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RESEARCH ARTICLE

Optimized Cooperative Spectrum Sensing in Cognitive Radio Sensor Networks Using Extended XGBoost Model

Anu Maria Joykutty
Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India.
aj7049@srmist.edu.in

B. Baranidharan
Department of Computing Technologies, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India.
baranidb@srmist.edu.in

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Abstract – Cognitive radio (CR) is a transformative technology designed to address the growing demand for spectrum resources. By intelligently sensing the radio environment, CR devices identify unused spectrum bands and dynamically adapt their transmission parameters to efficiently utilize these resources. Cooperative Spectrum Sensing (CSS) is a crucial method used in cognitive radio networks to enhance spectrum sensing reliability and accuracy. By collaborating, multiple secondary users (SUs) improve their ability to detect primary user (PU) activity and identify available spectrum opportunities. In a traditional cooperative spectrum sensing paradigm, each user independently senses the spectrum and reports the local decision to the fusion center. The fusion center combines these individual decisions to make a more accurate global decision about spectrum availability. Such a static approach is unsuitable for achieving cooperative gain and adapting to a large cognitive radio sensor network (CRSN). The primary challenges are reduced sensing accuracy, limited scalability, and increased communication overhead because of unreliable or redundant local decisions. These issues necessitate the development of more adaptive and optimized methods for the efficient utilization of spectrum in dynamic environments. Thus, the proposed study presented effective Optimized cooperative spectrum sensing in CRSN (OCSS-CRSN). The proposed framework performs a clustering process using novel enhanced agglomerative hierarchical clustering (EAHC). The cluster heads are then selected using a novel chaotic pelican optimization algorithm (CPOA). Then, FC combines the local decisions made by cluster heads to reach a final decision using a novel machine learning-based extended XGBoost model (E-XGBoost). Finally, simulation results show that the proposed CSS algorithm achieves a throughput of 50.91kbps in static CRSNs and 53.33kbps in static CRSNs while maintaining CSS performance.

Index Terms – Cognitive Radio, Cognitive Radio Sensor Network, Cooperative Spectrum Sensing (CSS), Enhanced Agglomerative Hierarchical Clustering, Fusion Center, Pelican Optimization, Primary User, Secondary User, XGBoost.

1. INTRODUCTION

Wireless sensor networks (WSNs) have transformed how data is acquired and handled from the physical environment. A WSN is made up of sensor nodes, each of which can sense, process, and communicate [1]. In recent years, WSNs has shown considerable improvement in terms of size, memory, and processing capabilities using power savings schemes [2, 3]. The rise in number of sensor nodes adds additional complexity and memory usage of the underlying infrastructure. WSNs usually operate in unlicensed ISM bands. Nowadays, the unlicensed ISM bands are crowded due to the increase in usage of applications, thereby causing co-existence problems [4, 5]. Therefore, WSNs needed additional capabilities to combat the interference received from other applications. The most interesting solution to this problem is to use cognitive radio (CR) networks, which provide sensor nodes with spectrum access capabilities. The CR communicates with licensed bands by sensing for unoccupied bands [6,7]. The increased use of wireless services has succeeded in a spectrum deficit in wireless communication networks. Due to limited spectrum usage and limited spectrum availability, an effective communication system is required to optimally assign the spectrum [8].

The cognitive radio network (CRN) was developed as a possible approach for making better use of spectrum. The cognitive radio sensor network (CRSN) is an emerging sensor networking standard that integrates opportunistic spectrum access with the WSN. Because the sensor nodes have limited energy, it is critical to develop efficient spectrum sensing

RESEARCH ARTICLE

algorithms for CRSN implementation [9, 10]. Spectrum sensing is a secondary user technique that the CRN uses periodically to access the spectrum and prevent interference during transmission. The alternative sensing approaches proposed to reduce noise uncertainty include the Aigen-value-based and cyclostationarity-based methods [11]. However, the use of sensing techniques requires energy for periodic detection and decision-making in the CRN environment. This necessitates the need for energy-efficient CRN to extend the battery life. Nowadays, energy-efficient sensing has gained attention due to the gathering of energy from radio frequency signals to energy required for CRN [12, 13]. Thus, energy-efficient CRN provides an unlimited amount of energy while avoiding the need to replace batteries.

The energy-efficient CRN faces a throughput trade-off challenge between primary and secondary users. To address this, jointly optimize the sensing duration and threshold parameters in the CRN. The reliability is affected by shadowing and fading [14]. Cooperative spectrum sensing (CSS) improves sensing performance by involving many secondary users in spectrum sensing. CSS utilizes more energy for sensing and reporting compared to a single SU [15, 16]. Thus, final decisions are made using decision-making and data fusing. The data fusion process causes significant overhead and computational complexity due to the participation of a larger number of nodes. Thus, data-fusing techniques are applied to enhance the performance of sensing [17, 18]. The fusion process consists of both hard and soft fusion, with hard fusion sensor nodes converting received energy into binary values and sending them to the fusion center. In soft fusion, the sensor node sends energy directly to the fusion center without processing. However, hard fusion prioritizes time, and soft fusion prioritizes cooperative gain. Overall, the fusion procedure failed to strike a proper compromise between CSS performance and efficiency [19, 20]. Spectrum sensing is an important component of cognitive WSN because it provides sensor nodes with access to available spectrum. Individual node spectrum sensing is susceptible to a wide range of issues, including multipath fading, noise uncertainty, shadowing, and so on. CSS is thus used to optimize resource use while avoiding interference among major users. Numerous cooperative spectrum sensing systems are now being presented based on traditional spectrum sensing methods.

1.1. Motivation

Over the past few years, the number of wireless devices has increased at an exponential rate due to advancements in the wireless technology field. There is a steady stream of new products hitting the market, and customers are adopting these gadgets at an accelerated rate. Typically, wireless devices work in the radio frequency band, which runs from 3 kHz to 300 GHz. The allocation of spectrum to these devices is overseen by regulatory bodies such as the International Telecommunications Union. The most frequent technique of allocating spectrum is static allocation, which assigns spectrum to registered or licensed users. Due to the massive rise in wireless users, this static method of spectrum allocation has become decreasingly effective. This approach leads to inefficiencies and underutilization of the available resources because many spectrum segments are left unused or underutilized while other spectrum segments are heavily occupied. This study introduces an optimized cooperative spectrum sensing framework to achieve a balance between energy efficiency and sensing precision in Cognitive Radio Networks (CRNs). It reduces redundancy and communication overhead by incorporating intelligent cluster head selection and hierarchical clustering. Enhanced sensing accuracy is achieved in dynamic network environments by employing a decision fusion approach based on machine learning, while energy efficiency is preserved. The major contributions of the proposed framework are discussed as follows:

- To enhance the sensing accuracy and energy efficiency of cognitive radio sensor networks, a novel Chaotic optimized enhanced agglomerative hierarchical clustering approach for cooperative spectrum sensing was proposed.
- To develop a clustering approach for CRSN with reduced energy consumption, increased lifetime and stability using an enhanced agglomerative hierarchical clustering method.
- To select an optimal cluster head from the cluster using a chaotic pelican optimization algorithm.
- Finally, the fusion center aggregates the data received from the cluster head and makes the final decision using a novel machine learning-based extended XGBoost model.

The remaining paper is organized as follows. Section 2 explains relevant works on CRSNs, Section 3 discusses on the system model and suggested method, Section 4 shows simulation results to verify the efficacy of the suggested approach, and Section 5 discusses the work's conclusion and future scope.

2. RELATED WORK

Jyothi et al. [21] presented a fuzzy-clustering-based congestion control mechanism for CRSN. In WSN, the availability of frequency spectrum was sparse, and energy consumed was expensive; thus, CR was introduced in WSN to overcome this problem. In the CR network, the principal user utilizes the licensed band, and the secondary user uses the licensed channel. Clustering techniques are used to improve network scalability based on lifetime and energy usage. The challenges of replacing and charging battery nodes necessitate the use of clustering algorithms. Clustering methods use energy-efficient fuzzy clustering and congestion management

RESEARCH ARTICLE

algorithms to access the spectrum efficiently. The cluster heads are selected according to residual energy, queue length, and spectrum availability. The strategy produced better results in terms of energy usage and network lifespan.

Govindasamy et al. [22] adopted a multi-objective crow-swarm intelligence algorithm for increasing energy and spectrum efficiency in cognitive radio ad-hoc networks (CRAHN). The CRSN are deployed in the sensor field to form a network, followed by spectrum sensing to determine the available spectral band using energy detection, wavelet-based detection, and matching filtering. The spectrum decision was based on quality of service (QoS), system accessibility, and scalability. The CR broadcasts data on a specific frequency with low energy and uses spectrum handoff techniques when shifting to a newer frequency. The CRSN combine the data collected from sensor nodes and transmits the data through the interaction method.

