energies

Article

Maximizing Energy Efficiency in Hybrid Overlay-Underlay Cognitive Radio Networks Based on Energy Harvesting-Cooperative Spectrum Sensing

Yan Liu [1], Xizhong Qin [1,*], Yan Huang [2], Li Tang [2] and Jinjuan Fu [1]

[1] College of Information Science and Engineering, Xinjiang University, Urumchi 830000, China; dandelion@stu.xju.edu.cn (Y.L.); fujinj@stu.xju.edu.cn (J.F.)
[2] Network Department, China Mobile Communications Group Xinjiang Co., Ltd., Urumchi 830000, China; huangyan@xj.chinamobile.xh.com (Y.H.); tangli@xj.chinamobile.com (L.T.)
* Correspondence: qinxz@xju.edu.cn; Tel.: +86-13899880031

Abstract: Spectrum demand has increased with the rapid growth of wireless devices and wireless service usage. The rapid development of 5G smart cities and the industrial Internet of Things makes the problem of spectrum resource shortage and increased energy consumption even more severe. To address the issues of high energy consumption for spectrum sensing and low user access rate in the cognitive radio networks (CRN) model powered entirely by energy harvesting, we propose a novel energy harvesting (EH)-distributed cooperative spectrum sensing (DCSS) architecture that allows SUs to acquire from the surrounding environment and radio frequency (RF) signals energy, and an improved distributed cooperative spectrum sensing scheme based on energy-correlation is proposed. First, we formulate an optimization problem to select a leader for each channel; then formulate another optimization problem to select the corresponding cooperative secondary users (SUs). Each channel has a fixed SUs cluster in each time slot to sense the main user state, which can reduce the energy consumption of SUs sensing and can reduce the sensing time, and the remaining time can be used for data transmission to improve throughput, and finally achieve the purpose of improving energy efficiency. Simulation results show that our proposed scheme significantly outperforms the centralized scheme in terms of SUs access capability and energy efficiency.

Keywords: cognitive radio networks; hybrid underlay-overlay scheme; cooperative spectrum sensing; energy harvesting; energy-efficiency

Citation: Liu, Y.; Qin, X.; Huang, Y.; Tang, L.; Fu, J. Maximizing Energy Efficiency in Hybrid Overlay-Underlay Cognitive Radio Networks Based on Energy Harvesting-Cooperative Spectrum Sensing. *Energies* **2022**, *15*, 2803. https://doi.org/10.3390/en15082803

Academic Editor: Alon Kuperman

Received: 19 March 2022
Accepted: 7 April 2022
Published: 12 April 2022

1. Introduction

The combination of 5G smart cities and the Internet of things (IoT) is expected to revolutionize the networking paradigm by connecting a large number of devices, which are expected to have different capabilities, functions, structures and requirements [1]. The number of such devices is expected to exceed tens of billions by 2021 [2]. As the number of wireless users increases, spectrum shortage and underutilization is a serious problem today [3–6]. Currently, a large portion of the spectrum is allocated through static spectrum allocation methods [4]. Therefore, as long as the primary user, which is the licensed user, does not use the channel, the channel remains vacant, resulting in the underutilization of the spectrum. The Federal Communications Commission (FCC) is addressing this issue in three different ways, namely spectrum sharing, leasing, and spectrum reallocation [7]. At the same time, the country actively advocates green and energy-saving communication, and energy harvesting and energy limitation issues in CRN have received extensive attention. In order to solve the scarcity of spectrum resources and have energy-saving communication systems, energy collection in CRN is a promising solution [8,9], and there are many research achievements in improving throughput, spectrum sensing performance and energy efficiency.

There are two transmission modes in the CRN spectrum sharing mechanism: overlay and underlay. In the overlay transmission mode, the secondary user can use the channel when the primary user is not using it, while in the underlay transmission mode, the SU and the primary user (PU) can transmit signals at the same time, provided that the transmission process of the PU is not affected. The success of CRN faces the following problems: SU interference to PU must be within tolerable limits specified by PU, SU throughput must be maximized in terms of efficient use of spectrum bandwidth, SU connectivity must be maximized, SU needs to be provided with required quality of service (QoS) [10–12]. For example, Yan et al. [13,14] enable secondary users to harvest ambient RF energy from active transmitters and derive transmission probabilities and maximum throughput under outage conditions. Zhang et al. [15] focus on the harvest-perception-throughput trade-off, maximizing the achievable secondary throughput when the primary user is adequately protected. Zheng et al. [16] studied cooperative EH-CRNs, in which a secondary transmitter (ST) relays PU packets and harvests energy from the primary signal, through power allocation to the SU data transmission as well as the relay and the power split (PS) ratio of the secondary transmitter to maximize the system throughput.

One of the biggest challenges in implementing spectrum sensing is the hidden terminal problem, where cognitive radios may not be able to detect the existence of PUs. Therefore, it is particularly important to improve the accuracy of spectrum sensing by optimizing the sensing threshold. Pranabesh et al. [17] studied the trade-off between spectrum sensing and spectrum sharing, optimizing the spectrum sensor detection threshold for secondary users for the achievable secondary throughput. Kumar et al. [18] used a low signal-to-noise ratio (SNR) to decide the optimal threshold so that our proposed threshold selection method improves detection accuracy at low SNR. In addition, multipath fading and shadowing may affect the detection performance of SU in spectrum sensing. Collaborative sensing can improve the overall detection performance by combining sensing observations of spatially localized Sus [19,20]. Liu et al. [21] focused on CSS in mobile EH-CRN and developed an optimal CSS strategy to maximize the expected throughput of EH-CRN based on the final decision threshold under collision constraints and energy causality constraints. Al-Jarrah et al. [22] proposed an effective adaptive detection scheme for the problem of cooperative identification of idle frequency bands by multiple secondary users in cognitive radio networks. Local binary decisions on relays and cognitive radio base stations (CRBs) are regenerated based on dynamic thresholds, which are chosen to minimize the spectrum sensing error probability by considering the imbalance of spectrum occupancy and the reliability of spectrum occupancy decisions.

In recent years, the rapid development of applications, such as wireless sensor networks (WSN) and IOT in smart homes and smart factories has attracted widespread attention. Efficient resource allocation, such as power supply and energy harvesting element technology, will extend sensor life and play an important role in maximizing system performance. Ding et al. [23] studied iterative joint resource management and time allocation to maximize energy efficiency, while Yang et al. [24] tried to maximize the total energy consumption by minimizing the total energy consumption in a cluster-based IoT with energy harvesting element properties to maximize energy efficiency. Azarhava et al. [25] considered energy efficient resource allocation for a TDMA-based wireless energy harvesting element sensor network (WEHSN) and maximized energy efficiency by reducing the total energy consumption of the sensors.

In this paper, the problems of insufficient spectrum resources, spectrum sensing accuracy and energy limitation in the existing work are mainly improved. The goal is to improve the system energy efficiency by considering CRN energy analysis and CRN transmission mode diversity and realize an energy-saving communication system. References [26,27] have made great progress in improving spectrum utilization and energy-efficient communications. However, there are also shortcomings: (1) In the energy analysis process, the SUs are only divided into two parts that can perform spectrum sensing and those that cannot perform spectrum sensing. Among them, SUs with residual energy greater than or equal to the energy consumption of data transmission and spectrum sensing can perform spectrum sensing and are in an active state, SUs whose residual energy is less than the energy consumption of data transmission and spectrum sensing cannot perform spectrum sensing and are in an inactive state, which will cause many SUs to fail to perform data transmission due to insufficient residual energy. (2) Failure to consider multipath fading and shadowing may impair the detection performance of SUs in spectrum sensing. By combining the sensing observations of spatially localized SUs, cooperative sensing can improve the overall detection performance. (3) In addition, although the literature [18] considers the influence of multipath fading and shadowing on the sensing performance, it does not consider the diversity of transmission modes in the CRN.

