}$$

From the SINR at information receivers and the received power at energy receivers, it can be observed that by adjusting the active beamforming at the CBS and the reflection phase parameters at IRS to form passive beamforming, a balance can be achieved between the communication and energy reception levels at the information and energy receivers. Therefore, in the context of CR, considering the constraints on the CBS's transmission power, SINR constraints at all information receivers, and the reflection phase constraints on the reflecting elements at IRS, this article aims to maximize the minimum received power among all energy receivers in the secondary network. Hence, the problem considered in this article can be represented as (6)–(11):

$$\max_{\{w_i S_E,\theta\}} \min_{j\in\overline{K}_{esu}} Q_j(\{w_i\}, S_E, \theta) \tag{6}$$

$$s.t.\gamma_i(\{w_i\},\theta) \geqslant \Gamma_i,\ \forall i \in \overline{K}_{isu} \tag{7}$$

$$P_k(\{w_i\}, S_E, \theta) \leqslant I_{max},\ \forall i \in \overline{K}_{isu},\ \forall k \in \overline{K}_{ipu} \tag{8}$$

$$\sum_{i \in \overline{K}_{isu}} \|w_i\|^2 + tr(S_E) \leqslant P \tag{9}$$

$$0 \leqslant \theta_n \leqslant 2\pi, \ \forall n \in \overline{N} \tag{10}$$

$$S_E \succeq 0 \tag{11}$$

Furthermore, Γ_i, $\forall i \in \overline{K}_{isu}$ represents the minimum communication SINR threshold for the i-th information receiver in the secondary network, and $I_{\max}$ represents the interference power threshold received by PUs.

Observing the above equation, it is evident that the active beamforming variable $\{w_i\}, S_E$ and the passive beamforming reflection phase parameters θ are highly coupled in both the objective functions, making them unable to obtain the global optimal solution, so further decomposition is needed. We introduce variable t and reformulate the above equation in a conic form, represented as (12)–(18):

$$\max_{\{w_i\}S_E,\theta,t} \ t \tag{12}$$

$$s.t. Q_j(\{w_i\}, S_E, \theta) \geqslant t, \ \forall j \in \overline{K}_{epu} \tag{13}$$

$$\gamma_i(\{w_i, \theta\}) \geqslant \Gamma_i, \ \forall i \in \overline{K}_{ipu} \tag{14}$$

$$P_k(\{w_i\}, S_E, \theta) \leqslant I_{max}, \ \forall i \in \overline{K}_{isu}, \ \forall k \in \overline{K}_{ipu} \tag{15}$$

$$\sum_{i \in \overline{K}_{isu}} \|w_i\|^2 + tr(S_E) \leqslant P \tag{16}$$

$$0 \leqslant \theta_n \leqslant 2\pi, \ \forall n \in \overline{N} \tag{17}$$

$$S_E \succeq 0 \tag{18}$$

Due to the coupling of variables, this article will employ an iterative approach to optimize and solve for different variables. Specifically, we will first fix the passive beamforming reflection phase variable θ and solve for the active beamforming variables $\{w_i\}, S_E$ in the secondary network. Once the optimal solution for $\{w_i\}, S_E$ is obtained and remains unchanged, we will then optimize the passive beamforming variables. This iterative optimization process will continue until the system converges.

3. Beamforming Design

3.1. Active Beamforming Design for the System

With the passive beamforming fixed as θ, which becomes a constant in the local context, this article focuses solely on solving for the active beamforming variables $\{w_i\}, S_E$ within the cognitive network. The combined channel information for the direct and reflected paths at the information and energy receivers in the secondary network is denoted as $p_i = T^H \Theta^H p_{r,i} + p_{d,i}$, $\forall i \in K_{ipu}$, $g_j = T^H \Theta^H g_{r,j} + g_{d,j}$, $\forall j \in K_{jsu}$. After channel aggregation, the optimization problem for active beamforming can be represented as (19)–(24):

$$\max_{\{w_i\},S_E,t} \ t \tag{19}$$

$$s.t. \sum_{i \in \overline{K}_{isu}} \left| w_i^H g_j \right|^2 + g_j^H S_E g_j \geqslant t, \ \forall j \in \overline{K}_{esu} \tag{20}$$

$$\sum_{i \in \overline{K}_{isu}} \left| w_i^H p_k \right|^2 + p_k^H S_E p_k \leqslant I_{\max}, \ \forall k \in \overline{K}_{ipu} \tag{21}$$

$$\frac{\left| w_i^H h_i \right|^2}{\Gamma_i} - \sum_{n \neq i, n \in \overline{K}_{isu}} \left| w_n^H h_i \right|^2 - \sigma^2 \geqslant 0, \ \forall i \in \overline{K}_{isu} \tag{22}$$

$$\sum_{i\in\overline{K}_{ipu}} \|w_i\|^2 + tr(S_E) \leqslant P \tag{23}$$

$$S_E \succeq 0 \tag{24}$$

Because of the existence of non-convex quadratic constraints in Problems (20) and (22), optimization Problem (19)–(24) is a non-convex quadratic programming problem that cannot be directly solved.

