A Proposal of a Sensor Exclusion and Dynamic Cluster Head Selection Algorithm to Improve Energy Efficiency in Cognitive Radio Networks

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***Abstract*—Cognitive Radio (CR) emerges as a solution for efficient spectrum utilization in response to the growing demand for connected devices driven by 5G and beyond. In this context, numerous devices share network resources, leading to high energy consumption. It is therefore essential to develop strategies that reduce this consumption and extend the operational lifetime of Cognitive Radio Networks (CRNs). This article proposes an algorithm that combines sensor exclusion with the dynamic selection of Cluster Heads (CHs), aiming to reduce energy consumption while balancing detection capability and network longevity. Simulation results for different numbers of Secondary Users (SUs) show that the proposed algorithm maintains a high detection probability with negligible false-alarm probability, while significantly increasing the network lifetime when compared with classical and cluster-based cooperative sensing schemes. In the evaluated scenarios, the proposed solution increases the CRN lifetime from approximately 3×10^4 to about 6×10^4 sensing cycles, which corresponds to an average network lifetime gain close to 100% relative to the classical method, without compromising sensing performance.**

Keywords-Clustering; K-Means; energy efficiency; cognitive radio network; cooperative spectrum sensing; energy detector; probability of detection.

I. INTRODUCTION

In recent years, the rapid growth of wireless communication systems has increased the scarcity of the Radio Frequency (RF) spectrum. This occurs mainly due to the fixed allocation policy, which grants exclusive spectrum usage rights to a network of licensed users, known as Primary Users (PUs). The demand for new telecommunication services drives research and technologies such as the Fifth Generation of mobile communication networks (5G), the Internet of Things (IoT) and, in the future, the Sixth Generation of mobile communication networks (6G). However, to enable most wireless communication services, it is essential to overcome spectrum limitations, since multiple frequency bands are required to support the growing number of transmitters and receivers expected in 5G, 6G and IoT networks. In this context, the concept of spectrum sensing through CR emerges as a promising alternative to provide more efficient spectrum access [1].

From a practical standpoint, CRNs must simultaneously satisfy regulatory constraints on detection probability (P_d) while operating with battery-powered Secondary Users (SUs) [2]. High reporting overhead, unbalanced energy consumption among SUs and heterogeneous propagation conditions (e.g., shadowing and fading) often lead to premature network death and performance instability, especially in dense IoT and 5G/6G scenarios [3] [4]. These aspects make the joint design of Cooperative Spectrum Sensing (CSS) and energy-management mechanisms a difficult task. Therefore, there is a clear need for CSS strategies that extend network lifetime without violating minimum detection requirements, thus improving the reliability and operational cost of spectrum-sharing services [5].

From a scientific and engineering perspective, the main problem addressed in this proposal is how to jointly design sensor-selection and CH management policies in CRNs so as to minimize energy consumption while preserving cooperative detection performance. Prolonging the lifetime of the secondary network is particularly relevant for large-scale applications such as environmental monitoring, smart-grid supervision, and massive IoT connectivity, where battery replacement is costly or even infeasible. In this context, this proposal investigates a cluster-based CSS scheme that introduces temporary and permanent exclusion of low-performance sensors together with dynamic CH selection based on spatial position [6] [7].

The central research questions are:

- (i) To what extent can sensor exclusion and dynamic CH selection increase the lifetime of a secondary network when compared with classical and cluster-based CSS schemes?
- (ii) What is the impact of these mechanisms on the probability of detection and on the false-alarm probability for different numbers of SUs?

Accordingly, the purpose of this article is to quantify the energy–reliability trade-off provided by the proposed algorithm and to compare its performance with established CSS approaches through numerical simulations.

A. Contributions and Structure of the Article

This article proposes a sensor exclusion algorithm combined with dynamic CH selection, aiming to reduce the energy consumption of the secondary network and, thus, increase its lifetime without compromising the system's detection capability. The main contributions of this proposal are as follows:

- Temporary exclusion of low-performance sensors, which can be reintegrated if their performance improves, and permanent exclusion applied after a defined number of consecutive inactivity periods.
- Dynamic CH selection, defined as the sensor closest to the Center of Mass (CM).

The proposed algorithm is evaluated through simulations in *MATLAB*, considering a CRN with a static set of SUs and having the secondary network lifetime as the main focus. An important limitation of this study is that SU mobility was not considered in the analysis and is therefore left as a perspective for future work.

The remainder of this article is organized as follows. Section II presents the related work. Section III describes the system model. Section IV discusses the cluster-based cooperative spectrum sensing scheme. Section V details the signal and channel modeling. Section VII introduces the proposed algorithm. Section VIII presents the analysis and results. Finally, Section IX concludes the paper.

II. Related work

Cluster-based CSS has been widely explored as a strategy to reduce energy consumption in CRNs. Due to the various contributions presented in this proposal, we conducted a literature review on works related to sensor selection techniques, CH election, fusion algorithms, and communication schemes, each presenting specific benefits and limitations. Below is a review highlighting the main contribution of each work. Table I summarizes the analyzed studies.

In [8], a hybrid information fusion scheme is proposed. This model employs the Pietra–Ricci (PRIDe) detector for data fusion at the CH level and decision fusion at the Fusion Center (FC) level. This technique improves the robustness of decision-making and can minimize the impact of CH energy depletion. However, simulations indicate that, in dense networks, this approach may not yield significant energy savings, as the high cost of intra-cluster communication and between CHs and the FC compromises some of the gains achieved.

In [9], a model for sensor alternation between active and idle modes was developed, aiming to distribute energy consumption more evenly. As an alternative to minimize overhead and better balance consumption, the use of pairs of sensors operating synchronously, alternating between active and idle states, is proposed. Although this approach offers this advantage, the constant alternation between states may introduce latency, particularly in scenarios that require a high detection rate and fast response.

In [10], a distributed CH election method based on the residual energy of the nodes is proposed. In this approach, in each round, the node with the highest energy within the cluster is selected as the CH, responsible for transmitting the data to the FC. This method reduces the need for frequent alternation between sensors and improves the energy efficiency of communication. However, the continuous selection of the same CH nodes tends to cause premature depletion of these nodes, compromising the network's stability over time.

