Received: 23 July 2020 | Accepted: 13 August 2020

IET Networks

DOI: 10.1049/ntw2.12027

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH PAPER

Comparative analysis of distributive linear and nonlinear optimized spectrum sensing clustering techniques in cognitive radio network systems

Ganesh Babu R[1] | Mohammad S. Obaidat[2,3,4] | Amudha V[5] | Rajesh Manoharan[6,7] | Sitharthan R[8]

[1]Department of Electronics and Communication Engineering, SRM TRP Engineering College, India

[2]College of Computing and Informatics, University of Sharjah, UAE

[3]KASIT, University of Jordan, Amman, Jordan

[4]University of Science and Technology, Beijing, China

[5]Saveetha School of Engineering, Tamil Nadu, India

[6]Department of Computer Science and Engineering, Sanjivani College of Engineering, Kopargaon, India

[7]RaGa Academic Solutions, Chennai, TN, India

[8]School of Electrical Engineering, Vellore Institute of Technology, Vellore, Tamilnadu, India

Correspondence

Rajesh M, Research Associate, RaGa Academic Solutions, Chennai, India.
Email: rajesmano@gmail.com

Funding information

RaGa Academic Solutions

Abstract

In this paper, a study has been conducted to compare the performance of different heuristic optimization algorithms such as Distributed Swarm Optimized Clustering (DSOC), Distributed Firefly Optimized Clustering (DFOC) and Distributed Jumper Firefly Optimized Clustering (DJFOC) techniques used for the dynamic clustering. In DSOC, every group of clustering nodes moves towards its best swarm particle having the best neighbor location with random velocity to form an organized cluster. DFOC and DJFOC are nonlinear optimization methods based on the random attractiveness of firefly intensity behaviour with the least computation time. DJFOC is used to collect the whole situation in the current records and support to change the new appropriate situation by the status table. The DJFOC aims to reduce transmit power with shortest distances and less control overhead when Secondary Users (SUs) or Primary Users (PUs) changes its position. The convergence rate of DJFOC is better than the DSOC and DFOC. The results show that the proposed DJFOC has a better efficiency of 10.137% when compared to the DSOC and 2.801% with DFOC in SUs average node power. For small Signal-to-Noise Ratio (SNR) < 2 dB, probability of detection is high. In primary detection, the proposed DJFOC is yielding a low false alarm rate compared to DSOC and DFOC.

1 | INTRODUCTION

A wireless mesh network is offered with a high-speed internet connection. However, with the increased network density, the network needs more capability to meet the applications [1].

As the sensible Cognitive Radio (CR) technology gets into larger radio frequencies, the NeXt Generation (xG) network with mesh network situated in dense urban areas becomes significantly potential [2]. The xG network can access the existing spectrum by keeping priority communication and response time without requiring the infrastructure [3]. The CR network provides to secure communication in the hostile environment and assures the spectrum handoff to perform a secured spectral band, where reliable communication is guaranteed with minimal delays [4]. The process of dynamically accessing the unused spectral bands (spectrum holes/white spaces) is known as Dynamic Spectrum Access (DSA) [5]. Better spectrum communication of the xG network is maintained without spectrum space, by allowing CR to operate any one of the best available spectrum bands [6]. The CR network gets spectral efficiency when cooperative features incorporated with spectrum sensing and spectrum sharing with each other. The primary network can support a cooperative leased communication network with a third party to access the licensed radio spectrum without any interferences [7–10].

There are various clustering techniques already studied in other works such as Groupwise Constrained Agglomerative Clustering, k-neighborhood clustering, k-means clustering and Distributed Spectrum Aware Clustering (DSAC) [11, 12]. Fine-tuning of clustering is made by particle swarm optimization (PSO), Firefly Algorithm (FA) and jumper firefly algorithm (JFA). In [13], the authors discussed the best energy-efficient protocol on low Energy Adaptive Clustering Hierarchy (LEACH) to diminish energy consumption and it can develop the lifetime of Wireless Sensor Networks (WSN). Clustering procedures can be used to communicate with the cluster head and base station. In the event that the sink station is away from the Cluster Head (CH), energy consumption will be raised and it can diminish the lifetime of WSN. To overcome these, the PSO strategy is realized with this protocol to achieve the most astounding lifetime of WSN. PSO is used to augment the adaptable and energy efficiency. It is definitely not difficult to complete and the change estimation rate is to a great degree rapidly. PSO technique is used to improve the lifetime performance of the network. By using optimization technique, we first create clusters and cluster head selection based on energy. After this whole process data transfer begins for this node on the shortest path. Authors in [14] showed that the clustering using the firefly technique can be categorized into two types: hierarchical and partitioned clustering. It has two methods: (i) the agglomerative method consists of two or smaller clusters merged into a large cluster (ii) the divisive method divides a larger cluster into two or smaller clusters. The partitional clustering tries to divide a set of disjoint clusters from the data set without forming a hierarchical structure. The prototype-based partitional clustering creates cluster centers and further, it is used to classify the data set.

In [15], the authors discussed JFA at the base station instead of FA. Among the population in every living creature, there is diversity in quality and fitness. In general, low quality, members are not able to reach high-quality achievements. Each population quality is estimated with respective members and qualifies the probability situation to obtain the eligibility. In order to avoid that problem, the author developed JFA to improve appropriate solutions by making the changes to eligible situations and find the optimal solution in the status table. From the status table, it is observed that all the current situation records help to change the new suitable situation by the jumping process. This process executes search agents (fireflies) to jump the option to make the decision process. In the status table, each and every firefly location is situated in a particular search space at the i^{th} stage and fitness maintains solution quality at the ith stage by the fireflies. Every firefly's worst solution is attained by each firefly at searching phases. After the search process, the fitness of each firefly qualification is investigated from the status table. The above various optimized clustering problem is solved in the present work.

In this paper, a new optimization algorithm has been proposed that will increase the lifetime of cognitive radio sensor networks by forming energy-efficient clusters. This work mainly focuses on cooperative sensing among all secondary users. The objective of the paper is to acquire accurate sensing information with shortening sensing time, maximize the system reliability, reduce the number of false alarms, and increase the detection rate. The study presented in this paper analyzes Distributed Swarm Optimized Clustering, distributed firefly optimized clustering, and distributed jumper firefly optimized clustering. The first method of Distributed Swarm Optimized Clustering (DSOC) proposed every group of clustering nodes moves randomly towards its best swarm particle having the least neighborhood distance [9]. Each particle's best position and velocity are evaluated according to the objective function until an optimum global best position is reached. The convergence rate of DSOC is similar to the genetic algorithm (GA). DSOC has the drawback of slow convergence in the large search space and weak local searchability. The second proposed method of Distributed Firefly Optimized Clustering (DFOC) has been studied. The DFOC is best known for the grouping of nodes [10]. All the cognitive nodes move towards the brighter firefly with random velocity to form an organized cluster with the least computation time. In DFOC, fireflies at critical positions disappear while doing the clustering without using a status table and it cannot memorize any history of the past positions. To overcome this problem, a third proposed method Distributed Jumper Firefly Optimized Clustering (DJFOC) technique is presented. DFOC and DJFOC are nonlinear optimization tools based on the random attractiveness of firefly intensity behavior. DJFOC is used to collect the whole situation in the current records and supports to change the new appropriate situation by the status table. This work shows how to employ a Firefly algorithm to implement Dynamic Spectrum Access (DSA) using energy-efficient cooperative distributive algorithms. The DJFOC is efficiently improving the dynamic spectrum access for both Primary Users (PUs) and Secondary Users (SUs) than DFOC. The convergence rate of DJFOC is better than the DSOC and DFOC. The DJFOC is having an optimal number of cluster communication and a high probability of detection. The proposed DJFOC compared its performance with DSOC and DFOC. The performance analysis of different optimization algorithm for clustering in terms of convergence time, average node power for different cluster numbers, PUs node power, SUs node power, probability of false alarm, probability of detection and probability of missed detection.