We define a positive semi-definite matrix $W_i = w_i w_i^H$, $\forall i \in \overline{K}_{isu}$ for beamforming, with a rank of 1, denoted as $rank(W_i) \leqslant 1$, $\forall i \in \overline{K}_{isu}$. Consequently, we can derive the equivalent form of the above optimization problem as (25)–(32):

$$\max_{\{W_i\},S_E,t} \ t \tag{25}$$

$$s.t. \sum_{i\in\overline{K}_{isu}} tr\left(g_j g_j^H W_i\right) + tr\left(g_j g_j^H S_E\right) \geqslant t,\ \forall j \in \overline{K}_{esu} \tag{26}$$

$$\sum_{i\in\overline{K}_{isu}} tr\left(p_k p_k^H W_i\right) + tr\left(p_k p_k^H S_E\right) \leqslant I_{\max},\ \forall k \in \overline{K}_{ipu} \tag{27}$$

$$\frac{tr\left(h_i h_i^H W_i\right)}{\Gamma_i} - \sum_{n\neq i, n\in\overline{K}_{isu}} tr\left(h_i h_i^H W_n\right) - {\sigma_i}^2 \geqslant 0,\ \forall i \in \overline{K}_{isu} \tag{28}$$

$$\sum_{i\in\overline{K}_{ipu}} \|w_i\|^2 + tr(S_E) \leqslant P \tag{29}$$

$$S_E \succeq 0 \tag{30}$$

$$W_i \succeq 0,\ \forall i \in \overline{K}_{isu} \tag{31}$$

$$rank(W_i) \leqslant 1,\ \forall i \in \overline{K}_{isu} \tag{32}$$

However, due to the rank constraint (32), optimization Problem (25)–(32) remains non-convex and cannot be directly solved. Therefore, this article employs the SDR method to address this problem, resulting in the following semidefinite relaxation (Appendix A) form with matrices $\{W_i\}$ and S_E as variables:

$$\max_{\{W_i\},S_E,t} \ t \tag{33}$$

$$s.t. \sum_{i\in\overline{K}_{isu}} tr\left(g_j g_j^H W_i\right) + tr\left(g_j g_j^H S_E\right) \geqslant t,\ \forall j \in \overline{K}_{esu} \tag{34}$$

$$\sum_{i\in\overline{K}_{isu}} tr\left(p_k p_k^H W_i\right) + tr\left(p_k p_k^H S_E\right) \leqslant I_{\max},\ \forall k \in \overline{K}_{ipu} \tag{35}$$

$$\frac{tr\left(h_i h_i^H W_i\right)}{\Gamma_i} - \sum_{n\neq i, n\in\overline{K}_{isu}} tr\left(h_i h_i^H W_n\right) - {\sigma_i}^2 \geqslant 0,\ \forall i \in \overline{K}_{isu} \tag{36}$$

$$\sum_{i\in\overline{K}_{ipu}} \|w_i\|^2 + tr(S_E) \leqslant P \tag{37}$$

$$S_E \succeq 0 \tag{38}$$

$$W_i \succeq 0,\ \forall i \in \overline{K}_{isu} \tag{39}$$

This turns the problem in this article into a semi-definite programming (SDP) problem that can be solved applying mature convex optimization tools.

3.2. Passive Beamforming Reflection Phase Design for the System

After solving the above problem, we have obtained the optimal solution for active beamforming, where the active beamforming vectors $\{w_i^*\}$, $\forall i \in \overline{K}_{isu}$ and $\{v_k^*\}_{k=1}^{r_E}$ are fixed. We then optimize the passive beamforming reflection phase parameters θ. For ease of notation, none of the active beamforming variables are denoted with an asterisk (*). Therefore, the optimization problem for passive beamforming can be represented as:

$$\max_{\Theta,t} t \tag{40}$$

$$s.t.\left(g_{r,j}^H \Theta T + g_{d,j}^H\right) S_E \left(g_{r,j}^H \Theta T + g_{d,j}^H\right)^H + \sum_{i \in \overline{K}_{isu}} \left|\left(g_{r,j}^H \Theta T + g_{d,j}^H\right) w_i\right|^2 \geqslant t,\ \forall j \in \overline{K}_{esu} \tag{41}$$

$$\frac{\left|\left(h_{r,i}^H \Theta T + h_{d,i}^H\right) w_i\right|^2}{\Gamma_i} - \sum_{k \neq i, k \in \overline{K}_{isu}} \left|\left(h_{r,i}^H \Theta T + h_{d,i}^H\right) w_k\right|^2 - \sigma_i^2 \geqslant 0,\ i \in \overline{K}_{isu} \tag{42}$$

$$0 \leqslant \theta_n \leqslant 2\pi,\ \forall n \in N \tag{43}$$

$$\sum_{i \in \overline{K}_{isu}} \left|w_i^H p_k\right|^2 + p_k^H S_E p_k \leqslant I_{\max},\ \forall k \in \overline{K}_{ipu} \tag{44}$$

Due to the non-convexity introduced by the fact that the desired passive beamforming vector θ is embedded within the passive beamforming diagonal matrix Θ, the optimization problem cannot be directly solved. Therefore, we perform algebraic equivalence transformations on constraints (41) and (42). First, we combine the following matrix forms:

$$C_{k,i} = \begin{bmatrix} c_{k,i} c_{k,i}^H & c_{k,i} d_{k,i}^H \\ c_{k,i}^H d_{k,i} & 0 \end{bmatrix},\ \forall k \in K_{isu},\ \forall i \in K_{isu} \tag{45}$$

$$E_{j,i} = \begin{bmatrix} e_{j,i} e_{j,i}^H & e_{j,i} f_{j,i}^H \\ e_{j,i}^H f_{j,i} & 0 \end{bmatrix},\ \forall j \in K_{esu},\ \forall i \in K_{isu} \tag{46}$$

$$O_{j,k} = \begin{bmatrix} o_{j,k} o_{j,k}^H & o_{j,k} q_{j,k}^H \\ o_{j,k}^H q_{j,k} & 0 \end{bmatrix},\ \forall j \in K_{esu},\ \forall k \in \{1, \ldots, r_E\} \tag{47}$$

$$M_{r,i} = \begin{bmatrix} m_{r,i} m_{r,i}^H & m_{r,i} n_{r,i}^H \\ m_{r,i}^H n_{r,i} & 0 \end{bmatrix},\ \forall r \in K_{esu},\ \forall i \in K_{ipu} \tag{48}$$

$$X_{r,k} = \begin{bmatrix} x_{r,k} x_{r,k}^H & x_{r,k} y_{r,k}^H \\ x_{r,k}^H y_{r,k} & 0 \end{bmatrix},\ \forall r \in K_{esu},\ \forall i \in K_{ipu} \tag{49}$$

