Exploiting Secure and Energy-Efficient Collaborative Spectrum Sensing for Cognitive Radio Sensor Networks

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Abstract—Cognitive radio sensor network (CRSN) has emerged as a promising solution to address the spectrum scarcity problem in traditional sensor networks, by enabling sensor nodes to opportunistically access licensed spectrum. To protect the transmission of primary users and enhance spectrum utilization, collaborative spectrum sensing is generally adopted for improving spectrum sensing accuracy. However, as sensor nodes may be compromised by adversaries, these nodes can send false sensing reports to mislead the spectrum sensing decision, making CRSNs vulnerable to spectrum sensing data falsification (SSDF) attacks. Meanwhile, since the energy consumption of spectrum sensing is considerable for energy-limited sensor nodes, SSDF attack countermeasures should be carefully devised with the consideration of energy efficiency. To this end, we propose a secure and energy-efficient collaborative spectrum sensing scheme to resist SSDF attacks and enhance the energy efficiency in CRSNs. Specifically, we theoretically analyze the impacts of two types of attacks, i.e., independent and collaborative SSDF attacks, on the accuracy of collaborative spectrum sensing in a probabilistic way. To maximize the energy efficiency of spectrum sensing, we calculate the minimum number of sensor nodes needed for spectrum sensing to guarantee the desired accuracy of sensing results. Moreover, a trust evaluation scheme, named FastDtec, is developed to evaluate the spectrum sensing behaviors and fast identify compromised nodes. Finally, a secure and energy-efficient collaborative spectrum sensing scheme is proposed to further improve the energy efficiency of collaborative spectrum sensing, by adaptively isolating the identified compromised nodes from spectrum sensing. Extensive simulation results demonstrate that our proposed scheme can resist SSDF attacks and significantly improve the energy efficiency of collaborative spectrum sensing.

Index Terms—Spectrum sensing data falsification (SSDF) attack, Byzantine attacks, collaborative spectrum sensing, energy efficiency, security, trust evaluation.

I. INTRODUCTION

A S THE explosion of wireless devices and services make the unlicensed spectrum increasingly crowded, traditional sensor networks operating on the unlicensed spectrum may suffer from severe interference caused by the nearby applications working on the same spectrum band. This situation is getting worse with our proceeding to the Internet-of-Things era. An example could be a monitoring sensor network application in a crowded area, e.g., shopping mall, where battery-powered sensor nodes are deployed to sense temperature or human traffic data and send it to the control center through wireless systems, e.g., ZigBee. Since many overlapping wireless applications exist in the mall, such as WiFi, ad hoc networks, operating over the same 2.4 GHz ISM band as ZigBee, they can cause significant and uncontrollable interference to sensor nodes, which may greatly impact the performance of data collection. By applying cognitive radio technology into sensor network, cognitive radio sensor network (CRSN) has emerged as a promising solution to address the interference problem caused by spectrum-scarcity [1].

Sensor nodes in a CRSN can sense the availability of licensed channels and access the idle channels for data transmission. However, due to channel fading and shadowing, spectrum sensing by individual sensor node has inevitable sensing errors, which adversely impact the performance of both the CRSN and the primary users (PUs) of the licensed channels.

To overcome the limitation of individual spectrum sensing, collaborative spectrum sensing is generally employed in CRSNs to improve the spectrum sensing accuracy [2]. However, since sensor nodes may be compromised by adversaries, these nodes can send false sensing results, making CRSNs vulnerable to spectrum sensing data falsification (SSDF) attack [3], [4]. In SSDF attacks, compromised nodes may operate independently or collaboratively to mislead the channel availability decision, which can significantly reduce spectrum utilization and degrade overall network performance [5]. To resist SSDF attacks, a number of countermeasures,
including trust/reputation based approaches [6]–[9], abnormal statistical-behavior detection based approaches [10]–[14] and clustering based approaches [15], [16], have been proposed in cognitive radio networks (CRNs), which could be applied into CRSNs. However, few related works consider energy efficiency in SSDF attack countermeasure design [17], [18].

The energy consumption in spectrum sensing is considerable for energy-sensitive sensor nodes [19], [20], comparing to that for mobile devices in CRNs. Particularly, in a poor radio environment, sensor nodes have to use a long sensing duration to detect the availability of licensed channels (i.e., PU signals) [21], which consequently increases the energy consumption in spectrum sensing. When collaborative spectrum sensing is adopted, the energy consumption would linearly increase with the number of sensor nodes participating in spectrum sensing [22]. If the number of spectrum sensing nodes can be reduced, the energy efficiency of collaborative spectrum sensing could be greatly improved. On the other hand, the number of spectrum sensing nodes and associated decision rule have significant impacts on the security of collaborative spectrum sensing [8]. Therefore, it is critical to study the minimum number of sensor nodes and optimal decision rule to optimize the energy efficiency under a desired security requirement.

In addition, in the presence of compromised nodes, how to design an evaluation/detection scheme that can quickly identify the compromised nodes with high accuracy becomes another key issue for securing collaborative spectrum sensing. Generally, compromised nodes can be identified with a higher accuracy during a longer evaluation period, since the historical records can provide more evidence for identification. Thus, a trade-off could be achieved between the speed and accuracy of the compromised nodes identification. Meanwhile, by isolating the identified compromised nodes from spectrum sensing, the evaluation scheme can be further exploited to adaptively reduce the number of spectrum sensing nodes, and hence to improve the energy efficiency of collaborative spectrum sensing.

In this paper, we propose a secure and energy-efficient collaborative spectrum sensing scheme to resist SSDF attacks and enhance the energy efficiency in CRSNs. Specifically, we focus on two types of SSDF attacks, i.e., independent and collaborative SSDF attacks, and analyze their impacts on the accuracy of collaborative spectrum sensing in a probabilistic way. Under both types of SSDF attacks, we derive the relationships between energy efficiency and security, respectively. Moreover, we develop a trust evaluation scheme with asymmetric rewarding and punishing mechanism to distinguish the compromised nodes and honest nodes. With the trust evaluation, compromised nodes can be accurately identified and isolated from collaborative spectrum sensing. As a consequence, the required number of spectrum sensing nodes can be adaptively reduced to meet the desired security requirement, leading to a further improvement of the energy efficiency. In summary, the main contributions of this paper are three-fold.

• We theoretically analyze the trade-off between energy efficiency and security, and determine the minimum number of spectrum sensing nodes and associated decision rule for collaborative spectrum sensing to guarantee a certain level of spectrum sensing accuracy under two types of SSDF attacks.

• We develop a trust evaluation scheme, FastDtec, to evaluate the spectrum sensing behaviors and identify the compromised nodes. Furthermore, we determine the optimal detection threshold for FastDtec, which can accelerate the identification of compromised nodes and maintain the probability of identifying a honest node as compromised below a certain probability.

• By isolating the identified compromised nodes from spectrum sensing, a secure and energy-efficient collaborative spectrum sensing scheme is further proposed to adaptively reduce the required number of spectrum sensing nodes, and hence to improve the energy efficiency of collaborative spectrum sensing.

The remainder of this paper is organized as follows. Section II reviews related works and Section III introduces the system model and design goals. We analyze the attack impacts and the trade-off between security and energy efficiency in Section IV, and then propose the FastDtec scheme in Section V. The secure and energy-efficient collaborative spectrum sensing scheme is detailed in Section VI. Simulation results are provided in Section VII to evaluate the performance of the proposed schemes. Finally, Section VIII concludes the paper and outlines our future work.

