Hindawi
Wireless Communications and Mobile Computing
Volume 2020, Article ID 2509081, 10 pages
https://doi.org/10.1155/2020/2509081

Research Article

A Genetic Algorithm-Based Soft Decision Fusion Scheme in Cognitive IoT Networks with Malicious Users

Muhammad Sajjad Khan,[1,2] **Noor Gul**,[3] **Junsu Kim**,[1] **Ijaz Mansoor Qureshi**,[4] **and Su Min Kim**[1]

[1]*Department of Electronics Engineering, Korea Polytechnic University, Siheung, Republic of Korea*
[2]*Department of Electrical Engineering, International Islamic University Islamabad, Islamabad, Pakistan*
[3]*Department of Electronics, University of Peshawar, Peshawar, Pakistan*
[4]*Department of Electrical Engineering, Air University, Islamabad, Pakistan*

Correspondence should be addressed to Su Min Kim; suminkim@kpu.ac.kr

Received 4 November 2019; Accepted 30 December 2019; Published 31 January 2020

Guest Editor: Hasan Ali Khattak

Internet of Things (IoT) is a new challenging paradigm for connecting a variety of heterogeneous networks. Since its introduction, many researchers have been studying how to efficiently exploit and manage spectrum resource for IoT applications. An explosive increase in the number of IoT devices accelerates towards the future-connected society but yields a high system complexity. Cognitive radio (CR) technology is also a promising candidate for future wireless communications. CR via dynamic spectrum access provides opportunities to secondary users (SUs) to access licensed spectrum bands without interfering primary users by performing spectrum sensing before accessing available spectrum bands. However, multipath effects can degrade the sensing capability of an individual SU. Therefore, for more precise sensing, it is helpful to exploit multiple collaborative sensing users. The main problem in cooperative spectrum sensing is the presence of inaccurate sensing information received from the multipath-affected SUs and malicious users at a fusion center (FC). In this paper, we propose a genetic algorithm-based soft decision fusion scheme to determine the optimum weighting coefficient vector against SUs' sensing information. The weighting coefficient vector is further utilized in a soft decision rule at FC in order to make a global decision. Through extensive simulations, the effectiveness of the proposed scheme is evaluated compared with other conventional schemes.

1. Introduction

Wireless communication networks have a tremendous progress for the last 30 years to support the growth of application devices from 1G to 4G LTE-advanced wireless networks [1]. Each generation has played its role in order to enhance data rate, reliability, latency, and so on. During the past years, connecting each device with another device at anytime and anywhere is a big challenge in wireless communication networks. In a line of evolutions, 5G will provide an unexpected contribution and a big step forward toward spectrum management, public safety, energy efficiency, high data rate, low latency, and so on [2–4]. The future 5G wireless system is on the horizon, and Internet of Things (IoT) is going to take the center stage since the IoT devices are expected to form a major portion of this 5G network paradigm [5].

IoT was first mentioned by Ashton, who introduces a technological revolution to bring heterogeneous networks under a single umbrella of IoT [6], and it has drastically changed landscape of various industries [7]. IoT is a promising subject of technical, social, and economic implications; it can be presumed that IoT has a strong and meaningful impact on daily life in the near future, such as automation, improvised learning, logistic, intelligent transportation, and e-health care [8, 9]. Technically, the most focused area of paradigm is computing, communication, and connectivity. Among them, the connectivity and

spectrum management are more challenging and of great concern. As over 50 billion wireless devices will be connected by 2020, all of which will demand a lot of spectrum resources [10]; the authors in [11] argued the importance of cognitive capability, that is, without comprehensive cognitive capability, IoT is just like an awkward stegosaurus: all brawn and no brains. Today, we already have over a dozen wireless technologies in use: WiFi, Bluetooth, ZigBee, NFC, LTE, earlier 3G standards, satellite services, and so on. Due to proliferation of these wireless networks and explosive increase in the number of users, a spectrum scarcity problem is raised and becomes more serious. The static allocation and management of spectrum resources are not efficient to meet requirements of wireless devices and applications. With the static allocation, some of spectrum bands are able to be heavily overloaded, whereas another part of spectrum bands is rarely used. Federal communication commission (FCC) has been considering a more flexible and comprehensive use of the spectrum resources using cognitive radio (CR) technology by allowing secondary users (SUs) to utilize free spectrum holes, which are not used by primary users (PUs) [12]. In CR networks (CRNs), efficient spectrum sensing and reporting is mandatory to avoid interference to the legitimate PUs [13, 14].

In the CRN, a PU owns a right to access spectrum bands, and therefore, the interference level caused by SUs must be limited to a certain level. In the literature, SUs adopt different types of sensing detectors such as matched filter detector (MFD), cyclostationary detector, feature detector, and energy detectors (ED) [15, 16]. Although the MFD has a superior performance, it requires prior knowledge on the PU channel which makes it difficult to implement. On the contrary, the ED is easy to implement, thanks to its simple hardware requirements and less complexity. In distributed sensing environments, the sensing information provided by individual sensing users cannot be trusted due to wireless channel effects, such as multipath fading, shadowing, and receiver uncertainties. Hence, it is more feasible to adopt cooperative spectrum sensing (CSS) techniques to overcome these matters [17].

Cooperation among sensing users can be implemented in a centralized or distributed manner. In the distributed CSS, individual users can share the sensing information with each other without the fusion center (FC), while in the centralized CSS, the fusion center (FC) collects sensing reports from individual users in order to make an appropriate final decision [18, 19]. The combination of local sensing reports at the fusion center (FC) is categorized as soft and hard decision fusion schemes. The hard decision fusion (HDF) schemes such as logical AND, logical OR, and voting allow each user to take a local decision and send a binary decision result to the FC [20, 21]. The benefit of HDF is optimality in transmitting energy while reporting to the FC, but it is not fully capable of accurately estimating the PU's status [22]. In soft decision fusion (SDF) such as maximum gain combining (MGC), equal gain combining (EGC), and Kullback–Leibler (KL) divergence-based combining techniques, the SUs sense and forward energy statistics on the PU's channel to the FC, where the final channel estimation is carried out [23–26].