2 | PROPOSED CLUSTERING MODEL FOR DYNAMIC CHANNEL ALLOCATION IN COGNITIVE RADIO NETWORKS

The DSOC technique enables energy-efficient optimal clustering based on the number of cognitive nodes maintaining a fixed value of inertia weight W, cognitive factor C1 and social factor C2 can't be changed within a particular time. A small inertia weight (W) enables a local search. Whereas a large inertia weight enables a global search. DSOC provides a simple linear mechanism and the best of master particles use the objective function until an optimum global best position is reached [16–20]. The most important drawback of normal PSO is the fact that it has no proper communication between particles for merging. The study considers the size of 5 best swarm particles at different position namely X1, X2, X3, X4 and X5 to form an organized cluster by following two-dimensional search space. There are 100 normal particles which can be moved towards their best swarm particle having the best neighbor location with random velocity to form an organized cluster in the least computation time. An individual particle moves to its nearest best master particle. The movement of a particle is in small/large distance depends on the best particles. Initially evaluate the best fitness function of each particle group which is directly proportional to best of master particles such as Pbest1, Pbest2, Pbest3, Pbest4 and Pbest5. Now, it compares the best neighbor location of all the master particles. For example, if (Pbest3 < Pbest2) then master particle 3 group will merge with master particle 2 after communicating with master particle 2. Similarly, the iteration is carried over to select the global best (Gbest) among the master particles. The global best master particle has been selected and is sent to the data to the sink. Then it updates the position and velocity of master particles from the distance of each particle with other particles for every iteration [21–25].

Similarly, the DFOC technique enables energy-efficient optimal clustering based on the number of cognitive nodes, with attractiveness factor β, and absorption coefficient γ. All the design parameters maintain a fixed value and can't be changed within a particular time. DFOC provides a highly nonlinear attraction mechanism and light intensity of master fireflies using the objective function. In the search space, the whole fireflies are automatically subdivided into sub-swarms of fireflies and it considers a size of 5 master fireflies at different position namely X1, X2, X3, X4 and X5 to form an organized cluster by following two-dimensional search space. There are 100 normal fireflies that can be moved towards their brighter firefly having the highest attractiveness with random velocity to form an organized cluster in the least computation time. Individual firefly moves to their nearest brighter master firefly. The movement of firefly is small/large distance depends on the brightness of the firefly [26–31]. Initially, we evaluate the best fitness function of each firefly group which is directly proportional to the light intensity of master fireflies such as I1, I2, I3, I4 and I5. Then, we compare the intensity of all the master fireflies. For example, if (I2 < I1) then master firefly 2 group will merge with master firefly 1 after communicating with master firefly 1. Likewise that the iteration is carried out to select global best (Gbest) among the master fireflies. Further, it updates the position and light intensity of master fireflies from the distance, the attractiveness of each firefly with other fireflies for every iteration. Similarly, the most important drawback of normal FA is that there is no proper communication between fireflies for merging. The main advantage of the DFOC algorithm it provides at the end of each iteration, is that the clustering center of every firefly knows the position and clustering of all other fireflies. DSOC has slow convergence in refined search space, less flexibility, and weak local search ability than DFOC. The main drawback of DSOC and DFOC is that it can't memorize any history activity.

To overcome this problem, we devise our DJFOC technique; see Figure 1. In the analysis, it consists of a size 5 master fireflies

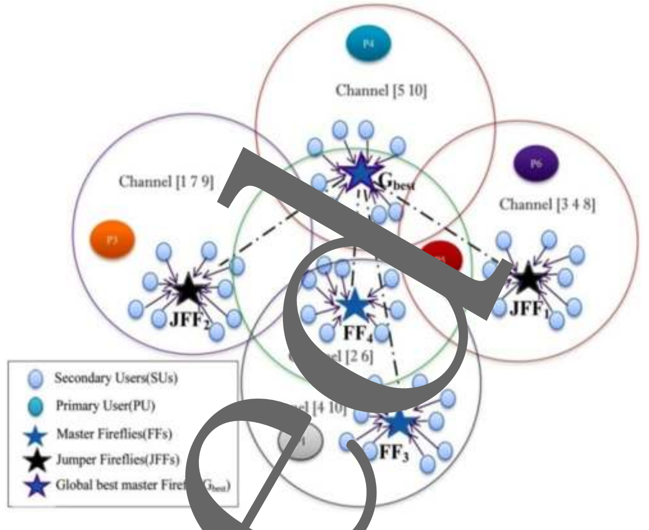

FIGURE 1 Architecture of Cooperative DIFOC Clustering Structure

at different positions namely X1, X2, X3, X4, and X5 to form an organized cluster by following status table records in the two-dimensional search space. 100 normal fireflies can be moved towards their brighter firefly with the least computation time. The movement of a firefly is small/large distance depends on the brightness of the firefly. Initially, we evaluate the best fitness function of each firefly group, which is directly proportional to the light intensity of master fireflies such as I1, I2, I3, I4, and I5. Next, we compare the intensity of all the master fireflies. For example, if (I2 < I1), then master firefly 2 group will merge with master firefly 1 after communicating with master firefly 1. Similarly, the iteration is carried over to select a global best (Gbest) among the master fireflies. Some of the master fireflies will not come for merging. For example, if the master firefly (I4) is not initiated from the size of 5 master fireflies, then it will obtain the information from the status table. From the status table, it is observed that all the current situation records are read and it helps to change the new suitable situation by jumping towards the highest brightness master firefly for example I1. The new suitable situation performs firefly's re-initialization and rearranging in a new position and then updates the status table, which is known as Jumper Firefly (JFF). We update the position and light intensity of master fireflies from the distance, the attractiveness of each firefly with other fireflies for every iteration. The master and jumper fireflies since the commonly available channels and assign those channels to all its cluster members. They also communicate with the selected global best master firefly through the free channel. If PUs are not occupied by commonly available channels in the clusters, then master fireflies should provide access to the SUs that belong to the same cluster. The primary and secondary users who reside in different channels are represented by corresponding colors. To overcome the multimodal optimization problems, different clustering of master and jumper firefly groups are communicating to select a global best master firefly. The global best master firefly to send the data to the sink and then update the information to the status table. The most important drawback of normal JFA is that there is no proper communication between fireflies for merging. The main advantage of DJFOC algorithm is that at end of each iteration, the clustering of every firefly knows the position and clustering of all other fireflies. This behavior is the cognition property of the DJFOC algorithm. DJFOC has increased the speed of convergence by grouping the fireflies among multi-users. Further, it can deal with multi-modal optimization problems very efficiently than other optimization techniques.

