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Research Article

EESS: An Energy-Efficient Spectrum Sensing Method by Optimizing Spectrum Sensing Node in Cognitive Radio Sensor Networks

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In cognitive radio sensor networks (CRSNs), the sensor devices which are enabled to perform dynamic spectrum access have to frequently sense the licensed channel to find idle channels. The behavior of spectrum sensing will consume a lot of battery power of sensor devices and reduce the network lifetime. In this paper, we aim to answer the question of how many spectrum sensing nodes (SSNs) are required. In order to achieve this, SSN ratio effects on the accuracy of spectrum sensing from the perspective of network energy efficiency are analyzed first. Based on these analyses, the optimal SSN ratio is derived for maximizing the network lifetime by optimizing the cooperative detection probability (CDP). Simulation results show that the optimal SSN ratio can guarantee the spectrum sensing performance in terms of detection and false alarm probabilities and effectively extend the network lifetime.

1. Introduction

Traditional wireless sensor networks (WSNs) have been an attractive area of research since last decade and usually operate on the license-free industrial, scientific, and medical (ISM) band. However, as the number of wireless devices and applications has seen explosive growth over the past few decades, there has been increasing pressure on the limited spectrum resources [1, 2]. Moreover, the improvement in throughput of wireless networks largely depends on the utilization of channels [3]. In this situation, the concept of cognitive radio (CR) has emerged to alleviate the scarcity of limited radio spectrum resources by improving the utilization of spectrum resources [4]. The CR is a dynamically programmable and configurable radio that opportunistically uses an idle licensed channel in its vicinity to address the problem of unlicensed spectrum resources shortage and the underutilization of the licensed spectrum resources [5, 6]. Such a radio can be applied in the existing network technologies, like wireless sensor networks, machine to machine networks, wireless body area networks, etc., enabling the PHY (PHYsic) and MAC (Media Access) layers of the devices to automatically and dynamically detect available channels and then accordingly change their transmission or reception parameters to allow more concurrent wireless communications in a given spectrum band. As a specific application of the CR technology, cognitive radio sensor network (CRSN) is recently regarded as one of the most attractive topics in IoT paradigms [7].

Not the same as the traditional WSNs [8–12], CRSNs operate on licensed bands, periodically sense the spectrums, and determine vacant channels. In order to achieve this, CRSDs (cognitive radio-enabled sensor devices) in CRSNs have to frequently sense the licensed channels to identify an idle one and detect the active state of primary users (PUs) signal with strictly limited interference to PUs [13]. On the other hand, different from CR networks [14, 15], CRSNs inherit the basic limitations of traditional WSNs of which the lifetime is strictly constraint due to energy limitations. In addition, spectrum sensing (SS) [16, 17] is a crucial element

in the implementation of a CRSN, and energy consumption is also a major consideration in spectrum sensing. The more SUs that participate in spectrum sensing will result in higher energy consumption of the network and shorter network lifetime. For this reason, our goal is to improve the network energy efficiency by optimizing the number of spectrum sensing nodes (SSNs) that participate in spectrum sensing while still guaranteeing the spectrum sensing accuracy.

Moreover, it has been shown that cooperative spectrum sensing (CSS) can not only deal with multipath fading and shadow effects but also improve the accuracy of spectrum sensing [18–21]. The idea of CSS scheme is to use multiple SUs and combine their sensing results at a fusion center (FC). There are two possible CSS strategies: the first one is that all nodes perform CSS, and the second one is that some nodes sense spectrums. But if their performance is similar, the second one is obviously more suitable. To this end, there are some existing node selection methods in various works [3, 22–27]. Specifically, an optimal hard fusion strategy was proposed to maximize the energy efficiency in [22]. In [23], an optimal number of multihop-based SUs was derived. To minimize the total energy consumption, a closed-form equation and optimal conditions due to *KKT* were proposed in [24] to determine the SUs which sense the spectrum. An energy-efficient CSS was also proposed in [25] to solve the problem of sensing node selection. Taking into consideration the scenario when only partial information of SUs and PUs is available in [26], an energy-efficient SUs selection algorithm has been proposed to save energy and improve the detection performance. In [3], a correlation-aware node selection scheme was proposed to adaptively select uncorrelated nodes for CSS, because of the openness, dynamics, and uncertainty of wireless environment. Moreover, in [27], general criteria for decision-approach selection were analyzed and derived when there are actual channel propagation effects.

However, when the environment of network changes dynamically, fewer nodes cannot guarantee the accuracy of spectrum sensing, and more nodes involving spectrum sensing will increase the energy consumption of the network. Therefore, all of the above existing work cannot ensure the accuracy of spectrum sensing and less energy consumption at the same time. In addition, there is no efficient mathematical model which quantitatively describes the relationship between the number of SSNs and spectrum sensing performance.

In this paper, we analyze the optimal SSN selection strategy from the following three aspects. The first is to explore the relationship between the SSN ratio and the received signal power of PU, i.e., signal-to-noise ratio (SNR), in randomly deployed networks (which means that both of CRSDs and PUs are randomly deployed) for analyzing the number of SSNs impacts on the performance of individual spectrum sensing. Secondly, a mathematical formula which describes the relationship between the ratio of SSN and cooperative detection probability (CDP) is explored to ensure the accuracy of cooperative spectrum sensing. Finally, an optimization function is proposed to derive the optimal SSN ratio which can prolong the network lifetime and guarantee the accuracy of cooperative spectrum sensing.