The CSS leads to a high detection probability with minimum false alarm that results in reduced error probability at the FC. Meanwhile, the CRN is highly vulnerable to security threats. The security threat is an important part, which disturbs the normal operation of the underlying network infrastructure [27, 28]. Various attacks which severely degrade the performance of the CSS have been studied in the CRN. The representative attacks are Byzantine users' attack, jamming attack, and primary user emulation attack (PUEA) [29–33]. The Byzantine users' attack is a type of spectrum sensing data falsification (SSDF) attack, where malicious users (MUs) report false information to the FC. SSDF attacks severely degrade the spectrum sensing reliability and spectrum utilization. SSDF attacks are always yes, always no, and random attacks. In [30], the authors isolated SSDF outliers by utilizing Z-test; the SSDF attack is mitigated via q-out-of-m scheme. Similarly, in [31], the authors utilized a linear-weighted combination scheme to eliminate the effect of the SSDF attack on the final sensing decision. Furthermore, an adaptive reputation evaluation mechanism is introduced to discriminate malicious users from legitimate users. The traditional jamming attack targets to inject malicious signals into an operating frequency band so that the desired signals are interfered from them [32]. The PUEA prevents access to licensed user's spectrum by masquerading as a PU so that legitimate PUs cannot successfully access their own spectrum [33].

Some heuristic approaches in CSS can lead to an optimal global decision. Among them, a genetic algorithm (GA), which is a class of computational algorithm motivated by evolution, is a good candidate to find the optimal solution by adopting biologically inspired approaches to given problems [34, 35]. In [36], the authors highlighted and discussed GA techniques which can be applied to various applications and issues for wireless networks. In [35, 37], the authors focused on optimization of detection and false alarm probabilities of a particular SU using the GA in a centralized CRN.

In this paper, we evaluate the performance of CSS in the presence of MUs in CRNs. We consider several different operating criteria of MUs: always yes (AY), always no (AN), always opposite (AO), and random opposite (RO). Cooperative users are assumed to be located at different geographical locations and experience independent Rayleigh fading. Therefore, it is almost impossible to treat all the sensing information. In this paper, we exploit a GA approach to determine the optimal weighting coefficient vector. Once the optimal weighting coefficient vector is found by the proposed GA-based SDF scheme, the weighting vector is further utilized in SDF at the FC to make a final global decision. To this end, we employ an energy detector for each sensing user, where the observed energy is compared with an adaptive threshold determined by the proposed GA-based SDF scheme. Through extensive simulations, it is shown that the proposed GA-based SDF scheme achieves better detection and error performance than conventional count (voting)-HDF, MGC-SDF, and KL-SDF schemes.

The rest of the paper is organized as follows. In Section 2, the system model considered in this paper is presented. In Section 3, a GA-based SDF scheme is proposed and discussed in detail. In Section 4, the proposed scheme is evaluated through extensive simulations, compared with conventional schemes. Finally, conclusive remarks are drawn in Section 5.

2. System Model

We consider a cooperative spectrum sensing scenario that consists of a PU, normal SUs, malicious SUs (MUs), and FC as shown in Figure 1. All SUs perform spectrum sensing to determine presence or absence of the PU in the network.

At the beginning, each SU performs own local sensing. The local sensing can be represented as a binary hypothesis testing for presence or absence of the PU in the network and is measured as

$$\left\{\begin{array}{c} H_0\colon X_i[n] = W_i[n] \\ H_1\colon X_i[n] = g_i S[n] + W_i[n] \end{array}\right\}, \quad \begin{array}{l} i \in 1, 2, \ldots, M, \\ n \in 1, 2, \ldots, K, \end{array} \tag{1}$$

where H_0 denotes the hypothesis when no PU is active and H_1 denotes the hypothesis when a PU is active on the channel. $X_i[n]$ is the received signal at the ith user in the nth time slot. The total number of samples for sensing is $K = 2BT_s$, where B is the used bandwidth and T_s is the sensing time period. We assume that K is a sufficiently large value so that sensing energy of the signal follows a Gaussian distribution. In (1), g_i denotes the channel gain between the ith user and the PU. Similarly, $S[n]$ is the nth sample of the PU signal that is regarded as an independent and identically distributed (i.i.d.) Gaussian random variable with zero mean and variance σ_S^2, i.e., $S[n] \sim N(0, \sigma_S^2)$. $W_i[n]$ denotes the additive white Gaussian noise (AWGN) at the ith user, which follows a Gaussian distribution with zero mean and variance $\sigma_{W_i}^2$, i.e., $W_i[n] \sim N(0, \sigma_{W_i}^2)$.

The total sensing energy reported by the ith user to the FC is expressed as

$$Z_i = \sum_{n=1}^{K} \left|U_i[n]\right|^2, \tag{2}$$

where $U_i[n] = \sqrt{P_{R,i}} h_i X_i[n] + N_i[n]$ is the signal received at the FC reported from the ith user in the nth time slot. Here, $P_{R,i}$ is the transmit power of the ith user, h_i is the channel gain between the ith user and the FC, and $N_i[n]$ is an AWGN with zero mean and variance δ_i^2, i.e., $N_i[n] \sim N(0, \delta_i^2)$.

3. Proposed Cooperative Spectrum Sensing and Soft Decision Fusion Schemes

In this section, we provide detailed descriptions of the proposed cooperative spectrum sensing (CSS) scheme in the presence of MUs and the proposed GA-based SDF scheme that determines the optimal weighting coefficient vector.

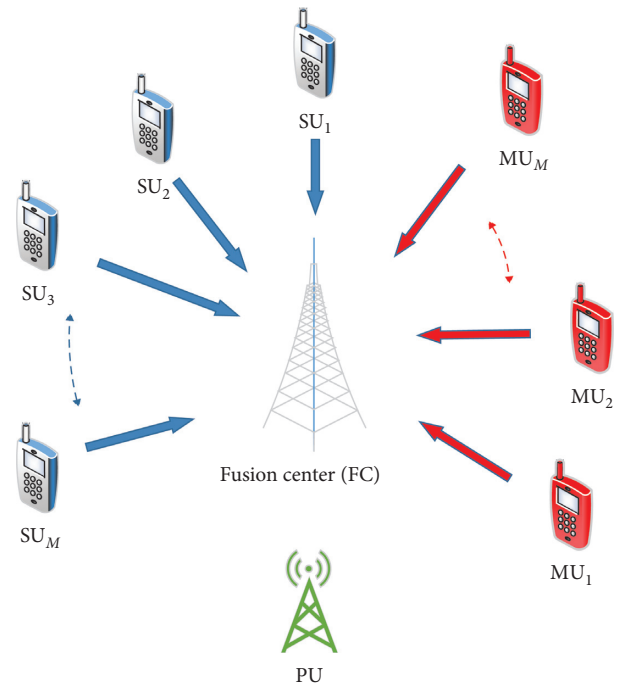

Figure 1: System model.