3 | FUNCTION OF PROPOSED DJFOC ALGORITHM

Figure 2 shows the flowchart of the DJFOC. The distributed sensor network in the study consists of *'N'* number of user nodes and *'K'* is the predetermined number of clusters. The function of DJFOC is as described briefly below.

i. Generate the initial population of fireflies in the solution space. Set *'S'* elements to comprise *'K'* arbitrarily chosen Cluster Heads (CHs) among all the suitable cluster head candidates.
ii. Estimate the cost function of each user node: For each user node point, n_i, i = 1, 2,…,N. Estimate the distance $d(n_i, CH_{p,k})$ between each user node and all CHs point position. The optimal number of clusters can be found by the following equation [12],

$$K = \left[\frac{N}{d_{max}\sqrt{3\varrho}} + 0.5\right] \quad (1)$$

where N is the total number of nodes, ϱ is the number of CRSN nodes per unit area and d_{max} is the maximum transmission range of CRSN nodes. Allocate each user node point n_i to CH where: $d(n_i, CH_{p,k}) = \min\{d(n_i, CH_{p,k})\}$ for k = 1, 2, …, K.

iii. Find the best CH for transmission using the fitness function of f_1 and f_2. All the clustering set of rules will be ensured at Base Station (BS) by the centralized algorithm [16]. The BS runs fitness function to find the best CHs and minimizes the cost function.

$$cost = f_1 \times \beta + f_2 \times (1 - \beta) \quad (2)$$

$$f_1 = \max_{k=1,2,,K}\left\{\sum\nolimits_{\forall n_i \in C_{p,k}} d(n_i, CH_{p,k}) / |C_{p,k}|\right\} \quad (3)$$

$$f_2 = \frac{\sum_{i=1}^{N} E(n_i)}{\sum_{k=1}^{K} E(CH_{p,k})} \quad (4)$$

where β is the user-defined constant. Let β = 0.5, f_1 is the maximum average of distance between the user nodes with associated Cluster Heads (CHs) and $|C_{p,k}|$ is the cluster particle p (i.e. the node). Function f_2 is average node energy.

iv. In each cluster, we check the fitness function of each user node and identify the light intensity associated with fireflies. All the remaining nodes move towards the brighter firefly with random velocity to form an organized cluster.
v. Improve the appropriate solutions by making the changes to eligible situation and find the optimal solution by status table. From the status table, observe all the current situation records which help to arrange the new suitable situation by the jumping process. If the firefly is in hazard state then it wants to manage jump operation to start a new updating and rearranges the new situation to obtain the status table, which is called Jumper Firefly (JFF).
vi. Update the position and light intensity of fireflies from the distance, and attractiveness of each firefly with other fireflies for next iteration.
vii. Go to step iii and repeat until reached maximum number of swarm iterations for optimization.
viii. The chosen master and jumper fireflies sense the available channel in its range. Thus, we select the channel with high channel quality with the condition that the selected channel should not be used by the nearby PUs.
ix. The global best firefly aggregates the data from the cluster members through the local common available channel. The global best firefly transmits the collected information to the base station.

3.1 | Analytical study of firefly attractiveness, distance and movement position

The firefly flash primary purpose is referred to in [17] acts as a signal system for attracting other fireflies. The light intensity is inversely proportional to the squared distance and directly proportional to the source intensity brightness; see below.

$$I(r) = \frac{I_0}{r^2} \quad (5)$$

where $I(r)$ is the light intensity at distance r and I_0 is the source intensity. Light intensity medium is calculated as follows:

$$I(r) = I_0 \exp\left(-\gamma r^2\right) \quad (6)$$

where γ is the medium absorption coefficient. To avoid singularity condition at r = 0 Gaussian approximation is evaluated as follows:

$$I(r) = I_0 \exp\left(-\gamma r^2\right) = \frac{I_0}{1 + \gamma r^2} \quad (7)$$

The firefly attractiveness factor β is directly proportional to light intensity visited by the adjoining fireflies.

$$\beta = \beta_0 \exp(-\gamma r^m) \quad (8)$$

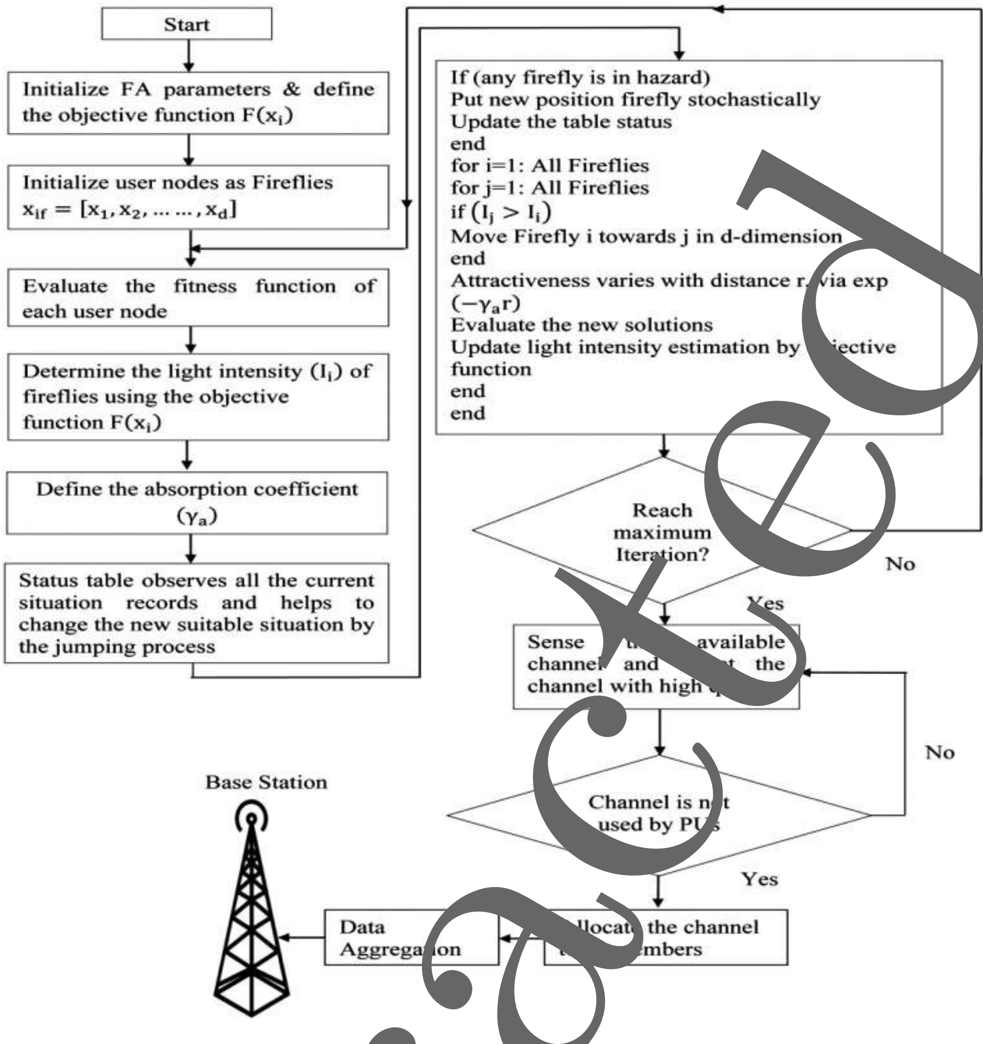

FIGURE 2 Flowchart of the proposed DJFOC

where β_0 is the attractiveness at $r = 0$. The $r_{i,j}$ is the distance between any two fireflies (i and j) placed at x_i and x_j is given by,

$$r_{i,j} = \sqrt{\sum_{k=1}^{d} \left(x_{i,k} - x_{j,k}\right)^2} \tag{9}$$

where $x_{i,k}$ is the coordinates of kth component firefly i, $x_{j,k}$ is the coordinates of kth component firefly j and d is the dimensions index number. A firefly ith firefly movement towards more brighter j^{th} firefly is given by,

$$x_i = x_i + \beta_0 e^{-\gamma r_{i,j}^2}(x_j - x_i) + \alpha(\text{rand}() - 1/2) \tag{10}$$