where $c_{k,i} = \mathrm{diag}\left(h_{r,k}^H\right) T w_i$, $d_{k,i} = h_{d,k}^H w_i$, $e_{j,i} = \mathrm{diag}\left(g_{r,j}^H\right) T w_i$, $f_{j,i} = g_{d,j}^H w_i$, $o_{j,k} = \mathrm{diag}\left(g_{r,j}^H\right) T v_k$, $q_{j,k} = g_{d,j}^H v_k$, $m_{r,i} = \mathrm{diag}\left(p_{r,i}^H\right) T w_i$, $n_{r,i} = p_{d,i}^H w_i$, $x_{r,k} = \mathrm{diag}\left(p_{r,i}^H\right) T v_k$, $y_{r,k} = p_{d,i}^H v_k$. Additionally, we rearrange the variables related to the passive beamforming reflection phase parameters into a vector form, $\phi = \left[e^{-j\theta_1}, \ldots, e^{-j\theta_N}, l\right]$, where $l^2 = 1$. The rearranged passive beamforming matrix is denoted as $\Phi = \phi^H \phi$, with a rank of 1 denoted as $rank(\Phi) = 1$. After algebraic rearrangement, optimization Problem (40)–(44) can be expressed as:

$$\max_{\Phi,t} t \tag{50}$$

$$s.t. \sum_{i \in K_{isu}} tr\left(E_{j,i}\Phi\right) + \sum_{k=1}^{r_E} tr\left(O_{j,k}\Phi\right) + \sum_{i \in K_{isu}} \left|f_{j,i}\right|^2 + \sum_{k=1}^{r_E} |q_{j,k}|_2 \geqslant t,\ \forall j \in K_{esu} \tag{51}$$

$$tr(C_{k,i}\Phi) + |d_{k,i}|_2 \geqslant \Gamma_i \sum_{k\neq i,k\in K_{isu}} tr(C_{i,k}\Phi) + \Gamma_i \left\{ \sum_{k\neq i,k\in K_{isu}} |d_{i,k}|_2 + \sigma_i^2 \right\}, \ \forall i \in K_{isu} \quad (52)$$

$$\varphi_{n,n} = 1, \ \forall n \in \{1, \ldots, N+1\} \quad (53)$$

$$\Phi \succeq 0 \quad (54)$$

$$rank(\Phi) = 1 \quad (55)$$

where $\varphi_{n,n}$ represents the n-th diagonal element of matrix Φ. However, because the non-convex rank constraint requirement (55), optimization Problem (50)–(55) is still not convex. We employ the sequential rank-one relaxation algorithm to transform Problem (50)–(55) into an optimization problem:

$$\max_{\Phi,t} t \quad (56)$$

$$s.t. \sum_{i\in K_{isu}} tr\left(E_{j,i}\Phi\right) + \sum_{k=1}^{r_E} tr\left(O_{j,k}\Phi\right) + \sum_{i\in K_{isu}} \left|f_{j,i}\right|^2 + \sum_{k=1}^{r_E} |q_{j,k}|_2 \geqslant t, \ \forall j \in K_{esu} \quad (57)$$

$$tr(C_{k,i}\Phi) + |d_{k,i}|_2 \geqslant \Gamma_i \sum_{k\neq i,k\in K_{isu}} tr(C_{i,k}\Phi) + \Gamma_i \left\{ \sum_{k\neq i,k\in K_{isu}} |d_{i,k}|_2 + \sigma_i^2 \right\}, \ \forall i \in K_{isu} \quad (58)$$

$$\varphi_{n,n} = 1, \ \forall n \in \{1, \ldots, N+1\} \quad (59)$$

$$u_{\max}\left(\Phi^{(i)}\right)^H \Phi u_{\max}\left(\Phi^{(i)}\right) \geqslant \alpha^{(i)} tr\{\Phi\} \quad (60)$$

$$\Phi \succeq 0 \quad (61)$$

where $\Phi^{(i)}$ is the optimal solution for the i-th iteration, and $\alpha^{(i)}$, $u_{\max}\left(\Phi^{(i)}\right)$ represents the eigenvector corresponding to the maximum eigenvalue of $\Phi^{(i)}$.

3.3. Algorithm Design

Due to the coupling between active beamforming variables and passive beamforming variables, it is not possible to directly solve Problem (6)–(11). It requires fixing one of them and then iteratively optimizing the other. Therefore, the approach to solving Problem (6)–(11) involves iteratively optimizing Problems (33)–(39) and (50)–(55). The iterative algorithm for solving Problem (50)–(55) is shown in Algorithm 1, and the overall iterative algorithm is shown in Algorithm 2.

Algorithm 1: Iterative Algorithm for Solving Problem (50)–(55)

Initialize convergence threshold ξ_1, ξ_2 and a feasible Φ^0.
For Φ^0, solve Problem (50)–(55) using w^0.
Set $i = 1,$ initialize step size $\delta^{(i)}$:
  1: Repeat;
  2 : Use $w^{(i)}, \ \Phi^{(i)}$ to solve Problem (50)–(55);
  3: If Problem (50)–(55) is resolved, then
  4 : The optimal solution is denoted as $\Phi^{(i+1)}$;
  5 : $\delta^{(i+1)} = \delta^{(i)}$;
  6 : Otherwise $\delta^{(i+1)} = \delta^{(i)}/2$, $\Phi^{(i+1)} = \Phi^{(i)}$;
  7: Finally, if
  8: $w^{(i+1)} = \min\left(1, \frac{\lambda_{\max}\left(\Phi^{(i+1)}\right)}{tr\left(\Phi^{(i+1)}\right)} + \delta^{(i+1)}\right)$,
  9 : $i = i + 1$;
  10 : Until $\left|1 - w^{(i-1)}\right| \leqslant \xi_1$ and the objective value are less than ξ_2.

