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RESEARCH

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Energy consumption optimization in green cognitive radio networks based on collaborative spectrum sensing

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Abstract

In the realm of green communications, the focus is on achieving high spectrum efficiency and low energy consumption. This paper addresses the crucial goal of reducing energy usage in green cognitive radio networks (CRNs) during communication between secondary users (SUs) and primary users (PUs). This paper proposed an energy consumption optimization model (ECOM) for green CRN utilizing collaborative spectrum sensing thereby minimizing the environmental impact and prolonging the operational lifetime of devices. The collaborative spectrum sensing proved its role in optimizing the energy consumption in the green CRN. An energy-efficient scheduling algorithm is implemented in ECOM, in which the SUs can be scheduled to perform their sensing process in a time-division manner to reduce energy consumption. Applied collaborative spectrum sensing serves as a valuable resource for researchers, network operators, and policymakers seeking to balance the increasing demand for wireless communication services with the imperative of sustainability. The simulation results and mathematical proof emphasize that ECOM demonstrates reduced energy usage and increased average effective throughput when compared to other recent models.

Keywords: Energy consumption, Optimization, Green cognitive radio networks, Collaborative spectrum sensing, Energy-efficient scheduling

1 Introduction

To meet the continuously growing need for wireless communication services while effectively utilizing the existing spectrum resources, green cognitive radio networks (GCRNs) emerged as a subset of CR networks [1] that aim to optimize energy consumption, thereby minimizing the environmental impact and prolonging the operational lifetime of devices. This paper explores the critical aspect of energy consumption optimization in GCRNs, focusing on collaborative spectrum sensing as a key strategy. Collaborative spectrum sensing involves multiple CR devices working together to detect and share spectrum availability information. It enhances spectrum awareness and provides an opportunity to reduce energy consumption significantly. Three primary forms of spectrum sensing have been identified: cooperative sensing, interference-based sensing, and non-cooperative sensing (transmitter detection) [2]. The energy detection approach, the matched filter detection method, and the cyclostationary feature detection method can all be applied to these categories. In this paper, the collaborative spectrum sensing is applied to reduce energy consumption in CRN. The collaborative spectrum sensing involved multiple secondary users (SUs) cooperatively sensing the spectrum and sharing their sensing results to improve the overall accuracy and reduce individual energy consumption.

A description of the proposed collaborative spectrum sensing implementation in the proposed model is as follows.

- SU cooperation: SUs' in the network form a cooperative sensing group and exchange their spectrum sensing results. Each SU performs local spectrum sensing and shares the detected primary user (PU) activity information with other SUs in the group.
- Selective sensing: Instead of all SUs sensing all channels, a selective sensing strategy can be employed. SUs can coordinate among themselves to divide the frequency bands into sub-bands and assign each SU to sense specific sub-bands. This way, each SU focuses its energy on a subset of channels, reducing the overall energy consumption.
- Energy-efficient scheduling: To further reduce energy consumption, SUs can take turns in performing spectrum sensing, allowing others to enter a low-power or sleep mode. This scheduling mechanism ensures that only a subset of SUs is actively sensing at any given time, reducing the overall energy expenditure. By implementing collaborative spectrum sensing in the proposed ECOM, CRNs can benefit from improved spectrum sensing accuracy, reduced energy consumption per SU, and enhanced spectrum efficiency, leading to a more sustainable and efficient operation.
- Fusion center: A fusion center or a central entity collects the sensing results from all participating SUs and applies fusion techniques, such as majority voting or weighted averaging, to decide in the final decision about the PU activity in each channel.
- Collaborative decision threshold: By sharing their individual sensing results, SUs can collectively determine a decision threshold that ensures accurate detection while minimizing false alarms and missed detections. This threshold can be dynamically adjusted based on the network conditions and PU activity patterns.

The rest of this paper is organized as follows. Section 1 presented an introduction to green cognitive radio networks. The related studies are discussed in Sect. 2. Section 3 provides an overview of the CRN's system model, encompassing the spectrum sensing, CR network and energy harvesting models. In Sect. 4, the proposed ECOM model structure and its corresponding algorithm are presented. The experiment setting of the paper investigation is shown in Sect. 5. Detailed simulation results and comprehensive comparisons for the performance of the ECOM model are presented in Sect. 6. Finally, the conclusions of the paper are outlined in Sect. 7.