The term x_i is the firefly current position, $\beta_0 e^{-\gamma r_{i,j}^2}(x_j - x_i)$ is equivalent to the brightness attraction, α is the randomization parameter and rand() is the random numbers distributed uniformly in the interval [0,1]. After that Fireflies are ranked and obtain the current best cost function.

Algorithm The pseudo code for DJFOC Algorithm is described below:

```
Input:
f(x)-no.of fireflies
p=f(x)
g=0.9
α=0.2
Output:
Global best firefly
Step 1: Random node creation
      Foreach {n_i} {node($i)}
      {
       d=d(n_i,CH_p,k)
     Assign node n_i to cluster head CH_p,k
     where:
      d(n_i,CH_p,k)=^min ∀k=1,2..k{d(ni,CHp,k)}
      }
Step 2: Channel selections
    foreach {ch} {CHL}
     {
         cluster($cl_no) [list]
```

```
        foreach {cm} {Clustermember($ch)}
      {
              cluster($cl_no) $cm
      msgdisply("Cluster Head selection")
       }
Step 3: To find the best cluster head
selection cost function
  f1=max k=1,2,..,K{Σ∀ni∈Cp,k d(ni,CHp,k)/Cp,k}
     f2=sum{i=1,2,..,N} E(ni) / sum{i=1,2,..,K} E
(CHp,k)
  fitness=f1*β+f2*(1-β)
Step 4: Firefly attractiveness with objective
function
        β(r)=β0exp(-γr^m)
Step 5: Status table updation
while {$I!=$p($i)} {
  if(f(x)=hazard(true))
  {
   pos=$x_pos*$x_pos+$y_pos*$y_pos
   d=sqrt($pos)
msgdisplay("update status table"+$now list
($i))
}
for {set i 1} {$i<=$p} {incr i}
   {
   for {set j 1} {$j<=$p} {incr j}
     {
     if {$fx($i)} < {$fx($j)}
      {
      β(r) //attractiveness
      di,j=distance(x^i,x^j)
      I$d= ($p)/1+$g*pow($d)2
      fxi= $fxi+$b*($fx($j)-$fx($i)+$g*
      (rand(0,1)-0.5)
      msgdisply("update status table")
        }
       }
      }
Step 6: Maximum Iterations
    Iter=$iter+1
    while ($iter > $MAX)
     {
     $n($i) incr
     }
Step 7: Reclustering process
  If(firefly($i)=true)
  {
  f($i)->$gbffly
  }else if($gbffly=true)
  {
  $gbffly->BS
  }
  Else
  {
  Update the re-clutering process
  Repeated Steps 4, 5, 6
}
```

4 | RESULTS AND DISCUSSION

In order to evaluate the performance of the proposed DJFOC, an NS2 simulation study is carried out for CR networks. The parameters used in the simulation study are listed in Table 1. Figure 3 shows the number of PU's and SU's that dynamically access the channels with 'K' optimal number of clustered structures respectively. In Figure 3, 10 primary user nodes, 90 secondary user nodes, and 1 common receiver (sink) node are considered. Each user node is randomly placed in a 1000 × 1000 meter field and 10 common available channels marked by maroon, hot pink, cyan, yellow, yellow-green, deep pink, sky blue, violet red, green and blue colored selection. The notation for channel occupied by SUs are C0, C1,….C9 and PUs are 0,1,….9 in the NS2(Ver. 2.34) simulation environment. Each PU chooses any one of the common 10 channels and fortification range is 200 m so that remaining CRSN neighbors cannot access occupied channel. The analysis is carried over the time of simulation of 131.0 s and with constant packet size of 512 bytes. The PU activity checking interval is 0.2 s, sensing duration activity is considered to be within 5.6 s, and the initial energy of each node is 50 J. The SNR of sensed channel can be varied from 0 to 30 dB. The transmit and receive powers are 0.75 and 0.375W, respectively. The nodes are having sensing power of 0.25 W.

Figure 4 shows the performance comparison among DSOC, DFOC and DJFOC for CRSN Size Vs Average Converge Time. Cognitive Radio Sensor Network (CRSN) has combination of PUs and SUs. The CRSN size is a major constraint while simulating in NS2. It affects the converging time, node power and interferences. Hence main objective of this work is to reduce the crucial factors by transmission through only by the global 'G_{best}' node. As the CRSN size increases, average converge time increases linearly. In the DSOC, the average converge time is 4.533 s for the CRSN size of 20 and similarly, in the method of DFOC, the average converge time is at 2.720 s. In the proposed method of DJFOC, the average converge time is 1.943 s, which is 2.590 s less than the DSOC method and 0.777 s less than the DFOC at 20 CRSN sizes. If the proposed DJFOC is having less converge time compared to DSOC and DFOC at 280 CRSN sizes, the converging time of DJFOC is better by 50.133 s with DSOC and 15.040 s with DFOC. In this work maximum CRSN size of 280 is considered.

Figure 5 shows the analysis between cluster number and the average node power that was plotted. The graph shows power observed for different cluster number from 2 to 28. Average node power for CRSN is defined as the ratio of the sum of the total energy of PUs and SUs to the total number of nodes in clusters; often expressed in watt (W).

Average Node Power for CRSN is given as,

$$= \frac{\sum_{i=1}^{N} PU_i(\text{Energy}) + \sum_{i=1}^{N} SU_i(\text{Energy})}{\text{Total number of nodes in clusters}} \quad (11)$$

TABLE 1 Simulation parameters of optimized clustering techniques

Parameter Name	Specification
Channel type	Wireless channel
MAC layer	802.11
Network interface type	Phy/Wireless Phy
Interface queue type	Queue/Drop Tail/Pri Queue
Radio propagation model	Two-Ray Ground
Antenna model	Omni Antenna
Mobility model	Random Way Point
Mobility speed	5 m/s
Number of channels	10
Channel Bandwidth	6 MHz
Carrier Frequency	fc,1 = 800 MHz fc,i+1-fc,i = 6MHz; i = 1,....,9
Data traffic model	CBR over UDP
Data packet size	512 bytes
Data packet interval	0.0625 s
Routing protocol	AODV
Simulation software	NS-2, version 2.34
Simulation coverage area	1000 × 1000 m
Simulation time	131 s
Number of SUs	90
Transmission range radius of SUs	150 m

The graph shows Cluster Number Vs Average Node power values of DSOC, DFOC and DJFOC during the simulation analysis for combination of PUs and SUs in the network. At cluster number 2, average node power of DSOC is 6506.954 μW and similarly in the method of DFOC is 5142.954 μW. This is too high in practice, but in the proposed method DJFOC, the power is 2421.95[illegible] μW, which is 62.77% lesser than the DSOC method and 52.[illegible]% lesser than the DFOC. As the number of the cluster has increased, the average node power is reduced for the proposed DJFOC than DSOC and DFOC. At cluster number 28, average node power of DJFOC is better by 64.59% with DSOC and [illegible]4.86% with DFOC. This shows that there is a power saving of 92.23% in the proposed method compared to the DSOC and 72.61% with DFOC. In the simulation, the number of clusters from 2 to 28 is considered. We calculate the consumption of average node power by combination of PUs and SUs in the cognitive radio networks. From Figure [illegible], it is observed that the power remains constant for cluster number above 28, so the simulation was stopped at cluster number 28.