SMKM et al. [23] demonstrated an energy- and spectrum-aware clustering protocol for CRSN. Dynamic spectrum access in CRSN resulted in energy depletion. To tackle the scalability issue with clustering-based techniques, energy and spectrum-aware routing algorithms for CRSN were presented. This optimizes energy consumption and spectrum utilization in large-scale networks. The network was separated into multiple clusters, with the cluster head selected based on criteria such as energy and channel availability rate. The data collected is sent to the sink node via multi-hop interaction among cluster heads. Finally, the performance was measured using the packet delivery ratio and energy usage.

Optimization techniques help to reduce energy usage and interference during data transfer. Sharada et al. [24] utilized the adaptive ant colony distributed intelligent clustering method (AACDIC) to enhance energy efficiency by determining the optimal number of clusters through cluster-based sensing. The AACDIC approach surpassed existing optimization methods by making use of multi-user clustered communication. The experimental results demonstrated the algorithm's effectiveness in reducing the identified shortcomings, emphasizing the importance of SNR attentions in maximizing detection reliability in energy-constrained WSNs.

Nageswari et al. [25] introduced Cognitive Radio, which enables cognitive operations in radio and network technologies. Cognitive Radio regulates transmission parameters by automatically identifying available channels in the wireless spectrum. This enhances communication within the electromagnetic environment by automatically sensing and adjusting control factors such as interoperability, throughput, and interference.

The challenges include variations in spectrum use, channel quality, and transmit power. Thus, Lagrangian multipliers are utilized to improve frequency access capacity, whereas Proportional Fair scheduling techniques are used to increase throughput. The integration of Cognitive Radio into wireless networks allows for intelligent and efficient spectrum utilization. The comparison of existing studies is provided in Table 1.

Table 1 Comparative Study

Author	Method	Advantages	Limitations
Jyothi et al. [21]	Energy-efficient fuzzy clustering and congestion control algorithm	Adapt to changes in network conditions	Fuzzy logic was expensive for large-scale network
Govindasamy et al. [22]	Multi-objective crow-swarm intelligence algorithm	Faster convergence speed	Algorithms suffer from premature convergence and get stuck in local optima.
SMKM et al. [23]	Energy and spectrum-aware clustering protocol for CRSN	Optimizes energy usage and reduces energy consumption	Increased complexity and overhead
Sharada et al. [24]	AACDIC	Adapt to changes in network conditions	Increases convergence time and reduces performance
Nageswari et al. [25]	Lagrangian multiplier and Proportional Fair scheduling algorithms	Efficient allocation of resources	Converge to local optima, thus problematic for dynamic environment

RESEARCH ARTICLE

2.1. Problem Statement

The conventional method of spectrum sensing involves the sensing process being carried out by a single SU. This may lead to degradation in detection performance owing to various factors like noise, multipath fading, etc. To improve sensing performance and energy efficiency, a cooperative sensing approach is used in which several secondary users jointly watch the spectrum. Individual sensing results are then integrated to produce a result indicating the existence or non-existence of a PU. The Nodes may be unable to detect each other due to obstacles or distance, resulting in interference. Malicious nodes use primary user signals to disrupt the network. Inaccurate spectrum sensing causes interference with primary users and inefficient spectrum utilization. Continuous sensing, data processing, and communication drain the battery power of sensor nodes. Thus, effective power management approaches are required to extend the lifespan of sensor nodes.

3. PROPOSED MODELLING

An adaptive clustering and machine learning algorithm is used to solve the problems with enhanced spectrum sensing in CRSN. Clustering divides the sensor network into multiple groups, each led by a cluster head (CH) that coordinates spectrum sensing within its cluster. The CH receives the results of local spectrum sensing conducted by each cluster member. The CH evaluates the results and makes a local decision, which is subsequently forwarded to a fusion center (FC) or a central decision maker. This layout reduces energy usage throughout the network by lowering the number of nodes required to relay data to the FC. The CH or FC can use machine learning algorithms to increase spectrum sensing accuracy. The workflow of the proposed CSS is shown in Figure 1.

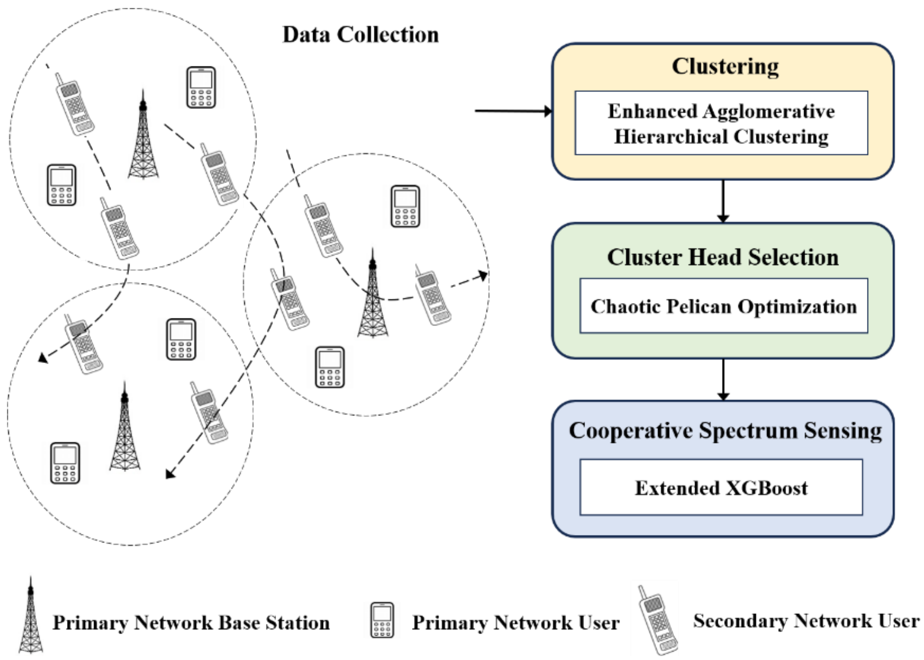

Figure 1 Block Diagram of CSS in CRSN

This study involves the following steps: data collection, clustering, aggregation, and cluster head selection. Initially, the input data are gathered from various sensor nodes in the cognitive radio network environment. Clustering with cluster head selection is used to group data, maintaining energy efficiency by providing a revolutionary Chaotic optimized enhanced agglomerative hierarchical clustering approach. The organization of sensor nodes into clusters is achieved by enhanced agglomerative hierarchical clustering. The cluster heads are selected in an efficient manner using Chaotic pelican optimization. Traditional models often use static clustering methods which rely on fixed decision mechanisms. In contrast to this, the proposed model introduces a novel approach that brings in adaptability and randomness, thereby enhancing the robustness of the system. Finally, the local decisions from the selected cluster heads are intelligently aggregated and transmitted to the fusion center for decision-making via a machine learning-based extended XGBoost model. This process improves the accuracy of spectrum sensing and reduces energy consumption and communication overhead. Therefore, combining hierarchical clustering, chaotic optimization and machine learning, the proposed model differs from other existing models by providing better energy efficiency, decision accuracy and stability, particularly in the scenario of dynamic cognitive wireless sensor network environments.

The CRSN system model is depicted in Figure 2. The CRN environment consists of a PU as well as a SU operating in the same spectrum band. The PU has exclusive access to the communication channel, whereas the SU leverages the frequency gaps left by the PU to function in a cognitive radio network. The CR is an enabling technology that allows for efficient utilization of resources. The CR system employs wireless devices to adjust transmission power, frequency, and modulation according to the surrounding environment. The CRSN consists of cluster heads (CHs) and member nodes. The nodes are reduced-function devices that communicate collected data to the CH over an available channel. The CH coordinates the communication between nodes. The CRSN consist of a base station (BS), the primary user positioned randomly as well as number of sensor nodes.

