Efficient Spectrum Sensing for the Relay Based Cognitive Radio Network for Enhancing the Network Coverage for Wireless Patient Monitoring System

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***Abstract*—The wireless Patient Monitoring System (PMS) is facing the issue of spectrum congestion. The 5G technology based wireless PMS is a promising solution. With the advancement in the wireless telecommunication technology from 4G to 5G, the important paradigm to be considered for the state of the art technique for the 5G is the device to device (D2D) communication. One of the important issue associated with the advanced wireless communication technology is the network disconnection due to network blockage. Moreover, inefficient usage of the spectrum is the another major concern in wireless communication services. In this paper, by efficiently utilizing the unused spectrum the Cognitive Radio (CR) Relay assisted cooperative D2D communication has been aimed to enhance the network capacity (data rate) of the User Equipment (UE)/Licensed User (LU) which is in the network blockage area for wireless remote PMS. The CR enabled with Expert Whale Optimization Algorithm (EWOA) has been proposed for efficient spectrum sensing. The CR based relay technique for D2D communication with UE can significantly improve the performance of the network capacity without any investment on deploying new base stations. Simulation results exhibits that the performance of the network with EWOA-CR based relay technique has significantly improved.**

***Keywords*-Cognitive Radio Network; Whale Optimization Algorithm; Spectrum sensing; Device 2 Device Communication**

I. Introduction

In the current scenario, the wireless PMS can play a major role in improving the well being of a population. The wireless PMS gives more flexibility and mobility to the patients. In human diseases takes certain time period to develop. During the period human body vitals fluctuates. A continuous patient monitoring can help in predicting the early signs of diseases via patient body vital data. But a seamless connection is required between patient and the supervisors (Doctors, Nurses etc.). Such seamless connection without affecting the mobility of the patients and operating remotely in any condition calls for the need of wireless PMS. But the wireless cellular network is facing the problem of the capacity bottleneck. Moreover, mmWave (Millimeter Wave) frequency does not have much penetration ability. Such a scenario results in a network blockage condition. In 4G, to overcome such problems techniques like carrier aggregation and Multiple Input Multiple Output (MIMO) antenna scheme was deployed [1]. Turbo coding and Space time block coding schemes were employed to enhance the channel capacity [2-4] via multipath wireless communication. These schemes could not completely solve the problem of network capacity as channel capacity can not be increased infinitely by incorporating multiple antennae which further results in additional hardware costs. With the D2D link, it is possible to increase network capacity without additional cost on network infrastructure. A D2D link is a key enabler of 5G wireless communication technology [21] and the release 12 of the Long Term Evolution (LTE) from 3GPP is its clear proof [22]. The 3GPP release 12 of LTE has also mentioned about the D2D communication for public-safety and proximity based communication and services [24] [25]. The D2D communication can be employed for enhancing the data rates, decreasing the power consumption, decreasing the network latency and providing different application specific services [23]. In addition to that D2D communication also enables offloading of the cellular network, communication between vehicle to vehicle, and low latency applications [26] [27]. The UE-UE based relay system is studied in [5] in which a UE acts as a relay to the other UEs which are in network blockage area with the aim of enhancing the network capacity without additional cost for the operator for establishing relay BS infrastructure [28]. The drawback associated with the UE-UE communication is that the UE relay is not stationary and there are chances that UE relay can itself get into some network blockage condition. With the increasing demands in the D2D based application can result in the network congestion, spectrum scarcity which can cause reduced data rate and enhanced latency [29] [31].

To overcome such problems a CR based relay system is proposed to establish link from UE to the Base Station (BS) corresponding to the UE and vice versa, throughout the paper the base station corresponding to the UE is denoted as BS and the base station corresponding to the LU is denoted as LU_{BS}. The CR based relay network can potentially proved as effective in overcoming the fading problem in D2D communication by providing high channel capacity with low cost [30] [31]. A CR network can dynamically adapt and allocate different spectrum resources to the cognitive radio users/ secondary users via efficient spectrum sensing and sharing [6]. The CR based relay scheme is effectively employed in [32] for cooperative D2D communication. Authors in [33] implemented CR based relay network with cooperative communication aided Secondary Users (SUs) are served by the base station. In the above mentioned works [30-33], the CR for relay network employed conventional energy detection technique for the spectrum sensing. The spectrum sensing is the most important paradigm of the CR network. An effective spectrum sensing is very crucial for efficient detect detection of spectrum holes. Inefficient spectrum sensing can cause interference and can also results in low opportunistic throughput. The conventional energy detection techniques is the least complex but suffers at low SNR [6]. Therefore, in this paper an effective CR based relay network is implemented for overcoming network blockage issue with the efficient spectrum sensing technique. The spectrum sensing employed in this CR system is the weighted cooperative spectrum sensing scheme in which the weight values are optimized using novel EWOA, thus guarantying an efficient spectrum hole detection. The proposed scheme is compared with the existing Particle Swarm Optimization (PSO) and Whale Optimization Algorithm (WOA) based CR network. The PSO and its modified version is extensively employed for spectrum sensing [34] [35] [36] [37]. The prime drawback associated with PSO is that it is capable of finding very good solution but it converges before obtaining global optimum solution [38]. For spectrum sensing it is very important that the algorithm do not converge to the near global solution but should obtain Global optimum solution so as to avoid interference with the PU and to carryout the remaining process of a CR network i.e opportunistic data transmission, spectrum sharing, spectrum mobility more effectively.