Figure 6 shows the performance comparison among DSOC, DFOC and DJFOC for PU Number Vs Average Node Power. Average node power for Pus is defined as the ratio of the sum of the total energy in PUs to the total number of Pus that is often expressed in watt (W).

Average Node Power for Pus:

$$= \frac{\sum_{i=1}^{N} \mathrm{PU_i(Energy)}}{\text{Total number of PUs}} \tag{12}$$

As the number of PUs increases, average node power increases linearly. If more PUs are considered in the transmission range, then the clustering process will involve more spectrum resource opportunistically. Thus, clustering will affect energy consumption [12]. In our simulation analysis, 10 primary user nodes only are considered within the fortification range of 200 m. In the DSOC, the power is constant at 759 μW for the primary users 1 to 5, and similarly, in the DFOC, the power is at 753 μW. The proposed DJFOC power is constant at 740 μW, which is 2.50% less the DSOC method and 1.72% less than the DFOC. For the proposed DJFOC, the power varies from 750 to 782 μW, which is less from 2.08% to 1.51% with DSOC and similarly the power is less; from 1.18% to 0.50% with DFOC. This shows that there is a power saving in the proposed method of 2.167% compared to the DSOC and 1.162% with DFOC.

Figure 7 shows the performance comparison among DSOC, DFOC and DJFOC for SU Number Vs Average Node power. Similarly, average node power for SUs is defined as the ratio of the sum of the total energy in SUs to the total number of SUs often expressed in watt (W).

Average Node Power for SUs

$$= \frac{\sum_{i=1}^{N} \mathrm{SU_i(Energy)}}{\text{Total number of SUs}} \tag{13}$$

In the simulation, 90 secondary user nodes are considered within the fortification range of 150 m. As the number of SUs increases, average node power increases linearly. In the DSOC, the power is constant at 759 μW for the primary users 11 to 15, and similarly, in the DFOC, the power is at 753 μW. The proposed DJFOC power is constant at 740 μW which is 2.50% less the DSOC method and 1.72% less the DFOC. For the proposed DJFOC, the power varies from 748.50 to 1584.50 μW, which is less than 3.04% to that of 13.36% with DSOC and similarly, the power is less than 2.28% to that of 3.50% with DFOC. This shows that there is a power saving in the proposed method of 10.137% compared to the DSOC and 2.801% with DFOC.

The single threshold detector performs well in cooperative spectrum sensing networks by high detection probability with less false rate. At the detection stage, the sensing error (noise) in cooperative nodes over channel is removed with reliable decisions. The detection performance of a spectrum sensing technique can be evaluated using the probability of false alarm, detection and missed detection [18]. Estimate the SNR for the detection of received signal and decide output from detection performance of spectrum sensing techniques. The threshold $\lambda = 4$ dB is based on the experimental results and observations [19].

