Algorithm for Sensor Exclusion and Dynamic Cluster Head Selection in Cognitive Radio Networks

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***Abstract*— Cognitive Radio (CR) is a promising technology for optimizing spectrum utilization in wireless communication networks, particularly in fifth (5G) and sixth (6G) generationscenarios. In massive Internet of Things (IoT) environments, where numerous devices share network resources, reducing energy consumption is essential to extend the lifespan of both devices and the secondary network (CR network). This article proposes an algorithm that combines temporary and permanent sensor exclusion with the dynamic selection of Cluster Heads (CHs). The goal is to reduce energy consumption without compromising the system's detection capability, thereby ensuring greater network longevity. The simulations conducted prove that the proposed algorithm ensures robust and efficient detection, while significantly increasing the lifespan of the secondary network.**

Keywords— Cognitive radio network; cooperative spectrum sensing; energy detector; k-means clustering; network lifespan.

I. INTRODUCTION

In recent years, the rapid growth of wireless communication systems has intensified the scarcity of Radio Frequency (RF) spectrum. This is 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 Fifth Generation (5G), the Internet of Things (IoT), and, in the future, Sixth Generation (6G). However, to enable most wireless communication services, overcoming spectrum limitations is essential, as many frequency bands are required to support the increasing number of transmitters and receivers expected in 5G, 6G, and IoT networks. In this context, the concept of Cognitive Radio (CR) emerges as a proposal to efficiently utilize idle bands in the RF spectrum allocated to PUs. The concept of CR was initially proposed by Joseph Mitola III in 1999 [1]. This technology consists of intelligent transceivers integrated into a secondary network, which, among other functions, perform Spectrum Sensing (SS) to opportunistically transmit in the gaps left by the primary network. SS is one of the main attributes of CRs and is considered a fundamental element for enabling dynamic spectrum access.

A. Related work

Numerous studies have proposed cluster-based Cooperative Spectrum Sensing (CSS) approaches in Cognitive Radio Networks (CRNs) to reduce energy consumption. CSS involves multiple Secondary Users (SUs) co-participating in the sensing process to improve the accuracy of channel occupancy state decisions. The most common form of CSS is the centralized approach, in which the sensing information gathered by the SUs is transmitted to the fusion center (FC) of the secondary network, where the decision on the state of the sensed channel is made [2].

In [3], a sensor node selection scheme is proposed, which prioritizes sensors with higher Signal-to-Noise Ratio (SNR) and greater residual energy. This ensures that only an optimized subset of nodes performs CSS, while the remaining ones stay in energy-saving mode. Although effective in reducing energy consumption in CRNs, the main limitation of this approach is the absence of a node rotation strategy, which may compromise the long-term efficiency of the network. In [4], a sensor selection method based on residual energy levels is proposed, prioritizing nodes with higher energy for cooperative sensing. Although this approach is energy-efficient, it may introduce overhead in dense networks and compromise detection accuracy, which constitutes its main limitation.

In [5], a scheme is proposed that employs peer-to-peer coupling of sensor nodes, alternating between sleep and wake modes to balance energy consumption. Although effective in conserving energy, its main limitation lies in the potential latency introduced in scenarios with high detection demands, due to the constant switching between modes. In [6], a distributed Cluster Head (CH) election scheme based on the residual energy of nodes is proposed. In each round, the node with the highest residual energy within each cluster is selected as the CH, responsible for transmitting data to the fusion center. Although this scheme effectively reduces energy consumption, its main limitation lies in the continuous selection of CHs based solely on available energy, which may favor certain nodes and accelerate their energy depletion, potentially compromising the network's long-term stability.

B. Contribution and structure of the article

In CRNs, energy efficiency and detection performance are priorities due to energy limitations and the variability of the sensing environment. This paper proposes an innovative algorithm that combines temporary and permanent sensor exclusion with dynamic CH selection. The exclusion works as follows: at each sensing cycle, the detection performance of each participating sensor is evaluated. If a sensor makes an incorrect decision about the spectrum occupancy state, it is penalized and remains inactive for some cycles, which characterizes temporary exclusion, or *backoff*. After this inactivity period, the sensor is reintegrated into the process. Sensors with sufficient energy and good performance are prioritized for CSS.