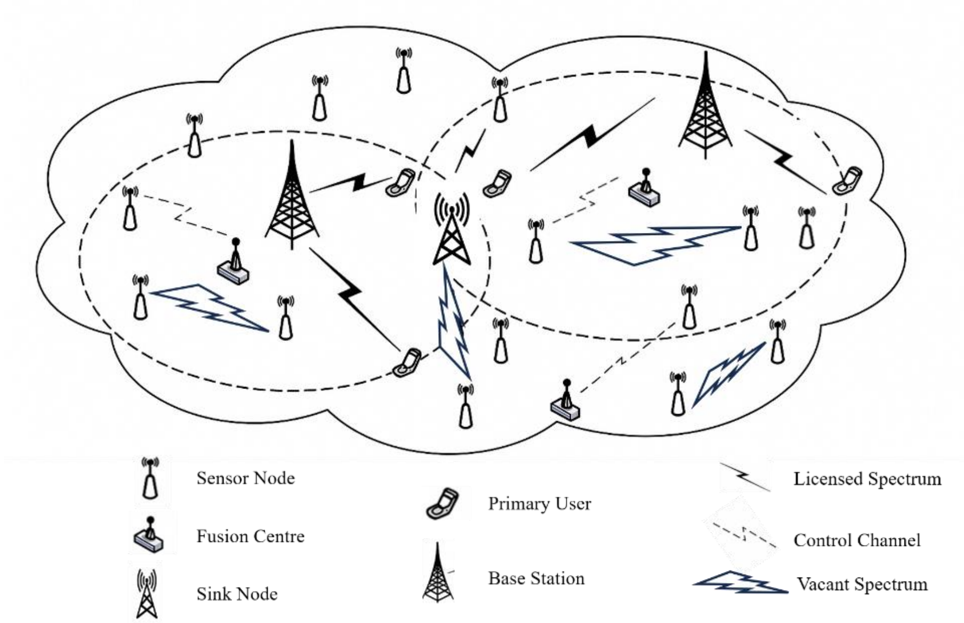

Figure 2 System Model

The PU and sensor nodes are distributed randomly, while the channel is modelled based on path loss, fading, and shadowing. The major objective of the suggested model is to allow nodes to sense the channel and harvest energy efficiently [26] as shown in equation (1).

$$\forall_{s_s}, s_h \subset \{1,2,..,n\} \begin{cases} s_h \cap s_s = \Phi \\ s_h \cup s_s = m \end{cases} \quad (1)$$

Where, s_s represents channel sensing sensors, s_h represents energy harvesting sensors. In CRSN, each mobile station acts as several sensor nodes surrounding CR. The sensor nodes forward the sensing results to CR, which serves as the cluster head. The CR can move in any direction within a predetermined area because it knows the position of the sensor nodes. After estimating the channel occupancy by spectrum sensing, each sensor node sends the sensing data to the fusion center for centralized decision-making. The fusion center makes a final decision that is sent to the sensor nodes. The local decision made by the sensor node is a binary variable 0 or 1, here '0' indicates that the spectrum is accessible to secondary nodes as well as '1' indicates that the spectrum is unavailable. CRSN nodes sense the spectrum using binary hypotheses I_0 and I_1 where, I_0 represents the absence of a binary signal, I_1 represents the presence of the binary signal. The sensor nodes collect S_0 samples in one sampling period; the Hth observation sample $o_i[H]$ sensed by the node i is given in equation (2) and (3).

$$I_0: o_i[H] = g_i(H), H = 1, \dots, M \quad (2)$$

$$I_1: o_i[H] = p_i(H) + g_i(H), H = 1, \dots, M \quad (3)$$

where, M represents the number of CRSN, $p_i(H)$ represents the signal received by the primary user, $g_i(H)$ represents white Gaussian noise signal with zero mean as well as variance σ_g^2. The sensor node detects the licensed spectrum through energy sensing, and the fusion center aggregate collected at the node i is given in equation (4).

$$E_i = \sum_{H=1}^{T} x_i^2 \, [H] \quad (4)$$

3.1. Clustering Using Enhanced Agglomerative Hierarchical Clustering

The proposed methodology used enhanced agglomerative hierarchical clustering (EAHC) [27] by modifying the hierarchical clustering algorithm. The knowledge behind

RESEARCH ARTICLE

EAHC is that constructing a cluster node requires only one hop neighbor knowledge. To illustrate the EAHC approach, CRSN makes the following assumptions. The population of nodes in the network operates quasi-stationary, which means that the number of nodes remains relatively constant over short periods of time. After deployment, the nodes are left alone, and each node is only aware of local information about one neighbor. Every node has comparable processing, communication, and energy capacities. The channel is considered symmetric, and the range of nodes can be adjusted. The fundamental concept of the proposed clustering method is to integrate weak and strong nodes to form a cluster that exhibits an extended lifespan. To ensure that each cluster member receives an equal share of the load, the cluster head is chosen within each cluster. EAHC is a bottom-up technique wherein nodes that discharge at a faster rate merge with other nodes to create a new cluster. To generate a new cluster with greater energy efficiency, the clustering algorithm iteratively selects the cluster with the shortest residual lifespan and unites it with a nearby cluster. The procedure repeats until the entire network is combined into one single cluster having the longest lifetime. Algorithm 1 demonstrates the clustering procedure using the EAHC method.

Input: Set of nodes L

Output: Clusters

$E_{net} \leftarrow \{\{a\}|a \in L\}$

$E_{net}^{opt} \leftarrow E_{net}$

$T_{net}^{opt} \leftarrow min_{C \in E_{net}} T_{CL}$

function Clustering (L)

while $|E_{net}| > 1 \ do$

$CL_{weakest} \leftarrow argmin_{CL \in E_{net}} T_{CL}$

$CL_{partner} \leftarrow argmin_{CL \in E_{net}/\{CL_{weakest}\}} T_{CL \cup CL_{weakest}}$

$CL_{merged} \leftarrow CL_{weakest} \cup CL_{partner}$

$E_{net} \leftarrow E_{net}/\{CL_{merged}\}$

$T_{net} \leftarrow min_{CL \in E_{net}} T_{CL}$

If $T_{net} > T_{net}^{opt} then$

$E_{net}^{opt} \leftarrow E_{net}$

$TC_{net}^{opt} \leftarrow Tc_{net}$

End if

End while

Return E_{net}^{opt}

End function

Algorithm 1 Enhanced Agglomerative Hierarchical Clustering (EAHC)

Where, L denotes the number of nodes in the CRSN, CL represents a cluster of nodes, T_{CL} represents cluster lifetime, E_{net} represents the family of clusters, T_{net} represents network lifetime as shown in equation (5).

$$T_{net} = \min_{CL \in E_{CL}} T_{CL} \quad (5)$$

Initially, each cluster is considered as a cluster with only one node represented as $E_{net} = \{\{a\}|a \in L\}$. The number of transmissions needed to transfer data from the CH to the sink node determines cluster lifespan.

$$Energy_a^{ini} \geq Energy_{a \to sink} P_a \quad (6)$$

In equation (6), $Energy_a^{ini}$ represents the initial energy of node, $Energy_{a \to sin\,k}$ represents amount of energy node consumed to transmit to sink node. P_a represents the number of rounds which is an integer considered as floating point number evaluated as given in equation (7).

$$P_a = \frac{Energy_a^{ini}}{Energy_{a \leftarrow sink}} \quad (7)$$

The cluster with a single node is identified as the weakest cluster and represented as $a^* = argmin_{a \in L} P_a$. Therefore, the network lifetime is evaluated using the equation (8) given as,

$$T_{net} = P_a^* \quad (8)$$

After the initialization of parameters, the clustering process begins by selecting the weakest cluster among the clusters. Then, new clusters are formed by merging weak cluster CL_{weak} with other clusters $CL_{partner}$ to form a merged cluster with a longer lifetime. Thus, the newly established merged cluster CL_{merged} exist in the network instead of two distinct clusters. Also, the network lifetime T_{net} is updated based on modified E_{net}. If the modified lifetime T_{net} is greater than the T_{net}^{opt} then replace T_{net}^{opt} by T_{net} making the network configuration E_{net} the provisional optimal cluster configuration E_{net}^{opt}. Eventually, the iterations converge to the network's maximum lifespan. This step is associated with optimal network lifetime, referred as L_{net}^{opt}, and the development of clusters at this stage is considered the optimal cluster formation, labeled as opt E_{net}^{opt}.

3.2. Cluster Head Selection Using Chaotic Pelican Optimization Algorithm (CPOA)

In CRSN, each node looks for channels in the network, and the nodes are divided into clusters using an upgraded agglomerative hierarchical clustering technique, avoiding the re-clustering problem. The frequency is assigned to both primary and secondary users in a consistent and sequential manner. To ensure proper data transmission from the base station to the remaining nodes in the CRSN, a group of cluster heads from each cluster must be chosen. An optimal cluster head is selected from the clusters using CPOA. The optimal

RESEARCH ARTICLE

cluster head is randomly selected from clusters [14] based on equation (9).

$$H_{opt} = \left[\frac{M}{D_{max}\sqrt{3\delta}} + 0.5\right] \quad (9)$$

Where, M represents total number of nodes available, δ represents density of node in CRSN, D_{max} represents the maximum distance between nodes. The CH is evaluated using CPOA, which reduces time and improves energy efficiency. The base station was chosen so that the communication range was within the CH's capabilities, allowing both to interact efficiently. To ensure the CH works properly, the transmission power is tested using the following methods as shown in equation (10).

$$Power_{TX} = \sum_{k=1}^{K} \sum_{i=1}^{I} Dist_{min}\,(node_i^k, center(CH)) \quad (10)$$

Where, $Dist_{min}$ represents the shortest possible distance and is calculated as given in equation (11).

$$Dist_{min} = \sqrt{(a1-a2)^2 + (b1-b2)^2} \quad (11)$$

As a result, cluster head is chosen based on the shortest distance and the lowest power consumption while using CPOA.