3.1. Proposed Cooperative Spectrum Sensing Scheme. The proposed CSS scheme using weighted SDF is shown in Figure 2. In the figure, an FC receives sensing statistics of the PU channel from M users including both normal SUs and MUs. According to the operating criteria of MUs, an AY MU reports higher energy statistics to the FC irrespective of the actual status of the PU channel as if the PU channel is always busy [29]. Thus, if there exist AY MUs in CSS, the data rate of the secondary system can be severely reduced. In contrast, AN MU reports lower energy statistic to the FC than the actual PU channel condition, and thus, interference to the legitimate PU occurs. Similarly, since an AO MU always feedbacks opposite energy statistics to the FC, the data rate of the secondary system is reduced, and interference to the legitimate PU occurs. Finally, an RO MU probabilistically operates as an AO MU with probability p and as a normal SU with probability $(1-p)$. The role of cooperative SUs in Figure 2 is similar to cooperative relays that receive and forward the statistics of the PU channel to the FC. Consequently, the FC makes the global decision on the PU channel status based on a linearly weighted SDF approach using channel sensing statistics collected from multiple SUs.

For M cooperative SUs, the final test statistic observed at the FC is expressed as

$$Z = \sum_{i=1}^{M} (w_i Z_i), \tag{3}$$

where w_i is the weighting factor assigned to the sensing energy of the ith user. Since the sensing reports Z_i for the ith user are Gaussian-distributed, the final test statistic Z is also Gaussian-distributed [37].

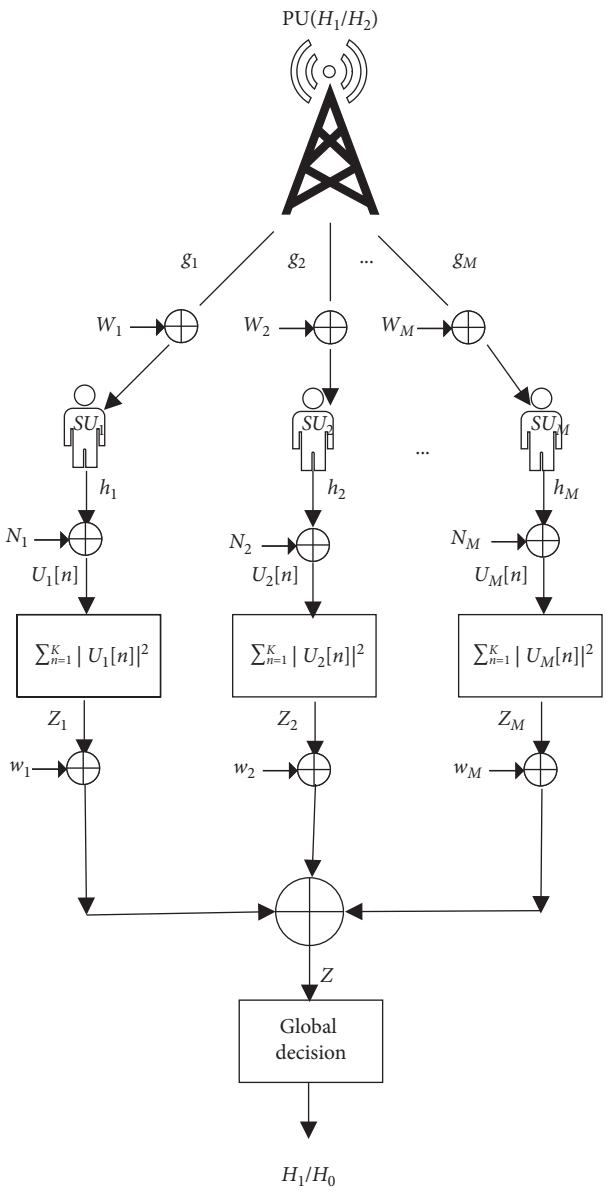

Figure 2: Proposed CSS scheme.

$$E\left(Z|H_0|\right) = \sum_{i=1}^{M} w_i K \sigma_{0,i}^2, \tag{4}$$

$$E\left(Z|H_1|\right) = \sum_{i=1}^{M} w_i K \sigma_{1,i}^2, \tag{5}$$

$$\mathrm{var}\left(Z|H_0|\right) = \sum_{i=1}^{M} 2w_i^2 K\left(\sigma_{0,i}^2 + \delta_i^2\right)^2 = \vec{w}^T \Phi_{H_0} \vec{w}, \tag{6}$$

$$\mathrm{var}\left(Z|H_1|\right) = \sum_{i=1}^{M} 2w_i^2 K\left(\sigma_{1,i}^2 + \sigma_{0,i}^2\right)^2 = \vec{w}^T \Phi_{H_1} \vec{w}, \tag{7}$$

where $\sigma_{0,i}^2$ and $\sigma_{1,i}^2$ are the variances of $U_i[n]$ under the H_0 and H_1 hypotheses for the ith user that are equivalent to $\sigma_{0,i}^2 = P_{R,i}|h_i|^2\sigma_{W_i}^2 + \delta_i^2$ and $\sigma_{1,i}^2 = P_{R,i}|g_i|^2|h_i|^2\sigma_s^2 + \sigma_{0,i}^2$, respectively.

In (4)–(7), $\vec{\mathbf{w}} = [\, w_1 \;\; w_2 \;\; \ldots \;\; w_M \,]^T$ is the weighting coefficient vector to be optimized in order to determine an appropriate threshold value β for minimizing sensing error probability.

The covariance matrices for H_0 and H_1 hypotheses are given by

$$\begin{aligned} \Phi_{H_0} &= \mathrm{diag}\left(2K\sigma_{0,i}^4\right), \\ \Phi_{H_1} &= \mathrm{diag}\left(2K\left(P_{R,i}|g_i|^2|h_i|^2\sigma_S^2 + \sigma_{0,i}^2\right)^2\right), \end{aligned} \tag{8}$$

where diag(.) is a diagonalization operation of a matrix. Finally, the detection and false alarm probabilities at the FC are expressed as

$$\begin{aligned} P_f &= P\left(Z > \beta \mid H_0\right) = Q\left(\frac{\beta - E\left(Z|H_0|\right)}{\sqrt{\mathrm{var}\left(Z|H_0|\right)}}\right) = Q\left(\frac{\beta - \vec{w}^T\vec{\mu}_0}{\sqrt{\vec{w}^T\Phi_{H_0}\vec{w}}}\right), \\ P_d &= P\left(Z > \beta \mid H_1\right) = Q\left(\frac{\beta - E\left(Z|H_1|\right)}{\sqrt{\mathrm{var}\left(Z|H_1|\right)}}\right) = Q\left(\frac{\beta - \vec{w}^T\vec{\mu}_1}{\sqrt{\vec{w}^T\Phi_{H_1}\vec{w}}}\right), \\ \beta &= \left(\frac{\sqrt{w^T\Phi_{H_1}w}\,\mu_0^T\vec{w} + \sqrt{\vec{w}\Phi_{H_1}w}\,\mu_1^T w}{\sqrt{w^T\Phi_{H_0}w} + \sqrt{w^T\Phi_{H_1}w}}\right). \end{aligned} \tag{9}$$