The CH selection is performed after a predefined number of cycles, based on the calculation of the cluster's Center of Mass (CM), weighted by the residual energy of the sensors with sufficient energy levels. The sensor closest to the CM and with the highest available energy is chosen as the CH. It is assumed that the reporting channel is error-free, ensuring accurate communication between the CH and the FC for sensing decisions.

The integration of these strategies allowed the network's operation to be extended without compromising the Detection Probability (P_d). For example, the dynamic selection of CHs ensured a balanced load distribution among the sensors, which increased the secondary network's lifespan and provided a more stable P_d over several sensing cycles, surpassing the performance of other systems. The sensors' energy decreases as they participate in sensing, and those that reach critical levels are deactivated to ensure network reliability and energy load balance.

The remainder of this paper is organized as follows: Section II presents the system model. Cooperative spectrum sensing using energy detection is discussed in Section III. Signal and channel modeling are addressed in Section IV. Section V focuses on energy consumption modeling. The proposed algorithm is detailed in Section VI. Section VII provides the results, while Section VIII concludes.

II. SYTEM MODEL

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 Primary Users (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 $r = 1000\,m$. 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 Figure 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 shaded 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.

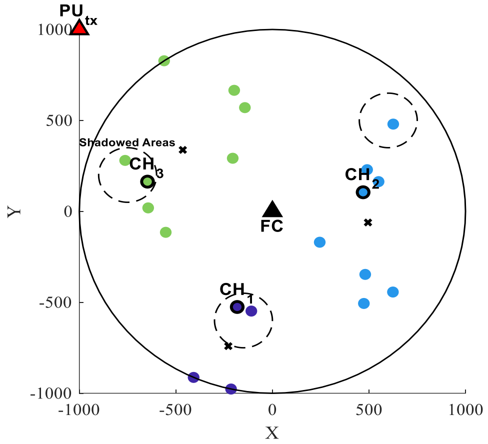

Figure 1. Model of the spatial distribution of SUs, clustering using *k-means* algorithm and representation of shadowed areas.

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.

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}).

III. COOPERATIVE SPECTRUM SENSING USING ENERGY DETECTION

Spectrum sensing is a binary hypothesis test where H_1 and H_0 represent the hypotheses of the presence and absence of the primary signal in the sensed band, respectively. The decision is made by comparing a test statistic T with a predefined decision threshold γ. If $T > \gamma$, the hypothesis H_1 is chosen. Otherwise, the hypothesis H_0 is selected [7].

Spectrum detection performed individually by each SU is prone to performance degradation, making CSS the preferred approach. In CSS without clustering (classic), each SU operates independently, acting as a CH and directly reporting its detection decision to the FC. In cluster-based CSS, the nodes are organized into groups, and the cluster members send their detection information to the CHs. The CHs, in turn, forward the received data (with or without their own sensing information) to the FC. At the FC, a global decision is made using a $k-out-of-m$ fusion rule: the presence of the primary signal is confirmed if k or more SUs agree on the channel state.

In decision fusion-based CSS, each SU generates a test statistic that allows it to locally determine the spectrum occupancy state. There are different methods to construct this test statistic, resulting in various types of detectors. The Energy Detector (ED) is the most widely used due to its simplicity of implementation. The ED differentiates between the presence and absence of the primary signal based on the energy of the samples collected during the sensing interval. The test statistic of the ED for the $j-th$ SU is:

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

where n is the number of samples at the $j-th$ SU, and $|y_{ji}|$ 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 SS is commonly measured using two main metrics: the Probability of False Alarm (P_{fa}) and the , mathematically defined by (2) and (3):

$$P_d = Pr[T > \gamma \mid H_1], \tag{2}$$

and P_{fa} is defined as:

$$P_{fa} = Pr[T > \gamma \mid H_0], \tag{3}$$

where H_1 and H_0 represent the hypotheses of the presence and absence of the signal transmited 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.