In [11], a weighted linear fusion scheme in CRSNs is proposed, assigning weights to the nodes based on the Signal-to-Noise Ratio (SNR) and historical detection accuracy. The technique has proven effective in increasing the P_d and reducing the error rate by better exploiting the differences between the nodes.

In [12], a selection method based on the remaining energy of sensors is presented, prioritizing those with higher energy levels for spectrum sensing. This model allows for more dynamic energy balancing between sensors, preventing the premature depletion of a specific subset. However, this approach tends to cause overload in dense networks, as sensors with more energy may be frequently activated, increasing communication consumption and reducing detection accuracy.

In [13], the use of multiple sequential reporting channels is proposed to reduce delays and improve decision accuracy at the FC. This strategy optimizes the sensing time of nodes and reduces transmission latency, achieving superior performance compared to conventional methods in terms of both accuracy and delay. In [14], a centralized routing protocol with clustering for mobile nodes in Wireless Sensor Networks (WSNs) is proposed, optimizing cluster formation based on energy and mobility.

In [15], the selection of sensors with higher SNR and residual energy is proposed for CSS. This approach significantly reduces energy consumption by enabling only an optimized subset of sensors to participate in sensing, while others remain in energy-saving mode. However, the lack of a sensor rotation mechanism may result in uneven wear of selected nodes, thus reducing the network's lifespan.

In [16], a comprehensive review of energy-efficient CSS techniques is presented, classifying methods according to various criteria and highlighting the potential for integrating dynamic sensor selection, adaptive clustering, and intelligent information fusion. In [17], a dynamic clustering algorithm for large-scale Mobile Sensor Networks (MSNs) is developed, considering residual energy and transmission delays, making the system more adaptable to mobility and uneven energy consumption.

In all the studies analyzed, clustering is used as the initial technique for energy savings. However, in [18], clustering is not applied. Instead, a CSS scheme without clustering is proposed, specifically adapted for CRSNs. The distinguishing feature of the model is the use of real data correlations collected by the sensors (e.g., temperature and humidity) to more efficiently select nodes participating in the detection process. This approach reduces the number of active nodes in sensing, allowing others to remain in idle mode, thus leading to greater energy savings and lower latency. However, the effectiveness of this solution depends on the accuracy of correlation estimation and the SNR scenario, which may require additional adjustments in dense networks.

Thus, the literature encompasses multiple strategies — from node selection and CH rotation to hybrid fusion schemes and mobile protocols — but still presents gaps in integrative approaches that reconcile energy efficiency, detection robustness, and support for dynamic environments. This proposal contributes by suggesting an algorithm that combines temporary and permanent sensor exclusion with dynamic CH selection, thereby extending the network's lifespan without compromising the reliability of CSS.

TABLE I. ANALYSIS OF RELATED WORK

Reference	Year	Energy	Cluster	CSS	Fusion	Main Contribution
[8]	2023	✓	✓	✓	✓	Hybrid fusion scheme using Pietra–Ricci (PRIDe) detector at the CHs and decision at the FC.
[9]	2021	✓	✓	✓		Clustering model with active/idle alternation for paired nodes.
[10]	2021	✓	✓	✓		Distributed clustering algorithm for CH election based on residual energy.
[11]	2021	✓	✓	✓	✓	Weighted linear fusion with weights based on SNR and historical accuracy.
[12]	2020	✓		✓		Sensor selection method based on residual energy.
[13]	2020	✓	✓	✓	✓	Proposal for multiple sequential reporting channels to reduce latency and increase accuracy at the FC.
[14]	2019	✓	✓			Centralized routing protocol with efficient clustering for mobile nodes in WSNs.
[15]	2019	✓	✓	✓		Sensor node selection for CSS based on energy and SNR.
[16]	2016	✓	✓	✓	✓	Review and classification of energy-efficient CSS techniques.
[17]	2013	✓	✓			Dynamic clustering algorithm in large-scale mobile sensor networks based on residual energy and transmission delays.
[18]	2013	✓		✓		Explores the correlation of real data collected by sensors to select participating nodes in the sensing process.

III. SYSTEM MODEL

This section describes the cognitive radio network considered in this work, detailing the spatial distribution of SUs, the formation of clusters, and the role of CHs and the FC. We first present how SUs and the primary transmitter are positioned in the coverage area, including the definition of shadowed regions and their impact on sensing performance. Then, we introduce the clustering model adopted to organize the SUs into groups and to support cooperative spectrum sensing and energy-management mechanisms.

A. Spatial distribution of SUs

The SUs are devices that operate in CRNs, using radio spectrum dynamically and without a license. In other words, SUs take advantage of spectrum gaps that are not used by PUs, without interfering with the operations of these licensed users. The positions of the SUs are determined by two-dimensional coordinates (x, y), randomly distributed within the coverage area of the primary network. This coverage area has a radius r around the FC, located at coordinate $(0, 0)$. The Primary Network Transmitter (PU_{tx}) is positioned at coordinates $(-r, r)$, with the coverage area radius defined as $r = 1000\,\mathrm{m}$. Additionally, shadowed areas are defined to evaluate the impact of the received signal on SUs located in these regions. Due to attenuation caused by obstacles, these sensors are more susceptible to detection failures and are consequently penalized more frequently.

This penalty results in periods of inactivity during which the sensors cease to participate in the sensing process and enter energy-saving mode. However, they can still transmit data if the channel is detected as free and, if their performance improves, they may be reintegrated into the network. On the other hand, sensors with successive cycles of inactivity are permanently excluded to prevent compromising the decisions of the cluster and, consequently, the FC.

Figure 1 illustrates the execution of the k-means clustering process. As shown in Fig. 1, the process was carried out with $m_T = 20$ and $c_{\max} = 3$, generated in MATLAB. The colors of the points distinguish the clusters and their respective SUs, while the shadowed areas are represented by dashed circles. The centroids resulting from the clustering are marked with crosses. The PU_{tx}, FC, and CHs are also highlighted, along with the circular coverage area of the primary network.

The secondary network consists of three main components: the FC, which makes global decisions; the SUs, which perform spectrum sensing; and a subset of SUs that act as CHs, coordinating the cluster decisions.