The remainder of the paper is organized as follows. Section 2 gives the system model and problem definition. Analysis of optimal SSN ratio is formulated in Section 3. Simulation results are discussed in Section 4. Finally, Section 5 concludes the paper and discusses the future work.

2. System Model and Problem Definition

This section first describes the network model for CRSN and then presents the spectrum sensing. Afterwards, this section gives the definition of the problem for the optimal SSN ratio selection.

2.1. Network Model

2.1.1. The Channel Model. The network environment of a CRSN under consideration, where a set of CRSDs, N, are distributed to monitor the area of interest, includes a PU and a FC, as shown in Figure 1. The CRSDs can be regarded as the secondary users (SUs) in traditional CR networks that can access idle channels opportunistically. According to the practical requirements, CRSDs periodically sense the environment with different sampling rates and then report their sensed data to the FC [28]. In general, the available licensed spectrum consists of multiple primary channels whose active state follows different traffic patterns. For simplicity, in this paper, a single primary channel is assumed, and the PU traffic pattern follows a stationary exponential ON/OFF random process [29].

The ON state denotes that the PU is occupying the channel and the OFF state indicates that the channel is idle. Let H_0 and H_1 denote the hypotheses of the absence and present of the PU, respectively. In addition, let V and L denote the exponential random variables, which describe the idle and occupancy state with means v and l, respectively. Therefore, for a channel, the probability of the channel having occupancy P_{on} and the probability of the channel idle P_{off} are given by

$$\begin{aligned} P_{off} &= \frac{v}{(v+l)}, \quad H_0 \\ P_{on} &= \frac{l}{(v+l)}, \quad H_1. \end{aligned} \tag{1}$$

2.1.2. The Signal Propagation Model. To address the optimal number of SSNs selection problem conveniently, the signal propagation model is modeled firstly. According to [30], the relationship between the received power of the CRSDs and the transmission power of the PU can be denoted as follows:

$$P_j(d) = \beta d_j^{-\alpha} P_{PU}, \tag{2}$$

where $P_j(d)$ is the received power of the j-th CRSD, P_{PU} is the signal power of the PU, β is a scalar, d_j is the distance between the j-th CRSD and the PU, and α is the path loss factor. The signal-to-noise ratio (SNR) of the PU received at each CRSD is computed by

$$\gamma_j = 10 \log \frac{P_j(d)}{\sigma^2}, \quad j = 1, 2, \ldots, N, \tag{3}$$

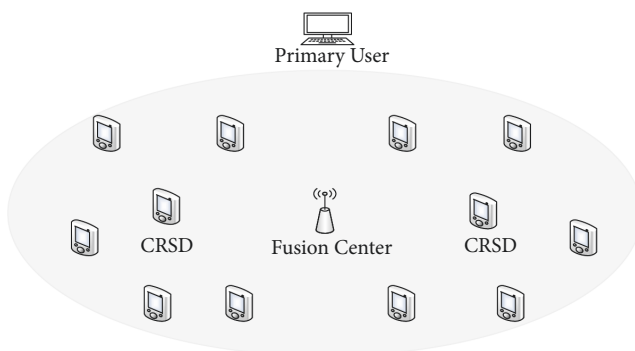


Figure 1: The network model of cognitive radio sensor network.

where σ^2 is the noise power and N is the total number of CRSDs in the network.

2.2. Spectrum Sensing

2.2.1. Spectrum Sensing Hypothesis. In a CRSN, the received signal sample of the CRSDs can be formulated as a binary hypothesis testing; the hypothesis H_0 represents that no PU exists in the spectrum, and hypothesis H_1 represents that the PU exists in the spectrum; that is [31],

$$y(m) = \begin{cases} n(m), & H_0 \\ s(m) + n(m), & H_1, \end{cases} \tag{4}$$

where $y(m)$ is the received signal at a CRSD, $s(m)$ is the signal of the PU and is assumed to be an iid random process with zero mean and variance, σ_s^2. The noise, $n(m)$, is assumed to be Gaussian iid random process with zero mean and variance, σ_n^2, and $s(m)$ and $n(m)$ are independent.

In the channel sensing, the probability of detection, P_d, and the probability of false alarm, P_f, are significant indicators for measuring the spectrum sensing accuracy. P_d and P_f are defined as the probabilities of detecting the PU under hypotheses H_1 and H_0, respectively.

2.2.2. PU Detection. The energy detection [32] method can be utilized by the CRSDs as their channel sensing method. The test statistics for energy detector is given by

$$T(y) = \frac{1}{M}\sum_{m=1}^{M} |y(m)|^2, \tag{5}$$

where $T(y)$ is the sample of received signal at CRSDs and $M = 2TW$ where TW represents the product of detection time, T, and signal bandwidth, W. When M is relatively large (e.g., $M > 200$), $T(y)$ can be approximated as a Gaussian random variable under both hypotheses H_0 and H_1, with means μ_0, μ_1 and variances σ_0^2, σ_1^2 respectively, which can be given by [33]

$$\begin{aligned} \mu_0 &= M \\ \mu_1 &= M(\gamma_j + 1) \\ \sigma_0^2 &= 2M \\ \sigma_1^2 &= 2M(2\gamma_j + 1), \end{aligned} \tag{6}$$

where γ_j is SNR of the PU signal at the j-th CRSD.