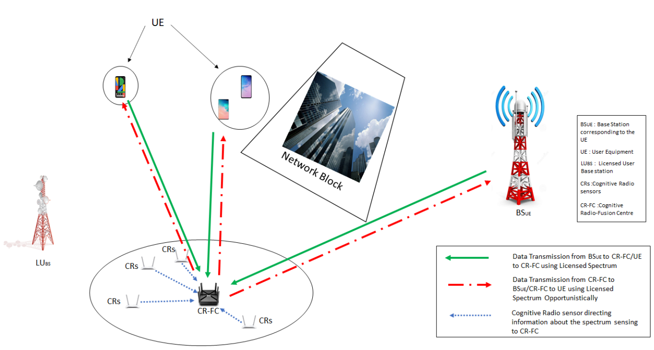

Figure 1: Flow diagram of the proposed model

From Figure 1 it can be illustrated that when a UE enters the network blockage region the proper link between BS and UE does not exist and can affect its network performance. The deployed Cognitive Radio-Fusion Center (CR-FC) assisted with Cognitive Radio sensors (CRs) acting as a relay between UE and BS, UE and UE can significantly improve the network performance. In this scenario, BS has prior knowledge of the nearby CR-FC in a particular geographical location and CR-FC is able to establish a proper link with the BS. In the case of network blockage during downlink, the BS communicates to CR-FC and CR-FC with the assistance of CRs performs spectrum sensing to detects the presence and the absence of the Licensed User (LU)/Primary User (PU) of a particular geographical location. The vacant spectrum is detected and data is transferred to UE by opportunistically accessing the licensed spectrum holes. Here th LU corresponds to TV broadcast system and CR-FC is employed to detect the TV white spaces. The UE gets the information of the CR-FC and transmit data back to the CR-FC via the licensed spectrum. The CR-FC again opportunistically access the licensed spectrum holes and transmits data back to the BS, thus establishing BS-UE connection. Similar process is carried out by the CR-FC to establish UE-UE connection within the same network blockage region. The CR-FC can also communicate with the other CF-FCs deployed in the specified region to have better network coverage.
The proposed spectrum sensing scheme is performed in a weighted cooperative manner, where each CRs performs spectrum sensing and transmits information to the CR-FC via weights. The CR-FC performs weight optimization using MWOA and efficiently detects the vacant spectrum.

II. Mathematical Modeling of the Proposed Spectrum Sensing Scheme

In this paper, throughput is analyzed for the data transmission from BS (Corresponding to the UE) to UE via CR-FC, and UE to BS via CR-FC. In order to have generic problem following considerations have been made: Let j be the number of UE in the network blockage area located in a 2D plane, $k = 1, 2, 3...M$ denotes the orthogonal subcarrier each having bandwidth = W. These subcarriers are available in CR-FC and BS for resource allocation. There are $l = 1, 2, 3, ...CR_s$ number of CRs and 1 CR-FC forming the relay for assisting data transmission between BS to UE and UE to BS.
Channel gain between BS and CR-FC for the transmission meant for the j^{th} UE over k^{th} subcarrier at time slot t can be written as $h^{B,CRFC}_{j,k,t}$. Similarly channel gain between CR-FC and j^{th} UE over k^{th} subcarrier at time slot t can be denoted as $h^{CRFC,UE}_{j,k,t}$. The transmission power from BS to CR-FC for the j^{th} UE over k^{th} subcarrier and at time slot t can be written as $Tp^{B,CRFC}_{j,k,t}$. The CR-FC transmission power is fixed value for any subcarrier and it is denoted as CR_p. It is assumed that each CR-FC based relay is having unit buffer size, i.e. if BS to CR-FC transmission occurs at t^{th} time slot then CR-FC to UE transmission occurs at $(t + 1)^{th}$ time slot. In the weighted cooperative spectrum sensing scheme while the CR-FC makes the final decision

and performs data transmission, the CRs parallelly performs spectrum sensing so that the buffer size would be unity.

The BS power received at CR-FC can be estimated as Eq.1:

$$Tp_{j,k,t}^{B,CRFC,r} = Tp_{j,k,t}^{B,CRFC} \times \left\{ \frac{4\pi f_c d_o}{c} \right\}^{-2} \times d_{BS}^{-n'} / N_{bs} \tag{1}$$

here, f_c is the licensed carrier frequency associated with the BS, d_o is a reference distance, d_{BS} is the distance between BS and the CR-FC calculated as $\sqrt{(x_{BS} - x^{CRFC})^2 + (y_{BS} - y^{CRFC})^2 + (h_{BS} - h)^2}$, (x_{BS}, y_{BS}, h_{BS}) is the coordinates associated with the BS location, n' is the path loss exponent, N_{bs} is the average number of users associated with the BS.