Algorithm 2: Overall Iterative Algorithm

1: Initialize passive beamforming variables θ.
2: Repeat:
Solve Problem (33)–(39) to obtain $\{W_i^*\}$, S_E^*;
Perform EVD decomposition on $\{W_i^*\}$, S_E^* to obtain the vector sets $\{w_i^*\}$, $\forall i \in K_{isu}$ and $\{v_k^*\}_{k=1}^{r_E}$;
Formulate optimization Problem (50)–(55) and solve Problem (56)–(61) to obtain Φ^*;
Apply Algorithm 1;
If the absolute difference between the objective function value of this iteration and the previous iteration is less than the threshold β, stop.
3 : Take the obtained $\{W_i\}$, S_E and θ at the stopping point as the solution to optimization Problem (6)–(11).

4. Analysis of Simulation Results

We employ MATLAB software (https://www.mathworks.com/products/matlab.html, accessed on 31 December 2023) to validate the behavior of the iterative algorithm for the MISO wireless energy-harvesting communication system with IRS using specific data inputs. First, concerning the channel model, the location of IRS is often manually determined and can be constructed within a relatively close line-of-sight (LOS) range from the transmitting base station. We assume that the channel from the CBS to IRS follows a Rician channel model, which can be represented as a superposition of a direct LOS component and a Rayleigh fading component:

$$T = \sqrt{\frac{\rho_r}{1+\rho_r}}T^{\mathrm{LOS}} + \sqrt{\frac{1}{1+\rho_r}}T^{\mathrm{NLOS}} \tag{62}$$

where ρ_r is the Rician factor, matrix T^{LOS} represents the LOS path channel component, and matrix T^{NLOS} represents the Rayleigh channel component. We assume the Rician factor of the system to be $\rho_r = 10$ dB. As for the channels from the IRS to the receiver and from the cognitive base station to the receiver, since the receiver can move with the user, the impact of obstacles on system performance often needs to be considered to some extent depending on the user's location. In real-world wireless communication channel environments, there may not always be a strong LOS path, and the characteristics, such as signal strength and phase, are subject to fluctuations due to physical factors, often following a Rayleigh distribution. Therefore, we assume the above channels to be Rayleigh channels.

For the channel fading model, we set it as:

$$PL = \frac{P_r}{P_t} = \kappa\left(\frac{d}{d_0}\right)^{-\alpha} \tag{63}$$

where P_r represents the received power at the receiver, P_t represents the transmit power at the transmitter, PL represents the path loss, coefficient $\kappa = -30$ dB is the channel fading value at the reference distance $d_0 = 1$ m, d is the actual distance between the two communication devices, and α is the channel fading exponent. Due to the relatively short distance between the IRS and the CBS in the system model, they often have a better LOS path. The purpose of establishing the IRS is to assist the CBS. Therefore, the channel fading factor from the CBS to the primary user's information receiver can be denoted as $\alpha_{AP-PU} = 3.8$, and the distance to the right of the IRS is $d_{PU} = 50$ m. The channel fading factor from the CBS to the secondary user's information receiver is denoted as $\alpha_{AP-SU} = 3.5$; the distance is $d_{SU} = 50$ m. The channel fading factor from the CBS to IRS is denoted as $\alpha_{AP-IRS} = 2$; the distance is $d_{IRS} = 20$ m. For a secondary-user energy receiver, in order to minimize energy loss, it is advantageous to have the secondary-user energy receiver receive a high-power radio frequency signal transmitted from the CBS. Therefore, in the system, the distance between the CBS and the secondary-user energy receiver is relatively short, and we set the distance as $d_{EH} = 3$ m. Additionally, we assume that the number of reconfigurable reflecting units on IRS is $N = 40$.

The simulation settings in all the simulation analyses below are shown in the Table 2 below:

Table 2. Model simulation settings.

Simulation Settings	Value
Noise Power	−80 dBm
The Number of PUs Information Receivers	2
The Number of Information Receivers	3
The Number of Energy Receivers	3
The Interference Power Threshold for Pus	−110 dBm
The Minimum SINR Threshold Range	10 dB

First, observe Figure 2, which represents the convergence speed of the iterative algorithm studied in this article for solving Problem (6)–(11). Since Problem (6)–(11) cannot be directly solved, we use an iterative algorithm to calculate variables with different beam types separately. Our iterative algorithm ensures the monotonicity of optimizing the maximum minimum energy reception power. In channel realization 1, approximately in the first three iterations, the minimum energy received power has reached over 90% of the overall power. By the fourth iteration, the energy received power tends to stabilize and the image approaches a straight line. In channel realization 2, approximately in the first five iterations, the minimum energy received power has reached over 80% of the overall output. In the sixth iteration, the minimum energy received power has reached over 90%. By the seventh iteration, the energy received power tends to stabilize, the image approaches a straight line, and the simulation time required for system convergence is about 52 s. It is evident that our iterative algorithm is efficient and can quickly iterate high-quality beamforming solutions. This provides a degree of assurance for optimizing and adjusting related variables in our subsequent models.

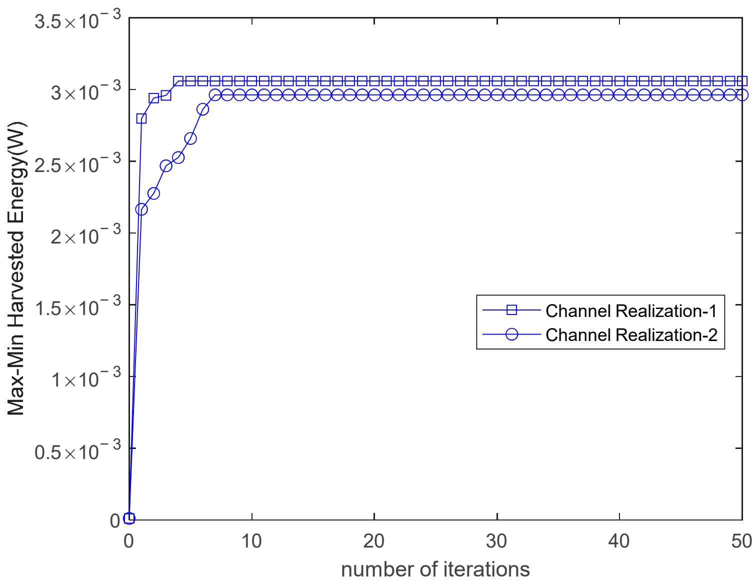

Figure 2. Illustrates the convergence progress of the iterative algorithm for optimizing Problem (6)–(11).