For a given threshold, ϵ, the probability of false alarm and detection probability of the j-th CRSD are given by

$$P_{f,j} = Pr(T(y) > \epsilon \mid H_0) = Q\left(\left(\frac{\epsilon}{\sigma_n^2} - 1\right)\sqrt{M}\right), \tag{7}$$

$$\begin{aligned} P_{d,j} &= Pr(T(y) > \epsilon \mid H_1) \\ &= Q\left(\left(\frac{\epsilon}{\sigma_n^2} - \gamma_j - 1\right)\sqrt{\frac{M}{2\gamma + 1}}\right), \end{aligned} \tag{8}$$

where $Q(\cdot)$ denotes the Gaussian Q-function. Without loss of generality, we set the detection threshold of all the CRSDs to be the same; hence, the false alarm probability of all the CRSDs becomes fixed and is denoted by $\overline{P_f}$. Therefore, (7) and (8) can be represented by (9) and the probability was denoted by [34]

$$\begin{aligned} P_{d,j} &= Pr(T(y) > \epsilon \mid H_1) \\ &= Q\left(\frac{Q^{-1}(\overline{P_f}) - \sqrt{M}\gamma_j}{\sqrt{2\gamma_j + 1}}\right). \end{aligned} \tag{9}$$

2.2.3. Cooperative Spectrum Sensing. In a densely deployed network, we consider that the sensing results of neighboring CRSDs are similar. And the network can be divided into multiple clusters based on the method proposed in Section 3. Therefore, the sensing results in a cluster can be represented by one node which is called SSN in this paper. To reduce the communication overhead, each SSN sends the final 1-bit decision to the FC which is an energy-unconstrained center for data aggregation and decision making and can decode and combine all the decoded information from all SSNs using the logic-OR-rule to make a final decision [35]; that is to say, the PU is considered to be occupying the channel if at least

one sensor node claims the presence of the PU. Then, all the SSNs in different clusters are selected to cooperatively sense the channel; the cooperative detection probability F_d and the cooperative false alarm probability F_f for the channel are as follows:

$$F_f = 1 - \prod_{j=1}^{N_{SSN}} \left(1 - \overline{P_f}\right), \tag{10}$$

$$F_d = 1 - \prod_{j=1}^{N_{SSN}} \left(1 - P_{d,j}\right), \tag{11}$$

where N_{SSN} is the number of selected SSNs cooperating. The cooperative misdetection probability F_m is defined as the probability of not detecting the presence of the PU; i.e., $F_m = 1 - F_d$.

2.3. Problem Definition. This paper focuses on providing the optimal number of SSNs for CSS in the random deployed CRSNs. The selection of optimal SSNs, under the premise that the probability of interfering with the PU should be below a predefined threshold F, must guarantee that all SSNs can accurately detect the available licensed channel information and send their sensed information to the FC for further processing. In other words, there is a constraint on N_{SSN} such that

$$P_{on} * F_m = P_{on} * \prod_{j=1}^{N_{SSN}} \left(1 - P_{d,j}\right) \leq F. \tag{12}$$

The ratio of SSN is p, and $0 < p < = 1$. When $p = 1$, it means that all CRSDs are involved in spectrum sensing, and $0 < p < 1$ denotes that some nodes are selected from CRSDs for spectrum sensing. The objective is to select optimal SSN ratio p under the consideration of cooperation detection probability F_d and the constraint of (12) among the whole nodes. Hence, our optimization function is

$$\begin{aligned} \min_{p \in (0,1]} \quad & F_d(p) \\ s.t. \quad & P_{on} * F_m \leq F, \end{aligned} \tag{13}$$

where the objective function $F_d(p)$ is result of a comprehensive consideration of the effect of the SSNs ratio p on the cooperation detection probability F_d, and the relationship between cooperation detection probability F_d and SSNs ratio p will be discussed in Section 3.2.

3. Analysis of the Optimal SSN Ratio

In this section, we first study the impact of the SSN ratio on the PU detection, and the relationship between the SSN ratio and the received signal power of PU is derived. Then a mathematical formula which describes the relationship between the SSN ratio and cooperative detection probability (CDP) is explored to ensure the accuracy of cooperative spectrum sensing. Finally, a cluster method based on spectrum sensing nodes is proposed.

Table 1: Table of notations.

Notation	Parameters
N	The total number of nodes
N_{SSN}	The number of SSNs
p	SSNs ratio defined as $p = N_{SSN}/N$
λ_{SSN}	The density of SSNs defined as $\lambda_{SSN} = Np/A = N_{SSN}/A = \lambda p$
λ'	The density of all nodes defined as $\lambda' = \lambda(1-p)$
R	Transmission radius of the network
r	Transmission radius of SSNs

3.1. The Impact of the SSN Ratio on the PU Detection. In this paper, a densely deployed network is assumed where the connectivity of CRSDs can be guaranteed and each CRSD receives signals from the primary user with different SNRs. Figure 2 shows a specific example where N_{SSN}=2 SSNs randomly deployed in the network, i.e., SSN1 and SSN2. For CRSD1, CRSD2, and CRSD3, because they are close to SSN1, they will join SSN1 by utilizing a clustering method. The other CRSD4, CRSD5, and CRSD6 form another cluster 2 with SSN2 (if $N_{SSN} = N$, it means all of nodes will perform the spectrum sensing; N-N_{SSN} CRSDs will join the nearest SSN as its cluster members). In this way, the SSNs can form a number of clusters and can periodically transmit their sensed data to the FC for further process via data channels. The data channel may not be perfect, but this is beyond the scope of our discussion in this paper.