Through further analysis of the remaining energy of SUs, the centralized cooperative spectrum sensing based on energy analysis is introduced, and some improvements are made to the above shortcomings. However, there are still some deficiencies that need to be improved: (1) Using a combination of centralized cooperative spectrum sensing and energy analysis, for scenarios where there are multiple pairs of PUs and multiple pairs of Sus; each SU participating in cooperation when sensing the state of PUs needs to sense all the SU states causing double waste of energy and frequency band, and cannot be applied to scenarios with a large number of primary users and secondary users; (2) Although the mixed overlay-underlay mode is used to increase the throughput of the SUs system, each time slot is only allocated to one SU due to the influence of the sensing time. Therefore, this paper improves the energy-based cooperative spectrum sensing and resource allocation scheme. The specific improvements are as follows:

1. In order to improve the double waste of energy and frequency band caused by centralized cooperative spectrum sensing, we introduce distributed cooperative spectrum sensing based on energy-correlation. Each PUs has a fixed SUs cluster in each time slot to sense the state of the master user, so as to reduce the energy consumption of SUs sensing.
2. We improve the energy-based cooperative user selection algorithm and propose an energy-based multi-band multi-user selection scheme, where we first formulate an optimization problem to select a leader for each channel. Then we formulate another optimization problem to select the corresponding cooperative SU.
3. Through energy-based distributed cooperative spectrum sensing, the sensing time is effectively reduced, and more time slots are allocated to SUs.
4. Simulation results show that our proposed scheme is significantly better than the centralized scheme in terms of SUs access capability and energy efficiency.

The rest of the paper is arranged as follows: The second section introduces the system model and symbols and describes the process of region division, energy collection, spectrum sensing and channel allocation. Section 3 focuses on the overall process and optimization process for maximizing energy efficiency. The fourth section provides the simulation results and discussion. Finally, the fifth section summarizes this paper.

2. System Model

We describe our system model from four aspects of region division, energy collection, spectrum sensing and channel allocation. We improve system access capability by combining energy analysis and distributed cooperative spectrum sensing and determine SUs optimal transmission mode and channel allocation scheme according to region division and spectrum sensing results.

2.1. Network Model

The system considered in this article is IEEE 802.22 WRAN, and it provides wireless broadband access to rural areas in point-to-multipoint scenarios. Figure 1 illustrates the network structure of the WRAN, where the TV transmitter and the wireless microphone are a pair of PUs, the WRAN BS and CPEs are a pair of SUs [27], and the CPEs send the collected information to the WRAN BS. There are m PUs $\mathrm{PU} = \{\mathrm{PU}_1, \ldots, \mathrm{PU}_\mathrm{m}\}$ and n SUs

$SU = \{SU_1, \ldots, SU_n\}$ in the macro cell, each PUi has a licensed spectrum CHi, and the channel set is denoted as $C = \{CH_1, \ldots, CH_m\}$. SUs obtain energy from the surrounding environment through energy harvesting and use PUs spectrum resources in a hybrid overlay-underlay mode, respectively, use the idle spectrum of PUs in the overlay mode and share the spectrum with PUs in the underlay mode.

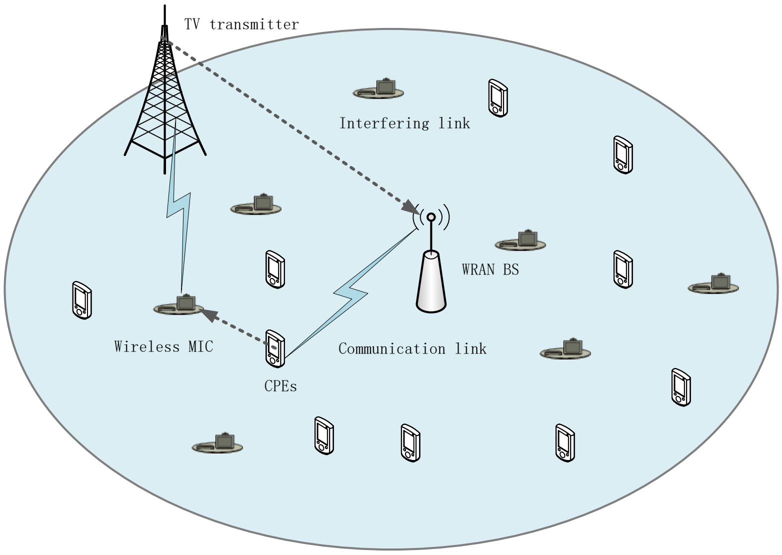

Figure 1. System model diagram.

Consider that the PU receives the information from the TV transmitter in the macro cell; the CPEs send the collected data to the WRAN BS. Studies [26,27] examined the throughput performance of a novel cognitive radio network (CRN) scenario with a mobile energy-harvesting secondary transmitter (ST). The hybrid overlay-underlay scheme allows SUs to access the spectrum even if the primary signal is detected. To facilitate the spectrum allocation, the unit area is divided into two parts: the overlay mode area and the underlay mode area. The shape of the area does not affect our results. The primary user receiver is found within the center of the unit space to receive the data from the transmitter. The PUs arrive randomly at a certain percentage in each time slot t, and the spectrum authorized to the primary user switches between idle and busy. The ST transmits in overlay mode or underlay mode. SUs have exclusive access to the spectrum in overlay mode when the licensed spectrum is free; in the underlay mode, the SUs coexist with the PUs when their interference with the PUs is below a certain threshold. We believe that SUs transmit data packets in overlay-underlay mode with constant power.

We define the overlay region as a disk of radius r_o, where the radius r_o is determined by the interference threshold Φ of the primary user receiver and the transmit power of the SUs in the underlay mode. Specifically, the transmit power of the SUs in underlay mode is denoted by P_u, and the interference threshold of the PUs receiver is denoted by Φ. We have $P_u r_o^{-\alpha} = \Phi$, where α is the path loss. In the overlay mode region, the SUs transmit information in overlay mode when the licensed spectrum is detected to be free; when a busy licensed spectrum is detected, the SUs are not allowed to transmit information in underlay mode. This is because overlay area users transmitting information in underlay mode when the licensed spectrum is busy can cause excessive interference to the PUs. The underlay area is defined as the disc area that is greater than r_o from the main user receiver. Based on the definition of the unit circular area and the considered scene, there is no need to define the area radius r_o of the underlay mode. Figure 2 shows the division of each PUs unit cell area. In the underlay mode region, based on the fact that the ST is far away from the PT and the interference from the SUs to the PUs is within tolerable limits, the ST information in overlay mode when the licensed spectrum is detected to be free; SUs transmits information in underlay mode when a busy licensed spectrum is detected. Underlay mode communication can only occur in the underlay area, overlay mode communication can occur in any area when the secondary user has sufficient energy and the PUs is detected to be idle. Therefore, both underlay mode communication and overlay mode communication can occur in the underlay area.

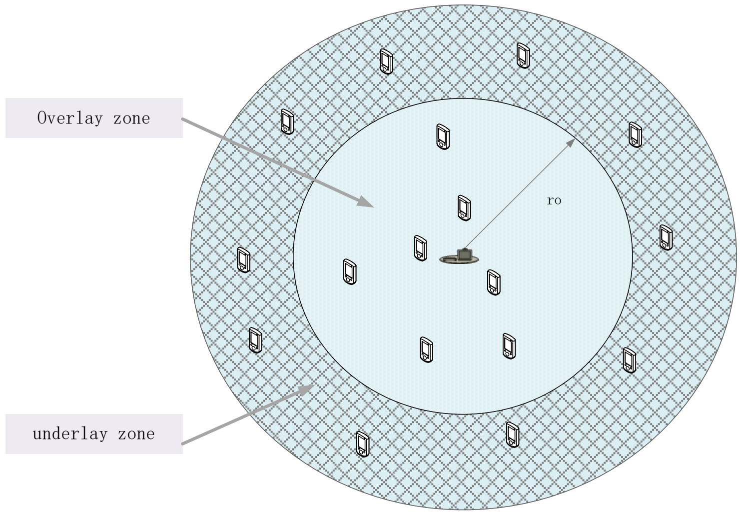

Figure 2. Area division map.