The transmission power CR_p of CR-FC at some height h as shown in Figure 2 is different from the CR-FC power received at UE CR_p^r. The received CR-FC power at UE is derived as under:

The coordinates of UE $j \in \ell$ is (x_j, y_j) and the coordinates

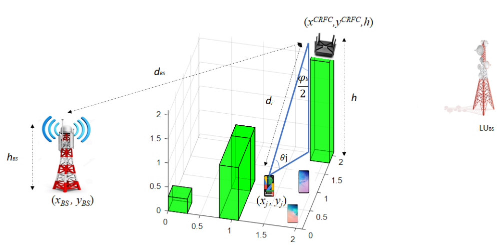

Figure 2: Detailed representation of the proposed model

of CR-FC is (x^{CRFC}, y^{CRFC}, h). For the communication link between CR-FC and UEs, the CR-FC with directional antenna with half beamwidth φ_b. The CR-FC antenna gain can be denoted as [13]:

$$g_a = \begin{cases} g_a^{3dB} & \frac{-\varphi_b}{2} \leq \psi \leq \frac{\varphi_b}{2} \\ g_a(\psi) & otherwise \end{cases} \tag{2}$$

here ψ is the sector angle, $g_a^{3dB} \approx \frac{29000}{\varphi_b^2}$, φ_b in degree is the gain of the main lobe [14], $g_a(\psi)$ is the gain outside the main lobe. Because of the uncertainity associated with the UE location, height and the obstacles, it is important to consider the randomness in the link between CR-FC and UE and also vice versa. Therefore, the link between CR-FC and UE can be of Line of Sight (LoS) and Non Line of Sight (NLoS) with certain probabilities [16].

As per the 3GPP 3D model of the Urban Macro scenario for the UE of height 1.5m [15], the LoS probability between CR-FC and UE can be modelled as [16] [18] [20]:

$$Pr^{LoS} = \frac{1}{1 + \alpha \times exp(-\beta \left| \theta_j - \alpha \right|)} \tag{3}$$

here α, β are the constants corresponding to carrier frequency and the environment type like rural, urban, and urban dense, $\theta_j = \frac{180}{\pi} \times sin^{-1}(\frac{h}{d_j})$, d_j is the distance between CR-FC and UE, calculated as $\sqrt{(x_j - x^{CRFC})^2 + (y_j - y^{CRFC})^2 + h^2}$.

The NLoS probability can be written as Eq.(4):

$$Pr^{NLoS} = 1 - Pr^{LoS} \tag{4}$$

The coverage of directional antenna with beamwidth φ_b is given as $r_a = h \times tan(\frac{\varphi_b}{2})$ [17].

For the transmission power of CR_p, the received power of CR-FC at j^{th} UE for the LoS and NLoS link is given as in Eq.(5):

$$CR_p^r = \begin{cases} CR_p + g_a^{3dB} - Lo_{dB}^{UE} - E_{LoS}, & \text{LoS Link} \\ CR_p + g_a^{3dB} - Lo_{dB}^{UE} - E_{NLoS}, & \text{NLoS Link} \end{cases} \tag{5}$$

For a fixed location of CR-FC and varying locations of the UEs the path loss associated with this situation is to be considered averaged path loss. Therefore, The path loss Lo_{dB}^{UE} between CR-FC and UE is calculated as in Eq.(6):

$$Lo_{dB}^{UE} = Pr^{LoS} \Upsilon_1 \left\{ \frac{4\pi f_s^c d_j}{c} \right\}^{n'} + Pr^{NLoS} \Upsilon_2 \left\{ \frac{4\pi f_s^c d_j}{c} \right\}^{n'} \tag{6}$$

where, f_s^c is the spectrum sensed carrier frequency of the CR-FC, n' is the path loss exponent, d_i is the distance between CR-FC and UE and c is the speed of light, Υ_1, Υ_2 are the coefficients of the excessive path loss during LoS and NLoS conditions respectively.

The shadow fading in dB for the LoS and NLoS link is denoted as E_{LoS} and E_{NLoS} respectively. The E_{LoS} and E_{NLoS} has the normal distribution as $E_{LoS} \sim \mathbb{N}(\mu_{LoS}, \sigma_{LoS}^2)$, $E_{NLoS} \sim \mathbb{N}(\mu_{NLoS}, \sigma_{NLoS}^2)$ respectively. The $\sigma_{LoS}, \sigma_{NLoS}$ depends on environmental condition and the elevation angle as denoted in Eqs.(7) and (8) [18]:

$$\sigma_{LoS} = J_1 e^{(-J_2 \theta_j)}, \tag{7}$$

$$\sigma_{NLoS} = G_1 e^{(-G_2 \theta_j)} \tag{8}$$

where, J_1, J_2, G_1, G_2 are the constants depending on environmental constraints.