Let us assume that $P_f = P_m$, where P_m is the miss detection probability and $P_f = 1 - P_d$, and therefore, the total error probability P_e is determined as

$$P_e = P_f + P_m = Q\left(\frac{\beta - \vec{w}^T\vec{\mu}_0}{\sqrt{\vec{w}^T\Phi_{H_0}\vec{w}}}\right) + Q\left(\frac{\vec{w}^T\vec{\mu}_1 - \beta}{\sqrt{\vec{w}^T\Phi_{H_1}\vec{w}}}\right). \tag{10}$$

In (10), it is noticeable that the error probability is highly dependent on the weighting coefficient vector $\vec{w}$. Therefore, the optimal threshold β needs to be determined for satisfying high detection, minimum false alarm, and low error probabilities, and then it is substituted into (10). In the proposed CSS scheme, the choice of $\vec{w}$ is performed such that $0 < w_i < 1$ and $\sqrt{\sum_{i=1}^{M} w_i^2} = 1$ in order to reduce the search space and computational complexity.

3.2. Proposed GA-Based SDF Scheme. The GA is a biological inspired method which is widely used for searching optimized solutions in various science and engineering problems. It is referred to the chromosomes as the strings of binary symbols encoding a candidate solution to the given problem [34, 38].

In our proposed GA-based SDF scheme, the GA tries to find an optimal set of weighted coefficient vectors for combining the sensing reports received from all cooperative

```
For n = 1 to Sensing Interval
    For i = 1 to M
        Energy reported by the i^th SU as Z_i
    End
  // Determine optimal threshold and weighting coefficient values
    Initialize randomly weights w as an N × M
    Normalize weights w.
    Calculate (Φ_{H_1}, Φ_{H_0}) based on Z_i.
    For k = 1 to N
        Investigate threshold against the k^th vector as β(k).
        Determine P_f(k) based on β(k) and w(k).
        Find P_d(k) based on β(k) and w(k).
        Estimate P_e(k).
    End
    Sort w in ascending order probabilities.
    The chromosomes at the top are selected as parents.
    Crossover (w)
    Mutate (w)
    // End i^th sensing
    Select the optimal β and w with minimum P_e
    For i = 1 to M
        Z'_i = w_i × Z_i // new energies against users
    End
    If Σ_{i=1}^{M} (Z'_i) > β
        G_B(i) = H_1
    Else
        G_B(i) = H_0
    End
End
```

Algorithm 1: Proposed GA-based SDF scheme.

users. In a random normalized set of coefficient vectors, a vector resulting in low error probability can be chosen as an optimal set of the vectors, and then, it is further utilized to make a global decision for SDF.

The proposed GA-based SDF scheme consists of the following five steps:

Step 1: initial population

N total number of chromosomes is considered at initial. The algorithm is initialized with an initial population of randomly generated N chromosomes that consist of M genes, i.e., $\vec{\mathbf{w}}_S = [\, w_1 \;\; w_2 \;\; \ldots \;\; w_M \,]^T, s \in 1, \ldots, N$, normalized in the range of 0 to 1.

Step 2: fitness of the particles

The suitability of each coefficient vector is determined by measuring their fitness scores: $P_e(\vec{w}_1)$, $P_e(\vec{w}_2), \ldots, P_e(\vec{w}_N)$. The population is sorted in the ascending order of their fitness measurements.

Step 3: crossover and mutation

The chromosomes with minimum error probability results from the top are selected as parent chromosomes. A crossover point is randomly selected in this work that changes the subsequences before and after the locus in the parents to form kid's reproduction. After then, a random mutation operation is performed for the selected weighting coefficient vector.

Step 4: new population

The fitness of the kid's population is determined as in step 2, and the results are sorted in the ascending order of their fitness. The crossover and mutation operations are performed for the newly established population.

Step 5: stopping criteria

The GA starts to repeat step 2 if the fitness functions (i.e., minimum P_e) are not achieved or if the number of iterations is not completed.

The implementable algorithm of the proposed GA-based SDF scheme is explained in detail in Algorithm 1, and the overall flowchart of the proposed scheme is shown in Figure 3.

4. Numerical Results and Analysis

In this section, we provide numerical results of the proposed GA-based SDF scheme in comparison with other conventional schemes. In our simulation environments, the number of SUs in the CRN is adjusted to 10 and 14 users. Among whole SUs, four users are selected as AY, AN, AO, and RO MUs, respectively. In the results, SNR values are varying from 30 dB to 0 dB. The sensing interval is set to 1 ms with 270 to 335 samples. The SUs are placed at different locations with varying SNRs and each of which senses the PU channel independently. A crossover point is randomly chosen in the

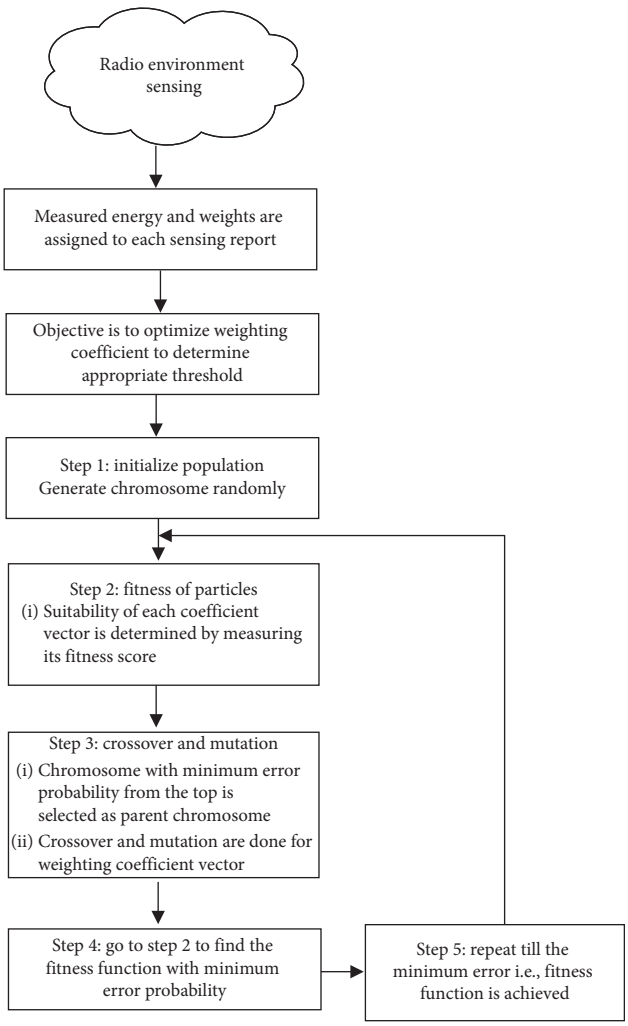

Figure 3: Flowchart of the proposed GA-based SDF scheme.

range of 1 to M. The proposed GA-based SDF scheme finds the optimum coefficient vector, which is further used to make a global decision for SDF at the FC.