B. Clustering model

For cluster formation, the K-Means clustering algorithm was used due to its simplicity, ease of implementation, and computational efficiency. This algorithm aims to partition the SUs into k clusters, where each SU corresponds to the cluster whose centroid is the closest [19].

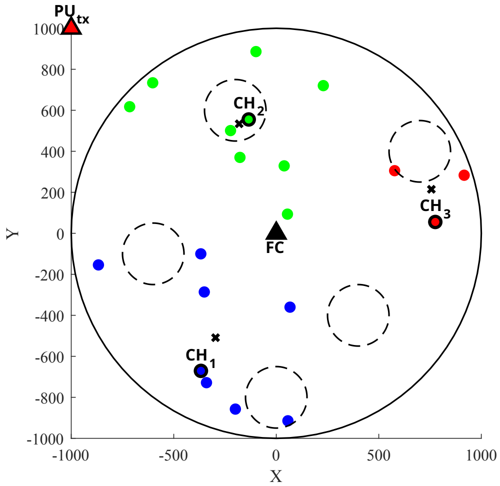

Figure 1. Spatial distribution of SUs, shadowed regions, and cluster formation using the K-Means algorithm.

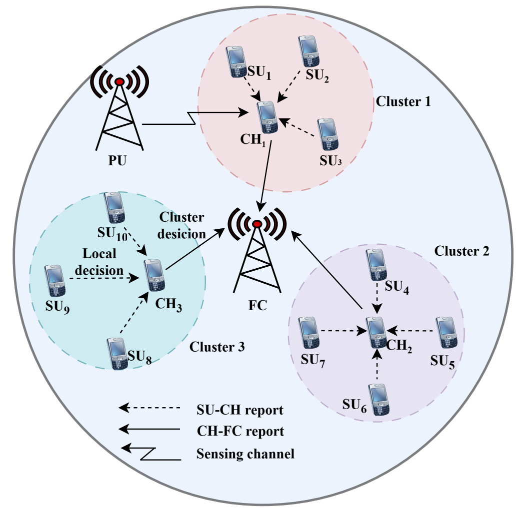

Figure 2. Architecture of a CSS based on cluster.

The process begins with the random selection of k initial centroids, which are iteratively adjusted until the cluster positions stabilize or no longer change significantly. This method allows the partitioning of SUs based on their two-dimensional positions (x, y). The necessary information for the clustering process includes the total number of SUs (m_T) and the maximum number of clusters ($c_{\max}$).

IV. Cluster-Based Cooperative Spectrum Sensing

In cluster-based CSS, all SUs equipped with spectrum sensing capability actively participate in the spectrum detection process by collecting samples of the primary signal within their respective operating regions. Moreover, each SU is capable of processing this information and making a local decision regarding the presence or absence of the PU. Instead of reporting directly to the FC, the SUs forward their local decisions to the CH, which is responsible for aggregating the detection decisions within its cluster.

The CH considers the decisions of the nodes belonging to its cluster and its own decision to determine the final decision of the cluster and transmits this decision to the FC. The FC processes the decisions of multiple CHs and makes the final decision on spectrum occupancy, determining whether the channel is available or if there is an active primary user in the network. All sensors have direct communication capability with the FC and, for this reason, can assume the role of CH when selected.

Figure 2 shows the architecture of a cluster-based CSS, highlighting the different decision reporting channels. The SUs transmit their local decisions to the corresponding CH via reporting channels, represented by dashed lines. Then, the CHs forward the cluster decisions to the FC using channels indicated by solid arrows, ensuring data consolidation for the final decision-making. Additionally, the sensing channel, represented by a zigzag arrow, illustrates the reception of the primary signal by the SUs.

A. Binary hyphotesis test

Spectrum sensing can be mathematically modeled as a binary hypothesis test, where the objective is to decide between two possible conditions of the radio frequency (RF) spectrum:

- H_0 (Null Hypothesis): The spectrum does not contain a primary signal, e.g., the band is unoccupied. In this case, the received signal consists only of noise.
- H_1 (Alternative Hypothesis): The spectrum contains an active primary signal, indicating that the band is occupied. Thus, the received signal is composed of the sum of the PU signal and noise.

This decision is made by comparing a test statistic T with a pre-established decision threshold γ. The criterion for choosing the hypothesis follows the following rule:

$$T > \gamma \Rightarrow H_1, \tag{1}$$

$$T \leq \gamma \Rightarrow H_0, \tag{2}$$

If the statistic T exceeds the threshold γ, it is concluded that a primary signal is present in the sensed band (H_1). Otherwise, it is decided that there is no active transmission in the band (H_0). Mathematically, the hypotheses can be expressed as:

$$y(t) = \begin{cases} n(t), & \text{under } H_0, \\ h(t)x(t) + n(t), & \text{under } H_1, \end{cases} \tag{3}$$

where:

- $y(t)$: Signal received by the SU.
- $n(t)$: Additive white Gaussian thermal noise (AWGN).
- $h(t)$: Gain or attenuation factor of the transmission channel.
- $x(t)$: Signal transmitted by the Primary Transmitter.

The test statistic T is derived from the processing of the signal $y(t)$ received by the SU, and its construction varies according to the chosen sensing technique. Different methods for creating this statistic give rise to various types of detectors, with Energy Detection (ED) being the most widely used due to its low implementation complexity.

B. Energy Detection

ED differentiates the presence or absence of the primary signal based on the energy of the samples collected during a sensing interval. This technique is widely used due to its simplicity and effectiveness, especially when there is no prior knowledge of the transmission signal characteristics [10].

The test statistic of the ED for the j-th SU is:

$$T_j = \frac{1}{n}\sum_{i=1}^{n} |y_{j,i}|^2, \tag{4}$$

where n is the number of samples at the j-th SU, and $|y_{j,i}|$ represents the magnitude of the i-th sample at the j-th SU. In CSS with decision fusion, local decisions (at the SUs) are made by comparing T_j with the corresponding decision threshold.

The performance of spectral sensing is commonly measured using two main metrics: the probability of false alarm (P_{fa}) and the P_d, mathematically defined by (5) and (6):

$$P_d = \Pr\left[T > \gamma \mid H_1\right], \tag{5}$$

and P_{fa} is defined as:

$$P_{\text{fa}} = \Pr\left[T > \gamma \mid H_0\right], \tag{6}$$

where H_1 and H_0 represent the hypotheses of the presence and absence of the signal transmitted by PUs, respectively.