IV. 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 into a matrix $\boldsymbol{Y} \in \mathbb{C}^{m\times n}$, given by:

$$\boldsymbol{Y} = \boldsymbol{HX} + \boldsymbol{V}, \tag{4}$$

the vector $\boldsymbol{H} \in \mathbb{C}^{m\times p}$ models the Rayleigh fading channels between the PU and the SUs, with elements $\{h_j\}$, where $j = 1, 2, \ldots, m_T$, representing the channel gains between the PU and the $j-th$ SU. $\boldsymbol{X} \in \mathbb{C}^{n\times p}$ models the signal transmitted by the PU, while $\boldsymbol{V} \in \mathbb{C}^{m\times n}$ represents the additive white Gaussian noise (AWGN) at the SUs. Under $\boldsymbol{H_1}$, the expression $\boldsymbol{Y} = \boldsymbol{HX} + \boldsymbol{V}$ holds, whereas under $\boldsymbol{H_0}$, $\boldsymbol{Y} = \boldsymbol{V}$, where $\boldsymbol{Y}$ represents the signal received by the SUs.

The Gaussian distribution was adopted for the transmitted signal ($\boldsymbol{X}$) as it simplifies mathematical analysis [8]. 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 $\boldsymbol{H}$ are complex samples of zero-mean Gaussian variables, Independent and Identically Distributed *(i.i.d.)*, modeling a flat Rayleigh fading channel between PU and each SU [8]. 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 $\boldsymbol{X}$ are complex Gaussian random variables with zero mean and variance P_{txPU}, where P_{txPU} represents the transmission power of the PU. Thus, the power of the primary signal received by the $j-th$ SU (P_{rxSU_j}) is given by the Log-Normal prediction model [2], as described by (5):

$$P_{rxSU_j}(dB) = P_{txPU}(dB)10\alpha \, log_{10}\left(d_{PU_j}\right), \tag{5}$$

where d_{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.

V. ENERGY CONSUMPTION MODELING

Initially, the SUs perform sensing simultaneously during the period τ_s. Subsequently, they transmit their decisions to the corresponding CH within the period τ_{rSU}. The CH then makes the cluster decision and forwards it to the FC within the period τ_{rCH}.

Energy consumption in the sensing process is directly related to the adopted fusion mode. In decision fusion, sensing requires higher energy consumption compared to data fusion, as the processing of the received signal goes beyond simple sample collection. However, in the reporting stage, the local decision can be represented by just 1 bit, significantly reducing energy expenditure compared to transmitting multiple bits per sample in data fusion. In this work, the decision fusion approach was adopted.

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

$$E_r^{(j)} = E^{(j)} - \left(P_s * \tau_s + P_{txSU}^{(i,j)} * \tau_{rSU} + P_{txCH}^{(j)} * \tau_{rCH}\right), \tag{6}$$

$\tau_{rCH}$where $E_r^{(j)}$ represents the residual energy of the $j-th$ SU during the sensing process, $E^{(j)}$ refers to the energy available in the $j-th$ SU, which is initially uniform across all SUs. P_s is the power for SS, $P_{txSU}^{(i,j)}$ is the power used by the $j-th$ SU to transmit its decision to the $i-th$ CH, and $P_{txCH}^{(j)}$ is the power of the signal transmitted by the $j-th$ CH to communicate the cluster decision to the FC, calculated in (7) and (*8*). If the reporting occurs from SU to CH, the term $P_{txCH}^{(j)} * \tau_{rCH} = 0$. On the other hand, if the reporting is from CH to FC, the term $P_{txSU}^{(i,j)} * \tau_{rSU} = 0$.