II. RELATED WORKS

With the rapid development of cognitive radio technology, increasing attention has been paid to securing spectrum sensing against SSDF attacks [2]. Most of the countermeasures in CRNs can be effectively applied to CRSNs which are special types of CRNs. Therefore, we briefly review some existing countermeasures in CRNs by dividing them into three main categories: trust/reputation based approaches, abnormal statistical-behavior detection based approaches, and clustering based approaches.

Trust and reputation based approaches are the most widely studied techniques in the literature [6]–[9]. The main idea of these approaches is to update the trust values of spectrum sensing nodes according to their historical sensing behaviors, and design weighted decision making strategies to resist SSDF attacks based on the evaluated trust values. Qin et al. [6] propose a trust-based model and design a weighted sensing result aggregation scheme to remove attackers from the decision making process. In [8], Rawat et al. analyze the performance limits of collaborative spectrum sensing under independent and collaborative SSDF attacks, respectively, and then propose a simple reputation-based scheme to resist SSDF attacks. They prove that, by employing the theory of Kullback-Leibler divergence metric, a certain fraction of attackers can make collaborative spectrum sensing no better than random guess. Another category of promising countermeasures is to identify SSDF attackers by detecting their abnormal statistical spectrum sensing behaviors [10]–[14]. From this perspective, two hidden Markov models (HMMs), with respect to honest and malicious users, are adopted in [10] to characterize
their different sensing behaviors. Attackers are identified by the difference in the corresponding HMM parameters. He et al. [12] use two conditional frequency check statistics to identify SSDF attackers based on the Markovian model of spectrum state. In addition, several recent research works focus on securing the collaborative spectrum sensing based on clustering the cooperating sensors [15], [16], [23]. Hyder et al. [16] develop a reputation-based clustering algorithm to divide nodes into a number of virtual clusters based on their evaluated reputation values. A bi-level voting strategy, consisting of intra-cluster and inter-cluster decision voting, is then proposed to make the final decision. There are also some works resisting SSDF attacks by using consensus-based approaches [24]–[26], radio propagation characteristics [27], data cleansing approaches [28], and incentive-based mechanisms [29].

Despite their effectiveness in resisting SSDF attacks, most of existing works do not consider the energy efficiency of SSDF attack countermeasures [17], [18]. In a CRSN, sensor nodes have to consume considerable energy for collaborative spectrum sensing, which may degrade the energy efficiency of the network. However, if the unlicensed channel is facing significant interference when a CRSN starts to collect data, the performance of data collection would be hardly guaranteed by keeping working on the channel. It makes sensing and accessing a licensed channel as a necessary way to guarantee the network performance. Meanwhile, it also motivates us to carefully consider the energy efficiency in spectrum sensing and SSDF countermeasure design. Several recent works pay attention to the significance of energy efficiency in resisting SSDF attacks for CRNs. In [20], a low-overhead scheme is proposed for CRNs to address the always-1 SSDF attack under a trade-off between security and the energy efficiency of sensing report transmission. Recently, Mousavidar and Leung [18] develop a collaborative spectrum sensing scheme based on trust management to resist independent SSDF attacks in a CRN with a fixed number of compromised nodes and honest nodes. It is verified as effective to reduce the required sensing reports to achieve a targeted accuracy requirement. However, as more powerful SSDF attacks than independent SSDF attacks, collaborative SSDF attacks, where compromised nodes can collaboratively launch SSDF attacks, are not studied in both of the aforementioned works.

III. SYSTEM MODEL AND DESIGN GOALS

A. Network Model

Consider a CRSN application in a crowded area, where $S$ cognitive sensor nodes are deployed to periodically transmit the sensed data, e.g., temperature or traffic information, to a sink node (or access point). The network operation can be divided into a sequence of time periods. There are also a number of overlapping wireless systems in this area, such as WiFi and ad hoc networks, causing significant and uncontrollable interference over the unlicensed channel. To guarantee the performance of data transmission, the sink node coordinates sensor nodes to perform spectrum sensing over licensed channels and opportunistically access the idle ones for data transmission, when the unlicensed channel is suffering from significant interference. Since we aim to study the performance of spectrum sensing, we only focus on the time periods wherein spectrum sensing is required for licensed channel access. There are a number of orthogonal licensed channels owned by PUs in the primary network coexisting with the CRSN. At the beginning of each time period, a number of sensor nodes are randomly selected to sense the licensed channels and report their local binary decisions to the sink. Then, the sink makes global decisions based on the local reports and schedule sensor nodes to access the idle channels for data transmission.

We consider the radio environment in this area is poor, which causes that sensor nodes have to use a relatively long sensing duration to detect the availability of licensed channels (i.e., PU signals) within a required accuracy [21], [30]. It consequently increases the energy consumption for spectrum sensing. As all the sensor nodes are battery-powered, the energy-hungry spectrum sensing makes energy efficiency critical for the CRSN. Meanwhile, due to the lack of physical protection, sensor nodes may be compromised and manipulated by attackers to send false sensing results, with the purpose of misleading the global decisions. Wrong decisions can lead to interference with PUs or missing transmission opportunities, both of which may significantly degrade the performance of the CRSN. We consider the attacks to each channel sensing are homogeneous and independent [16], [17]. Such that, we can focus on securing the spectrum sensing over a specific licensed channel. To ease the presentation, the key notations are listed in Table I.

B. Channel Sensing Model and Decision Rule

Sensor nodes adopt a threshold-based energy detection approach for spectrum sensing [21], [31]. Due to channel fading and shadowing, there are unavoidable errors in individual channel sensing. We define conditional false alarm probability as the probability of an idle channel being detected as occupied, and conditional missed detection probability as the probability of an occupied channel being detected as idle. The two probabilities are predetermined and can be controlled by adjusting spectrum sensing parameters (e.g., sensing duration and energy detection threshold). For analysis simplification, we assume that all the sensor nodes have the same conditional false alarm probability $P_{cf}$ and conditional missed detection probability $P_{cm}$ [8], [16], which can be expressed as $P_{cf} = P(s_j = 1 | \not H_0)$, $P_{cm} = P(s_j = 0 | H_0)$, where $s_j$ is the local sensing result of node $j$; $\not H_0$ and $H_0$ represent the hypotheses that the licensed channel is idle and occupied, respectively. According to the PU’s temporal channel usage statistics, the probability of the channel being idle (i.e., $P(\not H_0)$) and the probability of the channel being occupied (i.e., $P(H_0)$) are $P_0$ and $P_1$.

To enhance the accuracy of sensing results, collaborative spectrum sensing is recommended to detect the availability of the licensed channel. Let $\mathcal{N} = \{1, \ldots, N\}$ be the set of spectrum sensing nodes that are selected to sense the licensed channel. At the beginning of each time period, each node $i \in \mathcal{N}$...
the global decision detects the PU presence independently and reports its binary decision report to the sink, i.e., $r_i = s_i$. The decision rule depends on $L$. For example, when $L = 1$, the decision rule is OR rule; when $L = N$, it refers to the AND rule; when $L = \lfloor N/2 \rfloor + 1$, it represents the Majority Voting rule. Since the decision rule directly impacts the accuracy of the global decision, the general rule is flexible to different system requirements. Note that, since compromised nodes may report false sensing results to the sink, $s_i$ and $r_i$ could be different when node $i$ is a compromised node. In addition, the CRSN (or the sink) can obtain the actual availability information of the licensed channel during a time period at the end of this time period [16], [18] (e.g., by communicating with the PU base station or monitoring the signal/interference over the licensed channel during the whole time period).