A low P_{fa} is desirable, as it maximizes efficient spectrum utilization, allowing the secondary network to exploit communication opportunities when the spectrum is truly unoccupied. Conversely, a high P_d is crucial to ensure the protection of the primary network, minimizing the risk of interference caused by the secondary network.

V. Signal and Channel Modeling

Consider a CSS with m_T SUs, each collecting n complex samples of the signal transmitted by the PU in each sensing interval. The samples collected by the SUs can be organized as in [8].

The Gaussian distribution was adopted for the transmitted signal x, as it simplifies mathematical analysis. Moreover, the choice of the Gaussian distribution facilitates the evaluation of detection performance, proving to be an effective and reasonable approach for signal modeling in various practical communication scenarios.

The elements of h are complex samples of zero-mean Gaussian variables, independent and identically distributed (i.i.d.), modeling a flat Rayleigh fading channel between the PU and each SU. The Rayleigh channel was chosen to represent a scenario without a direct line of sight between the transmitter and receiver, characterizing an environment dominated by multipath propagation and reflections.

The samples in x are complex Gaussian random variables with zero mean and variance $P_{\text{tx,PU}}$, where $P_{\text{tx,PU}}$ represents the transmission power of the PU. Thus, the power of the primary signal received by the j-th SU ($P_{\text{rx,SU}_j}$) is given by the log-normal prediction model, as described by (7):

$$P_{\text{rx,SU}_j}(\text{dBm}) = P_{\text{tx,PU}}(\text{dBm}) - 10\alpha \log_{10}\left(d_{\text{PU},j}\right), \tag{7}$$

where $d_{\text{PU},j}$ is the distance from the PU to the j-th SU, and α is the path loss exponent. Higher values of α indicate greater signal attenuation. The shadowing effect was considered by adjusting the value of α, resulting in greater attenuations in the power received by the SUs in these regions.

VI. Energy Consumption Modeling

The energy of the SUs decreases as they participate in the sensing process. SUs that reach energy levels below the threshold are deactivated to preserve the reliability of the network and maintain the balance of energy load.

Initially, the SUs perform sensing simultaneously during the period τ_s. Subsequently, they transmit their decisions to the corresponding CH within the period $\tau_{r,\text{SU}}$. The CH then makes the cluster decision and forwards it to the FC within the period $\tau_{r,\text{CH}}$.

Energy consumption in the sensing process is directly related to the fusion method adopted. In decision fusion, energy consumption is higher than in data fusion because the processing of the received signal involves additional steps beyond simply collecting samples. However, in the reporting step, the local decision can be represented by just 1 bit, significantly reducing energy consumption compared to transmitting multiple bits per sample in data fusion. Given this advantage in the reporting step, the decision fusion approach was adopted in this work. It is assumed that the reporting channel is error-free, ensuring accurate communication between the SUs and the CH, as well as between the CH and the FC, for sensing decisions.

SUs whose energy falls below a certain threshold are permanently excluded from sensing, being classified as inactive or "dead." Since any SU can assume the role of CH, the energy threshold (λ) was calculated as the minimum energy required to perform sensing and report the decision to the FC. This value considers the distance between the SU and the FC to be equal to the coverage area radius (r), as shown in the equation below:

$$\lambda = \left(P_s + P_{\text{rx,FC}}\, r^{\alpha}\right), \tag{8}$$

where P_s is the power used for spectrum sensing, and $P_{\text{rx,FC}}$ corresponds to the receiver sensitivity of the FC, representing the minimum acceptable received power level.

The residual energy, in joules, of the j-th SU in the secondary network during a sensing cycle can be calculated by:

$$E_r^{(j)} = E^{(j)} - \left(P_s\, \tau_s + P_{\text{tx,SU}}^{(i,j)}\, \tau_{r,\text{SU}} + P_{\text{tx,CH}}^{(j)}\, \tau_{r,\text{CH}}\right), \tag{9}$$

where $E_r^{(j)}$ represents the residual energy of the j-th SU during the sensing process, and $E^{(j)}$ refers to the energy available in the j-th SU, which is initially uniform across all SUs. P_s is the power for spectral sensing, $P_{\text{tx,SU}}^{(i,j)}$ is the power used by the j-th SU to transmit its decision to the i-th CH, and $P_{\text{tx,CH}}^{(j)}$ is the power of the signal transmitted by the j-th CH to communicate the cluster decision to the FC, calculated in (10) and (11). If the reporting occurs from SU to CH, the term $P_{\text{tx,CH}}^{(j)}\tau_{r,\text{CH}} = 0$. On the other hand, if the reporting is from CH to FC, the term $P_{\text{tx,SU}}^{(i,j)}\tau_{r,\text{SU}} = 0$.

Applying the distance path loss model, the values of $P_{\text{tx,SU}}^{(i,j)}$ and $P_{\text{tx,CH}}^{(j)}$ are calculated as follows:

$$P_{\text{tx,SU}}^{(i,j)} = P_{\text{rx,CH}}\, d_{\text{CH}_{ij}}^{\alpha}, \tag{10}$$

and

$$P_{\text{tx,CH}}^{(j)} = P_{\text{rx,FC}}\, d_{\text{FC}_j}^{\alpha}, \tag{11}$$

where $d_{\text{CH}_{ij}}$ represents the distance from the j-th SU to the i-th CH, and d_{FC_j} is the distance from the j-th CH to the FC. $P_{\text{rx,FC}}$ and $P_{\text{rx,CH}}$ are the sensitivities of the FC's and CHs' receivers (minimum admissible levels of received power), and α is the path loss exponent.

At each sensing cycle, the energy of the active SUs is reduced as described in [12]. Active SUs are those that have not been excluded, either temporarily or permanently, and have sufficient energy to continue participating in the sensing process.

VII. Proposed Algorithm

An algorithm is presented that integrates temporary and permanent sensor exclusion with the dynamic selection of CHs. The components of the algorithm are detailed individually, as described below:

A. SUs Exclusion Algorithm

The exclusion of SUs is determined based on the individual performance of each one, continuously evaluated during the sensing cycles. This performance is monitored by the system's global decision, made by the FC, which penalizes SUs that make detection errors. This approach ensures that only SUs with satisfactory performance remain active in the sensing process.