Figure 3 studies how the minimum energy received power in the energy receiver in the secondary network varies with the SINR threshold at the information receiver. V in Figure 3 represents the energy beam. At this point, the CBS transmit power is $P = 30$ dBm, the number of CBS transmission antennas is $M = 8$, the number of PU information receivers is $K_{ipu} = 2$, the numbers of information receivers and energy receivers in the cognitive network are $K_{isu} = 3$ and $K_{esu} = 3$, respectively, the interference power threshold for Pus is $I_{\max} = -110$ dBm, and the number of reflector elements is $N = 40$. The minimum SINR threshold range for the information receiver spans from 10 dB to 25 dB. In Figure 3, the model group with IRS is significantly better than the model group without an IRS regarding receiving power. This is because the presence of an IRS allows the signals from the CBS to be reflected, increasing the signal utilization efficiency and, consequently, the minimum received power at the receiver. When comparing models with and without energy beams, it can be observed that the models with energy beams generally exhibit better performance compared to those without energy beams. As the SINR threshold increases, the minimum received power at the energy receivers for all model groups starts to decrease.

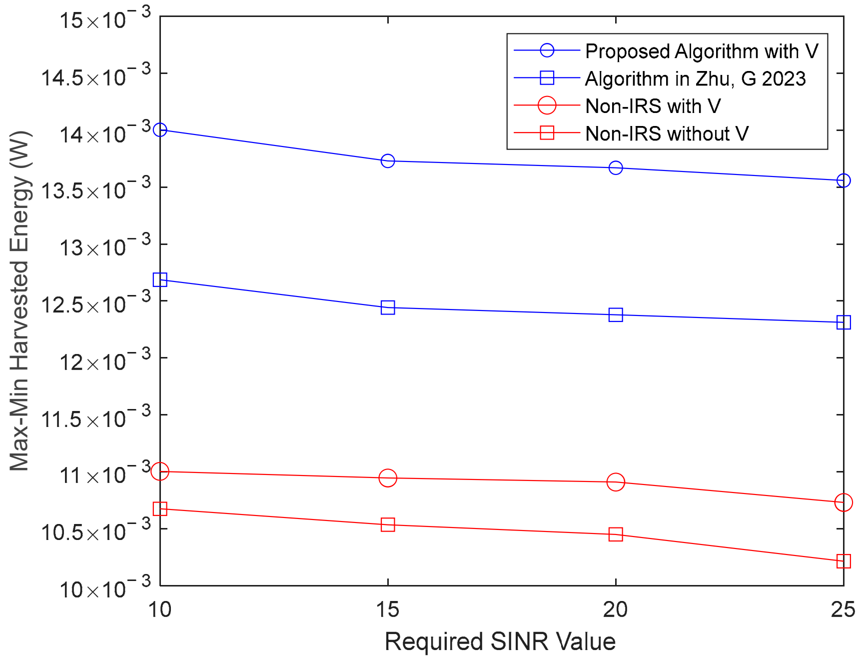

Figure 3. The variation of the minimum energy received power with the SINR threshold of the information receiver in the secondary network [27].

Figure 4 shows the influence of transmitting antennas at the secondary base station side on fair energy acquisition among energy users in all cognitive networks. V in Figure 4 represents the energy beam. At this point, the CBS transmit power is $P = 30$ dBm, the number of PUs information receivers is $K_{ipu} = 2$, the numbers of information receivers and energy receivers in the cognitive network are $K_{isu} = 3$ and $K_{esu} = 3$, respectively, the interference power threshold for Pus is $I_{\max} = -110$ dBm, and the number of reflector elements is $N = 40$. Observing from the graph, it can be noted that the system with an IRS and energy beams performs the best. Systems with an IRS consistently outperform those without an IRS. As the number of transmit antennas at the transmitter increases, the minimum received power at the energy receiver gradually increases. This is because the larger the number of transmitting antennas, the more signal propagation paths there are, and IRS contributes to signal propagation through refraction. Thus, the IRS plays a certain role in mitigating signal fading, enhancing system performance, and allowing the energy receiver to receive higher power. Under the same conditions in other aspects, systems with energy beams always outperform those without energy beams. This is because energy beams effectively focus and enhance the signal, enabling the energy receiver to capture more energy without being affected by the surrounding environment's interference and losses. Consequently, the energy receiver can receive higher power.