1.1 Methods/experimental

It is not applicable.

2 Related works

Recent studies have contributed to the advancement of cognitive radio networks, addressing various aspects such as energy efficiency, routing, security, and management. Some of these relevant works are discussed below:

Chettiyar et al. [4] introduced an approach to enhance energy efficiency in cognitive radio networks, specifically for telemedicine services. Their work explores the application of compressed sensing to reduce energy consumption during data transmission. Ganesh et al. [5] introduced an optimized Levenshtein centroid cross-layer defense mechanism designed specifically for cognitive radio multi-hop networks. The primary objective of this study is likely to enhance the security of such networks. In another study, authors in [6] developed an efficient replication management system, which could potentially be applied to the management of data stored in the Hadoop Distributed File System (HDFS). This research has significant implications for data management in cognitive radio networks. Anal Paul et al. [7] investigated the performance of Q-routing reinforcement learning in cognitive radio network topologies. This research explores different routing strategies and their network performance impact. In their study, Reddy and colleagues [8] directed their attention toward identifying instances of falsified data attacks in cognitive radio networks through the use of a hierarchical ensemble extreme learning machine, employing a cat and mouse approach. This work holds great importance for ensuring network security and preserving data integrity.

In addition, Dynamic Spectrum Access (DSA) [9] coupled with energy harvesting has proven to be an effective approach for significantly reducing the energy consumption of cognitive radio (CR) systems. During the energy harvesting process, the conversion of radio frequency (RF) energy from received signals takes place. This harvested energy, obtained through RF conversion, is then stored in the device's battery using an energy harvesting circuit. This storage capability not only facilitates information transmission, but also powers the device's circuitry [10]. To assess the energy and data states of individual SUs, researchers such as Liu et al. [11] have developed two-dimensional finite-state Markov chains. This model allows the calculation of average secondary throughput and analysis of factors influencing it. In the context of green cognitive radio networks, Huang et al. [12] aimed to minimize energy consumption and maximize utility by proposing energy harvesting architectures. Specifically, they explored concepts such as harvest-use and harvest-store-use. Liu et al. [13] focused on optimizing multiple factors such as receiver mode switching, transmission power, and information and energy transmission scheduling to achieve the best balance between energy harvesting and information transfer in fading channels. Nguyen et al. [14] developed sensor nodes for wireless sensor networks that employ a time-switching structure to concurrently extract energy from various power sources. The objective was to increase the received power to its maximum while considering various factors. Xu et al. [15] used semidefinite relaxation (SDR) in conjunction with spatial multiplexing to harness energy harvesting. The received signal was divided for energy harvesting in a system with multiple single-antenna receivers, and its energy efficiency was maximized under restrictions pertaining to energy harvesting and the signal-to-interference-plus-noise ratio (SINR) [16].

In another investigation, the energy consumption of wireless body area networks was effectively reduced through the integration of energy harvesting techniques with sensor sleep scheduling. In the context of green cognitive radio networks, secondary users possess the ability of radio frequency (RF) energy harvesting from primary users, thereby establishing a sustainable energy source [17].

Reinforcement learning (RL) [18] has emerged as the standard method for addressing challenging issues in wireless networks, presenting a robust framework for implementing an intelligent optimizer that effectively tackles intractable problems [18]. The traditional models for energy harvesting lack the adaptability provided by RL to switch dynamically between information transmission and energy harvesting based on the prevailing spectrum conditions [19, 20].