In the considered model, each SU makes a local decision about the channel status (free or occupied) and sends it to the CH, which in turn aggregates the decisions of its SUs and forwards the cluster's final decision to the FC. The FC then makes the final decision that prevails for the network, referred to here as the global decision. Since the true spectrum status is unknown, the SUs do not have access to their actual sensing performance. However, the FC is able to compare each SU's local decision with its global decision. If the spectrum is considered idle, the SUs compete for spectrum access using appropriate multiple access techniques; otherwise, a new sensing cycle is initiated.

To better understand how decisions are made, the following terms are used:

- **TX (Transmission Medium State)**: Represents the true state of the spectrum. $\text{TX} = 0$ indicates that the medium is free (idle, not occupied by the PU), while $\text{TX} = 1$ indicates that the medium is occupied by the PU.
- **GD (Global Decision)**: Decision made by the FC based on the local decisions reported by the CHs. $\text{GD} = 0$ indicates that the system decided under hypothesis H_0 (spectrum idle), while $\text{GD} = 1$ indicates hypothesis H_1 (spectrum occupied).
- **LD (Local Decision)**: Individual decision of each SU about the spectrum state, based on its local sensing. $\text{LD} = 0$ indicates that the SU judged the spectrum as idle, and $\text{LD} = 1$ indicates that the SU considered the spectrum to be occupied.

An SU's failure in the sensing process is referred to as a local failure, while the FC's failure is referred to as a global failure. Furthermore, failures are classified as either verifiable or non-verifiable. If there is a transmission by the SU, which occurs when $\text{GD} = 0$, the success or failure of the decision can be verified, since it is assumed that an acknowledgment message from the receiver will indicate whether the message was correctly received, characterizing a successful decision, or if it was received incorrectly or not at all, resulting in a negative acknowledgment or absence of acknowledgment, which characterizes a failed decision.

If there is no transmission by the SU, which occurs when $\text{GD} = 1$, both the SU and the FC are unable to determine whether their decisions were actually correct or incorrect. Thus, if $\text{LD} = 1$ and $\text{GD} = 1$, the SU's decision matches the FC's decision, and the outcome of the decision process is undefined. Similarly, if $\text{LD} = 0$ and $\text{GD} = 1$, since the true channel state is unknown, this situation is again considered undefined. If the SU fails in its decision, whether verifiable or non-verifiable, a penalty is assigned, which will be used in the SU exclusion algorithm. Sensors with verifiable failures receive more severe penalties, with a weight of 2, while those with non-verifiable failures are penalized less severely, with a weight of 1. Table II summarizes all possible scenarios.

The penalty weight of the j-th SU, denoted by f_j ($f_j = 1$ or 2), is reset at each cycle and varies according to the type of failure committed in the current cycle, as described above. If $f_j \neq 0$, a backoff time is assigned to the SU, given by (12), which determines the number of cycles during which the sensor will be temporarily excluded from the sensing process.

The backoff is defined to prevent unnecessary energy consumption by SUs with low detection performance. However, these inactive SUs can still participate in the data transmission process if the channel is detected as idle ($\text{GD} = 0$). The type of failure determines the penalty value, which directly affects the backoff time. The backoff time is calculated as follows:

$$\text{backoff}_j = \left(2^{f_j} - 1\right), \tag{12}$$

where backoff_j is the number of sensing cycles during which the sensor will not participate in the sensing process.

The proposed algorithm also considers the possibility of permanently excluding the SU from the decision process. For

TABLE II. POSSIBLE SCENARIOS OF SUCCESS AND FAILURE IN THE SENSING PROCESS

TX	LD	GD	Result	Action taken
0	0	0	Verified Local and Global Success	None
0	0	1	Undefined	None
0	1	0	Verified Local Failure	SU is penalized with weight 2
0	1	1	Undefined	None
1	0	0	Verified Local and Global Failure	SU is penalized with weight 2
1	0	1	Unverified Local Failure	SU is penalized with weight 1
1	1	0	Verified Local Success and Global Failure	None
1	1	1	Undefined	None

this purpose, a consecutive backoff occurrences counter (β) is defined, which is incremented by 1 each time the SU enters a backoff. After the backoff, when the sensor is reintegrated into the sensing process, if the SU successfully detects the signal, β is reset to zero. Otherwise, β is incremented by 1 again. When β reaches a predefined limit, the SU is considered dead or permanently excluded from the spectrum sensing process.

B. Dynamic CH selection algorithm

After grouping the SUs, k clusters are formed, each with a centroid representing the cluster's CM. The CH is selected as the SU closest to the CM, considering that all SUs have the same initial energy. However, after a certain number of cycles, the CM is recalculated, now weighted by the residual energy of the SUs in the cluster. This new centroid reflects the current energy distribution of the SUs, and the SU closest to the centroid, with the highest available residual energy, is selected as the new CH. The CM is calculated as follows:

$$X_{\text{cm}} = \frac{\sum_{j=1}^{m} E_r^{(j)}\, x_j}{\sum_{j=1}^{m} E_r^{(j)}}, \tag{13}$$

$$Y_{\text{cm}} = \frac{\sum_{j=1}^{m} E_r^{(j)}\, y_j}{\sum_{j=1}^{m} E_r^{(j)}}, \tag{14}$$

where m is the total number of sensors in the cluster, $E_r^{(j)}$ represents the residual energy of the j-th sensor, and x_j and y_j represent the x and y coordinates of the j-th sensor, respectively.

The energy consumption of SUs directly impacts the position of the CM, as after a certain number of cycles, some sensors may be deactivated (considered dead) when their residual energy falls below the desired threshold. To maintain an efficient energy balance within the cluster, the current CH is replaced by an eligible SU that meets the minimum energy requirements. This process is continuously repeated until no qualified SUs remain to take on the role of CH, ensuring that sensors with available energy continue to actively participate in the system. The following pseudocode outlines the main steps of this dynamic CH selection process.