The optimal CH is selected using CPOA, where the CPOA is modified by hybridizing the chaotic circle map with the pelican optimization algorithm. The pelican optimization technique is modified by incorporating the circular chaotic map equation into the exploration and exploitation phases. The circle chaotic map equation [28], is given by equation (12).

$$C_{t+1} = C_t + k - \left(\frac{Q}{2\pi}\right) sin(2\pi t)\, mod(1) \quad (12)$$

Where, C_t represents t_{th} chaotic particle, C_{t+1} represents $(t+1)_{th}$ chaotic particle, $Q = 0.5$ & $k = 0.2$, Q represents control parameter. Thus, this equation will generate chaotic random numbers between (0, 1). The pelican is a population-based optimization algorithm [29]. The proposed approach uses a population-based metaheuristic approach, in which each pelican agent searches for prey by imitating a real pelican, with the prey standing in for cluster heads. The members of the population are randomly initialized using the following equation (13).

$$p_{x,y} = lb_y + random(ub_y - lb_y),$$

$$x = 1,2,..,X, y = 1,2,..,Y \quad (13)$$

Where, $p_{x,y}$ represents the candidate solution, X represents the number of populations, Y represents the problem variable, $random$ represents the random number in the interval [0, 1], lb_y, ub_y represents yth lower and upper bound of problem variables. The population of search agent are given by equation (14).

$$P = \begin{bmatrix} P_{1,1} & P_{1,2} & \dots & P_{1,Y} \\ P_{2,1} & P_{2,2} & \cdots & P_{2,Y} \\ \vdots & \vdots & \vdots & \vdots \\ P_{X,1} & P_{X,2} & \dots & P_{X,Y} \end{bmatrix}_{X \times Y} \quad (14)$$

Where, P represents the population of search agents. The fitness function of the proposed CPOA is assessed based on the minimum distance as given in equation (15).

$$Fitnessfunction = Minimization\{distance\} \quad (15)$$

To update the candidate solution, the suggested CPOA for cluster head selection mimics the hunting and attacking behaviors of a search agent. The strategy involved two phases: exploration as well as exploitation. The exploration phase defines the search agent's movement towards prey, whereas the exploitation phase defines the search agent's movement while winging on the surface of water.

Exploration Phase: In this phase, the search agent identifies the location of CH and moves towards the cluster head. This technique involves scanning the search space, which defines the proposed CPOA's exploring power. The search agent's movement towards CH is given in equation (16).

$$P_{x,y}^{ex} = \begin{cases} P_{x,y} + random(CH_y - R.P_{x,y}) + C_{t+1}, Fit_{ex} < Fit_x \\ P_{x,y} + random(CH_y - R.P_{x,y}), else \end{cases} \quad (16)$$

Where, $P_{x,y}^{ex}$ signifies the position of xth search agent in yth dimension during the exploration phase, R represents the random number, CH_y represents the location of cluster head in yth dimension, Fit_{CH} represents fitness evaluated in the exploration phase. To avoid moving to less ideal solutions, a search agent's position is only altered if the new location results in a higher fitness value as given in equation (17).

$$P_x = \begin{cases} P_x^{ex}, Fit^{ex}{}_x < Fit_x \\ P_x, else \end{cases} \quad (17)$$

Where, P_x^{ex} represents the position of xth search agent, $Fit^{ex}{}_x$ represents fitness function evaluated on exploration phase.

Exploitation Phase: In this phase, the search agent improves its search power by examining nearby points to arrive at an optimal solution. The behavior is modelled as shown in equation (18).

$$P_{x,y}^{exp} = P_{x,y} + C\left(1 - \frac{n}{N}\right)(2.random - 1)P_{x,y} + C_{t+!} \quad (18)$$

Where, $P_{x,y}^{exp}$ signifies location of the search agent in the exploitation phase, C characterizes constant value of 0.2, $C(1 - \frac{n}{N})$ represents neighborhood radius of $P_{x,y}$, $n$represents iteration count, N represents iteration number. Through this

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RESEARCH ARTICLE

phase, updating the search agent position based on accepting or rejection is modelled as shown in equation (19).

$$P_x = \begin{cases} P_x^{exp}, Fit^{exp}{}_x < Fit_x \\ P_x, else \end{cases} \quad (19)$$

Where, P_x^{exp} represents the position of xth search agent, $Fit^{exp}{}_x$ represents fitness function evaluated on exploitation phase. As a result, the entire population are updated in line with the exploration and exploitation phases. The objective function and population values are used to update the optimal solution. The method was continued until the optimal cluster heads were identified. At last, the ideal candidate solution discovered through method iterations is offered as a quasi-optimal solution to the given issue. As a result, the optimal cluster is identified using the CPOA and selected as the cluster head. The flowchart of CH selection using CPOA is shown in Figure 3.

Data Aggregation: After the formation of clusters using the advanced agglomerative hierarchical clustering method, the cluster heads are selected from the available clusters using CPOA. The members of clusters disseminate the information to the CH. The CH aggregates the data received from the cluster members, which are sensor nodes and it to the BS for transmission of data. After receiving the data from CHs, the fusion center makes a final determination about the spectrum's suitability for transmission.

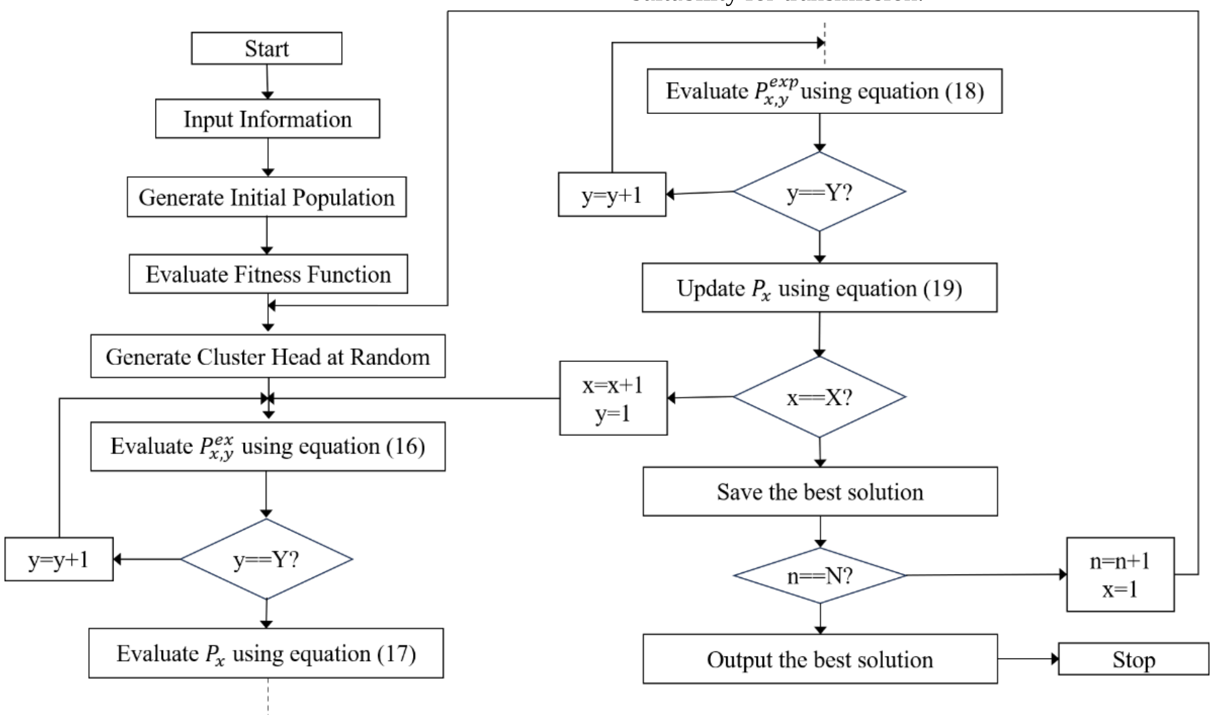


Figure 3 Flow Chart of CPOA

3.3. Cognitive Spectrum Sensing Using Extended XGBoost Model

The proposed E-XGBoost model-based spectrum sensing detects if the spectrum is occupied or available for data transmission. The ML algorithms are used to make informed decisions about spectrum allocation and access by categorizing spectrum usage as occupied or idle. The objective of the proposed CRSN is to increase the likelihood of recognition and reduce energy consumption. The E-XGBoost model-based CSS is a reliable machine-learning technique that increases spectrum sensing accuracy. The XGB model improves the suggested model's detection ability by combining multiple weak classifiers. In CRSN, CSS is crucial for effective spectrum utilization and detection. The E-XGBoost model integrates information from several sensors, extracts characteristics, and makes precise predictions about whether users will be present in the spectrum.