The received j^{th} UE power at CR-FC is calculated as in Eq.(9):

$$Tp_{j,k}^{UE,CRFC,r} = \begin{cases} Tp_{j,k}^{UE,CRFC} - Lo_{dB}^{UE} - E_{LoS}, & \text{LoS Link} \\ Tp_{j,k}^{UE,CRFC} - Lo_{dB}^{UE} - E_{NLoS}, & \text{NLoS Link} \end{cases} \tag{9}$$

The link between CR-FC and BS can be modeled as in Eq.(10), the received CR-FC power at BS is:

$$CR_{p,BS}^r = CR_p \times \left\{ \frac{4\pi f_c d_o}{c} \right\}^2 \times d_{BS}^{-n'} \tag{10}$$

The achievable throughput $T_{j,k}^{h,B-UE}$ for the transmission from the BS to the j^{th} UE over the k^{th} subcarrier can be evaluated as in Eq.(11)[5][7]:

$$T_{j,k}^{h,B-UE} = \frac{1}{2} log_2 \left\{ 1 + \frac{Tp_{j,k,t}^{B,CRFC,r} \times CR_p^r \times h_{j,k,t}^{B,CRFC} \times h_{j,k,t}^{CRFC,UE}}{(N_0 W) \times (Tp_{j,k,t}^{B,CRFC,r} \times h_{j,k,t}^{B,CRFC} + CR_p^r \times h_{j,k,t}^{CRFC,UE})} \right\} \tag{11}$$

here N_0 is the noise power spectral density. As time index considered is of unit buffer size, so time index can be omitted. Therefore Eq.(11) can be re-written as Eq.(12):

$$T_{j,k}^{h,B-UE} = \frac{1}{2}log_2\left\{1 + \frac{Tp_{j,k}^{B,CRFC,r} \times CR_p^r \times h_{j,k}^{B,CRFC} \times h_{j,k}^{CRFC,UE}}{(N_0W) \times (Tp_{j,k}^{B,CRFC,r} \times h_{j,k}^{B,CRFC} + CR_p^r \times h_{j,k}^{CRFC,UE})}\right\} \tag{12}$$

Similarly, the throughput achieved for the data transmission from UE to BS can be denoted as in Eq.(13):

$$T_{j,k}^{h,UE-B} = \frac{1}{2}log_2\left\{1 + \frac{Tp_{j,k}^{UE,CRFC,r} \times CR_{p,BS}^r \times h_{j,k}^{UE,CRFC} \times h_{k}^{CRFC,BS}}{(N_0W) \times (Tp_{j,k}^{UE,CRFC,r} \times h_{j,k}^{UE,CRFC} + CR_{p,BS}^r \times h_{k}^{CRFC,BS})}\right\} \tag{13}$$

where $Tp_{j,k}^{UE,CRFC}$ is the transmission power of the j^{th} UE transmitting data over the k^{th} subcarrier to the CR-FC, $h_{j,k}^{UE,CRFC}$ is the channel gain between UE and CR-FC, $h_{k}^{CRFC,BS}$ is the channel gain between CR-FC and BS.

A. Weighted Cooperative Spectrum Sensing and the Optimization Function

In this paper, the cooperative spectrum sensing scheme is considered in which energy samples from each CRs are fed to the CR-FC. The weight values are combined with the energy samples from each CRs. Therefore, the optimization problem here is to obtain the optimum weight values so as to maximize the probability of detection or minimize the probability of false alarm. For solving the optimization problem the Modified Whale Optimization Algorithm is employed. The optimal values of the fusion weights maximize the probability of correct detection for a specific value of the false alarm probability/minimize the probability of false alarm for a specific value of the probability of detection. The high detection probability and low false alarm probability implies that the spectrum sensing scheme can efficiently detect the presence and the absence of the Primary Users (PU) and can effectively provide the information about the vacant spectrum.

The mathematical model considered for spectrum sensing in this paper is as discussed below:

Spectrum Sensing for the transmission between CR-FC and BS:

$$\begin{array}{ll} \mathrm{H}_0 : y_l(t) = n_l(t) & \{(\text{PU Absent})\} \\ \mathrm{H}_1 : y_l(t) = h_l s(t) + n_l(t) & \{(\text{PU Present})\} \end{array} \tag{14}$$

here, $y_l(t)$: Signal sensed by the l^{th} CRs at the t^{th} time instant. At each time instant an energy sample is sensed, the t varies from 0 to $N-1$.

h_l: Channel gain during the spectrum sensing performed by the l^{th} CRs.

$s(t)$: Licensed User/Primary User (PU) signal sensed at t^{th} time instant.

$n_l(t)$: Zero mean AWGN for the l^{th} CRs at the t^{th} time instant with variance σ_l^2.

If N is the number of spectrum sensing samples sensed by CRs, then the test statistics for each CRs can be written as in Eq.(15):

$$U_l = \sum_{t=0}^{N-1} |y_l(t)|^2 \tag{15}$$

The statistics for the fusion center is: $\{z_l\}_{l=1}^{CRs}$, where $z_l = U_l + b_l$, b_l is the noise induced by the control channel while transmission taking place between l^{th} CRs and CR-FC. The noise so induced is a AWGN with variance v_l^2.

The fusion center calculates weighted value as in Eq.(16):

$$\sum_{l=1}^{CRs} w_l z_l = \mathbf{w}^T\mathbf{z} \tag{16}$$

where, $\mathbf{w} = [w_1, w_2, w_3, ...w_{CRs}]^T$

$\mathbf{z} = [z_1, z_2, z_3, ...z_{CRs}]^T$

$[.]^T$:Transpose of the matrix.