After the clustering, for example, when primary user appears in cluster 1, SSN is responsible for sensing the spectrum instead of all to perform spectrum sensing and decide the active state of the PU; finally, it shares its spectrum sensing results with the rest of the CRSDs. Therefore, the rest of the CRSDs belonging to cluster 1 do not need to sense the licensed channel to make a decision before transmitting their sensing data. Consequently, the overall spectrum sensing energy in the CRSN can be saved and the lifetime of the network can be prolonged.

Specifically, we assume that all nodes are deployed in a network area A using Poisson point process (PPP) [36] with intensity λ. And then N_{SSN} SSNs are deployed in the network randomly. After clustering process, the network is divided by N_{SSN} Voronoi cells [37, 38]. In order to analyze the signal propagation characteristic in a Voronoi cell, i.e., a cluster, the following parameters are defined in Table 1.

Firstly, the average radius of a cluster is derived. Foss and Zuyew [38] analyzed the geometrical properties of Voronoi cells in a polar coordinate and assumed that a SSN is in 0 point. One of the significant conclusions they got was the expected number of nodes in a Voronoi cell, which can be given as follows (the complete proof of (14) can be seen at [38]).

$$E(N_{tot}) = \lambda' 2\pi \int_0^k l e^{-\lambda_{SSN}\pi l^2} dl = \frac{\lambda'}{\lambda_{SSN}}, \tag{14}$$

where $k \longrightarrow +\infty$, l and $E(N_{tot})$ represent the radius of a cluster and the total number of nodes in a cluster, respectively.

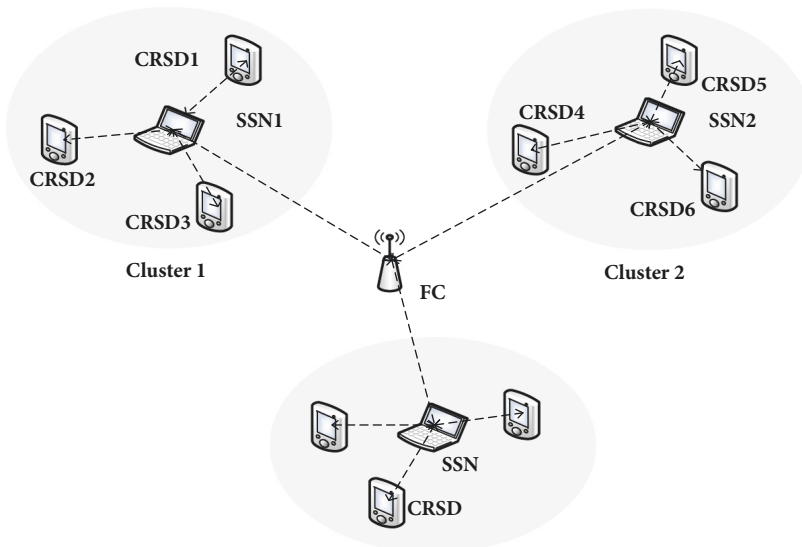


Figure 2: The architecture of SSN-based cognitive radio sensor network.

Secondly, the one-hop link lengths between SSN and its cluster member are derived. Since the shape and radius of a cluster are all random, the expected average radius value of a cluster is also random which can be defined as $E[l]$, and the resulting from [38] can be utilized, which showed that the total direct link length of a cluster is $E[L_{tot}] = \lambda'/2\lambda_{SSN}^{3/2}$. Finally, $E[l]$ can be calculated as follows:

$$E[l] = \frac{E[L_{tot}]}{E[N_{tot}]} = \frac{1}{\sqrt{4\lambda_{SSN}}} = \sqrt{\frac{A}{4Np}}, \tag{15}$$

where p represents the ratio of the SSNs to the nodes.

During signal propagation, signal power decreases with distance increase. This phenomenon is statistically modeled using the signal propagation model $P_j(d)$ defined in Section 2.1.2. Let $\overline{P(d)}$ denote the average path loss in a cluster, i.e., $\overline{\gamma} = 10\log(\overline{P(d)}/\sigma^2)$. Based on the result $\overline{\gamma}$ and (14), the average SNR in a cluster can be derived as follows:

$$\overline{\gamma} = 10\log\frac{\overline{P(d)}}{\sigma^2} = 10\log\frac{P\left(\sqrt{A/4Np}\right)}{\sigma^2}, \tag{16}$$

where $P_j(d) = \beta d_j^{-\alpha} P_{PU}$, σ^2 is the noise power, and α and β are determined by the type of approximation and modulation, respectively.

Therefore, $\overline{\gamma}$ can be determined based on the SSNs ratio p and the stationary network parameters, i.e., network area A and the signal power of PU, P_{PU}.

3.2. Optimal SSN Ratio for Maximizing the CDP. The goal of the paper is to improve energy efficiency of the network by selecting the optimal ratio of SSNs, i.e., p, involved in spectrum sensing while still guaranteeing the spectrum sensing accuracy without interfering with the active state of the PU. Based on the above analysis, analyzing (9) the detection probability is determined by the SNR γ which is also determined by the SSNs ratio p. Hence, the formula of the average detection probability $\overline{P(d)}$ and the SSNs ratio p can derived as follows:

$$\overline{P_d} = Q\left(\frac{Q^{-1}\left(\overline{P_f}\right) - 10\sqrt{M}\log\left(P\left(\sqrt{A/4Np}\right)/\sigma^2\right)}{\sqrt{20\log\left(P\left(\sqrt{A/4Np}\right)/\sigma^2\right)+1}}\right), \tag{17}$$

where $P(\sqrt{A/4Np}) = \beta\sqrt{A/4Np}^{-\alpha}P_{PU}$. Without loss of generality, let $\alpha = 1$ and $\beta = 1$, which are valid to compare the impact of p on P_d; it can yield the following equation:

$$\overline{P_d} = Q\left(\frac{Q^{-1}\left(\overline{P_f}\right) - 10\sqrt{M}\log\left(P_{PU}\sqrt{4Np/A}/\sigma^2\right)}{\sqrt{20\log\left(P_{PU}\sqrt{4Np/A}/\sigma^2\right)+1}}\right). \tag{18}$$