### C. Attack Model

A portion of sensor nodes may be compromised and manipulated to launch spectrum sensing data falsification (SSDF) attacks in the CRSN. In such attacks, compromised nodes can independently or collaboratively send false spectrum sensing results to mislead the global decision of collaborative spectrum sensing. Let $\alpha$ be the percentage of compromised sensor nodes in the CRSN. Here, we do not consider the case with $\alpha > 50\%$, because it is costly to maintain a network with a majority of nodes being attackers [16]. Let $K$ be the number of compromised nodes chosen for spectrum sensing, then we have $K \leq N$. For each honest node $i$, it reports the actual sensing result to the sink, i.e., $r_i = s_i$. Comparatively, the compromised sensor nodes can launch SSDF attacks to change their reports independently or collaboratively. Specifically, we present two types of SSDF attacks as follows.

1. **Independent SSDF (I-SSDF) Attack**: Independent SSDF attack refers to that each compromised node independently changes its sensing result with specific probabilities. For each compromised node $i$, we can define two attacking probabilities, $P_{a,0}$ and $P_{a,1}$, as

$$
P_{a,0}, P_{a,1} = \begin{cases} 
P(r_i = 1|s_i = 0) = P_{a,0}, & P(r_i = 0|s_i = 0) = 1 - P_{a,0}, \\
P(r_i = 0|s_i = 1) = P_{a,1}, & P(r_i = 1|s_i = 1) = 1 - P_{a,1}. 
\end{cases}
$$

We assume that each compromised node has the same attacking probabilities $P_{a,0}$ and $P_{a,1}$ [8], [16]. However, our analytical results can be extended to the case where compromised nodes have different probabilities. Given $P_{a,0}$ and $P_{a,1}$ for each compromised node $i$, the conditional false alarm probability $P_{cf}$ and missed detection probability $P_{cm}$ are

$$
P_{cf} = P(r_i = 1|s_i = 0)P(s_i = 1|\bar{s}_i) + P(r_i = 1|s_i = 0)P(s_i = 0|\bar{s}_i) = (1 - P_{a,1})P_{cf} + P_{a,0}(1 - P_{cf})
P_{cm} = P(r_i = 0|s_i = 0)P(s_i = 1|\bar{s}_i) + P(r_i = 0|s_i = 0)P(s_i = 0|\bar{s}_i) = (1 - P_{a,0})P_{cm} + P_{a,1}(1 - P_{cm})
$$

2. **Collaborative SSDF (C-SSDF) Attack**: In C-SSDF attack, compromised nodes can collaboratively send false sensing results to mislead the global decision, when they are selected for spectrum sensing. In specific, they can first exchange their sensing results and collaboratively make a consistent decision about the availability of the licensed channel. Then, the compromised nodes send reports opposite to the consistent decision to the sink. The consistent decision of compromised nodes is made by the majority voting rule [8], [16]. Let $R$ be the consistent decision and $P_{a,c}$ be the probability that compromised nodes collaboratively launch attacks. Once the compromised nodes decide to attack, they collaboratively decide $R$ and report $r_i = R$ to the sink.

### TABLE I

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sink. Otherwise, the compromised nodes will report the original sensing results \( r_i = s_i \) to the sink. Here, \( \bar{R} \) is the opposite of \( R \). Therefore, for each compromised node \( i \), the conditional false alarm probability \( P_{cf} \) consists of two parts. The first is the conditional false alarm probability of node \( i \), when the compromised nodes do not launch C-SSDF attacks. That is \( P_{cf}(1 - P_{a,c}) \). The second part is the conditional false alarm probability of node \( i \), when the compromised nodes launch C-SSDF attacks. In such case, \( P_{cf}(1 - P_{a,c}) \). The total energy consumption of spectrum sensing would still linearly increase with the number of spectrum sensing nodes, which indicates the energy efficiency can be significantly enhanced by reducing \( N \) [20], [32].

E. Design Goals

The first objective is to defend collaborative spectrum sensing against SSDF attacks. Since SSDF attacks aim to mislead the global decision \( D \) made by the sink, the security level of resisting SSDF attacks can be measured by the accuracy of \( D \). Specifically, we define the false alarm probability (FAP) \( P_F = P(\bar{D} = 1|\bar{H}_0) \cdot P(\bar{H}_0) \) and the missed detection probability (MDP) \( P_M = P(D = 0|H_1) \cdot P(H_1) \) as security level indicators. Let \( \delta_F \) and \( \delta_M \) be the required security levels, then we should guarantee

\[
\begin{cases}
P_F = P(\bar{D} = 1|\bar{H}_0) \cdot P_0 \leq \delta_F \\
P_M = P(D = 0|H_1) \cdot P_1 \leq \delta_M
\end{cases}
\]

The second objective is to optimize the energy efficiency of collaborative spectrum sensing under the security requirements. According to the decision rule, the number of spectrum sensing nodes \( N \) and the value of \( L \) can remarkably impact the global decision accuracy, i.e., \( P_F \) and \( P_M \). On the other hand, the energy consumption model indicates that the energy efficiency can be improved by reducing the number of spectrum sensing nodes. Therefore, for a given \( a \), we aim to determine \( N_{min}^I \) and \( N_{min}^C \), which denote the minimum number of spectrum sensor nodes to resist I-SSDF and C-SSDF attacks respectively, as well as appropriate \( L_I \) and \( L_C \) denoting the corresponding decision rules, to satisfy the security requirement, i.e., Eq. (5).

Moreover, we aim to evaluate the spectrum sensing behaviors and identify the compromised nodes by developing a trust evaluation scheme. The trust evaluation scheme should be able to identify the compromised nodes with a high speed and accuracy. In addition, how to utilize the trust evaluation scheme to further reduce the number of required spectrum sensing nodes should be investigated for improving the energy efficiency of collaborative spectrum sensing.

IV. ANALYSIS ON ATTACK IMPACT AND TRADE-OFF BETWEEN SECURITY AND ENERGY EFFICIENCY

In this section, we study the impact of SSDF attacks on the global decision accuracy and propose an algorithm to determine the minimum \( N_{min}^I \), \( N_{min}^C \), and appropriate \( L_I \), \( L_C \), to satisfy the desired security requirements.

A. Detection Accuracy Analysis Under SSDF Attacks

We first analyze the global detection accuracy under the two types of SSDF attacks, respectively. The analysis and corresponding results are presented by the following lemmas and propositions.
Lemma 1: Given $K$, $N$ and $L$, the FAP $P_{F,K}^I$ and MDP $P_{M,K}^I$ under 1-SSDF attacks are

$$
P_{F,K}^I = \left( \sum_{i=0}^{N-K} P(X = i|\gamma_i) \sum_{j=L-i}^{K} Q(K, j, P_{cf}^I) \right) P_0^I,
$$

$$
P_{M,K}^I = \left( \sum_{i=0}^{N-K} Q(N - K, i, P_{cm}) \sum_{j=N-L-i+1}^{K} Q(K, j, P_{cm}^I) \right) P_1^I,
$$

(6)

where we define that $\sum_{i=a}^{b} Q(b, i, p) = 1$, if $a \leq 0$; and $\sum_{i=a}^{b} Q(b, i, p) = 0$, if $a > b$.

