*Review Article*

# Cooperative Spectrum Sensing in Cognitive Wireless Sensor Networks

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Cognitive wireless sensor network (CWSN) is a combination of cognitive radio and wireless sensor networks (WSNs), which can effectively solve spectrum resource scarcity problem in WSNs. As one of the key technologies in CWSNs, spectrum sensing enables sensors to detect and opportunistic access underutilized idle licensed bands, which remarkably improves the spectrum utilization and system performance. And cooperative spectrum sensing (CSS) has emerged to enhance detection performance of spectrum sensing. Focusing on CSS schemes in CWSNs, this paper explores the cooperative and noncooperative schemes comprehensively. The characteristics of the existing CSS schemes are analyzed in CWSNs. And then, according to the behavior of cognitive sensors, CSS techniques are classified into noncooperative and cooperative schemes. Concentrating on energy consumption, cooperative CSS schemes are classified into three categories: censoring, clustering, and sensor selection. The performance of three kinds of CSS schemes is compared and analyzed thoroughly. Finally, the difficulties and challenges of CSS scheme are addressed in CWSNs.

## 1. Introduction

Wireless sensor networks (WSNs) consist of a large number of tiny sensors which have limited communications and computing capabilities and are distributed in the different work areas [1]. WSNs operate in the industrial scientific medical (ISM) band, which does not need to be authorized [2, 3]. In recent years, with more and more applications using these bands, such as Bluetooth and ZigBee, the unauthorized spectrum resources become more and more nervous. Spectrum resource scarcity and coexistence of different networks have become the bottlenecks hindering the development and applications of WSNs [4, 5].

Cognitive radio (CR) uses the dynamic spectrum access (DSA) to make secondary users (SUs) having chance to access the opportunistic idle licensed spectrum without interference to primary users (PUS) [3, 6, 7], which effectively solves the problem of spectrum source shortage and remarkably

improves spectrum utilization. And CR is regarded as the most promising future wireless communications technology. CR may also be applied to WSNs since radio has the characteristic of secondary use, namely, cognitive wireless sensor networks (WCSNs), which can also solve spectrum scarcity and a variety of heterogeneous network coexistence issues in WSNs [4, 8, 9]. And the application implementation of CR technology was explored in details from the perspective of the physical layer and link layer in CWSNs [8].

Spectrum sensing, namely, spectrum holes detection [10], is one of the most important technologies in CWSNs and also is one of the differences between CWSNs and traditional WSNs. Cognitive sensor has the cognitive function to sense spectrum, detect the idle spectrum and opportunistic access it. It detects the PUs' band, discovers spectrum holes, and sends its sensing data to fusion center (FC). Since the PUs for the licensed spectrum have a higher priority to access the granted spectrum, the SUs need to evacuate immediately

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                          ┌─────────────────────┐
                          │ Cooperative spectrum │
                          │      sensing         │
                          └─────────────────────┘
               ┌──────────────────┐              ┌─────────────┐
               │  Noncooperative  │              │ Cooperative │
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| Energy detection [31] | Matched filter [39] | Feature detection [40] | Interference temperature [41] |

| Censoring | Clustering [21, 23] | User selection |

| Double-threshold [17, 18] | Credibility [19, 20] | Passive [24] | Active |

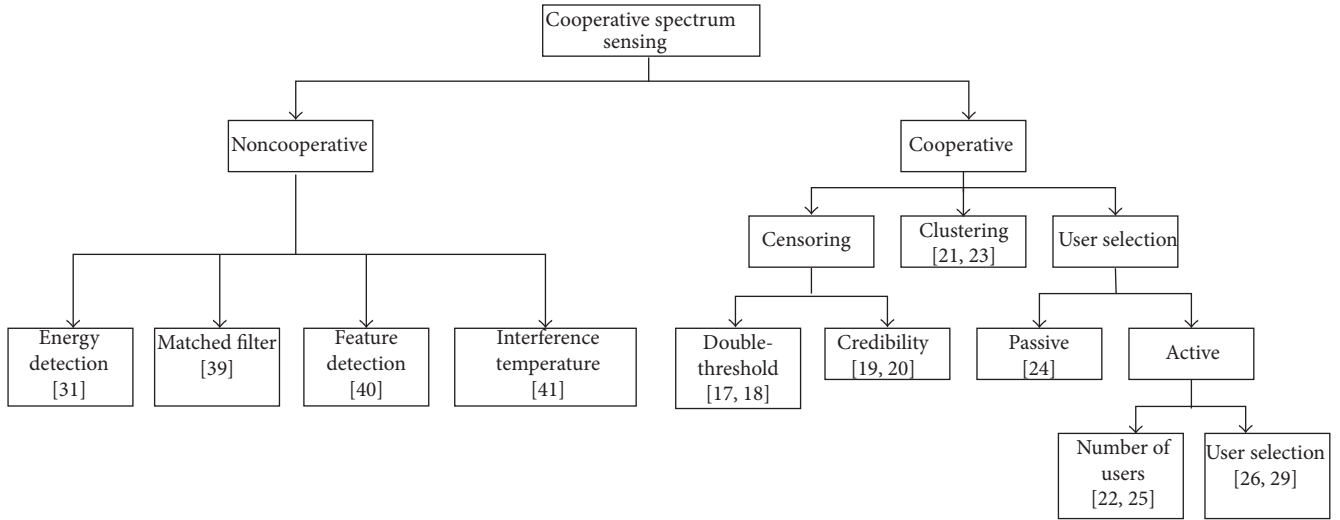| Number of users [22, 25] | User selection [26, 29] |

FIGURE 1: CSS classification in CWSNs.

from the authorized spectrum when PUs reuse the channel and continue to look for new spectrum hole without any interference to PUs.

However, a single cognitive sensor usually cannot make a precise decision whether the primary users are present or not, due to multipath fading or shadowing [11] and limited capacity. Cooperative spectrum sensing (CSS) with cooperation among multiple nodes can effectively overcome the shortcomings of single-node spectrum sensing to improve detection performance and save energy. In order to improve detection performance, a CSS scheme was proposed in CRN [2], which takes some important factors affecting spectrum sensing into consideration, such as SUs' signal-to-noise ratio (SNR), reliability, and location information. To find suitable CSS parameters, a scheme was designed to maximize the throughput between PUs and SUs without interference [4], which considers single-channel sensing and multichannel sensing, respectively. A hierarchical spatial clustering algorithm was proposed for cooperative spectrum sensing to reduce the total energy consumption in WSN [12], which selects cluster heads based on the weight of sensors.

Although, there are many effective CSS schemes in cognitive radio networks (CRNs) and WSNs, existing CSS approaches in WSNs are not applicable in CRSNs, and existing solutions in CRNs are also not suitable for WSNs. The reasons are as follows: (1) CSS in WSNs does not consider CR capabilities. (2) CSS in CRNs does not think over energy consumption, limited capacity, and limitation of hardware design.

Since the focuses are different, CSS in either CRNs or WSNs can be applied directly to the CWSNs. Then, designing a suitable CSS applying for CWSNs becomes more crucial. To find optimal sensing threshold and the optimal number of cognitive sensors to minimize the energy consumption, sensor-aided CRN was explored in [13], which is under the lowest detection probability and the highest alarm probability constraints. However it is only concerned with how to find

a minimal subset of energy consumption. And in low SNR condition, the proposed model will result in higher energy consumption. The scheme of choosing irrelevant sensors or low-relation sensors to carry out sensing can effectively improve the detection probability in CWSNs [14]. A repeated game model is applied to CSS in [15], where the participation frequency of node is regarded as motivation to promote the node to participate in collaboration. The rule is that the higher the sensing number of node, the more the data transmission time is assigned. Namely, the transmission time of sensor data is proportional to the sensing number of nodes. However, the complexity of repeated game algorithm is high. A compressed spectrum sensing model for wideband is proposed in [16]. However it requires all nodes to be involved in sensing. In addition, compressed sensing is based on sparse spectrum, which is inconsistent with the fact of radio spectrum.