The performance of the proposed GA-based SDF scheme is evaluated through simulations, and the results are compared with the conventional count-HDF, MGC-SDF, and KL-SDF schemes. We consider three different scenarios. In Scenario 1, we show the error probabilities for varying SNRs with fixed number of SUs. In Scenario 2, we discuss the error probabilities for varying number of SUs. Finally, in Scenario 3, we show the error probabilities for varying number of SUs with two fixed SNRs at −21.5 dB and −13.5 dB. The parameters for numerical results and analysis are summarized in Table 1.

4.1. Scenario 1. In the first scenario, we fix the number of SUs and sensing time, while SNR values are varying from −30 dB to 0 dB. The performance of the proposed GA-based SDF scheme is evaluated in terms of error probability. In Figure 4, we compare the proposed GA-based SDF scheme with count-HDF, MGC-SDF, and KL-SDF schemes when no MU exists in the network. It is obviously shown from

Table 1: Parameters for numerical results.

Parameter	Value
Total number of users	M
Malicious users	4
Number of genes in GA	M
Total number of GA chromosomes	$N = 30$
Random crossover	1 to M
GA iteration size	50
Count decision	$M/2$

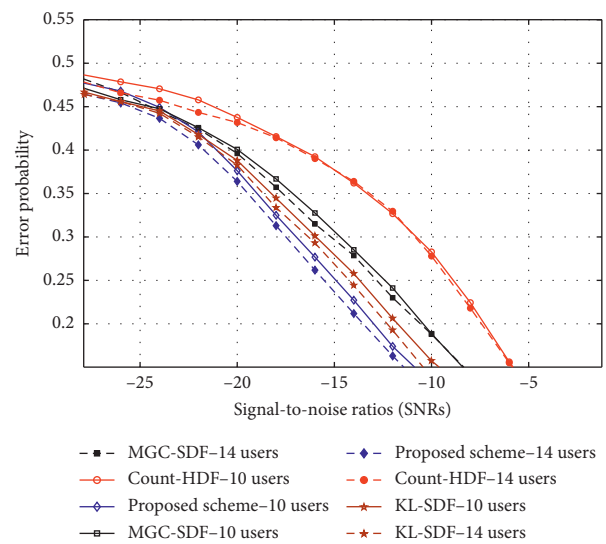

Figure 4: Error probability vs. SNR without MUs.

Figure 4 that the proposed GA-based SDF scheme outperforms the other schemes in terms of error probability. In Figure 5, the same parameters are considered to evaluate the proposed GA-based SDF scheme except that MUs at low SNR exist in the network. It can be observed that, with the existence of MUs in the network, the error probability of the proposed scheme is smaller to that of the other schemes. The other schemes are badly affected when there exist MUs in the network. Similarly, when there exist MUs at high SNR as in Figure 6, the performance of the other conventional schemes is highly affected, while the proposed GA-based SDF scheme is capable to mitigate the effect of MUs at the FC.

4.2. Scenario 2. In the second scenario, we consider fixed sensing time duration and SNR values (e.g., −21.5 dB and −13.5 dB) and varying number of SUs from 10 to 22. We evaluate the performance of the proposed GA-based SDF scheme, compared with other schemes, according to MU existence in the network: (i) no MU, (ii) MUs at low SNR, and (iii) MUs at high SNR. Figure 7 shows the error probability for varying number of SUs when no MU exists in the network. It is shown that the error probability decreases as the number of SUs increases. The reason is obvious that, with CSS, the detection probability increases, while the false alarm probability decreases, and thus, the error probability

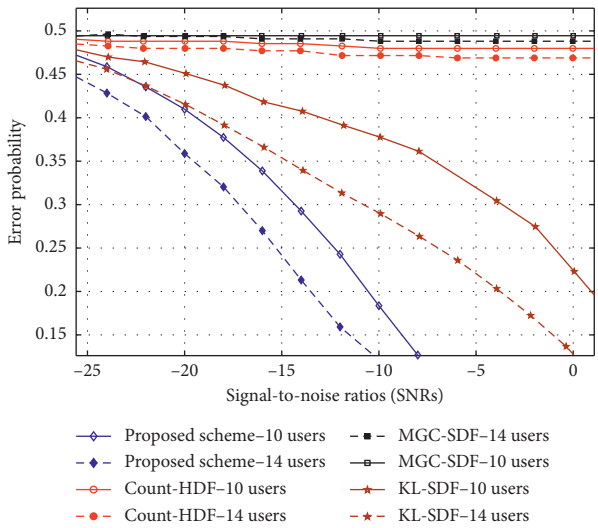

Figure 5: Error probability vs. SNR when MUs exist at low SNR.

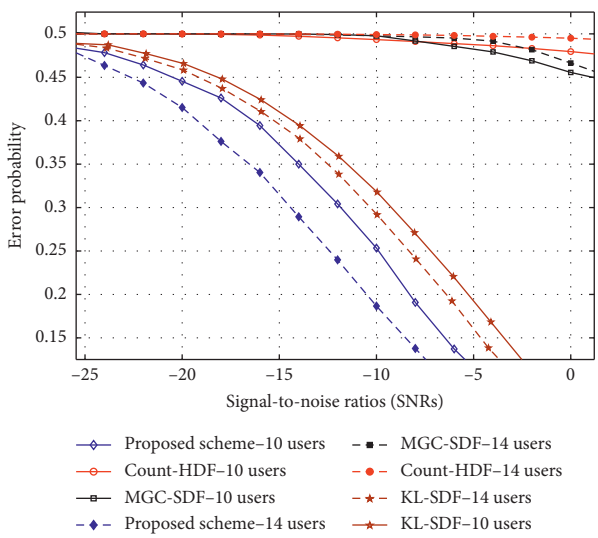

Figure 6: Error probability vs. SNR when MUs exist at high SNR.

