Robust Spectrum Sensing Employing PSO

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***Abstract*—In cognitive radio network (CRN) cognitive radio users (CRUs) try to utilize the radio spectrum of the licensed primary uses (PUs) without creating disturbances. To do that efficient spectrum sensing is one of the key jobs at the SUs part. As the individual user sensing performance is not considered authentic and reliable in the multiple channel effects of fading, shadowing, and receiver uncertainties, therefore, cooperative spectrum sensing (CSS) provides an optimal solution to be deployed in these environments. One major problem for CSS is to deal with abnormal sensing reports of the reporting users. A malicious user (MU) reports false sensing data to the fusion center (FC) so that to create confusion about the PU's existence. In this paper particle swarm optimization (PSO) algorithm is tested to reduce the impact of MUs in the FC decision. The cooperative users report their channel findings to the FC, where PSO tries to find the existence of any abnormality in the sensing data. The results are confirmed through extensive simulation at different combination of MUs that shows the proposed scheme effectiveness.**

***Index Terms*— Cognitive radio network, particle swarm optimization, fusion center, fading channel, malicious users.**

I. Introduction

The tremendous growth in wireless communication is observed in the last decade to meet with the growing number of wireless applications and devices [1]. The different technology generations in wireless communications such as 1G to 4G have played their role in providing reliability, high data rate, and minimum latency. Now the challenge in wireless communication is to allow devices to connect and communicate to each other at any time and anywhere. The evolution process of the 5G technology is expected to provide a significant contribution to public safety, energy efficiency, spectrum management, low latency, and better data rate [2],[3]. As the 5G communication technology is on the horizon with the internet of things (IoT) as its heart, therefore the IoT based devices will have a key role in the implementation structure of the 5G network [4].

The word IoT introduced by Ashton in [5] is a technological revolution to bring heterogeneous networks under the common IoT umbrella. Iot can change the landscape of numerous industries tremendously. It will also help in the improvised logistic learning, automation, intelligent transportation, and e-health care units as in [6],[7]. The enhancement of computation, reliable communication, and connectivity procedures in this paradigm is the major focus from a technological perspective. Out of the many, however, radio spectrum management and connectivity are the most crucial and challenging responsibilities yet to work out by the research community. It is expected that soon a large number of wireless devices will be in interconnection that may demand more spectrum resources [8]. The employment of IoT without cognition is similar to an awkward stegosaurus with all brawn and no brains [9]. The rapid increase in wireless communication technology is demanding new wireless services in both the used and unused parts of the radio spectrum [10]. The federal communication commission (FCC) has already legalized spectrum sharing in the 5.4 GHz band, where devices sense the military radar existence before accessing the channel [11].

Cognitive radio (CR) based wireless communication technology is intelligent enough with efficient radio spectrum utilization ability that learns and adjust the device's parameters relevant to the operation environment [12]. The primary users (PUs) in CR networks (CRNs) are legalized and free to transmit and access resources at any time, while the cognitive radio users (CRUs) also called the unlicensed users are allowed to transmit only when the channel is declared free of the PU. Therefore, it is very much critical in CRN to detect the primary activity promptly, otherwise, their incorrect detection could result in a false alarm and reduces the CRUs' opportunity to access the available spectrum. Similarly, interference is also expected to the ligitimate PUs from the CRUs transmission in case of any misdetection.

As spectrum sensing results of a single CRU are often limited by the fading and shadowing in the wireless channel [13]. Therefore, cooperative spectrum sensing (CSS) is one of the alternatives that can resolve this issue smartly. In the CSS, all sensing users forward their local sensing findings to the fusion center (FC), where the final decision is made about the PU's existence [14]. However, the presence of malicious users (MUs) in CSS is limiting the performance, where they report false

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sensing reports to the FC to compromise its global decision. Significant work exists in the literature about reducing MUs effects in CSS.