Different from the traditional CSS in CRNs and WSNs, good detection performance and energy efficiency are needed to be considered in CWSNs. Under the consideration of the two goals, the existing CSS in CWSNs most concentrates on optimization on how to select the number of nodes and node selection. However, the sensing results and overhead caused by cooperative sensing, such as energy and delay, should be considered in CWSNs. In this paper, focusing on reducing energy consumption in CWSNs, CSS is comprehensively explored from the perspective of cooperation, and the contributions of this work are described as follows.

The characteristics of CSS in CWSNs are analyzed. According to the behavior of cognitive sensor, CSS is classified into two categories: noncooperative and cooperative, as shown in Figure 1. In noncooperative spectrum sensing (NCSS), the existing spectrum detection methods are analyzed, and the advantages, disadvantages, and scope of application are explored comprehensively. According to how to reduce energy consumption in CWSNs, CSS schemes are further divided into three categories: censoring, clustering,

TABLE 1: Overview of spectrum sensing methods.

| Type | Advantage | Disadvantage | Scope of application |
| --- | --- | --- | --- |
| Matched filter | Short detection time, robustness in low SNR | Many constrained conditions, high complexity | Prior knowledge of PUs needed |
| Energy detection | Simple, low computation cost | Affected by noise uncertainty, long detection time, cannot identify signal and noise | Does not require prior information of PUs |
| Feature detection | High detection precision, identifying signal and noise | High computation cost | Require cyclostationarity of PUs signal |
| Interference temperature | Does not require prior information of PUs | High implementation complexity | Large range and high power |

and user selection. Then we analyze and compare their performance in detail. The difficulties and challenges of CSS scheme also are addressed in CWSNs.

The rest of the paper is organized as follows. NCSS will be explored in Section 2. Section 3 introduces CSS schemes and provides comprehensive comparisons of various CSS methods in CWSNs. Finally, Section 4 summarizes the paper.

## 2. Noncooperative Spectrum Sensing

Based the behavior of cognitive sensor, CSS schemes are classified into two categories: noncooperative and cooperative. NCSS means cognitive sensor performing spectrum sensing alone, while cooperative CSS represents cognitive sensor exchange information with others to achieve common goals or their own interests.

On the basis of detection sensor, spectrum sensing can be divided into two categories, transmitter detection and receiver detection. Depending on different test standards, transmitter detection can be classified as matched filter detection [17] based on signal modulation schemes in primary users, pulse waveform, and so forth, energy detection based on the energy values of the primary users [18], cyclostationary feature detection [19], and covariance matrix detection [20]. The receiver detection can be divided into local oscillator leakage power detection [21] and interference temperature detection [22]. There are many existing spectrum sensing methods in CRNs. However there are only a few detection methods in CWSNs [23]. Four spectrum detection methods are suitable for CWSNs: energy detection [24]; matched filter [25]; feature detection [26]; and interference temperature [7, 27, 28]. Table 1 shows the advantages and disadvantages of these spectrum sensing methods and applicable scope.

Although NCSS has the advantages of low computation and easy implementation, it usually cannot make the right decision on the status of PU due to terrible communication environment. There are four defects in NCSS.

*(1) Hidden Node Problem.* Since most detection methods are based on transmitter, when the node is out of the transmission range of PU, it cannot detect the PU's signal, which will cause interference to PU' receiver, namely, the hidden node problem. An example of hidden node problem in NCSS is shown in Figure 2. $CR_0$ is outside the transmission range of PU transmitter (TX). When PU is transmitting packets, $CR_0$
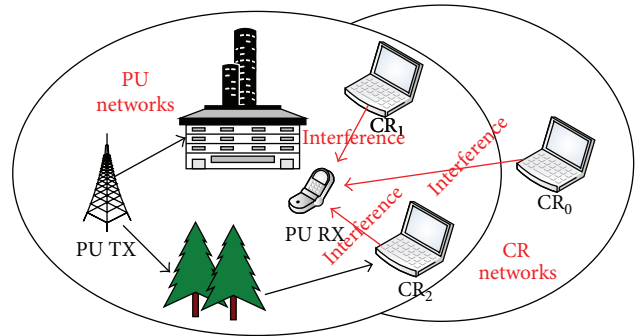


FIGURE 2: Hidden node problem in NCSS.

is not able to detect the PU' signal and will transmit its packet to PU receiver (RX), which will lead to collisions.

*(2) Shielding Effect.* As shown in Figure 2, $CR_1$ is in the transmission range of PU transmitter. Due to the shielding effect, it cannot detect any PU signal and mistakenly decides that PU is nonexistence. In fact, if $CR_1$ sends its packet to other nodes, it will affect the use of unlicensed spectrum.

*(3) Multipath Fading.* Multipath fading will lead the sensor to make incorrect decision on the existence of PU. For example, in Figure 2, $CR_2$ located in the transmission range of the PU TX, and it cannot decide the existence of PU based on the weakened signal received from PU TX through forest. $CR_2$ will transmit its data to PURX, and then it leads to the collision.

*(4) Unstable Wireless Communication.* Additionally, unstable wireless environment and stochastic noise are another factor, which will deteriorate channel performance and lead to interference to PU detection.

## 3. Cooperative Spectrum Sensing

*3.1. Censoring-Based CSS.* Censoring means to investigate whether the objects meet the predetermined criteria or not. If the conditions are satisfied, the objects will continue to perform one strategy. Otherwise, the other strategy will be implemented. In CSS, censoring can effectively reduce transmission of the unimportant or even wrong information, which not only saves energy consumption of sensors and
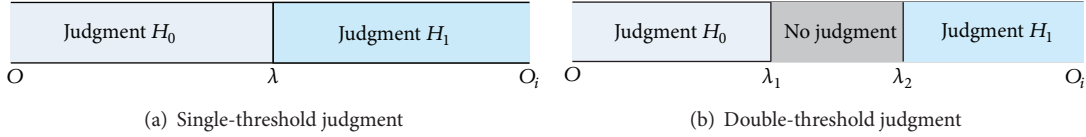
| Judgment $H_0$ | Judgment $H_1$ |
|:--:|:--:|

$O$ $\qquad\qquad\qquad\qquad$ $\lambda$ $\qquad\qquad\qquad\qquad$ $O_i$

(a) Single-threshold judgment

| Judgment $H_0$ | No judgment | Judgment $H_1$ |
|:--:|:--:|:--:|

$O$ $\qquad\qquad$ $\lambda_1$ $\qquad\qquad$ $\lambda_2$ $\qquad\qquad$ $O_i$

(b) Double-threshold judgment

FIGURE 3: Traditional decision and censoring judgment.

bandwidth, but also improves detection accuracy. In [29], the sensor's energy consumption of transmitting sensing data is far greater than that of spectrum sensing.

*3.1.1. Double-Threshold CSS.* The traditional judgment model and improved double-threshold censoring judgment model are shown in **Figure 3**. The former is generally based on the comparison of sensor data value with a predefined threshold, and sensors will report their sensing information to the FC regardless of results. In the improved judgment method, the double-threshold censoring requests sensors not to transmit their sensing information to the FC when the sensing data is within fuzzy region.