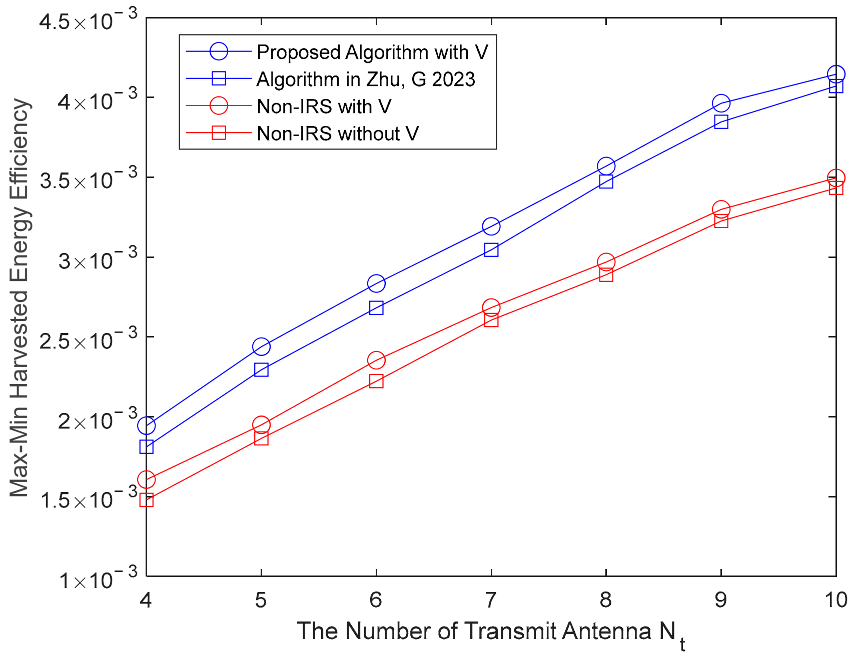

Figure 4. The variation of minimum energy received power with the number of transmitting antennas in CBS [27].

Figure 5 illustrates the results of a simulation that examines the minimum energy reception power as the horizontal distance between the energy receiver and the CBS changes in a cognitive network. V in the figure represents the energy beam. The distance between the CBS and IRS is $d_{AP-IRS} = 20$ m, the CBS transmit power is $P = 30$ dBm, the number of PU information receivers is $K_{ipu} = 2$, the numbers of information receivers and energy receivers in the cognitive network are $K_{isu} = 3$ and $K_{esu} = 3$, respectively, the interference power threshold for PUs is $I_{\max} = -110$ dBm, and the number of reflector units is $N = 40$. The horizontal distance between all energy receivers in the secondary network and the CBS or IRS is always equal. From Figure 5, it is evident that the model with the IRS consistently exhibits a higher minimum received power compared to the model without the IRS. When all energy receivers are within 15 m of the CBS, the minimum received power decreases as the distance between the energy receivers and the CBS increases. However, at a distance of 15 m from the CBS, there is a divergence in results. In the presence of the IRS, the minimum received power tends to increase with the horizontal distance. This is because, as the distance between the energy receivers and the CBS increases, the distance between the energy receivers and the IRS decreases. Consequently, the energy receivers receive signals that are reflected by the IRS, compensating for the fading caused by being far from the CBS. In contrast, in the model without IRS assistance, as the distance between energy receivers and CBS increases, the minimum received power gradually decreases.

Figure 6 shows an almost linear relationship between the minimum energy received power in the energy receiver in the secondary network and the transmitted power at the CBS in dBm units. V in the figure represents the energy beam. At this point, the number of CBS transmission antennas is $M = 8$, the number of PU information receivers is $K_{ipu} = 2$, the numbers of information receivers and energy receivers in cognitive network are $K_{isu} = 3$ and $K_{esu} = 3$, respectively, interference power threshold for the PUs is $I_{\max} = -110$ dBm, and the number of reflector units is $N = 40$. Figure 6 shows that models with IRSs perform better than models without them. The energy receiver receives more power, indicating that the presence of an IRS increases the coverage range of signals transmitted by the CBS. Even in relatively poor channel conditions, the energy receiver can still receive signals reflected from the IRS, enhancing the efficiency of signal transmission from the CBS and optimizing system operation. On the other hand, in terms of noise reduction in the system, coherent cancellation is achieved by superimposing interfering signals through both reflection and direct paths, reducing the additional power consumption provided at the CBS to ensure signal quality. From the graph, it can be observed that, regardless of the presence of an IRS, systems with energy beams perform better than systems without energy beams under the same transmit power conditions at the CBS. As for an energy beam's energy signals, they can be designed specifically for the energy receiver to receive energy beams generated by the CBS through a pseudo-random mechanism, indirectly avoiding further interference with information beam reception at the receiver end. For systems without energy beams, the system performance decreases as only the optimality of the information beam can be considered in conjunction with the energy receiver's channel. This emphasizes the crucial role of energy beams. In summary, with the presence of energy beams and an IRS, system performance is greatly improved.

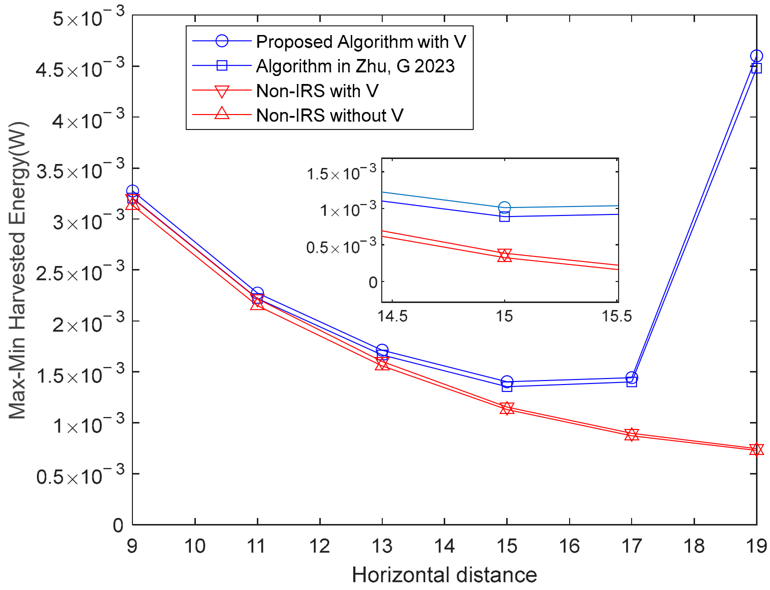

Figure 5. The variation of minimum energy received power with the horizontal distance between the receiver and the CBS [27].