Because there are a large number of SUs and PUs in our scenario, and SUs use the primary user spectrum resources in a mixed overlay-underlay mode area, we need to zone all users in the macro cell according to the above method. The distance between the PUs and the SUs is expressed as:

$$D = \begin{bmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{bmatrix} \tag{1}$$

Use r to denote the area in which the SU is based on the PU receiver, and (0, 1) to indicate that the SU is in the underlay area and the overlay area, as follows:

$$r_{ij} = \begin{cases} 1, d_{ij} < r_o \\ 0, d_{ij} > r_o \end{cases} \tag{2}$$

2.2. Distributed Energy Harvesting Model

Because we consider the problem that many users with insufficient energy are in an inactive state in a scenario where energy is only powered by energy harvesting, we need to select leaders and participants of collaborative SUs based on energy judgment. SUs harvest energy from ambient sources (e.g., heat, wind, solar, radio frequency signals), the harvested energy arrives randomly each time slot, is buffered in the battery and can be consumed at the beginning of the next time slot. It is assumed that the energy arrival process is static traversal regardless of the location, and is modeled as i.i.d. The random variable sequence means A, where t is the slot sequence number. It is assumed that the energy arrival process is statically ergodic irrespective of the location, and is modeled as a sequence of i.i.d. random variables with mean $E[e_{en}^t] = e_{en}$, where t represents the time slot sequence number. The second energy source is to harness the energy of the ambient RF signal, and the secondary user transmitter should be equipped with an energy conversion circuit that can extract DC power from the received electromagnetic waves. This circuit has practical sensitivity requirements, i.e., input power needs to be greater than a pre-designed threshold. Similarly, we model the energy arrival process of RF signals as an i.i.d. sequence of random variables with mean $E[e_{RF}^t] = e_{RF}$, and the harvested energy in time slot t is available for energy consumption at the beginning of the time slot (t + 1). The conversion efficiency of energy harvesting is η, and the energy collected and consumed per time slot is expressed as:

$$e_h^t = e_{en}^t + e_{RF}^t \tag{3}$$

Unlike the centralized scheme based on energy analysis, each SUs does not need to sense all PUs channels, but senses I PUs channels according to distributed energy constraints. According to reference [28], due to the limitation of SUs energy consumption and computational complexity, each jth SU is allowed to sense the maximum I channel. The energy consumed by each SUs in each slot is expressed as follows:

$$e_c^t = y(\varepsilon e_o + (1-\varepsilon)(1-r)e_u) + \sum_{i=1}^{m} (\beta_i(e_s + e_T) + \partial_i e_s) \tag{4}$$

The meaning of e_s is different from that in the centralized scheme. Here, it refers to a single SU sensing the energy consumption of one PU channel, and the centralized scheme refers to a single SU sensing the energy consumption of all PUs channels. e_o represents the energy consumed by SU to transmit data in overlay mode, e_u represents the energy consumed by SU in underlay mode, $r \in (0,1)$ indicates that the SU is in the underlay area and the overlay area, $\varepsilon \in (0,1)$ indicates that the main PU is in a busy state and an idle state, $y \in (0,1)$ indicates that PU spectrum resources are not allocated to SU and allocated to SU, $\partial \in (0,1)$ indicates that SU is not the leader to detect the PU channel and is the leader to detect the PU channel, $\beta \in (0,1)$ indicates that SU is not a participant in detecting the PU channel and a participant in detecting the PU channel, respectively, the SU residual energy is expressed as follows:

$$e_r^{t+1} = e_r^t - e_c^t + e_h^t \tag{5}$$

In order to enable more SUs to perform data transmission, we further divide the part of SUs that cannot perform spectrum sensing in the energy analysis process and divide them into those that can perform data transmission (the remaining energy is greater than or equal to the energy consumption of data transmission is less than that of data transmission and sensing). energy consumption) and inactive state (the remaining energy is less than the data transmission energy consumption). The specific representation is as follows:

$$\alpha = \begin{cases} 1, e_r^t \geq e_s + e_o + e_T \\ 0, e_o \leq e_r^t < e_s + e_o + e_T \\ -1, e_r^t < e_o \end{cases} \tag{6}$$

$$\delta = \begin{cases} 0, \alpha \neq 1 \\ 1, \alpha = 1 \end{cases} \tag{7}$$

$\alpha = 1$ indicates that the SUs have enough residual energy for spectrum sensing and data transmission, $\alpha = 0$ indicates that the remaining energy of the SUs is only capable of data transmission, $\alpha = -1$ indicates that the SUs are in an inactive state due to insufficient remaining energy, e_T represents the energy expended by the participant to send the local decision to the leader, $\delta = 0$ indicates that SU cannot join the leader and participant selection, $\delta = 1$ means SU joins the leader and participant selection.

2.3. Distributed Cooperative Spectrum Sensing

In order to improve the double waste of energy and frequency band caused by centralized cooperative spectrum sensing, we introduce distributed multi-band multi-user cooperative spectrum sensing (M2CSS) based on energy analysis, SUs make collaborative decisions by exchanging local observation information of multi-channel with adjacent users. In distributed CRNs, one challenge of multi-band CSS is the perceptual scheduling of specific channels by SUs. Based on channel state information, SUs have different channel awareness capabilities. Therefore, effectively selecting a subset of sensing channels for cooperative SUs can reduce sensing overhead and improve system performance, especially when multiple SUs have similar local sensing information [29]. The distributed M2CSS scheme based on energy analysis mainly includes three steps: (1) Leader selection: select a leader for each channel; (2) Selection of collaborators: select the appropriate collaborators for the selected leader of each channel. (3) SUs perform local multi-band spectrum sensing on the designated channel

Figure 3 shows an example of multi-band CSS in a distributed CSS system model. It is clear that PUs can either be using a particular channel for data communication or be staying in the idle mode (i.e., not using any channel). Each SU in the network is sensing multiple channels, where SUs assigned to sense the same channels are assumed to be cooperative. As shown in Figure 3, we divide existing SUs into two types: (1) SUs that act as the leader for the channel (SU-Leader), and (2) SUs (SU-No Leader) that only sense the allocated channel. SU-Leader assists in the scheduling of other SUs, where the blue mobile terminal represents the PUs, the red mobile terminal represents SU-Leader, and the yellow mobile terminal represents SU-No Leader. The first number below SU-Leader indicates that SU-Leader is the leader of the channel, and the second number indicates that SU-Leader can also be a partner of other channels. The number below SU-No Leader indicates that it is the partner of the channel. The same number means that they are in the same cluster sensing the same channel, and the cooperator sends its sensing results to the leader for decision, where each SUs can only be the leader of one channel but can be the cooperator of multiple channels.

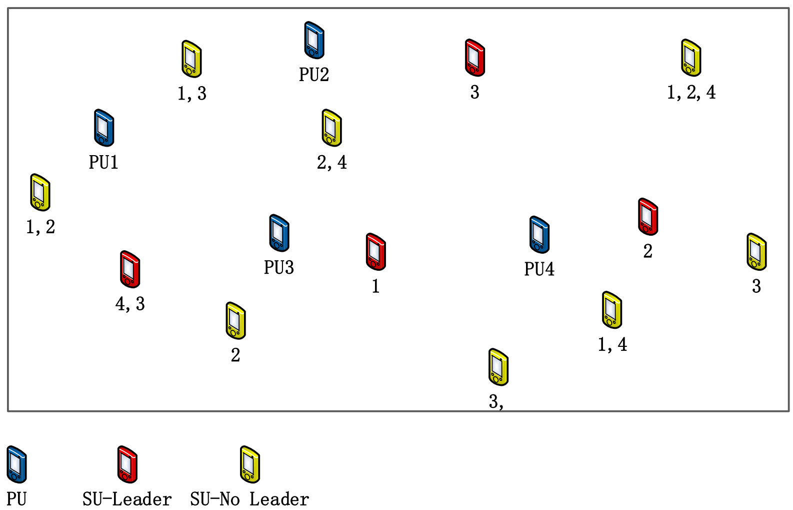

Figure 3. Distributed CSS Model Diagram.

In distributed M2CSS, we formulate two optimization problems, first selecting a leader for each channel, and then selecting appropriate cooperators for each leader. Leader selection means determining the best sensing SUs for each frequency band, and the leader is responsible for selecting the cooperative SUs of the distributed M2CSS—in order to select the cooperators with different local sensing information, the cooperators should have a lower correlation. Let SNR_{mn} and SNR_{avg} be the signal-to-noise ratio (SNR) of the n-th SU sensing the m-th channel and the average SNR of sensing all channels, respectively. We can define a binary indicator ∂_{mn} to indicate whether the nth SU can be elected as the leader of the mth channel.

$$\partial_{mn} = \begin{cases} 1, \text{If the nth SU is the leader of the mth channel.} \\ 0, \text{other.} \end{cases} \tag{8}$$

In terms of leader selection, we select the optimal leader for each channel according to the remaining energy and SNR, and each SUs can only serve as the leader of one channel. The optimization formula is as follows:

$$\begin{aligned} &\min_{\partial_{ij}} \sum_{i=j}^{n} \sum_{i=1}^{m} \delta_j \times \partial_{ij} \times \left|SNR_{ij} - SNR_{avg}\right| \\ &\text{Subject} \quad \text{to} \quad C1: \delta_j = 1, \forall n, \\ &\qquad C2: \sum_{j=1}^{m} \partial_{ij} = c_n, \forall n, \\ &\qquad C3: \sum_{i=1}^{n} \partial_{ij} = 1, \forall m, \end{aligned} \tag{9}$$

where SNR_{ij} represents the SNR of the ith SUs about the jth PUs, SNR_{avg} represents the average SNR of each SUs for each channel, $\delta_j = 1$ indicates that the SUs have enough residual energy for spectrum sensing and data transmission, ∂_{ij} indicates that the i-th SUs is the channel leader of the j-th PUs, C1 indicates that only SUs with sufficient remaining energy for sensing and data transmission can participate in leader selection. C2 indicates that one SU cannot act as the leader of multiple PU channels.C3 means that only one leader can be selected per PU channel.