Proof: We first calculate the false alarm probability. Let $X$ be the number of honest nodes reporting channel being occupied (i.e., $r_i = 1$), and $Y$ be the number of compromised nodes reporting channel being occupied. Therefore, we have $P_{F,K}^I = P(X + Y \geq L|\gamma_i) \cdot P(\gamma_i)$. Since all the honest nodes and the compromised nodes are independent, $X$ should follow a binomial distribution $X \sim B(N - K, P_{cf})$, while $Y$ follows a binomial distribution $Y \sim B(K, P_{cf})$. Then, we have

$$
P_{F,K}^I = P(X + Y \geq L|\gamma_i) \cdot P(\gamma_i)
$$

$$
= \left( \sum_{i=0}^{N-K} P(X = i|\gamma_i) \sum_{j=L-i}^{K} P(Y = j|\gamma_i) \right) P_0^I
$$

$$
= \left( \sum_{i=0}^{N-K} Q(N - K, i, P_{cf}) \sum_{j=N-L-i+1}^{K} Q(K, j, P_{cf}^I) \right) P_0^I.
$$

To ensure the equation suitable for different $K$ and $L$, we define that $\sum_{i=a}^{b} Q(b, i, p) = 1$, if $a \leq 0$; and $\sum_{i=a}^{b} Q(b, i, p) = 0$, if $a > b$. Similarly, we can calculate $P_{M,K}^I$ as shown in Eq. (6), which completes the proof.

Lemma 2: Given $K$, $N$ and $L$, the FAP $P_{F,K}^C$ and MDP $P_{M,K}^C$ under C-SSDF attacks are

$$
P_{F,K}^C = \left( \sum_{i=0}^{N-K} Q(N - K, i, P_{cf}^C) \sum_{j=L-i}^{K} P(Y = j|\gamma_i) \right) P_0^C
$$

$$
P_{M,K}^C = \left( \sum_{i=0}^{N-K} Q(N - K, i, P_{cm}) \sum_{j=N-L-i+1}^{K} P(Z = j|\gamma_i) \right) P_1^C
$$

(7)

where $P(Y = j|\gamma_i)$ can be obtained by Eq. (8) and $P(Z = j|\gamma_i)$ can be obtained by the equation replacing $P_{cf}$ in Eq. (8) with $P_{cm}$.

Proof: We prove this lemma with the procedures similar to Lemma 1. Denote $X$ and $Y$ as the number of honest nodes and compromised nodes that report channel being occupied, respectively. Under C-SSDF attacks, $X$ still follows a binomial distribution $X \sim B(N - K, P_{cf})$ but the distribution of $Y$ changes. If compromised nodes do not launch attacks, $Y$ follows a binomial distribution $Y \sim B(K, P_{cf})$, where $0 \leq Y \leq K$; otherwise, $Y$ can only be 0 (i.e., when $R = 1$) or $K$ (i.e., when $R = 0$). Therefore, we discuss the probability distribution of $Y$ under $\gamma_i$ from the following three cases.

(1) $Y = 0$. This case can be further divided into two cases. One is when no C-SSDF attack happens in spectrum sensing, we have $P(Y = 0|\gamma_i) = Q(K, 0, P_{cf})$. The other is when C-SSDF attack happens, there should be at least $M$ compromised nodes with $s_i = 1$. In such case, we have $P(Y = 0|\gamma_i) = \sum_{z=M}^{K} Q(K, z, P_{cf})$. Thus, according to the law of total probability, we have $P(Y = 0|\gamma_i) = (1 - P_{a,c}) Q(K, 0, P_{cf}) + \sum_{z=M}^{K} Q(K, z, P_{cf}) P_{a,c}$.

(2) $1 \leq Y \leq K$. It only happens under the condition of no C-SSDF attack in spectrum sensing. We can calculate the probability distribution as $P(Y = j|\gamma_i) = Q(K, 0, P_{cf})$, $0 \leq j < K$.

(3) $Y = K$. This case can also be further divided into two cases. According to the analysis in (1), we have

$$
P(Y = K|\gamma_i) = (1 - P_{a,c}) Q(K, K, P_{cf}) + \sum_{z=M}^{K} Q(K, z, 1 - P_{cf}) P_{a,c}.
$$

In summary, we can write the probability distribution of $Y$ under $\gamma_i$ as

$$
P(Y = j|\gamma_i) = \begin{cases} (1 - P_{a,c}) Q(K, 0, P_{cf}) \\ + \sum_{z=M}^{K} Q(K, z, P_{cf}) P_{a,c}, & \text{if } j = 0; \\ (1 - P_{a,c}) Q(K, j, P_{cf}), & \text{if } 1 \leq j < K; \\ (1 - P_{a,c}) Q(K, K, P_{cf}) \\ + \sum_{z=M}^{K} Q(K, z, 1 - P_{cf}) P_{a,c}, & \text{if } j = K. 
\end{cases}
$$

(8)

Since $X$ and $Y$ are two independent variables, $P_{F,K}^C$ can be calculated as

$$
P_{F,K}^C = P(X + Y \geq L|\gamma_i) \cdot P(\gamma_i)
$$

$$
= \left[ P(X = 0, Y \geq L|\gamma_i) + \ldots + P(X = N - K, Y \geq L - N + K|\gamma_i) \right] \cdot P(\gamma_i)
$$

$$
= \left[ P(X = 0|\gamma_i) P(Y \geq L|\gamma_i) + \ldots \right.
$$

$$
+ P(X = N - K|\gamma_i) P(Y \geq L - N + K|\gamma_i) \right] \cdot P(\gamma_i)
$$

$$
= \sum_{i=0}^{N-K} \left( Q(N - K, i, P_{cf}) \sum_{j=L-i}^{K} P(Y = j|\gamma_i) \right) P_0^C,
$$

where $P(Y = j|\gamma_i)$ can be obtained by Eq. (8). Accordingly, $P_{M,K}^C$ can be calculated in the same way, which completes the proof.
With Lemma 1 and 2, we can calculate the security levels under two types of SSDF attacks with given $K$, $N$ and $L$. However, $K$ is a random variable following a binomial distribution $K \sim (N, \alpha)$. The following proposition analyzes the FAP and MDP under given $\alpha$.

**Proposition 1**: Given $\alpha$, if $N$ sensor nodes are randomly selected for spectrum sensing, the FAP $P_F$ and MDP $P_M$ under I-SSDF attacks are

$$P_F = \frac{N}{K'} \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \beta^{N-K'},$$

$$P_M = \frac{N}{K'} \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \gamma^{N-K'},$$

while the FAP $P_F^C$ and MDP $P_M^C$ under C-SSDF attacks are

$$P_F^C = \frac{N}{K'} \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \eta^{N-K'},$$

$$P_M^C = \frac{N}{K'} \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \zeta^{N-K'},$$

**Proof**: Since $N$ sensor nodes are randomly selected for spectrum sensing, the probability that $K'$ out of $N$ sensor nodes are compromised is $Q(N, K', \alpha)$. As a result, the FAP $P_F$ and MDP $P_M$ under I-SSDF attacks are $P_F = \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \beta^{N-K'}$ and $P_M = \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \gamma^{N-K'}$. Similarly, the FAP $P_F^C$ and MDP $P_M^C$ under C-SSDF attacks can be derived as Eq. (10).

**B. Trade-Off Between Security and Energy Efficiency**

Based on the analysis in the previous subsection, we can see that $N$ and $L$ directly determine the security level, and the corresponding relationship is presented by Eq. (9) and (10).