The schemes in [30–32] adopted double-threshold detection model to report sensing data in CSS and choose cognitive sensors of sensing data within the scope of the target area. And they will sent 1-bit information ("1" or "0") to FC making a decision on the status of PU in hard fusion, where "1" means PU exists and "0" represents that PU is absent. The scheme assumes the prior knowledge about the probability of PU presence $P_1$ and the probability of PU absence $P_0$ is available [30]. $\mu$ denotes the ratio of the number of cognitive sensors performing sensing to all cognitive sensors in CWSN. And $\lambda_1$ are $\lambda_2$ ($\lambda_1 < \lambda_2$) are the predefined thresholds. The former decides the amount of cognitive sensors performing sensing which only allows some sensors to participate in cooperation, and the latter determines the number of cognitive sensors reporting sensing results to FC. $\theta_i$ represents the spectrum sensing data of cognitive sensor $i$; the judgment is made about whether the sensor $i$ reports the sensing result to FC according to the following rule:

$$d_i = \begin{cases} 0 & 0 \leq \theta_i \leq \lambda_1 \\ N, & \lambda_1 \leq \theta_i \leq \lambda_2 \\ 1 & \theta_i \geq \lambda_2. \end{cases} \tag{1}$$

If $\theta_i$ is in $(0, \lambda_1)$, sensor determines that PU does not exist and will send "0" to the FC. If $\theta_i$ is greater than $\lambda_2$, the PU exists and "1" will be transmitted to the FC. Otherwise, it indicates that sensor $i$'s sensing data is not accurate. The scheme considers the energy consumption of spectrum sensing process in two parts: the sensing energy consumption in sensing phase and transmission energy in reporting phase. Sensing energy consumption includes detecting data and processing and energy consumption in making local decision. Transmission energy consumption includes energy consumption in receiving the decisions from selected sensors and reporting sensing result. Considering the power consumption of sensing data, detection, data processing, decision and data

transmission, an energy consumption objective function of $\mu$, $\lambda_1$, and $\lambda_2$ was formulated. With the constraints on minimum global detection probability and maximum global alarm probability, optimized $\mu$, $\lambda_1$, and $\lambda_2$ can be obtained with minimizing the objective function. The scheme can reduce energy consumption and bandwidth consumption compared with traditional double-threshold energy detection. However, the scheme requires the presence and absence probability of the PU to be known. Besides, the scheme does not provide the solution to the objective function and method to select the eligible sensors to participate in spectrum sensing.

An improved double-threshold energy detection method was proposed in [32], which considered two cases: (1) the prior knowledge about the PU presence is known; (2) the prior knowledge about the PU presence is unknown. A sleeping and censoring scheme was adopted in a distributed CSS to reduce energy consumption to improve detection performance of spectrum sensing. The Bayesian criterion was introduced in Case 1, while the Neyman-Pearson criterion was adopted in Case 2 to simplify the minimization energy consumption problem as searching optimal sleeping and censoring design parameters $\mu$, $\lambda_1$, and $\lambda_2$ to guarantee the network performance. In traditional double-threshold energy detection, only the sensors whose sensing data is outside $(\lambda_1, \lambda_2)$ can report their sensing data to FC. Although FC will not receive any information from the sensors whose sensing data is in the range of $(\lambda_1, \lambda_2)$, it will automatically consider that the PU is absent. However, the proposed solution is impractical. Firstly, it assumes all sensors are with the same SNR, so that all sensors have the same detection probability. In fact they are usually different because of the different distances between sensors and PU. Secondly, in order to obtain optimal sensing threshold, the computation is very high. Furthermore, the proposed model only considers the OR hard fusion rule.

*3.1.2. Credibility-Based CSS.* Credibility-based CSS model can identify sensors with some fault sensing information and select sensors with high confidence value based on sensors credibility. Sensing information will be discarded due to its poor credibility, while sensors with good credibility will be allowed to transfer their sensing data to FC. The scheme can not only reduce the energy consumption of a sensor but also improve the detection performance.

A novel CSS model was proposed to identify malicious sensors with fault sensing data based on the concept of the discrete value, bi-weight, and punishment factor of the cognitive sensors sensing data in the clustered CWSN [33]. The scheme described two kinds of functions in discrete values factor of sensors sensing data.

TABLE 2: Comparison of censoring-based CSS schemes.

| Ref. | Stability | Threshold | Relationship | Remark |
|------|-----------|-----------|--------------|--------|
| [30] | No | Dynamic | No | Based on double-threshold detection method |
| [32] | No | Dynamic | No | Sleeping and censoring algorithm |
| [33] | Yes | Dynamic | Yes | Identify malicious sensors |
| [34] | No | Dynamic | Yes | Voting method based on credibility |

*Case 1.* The discrete value factor $H_i$ of cognitive sensor sensing data is a function of the sensing data and mean and standard deviation of all sensors selected in CSS. The function is expressed as follows:

$$H_i = f(e_i, u, \sigma), \qquad (2)$$

where $e_i$ is sensing data, $\mu$ and $\sigma$ are mean and standard deviation of all sensors selected in cooperation, respectively. Since the mean and standard deviation are more vulnerable by malicious data, the scheme sets different weights to sensors based on the distance between their sensing data and mean of all sensing data. The farther the distance is, the smaller the weight is. And when the distance is greater than a predefined threshold, the weight value becomes zero.

*Case 2.* Defining discrete values factor $H_i$ of sensor sensing data is a function of sensor sensing data and mean and standard deviation of all sensors in cooperation based on biweight. The function is formulated as follows:

$$H_i = f(e_i, \hat{u}, \hat{\sigma}), \qquad (3)$$

where $\hat{\mu}$ are $\hat{\sigma}$ are the mean and standard deviation of all the cognitive sensors' sensing data including the sensing calculated based on the bi-weight. If $H_i$ is greater than the predefined threshold $H_t$, the sensing data is discarded; otherwise, the sensor will report its sensing data to cluster head deciding whether or not primary user signal exists. Let $M$ denote the maximum allowed number of malicious sensors in CWSN. If the number $M'$ of sensors sensing data is greater than $M$, it chooses to discard the front $M$ sensing data with the largest gap. The penalty factor is defined as a function of cognitive sensors on nodes sensing performance to determine whether the node is a malicious node, which is

$$F_i = (z, y), \qquad (4)$$

where $F_i$ is the penalty factor of cognitive node $i$, $z$ is the total number of detections, $y$ is the number of erroneous determinations of cognitive node $i$. When $F_i$ is greater than the predefined threshold, the node $i$ is identified as a malicious node and cluster head will discard its sensing data. This model requires the system to perform sensing according to the predefined strategy, which has better performance and can effectively reduce the probability of error detection.

In order to reduce the transmission times to achieve the goal of saving energy, a CSS method was proposed in multiple channels [34], which adopts a confidence voting algorithm. Only when the sensor is considered to have enough confidence, is it allowed to report its sensing data to the FC. The scheme considers CSS system with multiple PUs and $M$ cognitive sensors opportunistic using spectrum holes in $N$ channels. All sensors need to detect the primary signal $N_s$ times in each sensing period. When sensors detect that the channel is available, each sensor starts to transmit sensing data to the FC. After the sensing data is transferred successfully, the FC will transmit acknowledgment frame to all cognitive sensors. In the spectrum detection phase, all sensors will participate in the spectrum sensing, but only part of them will have the opportunity to transmit their sensing data to the FC. The average power consumption $\overline{E}$ of each sensor is expressed as follows [34]:

$$\overline{E} = \frac{\sum_{i=1}^{N_s} (M \times e_s + M_i \times e_t)}{M} = \sum_{i=1}^{N_s} \left( e_s + \frac{M_i}{M} \times e_t \right), \qquad (5)$$

where $M$ denotes the number of sensors in CWSN, $M_i$ represents the number of sensors allowed to report their sensing data to FC, $e_s$ is the sensing energy consumption for each sensor in each detection, and $e_t$ means the transmission energy consumption for each sensor in each detection.