XGBoost: The gradient-boosting framework XGBoost [30] makes use of a set of decision trees. Regularization procedures such as L1 and L2 are used to reduce model complexity and avoid overfitting. XGBoost is a collective ML method that makes predictions by integrating many decision trees. The architecture of the XGBoost model is provided in Figure 4.

Initialization: Initially, the method constructs a single leaf tree with one leaf node. The leaf node shows the mean value of the desired variable.

RESEARCH ARTICLE

Boosting: In this step, new decision trees are integrated to the existing tree structure to improve prediction accuracy. In the ensemble, each new tree is taught to fix the prior tree's faults.

Tree Construction: Based on the greedy approach, a tree was built to select the split point, increasing data acquisition and decreasing variance.

Regularization: The algorithm employs regularization techniques to prevent overfitting and increase performance. L1 and L2 regularization are utilized, which adds a penalty term to the loss function and removes underperforming nodes via tree pruning.

Prediction: After the construction of the tree structure, the model makes predictions by averaging the predictions of each tree in the ensemble.

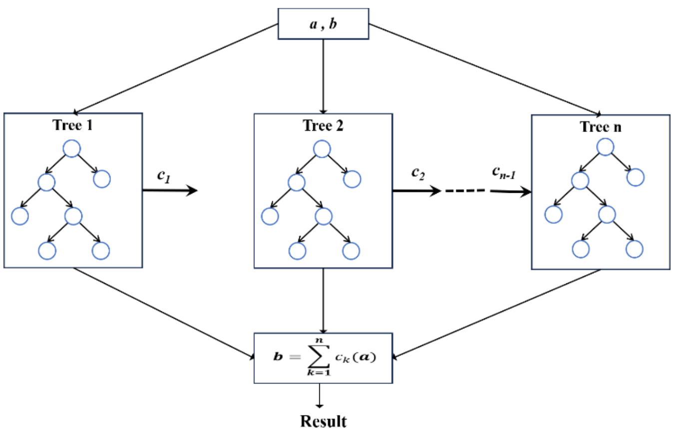


Figure 4 Architecture of XGBoost Model

The XGBoost consist of n decision trees that are base learners represented as shown in equation (20).

$$\mathrm{DT} = \{\mathrm{DT}_1, \mathrm{DT}_2, \mathrm{DT}_3, \ldots \mathrm{DT}_n\} \quad (20)$$

Where, DT represents decision tree, n represents the number of decision trees.

The resultant output XGB represented as given in equation (21).

$$\mathrm{XGB} = \{\mathrm{XGB}_1, \mathrm{XGB}_2, \ldots, \mathrm{XGB}_n\}$$
$$= \sum_{a=1}^{n} \mathrm{DT}_a(\mathrm{SF}_i) \quad (21)$$

Where, $\mathrm{SF}_i \subseteq \mathrm{SF}^*$ represents input vectors of size SF^*. In each iteration, decision trees are trained to reduce the prediction error, which is calculated as the gain or loss term presented in equation (22).

$$\mathrm{LT}_t = \sum_{i=1}^{\mathrm{SF}^*} \mathrm{LT}(\mathrm{XGB}, \mathrm{XGB}_{t-1} + \mathrm{DT}_t(\mathrm{SF}_i)) + \psi(\mathrm{DT}_t) \quad (22)$$

Where, $\mathrm{LT}\big(\mathrm{XGB}, \mathrm{XGB}_{t-1} + \mathrm{DT}_t(\mathrm{SF}_i)\big)$ and $\psi(\mathrm{DT})$ represents loss and regularization term. Taylor series expansion is used to analyze the exact loss of different learners, updating equation (22) as in given in equation (23) and (24).

$$\mathrm{LT}_t = \sum_{i=1}^{\mathrm{SF}^*} [\mathrm{G}_i \mathrm{DT}_t(\mathrm{SF}_i) + \tfrac{1}{2} \mathrm{H}_i \mathrm{DT}_t(\mathrm{SF}_i)] + \psi(\mathrm{DT}_t) \quad (23)$$

$$\psi(\mathrm{DT}_t) = \gamma \mathrm{K} + \tfrac{1}{2} \lambda \|\omega\|^2 \quad (24)$$

Where, $\mathrm{G}_i = \partial_{\mathrm{XGB}_{t-1}} \mathrm{LT}(\mathrm{XGB}, \mathrm{XGB}_{t-1})$ and $\mathrm{H}_i = \partial^2_{\mathrm{XGB}_{t-1}} \mathrm{LT}(\mathrm{XGB}, \mathrm{XGB}_{t-1})$ represents first as well as second order derivative of the loss function in the gradient, $\gamma, \lambda, \mathrm{L1}, \mathrm{L2}$ represents regularization coefficients, ω represents internal split tree weight, K represents the number of leaves in the tree. During every phase, the model receives selected features as input to forecast intrusions. The extended XGBoost approach combines the XGBoost and CART algorithms, with the CART algorithm chosen for its capacity to effectively manage classification and regression tasks efficiently. The tree structure aids in discovering the required features, therefore improving overall performance. The proposed extended XGBoost incorporate a split criterion, which improves performance by allowing the algorithm to identify more intricate patterns in the data. The goal is to collect and categorize less frequently occurring data using a gradient-weighted model with a reduced estimator size. The XGBoost classifier's constructor utilizes the CART tree function to generate an estimator based in its logistic objective model, which substantially influences the accuracy of the network model.

Classification and Regression Tree (CART): This method combines the advantages of other algorithms to achieve the best results. To build the regression tree, divide the data into partitions as well as branches iteratively. The CART algorithm accomplishes this by calculating the best sub node homogeneity using the Gini index. Based on the optimal characteristic and threshold value, the root node is deemed a training set and separated into two halves, as shown in equation (25).

$$\mathrm{OB}(\theta) = \sum_{j}^{m} (\mathrm{SF}_j, \mathrm{SF}_k) + \sum_{l=1}^{L} \Omega(\mathrm{SF}_l) \quad (25)$$

Where, $\mathrm{OB}(\theta)$ represents an objective function, Ωrepresents regularization term, L represents number of trees, SF_j represents prediction of instance j. In the CART method, the Gini index is employed for classification, as given in equation (26).

$$\mathrm{Giniindex} = 1 - \sum_{j=1}^{c} \mathrm{Q}_j \quad (26)$$

Where, j represents number of classes, Q_j represents probability of each class in the dataset. The decision tree algorithm increases the information gain and splits the nodes with the highest information gain, which is evaluated using equation (27).

RESEARCH ARTICLE

$$\mathrm{IG} = \mathrm{entropy}(X) - [(\mathrm{weightedaverage}) * \mathrm{entropy}(\mathrm{each\ feature})] \quad (27)$$

Where entropy is evaluated using the equation (28).

$$\mathrm{entropy}(X) = Q(\mathrm{yes}) \log 2\, Q(\mathrm{yes}) - Q(\mathrm{no}) \log 2\, Q(\mathrm{no}) \quad (28)$$

Thus, the proposed model effectively perceives the available spectrum.

4. RESULTS AND DISCUSSION

This section compares the experimental results of the proposed OCSS-CRSN to the existing framework. Throughput, packet delivery ratio, delay, overhead, and average energy consumption are all metrics used to assess performance. The protocols' scalability and reliability are assessed using the NS2 tool and simulation parameters in both static and dynamic environments. The system specification and simulation parameters considered are provided in Tables 2 & 3.

The performances of the proposed OCSS-CRSN framework are compared with existing protocols such as Artificial Bee Colony Clustering (ABCC), Advanced Threshold-sensitive Energy Efficient Network (ATEEN), conventional Low-Energy Adaptive Clustering Hierarchy (LEACH) as well as Dynamic Fuzzy-based Primary User Aware clustering (DFPC) [31]. The reliability and efficiency of the clustering process were evaluated using two network types with varied SU density under static and dynamic topologies. In the static topology, the location of each SU is fixed. In the dynamic topology, each SU navigates the network randomly at speeds ranging from 2 to 10 m/s.