Fig. 1 and 2 show the FAPs and MDPs under different $N$ and $L$, where the percentage of compromised nodes is $\alpha = 20\%$, $P_0 = 90\%$, $P_1 = 10\%$, $P_{cf} = P_{cm} = 20\%$, $P_{a,0} = P_{a,1} = P_{a,c} = 80\%$ and $S = 20$. From these figures, it can be seen that the number of spectrum sensing nodes $N$ and the decision rule $L$ can significantly impact the security levels, under both types of attacks. When $L = \lfloor N/2 \rfloor + 1$, the increasing $N$ leads to decreasing FAP and MDP under both types of SSDF attacks. However, MDP increases with the increasing $N$ when $L = N$. This is because MDPs can be calculated as $P_M = \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \beta^{N-K'}$ and $P_M^C = \sum_{K'=0}^{N} \binom{N}{K'} \alpha^{K'} \gamma^{N-K'}$. Moreover, for a fixed $N$, different decision rules (i.e., different values of $L$) can bring different security levels. Specifically, a larger $L$ produces lower FAPs but higher MDPs under both types of SSDF attacks.

Since we aim to optimize the energy efficiency under a fixed security level, the problem can be formulated as an integer programming problem. Given $\alpha$, $\delta_F$ and $\delta_M$, to resist I-SSDF attacks, we aim to determine the minimum $N_{\text{min}}^l$ and $L^l$ to satisfy

$$P_F \leq \delta_F, \quad P_M^C \leq \delta_M, \quad 1 \leq N_{\text{min}}^l \leq S, \quad 1 \leq L^l \leq N,$$

while to resist C-SSDF attacks, it changes to determine the minimum $N_{\text{min}}^C$ and $L^C$ to satisfy

$$P_F^C \leq \delta_F, \quad P_M^C \leq \delta_M, \quad 1 \leq N_{\text{min}}^C \leq S, \quad 1 \leq L^C \leq N.$$

Obviously, the searching space of the above integer programming problems is $(1+S)S/2$. It means that brute-force algorithm can be adopted to find the optimal solutions with computation complexity $O(S^2)$. The main idea is to search each pair of $N$ and $L$ to find the minimum $N_{\text{min}}$ and $N_{\text{min}}^C$, as well as the corresponding $L^l$ and $L^C$, for satisfy Eq. (11) and (12), respectively.

**V. FastDtec: Trust Evaluation for Fast Compromised Node Detection**

In this section, we develop a trust evaluation scheme, named FastDtec, to evaluate the periodic spectrum sensing behaviors and fast identify the compromised nodes.

**A. Trust Evaluation Design**

According to the system model, the CRSN can obtain the actual availability of the licensed channel during each time period. As a result, the actual information, denoted by a binary variable $\sigma$, can be used to evaluate the behaviors of spectrum
sensing nodes at the end of this time period. To this end, we propose FastDtec to evaluate the reported sensing results of spectrum sensing nodes by dynamically updating their trust values. Specifically, in FastDtec, the sink maintains a trust table to record the trust values of sensor nodes, and updates the trust table at the end of each time period according to the reported sensing results. For each spectrum sensing node \(i \in \mathcal{N}_f\), if \(r_i = \sigma\), node \(i\) should be rewarded a trust increment; otherwise, it should face a trust punishment. When the trust value of a sensor node decreases below a certain threshold, this node would be identified as a compromised node by FastDtec.

In order to reduce the trust values of compromised nodes and identify them in a small number of evaluation periods, the punishment should be defined heavy enough. However, since honest nodes may be punished with a certain probability due to the imperfect spectrum sensing, a large punishment could make the trust values of honest nodes drop quickly. Therefore, the evaluated trust score should be carefully determined to protect the honest nodes and punish the compromised nodes. Let \(P_e\) be the sensing error probability of node \(i\) in spectrum sensing. Then,

\[
\begin{align*}
    P_e &= P_e^H = P_{e_0} + P_{cm} P_1, & \text{if } i \text{ is honest}; \\
    P_e &= P_e^C = P_{e_0} + P_{cm} P_1, & \text{if } i \text{ is I-SSDF attacker}.
\end{align*}
\]

When node \(i\) is a C-SSDF attacker,

\[
P_e = P_e^C = \sum_{k=0}^{N} Q\left(N, k, a\right) \cdot \left( P_{e_0}^C P_0 + P_{cm}^C P_1 \right).
\]

Based on Eq. (13) and (14), FastDtec evaluates a trust score \(v_i\) for a spectrum sensing node \(i\), which is defined as

\[
v_i = \begin{cases} 
1, & \text{if } r_i = \sigma; \\
-\left(1 - P_e^H\right)/P_e^H, & \text{if } r_i \neq \sigma.
\end{cases}
\]

Here, we use a unit score as the reward and a well-chosen punishment for a correct and a wrong spectrum sensing result, respectively. The asymmetrical trust evaluation can keep the trust value of a honest node stable but efficiently reduce the trust value of a compromised node \([18]\), which can be proved by the following Lemma 3. Meanwhile, FastDtec updates the trust table based on the evaluated trust score as follows

\[
V_i = \min\{\max\{V_i + v_i, V_{min}\}, V_{max}\},
\]

where \(V_{min}\) and \(V_{max}\) are the minimum and maximum trust values in FastDtec, respectively.

Let \(V_0\) be the initial trust value of sensor nodes. The expected trust values of a honest node and a compromised node can be obtained according to Lemma 3.

**Lemma 3:** In FastDtec, if node \(i\) is selected for spectrum sensing \(T\) times, its expected trust value \(E(V_i)\) is

\[
E(V_i) = \begin{cases} 
V_0, & \text{if } i \text{ is honest}; \\
V_0 - \frac{P_e^I - P_e^H}{P_e^H} \cdot T, & \text{if } i \text{ is I-SSDF attacker}; \\
V_0 - \frac{P_e^C - P_e^H}{P_e^H} \cdot T, & \text{if } i \text{ is C-SSDF attacker}.
\end{cases}
\]

**Proof:** Let \(X\) be the number of the wrong sensing reports of node \(i\). Since each spectrum sensing is independent for node \(i\), \(X\) is a random variable following a binomial distribution as \(X \sim B(T, P_e)\), where \(P_e\) is the sensing error probability of node \(i\) shown in Eq. (13) and (14). Therefore, the expected trust value of node \(i\) after \(T\) times of trust evaluation is

\[
E(V_i) = V_0 + T \cdot E(X) - E(X) \cdot \frac{1 - P_e^H}{P_e^H} = V_0 + \frac{P_e - P_e^H}{P_e^H} \cdot T.
\]

By substituting \(P_e\) according to Eq. (13) and (14), the lemma can be proved.

Note that, to reduce the decision accuracy of collaborative spectrum sensing, a compromised node should have a larger sensing error probability than a honest node, i.e., \(P_e^I > P_e^H\) and \(P_e^C > P_e^H\). It also indicates that FastDtec can keep the trust values of honest nodes stable but decrease the trust values of compromised nodes linearly with the spectrum sensing times.

**B. Optimal Detection Threshold for Compromised Node Identification**

To identify the compromised nodes, FastDtec defines a detection threshold for the trust values of sensor nodes. Once the trust value of a sensor node is below the detection threshold, the node is identified as compromised. Intuitively, if the threshold is defined as a large value (close to \(V_0\)), the compromised nodes can be identified quickly. However, a large threshold may increase the probability of detecting a honest node as compromised at the same time. Therefore, there exists a trade-off between the detection speed and accuracy in compromised node identification. In this subsection, we determine the optimal detection threshold for FastDtec to accelerate the identification of compromised nodes while keeping the detection accuracy at a controllable level.

Let \(\xi\) be the detection threshold of FastDtec. Lemma 4 provides the probability of a honest node being identified as compromised based on \(\xi\).