Collaborators are then selected for each leader based on the correlation between each leader and other SUs. The correlation between any two SUs can be defined as:

$$Cr(d) = e^{-bd} \tag{10}$$

where d is the distance between any two SUs and b is an environment-based parameter. Based on the data reported in [30], $b \approx 0.1204/m$ in environments where direct line of sight is not available, and $b \approx 0.002/m$ otherwise. Since the correlation is an exponential function and the distance is non-negative, Cr(d) will vary from 0 (indicating no correlation) to 1 (indicating perfect correlation).

Then formula (10) is used to calculate the correlation between users, and the threshold τ is fixed. If $C_r(d) < \tau$, the actual correlation between the secondary user and is zero.

$$Cr(j, j') = \begin{cases} 0, & \text{if} \quad Cr(d) < \tau \\ Cr(d), & \text{otherwise} \end{cases} \tag{11}$$

After calculating the correlation $Cr(i, i')$ between SUs, the following $n \times n$ matrix can be obtained:

$$K = \begin{bmatrix} Cr'(1,1) & Cr'(1,2) & \cdots & Cr'(1,n) \\ Cr'(2,1) & Cr'(2,2) & \cdots & Cr'(2,n) \\ \vdots & \vdots & \ddots & \vdots \\ Cr'(n,1) & Cr'(n,1) & \cdots & Cr'(n,n) \end{bmatrix} \tag{12}$$

Then each leader selects the appropriate collaborator according to the energy update and correlation and uses the binary variable β_{mn} to indicate whether the nth SU is selected as the collaborator of the mth channel.

$$\beta_{mn} \begin{cases} 1, \text{If the nth SU is a collaborator of the mth channel} \\ 0, \text{other} \end{cases} \tag{13}$$

Then, the optimization problem for collaborators to select SUs can be formulated as:

$$\begin{aligned}
&\min_{\beta_{ij}} : \sum_{j=1}^{n} \sum_{i=1}^{m} \beta_{ij} \times \mathrm{Cr}(i,j) \times \delta_i \\
&\text{Subject} \quad \text{to} \quad C1 : \delta j = 1, \forall n, \\
&\qquad\qquad\qquad\quad C2 : \sum_{i=1}^{m} \beta_{ij} \geq 1, j \rightarrow \text{non} - \text{leaders}, \\
&\qquad\qquad\qquad\quad C3 : \sum_{i=1}^{m} \beta_{ij} \geq 0, j \rightarrow \text{leaders}, \\
&\qquad\qquad\qquad\quad C4 : \sum_{i=1}^{m} \beta_{ij} \leq I, j \rightarrow \text{non} - \text{leaders}, \\
&\qquad\qquad\qquad\quad C5 : \sum_{i=1}^{m} \beta_{ij} \leq I - 1, j \rightarrow \text{leaders},
\end{aligned} \tag{14}$$

where C1 means that only SUs with sufficient residual energy for sensing and data transmission can participate in the selection of cooperators, C2–C5 means that each channel is allocated at least one and no more than I SU for sensing.

On the basis of energy analysis, we select Sus with sufficient remaining energy for the next user selection and select the leader and collaborator of the sensing channel by formulas (9) and (14). Algorithm 1 summarizes the leader and collaborator selection process.

Algorithm 1 Based on Energy-Distributed User Selection (n)

1. Begin
2. int $\partial[n]$, $\beta[n]$, α, δ with all values set to zero, t = 0, $e_r^0 = 0$, $e_c^0 = 0$, $e_h^0 = 0$, T, e_s, e_o, e_u, e_T, SNRij, SNRavg
3.for int t = 0 to T do
4. for int j = 1 to n do
5. $e_r^{t+1} = e_r^t - e_c^t + e_h^t$
6.$e_c^t = y(\varepsilon e_o + (1-\varepsilon)(1-r)e_u) + \sum_{i=1}^{m} (\beta_i(e_s + e_T) + \partial_i e_s)$
7. if $e_r^t \geq e_s + e_o + e_T$
8. $\alpha = 1$
9. else if $e_o \leq e_t^r < e_s + e_o + e_T$
10. $\alpha = 0$
11. else
12. $\alpha = -1$
13. end for
14. if $\alpha = 1$
15. $\delta = 1$
16. else
17. $\delta = 0$
18. end for
19. end for
20. for int I = 1 to m do
21. for int j= 1 to n do
22. if $\delta_i = 1$
23. using formula (9), find the optimal solution through the branch-and-bound (B&B) algorithm.
24. renturn $\partial[n]$
25. using formula (14), find the optimal solution through the branch-and-bound (B&B) algorithm.
26. renturn $\beta[n]$
27. end for
28. end for
29. end for
30. t = t + 1
31.end

2.4. Distributed Channel Assignment

Compared to energy-based centralized spectrum sensing, since energy-based distributed cooperative spectrum sensing SUs do not need to sense all PUs, more time slots can be left for data transmission using a distributed approach. In terms of spectrum resource allocation, we adopt a hybrid overlay-underlay mode and allow SUs to use the same spectrum resources within the allowable range of interference. The data rates in both modes are expressed as follows:

$$R_o^{i,j} = B\log_2\left(1 + \frac{P_o h_{b,j}}{n_0}\right) \tag{15}$$

$$R_u^{i,j} = B\log_2\left(1 + \frac{P_u h_{b,j}}{n_0 + P_i h_{B,j}}\right) \tag{16}$$

where Po is the transmit power of the SU in overlay mode, Pu is the transmit power of SU in underlay mode, $h_{b,j}$ is the channel gain from SU to WRAN BS, $h_{B,j}$ is the channel gain from the PU transmitter to the WRAN BS, n_0 is the noise power. Through area division and spectrum sensing, we know the area where the SUs are located and whether the PU is idle or not. If the PU is sensed to be idle, both the SUs in the overlay and underlay regions can use this spectrum. If the PU is sensed to be busy, only the SU in the underlay area can use the spectrum.

It can be seen from Figure 4 that each channel is arranged with appropriate SUs for sensing in each time slot because distributed cooperative spectrum sensing is adopted and the sensing cluster is selected in advance, all of which are different from centralized cooperative spectrum sensing. All SUs sense all channels, leaving more time per slot to transmit more data. Algorithm 2 gives a distributed channel allocation scheme.

Algorithm 2 Distributed Channel Allocation Algorithm

1. Begin
2. int y [n] with all values set to zero, ε, r, T, ν, td, ∂,β, t = 1, s = 0
3. Calculate $R_o^{i,j} = B\log_2\left(1 + \frac{P_o h_{b,j}}{n0}\right)$ and $R_u^{i,j} = B\log_2\left(1 + \frac{P_u h_{b,j}}{n_0 + P_i h_{B,j}}\right)$, using (15) and (16).
4.for int t = 1 to T do
5. for int j = 1 to m do
6. for int i = 1 to n do
7. if $\partial_{ij} = 1$ or $\beta_{ij} = 1$
8. s = s + 1
9. end
10. $c = (T - s * \nu)/td$
11. for C = 1 to c do
12. $R = \varepsilon * r * R_{o,j} + (1-\varepsilon) * (1-r) * R_{u,j} + \varepsilon * (1-r) * R_{o,j}$
13. select R with maximum value in SUs
14. set $y_i^j = 1$ selected and delete i from SUs
15. end
16. end
17. end
18. t = t + 1
19.end

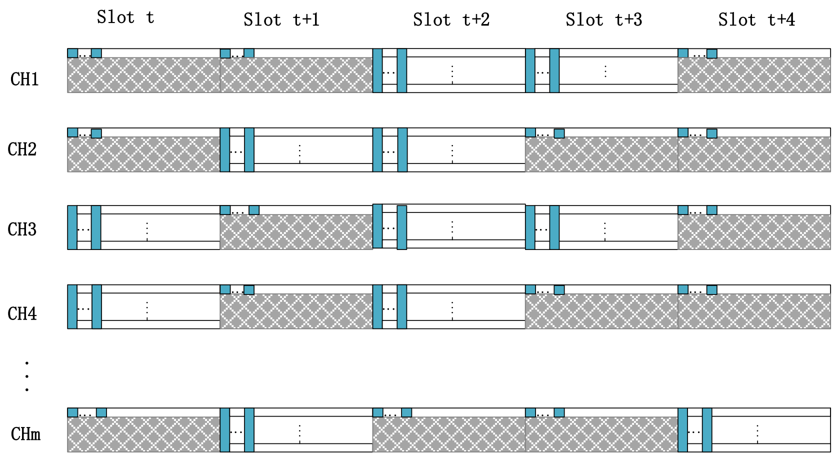

Figure 4. Distributed cooperative spectrum sensing.