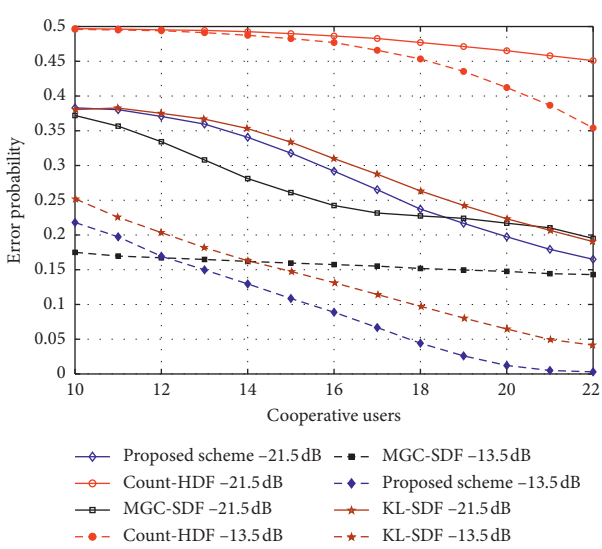

Figure 7: Error probability vs. number of SUs without MUs.

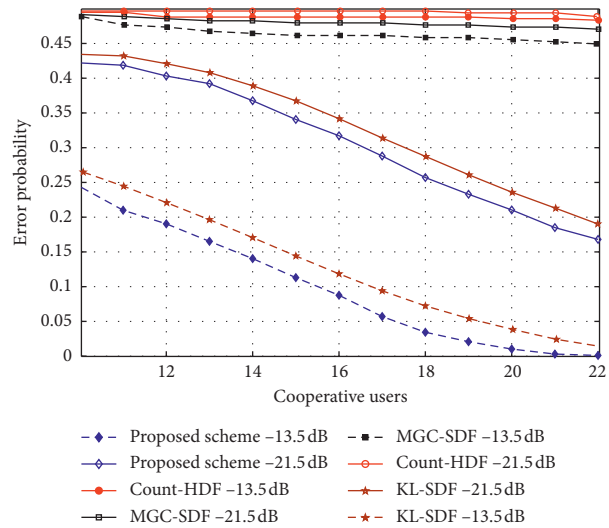

Figure 8: Error probability vs. number of SUs when MUs exist at low SNR.

can be consequently reduced. The error probability of the proposed GA-based SDF scheme is significantly reduced as the average SNR value varies from −21.5 dB to −13.5 dB. It always outperforms the conventional schemes in the whole SNR regions, while the conventional count-HDF and MGC-SDF schemes show very high error probabilities regardless of the SNR region.

Figure 8 shows the error probability for varying number of SUs when there exist MUs at lower SNR than normal SUs. In the figure, the error probabilities of the conventional count-HDF and MGC-SDF schemes do not quickly descend, different from the proposed GA-based SDF scheme. Similarly, Figure 9 shows the error probability when there exist MUs at higher SNR than normal SUs. We also consider two average SNR values of −21.5 dB and −13.5 dB. For the proposed GA-based SDF scheme, the error probability decreases more quickly compared with the conventional count-HDF, MGC-SDF, and KL-SDF schemes with increasing number of SUs.

4.3. Scenario 3. In the last scenario, the sensing time duration is varying from 270 to 335 when the number of SUs and SNR values are fixed. Figures 10–12 show the error probabilities of the proposed GA-based SDF scheme compared with the conventional schemes, when no MU exists, MUs exist at low SNR, and MUs exist at high SNR, respectively.

In Figure 10, it is shown that the proposed GA-based SDF scheme achieves the lowest error probability. The error probability is reduced further as average SNR increases from −21.5 dB to −13.5 dB. Basically, the error probabilities for all schemes are slightly reduced as the number of sensing samples increases. As shown in Figure 11, when MUs exist at low SNR, the conventional count-HDF and MGC-SDF schemes do not steeply reduce the error probability, while the proposed GA-based SDF and KL-SDF schemes still do it. A significant reduction in the error probability is presented when the average SNR is increased

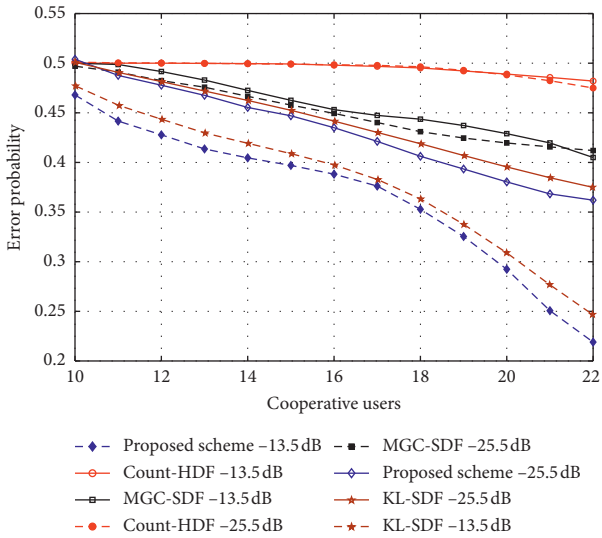

Figure 9: Error probability vs. number of SUs when MUs exist at high SNR.

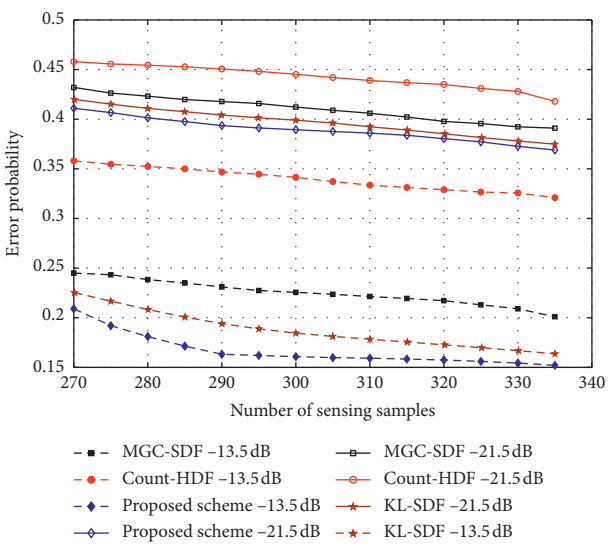

Figure 10: Error probability vs. number of sensing samples without MUs.