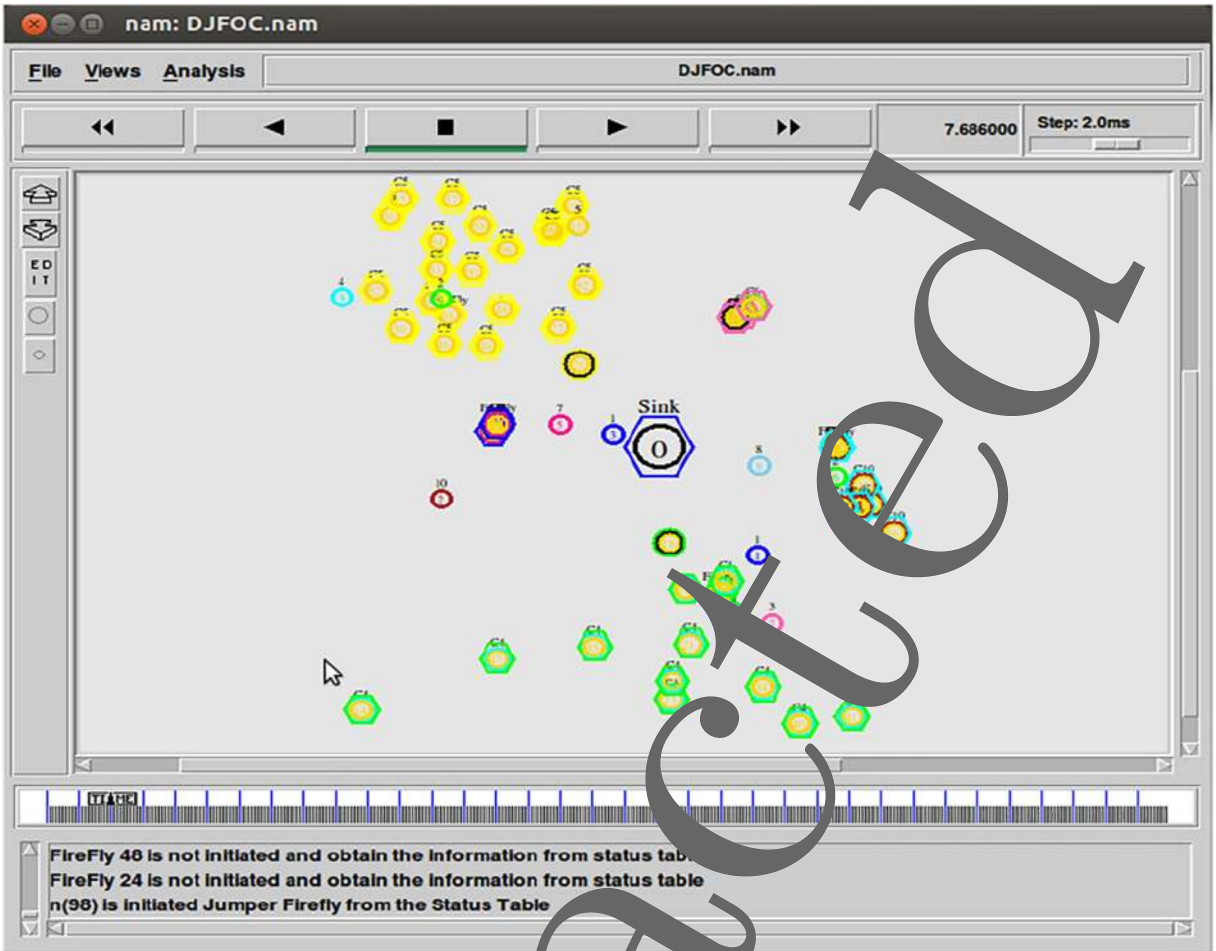

FIGURE 3 Channel Distribution for PUs and SUs in DJFOC

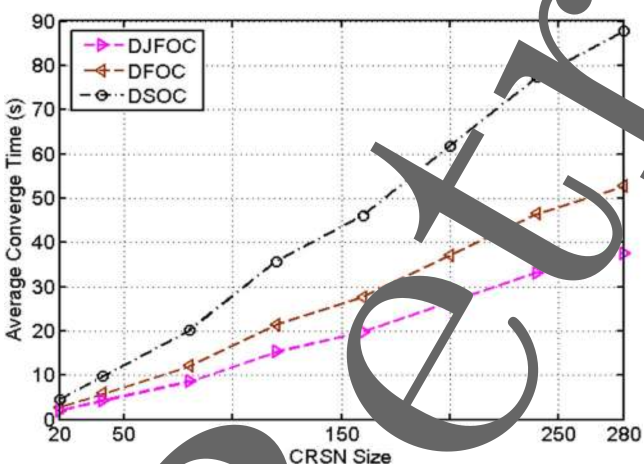

FIGURE 4 Comparison of CRSN Size Vs Average Convergence Time

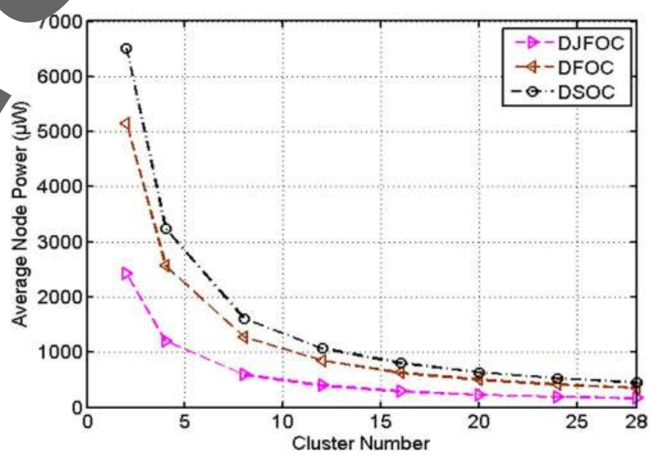

FIGURE 5 Comparison of Cluster number Vs Average Node Power

a. If threshold value λ is greater than SNR (the primary user over channel is wrongly detected 'H_1'), then the hypothesis model is performed by the probability of false alarm technique. that is, if $\lambda > SNR$, Accept $H = H_1|H_0$.
b. If threshold value λ is greater than SNR (the primary user over channel is correctly detected 'H_1'), then the hypothesis model is performed by the probability of detection technique. that is, if $\lambda > SNR$, Accept $H = H_1|H_1$
c. If threshold value λ is less than SNR (the primary user over channel is not detected 'H_0'), then the hypothesis model is performed by the probability of missed detection technique. that is, if $\lambda \leq SNR$, Accept $H = H_0|H_1$

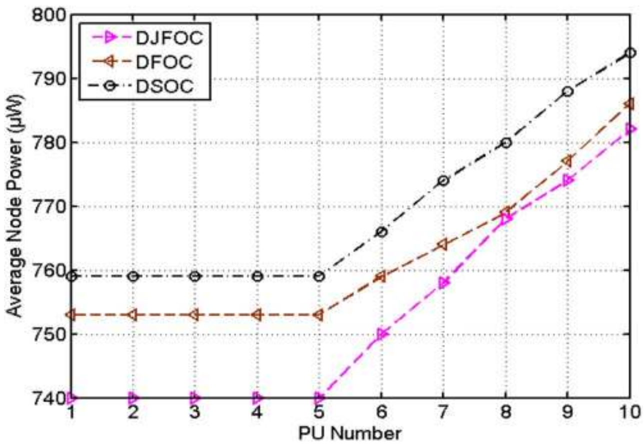

FIGURE 6 Comparison of PU Number Vs Average Node Power

The implementation is carried out using MATLAB R2013a. To determine whether the channel is being used by the primary user, the detection test statistic of output Y is compared with a predetermined threshold. Probability of false alarm (P_{FA}) is the probability that the hypothesis test chooses H_1 while it is in fact H_0.

$$P_{FA} = P(Y > \lambda | H_0) = \frac{\Gamma(m, \lambda / 2)}{\Gamma(m)} \quad (14)$$

Probability of detection (P_D) is the probability that correctly decides H_1 when it is actually H_1;

$$P_D = P(Y > \lambda | H_1) = Q_m\left(\sqrt{2\gamma_{avg}}, \sqrt{\lambda}\right) \quad (15)$$

where λ is the detection threshold, $\Gamma(.)$ is the complete gamma functions, $\Gamma(\ldots)$ is the incomplete gamma functio[illegible] is the average SNR, $Q_m()$ is the generalised Marcum Q-functio[illegible]nd $m = TW$ is the time-bandwidth product; considered as $m =$ [illegible] The equation for the probability o[illegible]tection is calculated using 'marcumq()' function in Matlab,

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int^{\infty} e^{\frac{u^2}{2}} \text{[illegible]} \quad (16)$$

The equation for probability [illegible]f false alarm is calculated using 'gamma()' and 'gammainc[illegible]' function[illegible] in matlab. gamma(x) represent[illegible]amma comp[illegible]ion is given as:

$$\Gamma(x) = \int_0^{\infty} \text{[illegible]} t^{x-1} dt \quad (17)$$

where gamma(a,x) [illegible]sents the gamma incomplete function,

$$\Gamma(a, x) = \int_x e^{-t} t^{a-1} dt \quad (18)$$

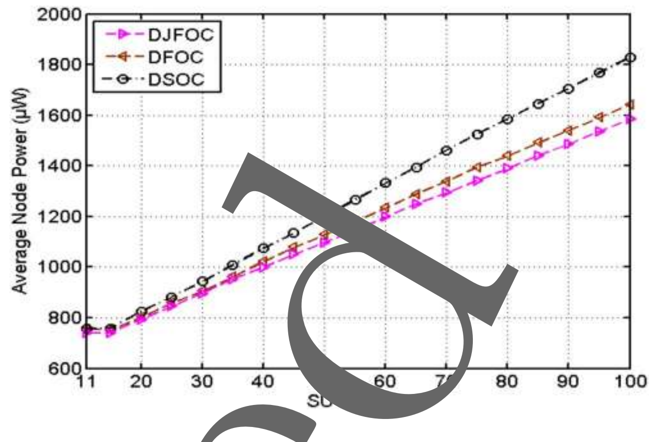

FIGURE 7 Com[illegible]parison of [illegible]U Num[illegible]ber Vs Average Node Power

(i.e.) igamma(a, [illegible] gamma(a) [illegible](1-gammainc(x, a))

The objective of [illegible]ity of missed detection (P_{MD}) is to [illegible]duce the P_{FA} and to increase P_D. In general, the performan[illegible]f P_{MD} is the probability that a PU is present over the cha[illegible]nel, [illegible] not able to detect the primary transmission signal. In terms o[illegible]thesis, it is written as:

$$P_{MD} = 1 - P_D = Pr(\text{Signal is not detected} | H_1) \quad (19)$$

[illegible]re 8 shows the performance comparison among DSOC, [illegible] and DJFOC for Probability of False Alarm Vs Probability of Detection in Receiver Operating Characteristics ([illegible]) cur[illegible]e. The performance of the detector under various values [illegible] probability of false alarm for SNR = 4dB. However, the leve[illegible] of SNR = 4dB is a little high for a proper range in the spectru[illegible]m sensing [19]. In the proposed method of DJFOC, the [illegible]ability of detection is optimum when the P_{FA} value is > 0.1 compared to DSOC and DFOC. The probability of a SU falsely decides a PU access over the channel in the spectrum band. Thus, the SUs missed the opportunity for efficient channel utilization. It is observed that DSOC and DFOC provide poor channel utilization by SUs.