3. Energy Efficiency Optimization Based on Energy Judgment-Distributed Cooperative Sensing

First, we divide the SUs within a certain interference range of the PU. The SU in the overlay area (r = 1) can only use the idle licensed spectrum, and the SU in the underlay area (r = 0) can use both the idle licensed spectrum and the busy spectrum. Then, SU energy is analyzed based on energy update, which can be divided into three parts: residual energy greater than or equal to the energy consumption of single channel detection and data transmission (a = 1), residual energy greater than or equal to the energy consumption of single channel detection and data transmission (a = 0), and residual energy less than or equal to the energy consumption of transmission (a = −1). The part of a = 1 can participate in cooperative spectrum sensing. Part a = 1 was selected by energy judgment to further select leaders and collaborators for each channel, and carry out cooperative spectrum sensing, respectively. Through spectrum sensing, we can know that the primary user is idle (ε = 1) or busy (ε = 0) at time slot t. Finally, channel allocation and data transmission are performed according to the information obtained in the above steps. The detailed flow chart is shown in Figure 5.

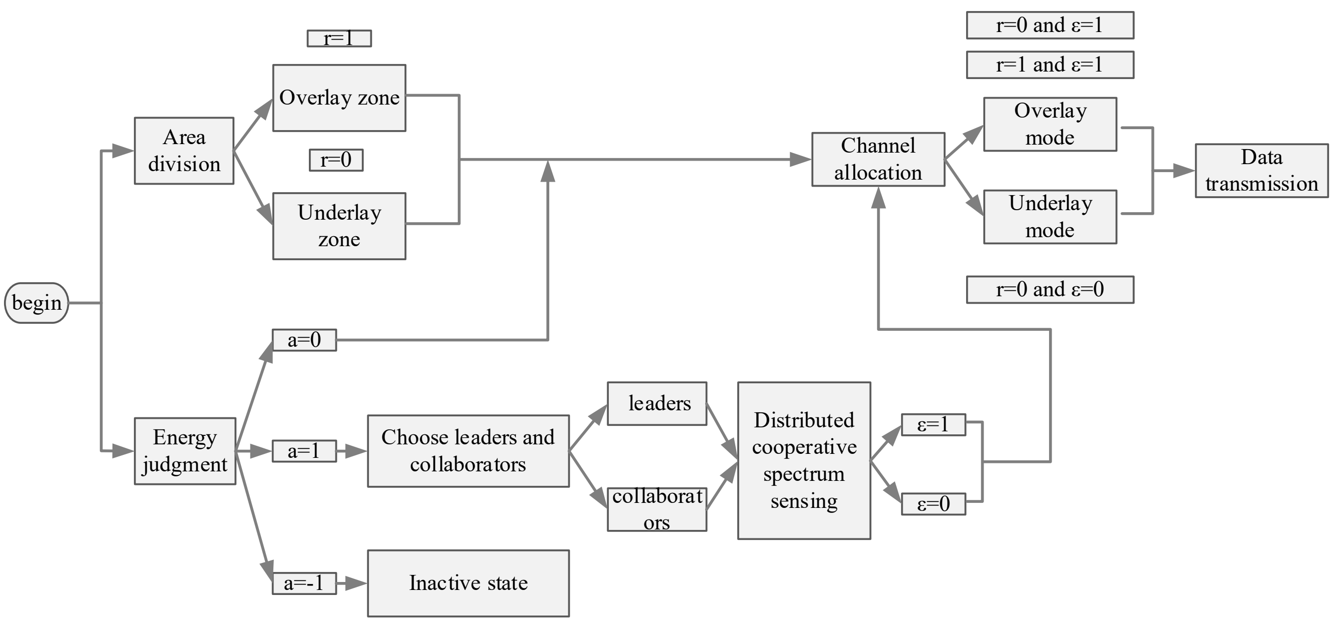

Figure 5. System flow chart.

The location of the SUs relative to the PUs can be known through the area division, which is convenient for determining the data transmission mode of the SUs in the subsequent channel allocation. Through energy judgment and two optimization problems, leaders and coordinators are selected for each channel. The part with a = 0 can directly enter the channel allocation state. The SUs participating in the cooperation do not need to sense all channels, which can improve the access rate and reduce energy consumption. Channel allocation is performed according to the results of spectrum sensing and area division. If the SU is in the overlay area and the PU is idle, or the SU is in the underlay area and the PU is idle, data transmission is performed in the overlay mode; if the SU is in the underlay area and the PU is busy, the underlay mode is used. At the same time, because the distributed CSS reduces the sensing time of each channel, each channel can allow more SUs to transmit data, which can further improve the system throughput and ultimately achieve the goal of maximizing system energy efficiency. The energy efficiency optimization formula is as follows:

$$\begin{aligned}
&\max \sum_{j=1}^{n} \sum_{i}^{m} \frac{y_i^j\left(\varepsilon_i R_o^{i,j} + (1-\varepsilon_i)\left(1-r_{i,j}\right) R_u^{i,j}\right)}{\delta_j y_i^j\left(\varepsilon_i e_o + (1-\varepsilon_i)\left(1-r_{i,j}\right)e_u + \beta_{i,j}(e_s+e_T)\partial_{i,j} e_s\right) + \left(1-\delta_j\right) y_i^j\left(\varepsilon_i e_o + (1-\varepsilon_i)\left(1-r_{i,j}\right)e_u\right)} \\
&\text{subject to} \quad C1: \delta \in \{0,1\}, \forall i \in m, \\
&\qquad C2: \varepsilon \in \{0,1\}, \forall j \in n, \\
&\qquad C3: r \in \{0,1\}, \forall j \in n, \forall i \in m, \\
&\qquad C4: y \in \{0,1\}, \forall j \in n, \forall i \in m, \\
&\qquad C5: \partial \in \{0,1\}, \forall j \in n, \forall i \in m, \\
&\qquad C6: \beta \in \{0,1\}, \forall j \in n, \forall i \in m,
\end{aligned} \tag{17}$$

4. Simulation Results and Discussion

4.1. Simulation Parameter Settings

In order to verify the effectiveness of the proposed scheme, a simulation is carried out based on Matlab 2019B platform. Experimental environment: Covering a hexagonal cell with a radius of 1200 m, primary user PUs and secondary user SUs are randomly distributed, of which the number of primary user PUs is 50 and the number of secondary user SUs is 100. Channel modeling considers path loss, shadow fading with lognormal distribution, and multipath fading with exponential distribution. The specific simulation parameters are shown in Table 1, and the experimental simulation data are from the literature [26,27].

Table 1. Simulation parameters.

Symbol	Name	Value
T	time slot duration	1 ms
ν	Sensing Duration	0.002 ms
Td	Transmission duration	0.098 ms
E	initial energy	range of random values [0, max(E)]
Ps	sense power	110 mW
Po	Overlay transmit power	50 mW
Pu	Underlay transmit power	30 mW
P_T	Primary user' s power	1W
$e^t{}_r$	Residual energy at the beginning of time slot t	mJ
A	Path-loss exponent	0.75
H	Harvesting conversion efficiency	0.75
SNR	Signal to interference plus noise ratio	dB
B	Bandwith	8 MHZ

4.2. Discussion of Simulation Results

We consider the existence of 50 PUs and 100 SUs randomly distributed in an area with a radius of 12 km. Figure 6 shows that the energy-based distributed cooperative user selection method has the lowest packet loss rate, and the centralized cooperative user selection method can enable SUs with insufficient remaining energy to transmit data without spectrum sensing; in the distributed collaborative user selection mode, appropriate sensors are selected for each PU by clustering, which further reduces the sensing energy consumption and enables more users with low energy to transmit data. The packet loss rate is not only affected by the energy analysis method and spectrum sensing method but also by the energy harvesting ability. It can be seen that the stronger the energy harvesting ability of SUs, the lower the packet loss rate, so we can reduce the packet loss rate of SUs by improving the energy harvesting ability. Figure 7 shows that the packet loss rate of the distributed cooperation method is significantly lower than that of the other two methods. With the enhancement of the energy harvesting capability, the packet loss rate of the centralized cooperation and the distributed cooperation tends to be the same.