A robust scheme that dealt with the Yes MUs is discussed in [15]. Similarly, a sequential cooperative scheme with minimum sensing reports and improved sensing performance in a malicious environment is discussed in [16]. In the soft combination schemes such as equal gain combination (EGC) and maximum gain combination (MGC), overall sensing statistics of cooperative users are combined to make a global decision [17]. Similarly, hard combination schemes allow the sensing users to report their hard decisions to the FC, where these decisions are combined using logical-OR, logical-AND, and majority voting schemes [18]. In [19], a genetic algorithm is employed to optimize the detection and false alarm probabilities with reducing sensing error. The particle swarm optimization (PSO) is implemented for the optimization of thresholds to enhance spectral efficiency and detect potential spectrum assets [20]. The Kullback-Leibler (KL) divergence scheme is investigated in [21] against malicious users based on users' soft energy collections. A combination of the double-sided neighbor distance (DSND) and outlier detection scheme is used as the GA algorithm fitness function in [22],[23] to reduce error probability in the FC decision.

This paper investigated the use of the PSO algorithm to search PU activity in the licensed spectrum. The PSO-based scheme in the paper enables the FC to overcome the effects of MUs. The cooperative cognitive users sense and inform FC about the PU, where the FC employs the PSO algorithm to derive the most relevant conclusion to the actual PU status. A composite outlier score is determined using one-to-many-hamming distance and z-score as the fitness function of the PSO. The PSO select the sensing report with minimum outlying results, out of the PSO population on behalf of cooperative users. Based on the selection results of the PSO algorithm, EGC, MGC, and majority voting schemes are further used to make the final decision. The proposed scheme results are confirmed in the presence of NO, YES, OPPOSITE, and RANDOM categories of MUs. In the YES malicious report a high-energy signal is reported to the FC regardless of the actual PU activity, while the NO malicious always reports a low-energy signal. Similarly, the OPPOSITE user reports always negate the actual PU statistics. In this work, the RANDOM malicious nature is assumed similar to the OPPOSITE probabilistically.

The remaining paperwork is divided into these sections. Section II, discusses the system model. In Section III detailed analysis of the PSO algorithm is discussed for finding accurate sensing data before any soft and hard combination schemes. Section IV is about simulation results, while the paper is concluded in Section V.

II. SYSTEM MODEL

As the individual user sensing is experiencing disturbances due to the wireless channel effects, therefore, the user's cooperation in the figure helps in reducing and overcoming the sensing problems experienced by the single user. The objective of this paper is to reduce false alarm P_f and misdetection P_m that further leads to a reduce in the error probability $P_e = P_f + P_m$, where $P_m = 1 - P_d$.

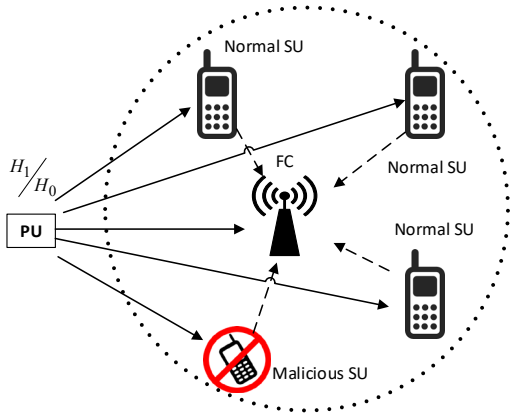

Figure 1. Centralized cooperative spectrum sensing environment.

In figure 1 the cooperative users including normal and MUs (YES, NO, OPPOSITE, RANDOM) sense the PU and report their sensing statistics to the FC. Based on the received sensing notifications of the users the FC makes its global decision of the channel.

The j^{th} CRU binary hypothesis at the l^{th} time slot is [15],[21].

$$y_j(l) = \begin{cases} H_0, & n_j(l) \\ H_1, & h_j s(l) + n_j(l) \end{cases}, \tag{1}$$

where, H_0 hypothesis shows the availability of the PU channel and H_1 shows the channel occupancy by the licensee. $y_j(l)$ is the signal received by the j^{th} CRU in lth time slot. $n_j(l)$ is the additive white gaussian noise at the j^{th} CRU, h_j is the channel gain and $s(l)$ is the PU transmitted signal in lth time slot.