Table 2 System Specification

Devices	Specification
NS2 tool	version 2.34
OS	Ubuntu 12.04
RAM	4GB
Hard drive	80 GB
Processor	Intel Core-i3

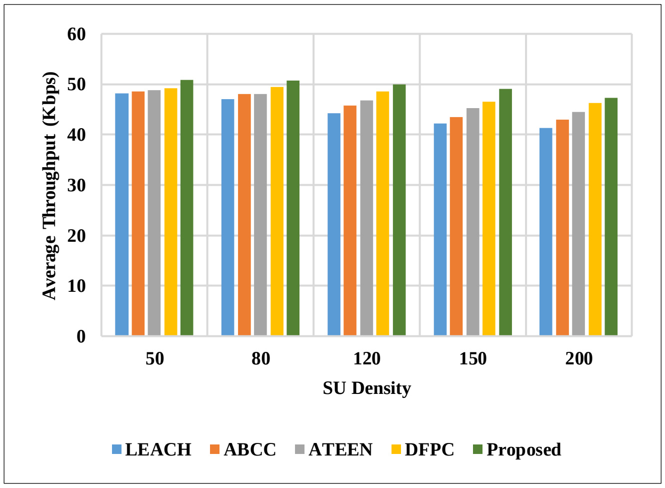
Table 3 Simulation Parameters

Parameters	Specification
Number of sensors	50-200
Channels used	6-10
MAC	802.11
Limit of Queue	50 packets
Simulation time	100 s
Transmission range	250 m
Number of connections	5
Network size	500 m × 500 m
Packet size	512 bytes

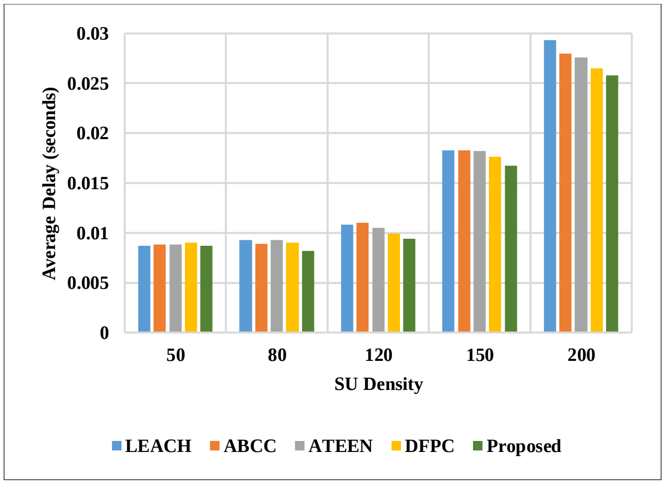
4.1. Performance Analysis for Static Topology

The simulation outcomes of proposed and existing approaches are compared for static CRSNs with changing user density. Figures show the average throughput, average delay, packet delivery ratio, overhead for routing, and the energy consumed for each clustering protocol.

The findings indicate that greater SU density decreases network performance. The average energy usage is the sole measure that is effective against higher SU density.



(a) Average Throughput



(b) Average Delay

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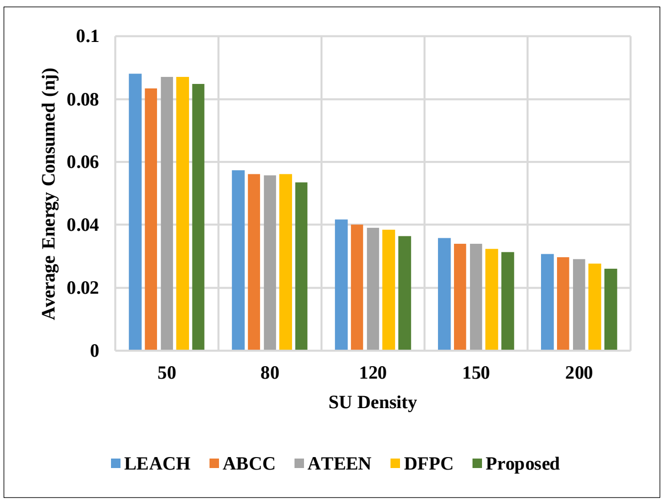
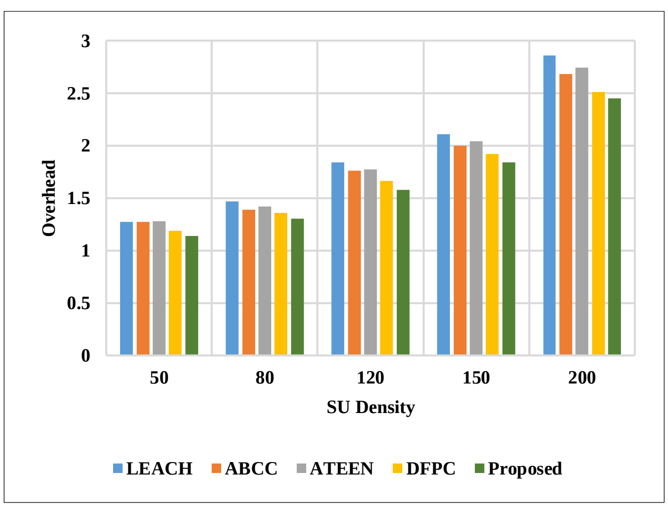
(c) Packet Delivery Ratio (PDR)



(d) Average Energy Consumed



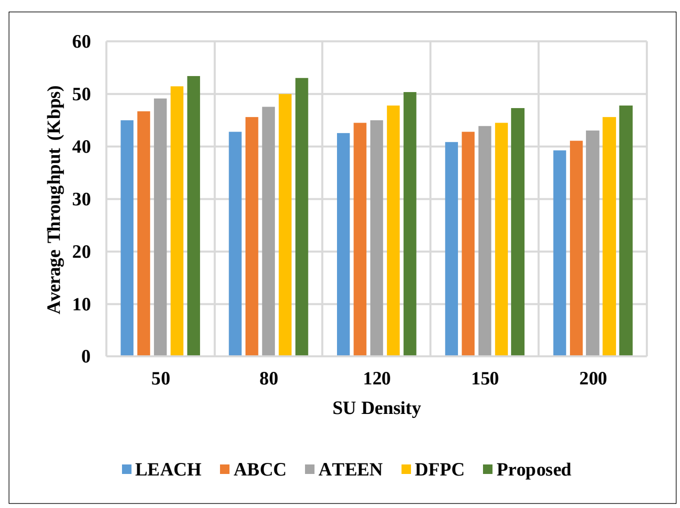
(e) Overhead

Figure 5 (a)-(e) Performance Analysis for Static Topology

Figure 5 shows the throughput, PDR, delay, overhead and energy consumption analysis of proposed and existing methods by varying the SU density. Higher secondary user densities provide the network with more chances for effective routing, which lowers energy usage. The suggested technique performed noticeably better than the other methods in terms of average throughput and PDR. This is primarily due to the protocols developed for optimal CH selection, ideal clusters, and reliable route building. In addition, the current network's overhead and communication latency were directly impacted by the greater PDR. The suggested approach lowers average latency and overhead performance by requiring fewer clustering iterations and packet retransmissions compared to alternative protocols. However, the DFPC, LEACH, ABCC, and ATEEN processes did not perform well since they depended significantly on static clustering with normal WSN settings for effective CH selection. The static environment performance analysis is mentioned in Table 4.

4.2. Performance Analysis for Dynamic Topology

Figure 6 demonstrate the average throughput, average delay, packet delivery ratio, overhead for communication, and the energy consumed for the proposed and existing methods. The networks were established using many SUs, varying from 50, 80, 120, 150, and 200. The mobility speeds of the SUs in each network ranged from 2 to 10 m/s. The results demonstrate that as density increases, performance of throughput and PDR decrease. This is mostly because CR-WSNs have more communication lines and interference. Average delay and communication overhead were affected by the growing SU density. The higher SU density necessitated frequent cluster construction and reconfiguration, which led to increased control overhead and network latency. However, because there was so many idle SUs in the network, increasing the density of SUs had a positive impact on average energy consumption.