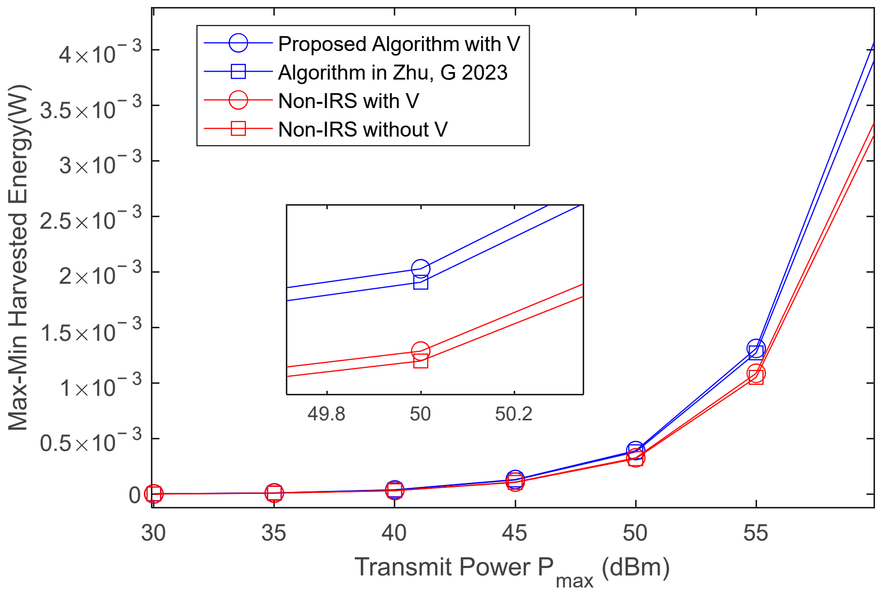

Figure 6. The variation of minimum received power of energy receivers with CBS transmission power in secondary networks [27].

Figure 7 demonstrates the variation of the minimum received power of the energy receiver in the secondary network with respect to the IRS reflection array element N. V in the figure represents the energy beam. At this point, the CBS transmit power is $P = 30$ dBm, the number of CBS transmission antennas is $M = 8$, the number of PU information receivers is $K_{ipu} = 2$, the numbers of information receivers and energy receivers in the cognitive network are $K_{isu} = 3$ and $K_{esu} = 3$, respectively, and the interference power threshold for PUs is $I_{\max} = -110$ dBm. It can be seen from Figure 7 that within a certain range, as the number of IRS reflex arrays increases, the minimum energy receiving power of the IRS model is gradually becoming larger. This is because, in the model of the deployment IRS, when the number of reflex arrangements of the IRS is increased, the IRS has more freedom to design more IRS-related reflex link channels to increase beamforming gain effect. On the other hand, the larger the number of reflex arrays of an IRS in the IRS model, the ways and power that can reflect the transmitting signal of the CBS will also become more, resulting in power gain. However, as the number of IRS units increases, the growth trend of the minimum energy receiving power has gradually become smaller, which indicates that raising the number of reflective units in an IRS within a certain range is beneficial for improving system performance. When this range is exceeded, the number of reflective units in the IRS is no longer the main factor affecting the minimum energy receiving power.

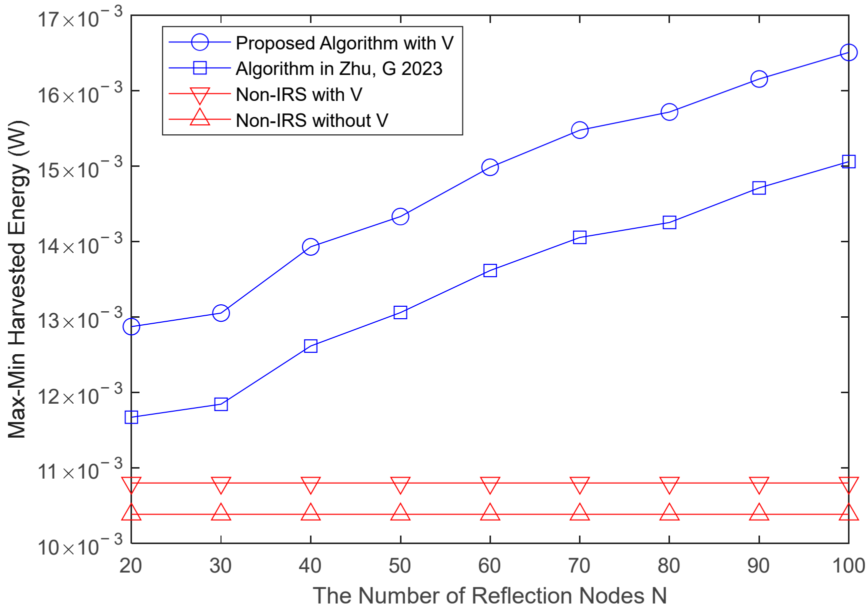

Figure 7. The variation of minimum received power of energy receiver with IRS reflection element N in the secondary network [27].

5. Conclusions

This article proposes a fair energy allocation algorithm for IRS-assisted cognitive MISO wireless-powered networks. When the SINR constraint is met and the interference power of the secondary network to the main network is less than the set threshold, the problem of maximizing the received power of the minimum energy receiver in the secondary network is established. The SDR algorithm is used to decouple and solve the complex and highly coupled objective function. The simulation results show that, under the constraint of interference power to the main user, compared with four system models, with energy beam and IRS, with energy beam and no IRS, without energy beam and IRS, and without energy beam and no IRS, the system model established in this paper with an energy beam and IRS has the highest energy power received by the minimum energy receiver, and this system considers the fairness of balancing energy reception and information decoding. While ensuring communication quality, it can also solve the energy supply problem of a large number of low-power devices in the IoT. However, this paper did not consider the presence of channel errors. In the future, we will consider how to design a robust cognitive resource allocation algorithm.