Figure 1 shows the related studies to green cognitive radio network which discussed in the following section. The authors in [21] focuses on optimizing delay in cognitive radio mesh networks using the routing protocol of the destination-sequenced distance vector (DSDV). The paper seeks to address the important issue of delay optimization in CR mesh networks, with a specific emphasis on using the DSDV routing protocol. This research is valuable for improving the efficiency and performance of these networks, particularly in scenarios where low latency and QoS are critical. In [22], the authors propose a novel approach that combines multiple networks with deep Q-learning for CR network dynamic spectrum access. They also integrate energy harvesting techniques to make the network more environmentally friendly. The authors combined the deep

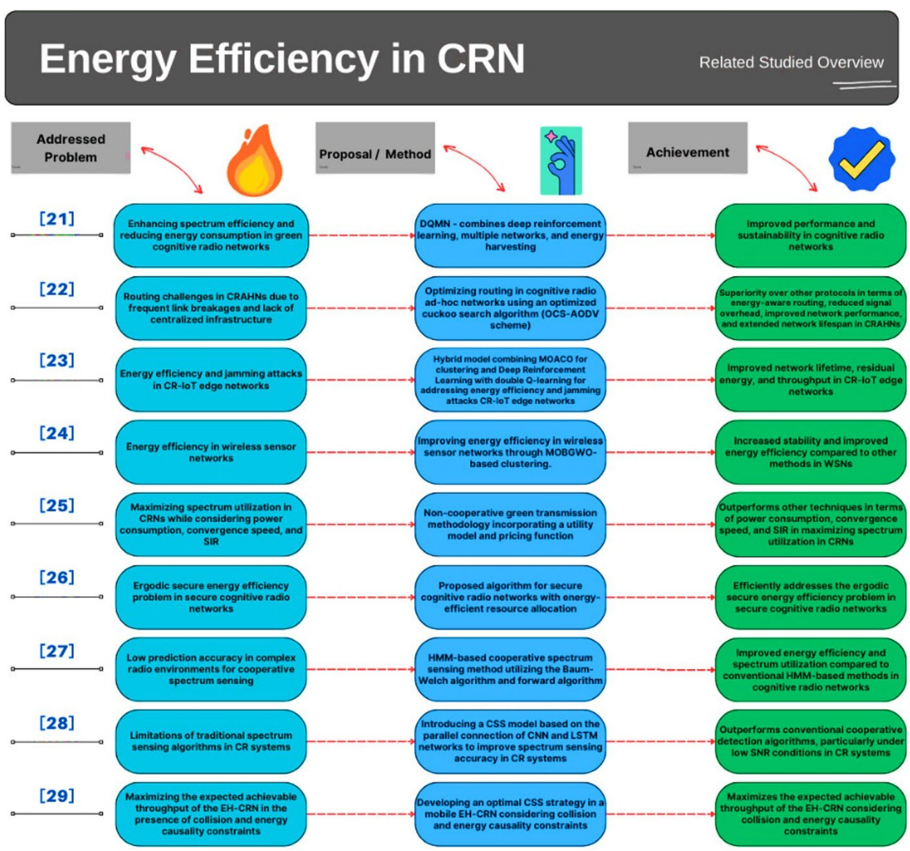

Fig. 1 Energy efficiency in green CRN. The figure summarizes some related studies methods and results in relation to the CRN energy efficiency

reinforcement learning, multiple networks, and energy harvesting for the improving of the performance and sustainability of cognitive radio networks, which are crucial for the future of wireless communication. Furthermore, the researchers presented a sustainable green cognitive radio (CR) network that combines dynamic spectrum access (DSA) and energy harvesting to reduce energy consumption and improve spectrum efficiency. The suggested method, known as deep Q-learning multiple networks (DQMN), utilizes multiple neural networks to manage diverse goals such as access mode, channel selection, communication power and spectrum sensing. Moreover, a sleep mechanism is integrated to optimize spectrum access and reduce energy consumption. Challenges include the complexity of the DQMN model and its single-primary user assumption. Further validation is required for real-world scenarios with multiple primary users.

3 Cognitive radio network's system model

Consider a base station, a primary user (PU), and multiple secondary users (SU) incorporate the CRN. Figure 2 shows the structure of the proposed cognitive radio network model. One PU is allocated to each channel, and when the PUs are not energetic, the SUs can select to access the free channels. To determine the channel condition and enable SUs to plan a suitable approach throughout the access period, spectrum sensing is employed. The SU i to channel n sensing performance is influenced by the possibility of both false positives and false alarms.