The number of sensors selected to transmit their sensing data depends on their confidence. Only if the sensors' confidence is up to a certain threshold, they can have the right to report sensing result to FC under the constraints of minimum detection probability and maximum false alarm probability. The confidence of each sensor changes with their detection accuracy and the results of data transmission. Depending on FC final decision, the sensor detection result, and data transmission result, the scheme considers credibility calculations under six kinds of the circumstances. Confidence voting algorithm essentially is choosing better performance sensors after a period of study and training. However, the scheme needs all sensors to performing spectrum sensing in the sensing phrase, which will result in unnecessary energy consumption. And when the channel is busy, all nodes are going to sleep, which also leads to serious delays.

*3.1.3. Performance Comparison.* Table 2 shows two CSS models based on censoring in CWSNs from the aspects of stability, threshold, and the relationship between detection metric and detection accuracy.

As shown in Table 2, we can see that double-threshold detection will not consider the sensor detection accuracy. Therefore, the stability of the double-threshold model is poor, because malicious nodes easily use its detection feature to manipulate the final results in CSS, where the schemes [30, 32] adopted a CSS method based on double-threshold. And the credibility-based CSS will take cognitive sensors
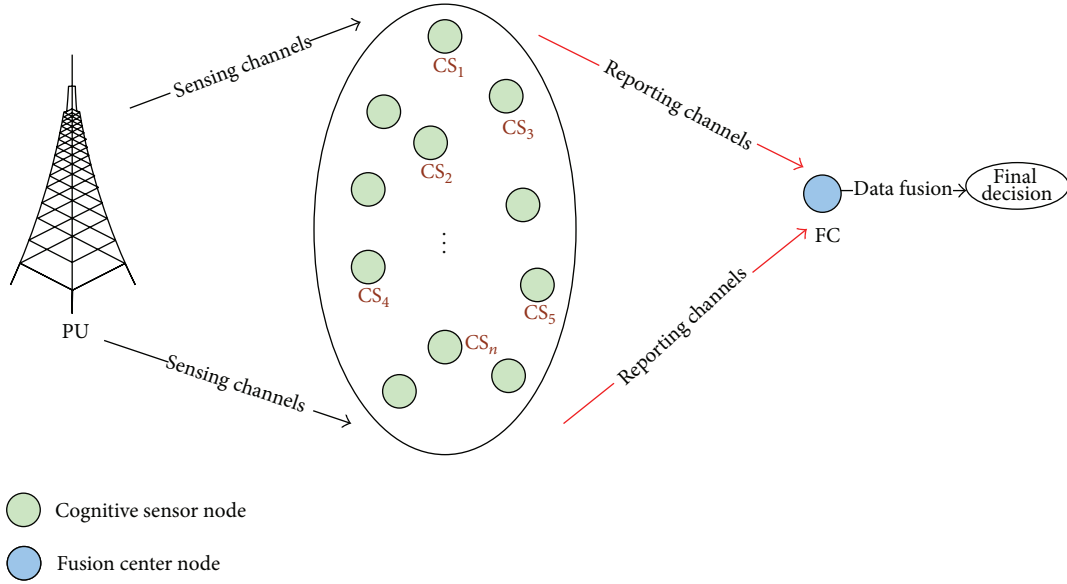
FIGURE 4: Generally CSS model.

detection accuracy into consideration, which can improve the stability of the spectrum sensing performance to some extent. However, due to different credibility criteria, not all credibility-based CSS algorithms can guarantee protecting spectrum sensing from influencing by malicious nodes. The detection accuracy was considered as a reference factor [34], but the proposed model is not able to achieve good performance when there are malicious nodes existing. Furthermore, the methods [30, 32–34], whether it used CSS based on double-threshold or adopted CSS based on credibility, should get an optimal threshold in each spectrum sensing period, which lead to relatively high computational complexity.

*3.2. Clustering-Based CSS.* A generally CSS model in CWSNs is shown in Figure 4, where all cognitive nodes detect the PUs' signal and then transmit their sensing data to the FC in transmission channels. FC comprehensive integrates received data from cognitive sensors making a final decision for the presence (or absence) of PUs and give feedback to each node.

With the number of nodes increasing, the system will face many problems, such as hidden terminal, congestion, and scarce frequency. Clustering means to assign all cognitive nodes into several sets according to the rules where each set has a cluster head, which can reduce the sensing overhead and improve detection performance. The cluster-based CSS model is shown in Figure 5.

And the clustering process is shown in Figure 6. Firstly, the cluster head node will be elected. Then the rest of the nodes are assigned into the corresponding clusters and the residual energy of the nodes is calculated. Finally, nodes will be selected to perform CSS [33].

A CSS method was proposed to improve detection performance and low energy consumption when environment deteriorates [35], which considers both clustering and finding the optimized number of sensors participating in sensing in each cluster. Low energy adaptive clustering algorithm

(LEACH) is used to assign the sensor to each cluster. LEACH clustering algorithm dynamically selects a different node as the cluster head, so that the energy consumption of each node is relatively uniform. With considering the sensor cluster head node energy consumption far greater than ordinary cognitive sensors, the scheme uses the method of election of cluster head node based on CR sensor nodes residual energy. The more residual energy of sensors, the greater the probability of sensor selected as cluster head. The probability $P_i(t)$ of sensor $i$ at the time $t$ is selected as cluster head node, which is expressed as follows [35]:

$$P_i(t) = \min\left\{\frac{E_i(t)}{E_{\text{total}}(t)} n_{\text{ch}}, 1\right\}, \tag{6}$$

where $E_i(t)$ denotes the residual energy of the sensor $i$ at time $t$, $E_{\text{total}}(t)$ is the total residual energy at time $t$, and $n_{\text{ch}}$ is the expected number of cluster nodes in CWSN. Each time selecting a cluster head node, sensors select a random number $a$ between 0 and 1. If $a$ is less than $P_i(t)$, the node is selected as the cluster head receiving the sensing data from other sensors in this cluster, judges the PU' presence, and reports its decision to link node. In fact, the detection performance will not be improved with the number of sensors increasing in cooperation. However the energy consumption will continue to increase with the amount of the sensors performing sensing increasing. Therefore, selecting the appropriate number of sensors participating in the collaboration is extremely important. With the consideration of balance between probability of detection and energy consumption, the benefit function of the number of sensors $k$ involved in collaboration within the cluster is defined as [35]:

$$\text{Benefit}(k) = P_d(k) - \alpha E_{\text{dissipation}}(k), \tag{7}$$
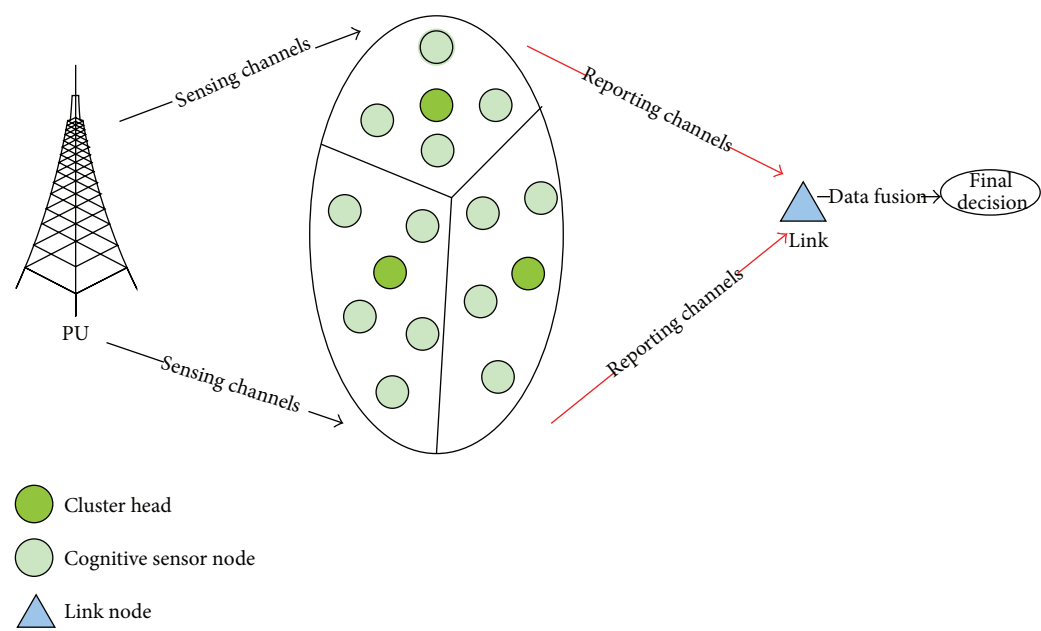
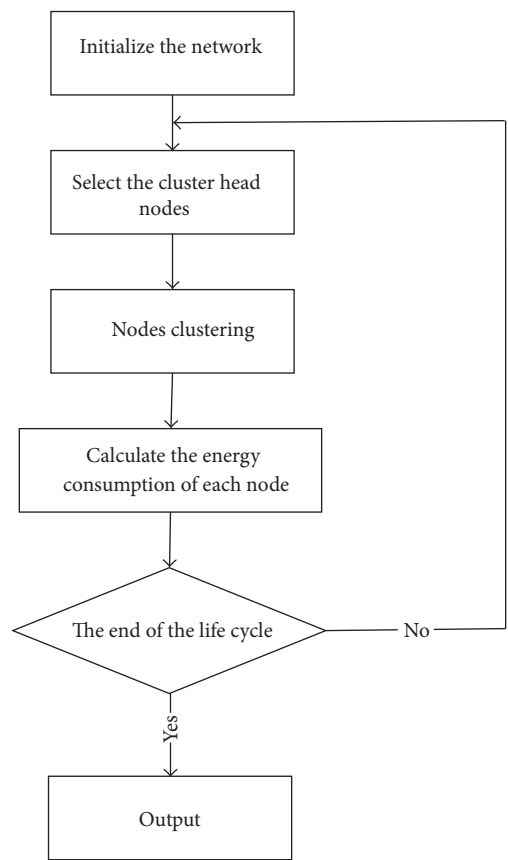FIGURE 5: Cluster-based CSS model.



FIGURE 6: Flow chart of clustering.

where $P_d(k)$ and $E_{\text{dissipation}}(k)$ are the detection probability and energy consumption for the number of sensors participating in the $k$th sensing, respectively. Then it specifically discussed the relationship between $P_d(k)$ and $E_{\text{dissipation}}(k)$ with $k$ within clusters. In order to optimize collaborative detection probability, the scheme allows sensors with a high SNR to participate in spectrum sensing. The scheme effectively reaches a trade-off between high detection performance and low energy consumption while it can effectively prolong the network lifetime.

The idea of clustering is also applied to reduce energy consumption and bandwidth [31]. Firstly, it obtains the minimum number of cognitive sensors to reduce the number of sensors for reducing energy consumption under the constraints of minimum detection probability and maximum false alarm probability. Simultaneously, a double-threshold detection scheme was adopted to reduce the amount of sensors reporting sensing data to cluster head node for minimizing network energy consumption. Finally, an improved clustering method was proposed to coordinate the sensors selection within each cluster for implementing energy balance between sensors and prolonging the network lifetime. The scheme assigns all sensors to different clusters depending on LEACH and chooses sensors with maximum residual energy as cluster head node in each cluster. Then it calculates the distance between cluster head node with all sensors within each cluster. These distances are sorted in descending order, where former $z$ sensors are not allowed to participate in sensing. And then $p$ sensors with largest residual energy from the remaining sensors will be selected to perform sensing. In the data transmission phrase, only $q$ sensors will be selected to report their sensing data to cluster head node after using double-threshold judgment, where the cluster head makes a comprehensive judgment on the received sensing data and reports final result to the link node. The scheme can reach a trade-off between node energy consumption and the network lifetime.

Differing from general clustering CSS, an event-driven clustering protocol CSS was proposed in CWSN [36]. Clustering occurs only when an event happens in CWSN, and clusters are no longer available after the end of the event. When an event occurs, the system will select eligible cognitive sensors performing sensing according to local position of sensors between event and sink. According to sensors selection algorithm, eligible sensors include the following: (1) they can detect the event effectively; (2) the nodes of eligible sensor's neighbors, and are closer to sink or event than the eligible sensor. A cluster-head first clustering protocol was adopted, and there are additional requirements to maximize the number of two-hop members who can reach the cluster head by one-hop members through the cluster channel. Clusters are not isolated between sink and event. Cognitive sensors report their neighbors by sending the EFC_REQ message that they have been selected to participate in spectrum sensing. Sensor receiving EFC_REQ message from its neighbors will inform its neighbors by sending EFC_REP message. Cluster heads send C_REQ message to the cluster members and receive C_REP messages from the cluster members to understand information of cluster members. The algorithm can effectively avoid unnecessary energy consumption caused by the clustering of information and maintenance clustering. However it will lead to delay due to clustering information.

### 3.3. User Selection-Based CSS.

In CSS, the detection probability and false alarm probability gradually increase with the number of sensing nodes increasing. A high detection probability means that, when PUs exist, the higher the possibility of the system is able to detect PUs' presence. A high alarm probability represents the higher possibility of the system finding the PU' absence, while PUs are absent in fact so that the spectrum utilization decreased. However, the increasing of detection probability almost becomes zero when the number of sensors in the cooperative sensing increases to a certain degree. The overhead caused by the increasing number of the sensors in cooperation still maintains a nearly linear growth. Hence how to choose the optimum cognitive sensors in cooperation, while the others are in sleeping mode, is a very critical part to save energy in CSS. There was the stabilizing number of sensors or the optimal number of sensors participating in spectrum sensing which can maximum the probability of average detection [37]. A dynamic power management (DPM) scheme was proposed [29], where sensor only turns on its radio when it is necessary; otherwise it switches off to save energy as far as possible. The sensor has five operating states: transmitting active state, receiving active state, sleeping, and closing and idle state. Obviously the power consumption of sensor node in sleeping mode is far less than when it is active [38].

CSS also is divided into active CSS and passive CSS. The main difference between them is whether the cognitive sensors are voluntary or mandatory to take part in spectrum sensing. Passive sensors will compare their income between collaborative and noncollaborative nodes; only when participating in collaboration brings more benefits than that in no collaboration, the sensors will take part in cooperative sensing.

### 3.3.1. Passive CSS.

Interactive decision of the cognitive sensors deciding to participate in CSS or local spectrum sensing (LSS) was considered according to their own interests as a noncooperative game [39]. All cognitive sensors eventually reach a stable state with game, namely, Nash equilibrium point. The benefit function was defined to represent income and expenses of the sensors performing CSS or LSS. Sensors obtain their income through transmission data in opportunistic occupying PUs' idle licensed spectrum and expense comes from the sensors performing spectrum sensing: the delay and energy consumption. There is a primary user occupying some licensed spectrum and $N$ selfish sensors. The sensors decide to participate in CSS or perform a separate LSS depending on the utility function at the beginning of each time slot. The utility function $U_i$ of cognitive sensor $i$ is

$$U_i = \alpha_i F_i(R_i) - \beta_i G_i(D_i) - \gamma_i H_i(E_i), \tag{8}$$

where $R_i$ represents the average data transmission rate of sensor $i$, $D_i$, and $E_i$ represent delay and power consumption, respectively, $F_i$ means the benefit obtained by data transmission, $H_i$ and $G_i$ represent the overhead caused due to delay $D_i$

and power consumption $E_i$, respectively, and $\alpha_i$, $\beta_i$, and $\gamma_i$ are the weight corresponding to them changing with the decision of sensors. With the constraint of PU interference probability meeting predefined threshold, the scheme considered two cases of noncooperative game based on the sensor node selection mechanism: (1) all sensors are similar with the same detection probability and same alarm probability in CWSN; (2) all sensors are with different detection probability and different alarm probability in CWSN. Compared with the model-based learning model, the scheme increases frequency spectrum utilization and decreases complexity. Although the method can maximize the benefits of the sensors and improve spectrum efficiency, all sensors are required to perform spectrum sensing, which will lead to energy consumption.