With the above considered model and for a fixed probability of false alarm P^f, the probability of accurate detection can be evaluated as in Eq.(17) [8]:

$$P^d = Q\left(\frac{Q^{-1}(P^f)\sqrt{\mathbf{w}^T\mathbf{C}\mathbf{w}} - e_s[\mathbf{h}]^T\mathbf{w}}{\sqrt{\mathbf{w}^T\mathbf{D}\mathbf{w}}}\right) \tag{17}$$

where, $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-a^2/2}da$, $e_s = \sum_{t=0}^{N-1}|s(t)|^2$,

$\mathbf{h} = [|h_1|^2, |h_2|^2, ... |h_{CRs}|^2]^T$

$\mathbf{C} = 2N \times diag^2(\sigma) + diag(v)$,

$\mathbf{D} = 2N \times diag^2(\sigma) + diag(v)$

$+4e_s \times diag(\mathbf{h}) + diag(v)$.

here diag(.) represents diagonal matrix.

$\sigma = [\sigma_1^2, \sigma_2^2, ...\sigma_{CRs}^2]^T$, $v = [v_1^2, v_2^2, ...v_{CRs}^2]^T$.

Similarly optimization function for minimizing the probability of false alarm can be written as in Eq.(18):

$$P^f = Q\left(\frac{Q^{-1}(P^d)\sqrt{\mathbf{w}^T\mathbf{D}\mathbf{w}}}{\sqrt{\mathbf{w}^T\mathbf{C}\mathbf{w}} - e_s[\mathbf{h}]^T\mathbf{w}}\right) \tag{18}$$

Using Eq.(12), the achievable throughput for CR-FC for the data transmission from BS to UE can be written as in Eq.(19)[9]:

$$T_{j,k}^{ach,B-UE} = P^{H_0}(\frac{t^f - t^s}{t^f})(1 - P^f)T_{j,k}^{h,B-UE} \tag{19}$$

here, t^f frame duration of the selected vacant channel's frame structure employed for data transmission, t^s is the spectrum sensing time and P^{H_0} is the probability that PU is inactive.
Similarly, the achievable throughput for CR-FC for the data transmission from UE to BS can be written as in Eq.(20):

$$T_{j,k}^{ach,UE-B} = P^{H_0}(\frac{t^f - t^s}{t^f})(1 - P^f)T_{j,k}^{h,UE-B} \tag{20}$$

The objective function for the optimization problem is to optimize **w** to maximize P^d in Eq.(7) or to minimize P^f in Eq.(8), such that $\sum_{l=1}^{CRs} w_l = 1$, and $0 \leq w_l \leq 1$. In this paper, both the optimization problems i.e. maximizing P^d and minimizing P^f have been considered.

III. Expert Whale Optimization Algorithm

A. *The Whale Optimization Algorithm*

The Whale Optimization Algorithm (WOA) developed in 2016 [10] is based on the hunting behavior of humpback whales. The WOA employs encircling mechanism, spiral position update technique and random search phase for finding an optimum solution.
Encircling Mechanism: In the encircling mechanism, the whales/search agents update their position as in Eq.(21) and Eq.(22) [10]:

$$\vec{\mathrm{D}} = \left|\mathrm{C} \cdot X_{f,n}^* - X_{f,n}\right| \tag{21}$$

$$X_{f,n+1} = X_{f,n}^* - \vec{\mathrm{A}} \cdot \vec{\mathrm{D}} \tag{22}$$

here, $\vec{\mathrm{C}}$ is the coefficient vector and it is equal to $2 \cdot \vec{r}$, the best solution found so far in the current iteration n (n=$0, 1, 2...n_{max}$) and at the f^{th} dimension (f=$0, 1, 2...d$) is represented as $X_{f,n}^*$, search agents' position for the next iteration is represented by $\vec{X}_{f,n+1}$, $\vec{\mathrm{A}}$ is the discrimination weight coefficient and can be calculated as in Eq.(23):

$$\vec{\mathrm{A}} = |2\vec{a} \cdot \vec{r} - \vec{a}| \tag{23}$$

here $\vec{a}$ is a linearly decreasing vector from 2 to 0, $\vec{r}$ is a random vector having values between 0 and 1.
The criteria for the encircling mechanism is that the $p \leq 0.5$ and $|A| \leq 1$, p is random number between 0 and 1.

The Figure 3 shows the pictorial representation of the encircling mechanism of the EWOA.
Spiral Position Update Technique: If $p > 0.5$ then the search agent will move towards the prey/best solution in a spiral shape. The Figure 4 shows the 3D representation

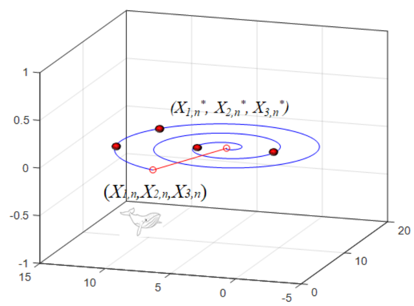

Figure 3: 3D representation of the Encircling position update of the search agent (Whale) towards the best solution

of the spiral position updates of the whales towards the best solution $(X_{1,n}^*, X_{2,n}^*, X_{3,n}^*)$ of a 3 dimensional problem. The equation governing this technique is as in Eq.(24) and Eq.(25):

$$X_{f,n+1} = \vec{D} \cdot e^{bl} \cdot cos(2\pi l) + X_{f,n}^*, \;\; l \in [-1, 1] \tag{24}$$

$$\vec{\mathrm{D}} = \left|X_{f,n}^* - X_{f,n}\right| \tag{25}$$

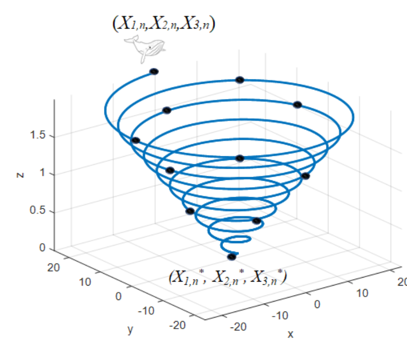

Figure 4: 3D representation of the spiral position update of the search agent (Whale) towards the best solution