The energy indicator of the SU can be calculated using signal-to-noise ratio (SNR) between the PU and the other users [1]. Considering the energy signal strength, the received signal strength (RSS) [3] helps identify whether PU signals are present or not. Every secondary user (SU) is able to calculate the RSS by applying the following equation:

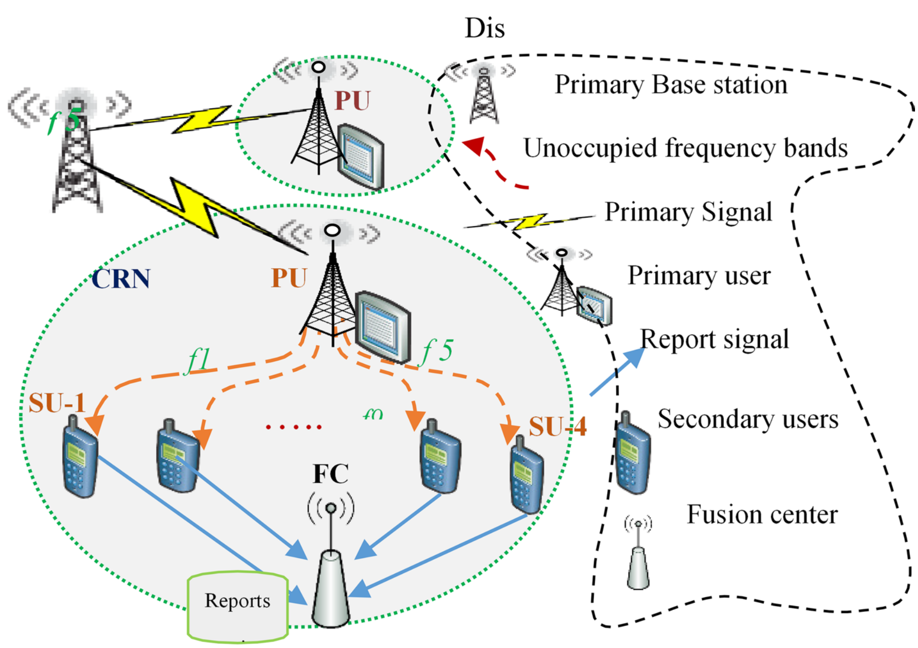

Fig. 2 Cognitive radio network's system model. An illustrative model to describe the component of the cognitive radio network

$$\mathrm{RSS}_i = \mathrm{SE}_i * (h_{\mathrm{PU}.i}) * h_{\mathrm{SU}.i}/\mathrm{Dis}_{\mathrm{PU-SU}} * n_i(t) \tag{1}$$

where $\mathrm{Dis}_{\text{PU-SU}}$ denotes the distance of propagation between PU and SU. Any changes in the channel due to fading and loss are considered by the channel increases between PU and SU, $h_{\mathrm{PU}.i}$ and $h_{\mathrm{SU}.i}$, correspondingly. Then, in order to help determine if the PU signal exists or not globally, the FC receives the energy of the established signal SE_i measured by each SU.

The core goal of the detection communication system is to exploit the opportunity of finding a signal (P_d s) while reducing the likelihood of false alarms (FA_P) and missed detections (P_ md_P).

The thresholds PU_γ are established with this goal in mind. The possibility of detection of the signal for the ith secondary user (SU) can be stated as follows:

$$P\_\mathrm{d}s_i = P\{\mathcal{D}_{\mathrm{Pres}}|H1_{\mathrm{PU}}\} = P\{\mathrm{SE}_i \geq \mathrm{PU}_\gamma|\mathrm{H1}_{\mathrm{PU}}\} \tag{2}$$

The possibility of false alarm of the ith SU can be expressed as:

$$\mathrm{FA}_{P-i} = P\{\mathcal{D}_{\mathrm{Pres}}|\mathrm{H0}_{\mathrm{PU}} = P\{\mathrm{SE}_i \geq \mathrm{PU}_\gamma|\mathrm{H0}_{\mathrm{PU}}\} \tag{3}$$