The energy representation of the j^{th} user observation is as:

$$E_j(i) = \begin{cases} \sum_{l=l_i}^{l_i+K-1} \left| n_j(l) \right|^2, & H_0 \\ \sum_{l=l_i}^{l_i+K-1} \left| h_j s(l) + n_j(l) \right|^2, & H_1 \end{cases}, \tag{2}$$

Here in (2) K is the total number of samples in the i^{th} sensing interval. The energy representation of each cooperative user is similar to the gaussian random variable under both H_0 and H_1 according to the central limit theorem as [15],[21]

$$E_j \sim \begin{cases} N\left(\mu_0 = K, \sigma_0^2 = 2K\right), & H_0 \\ N\left(\mu_1 = K(\eta_j + 1), \sigma_1^2 = 2K(\eta_j + 1)\right), & H_1 \end{cases}, \tag{3}$$

In (3), η_j is the signal-to-noise ratio (SNR) between j^{th} CRU

and PU. Similarly, (μ_0, σ_0^2) and (μ_1, σ_1^2) are the mean and variance values of the energies reported under the H_0 and H_1 hypotheses.

III. Proposed Scheme at the FC

In 1952 Eberhart and Kenedy derive the idea of PSO from bird flocking and fish swarming in [24]. PSO algorithm takes the help of the local and collective intelligence in finding enhance solution to the problems, where every novel population (group) is expected to improve.

A flowchart of the proposed CSS is shown in figure 2. In the model, individual users sense the PU channel and inform FC of their reports to form PSO population. The FC employs the PSO algorithm to determine sensing reports with minimum outlying results that closely resemble the actual PU status. The selected sensing reports are then inputted into the fusion combination schemes for making a final decision.

Step 1: Sensing data collection

The history matrix formed at the FC consisting of soft energy reports of the user's in N_0 sensing intervals is as

$$\boldsymbol{E} = \left[E_{ij}\right] = \begin{bmatrix} E_{11} & E_{12} & \dots & E_{1M} \\ E_{21} & E_{22} & \dots & E_{2M} \\ E_{31} & E_{32} & \dots & E_{3M} \\ \vdots & \vdots & \ddots & \vdots \\ E_{N_0 1} & E_{N_0 2} & \cdots & E_{N_0 M} \end{bmatrix}, i \in 1,...,N_0, j \in 1,...,M, \quad (4)$$

Here E_{ij} in (4) is the energy information of the j^{th} user in the i^{th} interval. M is the total sensing users and N_0 is total sensing intervals to form the PSO population.

The FC further modifies the particles position to note the difference between the sensing observations of each user with all other users in (5) as

$$\boldsymbol{E}' = \left[E'_{ij}\right] = \begin{bmatrix} E'_{11} & E'_{12} & \dots & E'_{1M} \\ E'_{21} & E'_{22} & \dots & E'_{2M} \\ E'_{31} & E'_{32} & \dots & E'_{3M} \\ \vdots & \vdots & \ddots & \vdots \\ E'_{N_0 1} & E'_{N_0 2} & \cdots & E'_{N_0 M} \end{bmatrix}, i \in 1,...,N_0, j \in 1,...,M, \quad (5)$$

where $E'_{ij} = \left| \frac{\left(\sum_{j=1}^{M} E_{ij} - E_{ij} \right)}{M-1} \right|$, that indicates the average of the reports reported by all other users while taking out the results of the given j^{th} user.

Step 2.1 Outliers identification using one-to-many-sensing-distance

The results in (4) and (5) are used to determined outlying factors based on the one-to-many sensing distances $\boldsymbol{d}_j(i)$ for the j^{th} CRU in the i^{th} sensing particle as

$$\boldsymbol{d}_j(i) = \left| E_{ij} - E'_{ij} \right|. i \in 1,...,N_0, j \in 1,...,M. \quad (6)$$

Similarly, the total outlying score of the i^{th} interval for all cooperative users is determined as

$$\boldsymbol{d}_i = \sum_{j=1}^{M} \left(\boldsymbol{d}_j(i) \right). i \in 1,...,N_o, j \in 1,...,M, \quad (7)$$

where the measurement in (7) is made for the N_0 intervals and the results are collected as

$$\boldsymbol{d} = \left[\boldsymbol{d}_1 \ \boldsymbol{d}_2 \ \boldsymbol{d}_3 \ \dots \ \boldsymbol{d}_{N_0} \right]^T, \quad (8)$$

where $\boldsymbol{d}$ is the outlier score results for all the N_0 sensing intervals. This measurement shows how far the report of each cooperative user is from the average sensing reports received from all other users. It will separate those sensing reports during which MUs and any other abnormality were misleading FC's final decision.