(a) Average Throughput

International Journal of Computer Networks and Applications (IJCNA)
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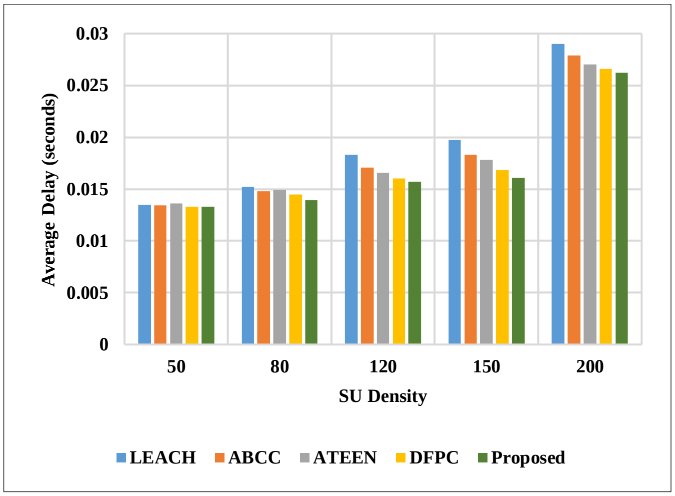
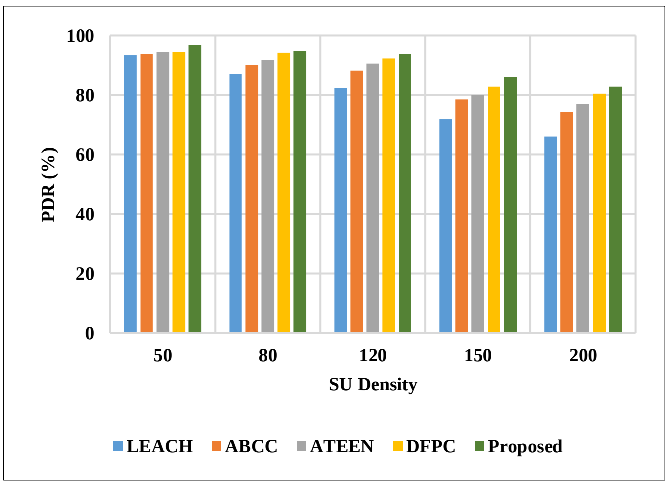
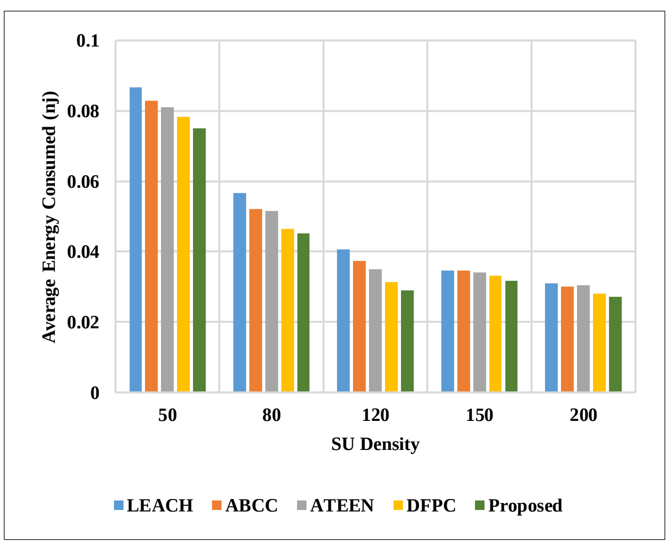
RESEARCH ARTICLE



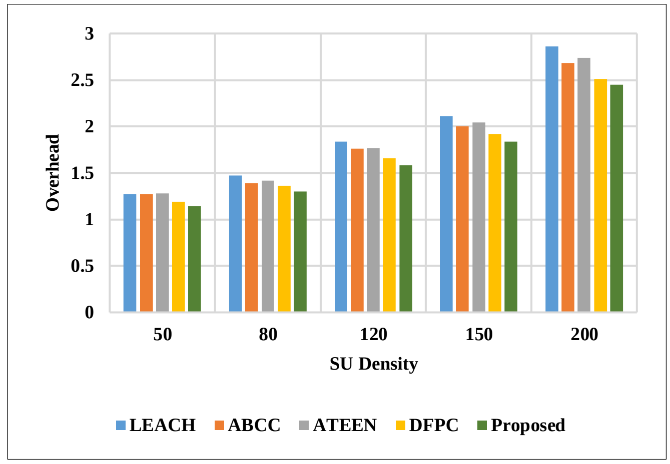
(b) Average Delay



(c) Packet Delivery Ratio (PDR)



(d) Average Energy Consumed



(e) Overhead

Figure 6 (a)-(e) Performance Analysis for Dynamic Topology

The experimental findings suggest that the suggested method outperforms the previous protocols. Several significant elements contribute to its supremacy. Initially the proposed technique differs from others in that it dynamically selects the optimal number of clusters. Additionally, it demonstrates superior performance in the selection of Cluster Heads (CHs), leading to an effective and dependable clustering methodology. Also, it displays superior performance in establishing reliable data transmission pathways. The clustering process's success is determined on the capacity to find ideal clusters and select appropriate cluster heads. The dynamic environment performance analysis is shown in Table 5.

4.3. Comparison of Proposed E-XGBoost Model with Other Models for CSS

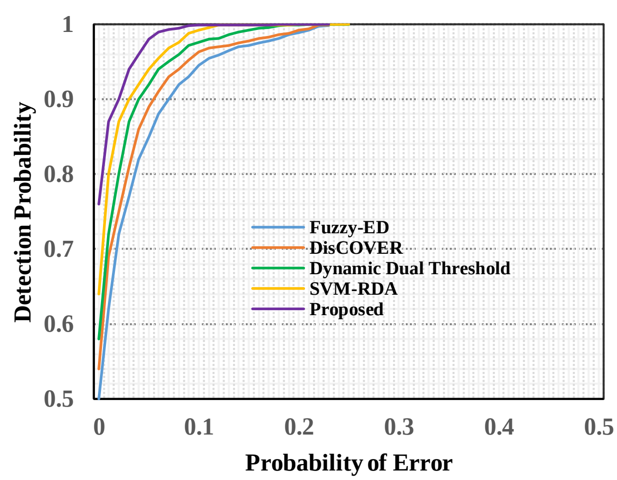


Figure 7 Detection Probability by Varying Probability of Error

RESEARCH ARTICLE

The performance of the E-XGBoost algorithm is compared with the Support vector machine red deer algorithm (SVM–RDA), Distributed Iterative Spectrum Exploration and Cognitive Radio Environment Observation (DISCOVER), Fuzzy Energy Detection (Fuzzy-ED) as well as dynamic dual-threshold [14].

Figure 7 signifies the detection probability by varying the probability of error under -12 dB SNR values. The existing method's detection performance degrades in the presence of low noise uncertainty. The suggested method shows a higher detection probability than other methods. The proposed approach (E-XGBoost) has a high detection probability and a low error rate.

Figure 8 depicts the detection probability of the proposed algorithm and existing algorithms. The detection probability rises with rising SNR where the SNR is varied among−20 dB and 20 dB. For dynamic dual-threshold models with 5 or 10 SUs, the detection probability is less than 20% for SNR values below -5 dB. The detection probability is less than 70% for SNR values below -5 dB for the proposed model (E-XGBoost). At SNR = 5 dB, the proposed method with 10 SU has a detection probability of 100%.

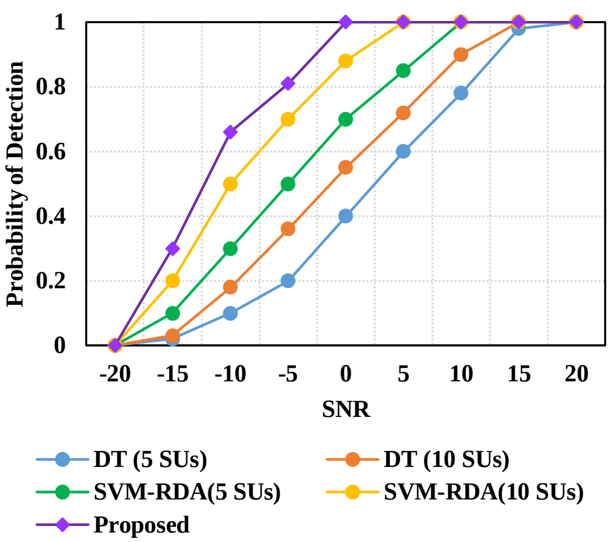


Figure 8 Detection Probability by Varying SNR

Figure 9 displays the error probability associated with the proposed and existing techniques after varying the SNR function for various amounts of SUs. The likelihood of mistake lowers as SNR increases. Furthermore, the mistake probability lowers as the number of collaborating SUs in a cluster grows. More secondary users improve the chance of cooperative sensing, lowering the error risk, especially at high signal-to-noise ratios. CSS-based clustering minimizes error risk by detecting unused spectrum among several users.