The possibility of miss detection of the ith SU is expressed as:

$$\mathcal{P}_{md-i} = P\{\mathcal{D}_{\mathrm{Abs}}|H1_{\mathrm{PU}}\} = 1 - P\_\mathrm{d}s_i \tag{4}$$

where $\mathcal{D}_{\mathrm{Pres}}$ is the PU signal presence decision by FC, while $\mathcal{D}_{\mathrm{Abs}}$ is the absence decision. The error probability $\mathcal{P}_{\mathrm{Er}}$ is the probability of FC making incorrect choices. The probability of the total error can be symbolized as:

$$\mathcal{P}_{\mathrm{Er}-i} = P\{\mathcal{D}_{\mathrm{Abs}}|H1_{\mathrm{PU}}\} + P\{\mathcal{D}_{\mathrm{Pres}}|H0_{\mathrm{PU}}\} = \mathcal{P}_{md-i} + \mathrm{FA}_{P-i} \tag{5}$$

4 The proposed energy consumption optimization model

This section presents the proposed energy consumption optimization model (ECOM) for green CRN based on the collaborative spectrum sensing (CSS). The proposed model applied the collaborative spectrum sensing, as it proved its role in optimizing the energy consumption in the green CRN. The high-level architecture of the proposed model implementation steps is shown in Fig. 3.

The detailed-description of each phase in the proposed ECOM is shown in Fig. 4. ECOM implements a collaborative spectrum sensing in the green CRN, using eight main phases as follows:

- Group formation phase: In this phase, the secondary users (SUs) in the network are divided into cooperative sensing groups. The grouping can be based on various criteria such as proximity, channel characteristics, or application requirements. Each group should have a sufficient number of SUs to ensure reliable sensing results.
- Channel assignment phase: Assign specific frequency channels to each SU within a group, in this phase. The channels can be divided equally among the SUs or based on their capabilities and sensing performance. Factors like channel availability, PU