Since the logic-OR-rule is adopted at the FC, according to (11), (18) can be described as the relationship between the cooperative detection probability F_d and the SSNs ratio p, and this is formulated by the following optimization function $F_d^*(p)$:

$$F_d^*(p) = \arg\max_{p\in(0,1]}\left(1 - \prod_{j=1}^{Np}\left(1 - Q\left(\frac{Q^{-1}\left(\overline{P_f}\right) - 10\sqrt{M}\log\left(P_{PU}\sqrt{4Np/A}/\sigma^2\right)}{\sqrt{20\log\left(P_{PU}\sqrt{4Np/A}/\sigma^2\right)+1}}\right)\right)\right). \tag{19}$$

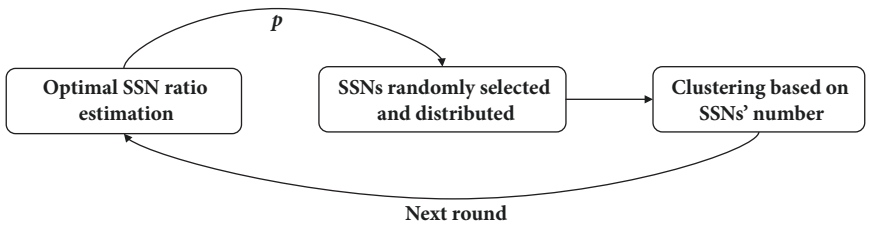


Figure 3: Illustration of SSNs selection and cluster formation process.

The objective function in (19) is the final result of the relationship between p and F_d. Therefore, p is obtained which maximizes the cooperation detection probability with the constraint in (12), and the optimization function in (13) can be rewritten as follows:

$$\begin{aligned} &\underset{p\in(0,1]}{\operatorname{argmin}} \quad F_d^*(p) \\ &s.t. \quad P_{on} * F_m \leq F, \end{aligned} \tag{20}$$

Figure 5 shows the results of (20), which indicates that the optimal SSNs ratio p values are 0.3, 0.15, and 0.1 for nodes densities of 300, 400, and 500, respectively, and the performance of the cooperative detection probability (CDP) is guaranteed.

3.3. The Process of Clustering Based on Spectrum Sensing Node. After the process of the optimal SSN ratio analysis, the optimal p values are obtained at different node densities. In order to guarantee the balance of the network load, we randomly select nodes in the network as SSN nodes to participate in spectrum sensing based on p values. When the SSNs are randomly deployed in the network, a SSN will send a message which contains a counter (initially set to 0) and its ID to neighbor nodes. If the counter is less than a constant C, the ID and counter will be recorded in the neighbor node's memory. Then the neighbor will forward it after increasing the counter by 1 and set a timer. If the timer is out, the node (e.g., CRSD) will join the SSN that has the lowest counter. If there are similar messages, it will select SSN that sent the first message. We illustrate the main idea of addressing the SSNs selection and cluster formation process in Figure 3 and summarize the detailed procedures of our solution in Algorithm 1.

4. Simulation Results

The performance of the proposed schemes is evaluated by extensive simulations on MATLAB. The radius of the simulation area is 100m ∗ 100m, the FC is located in the center, the PU station is assumed to be the DTV station which can cover the area, and the number of randomly deployed CRSDs is 300, 400, and 500. The SSNs are also randomly selected, each node selects the closest SSN to join based on cluster formation algorithm, and then the SSN in a cluster senses the spectrum and transmits its sensing result to the FC for decision making.

Table 2

Parameters	Values
Network size	$100m \times 100m$
FC station	(50, 50)
Detection time T	0.001
Signal bandwidth W	3MHz
Sampling frequency	6MHz
Path loss factor α	1
Scalar β	1
Occurrence probability of H_1 P_{on}	0.5
Occurrence probability of H_0 P_{off}	0.5
Initial energy of each node	$0.5J$
Data packet	4000 bits
Power amplification factor (multipath)	0.0013pJ/bit/m^4
Power amplification factor (free)	10pJ/bit/m^2
Energy consumption per 1-bit data	50nJ/bit

The specific parameters are shown in Table 2.

In Figure 4, we consider that the number of nodes is 300, they are evenly distributed in the network, and the area of interest is covered by the PU signal, and the position of the FC is in the center of the area. The circle represents the nodes and the red five-pointed star represents the FC.

For the CRSN, the most important issue in spectrum sensing is to ensure a high detection probability. In addition, we know that cooperative detection probability is more accurate than single detection probability. Thus the cooperative detection probability and SSN ratio are investigated with our proposed scheme. The relationship between the SSN ratio and the CDP is shown in Figure 5. From the figure, it can be seen that the optimal SSN ratio for the three densities is 0.3, 0.15, and 0.1, respectively. As the number of the nodes increases, the nodes in the network have better connectivity. Therefore, the proportion of the SSNs needed for CSS is reduced. In addition, it also can be found from the figure that the more the number of SSNs that are selected to participate in cooperative spectrum sensing, the closer the cooperative detection probability to 1.