Applying the distance path loss model [2], the values of $P_{txSU}^{(i,j)}$ and $P_{txCH}^{(j)}$ are calculated as follows:

$$P_{txSU}^{(i,j)} = P_{rxCH} * {d_{CH_{ij}}}^{\alpha}, \tag{7}$$

and

$$P_{txCH}^{(j)} = P_{rxFC} * {d_{FC_j}}^{\alpha}, \tag{8}$$

where $d_{CH_{ij}}$ 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_{rxFC} and P_{rxCH} are the sensitivities of the CHs' and FC's 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 (6). Active SUs are those that have not been excluded, either temporarily or permanently, and have sufficient energy to continue participating in the sensing process. Sensors with energy below a defined threshold are permanently excluded from the sensing process, being classified as inactive or "dead." Since any SU can be a CH, the energy threshold was defined as the minimum energy required to perform sensing and report the decision, considering the distance between the SU and the FC equal to the radius of the coverage area.

VI. PROPOSED ALGORITHM

A. Preliminaries

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:

Temporary and Permanent Exclusion of Underperforming SUs*:* This algorithm temporarily deactivates SUs with poor performance and permanently excludes them if the insufficient performance persists over consecutive sensing cycles.

Dynamic CH Selection*:* This approach is based on the calculation of the CM, weighted by the residual energy of the sensors assigned to the cluster. The new CH is selected as the sensor closest to the CM that also has the highest available energy within the cluster.

B. SUs Exclusion Algorithm

The exclusion of SUs is determined based on the individual performance of each sensor. During each sensing cycle, the algorithm evaluates the SUs, penalizing those that exhibited detection errors. The penalty, represented as f_j (penalty number of the $j-th$ SU), is assigned to the SU according to the type of failure identified.

Depending on the global decision, if the decision is incorrect, a collision may occur between the primary and secondary transmissions. The types of failures that may occur are:

Global Success and Local Failure - Proved (GSLF-P): When the global decision indicated that the medium was free (*GD=0*) and it was indeed unoccupied (*TX=0*), the sensor, however, incorrectly detected it as occupied (*LD=1*). In this case, there were no collisions, but those that made the error receive a penalty of 2.

GD represents the global decision of the system, where 1 indicates the presence of the signal and 0 indicates its absence. TX corresponds to the state of the transmission medium, while LD refers to the local decisions of the SUs.

Global and Local Failure - Proved (GLF-P): In this case, the global decision was free $(GD = 0)$, but the medium was occupied $(TX = 1)$, and the sensor incorrectly detected it as free $(LD = 0)$. This resulted in collisions, for which the sensor that made the error also receives a penalty of 2.

Global Success and Local Failure - Unproved (GSLF-U): In this case, the global decision was occupied $(GD = 1)$, the medium was occupied $(TX = 1)$, but the sensor incorrectly detected it as free $(LD = 0)$. There was no transmission, and the sensors that made the error are classified as having an unproven local failure and receive a penalty of 1.

The penalty is assigned to the sensor based on the type of local failure, which occurs due to signal detection errors. Sensors with proven local failures receive stricter penalties, while those with unproven failures are penalized more leniently. The penalty value is used to calculate the backoff, which determines the number of cycles during which the sensor will be temporarily excluded from the sensing process. The SU is permanently excluded after a predetermined number of consecutive backoffs.

Proven success and failure are determined based on the FC's feedback. When $GD = 0$, the SUs can compete for access to transmit their data. Based on the success or failure of the transmission, the FC can determine the actual state of the medium, resulting in stricter penalties for sensors that made errors. In the case of unproven successes and failures, when $GD = 1$, the FC cannot verify the actual state of the medium, which justifies lighter penalties for SUs that made mistakes. TABLE I summarizes this information:

TABLE I. SENSOR PENALITY BASED ON THE TYPE OF FAILURE

GD	TX	LD	Type of Failures	Penalty (f_j)
0	0	1	GSLF-P	2
0	1	0	GLF-P	2
1	1	0	GSLF-U	1

The *backoff* is designed to prevent unnecessary energy consumption by underperforming SUs. The type of failure determines the penalty value, which directly impacts the backoff time (number of inactivity cycles). In (9), $start_{time}$ is the initial base time value used for the backoff. The backoff is calculated as:

$$backoff_j = start_{time} * 2^{f_j} - 1, \tag{9}$$

C. 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:

$$X_{cm} = \frac{\sum_{j=1}^{m} E_r^{(j)} * x_j}{\sum_{j=1}^{m} E_r^{(j)}}, \tag{10}$$

$$Y_{cm} = \frac{\sum_{j=1}^{m} E_r^{(j)} * y_j}{\sum_{j=1}^{m} E_r^{(j)}}, \tag{11}$$

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.