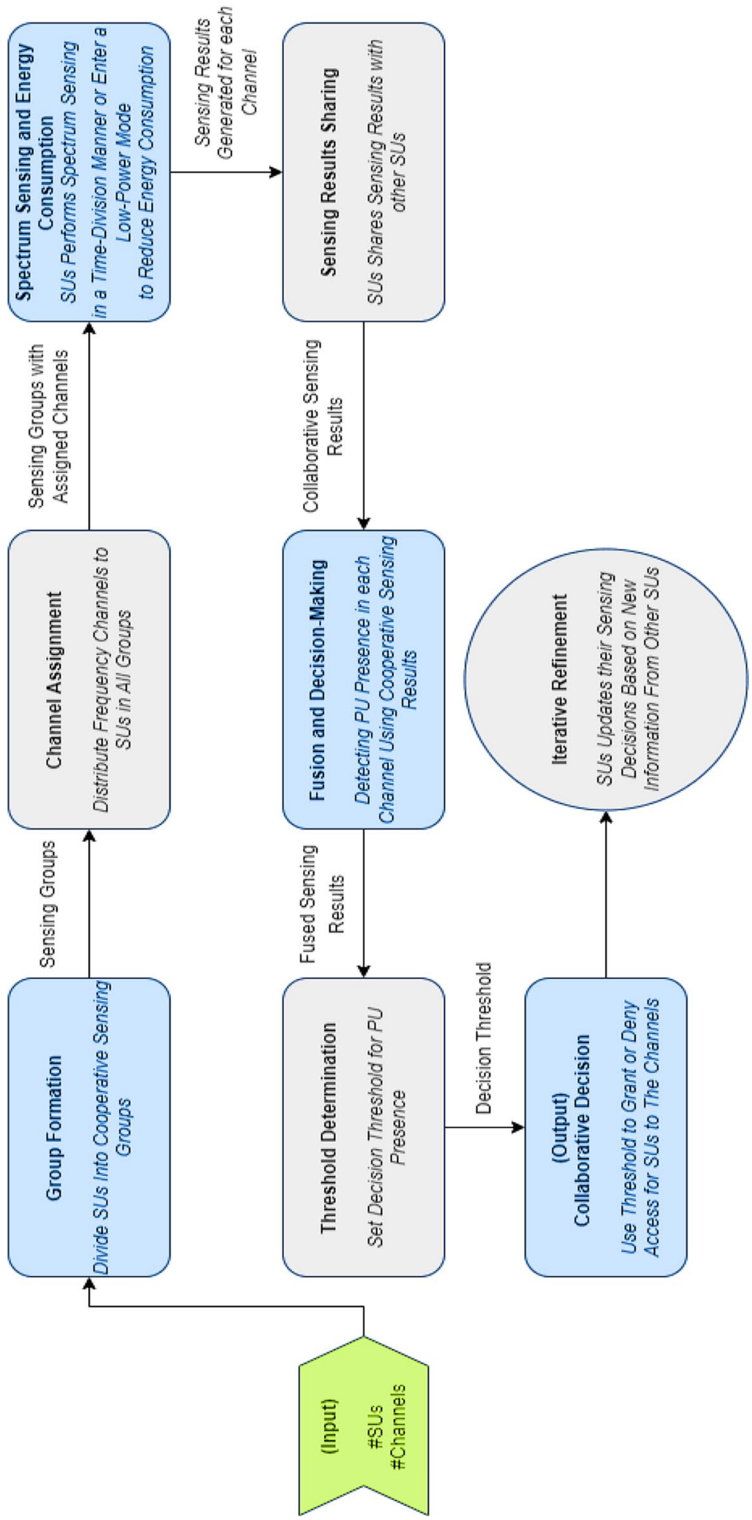

Fig. 3 High-level architecture of the proposed ECOM. General illustration for the steps of the proposed model