After the calculation and analysis of optimal number of SSN nodes, Figure 6 shows the distribution of spectrum sensing nodes, on all the subfigures, at different nodes densities.

According to the proposed cluster formation Algorithm 1, Figure 7 shows the relationship between the number of

Input: Optimal SSNs ratio p based on the Eq. (20);
All number of nodes in the network N;
The rest number of nodes in the network M^*.
initialization: counter $c = 0$; constant C;
$N_{SSN} \longleftarrow Np$, $M^* \longleftarrow N - Np$
for $i \in \{1 \ldots N^*\}$ **do**
randomly selected SSN i sends a message containing a counter c and its ID to neighbor node
end of for
repeat until timer stops
for $i \in \{1 \ldots N_{SSN}\}$ **do**
Timer i is on;
$c \longleftarrow c + 1$;
if $c <= C$
then The neighbor node of SSN i forward its ID and count c;
end of for
end of repeat
for $j \in \{1 \ldots M^*\}$ **do**
for $i \in \{1 \ldots N_{SSN}\}$ **do**
if node j has the lowest count c among every SSN in $\{1 \ldots N_{SSN}\}$
then node j join the SSN i
end of for
end of for
for $j \in \{1 \ldots M^*\}$ **do**
if node j has similar messages among every node in $\{1 \ldots M^*\}$
then node j select the SSN i who sent the first message
end of for
Output: clusters $i, \ldots, N_{SSN}$

Algorithm 1: Cluster formation algorithm based on optimal SSN selection.

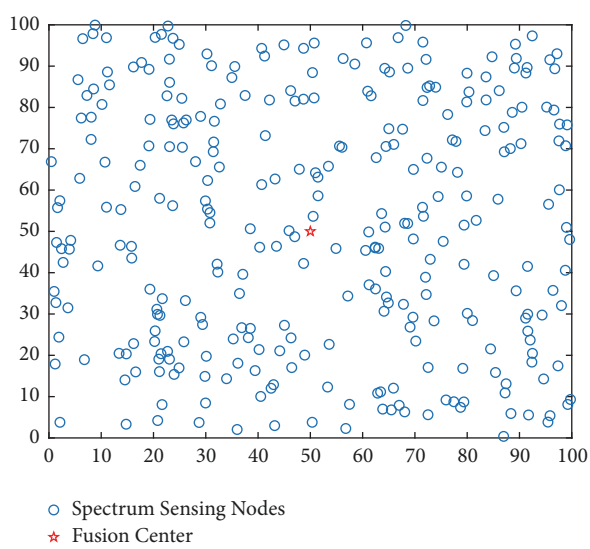


Figure 4: Nodes of CRSN deployment diagram ($N = 300$).

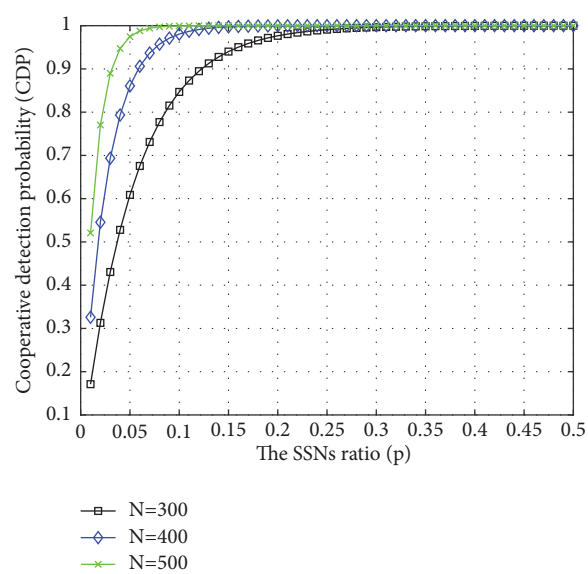
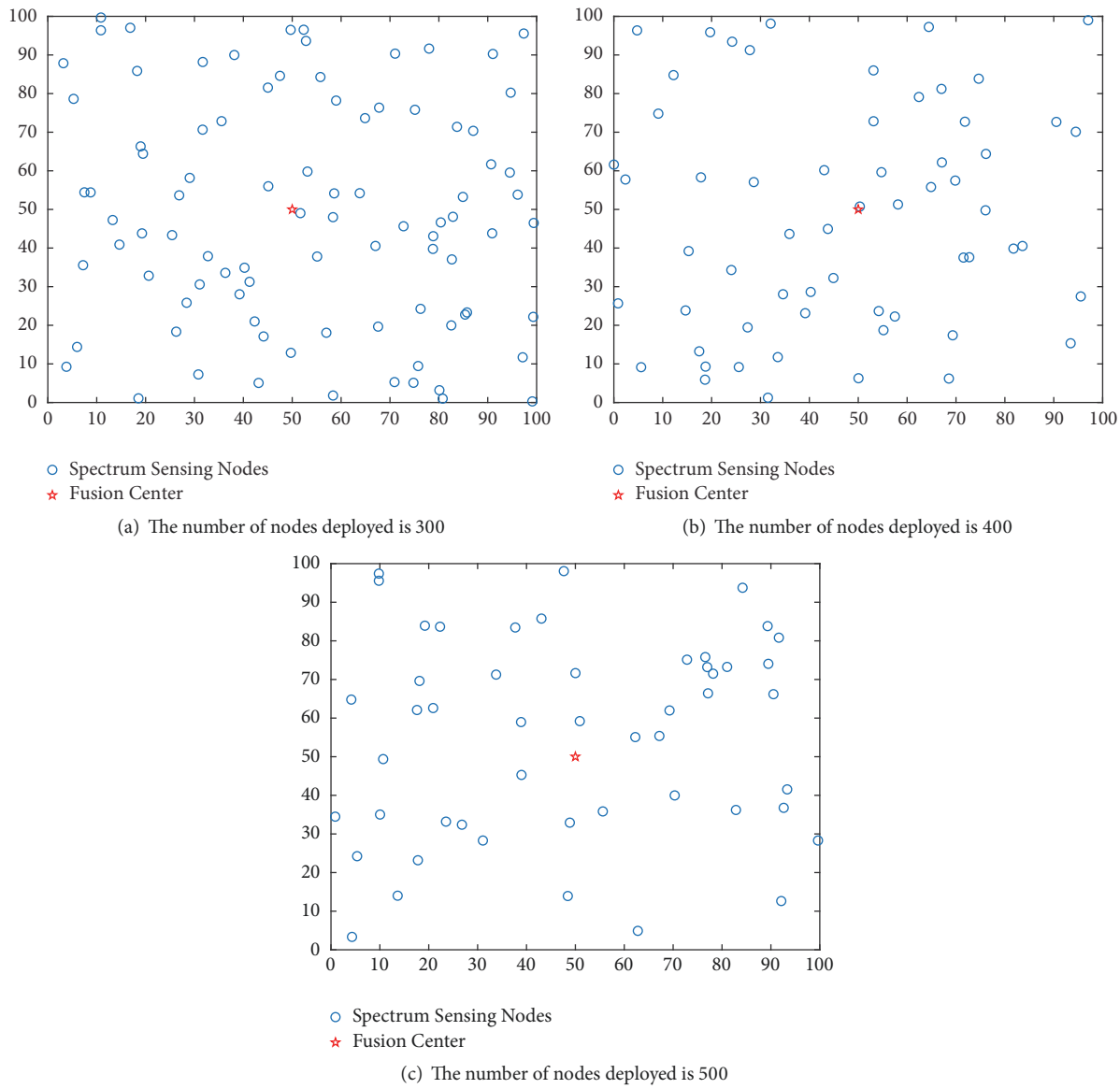