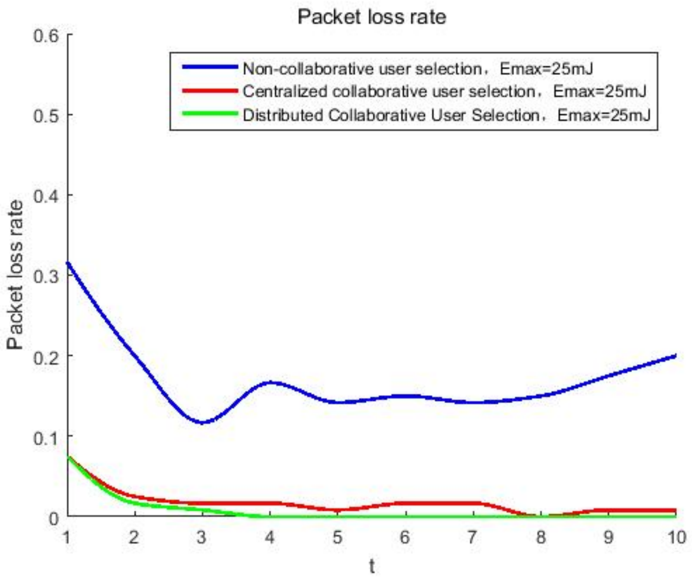

Figure 6. Packet loss rate under different sensing schemes.

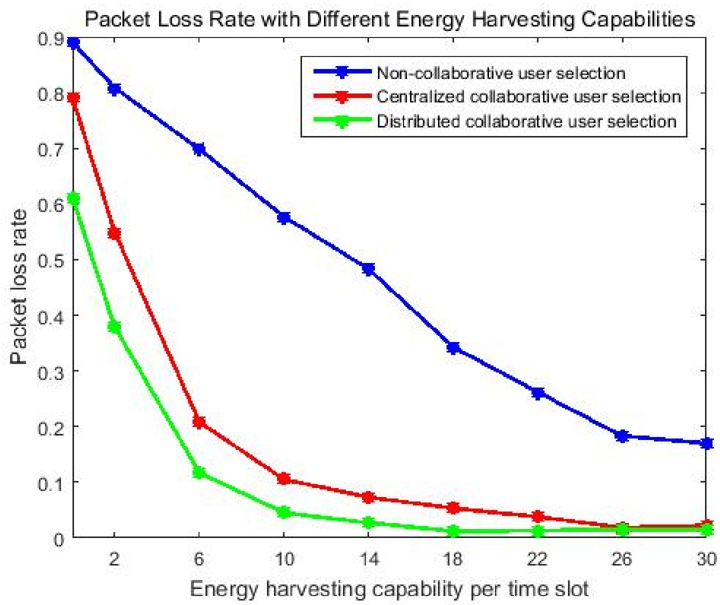

Figure 7. Packet loss rate under different energy harvesting capabilities.

Because the centralized cooperative scheme based on energy-relatedness selects appropriate SUs to participate in the cooperation according to the relatedness, the energy consumption is lower than that of the centralized non-cooperative scheme. Since the packet loss rate of the centralized cooperative scheme is lower than that of the centralized non-cooperative scheme, the throughput is better than that of the centralized non-cooperative scheme. In terms of energy consumption, throughput and energy efficiency, the cooperative spectrum sensing based on energy-relatedness proposed by us is superior to the energy-judgment-non-cooperative approach based on reference [26], but it also has shortcomings. We improve by the proposed distributed cooperative spectrum sensing based on energy analysis, which divides SUs into several clusters according to residual energy, SNR, and correlation, corresponding to each channel of the sensing PUs. Because each SU does not need to sense all channels, it only needs to sense the channels selected by optimization-clustering. Figure 8 shows that the energy consumption of the distributed scheme is lower than that of the other two schemes. Since each channel has selected a suitable SUs cluster for sensing, the time consumed by each time slot sensing is reduced, and each time slot can allow more SUs to transmit data. Therefore, the throughput of the distributed scheme is better than other schemes. Because the packet loss rate of the centralized cooperative scheme based on energy analysis is slightly better than that of the non-cooperative scheme, it can be seen from Figure 9 that the throughput of the centralized cooperative scheme based on energy analysis is also slightly better than that of the non-cooperative scheme. Our proposed improved scheme outperforms the other two schemes in terms of throughput and energy consumption; therefore, the energy efficiency of Figure 10 is better than the other two schemes.

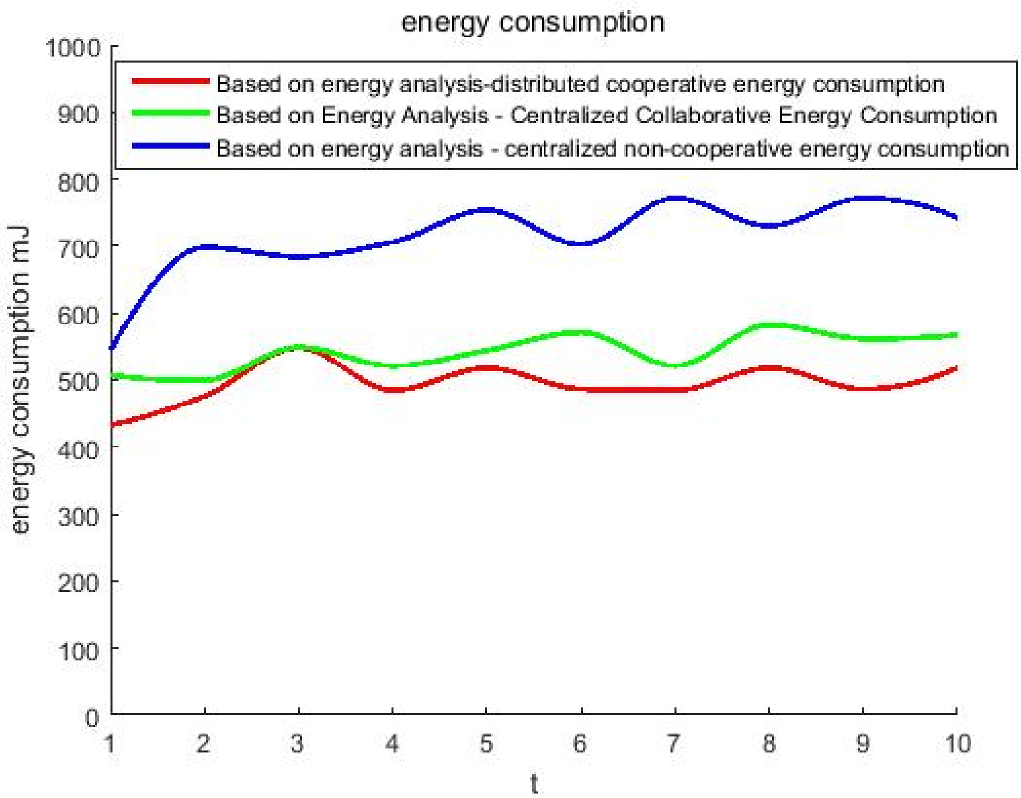

Figure 8. Energy consumption under different energy analysis-sensing methods.