**Lemma 4:** Given \(\xi\), if node \(i\) is honest and chosen for spectrum sensing \(T\) times, the probability that node \(i\) is identified as compromised by FastDtec is

\[
FP(\xi, T) = \sum_{k=\lceil T(\xi) \rceil}^{T} Q(T, k, P_e^H),
\]

where \(f(\xi, T)\) is

\[
f(\xi, T) = P_e^H \cdot (V_0 + T - \xi).
\]

**Proof:** Let \(X\) be the number of the wrong sensing reports of node \(i\), then we have \(X \sim B(T, P_e^H)\). After \(T\) times of spectrum sensing, node \(i\)’s trust value is \(V_i = V_0 + (T - X) - X \cdot \frac{1 - P_e^H}{P_e^H}\). If node \(i\) is identified as compromised, it means \(V_i \leq \xi\). Substituting \(V_i\), we have \(X \geq P_e^H \cdot (V_0 + T - \xi)\). Since \(X \sim B(T, P_e^H)\), the probability that
node $i$ is identified as compromised is $FP(ξ, T) = P[X ≥ f(ξ, T)] = \sum_{k=\lceil f(ξ, T) \rceil}^{T} Q(T, k, P_e^H)$, where $f(ξ, T) = P_e^H \cdot (V_0 + T - ξ)$.

To guarantee the detection accuracy of FastDtec, we introduce an accuracy requirement $ϕ (0 < ϕ < 1)$, which requires $FP(ξ, T) ≤ ϕ$. Therefore, the optimal detection threshold $ξ^*$ that can be used to identify compromised nodes quickly should be the maximum value satisfying $FP(ξ^*, T) ≤ ϕ$ for each $T \in \{1, \ldots, +\infty\}$. It also indicates that the optimal threshold $ξ^*$ varies with the value of $T$. We use $ξ^*(T)$ to denote the optimal threshold for given $T$, then $ξ^*(T)$ should adaptively change with the increment of $T$.

Unfortunately, according to Eq. (19), there is no closed-form expression that can describe the relationship between $ξ^*(T)$ and $T$.

To determine $ξ^*(T)$, we first introduce a numerical procedure, which can be applied to the case when $T$ is bounded as a relatively small value. Let $X$ be a binomial random variable to denote the number of wrong sensing reports, then $X ≈ B(T, P_e^H)$. To meet the detection accuracy requirement, we have $P(X ≥ f(ξ^*(T), T)) ≤ ϕ$, where $f(ξ^*(T), T)$ is shown in Eq. (20). For given $T$, $f(ξ, T)$ is a linearly decreasing function with respect to $ξ$, which means the minimum $f(ξ, T)$ corresponding to the optimal $ξ^*(T)$. Actually, the minimum $f(ξ, T)$ to satisfy $P(X ≤ f(ξ, T)) ≥ 1 - ϕ$ is known as the upper tolerance limit for the binomial distribution $B(T, P_e^H)$ with tolerance requirement $1 - ϕ$ [33], [34]. The upper tolerance limit can be derived as follows. We first compute right-tail probabilities $P(X = k), P(X = T - 1), \ldots$, until the sum of these probabilities is greater than or equal to $ϕ$. If this happens at $X = T - l$, that is, $\sum_{k=T-l}^{T} P(X = k) ≥ ϕ$ and $\sum_{k=T-l+1}^{T} P(X = k) < ϕ$, then $T - l$ is the required upper tolerance limit. Let $f(ξ^*(T), T) = T - l$ and substitute $f(ξ^*(T), T)$ according to Eq. (20), we have $ξ^*(T) = V_0 + T - l - \frac{l}{P_e^H}$. On the other hand, if there is no such upper tolerance limit that can make $P(X ≤ f(ξ^*(T))) ≥ 1 - ϕ$, it can be claimed that $T$ is not large enough for compromised node identification. We use $T_{min}$ to denote the minimum $T$ that can make $P(X = T) = (P_e^H)^T ≤ ϕ$. Due to $P_e^H < 1$, we have $T ≥ log_{P_e^H} ϕ$. Thus,

$$T_{min} = log_{P_e^H} ϕ = log_{2} ϕ / log_{2} P_e^H. \quad (21)$$

Only if $T ≥ T_{min}$, we could find an upper tolerance limit and the optimal $ξ^*(T)$, which can be derived by the numerical procedure.

The above numerical procedure can determine $ξ^*(T)$ for given $T$, however, it is not applicable and efficient when $T$ is large enough, due to the high computation complexity of combinatorial number. We use $T_{sw}$ to denote the value of $T$ which makes a sensor node unable to afford the computation burden of the numerical procedure. To determine $ξ^*(T)$ for $T > T_{sw}$, Proposition 2 provides an approximation solution.

Proposition 2: To guarantee that the probability of a honest node being identified as compromised by FastDtec is no larger than $ϕ$, the approximate optimal detection threshold $ξ^*(T)$, when $T_{sw} < T ≤ T_{max}$, is

$$\begin{cases}
ξ^*(T) \approx V_0 - \frac{z_{1-ϕ}\sqrt{T \cdot (1 - P_e^H)}}{P_e^H}, \\
T_{max} = \left(\left(\frac{V_0 - V_{min}}{\phi}\right)^2 \cdot \frac{P_e^H}{1 - P_e^H}\right).
\end{cases} \quad (22)$$

where $z_{1-ϕ}$ is $1 - ϕ$ quantile of standard normal distribution, $V_{min}$ is the minimum trust value.

Proof: Let $X$ be the number of wrong sensing reports with $X \sim B(T, P_e^H)$. When $T ≥ 20$, the binomial distribution $B(T, P_e^H)$ can be approximated as a normal distribution [33], [34], i.e., $X \sim N(T \cdot P_e^H, T \cdot P_e^H(1 - P_e^H))$. On the basis of the normal approximation to the quantity $X - T \cdot P_e^H$,

the $1 - ϕ$ quantile of $B(T, P_e^H)$, denoted by $L(T, P_e^H, 1 - ϕ)$, is given as

$$L(T, P_e^H, 1 - ϕ) ≈ T \cdot P_e^H + z_{1-ϕ} \sqrt{T \cdot P_e^H(1 - P_e^H)}, \quad (23)$$

where $z_{1-ϕ}$ is the $1 - ϕ$ quantile of the standard normal distribution. To guarantee $P(X ≥ f(ξ^*(T))) ≤ ϕ$, we have $f(ξ^*(T)) ≈ LL(T, P_e^H, 1 - ϕ)$. Thus, $f(ξ^*(T), T) = L(T, P_e^H, 1 - ϕ)$. By substituting $f(ξ^*(T), T)$ according to Eq. (20), we have the optimal $ξ^*(T)$ for given $T$ is

$$ξ^*(T) ≈ V_0 - \frac{z_{1-ϕ}\sqrt{T \cdot P_e^H(1 - P_e^H)}}{P_e^H}. \quad \boxed{}$$

Noting that, $ϕ$ is usually a small value, such as 5%, $z_{1-ϕ}$ is a positive value. Therefore, $ξ^*(T)$ is a decreasing function with respect to $T$, which indicates that the optimal threshold $ξ^*(T)$ decrease with the increasing $T$. Since $V_{min}$ is the minimum trust value, we can calculate the maximum $T$, denoted by $T_{max}$, which can make $ξ^*(T)$ below $V_{min}$. Let $ξ^*(T) ≤ V_{min}$, we have $T_{max} = \left(\left(\frac{V_0 - V_{min}}{ϕ}\right)^2 \cdot \frac{P_e^H}{1 - P_e^H}\right)$.