*3.3.2. Active CSS.* Existed active CSS mainly focuses on two facts: (1) how to select optimal number of cognitive sensors participating in cooperation; (2) how to select eligible cognitive sensors to perform cooperative sensing.

*(A) Optimal Number of Cognitive Sensors.* Two typical methods are used to obtain the optimal number of cognitive sensors $N^*$.

(1) Depending on constraints on the detection performance that is given by a minimum global detection probability and a maximum global alarm probability, the mathematical lower bound and upper bound of the number of cognitive sensors performing sensing are derived in

$$
Q_d \geq \alpha,
$$
$$
Q_f \leq \beta,
$$
(9)

$$
\begin{cases}
Q_d = 1 - \prod_{i=1}^{N} \left(1 - P_{d,i}\right), \\
\qquad\qquad\qquad\qquad\qquad \text{OR} \\
Q_f = 1 - \prod_{i=1}^{N} \left(1 - P_{f,i}\right),
\end{cases}
$$
(10)

$$
\begin{cases}
Q_d = 1 - \prod_{i=1}^{N} P_{d,i}, \\
\qquad\qquad\qquad\qquad \text{AND} \\
Q_f = 1 - \prod_{i=1}^{N} P_{f,i},
\end{cases}
$$

where $Q_d$ and $Q_f$ are the global detection probability and the global alarm probability, respectively, under the OR rule and the AND rule, where the former means that, as long as there is a cognitive sensor detecting PU presence, FC considers that PU exists; the latter represents that if and only if all the cognitive sensor nodes judge the presence of PU, then FC will determine that PU exists. $P_{d,i}$ and $P_{f,i}$ represent the detection probability and false alarm probability of the cognitive sensor $i$.

Taking energy consumption into account, the fewer cognitive sensors participating in spectrum sensing are, the less the total energy consumption will be. The scheme proposed in [40] selects the minimum number of cognitive sensors participating in collaborative sensing as the optimal

number of cognitive sensors performing spectrum sensing: $N^* = \lceil \min(N) \rceil$, where PU transmission channel model was explored as a two-state independent and uniformly distributed ON-OFF random process. And ON represents PU presence and OFF represents the fact that the primary user does not exist, respectively. Both states are distributed as exponential distribution, denoted by $T_{\text{on}}$ and $T_{\text{off}}$, and the probability of PU presence and the probability of PU absence are shown as follows:

$$
P_{\text{on}} = \frac{T_{\text{on}}}{T_{\text{on}} + T_{\text{off}}},
$$
$$
P_{\text{off}} = \frac{T_{\text{off}}}{T_{\text{on}} + T_{\text{off}}},
$$
$$
\widehat{P_{d_i}} = P_{\text{on}} P_{d_i},
$$
$$
\widehat{P_{f_i}} = P_{\text{off}} P_{f_i}.
$$
(11)

The lower bound and upper bound were obtained in each spectrum sensing with given detection probability threshold for the targeted goal to minimize the energy consumption. And the lower upper of the number of cognitive sensors in sensing is selected as the optimal number of sensors participating in CSS. The reason is that the fewer the sensors involved in CSS, the less energy consumption will be. However the scheme just got the optimal number of cognitive sensors participating in sensing, and it does not give a specific method for selecting these nodes. In addition, the proposed scheme suffers the poor performance under high noise and low SNR conditions.

(2) Under the constraints of global detection probability and global alarm probability, the optimal number of cognitive sensors selected to participate in CSS is obtained through solving the issues of minimizing energy consumption problem or maximizing system benefit:

$$
\min/\max_{\mu/k\cdots} O
$$
$$
\text{s.t.} \quad Q_d \geq \alpha, Q_f \leq \beta,
$$
(12)

where $\mu$ is the participating rate, that is, the ratio cognitive sensors participating in sensing of the cognitive sensors in CWSNs, and $k$ is the number of cognitive sensors performing the sensing; optimal $k^*$ was obtained by optimizing the benefit function making the system to obtain maximum benefit [35] and, at the same time, reducing network energy consumption as well as ensuring good enough detection performance. The scheme in [32] tried to address the problem for minimizing the total energy consumption to obtain the optimal $\mu^*$, so that the energy consumption in CSS reduces guaranteeing the detection performance of the system.

*(B) Eligible Cognitive Sensors.* The selection of eligible cognitive sensors includes two cases: (1) the number of cognitive sensors participating in CSS is known in each sensing;
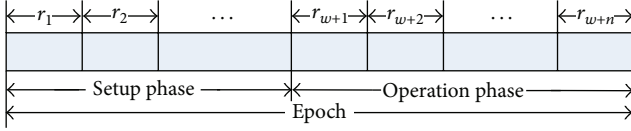
FIGURE 7: CSS process with two phases.

(2) the number of sensors performing CSS is uncertain in every sensing.

*(1) Known Number of Cognitive Sensors in CSS.* An energy-aware CSS scheme was proposed to select the eligible cognitive sensors, taking the detection accuracy and energy efficiency into account [41]. Firstly, the minimum number of cognitive sensors in sensing is inferred from optimization problems under constraints on meeting detection requirement. Then the probability-based approach is used to select the appropriate sensors to involve collaboration. Residual energy and detection accuracy of sensors are considered as the parameter factor in optimal user selection, which will avoid the fact that good sensors are selected in each sensing causing unbalanced energy consumption and guarantee sensors with good detection accuracy to be selected in each sensing. Detection accuracy is defined as the total number of differences between the sensor sensing decision and FC's final global decision. The scheme assumes PU does not know the performance of the cognitive sensors, and therefore the sensing process is divided into the setup phase and operation phase as shown in Figure 7.

In the setup phase, all sensors are required to participate in spectrum sensing. The weight of sensors based on residual energy and detection accuracy will be calculated after several spectrum sensing periods. Then a weight-based approach is used to select the most eligible sensors performing sensing in operation phase. The scheme in [35] selects the sensors with high SNR participating in sensing for the goal of maximizing global detection probability. In [31], the proposed scheme selects the sensors that have shorter distance between sensor and cluster head and have high residual energy conducting sensing when the number of sensors participating in sensing is known.

*(2) Unknown Number of Cognitive Sensors in CSS.* An energy-efficient CSS scheme based on sensor selection was proposed in [42], which allows some sensors to participate in sensing according to their correlation and SNR and allows the others to go to sleep. Let $D$ denote a distortion metric that shows the different contributions between two unrelated sensors and two sensors with correlation $\rho$; distortion metric $D$ represents the minimum mean square error (MMSE) error between the sufficient statistics of the above two cases, which can be calculated as

$$D = E\left[\left(l_{\text{uncor}} - l_{\text{cor}}\right)^2\right], \tag{13}$$

where $l_{\text{uncor}}$ represents the sufficient statistic of the two unrelated sensors and $l_{\text{cor}}$ represents the sufficient statistic of the two sensors with relation $\rho$. Since $l_{\text{uncor}}$ and $l_{\text{cor}}$ are functions of $r$ (SNR) and $\rho$, we can conclude that $D$ is also the function of $r$ and $\rho$. Each sensor's distortion metric is calculated when the SNR-relation pairs of sensors are known. If it is smaller than the predefined threshold, the sensor will be selected to conduct sensing; otherwise, the sensor will go to sleep. Considering high calculations each sensing for all sensors, the scheme will conduct predefined admittance regions called $S$, in which the sensors will perform sense when the SNR satisfies predefined value. In addition, since it is unrealistic to calculate the correlation coefficient $\rho$ of the sensing data detected by sensors in PU, $\rho$ is calculated using the actual sensor data that the sensors overhear from their neighbors, which is proved to be readily available. The scheme can reduce energy consumption and latency with good detection performance. However it does not provide relevant definitions and calculation methods for correlation coefficient $\rho$.