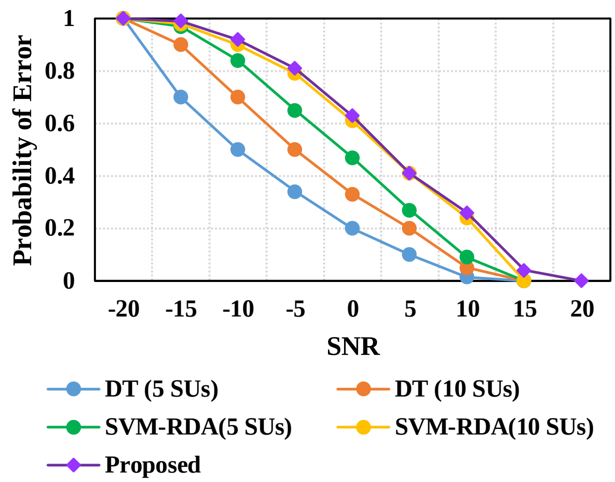


Figure 9 Error Probability

4.4. Discussion

The performance of the suggested study is compared with that of existing studies. The proposed study presented a novel CSS technique based on clustering and the ML based E-XGBoost method. The model demonstrates better performance than the existing models owing to the integration of advanced clustering, optimization, and machine learning techniques. The use of the EAHC guarantees more context-aware and energy-balanced cluster formation which significantly reduces communication overhead between clusters. EAHC has the capability to dynamically adapt to various factors like node distribution and energy levels, which increases the network lifetime. The application of CPOA for CH selection provides a non-deterministic, intelligent optimization strategy thereby ensuring the selection of optimal cluster heads. The utilization of E-XGBoost model for decision making at the FC plays a crucial role in improving the accuracy of classification and increasing the spectrum sensing accuracy. In comparison with the conventional methods based on majority voting, this machine learning driven approach learns patterns from the data aggregated from clusters and makes decisions. This results in precision detection of the availability of spectrum. The enhancements proposed in the study yield significant improvements in throughput, energy consumption reduction, and decreased communication overhead. The outputs of the suggested method are explained and compared to those of the current model. The suggested technique's efficiency is evaluated utilizing detection and error probability. The simulations show how cooperative radio spectrum sensing optimizes detection rates and reduces errors. The suggested approach has a detection rate of more than 99% and a false alarm chance of less than 1%, outperforming similar methods. The comparison of existing studies is provided in Table 6.

RESEARCH ARTICLE

Table 4 Static Environment Performance Analysis

Static Average Throughput					
SU Density	LEACH	ABCC	ATEEN	DFPC	Proposed
50	48.14	48.62	48.88	49.17	50.91
80	47.07	48.1	48.1	49.4	50.69
120	44.22	45.78	46.81	48.62	49.91
150	42.16	43.45	45.26	46.55	49.14
200	41.38	42.93	44.48	46.29	47.33
SU Density	Static Average Delay				
50	0.0087	0.0088	0.0088	0.009	0.0087
80	0.0093	0.0089	0.0093	0.009	0.0082
120	0.0108	0.011	0.0105	0.0099	0.0094
150	0.0183	0.0183	0.0182	0.0176	0.0167
200	0.0293	0.028	0.0276	0.0265	0.0258
SU Density	Static PDR				
50	96.53	95.95	96.53	97.11	96.53
80	91.33	94.22	95.38	97.11	98.27
120	86.71	90.75	93.06	95.38	97.11
150	82.66	87.28	90.17	93.06	94.8
200	78.61	84.39	86.71	90.17	93.06
SU Density	Static Energy Consumed				
50	0.088	0.0833	0.087	0.087	0.0849
80	0.0573	0.0562	0.0557	0.0562	0.0536
120	0.0417	0.0401	0.0391	0.0385	0.0365
150	0.0359	0.0339	0.0339	0.0323	0.0313
200	0.0307	0.0297	0.0292	0.0276	0.026
SU Density	Static Overhead				
50	1.27	1.27	1.28	1.19	1.14
80	1.47	1.39	1.42	1.36	1.3
120	1.84	1.76	1.77	1.66	1.58
150	2.11	2	2.04	1.92	1.84
200	2.86	2.68	2.74	2.51	2.45

RESEARCH ARTICLE

Table 5 Dynamic Environment Performance Analysis

Dynamic Average Throughput					
SU Density	LEACH	ABCC	ATEEN	DFPC	Proposed
50	45	46.67	49.17	51.39	53.33
80	42.78	45.56	47.5	50	53.06
120	42.5	44.44	45	47.78	50.28
150	40.83	42.78	43.89	44.44	47.22
200	39.17	41.11	43.06	45.56	47.78
SU Density	Dynamic Average Delay				
50	0.0135	0.0134	0.0136	0.0133	0.0133
80	0.0152	0.0148	0.0149	0.0145	0.0139
120	0.0183	0.0171	0.0166	0.016	0.0157
150	0.0197	0.0183	0.0178	0.0168	0.0161
200	0.029	0.0279	0.027	0.0266	0.0262
SU Density	Dynamic PDR				
50	93.36	93.75	94.53	94.53	96.87
80	87.11	90.23	91.8	94.14	94.92
120	82.42	88.28	90.63	92.19	93.75
150	71.88	78.52	80.08	82.81	85.94
200	66.02	74.22	76.95	80.47	82.81
SU Density	Dynamic Energy Consumed				
50	0.0866	0.0829	0.0811	0.0783	0.0751
80	0.0567	0.0521	0.0516	0.0465	0.0452
120	0.0406	0.0373	0.035	0.0313	0.029
150	0.0346	0.0346	0.0341	0.0332	0.0318
200	0.0309	0.03	0.0304	0.0281	0.0272
SU Density	Dynamic Overhead				
50	1.46	1.35	1.41	1.33	1.2
80	1.79	1.71	1.75	1.6	1.54
120	2.34	2.22	2.3	2.05	2
150	3.48	3.12	3.23	3.06	2.97
200	4.03	3.57	3.76	3.21	3.1

RESEARCH ARTICLE

Table 6 Comparative Analysis

Author	Method	Parameter
Jyothi et al. [21]	Energy-efficient fuzzy clustering and congestion control algorithm	Packet delivery ratio-89%
Govindasamy et al. [22]	Multi-objective crow-swarm intelligence algorithm	Energy efficiency-7.49bits/joule
SMKM et al. [23]	Energy and spectrum-aware clustering protocol for CRSN	Packet delivery ratio-94%
Sharada et al. [24]	AACDIC	Probability of Detection- 0.372, Probability of False alarm rate- 0.7, and Probability of Missed Detection- 0.628.
Nageswari et al. [25]	Lagrangian multiplier and Proportional Fair scheduling algorithms	Packet delivery ratio-90%
Proposed method	OCSS-CRSN	Static environment: Delay-0.0082s Throughput-50.91kbps PDR-98.27% Energy consumed-0.026nj Overhead-1.14
		Dynamic environment: Delay-0.0133s Throughput-53.33kbps PDR-96.87% Energy consumed-0.0272 Overhead-1.2

5. CONCLUSION AND FUTURE SCOPE

The proposed methodology employed an innovative energy efficient clustering-based cooperative spectrum sensing for CRSN. The main goal was to enhance the energy efficiency of a CRSN to extend its lifetime and stability. The proposed approach integrates XGBoost-based spectrum sensing, clustering algorithms, and energy-efficient cluster head selection to increase the reliability and longevity of CRSN. Future studies should examine methods for effective data fusion and convergence in the proposed system as well as the effect of primary user activity on network performance.

In the future, the technique will be applied to large-scale wireless CRSN, extending the network's lifetime. By using actuators to capture local decisions and sensing data, the method can be applied to large-scale sensor networks while also reducing energy consumption.

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Authors

Anu Maria Joykutty has completed her Master of Technology in Network Engineering from Rajagiri School of Engineering and Technology, Kochi, India and is currently enrolled as a research scholar in SRM Institute of Science and Technology, Chennai, India. She is also working as an Assistant Professor in the Department of CSE, Rajagiri School of Engineering and Technology and has more than 7 years of academic experience and 10 publications to her credit. Her areas of interest include Machine Learning, Wireless Sensor Networks and Cognitive Radio.

B. Baranidharan has completed his Master of Technology in Computer Science and Engineering from SRM Institute of Science and Technology, Chennai, India, and Ph.D. in Wireless Sensor Networks (specialization) from SASTRA Deemed University, Thanjavur, India. Currently, he is working as the Associate Professor in the Department of Computing Technologies, SRM Institute of Science and Technology. He has more than 16 years of academic experience and has published 70 papers in various International Journals and Conferences.

RESEARCH ARTICLE

Earlier his research involved designing new clustering architecture for Wireless Sensor Networks and Internet of Things using various computational techniques. Of late he has spanned his research interests to the fields of Artificial Intelligence, Machine learning, Deep learning, and the Internet of Things.

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