Step 2.2 Outliers identification using z-score

In step 2, z-score employed as outlier score measurement based on sensing reports received from the users as

$$\boldsymbol{o}_j(i) = \left| \frac{\left(E_{ij} - \mu(i) \right)}{\sigma(i)} \right|, i \in 1,...,N_0, j \in 1,...,M, \quad (9)$$

where $\mu(i) = \frac{\left(\sum_{j=1}^{M} E_{ij} \right)}{M}$ is the mean value while $\sigma(i)$ is the standard deviation of the i^{th} PSO population particle. $\boldsymbol{o}_j(i)$ is outlying factor using z-score outlying for the j^{th} user report in the i^{th} interval of the history log.

A sum of the z-score measurements for all particles is made to guarantee the authenticity of each i^{th} interval as:

$$\boldsymbol{o}_i = \sum_{j=1}^{M} \left(\boldsymbol{o}_j(i) \right), i \in 1,...,N_o, j \in 1,...,M. \quad (10)$$

Hence, the total z-score results for the N_0 particles are collected as

$$\boldsymbol{o} = \left[\boldsymbol{o}_1 \ \boldsymbol{o}_2 \ \boldsymbol{o}_3 \ \dots \ \boldsymbol{o}_{N_0} \right]^T. \quad (11)$$

The final selection of the sensing data received from the normal, maliciously reporting users is determined, and the one with a minimum abnormality is selected. The criteria for suitable particle selection is made using the results in (6) and (9) as

$$\boldsymbol{f}(i) = \boldsymbol{d}_i + \boldsymbol{o}_i. \quad (12)$$

The normal sensing reports that have minimum abnormality obtain a minimum score using (12) in comparison with disturbed sensing reports due to malicious users.

Step 3: Changes in PSO population

The particle with a minimum outlying score in E based on (12) is selected as the global best position $\boldsymbol{g}$. Selection of the local best particles is made as $P = E$. The position and velocities of all these particles are initially set to zero that are further modified using the collective and individual intelligence as

$$V_{(i+1)j} = V_{ij} + C_1 \times R_1 \times (P_{ij} - E_{ij}) + C_2 \times R_2 \times (\boldsymbol{g}_j - E_{ij}), \quad (13)$$

where C_1 and C_2 are the learning coefficients representing the individual and social contribution of the particles. R_1 and R_2 are uniformly distributed random numbers in the range 0 to 1.

The particle velocities are next rounded to the following two extremes as

$$V_{(i+1)j} = \begin{cases} \max(V), & V_{ij} \succ \max(V) \\ \min(V), & V_{ij} \prec \max(V) \end{cases}. \quad (14)$$

The measured velocity in (14) is used to update the particle position as

$$E_{(i+1)j} = E_{ij} + V_{(i+1)j}, \quad (15)$$

where $E_{(i+1)j}$ are the modified population reports for the j^{th} CRU.

Step 4: Changes in the local best and global best

The fitness score of the population in (15) is determined similar to the fitness in (15). The local best particle positions are looked for any modification as

$$P_i = \begin{cases} E_i, & f(E_i) \prec f(P_i) \\ P_i, & otherwise \end{cases}, i \in 1,...,N_0. \quad (16)$$

The local best position fitness in (15) is compared with the initially local best P in (16). Similarly, the fitness of updated local best particles in (16) is compared with the global best particle $\boldsymbol{g}$ to look for any improvement in the global best particle as

$$\boldsymbol{g} = \begin{cases} P_i, & f(P_i) \prec f(\boldsymbol{g}) \\ \boldsymbol{g}, & otherwise \end{cases}, \forall i \in 1,...,N_0. \quad (17)$$

In (17), if any of the new local best particles in the PSO population has its fitness found to be optimum with the minimum outlying score using (12) in comparison with the global best, and then it has to replace the global best. This search of the PSO continues until the stopping criterion is met.

The final global best particle at the end of desired iterations is elected as the accurate sensing report on behalf of all cooperative users for a global decision at the FC.