The on/off model was used in CSS to achieve the goal of reducing total energy consumption by selecting the sensors with less energy consumption in CSS and satisfying the conditions of the minimum global detection probability and the maximum global alarm probability [43]. Energy consumption in CSS includes two parts: (1) sensing energy consumption, including the detection data energy consumption and energy cost in the process of making sensors' local decision; (2) transmission energy consumption $C_t$, conducting in the process of the transmitting sensing decision from sensors to FC. Transmission energy consumption in CSS is proportional to the distance between sensors and FC. The scheme also assumes that all cognitive sensors in CWSN have same sensing energy consumption, denoted by $C_s$. $C_T$ is the total energy consumption in distributed spectrum sensing. $C_{ti}$ and $d_i$ represent the transmission energy consumption of the $i$th sensor and distance between sensor $i$ and FC, respectively. $M$ represents the number of sensors selected to participate in CSS. $\rho_i$ means whether sensor $\rho_i$ will be selected. If $\rho_i = 1$, the sensor will be selected to perform sensing. Otherwise, it will turn off. The total energy consumption $C_T$ is the function of $C_s$, $M$, $d_i$, and $\rho_i$:

$$C_T = f\left(M, C_s, d_i, \rho_i\right). \tag{14}$$

The scheme reduces the complexity of minimizing energy consumption by assuming $\rho_i$ as a continuous parameter ($\rho_i \in [0, 1]$). $C_T$ is simplified to a quadratic function through a convex optimization method under the Karush-Kuhn-Tucker (KKT) conditions. The cost function of the cognitive sensor $i$ has been further simplified as follows:

$$\cos t\,(i) = C_s + C_{ti} - \lambda P_{di}, \tag{15}$$

where $\lambda$ is the Lagrange factor and $P_{di}$ is the detection probability of sensor $i$. Finally, in order to find the optimal $\lambda$, an iteration bisection algorithm is used to solve the problem. The energy-efficient sensor selection (EESS) algorithm can save most energy.

Under the assumption that maximum allowable energy consumption is known in each spectrum sensing, sensor selection problem was addressed in CSS as familiar binary knapsack problem [37], which used dynamic programming to pick out the optimal sensors performing sensing under

TABLE 3: Summary of CSS based on sensor selection.

| Ref. | Number of cognitive sensors | | Metric of selection | | | Remark |
|---|---|---|---|---|---|---|
| | $A_1$ | $A_2$ | $B_1$ | $B_2$ | $B_3$ | |
| [30] | | √ | | — | | Sleeping-censoring algorithm based on double-threshold detection |
| [34] | — | | | — | | Voting based on credibility to reduce the number of sending nodes |
| [36] | — | | √ | | | Event-driven spectrum-aware clustering algorithm |
| [35] | | √ | | SNR | | Clustering model for achieving trade-off between high detection performance and low energy consumption |
| [31] | — | | √ | √ | | Double-threshold detection model based on clustered |
| [39] | — | | | — | | Cooperative between selfish cognitive sensors |
| [40] | √ | | | — | | Looking for the least cooperative sensing sensors |
| [41] | √ | | | √ | √ | Sensor selection under consideration of energy and detection accuracy |
| [43] | — | | Min set of energy | | | On/off model for optimizing sensor selection |
| [37] | — | | | √ | √ | Knapsack problem solving perceived node selection |
| [44] | — | | | √ | | Max-min method to maximize the network life |
| [42] | — | | Relationship | | | Selecting the low-relation sensors to perform sensing |
| [32] | | √ | | — | | Sleeping and censoring algorithm |

the constraints on networks performance. Optimal sensor selection was constructed as a biobjective knapsack problem, namely, maximizing performance and residual energy of selected sensors, as well as minimizing the total energy consumption, which is formulated as

$$\max \quad Q = \sum_{i=1}^{N} q_i x_i = \sum_{i=1}^{N} \left( \alpha_1 p_i + \alpha_2 U_i \right) x_i,$$

$$\min \quad E = \sum_{i=1}^{N} e_i x_i, \tag{16}$$

where $q_i$ is the utility function of cognitive sensor $i$. Coefficients $\alpha_1$ and $\alpha_2$ are constant whose sum is always equal to 1, and they can balance the spectrum sensing accuracy and the energy consumption by changing their value. If sensor $i$ is selected to participate in the spectrum sensing, then $x_i = 1$; otherwise $x_i = 0$. A window-based weighting scoring mechanism was adopted to calculate the sensing performance indicator. The score is calculated depending on whether the local sensing decision agrees with the global decision of FC after every sensing interval. If their decisions are consistent, the sensor gains one score but is zero otherwise. The sensing performance indicator of sensor $i$ after the $k$th sensing is formulated as follows:

$$p_i [k] = \sum_{i=1}^{n} \frac{1}{2^{i-1}} \text{score}_i [k - i + 1]. \tag{17}$$

Each sensor needs to calculate its sensing performance indicator and residual energy after every sensing interval and then transmits them to FC which is responsible for the energy consumption $e_i$ consumed by the selected sensors. The binary knapsack problem solutions can be effectively applied to optimize the sensor selection in CSS to minimize energy consumption. However, the scheme requires that maximum allowable energy consumption must be known in each spectrum sensing. Furthermore, the knapsack problem has a serious complexity which even is considered as an unsolvable problem. As the number of sensors in actual CWSNs is quite large, the application of the proposed solution is very limited.

Two CSS algorithms were proposed to maximize network lifetime in [44]. The first algorithm is max-min method or maximizing the minimum residual energy algorithm. The system will try to avoid choosing sensors with less residual energy to involve in sensing in each spectrum sensing. The less the energy consumption for sensor, the more the possibility that it is selected to perform sensing, which can achieve the balance between the sensors in the residual energy to prolong the lifetime of the network. The second algorithm is based on the weighted residual energy. The weight value of cognitive sensor is defined as the ratio between its initial energy and its residual energy before it is selected to perform sensing. Initial energy of all sensors is considered the same. The smaller the weight of remaining energy for sensor, which means that the energy consumption of the sensor is smaller, the more the probability that the sensor is involved in sensing in each selection. Since the sensor selection in CSS is known as a NP problem, in order to reduce the computational complexity, Lagrange algorithm is employed to solve the problem with convex optimization. In addition, considering the objective function in Lagrange problem with the characteristics of convex and differentiability, subgradient method was adopted to reduce computational complexity in finding Lagrange coefficients. The proposed two algorithms can effectively extend the network lifetime. However, the energy consumption is not minimized in these algorithms.

Sensor selection is one of the crucial parts in CSS, which not only affects the detection performance of CWSNs but also has a significant impact on energy cost. Table 3 shows the comparisons of CSS schemes mentioned above in CWSNs from the aspects of the number of sensors performing sensing

TABLE 4: A combination of CSS methods.

| Ref. | [37] | [44] | [40] | [43] | [30] | [32] | [24] | [33] | [34] | [35] | [31] | [36] | [39] | [42] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Censoring | | | | | √ | √ | | √ | √ | | √ | | | |
| Clustering | | | | | | | | √ | | √ | √ | √ | | |
| Nodes selection | √ | √ | √ | √ | √ | √ | √ | | | √ | √ | | √ | √ |

in CSS and sensor selection metrics, where $A_1$ and $A_2$ represent the methods of obtaining the optimal number of cognitive sensors: Cases 1 and 2, respectively. $B_1$, $B_2$, and $B_3$ denote metrics for choosing the most appropriate cognitive sensors, the distance, residual energy, and detection accuracy of sensors, respectively. "—" represents that the method has no relation with the item.