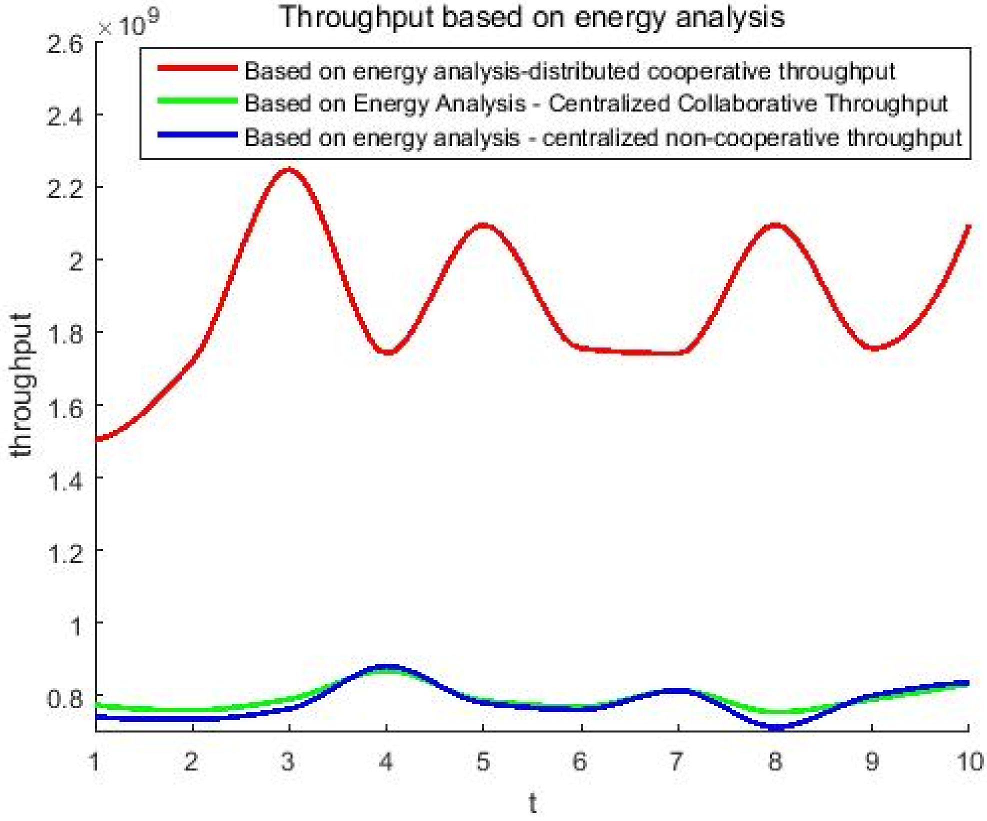

Figure 9. Throughput under different energy analysis-sensing methods.

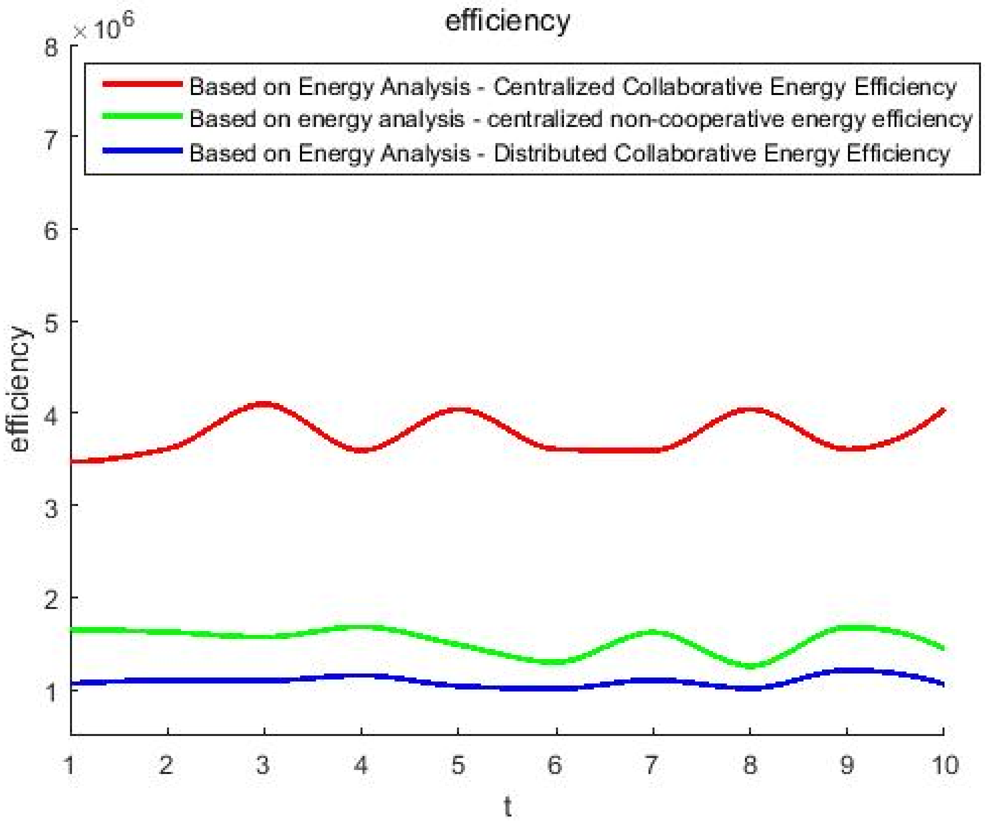

Figure 10. Energy efficiency under different energy analysis-sensing methods.

As in other studies [29], our goal is to select appropriate cooperative spectrum sensing nodes to maximize system energy efficiency. Figure 11 shows that the throughput of our method outperforms other algorithms. Average network throughput refers to the joint average throughput of primary user PUs and secondary user SUs. Because we adopt a hybrid overlay-underlay method, SU can access the licensed spectrum when PU is idle, and SU can access the licensed spectrum within a certain interference range when PU is busy, so our centralized scheme is better than other schemes. In the distributed scheme, SUs are divided into several clusters according to residual energy, SNR and relevance, corresponding to each channel assigned to PUs. Each SU does not need to sense all channels but only needs to sense the selected channels through optimization, which can reduce the sense energy consumption and sense time and allow more SUs to transmit data. Therefore, it can be seen from Figure 11 that the more SUs there are, the higher the average network throughput will be. Similarly, it can be seen from Figure 12 that the more SUs there are, the higher the energy efficiency will be.

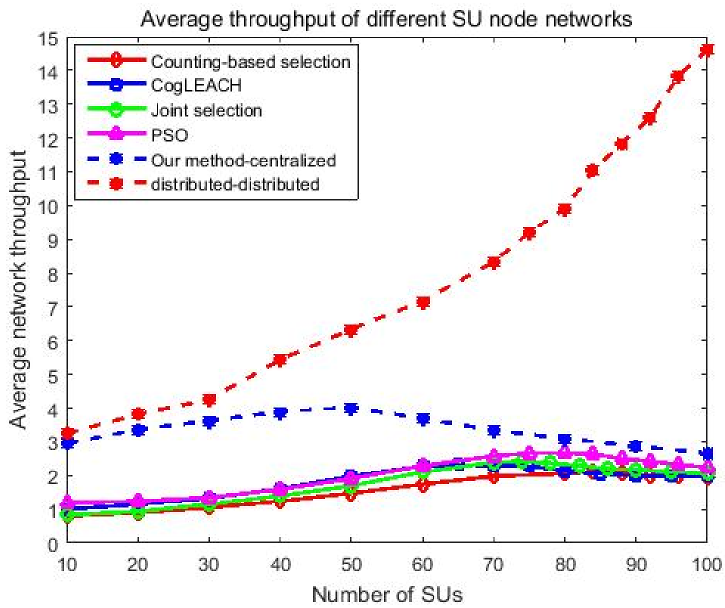

Figure 11. Average throughput of different SU node networks.

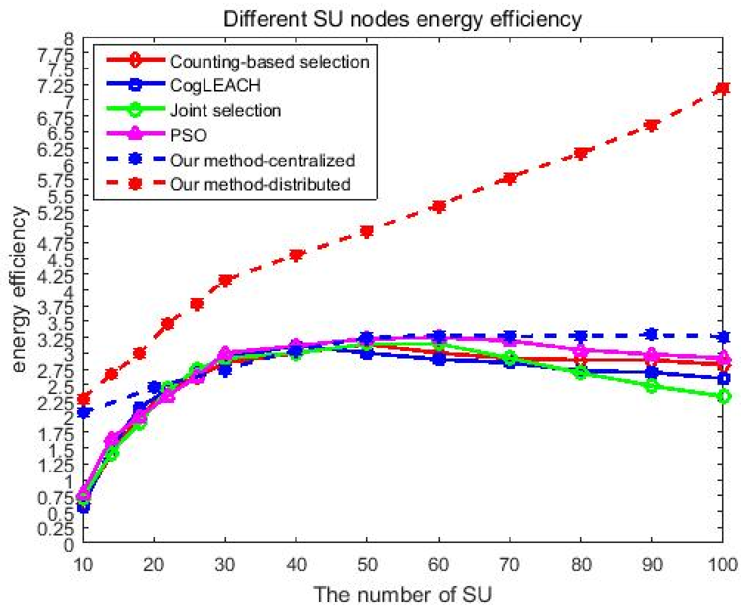

Figure 12. Energy efficiency of different SU nodes.