Step 5: Soft and Hard decisions

The final global best particle $\boldsymbol{g}$ is utilized at the FC in the EGC, MGC, and majority voting schemes for making final recommendations about the PU channel. The EGC scheme gives equal weightage to the sensing reports of all cooperative users and takes its decision as

$$\text{EGC} = \begin{cases} H_1: & \dfrac{\left(\sum_{j=1}^{M} \boldsymbol{g}_j\right)}{M} \geq \gamma \cdot \\ H_0: & otherwise \end{cases} \quad (18)$$

The detection and false alarm probabilities P_{d_EGC} and P_{f_EGC} determined against EGC based on its decision is

$$\begin{aligned} P_{d\_EGC} &= Pr\left\{ \frac{\left(\sum_{j=1}^{M} \boldsymbol{g}_j\right)}{M} \geq \gamma \,\middle|\, H_1 \right\}, \\ P_{f\_EGC} &= Pr\left\{ \frac{\left(\sum_{j=1}^{M} \boldsymbol{g}_j\right)}{M} \geq \gamma \,\middle|\, H_0 \right\}. \end{aligned} \quad (19)$$

In the MGC scheme, higher weights are assigned to the sensing reports with higher SNR values and low weights to report with low SNR

$$\text{MGC} = \begin{cases} H_1 : \sum_{j=1}^{M} \left(w_j \times \boldsymbol{g}_j \right) \geq \gamma \\ H_0 : otherwise \end{cases}, \quad (20)$$

In (20), $w_j = \dfrac{\eta(j)}{\sum_{j=1}^{M} \eta(j)}$. is the weighted gain received by the j^{th} user at the FC.

$$\begin{aligned} P_{d\_MGC} &= Pr\left\{ \left(\sum_{j=1}^{M} w_j \times \boldsymbol{g}_j \right) \geq \gamma \,\middle|\, H_1 \right\}, \\ P_{f\_MGC} &= Pr\left\{ \left(\sum_{j=1}^{M} w_j \times \boldsymbol{g}_j \right) \geq \gamma \,\middle|\, H_0 \right\}. \end{aligned} \quad (21)$$

The decision is made by the majority voting schemes is shown in (22), where the FC counts the number of CRUs with energies exceeding threshold as

$$\text{MV} = \begin{cases} H_1 : \sum_{j=1}^{M} \left(\boldsymbol{g}_j \geq \gamma_j \right) \geq k \\ H_0 : otherwise \end{cases}. \quad (22)$$

The three commonly used hard combination schemes are the majority voting, OR and, AND fusion combination schemes. In the majority voting scheme $k = \dfrac{M}{2}$, where M is the total

number of cooperative CRUs. The detection and false alarm probabilities measurement of the majority voting hard decision schemes based on the best selection of the PSO at the FC are as follows

$$P_{d\_MV} = Pr\left\{\sum_{j=1}^{M} \boldsymbol{g}_j \geq \frac{M}{2} \middle| H_1\right\},$$
$$P_{f\_MV} = Pr\left\{\sum_{j=1}^{M} \boldsymbol{g}_j \geq \frac{M}{2} \middle| H_0\right\}, \quad (23)$$

where P_{d_MV} and P_{f_MV} are cooperative detection and false alarm probabilities of the majority voting schemes when PSO is used as a detection mechanism at the FC.

IV. SIMULATIONS AND RESULTS

The total number of CRUs in this part of the simulation is $M = 11$. Out of the total users, 7 users are selected normal and 4 of them are randomly selected as YES, NO, OPPOSITE and RANDOME. The sensing time is kept at 1 ms with 270 samples. A total of $N = 100$ sensing iterations are selected. The interval of sensing during which RANDOM perform the malicious act is adjusted between 1 and N. The size of the PSO population is $N_0 \times M$ with total N_0 particles representing sensing reports of the M sensing users. In this section of the simulation results, MUs are deliberately selected first as YES and then changed to NO. It is visible from the results in figure 2, that the EGC, MGC, and majority voting schemes using PSO have improved detection results against the conventional combination schemes. Since NO and YES users are almost identical in nature hence the detection response in both the cases when only YES and the one with only NO users' considerations are very much similar. The PSO-based MGC scheme in figure 2 has superior results among all with better receiver operating characteristics (ROC) results followed by the EGC scheme. The majority voting has resulted in minimum detection results compared with EGC and MGC schemes.