TABLE III. PSEUDO-CODE 1: DYNAMIC CH SELECTION ALGORITHM

```
If cycle == cycle_CH then
  For the i-th cluster in the set, up to i = c_max do
    Obtain the m SUs of cluster i
    Identify the live SUs among the m SUs in cluster i
    Obtain the coordinates of the live SUs
    Obtain the residual energy of the live SUs
    Compute the CM weighted, based on 13 and 14 (new centroid)
    Select the new CH as the SU closest to the new centroid with the highest residual energy available in the cluster
    If the CH has changed then
      Update the CH coordinates and distances (d_CH, d_FC)
    End If
  End For
  cycle_CH = cycle_CH + 1000
End If
```

In this pseudocode, $cycle$ is the sensing cycle number, $cycle_{CH}$ represents the periodicity of the CH change process, which is initially set to 1000 cycles. Live SUs are the sensors with sufficient energy to participate in the sensing process.

VIII. Analysis and Results

The results presented in this section were obtained through computational simulations performed in MATLAB. Pseudocode 2 outlines the main steps of the code used to generate these results. Different CSS approaches were compared, with the following being evaluated:

- **Classic CSS (without clustering)**: each SU operates independently, can act as a CH, and reports its detection decision directly to the FC [18].

- **Cluster-based CSS**: the SUs are organized into clusters and send their local decisions to the corresponding CHs, which aggregate the cluster's decisions and forward the consolidated decision to the FC [10].
- **CSS with the proposed algorithm**: combines clustering with a strategy for temporary and permanent SU exclusion and dynamic CH selection, aiming to simultaneously improve detection capability and the lifespan of the secondary network.

The analyses consider a primary network composed of a single primary transmitter and a secondary network operating under different values of m_T and $\max_{\text{back}}$ in the CSS. The parameter $\max_{\text{back}}$ was defined as the maximum value that the consecutive backoff occurrence counter β can reach before the sensor is permanently excluded or considered dead in the sensing process.

The analysis of the systems is primarily conducted based on two metrics: system lifetime and P_d. The system lifetime is defined as the elapsed time until all SUs in the network become inoperative. To evaluate it, two complementary metrics were used: the average number of active SUs, representing the mean number of operational SUs (with sufficient energy for the sensing process) throughout the simulation cycles; and the average drop start, which corresponds to the cycle in which the first SU failure occurs during system operation.

The test statistic for the hypotheses H_0 and H_1 of the SUs was derived using the ED, with $P_{\text{fa}} = 0.1$ adopted in all scenarios, and the corresponding P_d determined from the sensing performance simulations. In all scenarios, decision fusion was implemented using the majority voting (MAJ) logic.

In this pseudocode, $E^{(j)}$ represents the energy available at the j-th SU, which is initially equal for all SUs. It is calculated as the minimum power required to perform sensing and report the decision to the FC, multiplied by the number of cycles the secondary network can operate. The shadowed areas were defined as indicated in Table V, considering regions where signal propagation experiences additional attenuation due to physical obstacles.

The energy parameters of the secondary network were adjusted so that, when implementing the classic method, the network lifetime is approximately 30,000 cycles for each SU draw, with this draw being performed 100 times. During the simulation, the metrics were collected, and the average of the results was then plotted. Table VI presents the system parameters used in the simulations.

In the simulation, the primary transmitter activity was modeled using the function `randi([0,1])`, which follows a Bernoulli distribution, alternating between active and inactive states. The signal attenuation was adjusted according to the path-loss exponent α, defined as:

- $\alpha = 2$ in areas without shadowing (lower attenuation);
- $\alpha = 4$ in areas with shadowing (higher attenuation).

Figure 3 shows the P_d performance of the SUs considering different values of m_T. In Fig. 3(a), for $m_T = 50$, it can be observed that the cluster-based systems and the proposed system exhibit a P_d below 0.9, while the classic system maintains a P_d at or above 0.9. This behavior is related to the fusion technique used at the FC: in the classic system, all SU reports are considered, increasing detection accuracy. In contrast, in the cluster-based and proposed systems, the decision is based only on the reports sent by the CHs, which reduces the accuracy of the decision-making process. This drop compromises the system's efficiency in the later stages.

In Fig. 3(b), corresponding to $m_T = 100$, it can be observed that all systems maintain a P_d above 0.9 during the first sensing cycles, indicating high detection accuracy and reflecting the robustness of the network and the reliability of the adopted fusion technique. In the classic system, performance also increases, approaching 1. In Fig. 3(c), with $m_T = 200$, the

TABLE IV. PSEUDO-CODE 2: STEPS ASSOCIATED IN MATLAB

Set the values of the system parameters
Define the simulation scenario (PU, FC and r)
Define the shading areas
Calculate the energy threshold λ
For each draw, do the following:
  Generate m_T SUs
  Run the algorithm *K-Means*
  Find the CH of each cluster
  Calculate the distances
  Calculate the reception power
  While $E^{(j)} > \lambda$, run the detection round:
    Calculate y_j for each SU
    Calculate the test statistic
    Find the local decision of the SUs (LD_j)
    Find the system's global decision (GD)
    Update the energy consumed
    Penalize SUs
    Find new CHs
    Calculate the distances
    Disable SUs
    Define which SUs are still active
    Calculate the current value of P_d
  End of sensing round
Calculate the average of the metrics
End of draw round

TABLE V. SHADED AREAS

Area	r	X	Y
1	150	-200	600
2	150	700	400
3	150	400	-400
4	150	0	-800
5	150	-600	-100

TABLE VI. SYSTEM PARAMETERS

Parameters	Values
m_T	50, 100 or 200
$c_{\max}$	5
r	1000 m
FC	$(0,0)$
P_{txPU}	1 W
n	60
α	$[2,4]$
P_s	1 μW
P_{ref}	0.1
n_{sensing}	30,000
$cycle_{CH}$	1000
P_{rxCH}	-100 dBm
P_{rxFC}	-100 dBm
max_{back}	10, 15 or 20

cluster-based and proposed systems exhibit even higher P_d values, close to 1, while the classic system remains stable with P_d equal to 1. These results highlight that increasing the number of SUs significantly contributes to improving system accuracy. The increase in the number of sensors raises the amount of available information, often redundant, strengthening the decision-making process, since the greater the number of reports transmitted, the higher the FC's ability to accurately identify the occupancy status of the band.