From the respective of the number of sensors involved in CSS, CSS can be divided into the minimum number of sensor for CSS and the optimal number of sensors for CSS, where the schemes in [40, 41] are based on the minimum number of sensors, and the methods in [30, 32, 35] are based on the optimal number of sensors, and the others do not consider the number of sensors in CSS.

From the respective of sensor selection metrics, CSS can be classified into distance-based CSS, residual energy based CSS, and detection accuracy based CSS and others. The scheme [44] selected eligible sensors depending on their remaining energy, and the method in [36] selected optimal sensors based on the distance between sensor and FC. However the schemes in [37, 41] used the selection method combining the detection accuracy and the residual energy and the method in [31] used a selection mechanism combining distance with the residual energy. The schemes of [35, 42, 43] optimized the CSS in CWSNs to obtain the eligible sensors participating in sensing, from the aspects of the relation of sensors' sensing data, the smallest subset of energy consumption, and SNR of the sensors.

*3.4. Hybrid CSS.* In order to get better performance, many hybrid CSS schemes were proposed in CWSNs (as shown in Table 4). An iterative on/off algorithm was employed to find the optimal Lagrange coefficient $\lambda$ [43], which updates $\lambda$ and selects the optimal sensors in iteration according to the cost function. However, as $\lambda$ decreases, the total energy consumption in the iteration may be more than energy consumption in the last iteration. The main reason is that the distance between sensors and FC has a greater impact on the transmission energy consumption.

Hence there may be some sensors relatively far away from FC selected to perform sensing. Based on the work in [43], an efficient hybrid CSS scheme was proposed to increase decision node to save more energy [24], which uses sleeping and censoring schemes to choose a sensor between selected sensors and FC to participate in CSS as a decision node, where all sensors involved in sensing are required to report their sensing decision to decision node that makes a global decision according to the selected sensors' local decision and transmits the final global decision to FC. The proposed scheme can shorten the distance between sensors and FC to reduce energy consumption and save bandwidth.

As shown in Table 4, most hybrid CSS schemes are based on the sensor selection, such as [24, 37, 39, 40, 42–44]. However, the method in [34] is based on the censoring and the work in [36] is based on the clustering. Meanwhile, the methods in [30, 32] used a combination of the censoring and sensor selection in CSS. A combination of censoring and clustering scheme was adopted in [33], and the combination of clustering and sensor selection method is used in [35]. The mechanism in [31] integrates three methods: clustering, censoring, and sensor selection.

*3.5. Performance Comparison.* CSS in CWSNs emphasizes on energy consumption due to the energy limitations of sensors, which includes the number of sensors participating in collaboration, the sensor involved in sensing, and sensing data transmission. The comparison of the CSS schemes in CWSNs are shown in Table 5, which considers the decision type, a priori knowledge about the probability of PUs existence (PKP), fairness of sensors selection, metric, participation and performance of sensors, common control channel, detection methods, and so forth. Where CNF denotes the nodes selection in censoring, accuracy indicates whether the sensor decision is consistent with the final decision made by FC, fairness means whether the nodes can be selected to perform spectrum sensing with equal probability, which makes a balance for the remaining energy of all sensors to prolong the network lifetime, "—" denotes the scheme does not consider the item, $P_1$ represents participation, and $P_2$ represents performance.

From the perspective of the decision type, CSS can be divided into centralized and distributed, where the schemes in [31, 33, 35] are distributed, and the others are centralized. Considering a priori knowledge on the probability of PUs, CSS can be classified into knowledge-aided CSS, blind-setup CSS and hybrid CSS, where the methods in [30, 33, 39] are based on knowledge-aided, the scheme in [30] is hybrid, and the others are based on blind-setup. The schemes in [31, 35, 37, 40, 44] consider the fairness, and methods of [34, 39] do not consider fairness due to all sensors involved in spectrum sensing. CSS also can be divided into accuracy-based CSS and nonaccuracy-based CSS, where the mechanisms of [34, 37] are based on the detection accuracy, and the others do not consider the detection accuracy.

Considering cognitive sensors participation, there are partial CSS and full CSS. For example, the schemes in [34, 39] are full CSS, and the others are partial CSS. CSS also can be divided into homogeneous CSS and heterogeneous CSS, where the schemes in [30–32] are the former; the method in [39] considers both cases, and the others are the latter. The existed CSS schemes almost adopt the energy detection

TABLE 5: Comparison of CSS schemes in CWSNs.

| Ref. | Decision | PKP | Fairness | CNF | CS Nodes | | CCC Requirements | PUs | Detection method |
|------|----------|-----|----------|-----|----------|----------|------------------|-----|------------------|
| | | | | | $P_1$ | $P_2$ | | | |
| [33] | Distributed | Known | Unfair | No | Partial | — | Yes | 1 | Energy |
| [39] | Centralized | Known | — | No | All | Both | Yes | 1 | Energy |
| [43] | Centralized | Unknown | Unfair | No | Partial | Different | Yes | 1 | Energy |
| [35] | Distributed | Unknown | Fair | No | Partial | Different | Yes | 1 | Energy |
| [30] | Centralized | Known | Unfair | No | Partial | Same | Yes | 1 | Energy |
| [34] | Centralized | Unknown | — | Yes | All | Different | Yes | 1 | Energy |
| [42] | Centralized | Unknown | Unfair | No | Partial | Different | Yes | 1 | Energy |
| [32] | Centralized | Both | Unfair | No | Partial | Same | Yes | 1 | Energy |
| [37] | Centralized | Unknown | Fair | Yes | Partial | Different | Yes | 1 | Energy |
| [40] | Centralized | Unknown | Fair | No | Partial | Different | Yes | 1 | Energy |
| [31] | Distributed | Unknown | Fair | No | Partial | Same | Yes | 1 | Energy |
| [44] | Centralized | Unknown | Fair | No | Partial | Different | Yes | 1 | Energy |

method which does not require a prior knowledge of the primary users and can be implemented simply in CWSNs.

## 4. Conclusions

Focusing on the sensors behavior and reducing energy consumption in spectrum sensing, the existing CSS schemes were classified, analyzed, and summarized comprehensively. An effective CSS can not only improve the detection performance to increase the utilization of spectrum and solving the problem of spectrum shortage but also significantly reduce the energy consumption to prolong the lifetime of energy-constrained CWSNs. Therefore designing a good CSS model is a promising and critical issue in CWSNs. There are many open issues that should be considered in the future work.

(1) *New spectrum detection technologies.* Considering low energy and low computing capacity in CWSNs, the conventional spectrum sensing methods depend on complex sensing strategy and consume more energy. New spectrum sensing methods are urgently needed to improve the detection accuracy and reduce sensing time and energy consumption in CWSNs.

(2) *Optimized CSS.* Optimization includes the number of CWSNs nodes, the node selection, node cooperative sensing results, and the overhead in cooperative sensing.

(3) *Control channel design.* Both WSNs and CWSNs use common control channel to achieve the sensing and management of the spectrum. Existed work usually assumes that channel is ideal. Therefore, how to design control channel on nonlicensed spectrum to successfully schedule control information exchange between SUs and FC and among SUs becomes one of the most challenging issues.

(4) *Mobile CWSNs.* Existing schemes basically assume that PUs and SUs are static. However the real users are often moving stochastically, where CSS problem becomes more complicated. Therefore, future research should pay more efforts on CSS in mobile CWSNs.

(5) *Multiple PUs.* Most schemes consider that there is one PU in CSS. While in practical system, multiple PUs will make CSS become more complex and difficult. Therefore, how to design a CSS model with multiple PUs is another considerable issue in CWSNs.

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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