Figure 9 shows the performance comparison between the DSOC and DFOC with DJFOC for Signal-to-Noise Ratio Vs Probability of Detection. The performance of detection is assumed that SNR varied from 0 to 30 dB values and the probability of false alarm is 0.1. As the SNR value increases, the probability of detection will increase linearly and reach constant of '1'. In a CR network, higher probability of detection corresponds to less interference with PUs. In the proposed method of DJFOC, the detection probability is about '0.888' compared to DSOC and DFOC when SNR is at '0 dB'. The Probability of a SU correctly decides PU access over the channel and it improves the efficient channel utilization. The DJFOC curve is converged to maximum probability of detection faster compared to DSOC and DFOC.

Figure 10 shows the performance comparison among DSOC, DFOC and DJFOC for Probability of False Alarm Vs Probability of Missed Detection. As the probability of false alarm rate increases, the probability of missed detection rate

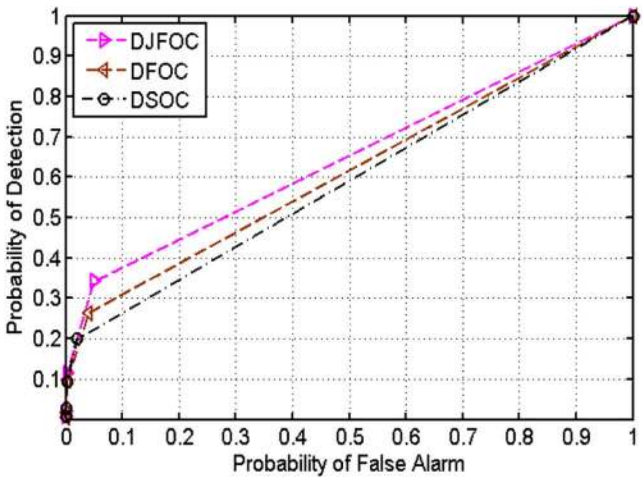

FIGURE 8 Comparison of Probability of False Alarm Vs Probability of Detection

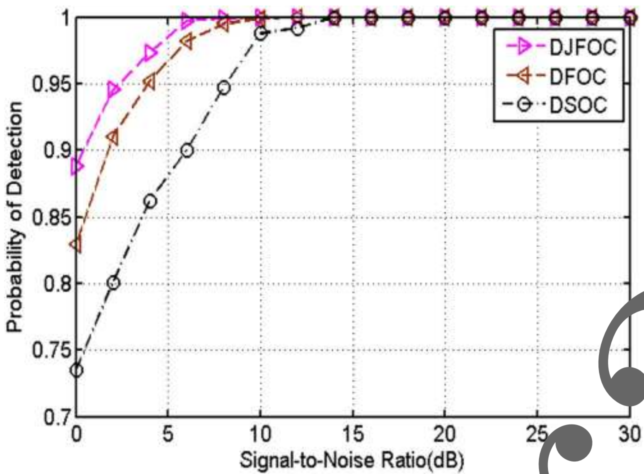

FIGURE 9 Comparison of Signal-to-Noise Ratio Vs Probability of Detection

decreases gradually for the complementary curve of ROC. The channel is active in the Pus, but unable to detect the primary transmission. This causes harmful interference to both PUs and SUs. In the DSOC method, P_{MD} value remains at '1' up to '0.5' value of P_{FA} and reaches '1' linearly, and similarly, in the DFOC, P_{MD} value remains at '1' up to '0.3' value of P_{FA} and reaches '1' linearly. In the proposed method of DJFOC, P_{MD} value is '1' when P_{FA} value is '0.2' and P_{MD} falls to '0' as P_{FA} is increased to '1'. Thus, our proposed DJFOC is better in detecting the primary transmission with its availability when the false alarm rate is high compared to DSOC and DFOC (e.g. at $P_{FA} = 0.7$, $P_D = 0.267$ and $P_{MD} = 0.733$).

5 | CONCLUSION

Dynamic clustering proves the individuality of the algorithms used for optimization. The obtained results show that DJFOC is an efficient algorithm for clustering in power saving and best

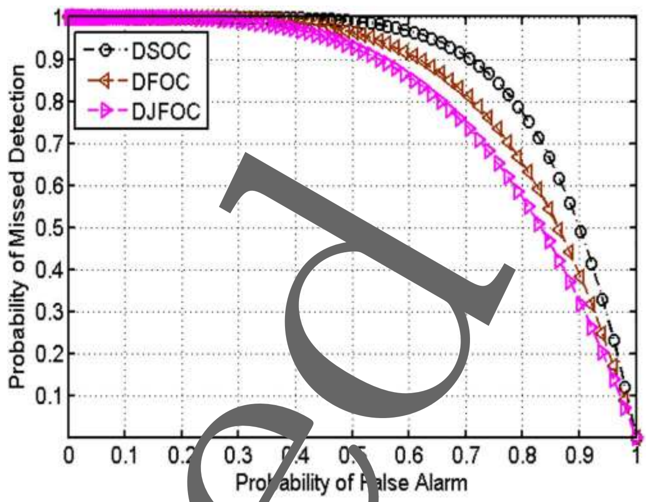

FIGURE 10 Comparison of Probability of False Alarm Vs Probability of Missed Detection

for channel sensing with better average converge time. The simulation performance shows superior, scalability, and constancy of DJFOC. The following observations can be made in the obtained results, which show the superior performance of our proposed DJFOC scheme.

i. The proposed algorithm has ranked master and jumper fireflies with high brightness value and obtained best among the cluster members, with a faster converging time of 37.60 s for 280 CRSN in size.
ii. The proposed algorithm uses different clustering of master and jumper firefly group in communicating to select a G_{best} master firefly with least clustering node power.
iii. The DJFOC is efficiently improving the converging rate by grouping clusters, which can observe all the current situation records and help to change the new suitable situation by the status table.
iv. The probability of detection is optimum in the proposed DJFOC with P_{FA} value above '0.1' and SNR is above 5dB compared to DSOC and DFOC.
v. The proposed DJFOC is better in detecting the primary transmission compared to DSOC and DFOC (e.g. at $P_{FA} = 0.7$, $P_D = 0.267$ and $P_{MD} = 0.733$).

Hence the performance analysis shows that there is 92.23% reduction in the proposed method compared to the DSOC and 72.61% with DFOC. DJFOC is better by 2.167% compared to the DSOC and 1.162% with DFOC in PUs average node power. Similarly, DJFOC is better by 10.137% compared to the DSOC and 2.801% with DFOC in SUs average node power. Therefore, the proposed optimization technique can be used to save transmit power with the shortest distances and achieve energy-efficient clusters while restricting interference to primary users.