Random Search Phase: This phase is initiated so that optimization algorithm performs good exploration and have global search.
The condition for random global search is that the $p \leq 0.5$ and $|A| > 1$. In this phase, instead of searching around the best solution X_n^*, the algorithm randomly selects a solution $X_{f,n}^{rand}$ and search agents move towards it as in Eq.(26) and Eq.(27):

$$\vec{\mathrm{D}} = \left|\vec{\mathrm{C}} \cdot X_{f,n}^{rand} - X_{f,n}\right| \tag{26}$$

$$X_{f,n+1} = X_{f,n}^{rand} - \mathrm{A} \cdot \vec{\mathrm{D}} \tag{27}$$

B. Expert balance between Exploration and Exploitation

For an optimization algorithm it is important to have proper tradeoff between exploration and exploitation abilities [12]. In WOA, exploitation is well carried out, but for exploration random solution is picked irrespective of its position from the best solution. This randomly chosen solution can also be near to the already exploited region. In order to have better global search so as to overcome local optima, a threshold is introduced for choosing a solution as random solution. The solutions which are far from the best solutions i.e. solutions which are in unexplored region is preferred for initializing the global search.
Modification can be mathematically modeled as in equations (28 to 31):

$$d_1 = \sqrt{X^{*}_{f,n} - X^{rand}_{f,n}} \tag{28}$$

$$d_2 = \sqrt{X^{*}_{f,n} - X^{best_2}_{f,n}} \tag{29}$$

where, $X^{best_2}_{f,n}$ is the 2nd best solution among all the search agents.
if $d_1 > d_2$, and $p \leq 0.5$ and $|A| > 1$ then update search agents as:

$$\vec{\mathrm{D}} = \left| \vec{\mathrm{C}} \cdot X^{rand}_{f,n} - X_{f,n} \right| \tag{30}$$

$$X_{f,n+1} = X^{rand}_{f,n} - \vec{\mathrm{A}} \cdot \vec{\mathrm{D}} \tag{31}$$

The proposed modification via Eqs.(28-31) can be termed as *Modified Random Search Phase*.

For an optimization algorithm it is important that its search agents reach almost all possible solution in the search space without slowing down the entire search process [19]. So, in this paper Mutation and Replacement strategy is applied. In each iteration, the search agents undergoes mutation and the corresponding solution then replaces the worst solution in the solution set to make sure proper that the search agents overcome local optima and progresses towards global best solution.

After *Encircling Mechanism* / *Spiral Update Mechanism* and *Modified Random Search Phase*, the search agents undergoes Polynomial Mutation Scheme, in which offspring is generated based on Eq. 32:

$$X^{mut}_{f,n} = X_{f,n} + (X^{U}_{f,n} - X^{L}_{f,n})\delta_{f,n} \tag{32}$$

here, $X^{U}_{f,n}$ and $X^{L}_{f,n}$ are the upper and lower bounds of $X_{f,n}$. The $\delta_{f,n}$ is computed via polynomial probability distribution:

$$P(\delta) = 0.5(\eta^m + 1)(1 - |\delta|^{\eta^m}) \tag{33}$$

$$\delta_{f,n} = \begin{cases} 2r_{f,n}^{\frac{1}{(\eta^m+1)}} - 1, & r_{f,n} < 0.5 \\ 1 - 2(1 - r_{f,n})^{\frac{1}{(\eta^m+1)}}, & \text{otherwise} \end{cases} \tag{34}$$

where, η^m is generally ≈ 20 and $r_{f,n}$ is random number ranging in [0,1]. Based on fitness of the solutions the search agents are categorized and the worst solution is replaced by the mutated solution $\vec{X}^{mut}_{f,n}$. In this way, the entire search agents would be led towards the global optimum solution. The proposed EWOA has efficient exploration scheme with which random search agent are selected such a way as shown in equations (28-31) that it overcomes local optima. With polynomial mutation scheme as described in equations (32-34) the proposed EWOA has double edge sword of efficient tradeoff between exploration and exploitation therefore it converge towards the global optimum solution as shown in Figures 3 and 4.