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.

Pseudocode: Dynamic CH Selection Algorithm

If cycle = = $cycle_{CH}$
  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 (10) and (11) (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
      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.

VII. Analysis and Results

The results presented in this section were obtained through computational simulations performed in MATLAB. Different systems were analyzed and compared: CSS classic, CSS with clustering, and the proposed system, which implements a temporary and permanent exclusion mechanism for underperforming SUs and dynamic CH selection. The comparison was carried out in two scenarios, considering $c_{max} = 3$ and $c_{max} = 5$. In all evaluated scenarios, the network ceases operations when the CHs deplete their energy and can no longer perform their functions.

The test statistic for the hypotheses H_0 and H_1 of the SUs was derived using the ED, with $P_{fa} = 0.1$ adopted in all scenarios, and the corresponding P_d determined from the sensing performance simulations. The analysis considered the secondary network's lifespan, designed to last up to $n_{Sensing} = 5000$ sensing cycles. The SUs were randomly distributed within a circular area with a radius of $r = 1000\,m$. In all scenarios, decision fusion was implemented using the majority voting (MAJ) logic. The TABLE II presents the system parameters used in the simulations.

TABLE II. System Parameters

Parameters	Values
$P_{tx}PU$	1 W
$P_{rx}CH$	-100 dBm
$P_{rx}FC$	-100 dBm
$\tau_r CH, \tau_r SU$	1 s
P_s	1 µW
α	[2 or 4]

The signal attenuation was adjusted through the value of α, set as $\alpha = 2$ in non-shadowed areas and $\alpha = 4$ in shadowed areas, reflecting greater signal attenuation in these regions. $back_{max} = 20$ was defined, representing the number of consecutive inactivity periods of the SUs before their permanent deactivation.

Figure 2 illustrates the performance of the analyzed systems in terms of P_d. Initially, all systems exhibit a high P_d, demonstrating high detection accuracy during the first sensing cycles, reflecting the robustness of the network and the reliability of the decision-making technique employed. However, as the cycles progress, a gradual decrease in P_d is observed, resulting from the unavailability of some SUs, which negatively impacts the detection rate and compromises efficiency in the later stages.

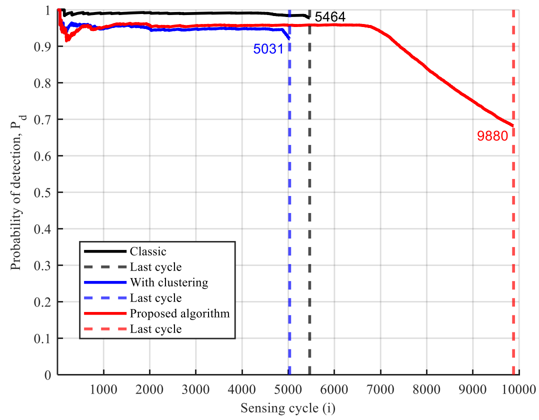

Figure 2. P_d for the different systems, for $m_T = 200$, $n = 60$ samples per SU, and $c_{max} = 3$.

In the classical system, P_d remains close to 1 during most of the cycles, due to the decision fusion technique applied at the FC, which considers the reports from all SUs. Furthermore, the greater the number of SUs reporting to the FC, the higher the detection accuracy. On the other hand, the proposed system demonstrates more consistent performance, with P_d remaining above 0.9 for a greater number of detection cycles. In the clustering system, although it shows consistent performance in terms of P_d, the final cycle performance is lower compared to the classical system. This happens because the operation of the cluster depends directly on the CH, and when it can no longer operate, the entire cluster is deactivated.