Figure 5: The impact of SSNs ratio p on the cooperative detection probability (CDP).

iterations and the number of SSN nodes when the number of network nodes is 300, 400, and 500, respectively.

Figure 7 reveals that, on all the subfigures, the greater the node density, the lower the number of nodes that need to be used as SSNs which also represent the number of clusters and the longer the network lifetime, which confirms that cluster formation algorithm can effectively and reasonably partition the network to prolong the lifetime of the network.

In Figure 8, we show the receiver operating characteristic (ROC) curves of two different methods for CSS. The first indicates the simulated and theoretical values when all nodes



(a) The number of nodes deployed is 300

(b) The number of nodes deployed is 400

(c) The number of nodes deployed is 500

Figure 6: The distribution of spectrum sensing nodes at different node densities.

perform spectrum sensing, while the second represents the simulated and theoretical values only when the selected SSNs participate in spectrum sensing. It can be seen that the simulated values and the theoretical values of these two methods are close to each other, which indicates that the derivation of (10) and (11) is correct. At the same time, it is proved that only a part of nodes is selected to perform spectrum sensing; the detection probability of the network does not decrease, which also indicates that our scheme is effective.

To evaluate the impact of the optimal SSN ratio selection strategy on the energy efficiency of the network, the simulation is performed for 5000 rounds, and Figure 9 shows that the proposed optimization strategy can greatly improve the energy efficiency of the network and thus prolong the lifetime of the network.

Finally, it can be clearly seen that the proposed optimal SSN ratio selection strategy not only can optimize the number of nodes that participate in spectrum sensing while still guaranteeing the spectrum sensing accuracy without interfering in the active state of the primary user, but also can prolong the lifetime of the network due to the reduced number of nodes for SS.

5. Conclusions

In this paper, an optimal SSN ratio selection scheme is proposed to improve the network energy efficiency by optimizing the number of nodes that participate in spectrum sensing while still guaranteeing the spectrum sensing accuracy without interfering in the active state of the primary user. Firstly, the mathematical analysis of the relationship