The performance in terms of P_{fa} is approximately zero in all analyzed scenarios, due to the criteria adopted in the system design.

The classic system showed higher P_d in all analyzed scenarios due to the fusion technique applied at the FC, as previously described. However, the proposed system demonstrates greater stability, maintaining satisfactory performance even in the final stages, when the SUs start being permanently deactivated. It is worth noting that, in the P_d graph, the curves end at the point where no more SUs are available in the network to perform sensing.

Figure 4 illustrates the lifespan of the secondary network. It can be observed in Fig. 4(a), (b), and (c) that the classic system operates for just over 30,000 cycles. Since the SUs are randomly positioned, some may be closer to the FC, resulting in lower energy consumption when transmitting their decisions. This variation causes certain SUs to take longer to be deactivated, slightly extending the overall network lifespan.

In all the curves of Fig. 4, it can be observed that the proposed system exhibits a longer lifespan compared to the others. However, Fig. 4(a), with $m_T = 50$, shows a more significant relative gain compared to the curves in Fig. 4(b) and (c), with $m_T = 100$ and $m_T = 200$, respectively. This can also be attributed to the higher dispersion of the SUs in scenarios with lower density, resulting in more varied energy consumption patterns. As the number of SUs increases, they tend to be positioned closer to each other, leading to more uniform energy consumption and, consequently, reducing the impact of heterogeneity on the network's lifespan.

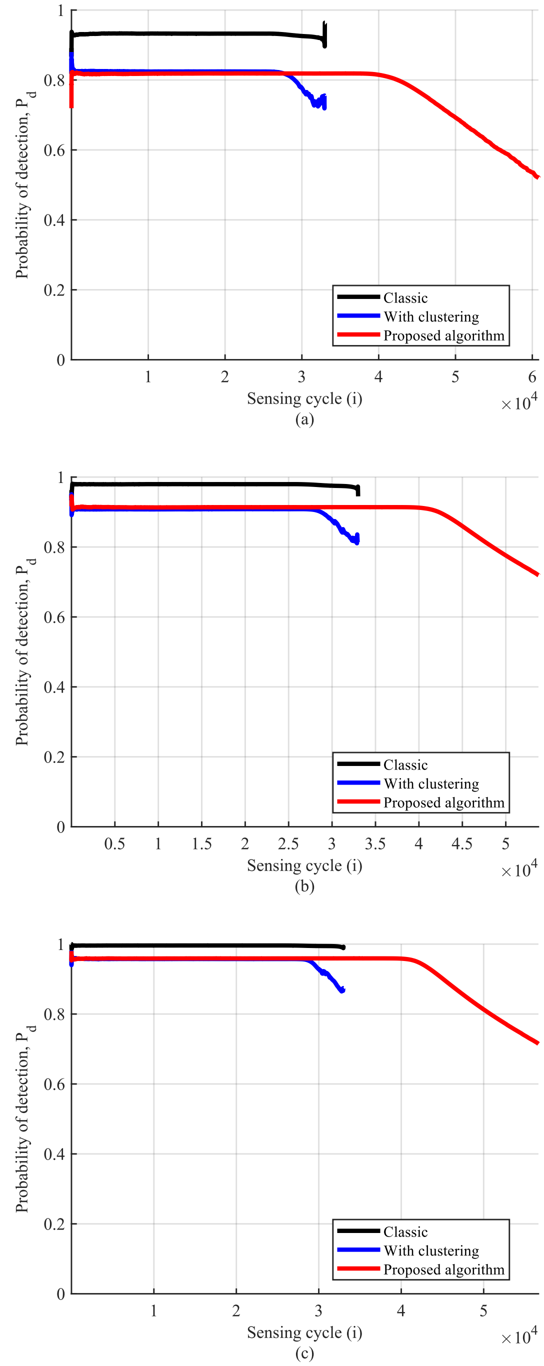

Figure 3. P_d for $c_{\max} = 5$, $n = 60$ samples per SU, with $m_T = 50$, 100, and 200 from top to bottom.

For this reason, the curves for $m_T = 100$ and $m_T = 200$ exhibit similar behaviors, with a slight reduction in lifespan observed in Fig. 4(c). Furthermore, it is important to highlight that in Fig. 4(b), the CSS is cluster-based, which means the network operation depends directly on the CHs. When a CH ceases to operate, all nodes in the associated cluster are deactivated. In contrast, in Fig. 4(c), where the proposed algorithm is applied, if a CH stops operating, another CH is assigned to the cluster.

It can be inferred, therefore, that increasing the number of SUs tends to stabilize the network's lifespan, as the SUs begin to operate under similar conditions. To ensure that the addition of more SUs continues to provide significant durability gains, it would be necessary to expand the network's coverage area, keeping the SUs relatively dispersed.

Although the classic system and the clustered system exhibit approximately the same lifespan, in the classic system all SUs send their decisions directly to the FC. In dense networks, this can cause communication overload, compromising system efficiency. On the other hand, the clustered system organizes the SUs into smaller groups, which improves network scalability and allows for the application of more efficient strategies for energy management, thereby contributing to the extension of the network's lifespan.

The oscillation observed in the average number of active SUs during the final cycles of the proposed algorithm results from the dynamics between penalties for detection failures, shutdown conditions due to low energy, and possible temporary reactivations of the SUs. SUs are disabled when their residual energy falls below a threshold λ and an additional parameter β. The system alternates between deactivating SUs with insufficient energy and reintegrating them when detection conditions become favorable. This intermittent behavior, combined with the use of an average-based metric, causes noticeable fluctuations in the curve, especially when the number of active SUs approaches the minimum threshold required for the system's continued operation.

Although the classic system exhibits higher P_d values, as illustrated in Fig. 3, it can be observed in Fig. 4(a)–(c) that the proposed system provides a significantly longer network lifespan.

Figure 5 illustrates the lifespan of the fixed scenario with variations in the maximum number of consecutive backoffs ($\max_{\text{back}}$). This parameter defines the limit for the consecutive backoff occurrence counter β of each sensor; that is, when the value of β_j (the backoff occurrence counter of the j-th sensor) reaches $\max_{\text{back}}$, the respective sensor is permanently disabled from the sensing process.