Although the classic system has a slightly higher number of cycles than the clustering system, clustering is essential for efficient network management, especially in scenarios with high SU density. In the classic system, all SUs send data directly to the FC, which, in dense networks,

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generates communication overload and compromises system efficiency. On the other hand, the clustering system organizes the network into smaller groups, is fundamental for efficient network management, as it enhances scalability and facilitates the adoption of strategies that help to extend its lifespan.

In the scenario with $c_{max} = 5$, a similar behavior was observed among the analyzed systems in terms of P_d performance. However, in the proposed system, there was a gain in the last cycle, resulting from the reduced distance between SUs and their respective CHs, which improves communication efficiency and extends network operation.

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

In Figure 3, the proposed system demonstrates the best performance in terms of lifespan, showing a significantly slower reduction in the number of live sensors compared to the other systems. The introduction of the backoff mechanism and the dynamic CH rotation promotes a more balanced distribution of the energy load among the sensors. Sensors in backoff mode conserve energy by temporarily withdrawing from the sensing process, while the dynamic CH selection in each cluster prioritizes the SU with the highest available energy. This mechanism substantially extends the network's lifespan while also increasing its overall efficiency.

It is also possible to observe that the classical system has a longer lifespan compared to the clustering-based system due to the proximity of some SUs to the FC, which results in energy savings when reporting their decisions. However, the clustering system shows a slower reduction in the number of active sensors compared to the classical system, thanks to the proximity of the sensors to their respective CHs. Despite this, the distance between the CH and the FC may lead to the premature deactivation of the cluster, thereby reducing the lifespan of this system.

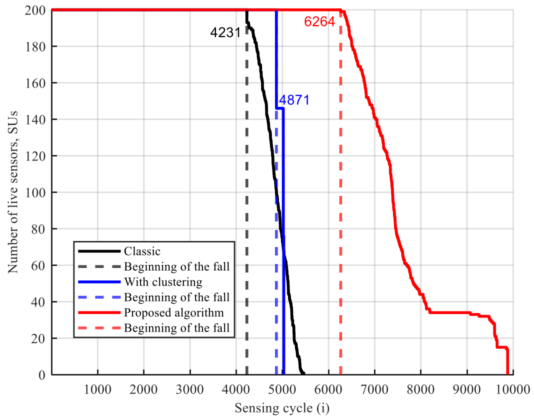

Figure 3. Network life cycle of the systems analyzed with $c_{max} = 3$.

In Figure 4, with $c_{max} = 5$, the increase in the number of clusters reduces the distance between the sensors and their respective CHs, facilitating decision transmission and reducing energy consumption. As a result, the lifespan of the proposed system is more than double the defined cycles, while the other systems show only slight improvements or remain virtually unchanged.

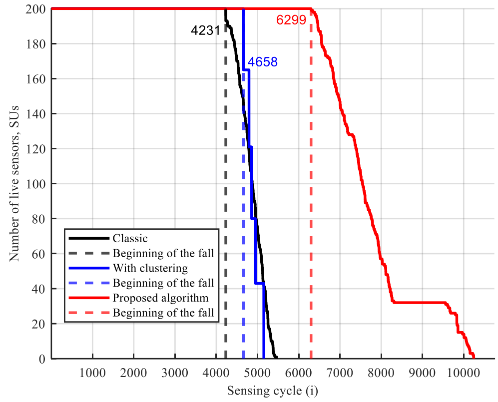

Figure 4. Network life cycle of the systems analyzed with $c_{max} = 5$.

The increase in c_{max} results in a longer operating time.

VIII. CONCLUSION AND FUTURE WORK

This article presents an algorithm that improves the lifespan of secondary networks by combining sensor exclusion with dynamic CH selection in CRNs. These strategies extended the network's operation without affecting performance P_d, maintaining approximately 90% P_d across multiple sensing cycles, while balancing the sensor load and increasing the network's lifespan.

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