Author Contributions: C.G., S.L., M.W., S.D. and J.X. conceived the idea, designed and performed the experiments, analyzed the results, drafted the initial manuscript, and revised the final manuscript. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Theorem A1. *The semidefinite relaxation problem of optimization Problem (33)–(39) is tight, meaning that* $rank(W_i) \leqslant 1,\ \forall i \in \overline{K}_{isu}$ *always holds.*

Proof of Theorem A1. First, the Lagrangian function for optimization Problem (33)–(39) can be determined as:

$$\begin{aligned}
&L\left(\{W_i\}, S_E, t, \{a_j\}, \{b_i\}, \{c_k\}, d, E, \{F_i\}\right) \\
&= t + \sum_{j=1}^{K_E} a_j \left[\sum_{i\in\overline{K}_{isu}} tr\left(g_j g_j^H W_i\right) + tr\left(g_j g_j^H S_E\right) - t \right] \\
&+ \sum_{i=1}^{K_E} b_i \left[I_{\max} - \sum_{i\in\overline{K}_{isu}} tr\left(p_k p_k^H W_i\right) - tr\left(p_k p_k^H S_E\right) \right] \\
&+ \sum_{i=1}^{K_E} c_k \left[\frac{tr\left(h_i h_i^H W_i\right)}{\Gamma_i} - \sum_{n\neq i, n\in\overline{K}_{isu}} tr\left(h_i h_i^H W_n\right) - {\sigma_i}^2 \right] \\
&+ d\left[P - \sum_{i\in\overline{K}_{ipu}} \|w_i\|^2 - tr(S_E) \right] + tr(ES_E) + \sum_{i=1}^{\overline{K}_{isu}} E_i W_i
\end{aligned} \tag{A1}$$

where $\{a_j\}, \{b_i\}, \{c_k\}, d, E, \{F_i\}$ are the Lagrange multiplier scalars and Lagrange multiplier matrices corresponding to (25)–(30). Then, we can obtain the Lagrangian dual function for optimization Problem (33)–(39) as:

$$\begin{aligned}
&g\left(\{a_j\}, \{b_i\}, \{c_k\}, d, E, \{F_i\}\right) \\
&= \sup_{\{W_i\}, S_E, t} L\left(\{W_i\}, S_E, t, \{a_j\}, \{b_i\}, \{c_k\}, d, E, \{F_i\}\right)
\end{aligned} \tag{A2}$$

Therefore, we can formulate the dual problem for optimization Problem (45) as:

$$\begin{aligned}
&\min g\left(\{a_j\}, \{b_i\}, \{c_k\}, d, E, \{F_i\}\right) \\
&s.t. a_j > 0, b_i > 0, c_k > 0, \forall j \in \overline{K}_{esu}, \forall i \in \overline{K}_{isu}, \forall k \in \overline{K}_{ipu} \\
&d \geqslant 0, E \geqslant 0, F_i \succeq 0, \forall i \in \overline{K}_{isu}
\end{aligned} \tag{A3}$$

Clearly, since optimization Problem (33)–(39) is an SDP problem, it has a compact optimal solution space with a zero duality gap to its dual Problem (A3). Due to the strict establishment of strong duality and the existence of strictly differentiable objective functions and all corresponding constraints in optimization Problem (33)–(39), the optimal solutions of both Problems (33)–(39) and (A3) must meet the Karush–Kuhn–Tucker (KKT) requirement. First, assuming the optimal solutions for optimization Problem (33)–(39) and dual Problem (A3) are $\{W_i^*\}, S_E^*, t^*$ and $\{a_j^*\}, \{b_i^*\}, \{c^*\}, D^*, \{E_i^*\}$, the KKT conditions can be formulated as:

$$K1 : a_j^* \geqslant 0, b_i^* \geqslant 0, c^* \geqslant 0, D^* \succeq 0, E_i^* \succeq 0,\ \forall j \in K_{esu},\ \forall i \in K_{isu} \tag{A4}$$

$$K2 : D^* S_E^* = 0, E_i^* W_i^* = 0,\ \forall i \in K_{isu} \tag{A5}$$

$$\begin{aligned} K3 : &\nabla_{W_i^*} \mathcal{L}\big(\{W_i\}, S_E, t, \{a_j\}, \{b_i\}, c, D, \{E_i\}\big) \\ &= \sum_{j=1}^{K_E} a_j^* g_j g_j^H + \frac{b_i^* h_i h_i^*}{\Gamma_i} - c^* I_M + E_i^* \end{aligned} \tag{A6}$$

where I_M represents an N-dimensional matrix, which is a full-rank matrix. For ease of representation, we define a matrix $F_i = \sum_{j=1}^{K_E} a_j^* g_j g_j^H + \frac{b_i^* h_i h_i^*}{\Gamma_i}$ and assume its maximum eigenvalue is denoted as $\lambda_{\max}^{(F_i)}$. Then, according to the KKT condition's K3 condition, the Lagrange multiplier matrix b can be expressed as:

$$E_i^* = c^* I_M - F_i \tag{A7}$$

From the complementary slackness condition K2, it is known that the space spanned by $\{W_i^*\}$ is the null space of $\{E_i^*\}$, meaning their rank relationship is $rank(E_I^*) + rank(W_I^*) = M$, $\forall i \in K_{isu}$. We can discuss three scenarios:

1. If $\lambda_{\max}^{(F_i)} \leqslant c^*$, then $\{E_i^*\}$ is a full-rank matrix, which makes $rank(W_i^*) = 0$, and this would conflict with SINR constraints when there are non-zero transmission power constraints at CBS, so this scenario is not valid;
2. If $\lambda_{\max}^{(F_i)} \geqslant c^*$, then $\{E_i^*\}$ would become a non-semidefinite matrix, which conflicts with condition K1, so this scenario is not valid;
3. Therefore, only $\lambda_{\max}^{(F_i)} = c^*$ is guaranteed to hold, which implies $rank(E_i^*) = M - 1$ will hold, and thus, $rank(W_i^*) \leqslant 1$, $\forall i \in K_{isu}$ is guaranteed to hold.

□

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