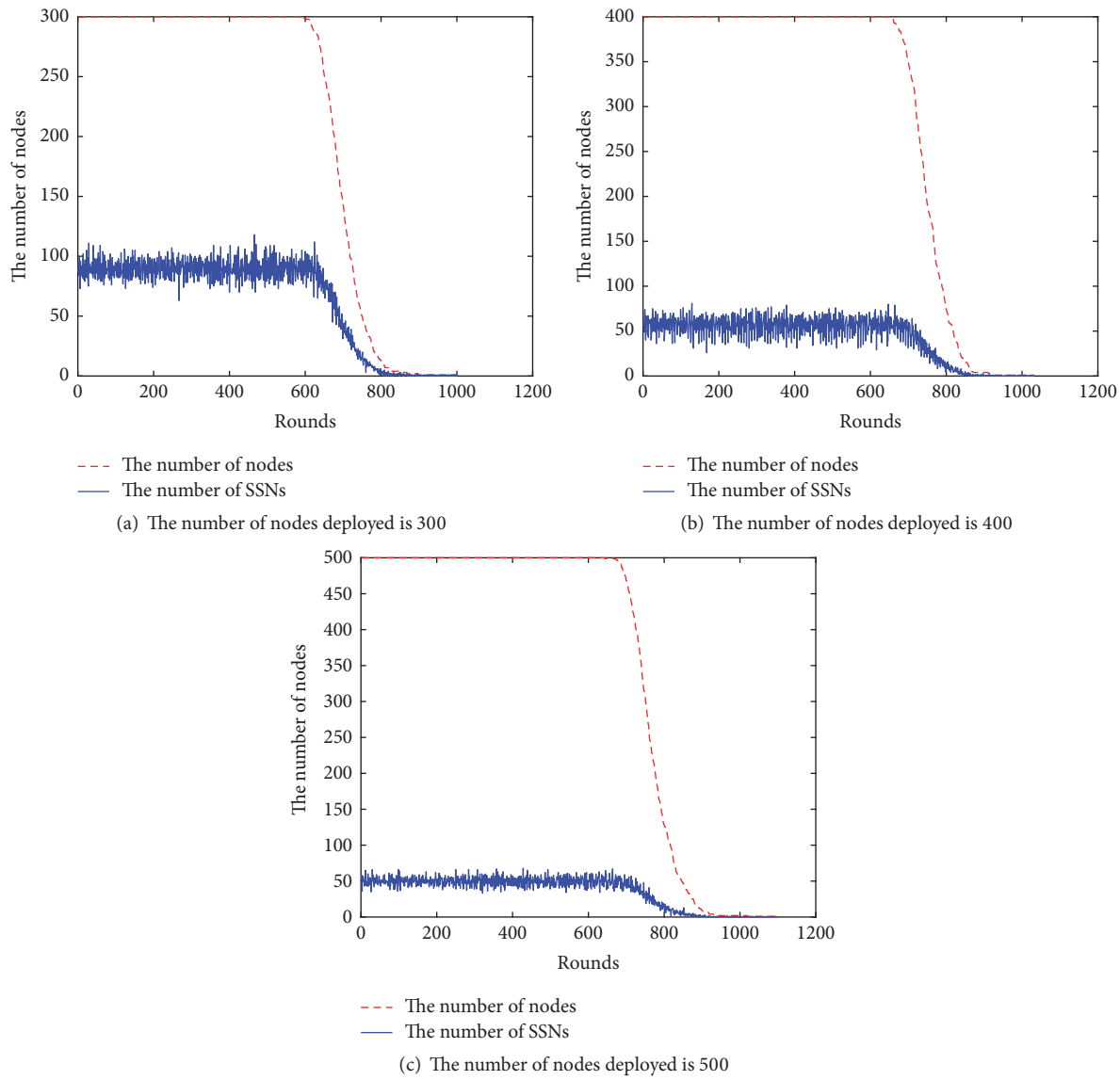


Figure 7: Comparison of cluster numbers at different nodes densities.

between SNR and the SSN ratio is carried out, and then an optimization problem is given to choose the optimal SSN ratio for cooperative spectrum sensing to maximize the cooperative detection probability. Finally, the simulation results demonstrate that this scheme not only can choose optimal SSN ratio to maximize the cooperative detection probability but also can effectively reduce the energy consumption to prolong the network lifetime. To the best of our knowledge, this is the first time to associate the SSN ratio with cooperative detection probability for CSS. Our future work is to explore the relationship between the selection of optimal SSNs and more decision-making schemes.

Data Availability

The data shown in the manuscript is available for the readers.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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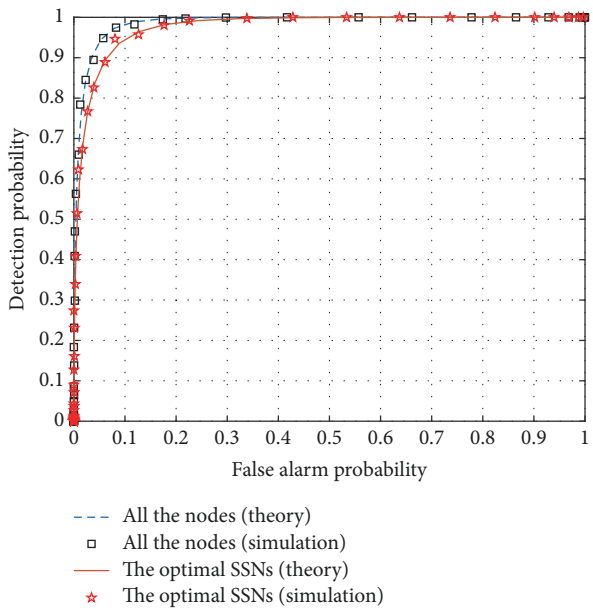

Figure 8: Detection performance at different number of nodes.

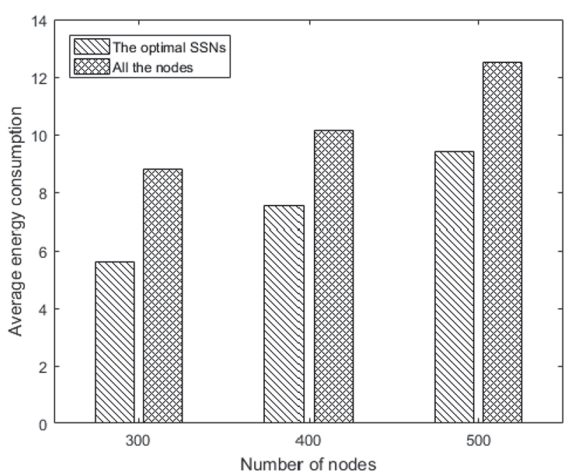

Figure 9: Average energy consumption at different nodes densities.

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