ACKNOWLEDGEMENTS
This work was supported by the RaGa Academic Solutions, Chennai, India.

REFERENCES

1. Ganesh Babu, R., Amudha, V.: A survey on artificial intelligence techniques in cognitive radio networks. In: Proceedings of 1st International Conference on Emerging Technologies in Data Mining and Information Security in Association with Springer Advances in Intelligent Systems and Computing Series, pp. 99–110 (2018). https://doi.org/10.1007/978-981-13-1951-8_10
2. Ganesh Babu, R., Amudha, V.: Cluster technique based channel sensing in cognitive radio networks. Int. J. Contr. Theor. Appl. 9(5), 207–213 (2016)
3. Rehmani, M.H., Dhaou, R.: Cognitive Radio, Mobile Communications and Wireless Networks. EAI/Springer Innovations in Communication and Computing (2018). https://doi.org/10.1007/978-3-319-91002-4
4. Zikria, Y.B., et al.: Opportunistic channel selection MAC protocol for cognitive radio ad hoc sensor networks in the internet of things. Sustain. Comput. Infor. Syst. 18, 112–120 (2018). https://doi.org/10.1016/j.suscom.2017.07.003
5. Pandit, S., Singh, G.: Spectrum Sharing in Cognitive Radio Networks: Potential Challenges and Future Perspective. Springer (2017). https://doi.org/10.1007/978-3-319-53147-2
6. Fernando, X., et al.: Cooperative Spectrum Sensing and Resource Allocation Strategies in Cognitive Radio Networks. Springer Briefs in Electrical and Computer Engineering (2018). https://doi.org/10.1007/978-3-319-73957-1
7. Ren, J., Zhang, N., Shen, X.S.: Energy-Efficient Spectrum Management for Cognitive Radio Sensor Networks. Springer (2017). https://doi.org/10.1007/978-3-319-60318-6
8. Mahmoodi, S.E., Subbalakshmi, K., Uma, R.N.: Spectrum-Aware Mobile Computing: Convergence of Cloud Computing and Cognitive Networking, Signals and Communication Technology. Springer (2019). https://doi.org/10.1007/978-3-030-02411-6
9. Ganesh Babu, R., Amudha, V.: Comparative analysis of distributive optimized clustering techniques in cognitive radio networks. Int. J. Eng. Technol. 7(3.27), 504–507 (2018). https://doi.org/10.14419/ijet.v7i3.27.18470
10. Ganesh Babu, R., Amudha, V.: Comparative analysis of distributive firefly optimized spectrum sensing clustering techniques in cognitive radio networks. J. Adv.Res. Dynam. Contr. Syst. 10(9), 1364–1373 (2018)
11. Wierzchon, S.T., Klopotek, M.A.: Algorithms of Cluster Analysis. Institute of Computer Science Polish Academy of Sciences (2015). https://doi.org/10.1007/978-3-319-69308-8
12. Zhang, H., et al.: Distributed spectrum aware clustering in cognitive radio sensor networks. In: Proceedings of the IEEE International Conference on Global Telecommunications, pp. 5266–5271, Houston (2011). https://doi.org/10.1109/GLOCOM.2011.6134296
13. Yadav, A., Kumar, S., Vijendra, S.: Network life time analysis of WSNs using particle swarm optimization. In: Proceedings of the 4th International Conference on Computational Intelligence and Data Science. Elsevier-Procedia Computer Science, pp. 805–815 (2018). https://doi.org/10.1016/j.procs.2018.05.092
14. Wang, H., et al.: A hybrid multi-objective firefly algorithm for big data optimization. Appl. Soft Comput. 69, 806–815 (2018). https://doi.org/10.1016/j.asoc.2017.06.029
15. Bidar, M., Kanan, H.R.: Jumper firefly algorithm. In: Proceedings of the Third IEEE International Conference on Computer and Knowledge Engineering (ICCKE), pp. 1–5 (2013). https://doi.org/10.1109/ICCKE.2013.6682839
16. Wierzchon, S.T., Klopotek, M.A.: Modern Algorithms of Cluster Analysis. Springer (2018). https://doi.org/10.1007/978-3-319-69308-8
17. Yang, X.-S.: Nature-Inspired Algorithms and Applied Optimization. In: Studies in Computational Intelligence. Springer (2017). https://doi.org/10.1007/978-3-319-67669-2
18. Shanmugavel, S., Bhagyaveni, M.A., Kalidoss, R.: Cognitive Radio: An Enabler for Internet of Things. River Publishers, Netherlands (2017)
19. Lavanya, S., Sindhuja, B., Bhagyaveni, M.A.: Implementation of an adaptive spectrum sensing technique in cognitive radio networks. In: Proceedings of the IEEE International Conference on Computing and Communications Technologies (ICCCT), 3… 49 (2015). https://doi.org/10.1109/ICCCT2.2015.7292773
20. Algorithms and Computational Technology, 12, 2, pp. 119–126 (2018)
21. Aavula, R., Bhramaramba, R.: XBPF: an extensible breast cancer prognosis framework for predicting susceptibility, recurrence and survivability. Int. J. Eng. Adv. Technol. 8(5), 2249–8958 (2019)
22. Sujatha, K., Muralikrishna, P., Chandramouleeswaran, M.: (S, T)-Normed intuitionistic fuzzy beta subalgebras. Bulletin Inter. Math. Virtual Inst. 7(2), 353–361
23. Anbarasan, M., et al.: Detection of flood disaster system based on IoT, big data and convolutional deep neural network. Comput. Commun. 150, 150–157 (2020)
24. Sujatha, K., et al.: Grey wolf optimiser-based feature selection for feature-level multi-focus image fusion. Int. J. Bus. Intell. Data Min. 16(3), 279–295 (…)
25. Sitharthan, R., Sundarabalaji, K.R., Jees, A.: An Levenberg-Marquardt trained feed-forward back-propagation based intelligent pitch angle controller for wind generation system. Renew. Energy Focus. 22–23, 24–32 (2017)
26. Krishnamoorthy, S., et al.: A secure privacy preserving proxy re-encryption scheme for IoT security using near-ring. In: Proceedings of the 2019 the International Conference on Pattern Recognition and Artificial Intelligence (2019)
27. Sitharthan, R., et al.: Automated power management strategy for wind power generation system using pitch angle controller. Meas. Contr. 52(3–4), 169–182 (2019)
28. Sitharthan, R., et al.: Analysis on smart material suitable for autogenous microelectronic application. Mater. Res. Express. 6(10), 105709 (2019)
29. Karthikeyan, M., Saraswady, D.: Reduced complexity sphere decoding using probabilistic threshold based Schnorr-Euchner enumeration. AEU Int. J. Electron. Commun. 70(4), 449–455 (2016)
30. Karthikeyan, M., Saraswady, D.: Performance analysis of layer pruning on sphere decoding in MIMO systems. ETRI J. 36(4), 564–571 (2014)
31. Nandagopal, V., et al.: Feasible analysis of gene expression – a computational based classification for breast cancer. J. Int. Meas. Confed. (2019)

How to cite this article: Babu R G, Obaidat MS, V A, Manoharan R, R S. Comparative analysis of distributive linear and nonlinear optimized spectrum sensing clustering techniques in cognitive radio network systems. *IET Netw.* 2021;1–11. https://doi.org/10.1049/ntw2.12027