The highlighted points in Fig. 5 indicate the average onset of SU deaths, i.e., the cycle in which the SUs begin to be deactivated due to poor spectral sensing performance. As this technique is exclusive to the proposed algorithm, the analysis focuses only on the curves corresponding to this system.

The backoff mechanism, described in (12), consists of assigning temporary inactivity periods to SUs with poor detection performance, reducing energy consumption during these intervals. SUs located in shadowed areas experience higher signal attenuation due to the presence of obstacles, which increases the likelihood of errors in spectral sensing. As a result, these SUs tend to fail more frequently, remaining in backoff for several consecutive cycles until, upon reaching the maximum allowed number of backoffs, they are permanently disabled from the sensing process.

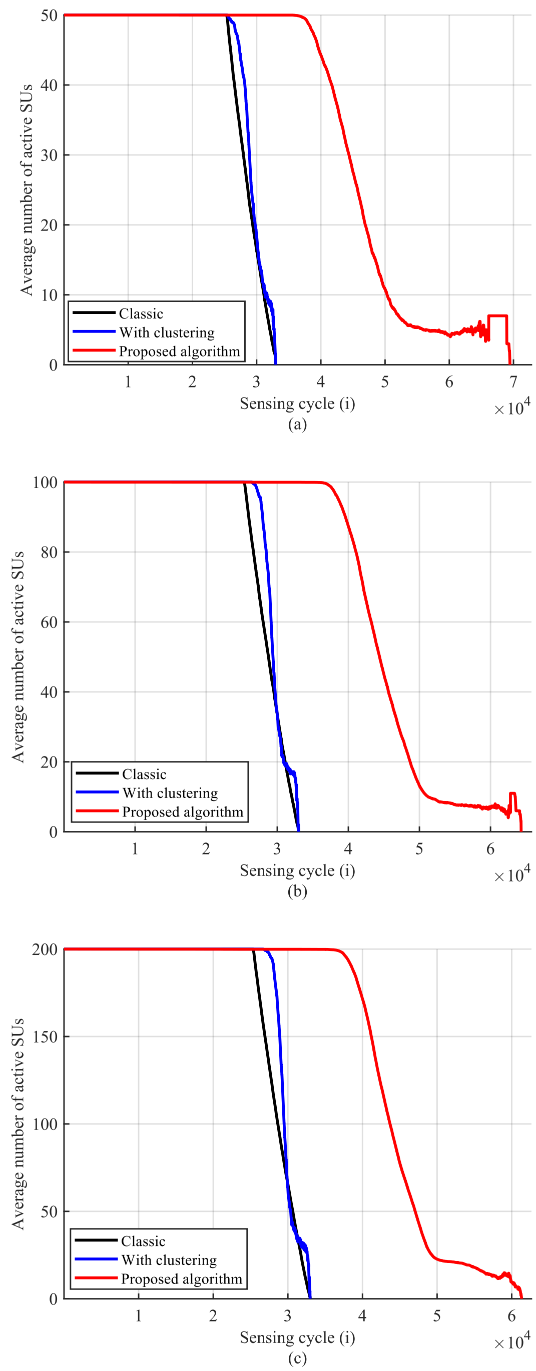

Figure 4. Network lifespan for $c_{\max} = 5$, $n = 60$ samples per SU, with $m_T = 50$ in graph (a), $m_T = 100$ in graph (b), and $m_T = 200$ in graph (c).

The premature deactivation of SUs is directly related to the value of $\max_{\text{back}}$. In Fig. 5, with $\max_{\text{back}} = 10$, SUs in unfavorable regions are disabled more quickly, as they accumulate consecutive backoffs in fewer cycles. When β_j reaches the limit, the SU is considered dead for the sensing process, even if it still has available energy.

In Fig. 5, with $\max_{\text{back}} = 15$, the SUs take longer to be permanently disabled. With $\max_{\text{back}} = 20$, the SUs remain active for an even longer period. This analysis shows that, in the proposed system, the quality of spectrum sensing is prioritized over residual energy. That is, a sensor may be excluded from the sensing process even if it has sufficient energy, if its detection performance is unsatisfactory.

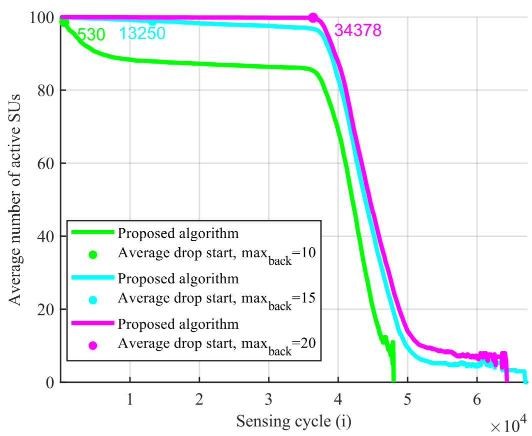

Figure 5. Network lifetime for $m_T = 100$, $c_{\max} = 5$, $n = 60$ samples per SU, with variable $\max_{\text{back}}$.

IX. Conclusion

The proposed algorithm, which integrates temporary and permanent sensor exclusion with dynamic CH selection, provides significant gains in energy efficiency and in the longevity of the secondary network in CRNs. In the evaluated scenarios, the proposed solution increases the CRN lifetime from approximately 3×10^4 to about 6×10^4 sensing cycles, which corresponds to an average network lifetime gain close to 100% relative to the classical method, without compromising sensing performance. Simulations demonstrated that, even in scenarios with varying SU densities and backoff configurations, the algorithm maintains a robust P_d while distributing energy consumption evenly among the sensors. Compared to the classical and clustering-based systems, the proposed method stands out for its performance stability, adaptability under adverse conditions, and reduction of the impact of localized failures. Thus, the algorithm contributes not only to the protection of the primary network by ensuring reliable sensing decisions but also to the operational sustainability of the secondary network, making it an effective approach for implementing more resilient and energy-efficient CRNs.

Acknowledgment

This work was partially supported by RNP, with resources from MCTIC, Grant No. 01245.020548/2021–07, under the Brazil 6G project of the Radiocommunication Reference Center (Centro de Referência em Radiocomunicações – CRR) of the National Institute of Telecommunications.

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