Algorithm 1 Pseudocode for MWOA

Initialize the population of whales randomly, X_f
Initialize a, A *and* C
Calculate the finess value of each whales
Initialize the value of p
While $n < nmax$
if $p \leq 0.5$ *and* $|A| \leq 1$
  Update the position of the whales as per the Eqs.(22) and (22)
else if $p > 0.5$ *and* $|A| \leq 1$
  Update the position of the whales as per the Eq.(24)
end
Calculate d_1 *and* d_2 *as per Eq.(28) and Eq.(29)*
if $d_1 < d_2$ *and* $p \leq 0.5$ *and* $|A| \leq 1$
  Update the position of the whales as per Eq.(31)
end
Perform Mutation and Replacement based on Eqs.(32-34)
Check for the boundary of search space and constraints
Calculate fitnees of the search agents
Update the best solution
n=n+1
end while
*Best Solution=X**

IV. System Model of the Cooperative Cognitive Radio Network

The Figure 5 shows the system model of the cooperative cognitive radio network considered. The EWOA is employed for the optimizing the weights in the fusion center as shown in Figure 5. The weights $\mathbf{w} = [w_1, w_2, w_3, ...w_{CRs}]^T$ employed in the Fusion Center are efficiently optimized by the proposed EWOA.

V. Simulation Results

In this paper, attempt is made to separately optimize the weights in Eq.(17) and Eq.(18) so as to minimize probability of false alarm and to maximize probability of detection. An efficient spectrum sensing algorithm is identified by its high probability of detection and low probability of false alarm. The proposed MWOA based spectrum sensing is compared with PSO, WOA and conventional energy detector based spectrum sensing. The comparison is made in terms

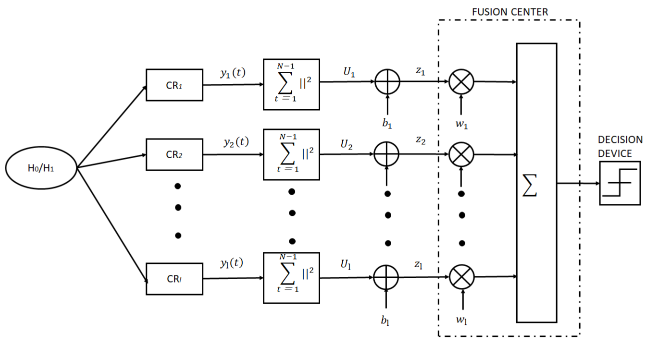

Figure 5: System Model of the Cooperative Cognitive Radio Network [34]

of convergence curve for P^f and P^d, and the average throughput for the relay based scenario. The parameters considered for simulation are: The number of CR_s=5, the AWGN variance is σ=$[0.06, 0.06, 0.06, 0.06, 0.06]^T$, control channel noise variance υ=$[0.06, 0.06, 0.06, 0.06, 0.06]^T$, $W = 60KHz$, $N_0 = 1 \times 10^{-6}W/Hz$. The base station transmission power ranges from 25 dBm to 45 dBm, CR-FC transmission power ranges from 20 dBm to 30 dBm [11]. The UE transmission power is set to 0.1W. The channel gains $h_{j,k,t}^{B,CRFC}$, $h_{j,k,t}^{CRFC,UE}$ and $h_{j,k,t}^{UE,CRFC}$, $h_{j,k,t}^{CRFC,B}$ are considered to be Rayleigh faded channel. The channel between LU and CRs is considered to be independent of the channels $h_{j,k,t}^{B,CRFC}$, $h_{j,k,t}^{CRFC,UE}$ and $h_{j,k,t}^{UE,CRFC}$, $h_{j,k,t}^{CRFC,B}$. The α=11.9, β=0.14, J_1=10.39, J_2=0.05, G_1=29.06, G_2=0.03, d_o reference distance=1m, Υ_1=3dB, Υ_2=23dB [20]. For optimizing P^f, the P^d is considered to be 0.9 and for optimizing P^d, the P^f is taken as 0.1 and P^{H_0} is considered 0.8. The number of search agents/whales/particles considered are 50 for MWOA,WOA and PSO. Each optimization algorithm run 30 times and each run is equal to the 500 iterations.

Table I: Simulation Parameter values

Parameter	Values
α	11.9
β	0.14
J_1	10.39
J_2	0.05
G_1	29.06
G_2	0.03
d_o reference distance	1m
Υ_1	3dB
Υ_2	23dB
h	30m
h_{BS}	20m

The Figure 6 and Figure 7 shows the comparison between optimization algorithms (EWOA, WOA and PSO) to efficiently optimize the weights in equations (6) and (7) so as to maximize P^d and minimize P^f. This is because the proposed EWOA is successful in maintaining the efficient balance between its exploration and exploitation abilities. The EWOA has good approach of avoiding local optima solution by effectively mutating the search agents and replacing the worst solution. In this way the algorithm move towards the global best solution. From the convergence curve it can be inferred that for the 500 iterations EWOA has successfully outperformed WOA and PSO to obtain P^d value of 0.97 and P^f value 0.02. The WOA and PSO has obtained P^d value as 0.90 and 0.92 respectively and for P^f the values for WOA and PSO are 0.1 and 0.18 respectively. The EWOA has 7.7% and 5.4% better performance compared to WOA and PSO in terms of convergence for Probability of detection. For the convergence of probability of false, the proposed EWOA has 80% and 88% better performance as compared to PSO and WOA respectively. The better values of P^f so obtained using EWOA is clearly reflected in the average throughput so obtained for BS to UE and UE to BS transmission using CR based relay under network blockage area as shown in Figures 8 and 9. For the sensing time of 3 ms and frame period 50 , the average throughput obtained for varying SNR values is higher for proposed MWOA based spectrum sensing as compared to WOA, PSO and conventional energy detection based spectrum sensing.