5. Conclusions

Although some progress has been made in improving user access rate and system energy efficiency based on the energy-correlation centralized cooperative spectrum sensing scheme, the time of centralized cooperative spectrum sensing is long, resulting in double waste of energy and frequency band. In order to further improve the user access rate and the system energy efficiency, we introduce the distributed cooperative spectrum sensing based on energy-relevance, each PUs has a fixed SUs cluster sensitive PUS state in each time slot, so that we can reduce the energy consumption of SUs sensor, and can reduce the sensing time, rest more time to improve the throughput of data transmission, ultimately achieving the purpose of improving energy efficiency. Our improved distributed cooperative spectrum sensing scheme based on energy analysis outperforms the centralized scheme by about 53.2% in terms of throughput and 59.4% in terms of energy efficiency. Although the scheme proposed by us has effectively improved the throughput and energy efficiency of the system, there is no further research on spectrum sensing performance, and we hope to make contributions to spectrum sensing performance in the future.

Author Contributions: Conceptualization, Y.L. and X.Q.; methodology, Y.L.; software, Y.L. and X.Q.; validation, Y.L., X.Q. and J.F.; formal analysis and investigation, Y.L.; resources, Y.H. and L.T.; writing—original draft preparation, Y.L.; writing—review and editing, Y.L. and X.Q.; All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Xinjiang Uygur Autonomous Region Major Science and Technology Special Fund Project.The funded project number is:2020A03001-2.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The author delare no conflict of interest.

References

1. Kolodzy, P.; Avoidance, I. *Spectrum POLICY Task Force*; Rep. ET Docket; Federal Communications Commission: Washington, DC, USA, 2002; Volume 40, pp. 147–158.
2. Xiao, Y.; Krunz, M.; Shu, T. Multi-operator network sharing for massive IoT. *IEEE Commun. Mag.* **2019**, *57*, 96–101. [CrossRef]
3. Abbas, G.; Abbas, Z.H.; Tanveer, M.; Ullah, S.; Naushad, A. HBLP: A hybrid underlay-interweave mode CRN for the future 5G-based Internet of Things. *IEEE Access* **2020**, *8*, 63403–63420.
4. Liu, Z.; Ding, G.; Wang, Z.; Zheng, S.; Sun, J.; Wu, Q. Cooperative Topology Sensing of Wireless Networks with Distributed Sensors. *IEEE Trans. Cogn. Commun. Netw.* **2020**, *7*, 524–540. [CrossRef]
5. Hsieh, S.H.; Liang, W.J.; Lu, C.S.; Pei, S.C. Distributed compressive sensing: Performance analysis with diverse signal ensembles. *IEEE Trans. Signal Process.* **2020**, *68*, 3500–3514. [CrossRef]
6. Ansere, J.A.; Han, G.; Wang, H.; Choi, C.; Wu, C. A Reliable energy efficient dynamic spectrum sensing for cognitive radio IoT networks. *IEEE Internet Things J.* **2019**, *6*, 6748–6759. [CrossRef]
7. Altinel, D.; Kurt, G.K. Modeling of multiple energy sources for hybrid energy harvesting IoT systems. *IEEE Internet Things J.* **2019**, *6*, 10846–10854. [CrossRef]
8. Cai, L.X.; Liu, Y.; Luan, T.H.; Shen, X.S.; Mark, J.W.; Poor, H.V. Sustainability analysis and resource management for wireless mesh networks with renewable energy supplies. *IEEE J. Sel. Areas Commun.* **2014**, *32*, 345–355. [CrossRef]
9. Ni, L.; Da, X.; Hu, H.; Zhang, M.; Cumanan, K. Outage constrained robust secrecy energy efficiency maximization for EH cognitive radio networks. *IEEE Wirel. Commun. Lett.* **2019**, *9*, 363–366. [CrossRef]
10. Gupta, I.; Sahu, O.P. An Overview of primary user emulation attack in cognitive radio networks. In Proceedings of the 2018 Second International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 15–16 February 2018; pp. 27–31.
11. Sarikhani, R.; Keynia, F. Cooperative spectrum sensing meets machine learning: Deep reinforcement learning approach. *IEEE Commun. Lett.* **2020**, *24*, 1459–1462. [CrossRef]
12. Huang, H.; Mu, J.; Jing, X. Cooperative spectrum sensing based on centralized double threshold in mcn. *China Commun.* **2020**, *17*, 235–242. [CrossRef]
13. Yan, J.; Liu, Y. A dynamic SWIPT approach for cooperative cognitive radio networks. *IEEE Trans. Veh. Technol.* **2017**, *66*, 11122–11136. [CrossRef]

14. Lu, W.; Nan, T.; Gong, Y.; Qin, M.; Liu, X.; Xu, Z.; Na, Z. Joint resource allocation for wireless energy harvesting enabled cognitive sensor networks. *IEEE Access* **2018**, *6*, 22480–22488. [CrossRef]
15. Zhang, W.; Wang, C.X.; Chen, D.; Xiong, H. Energy–spectral efficiency tradeoff in cognitive radio networks. *IEEE Trans. Veh. Technol.* **2015**, *65*, 2208–2218. [CrossRef]
16. Zheng, K.; Liu, X.; Zhu, Y.; Chi, K.; Liu, K. Total throughput maximization of cooperative cognitive radio networks with energy harvesting. *IEEE Trans. Wirel. Commun.* **2019**, *19*, 533–546. [CrossRef]
17. Olawole, A.A.; Takawira, F.; Oyerinde, O.O. Cooperative spectrum sensing in multichannel cognitive radio networks with energy harvesting. *IEEE Access* **2019**, *7*, 84784–84802. [CrossRef]
18. Gupta, N.; Dhurandher, S.K.; Sehgal, A. A contract theory approach-based scheme to encourage secondary users for cooperative sensing in cognitive radio networks. *IEEE Syst. J.* **2019**, *14*, 2400–2410. [CrossRef]
19. Maji, P.; Yadav, K.; Roy, S.D.; Kundu, S. Secrecy and throughput performance of an energy harvesting hybrid cognitive radio network with spectrum sensing. *Wirel. Netw.* **2020**, *26*, 1301–1314. [CrossRef]
20. Kumar, A.; Thakur, P.; Pandit, S.; Singh, G. Analysis of optimal threshold selection for spectrum sensing in a cognitive radio network: An energy detection approach. *Wirel. Netw.* **2019**, *25*, 3917–3931. [CrossRef]
21. Liu, X.; Zheng, K.; Chi, K.; Zhu, Y.H. Cooperative spectrum sensing optimization in energy-harvesting cognitive radio networks. *IEEE Trans. Wirel. Commun.* **2020**, *19*, 7663–7676. [CrossRef]
22. Al-Jarrah, M.A.; Al-Dweik, A.; Ikki, S.S.; Alsusa, E. Spectrum-occupancy aware cooperative spectrum sensing using adaptive detection. *IEEE Syst. J.* **2019**, *14*, 2225–2236. [CrossRef]
23. Ding, J.; Jiang, L.; He, C. User-centric energy-efficient resource management for time switching wireless powered communications. *IEEE Commun. Lett.* **2017**, *22*, 165–168. [CrossRef]
24. Yang, Z.; Xu, W.; Pan, Y.; Pan, C.; Chen, M. Energy efficient resource allocation in machine-to-machine communications with multiple access and energy harvesting for IoT. *IEEE Internet Things J.* **2017**, *5*, 229–245. [CrossRef]
25. Azarhava, H.; Niya, J.M. Energy efficient resource allocation in wireless energy harvesting sensor networks. *IEEE Wirel. Commun. Lett.* **2020**, *9*, 1000–1003. [CrossRef]
26. Zheng, K.; Liu, X.Y.; Liu, X.; Zhu, Y. Hybrid overlay-underlay cognitive radio networks with energy harvesting. *IEEE Trans. Commun.* **2019**, *67*, 4669–4682. [CrossRef]
27. Karaca, H.M. Throughput optimization of multichannel allocation mechanism under interference constraint for hybrid overlay/underlay cognitive radio networks with energy harvesting. *Electronics* **2020**, *9*, 330. [CrossRef]
28. Gharib, A.; Ejaz, W.; Ibnkahla, M. Enhanced multiband multiuser cooperative spectrum sensing for distributed CRNs. *IEEE Trans. Cogn. Commun. Netw.* **2019**, *6*, 256–270. [CrossRef]
29. Cao, Y.; Pan, H. Energy-efficient cooperative spectrum sensing strategy for cognitive wireless sensor networks based on particle swarm optimization. *IEEE Access* **2020**, *8*, 214707–214715. [CrossRef]
30. Gao, H.; Ejaz, W.; Jo, M. Cooperative wireless energy harvesting and spectrum sharing in 5G networks. *IEEE Access* **2016**, *4*, 3647–3658. [CrossRef]