According to Proposition 2, we can adaptively determine the optimal detection threshold $ξ^*(T)$ for FastDtec when $T_{sw} < T ≤ T_{max}$. We define $T_{max}$ as a trust evaluation cycle of FastDtec. When node $i$ is selected for spectrum sensing $T_{max} + 1$ times, we consider it is the first evaluation period of a new evaluation cycle, and reset its trust value to $V_0$. It indicates that a compromised node would be missed by FastDtec if it can keep its trust value large than $V_{min}$ after $T_{max}$ times of spectrum sensing. Lemma 5 analyzes the probability that a compromised node is not identified by FastDtec within a trust evaluation cycle.

Lemma 5: Given the required false identification probability $ϕ$, the missed identification probability of FastDtec is $MD(ϕ) = min\{MD(ϕ, T_{min}), \ldots, MD(ϕ, T_{max})\}$, where $MD(ϕ, T)$ is given as $MD(ϕ, T) = \sum_{k=\lceil f(ξ^*(T), T) \rceil}^{T} Q(T, k, P_e^H)$. $T_{min}$ and $T_{max}$ are in Eq. (21) and (22), and $P_e^H = P_e^l$ or $P_e^C$ according to Eq. (13) and (14) under I-SSDF or C-SSDF attacks, respectively.

Proof: We first focus on calculating the missed identification probability of FastDtec for given $T$. Let $X$ be the number of wrong sensing reports with $X \sim B(T, P_e^H)$.
Algorithm 1 The Procedures of FastDtec

**Input:** The parameters related to FastDtec, such as \( V_0, V_{\min}, V_{\max} \) and \( \phi \).

1: \( T_i \leftarrow 0 \) for each node \( i \in S, CM \leftarrow \emptyset \);
2: for each spectrum sensing node \( i \in \mathcal{N} \) do
3: \( T_i \leftarrow T_i + 1 \);
4: Evaluate a trust score and update its trust value table according to Eq. (15) and (16), respectively;
5: if \( T_{\min} \leq T_i \leq T_{\max} \) then
6: Determine the optimal detection threshold \( \xi^*(T) \) according to the numerical procedure;
7: else if \( T_{\max} < T_i \leq T_{\max} \) then
8: Determine the optimal detection threshold \( \xi^*(T) \) according to Proposition 2;
9: end if
10: if \( V_i \leq \xi^*(T) \) then
11: \( CM \leftarrow CM + \{i\} \);
12: end if
13: if \( T_i \geq T_{\max} \&\& i \notin CM \) then
14: \( T_i = 0, V_i = 0 \);
15: end if
16: end for

If a compromised node is missed by FastDtec, it means
\[ V_0 + (T - X) - X(1 - \frac{1 - P^H}{P_e}) \geq \xi^*(T). \]
Thus, we have that \( X \leq f(\xi^*(T), T) \) and the corresponding probability is \( MD(\phi, T) = P(X \leq f(\xi^*(T), T)) = \sum_{k=f(\xi^*(T),T)}^{} Q(T, k, P_e). \)

If a compromised node is missed by FastDtec, it means that the node is not identified by FastDtec at any \( T \in \{T_{\min}, \ldots, T_{\max}\} \). Thus, we have that the missed identification probability of FastDtec is \( MD(\phi) = \min(MD(T_{\min}), \ldots, MD(T), \ldots, MD(T_{\max})) \).

C. The Proposed FastDtec Scheme

Based on the preceding analysis, FastDtec can utilize asymmetric evaluation to stabilize the trust values of honest nodes and linearly reduce the trust values of compromised nodes. Moreover, an adaptive detection threshold is dynamically derived for FastDtec to accelerate the identification of compromised nodes while keeping the false identification probability below a specific requirement. We summarize the main ideas of FastDtec in Algorithm 1.

VI. SECURE AND ENERGY-EFFICIENT COLLABORATIVE SPECTRUM SENSING FOR CRSNs

In this section, we propose a secure and energy-efficient collaborative spectrum sensing scheme for CRSNs, which can utilize FastDtec to accurately identify the compromised nodes and adaptively reduce the number of spectrum sensing nodes for further enhancing energy efficiency.

A. The Proposed Scheme

Based on our analysis, FastDtec can fast and accurately identify the compromised nodes launching SSDF attacks in CRSNs. If we isolate the identified compromised nodes from collaborative spectrum sensing, we can adaptively reduce the number of spectrum sensing nodes, i.e., \( N \), to further improve the energy efficiency of collaborative spectrum sensing in CRSNs.

For example, after \( M \) sensor nodes are identified as compromised nodes, the probability of selecting a compromised node into spectrum sensing changes to \( \alpha' = \frac{aS - M}{S - M} \). Obviously, we have \( \alpha' < \alpha \). According to Proposition 1, the reduced \( \alpha' \) means the decreased false alarm probabilities \( P^F_F \), \( P^C_F \) and missed detection probabilities \( P^F_M \), \( P^C_M \) under fixed \( L \) and \( N \), which also indicates that reduced \( N^F_M \) and \( N^C_M \) could be derived to guarantee the required \( \delta_F \) and \( \delta_M \). Therefore, once there is a sensor node identified as compromised by FastDtec, we can re-determine the optimal number of spectrum sensing nodes. The main idea of the proposed secure and energy-efficient collaborative spectrum sensing scheme is illustrated in Fig. 3, and the detailed procedures are summarized in Algorithm 2.

B. Further Discussion

In the proposed scheme, all the spectrum sensing nodes are randomly selected from the sensor nodes without being blacklisted. Meanwhile, the reports from the spectrum sensing nodes have the same weights for the global decision making. A number of existing works have done in-depth investigation to leverage the evaluated trust values in spectrum sensing node selection and global decision making. It can also be applied into the proposed scheme to improve the accuracy of global decision making. For example, we can allocate higher priority to the sensor nodes with higher trust values when selecting the spectrum sensing nodes. However, the energy consumption balancing issue should be further studied to keep the sensor nodes with high trust values from exhausting their energy quickly. Moreover, when the sink fuses local decisions to make a global decision, the reports from the sensor nodes with higher trust values can be allocated with higher weights for decision making. The related techniques
Algorithm 2 The Proposed Secure and Energy-Efficient Collaborative Spectrum Sensing Scheme

**Input:** The percentage of compromised nodes $\alpha$, the required security levels $\delta_F$ and $\delta_M$, the set of sensor nodes $S$, $V_0$, $V_{min}$, $V_{max}$ and other parameters.

1: $\mathcal{SN} \leftarrow S, \alpha' \leftarrow \alpha, \mathcal{CM} \leftarrow \emptyset$;
2: $V_i \leftarrow V_0$ for each $i \in S$;
3: for each time period $t$ from 1 to $+\infty$ do
4:     at the beginning of time period $t$ :
5:     determine $N_{\min}^I$, $L^I$, $N_{\min}^C$ and $L^C$ with $\alpha'$, $\delta_F$ and $\delta_M$ by addressing Eq. (11) and (12);
6:     under I-SSDF and C-SSDF attack scenarios, randomly select $N_{\min}^I$ and $N_{\min}^C$ sensor nodes from $\mathcal{SN}$ with $L^I$ and $L^C$ for spectrum sensing, respectively;
7:     at the end of time period $t$ :
8:     update the trust values of spectrum sensing nodes according to Algorithm 1;
9:     if there exists node $i \in \mathcal{SN}$ with $V_i \leq \zeta^*$ then
10:        $\mathcal{SN} \leftarrow \mathcal{SN} - \{i\}, \mathcal{CM} \leftarrow \mathcal{CM} + \{i\};$
11:     $\alpha' \leftarrow \frac{|\mathcal{SN}|}{|\mathcal{CM}|}$;
12:     end if
13: end for

and analysis can be referred to [7], [16], and [18]. In [18], it is proved that the weighted decision making based on evaluated trust values has positive impacts on reducing the number of sensing reports. However, when weighted decision making is adopted, the designed SSDF countermeasure should be capable of resisting promotion attacks, where compromised nodes can collaboratively promote the trust values of several compromised nodes to mislead the decision making. In this work, we provide a probabilistic analysis for securing collaborative spectrum sensing, from the energy efficiency perspective. The proposed secure and energy-efficient collaborative spectrum sensing scheme can guarantee a desired security requirement and maximize the energy efficiency simultaneously. To the best of our knowledge, this is the first work to investigate the energy efficiency optimization for collaborative spectrum sensing under a desired security requirement in a probabilistic way.