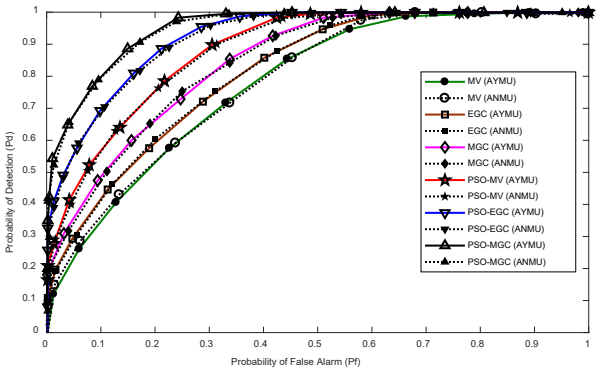

Figure 2. ROC curve, when YES and NO users contributed in sensing.

In the second part, the malicious response is first selected as OPPOSITE and then it is changed to RANDOM in figure 3. Here the PSO-based MGC scheme show improved response with high detection and low false alarm results compared with EGC and majority voting. It is noticeable that the reliability of the PSO-based combination techniques as compared with conventional schemes is sufficiently high in figure 3. The presence of the RANDOM user in figure 3 affects the sensing performance hazardously than the OPPOSITE. The superiority of the proposed scheme can be seen in both the OPPOSITE and RANDOM user's participation in CSS.

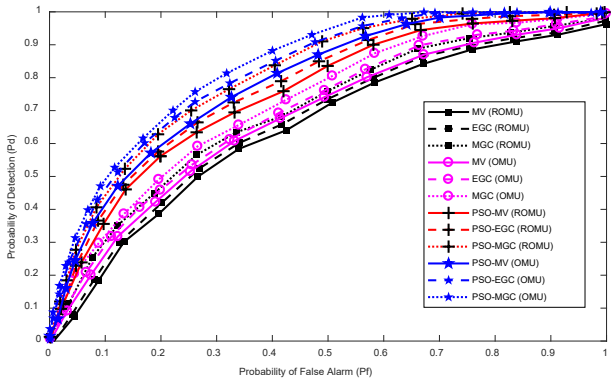

Figure 3. ROC curve, when OPPOSITE and RANDOM users contributed in sensing.

In this section of the simulation results, MUs are equally taken into consideration to see the improvements in the performance of the proposed PSO-based scheme in figure 4.

The graphical results in figure 4 under the consideration of all 4 categories of MUs with high upper ROC curves for the proposed scheme show the reliability of the proposed scheme. This leads to a clear improvement in the sensing response of the proposed scheme as compared with conventional combination schemes. In figure 4, the PSO-based MGC scheme has an accurate detection response as compared with the PSO-based EGC, PSO-based majority voting, and traditional schemes.

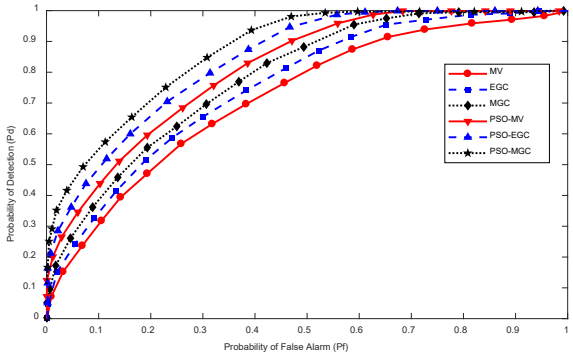

Figure 4. ROC curve, when YES, NO, OPPOSITE and RANDOM users contributed in sensing.

V. CONCLUSIONS

As the participation of MUs reduces the effectiveness of cooperation of the CIoT. It is therefore necessary to overcome and restrict MU's decisions in CSS to avoid any confusion due to their false sensing reports. This paper employed the use of

the PSO algorithm to make the FC decision authentic and reliable in the presence of different categories of MUs. The FC is allowed to take its global decision of the PU existence-using EGC, MGC, and majority voting schemes based on the results of the proposed PSO-based scheme. This leads FC decision to be more accurate in presence of YES, RANDOM, OPPOSITE, and NO categories of MUs in both the soft and hard combination schemes. Simulation results further confirmed the authenticity of PSO based scheme with high detection and minimum false alarm probability results for proposed schemes at the FC.

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