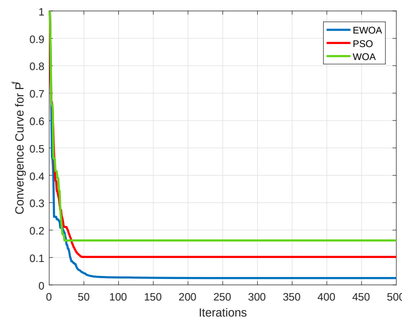

Figure 6: Convergence Curve of Probability of False Alarm

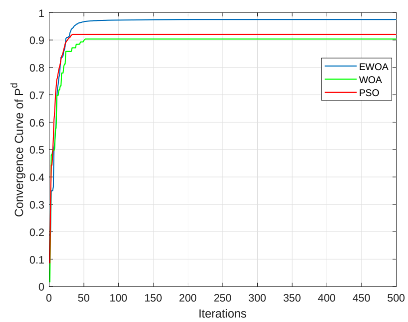

Figure 7: Convergence Curve of Probability of Detection

The optimized weights obtained via proposed EWOA is employed to obtain receiver operating characteristics (ROC) for different values of probability of detection and prob-

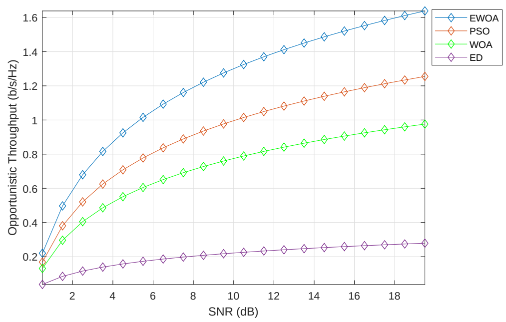

Figure 8: Opportunistic Throughput vs SNR (For UE to BS)

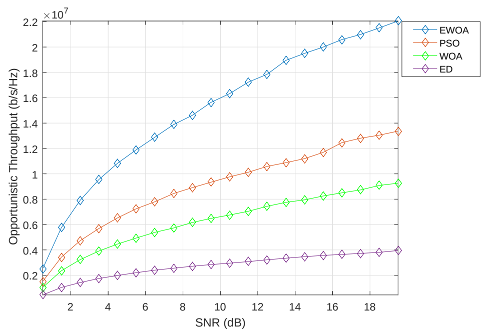

Figure 9: Opportunistic Throughput vs SNR (For BS to UE)

ability of false alarm as shown in Figure 10. The ROC for EWOA is compared with the PSO, WOA, and Energy Detector (ED).

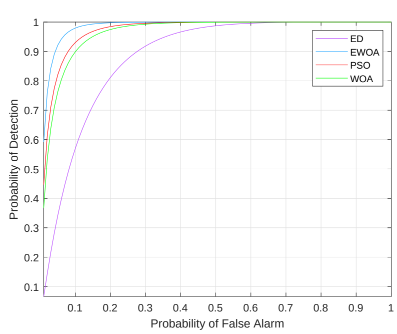

Figure 10: Receiver Operating Characteristics

From Figure 10, it can be inferred that even for the low probability of false alarm, the detection probability of MWOA based Cognitive radio network is better as compared to PSO, WOA and ED. The performance of EWOA in effectively detecting the spectrum holes is justified by the BER performance as shown in Figure 11. The efficient mutation and expert exploration scheme has efficiently enhanced the performance of the EWOA and as result the presence and the

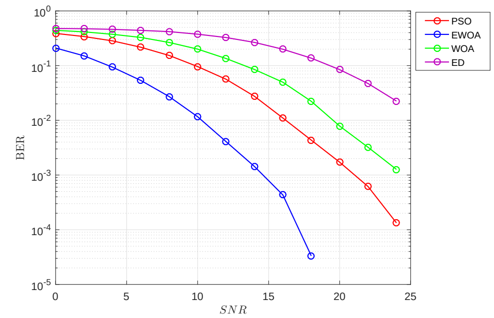

Figure 11: BER vs SNR

absence of the PU is detected with high detection probability and low false alarm probability.

VI. Conclusion

In this paper, to mitigate the problem of network blockage and to enhance the data connection for the wireless PMS, the cognitive radio based relay scheme is proposed to improve the network performance of the user equipment in the network blockage regions. Moreover, the modified whale optimization algorithm is employed for spectrum sensing optimization to increase the efficiency of the cognitive radio network. From the simulation results, it is proved that EWOA optimized spectrum sensing has significantly improved the performance of the cognitive radio network by efficiently detecting the vacant spectrum. The network performance with respect to opportunistic throughput from UE to BS of EWOA based cognitive radio network has increased by 33 % and 60 % as compared to existing PSO and WOA based system respectively. Whereas, the opportunistic throughput achieved for data transmission from BS to UE has increased by 57% and 120% as compared to PSO and WOA respectively. Therefore, with EWOA optimized spectrum sensing a wireless cognitive radio relay based PMS can efficiently detect the spectrum holes even in network blockage condition. Thus, it can provide seamless connection for efficient wireless remote PMS.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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