**VII. Performance Evaluation**

In this section, we validate our theoretical analysis and evaluate the performance of our proposed schemes by OMNET++ [35], [36]. We setup a CRSN with $|S| = 200$ sensor nodes and a sink node. The network process is divided into a sequence of time periods. At the beginning of each time period, the sink randomly chooses a number of sensor nodes to sense a licensed channel. The idle and busy probabilities of the licensed channel are $P_0 = 90\%$ and $P_1 = 10\%$, respectively. The parameters for individual spectrum sensing are set as $P_{cf} = 20\%$ and $P_{cm} = 20\%$. The percentage of compromised nodes in the CRSN is $\alpha = 20\%$, if it is not specified in the simulation figures. The desired missed detection probability and false alarm probability of collaborative spectrum sensing are set as $\delta_M = 1\%$ and $\delta_F = 5\%$, respectively. For the settings of FastDtec, we have $V_0 = 200$, $V_{min} = 0$ and $V_{max} = 255$. The requirement of the false identification probability of FastDtec is $\phi = 2.5\%$, and $T_{sw} = 20$.

A. Attack Impacts on Collaborative Spectrum Sensing

In this subsection, we first evaluate the impacts of I-SSDF and C-SSDF attacks on the accuracy of collaborative spectrum sensing. Then, we show the trade-off between security and energy efficiency determined by addressing Eq. (11) and (12).

Fig. 4 shows the accuracy of global decision by collaborative spectrum sensing under different percentages of SSDF attackers (i.e., compromised nodes). The accuracy of global decision is defined as $P(\varnothing = 1|\varnothing) + P(\varnothing = 0|\varnothing)$. 20 sensor nodes are involved in the collaborative spectrum sensing and the decision rule is “majority” rule, which mean $N = 20$ and $L = 11$. The individual sensing refers to that only one sensor node is selected for sensing the licensed channel. It can be seen from the figure that the accuracy of global decision is significantly reduced with the increasing percentage of compromised nodes. The collaborative spectrum sensing under C-SSDF attacks has a lower accuracy than that under I-SSDF attacks. Moreover, when the percentage of compromised nodes exceeds 39%, the global decision accuracy of collaborative spectrum sensing under C-SSDF attacks is below 50%. It means that collaborative spectrum sensing is no better than random guess for a network with more than 39% compromised nodes to launch C-SSDF attacks. A similar conclusion can be found in [8] and [16]. In addition, under C-SSDF attacks, individual sensing is more accurate than collaborative spectrum sensing when the percentage of compromised nodes is larger than 37%. Fig. 5 compares the required number of spectrum sensing nodes to guarantee desired security levels (i.e., $\delta_F$ and $\delta_M$) under different percentages of compromised nodes. It is shown that the required number of spectrum sensing nodes increases sharply with increasing compromised nodes, especially for resisting C-SSDF attacks.

B. Trust Evaluation and Compromised Node Identification by FastDtec

In this subsection, we evaluate the performance of the proposed FastDtec scheme, in terms of the speed and accuracy of compromised node identification.
Fig. 5. Required number of spectrum sensing nodes to guarantee a desired security level.

Fig. 6. Expected trust values of compromised nodes under different attacking probabilities.

Fig. 7. Comparison of determined detection threshold and optimal detection threshold.

Fig. 8. Comparison of determined detection threshold and optimal detection threshold.

Fig. 9. Comparison of determined detection threshold and optimal detection threshold.

Fig. 10. Comparison of determined detection threshold and optimal detection threshold.

Fig. 11. Comparison of determined detection threshold and optimal detection threshold.

The above figures illustrate the effectiveness of FastDtec in compromised node identification. The proposed scheme is shown to outperform existing methods in terms of both accuracy and speed of identification.

When $T$ is fixed, the number of times of participating spectrum sensing increases, the missed identification probability of FastDtec reduces significantly. Additionally, the identification accuracy increases with the attacking probability of compromised nodes and both FastDtec and CatchIt can achieve a high identification accuracy under different attacking probabilities. FastDtec has a faster identification speed than CatchIt. The comparison results of the two figures also demonstrate that by guaranteeing the identification accuracy and optimizing the identification speed, FastDtec can significantly improve the performance of.
C. Performance of Secure and Energy Efficient Collaborative Spectrum Sensing Scheme

In this subsection, we evaluate the performance of the proposed secure and energy-efficient collaborative spectrum sensing scheme. Since the proposed collaborative spectrum sensing scheme can guarantee the desired accuracy requirements by Eq. (11) and (12), we mainly focus on evaluating the energy efficiency enhancement. As the energy consumption of collaborative spectrum sensing is high and increases linearly with the number of spectrum sensing nodes, we use the required number of sensor nodes that can guarantee the accuracy requirements to evaluate the energy efficiency. Fig. 12 shows the required numbers of spectrum sensing nodes during different time periods. It can be seen that the number of required spectrum sensing nodes is significantly reduced with the increasing time period, under both types of SSDF attacks. And the number of spectrum sensing nodes decreases earlier
and faster under C-SSDF attacks, as the compromised nodes with C-SSDF attacks are identified faster by the proposed scheme.

VIII. CONCLUSION

In this paper, we have investigated the secure collaborative spectrum sensing for CRSNs, from the energy efficiency perspective. We theoretically analyze the impacts of independent and collaborative SSDF attacks on the accuracy of collaborative spectrum sensing. Our analysis and simulations show that the number of spectrum sensing nodes and associated global decision rule have significant impacts on the accuracy of collaborative sensing results. To achieve the trade-off between security and energy efficiency, we determine the minimum number of spectrum sensing nodes to guarantee desired security requirements. Moreover, we have developed a trust evaluation scheme, named FastDect, to evaluate the spectrum sensing behaviors and identify the compromised nodes. By determining an adaptive and optimal detection threshold, FastDect can fast and accurately identify compromised nodes. In addition, taking advantage of FastDect to isolate the identified compromised nodes from spectrum sensing, we have proposed a secure and energy-efficient collaborative spectrum sensing scheme to further enhance the energy efficiency of collaborative spectrum sensing. Extensive simulation results demonstrate that the proposed collaborative spectrum sensing scheme can effectively resist SSDF attacks, and fast and accurately identify compromised nodes, as well as improving energy efficiency. For our future work, we will extend our research to a more general network scenario, where the CRSN has no prior knowledge about the compromising probability of the network and the percentage of compromised node may increase time to time. Thus, we will design a scheme that can estimate the compromising probability based on historical records and adaptively adjust its defending strategy with the belief to the estimated results.

REFERENCES

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