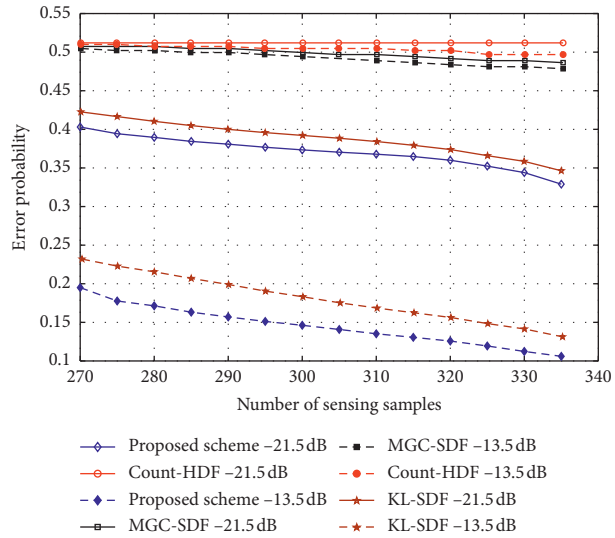

Figure 11: Error probability vs. number of sensing samples when MUs exist at low SNR.

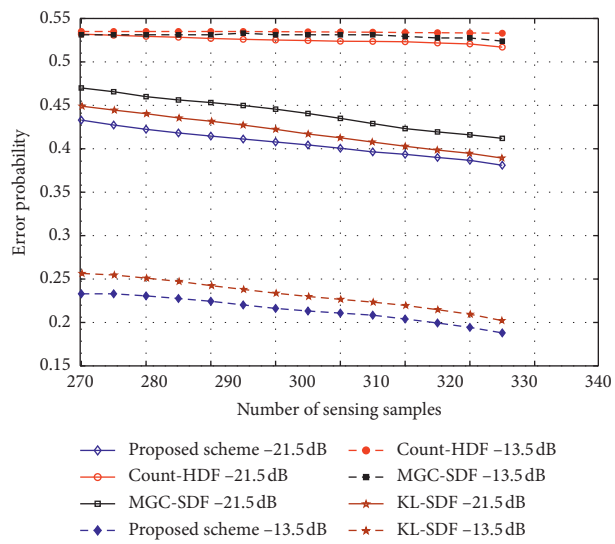

Figure 12: Error probability vs. number of sensing samples when MUs exist at high SNR.

from −21.5 dB to −13.5 dB. In this figure, it is shown that the count-HDF scheme achieves the worst error performance in the presence of MUs. In Figure 12, the sensing reports transmitted from MUs with high SNRs are collected. In the figure, as the average SNR is increased from −21.5 dB to −13.5 dB, the error probability of the conventional MGC-SDF scheme significantly degrades. However, since the proposed GA-based SDF scheme can mitigate the effect of MUs even at high SNR, it provides the best error performance and still has some performance gap with the conventional KL-SDF scheme, which achieves the best performance among the conventional schemes.

5. Conclusion

The integration of cognitive radio (CR) and Internet of Things (IoT) technologies seems to shift the future 5G and beyond wireless networks. The CR technology has the potential to efficiently utilize the spectrum via cooperative sensing. However, inaccurate sensing information caused by wireless fading effects and existence of malicious users (MUs) in the network can significantly affect the sensing performance. In this paper, we proposed a genetic algorithm (GA)-based soft decision fusion (SDF) scheme to determine the optimum coefficient vector for combining sensing reports collected from multiple secondary users (SUs). The weighting coefficient vector found by the proposed GA-based SDF scheme provides high detection, low false alarm, and low error probabilities. Through extensive simulations, the effectiveness of the proposed scheme was evaluated by considering number of SUs, average SNR, and sensing time duration. The results showed that the proposed GA-based SDF scheme significantly outperforms the conventional

count-HDF, MGC-SDF, KL-SDF schemes, even in the presence of MU in CR networks.

Data Availability

The data used to support the findings of this study are included within the article.

Disclosure

The work reported in this paper was conducted during the sabbatical year in Korea Polytechnic University in 2019.

Conflicts of Interest

The authors declare no conflicts of interest.

Acknowledgments

This work was supported in part by the MSIT (Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) Support Program (IITP-2019-2018-0-01426) supervised by the IITP (Institute for Information and Communication Technology Planning & Evaluation) and in part by the National Research Foundation (NRF) funded by the Korea government (MSIT) (no. 2019R1F1A1059125). Prof. J. Kim's work was conducted during the sabbatical year in Korea Polytechnic University in 2019.

References

[1] A. Agarwal, G. Misra, and K. Agarwal, "The 5th generation mobile networks-key concepts, network architecture and challenges," *American Journal of Electrical & Electronic Engineering*, vol. 3, no. 2, pp. 22–28, 2015.

[2] T. Q. Duong and N.-S. Vo, "Wireless communication and network for 5G and beyond," *Mobile Networks and Applications*, vol. 24, no. 2, pp. 443–446, 2019.

[3] B.-S. P. Lin, F. J. Lin, and L.-P. Tung, "The role of 5G mobile broadband in the development of IoT, big data, cloud and SDN," *Communications and Network*, vol. 8, no. 1, pp. 9–21, 2016.

[4] R. Chávez-Santiago, M. Szydełko, A. Kliks et al., "5G: the convergence of wireless communications," *Wireless Personal Communications*, vol. 83, no. 3, pp. 1617–1642, 2015.

[5] W. Ejaz, A. Anpalagan, M. A. Imran et al., "Internet of things (IoT) in 5G wireless communication," *IEEE Access*, vol. 4, pp. 10310–10314, 2016.

[6] K. Ashton, *That "Internet of Things": In the Real World, Things Matter More than Ideas*, Springer, Berlin, Germany, 2009.

[7] F. A. Awin, Y. M. Alginahi, E. A. Raheem, and K. Tepe, "Technical issues on cognitive radio based internet of things: a survey," *IEEE Access*, vol. 7, pp. 97887–97908, 2019.

[8] S. Chatterjee, R. Mukherjee, S. Ghosh, D. Gosh, S. Gosh, and A. Mukherjee, "Internet of things and cognitive radio- issues and challenges," in *Proceedings of the IEEE International Conference on Opto-Electronics and Applied Optics (Optronix)*, Kolkata, India, November 2017.

[9] A. A. Khan, M. H. Rehmani, and A. Rachedi, "When cognitive radio meets the Internet of things?" in *Proceedings of the IEEE International Wireless Communications & Computing Conference (IWCMC)*, Paphos, Cyprus, September 2016.

[10] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, "Internet of things: a survey on enabling technologies, protocols, and applications," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 4, pp. 2347–2376, 2015.

[11] Q. Wu, G. Ding, Y. Xu et al., "Cognitive Internet of things: a new paradigm beyond connection," *IEEE Internet of Things Journal*, vol. 1, no. 2, pp. 129–143, 2014.

[12] FCC, "Notice of proposed rule-making and order," Report No. 03-222, FCC, Washington, DC, USA, 2003.

[13] Y. Arjoune and N. Kaabouch, "A comprehensive survey on spectrum sensing in cognitive radio networks: recent advances, new challenges, and future research direction," *Sensors*, vol. 19, no. 1, p. 126, 2019.

[14] M. S. Khan, J. Kim, E. H. Lee, and S. M. Kim, "An efficient contention-window based reporting for internet of things features in cognitive radio networks," *Wireless Communications and Mobile Computing*, vol. 2019, Article ID 8475020, 9 pages, 2019.

[15] A. Ranjan, Anurag, and B. Singh, "Design and analysis of spectrum sensing in cognitive radio based on energy detection," in *Proceedings of the IEEE International Conference on Signal and Information Processing (IConSIP)*, Nanded, India, October 2016.

[16] I. Ilyas, S. Paul, A. Rahman, and R. K. Kundu, "Comparative evaluation of cyclo-stationary detection based cognitive spectrum sensing," in *Proceedings of the IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON)*, New York, NY, USA, October 2016.

[17] I. F. Akilidz, B. F. Lo, and R. Balakrishnan, "Cooperative spectrum sensing in cognitive radio networks: a survey," *Physical Communication*, vol. 4, no. 1, pp. 40–62, 2011.

[18] D. Cabric, S. M. Mishra, and R. W. Brodersen, "Implementation issues in spectrum sensing for cognitive radios," in *Proceedings of the Conference Record of the Thirty-Eighth Asilomar Conference on Signals, Systems and Computers*, Pacific Grove, CA, USA, November 2004.

[19] R. Tandra and A. Sahai, "Fundamental limits on detection in low SNR under noise uncertainty," in *Proceedings of the International Conference on Wireless Networks, Communications and Mobile Computing*, Maui, HI, USA, June 2005.

[20] D.-J. Lee, "Adaptive random access for cooperative spectrum sensing in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 14, no. 2, pp. 831–840, 2015.

[21] Y. He, S. Member, J. Xue, T. Ratnarajah, and S. Member, "On the performance of cooperative spectrum sensing in random cognitive radio networks," *IEEE Systems Journal*, vol. 99, pp. 1–12, 2016.

[22] D. B. Teguig, B. Scheers, and V. Le Nir, "Data fusion schemes for cooperative spectrum sensing in cognitive radio networks," in *Proceedings of the Military Communications and Information Systems Conference*, Canberra, Australia, October 2012.

[23] D. Hamza, S. Aissa, G. Aniba, S. Member, and G. Aniba, "Equal gain combining for cooperative spectrum sensing in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 13, no. 8, pp. 4334–4345, 2014.

[24] R. Biswas, J. Wu, and X. Du, "Mitigation of the spectrum sensing data falsifying attack in cognitive radio networks," in *Proceedings of the IEEE International Conference on Communication (ICC)*, Qingdao, China, May 2019.

[25] M. S. Khan and I. Koo, "Mitigation of adverse effect of malicious users by hausdorff distance in cognitive radio networks," *Journal of Information and Communication Convergence Engineering*, vol. 13, no. 2, pp. 74–80, 2015.

[26] V. V. Hiep and I. Koo, "A robust cooperative spectrum sensing based on kullback-leibler divergence," *IEICE Transaction on Communications*, vol. E95-B, no. 4, pp. 1286–1290, 2012.

[27] M. Jenani, "Network Security a challenge," *International Journal of Advanced Networking and Applications*, vol. 8, no. 5, pp. 120–123, 2017.

[28] I. S. Turbin, "Security threats in mobile cognitive radio networks," in *Proceedings of the IEEE East-West Design & Test Symposium (EWDTS)*, Kazan, Russia, September 2018.

[29] M. S. Khan, M. Jibran, I. Koo, S. M. Kim, and J. Kim, "A double adaptive approach to tackle malicious users in cognitive radio networks," *Wireless Communications and Mobile Computing*, vol. 2019, Article ID 2350964, 9 pages, 2019.

[30] I. Ngomane, M. Velempini, and S. V. Dlamini, "The detection of the spectrum sensing data falsification attack in cognitive radio ad hoc networks," in *Proceedings of the IEEE Information Communication Technology & Society (ICTAS)*, Durban, South Africa, May 2018.

[31] R. Wan, L. Ding, N. Xiong, and X. Zhou, "Mitigation strategy against spectrum sensing data falsification attack in cognitive radio sensor networks," *International Journal of Distributed Sensor Networks*, vol. 15, no. 9, 2019.

[32] H. A. B. Salmeh, S. Almajali, M. Ayyash, and H. Elgala, "Spectrum assignment in cognitive radio networks for Internet of things delay sensitive applications under jamming attack," *IEEE Internet of Things*, vol. 5, no. 3, pp. 1904–1913, 2018.

[33] S.-C. Lin, C.-Y. Wen, and W. A. Sethares, "Two-tier device based authentication protocol against PUEA attacks for IoT applications," *IEEE Transaction on Signal and Information Processing over Networks*, vol. 4, no. 1, pp. 33–47, 2018.

[34] U. Mehboob, J. Qadir, S. Ali, and A. Vasilakos, *Genetic Algorithms in Wireless Networking: Techniques, Applications, and Issues*, Springer, vol. 20, no. 6, Berlin, Germany, 2016.

[35] S. Bhattacharjee, P. Das, S. Mandal, and B. Sardar, "Optimization of probability of false alarm and probability of detection in cognitive radio networks using GA," in *Proceedings of the 2015 IEEE 2nd International Conference on Recent Trends in Information Systems (ReTIS)*, Kolkata, India, July 2015.

[36] M. Akbari and M. Ghanbarisabagh, "A novel evolutionary-based cooperative spectrum sensing mechanism for cognitive radio networks," *Wireless Personal Communications*, vol. 79, no. 2, pp. 1017–1030, 2014.

[37] M. Akbari, M. R. Manesh, A. A. El-Saleh, and M. Ismail, "Improved soft fusion-based cooperative spectrum sensing using particle swarm optimization," *IEICE Electronics Express*, vol. 9, no. 6, pp. 436–442, 2012.

[38] Z. Quan, S. Cui, and A. H. Sayed, "Optimal linear cooperation for spectrum sensing in cognitive radio network," *IEEE Journal of Selected Topics in Signal Processing*, vol. 2, no. 1, pp. 28–40, 2008.