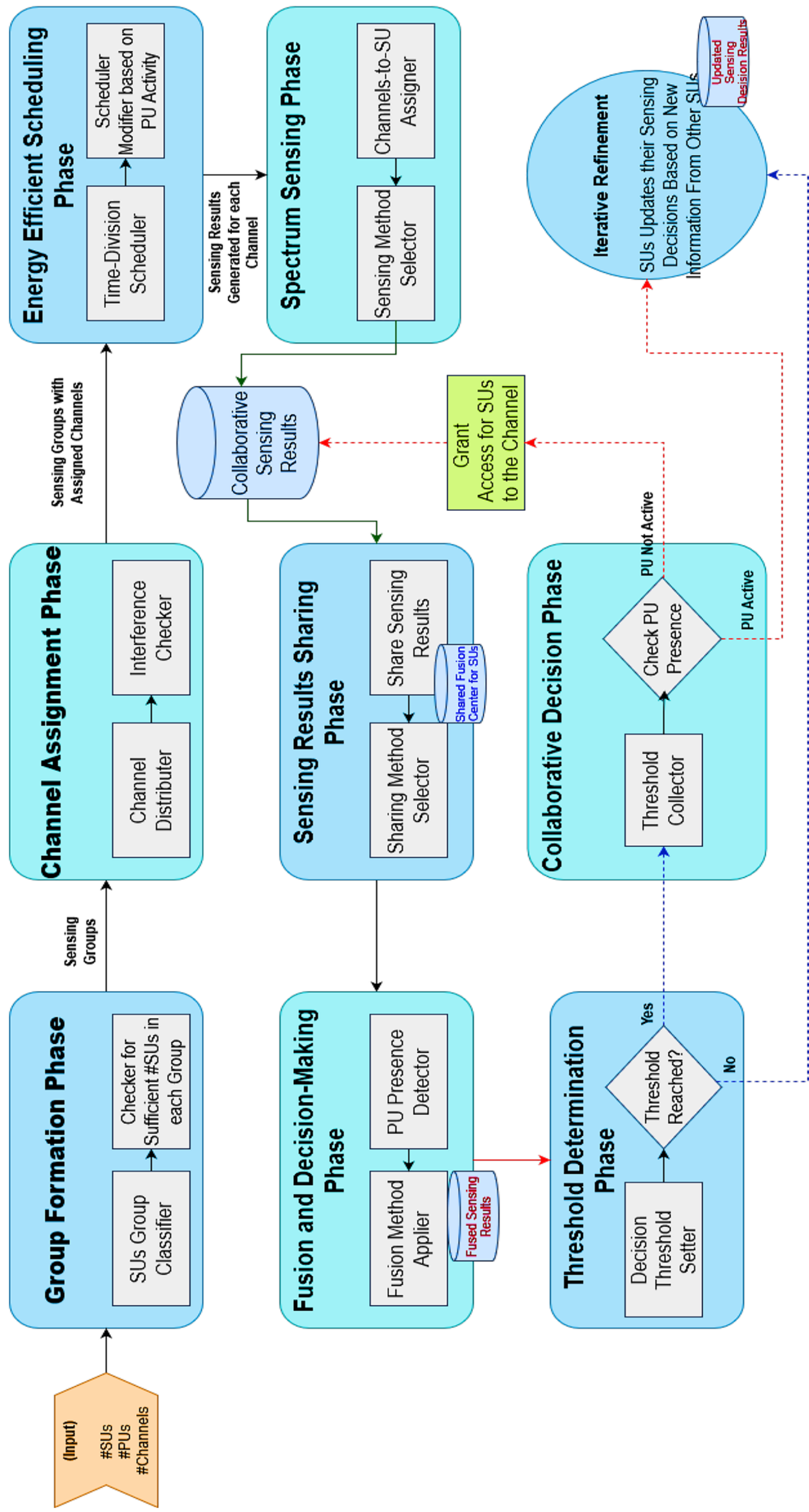

Fig. 4 Proposed energy consumption optimization model based on the cooperative spectrum sensing. A block diagram for the proposed model

activity patterns, and interference avoidance are considered in ECOM while assigning channels to SUs.

- Energy-efficient scheduling phase SUs can be scheduled to perform sensing in a time-division manner to reduce energy consumption. By allowing only a subset of SUs to sense at a given time, others can enter a low-power or sleep mode. The scheduling can be dynamically adjusted based on PU activity patterns and traffic load. In addition, an energy-efficient scheduling algorithm is implemented in ECOM, which the SUs in the green CRN can be scheduled to perform sensing in a time-division manner to reduce energy consumption.
- Local spectrum sensing phase: Each SU in this stage can now independently performs spectrum sensing on its assigned channels using suitable sensing techniques such as matched filtering and energy detection. The sensing results, denoted by Z_c (0 or 1), are generated for each channel c.
- Result sharing phase: SUs can share their individual sensing results with other SUs in their cooperative group. This can be achieved through direct communication or by using a central entity as a fusion center.
- Fusion and decision-making phase: At the fusion center or through distributed algorithms, all the received SUs sensing results in the group are used to decide the final decision about the PU activity in each channel. Fusion techniques like majority voting or weighted averaging can be applied to generate reliable decisions.
- Threshold determination phase: Based on the fused sensing results, a decision threshold can be set to discriminate between the presence and absence of PU signals. The threshold can be dynamically adjusted based on the network conditions, noise levels, and desired detection and false alarm rates.
- Collaborative Decision phase: Using the decision threshold, the presence or absence of PU signals (D_c) is determined for each channel c. These decisions are used for subsequent spectrum access or other cognitive radio functionalities.
- Iterative refinement phase: The collaborative spectrum sensing process can be iterative, where SUs continuously updates and refine their sensing decisions based on new information and feedback from other SUs. This iterative refinement improves the reliability of the collaborative sensing results over time.

Algorithm 1 provides a high-level overview of the steps involved in collaborative spectrum sensing used in ECOM model. The flowchart in Fig. 5 illustrates the steps of the proposed model algorithm.

4.1 The mathematical prove

Let us consider a CR network with N secondary users (SUs) performing collaborative spectrum sensing. Each SU independently senses the activity of M frequency channels denoted by:

$$C = \{c1, c2...cM\} \tag{6}$$

The binary sensing result for each channel c ∈ C is denoted by Z_c, where $Z_c = 1$ indicates the presence of a primary user (PU) signal, and $Z_c = 0$ denotes the absence of a PU signal. In non-cooperative spectrum sensing, each SU performs individual sensing on all M

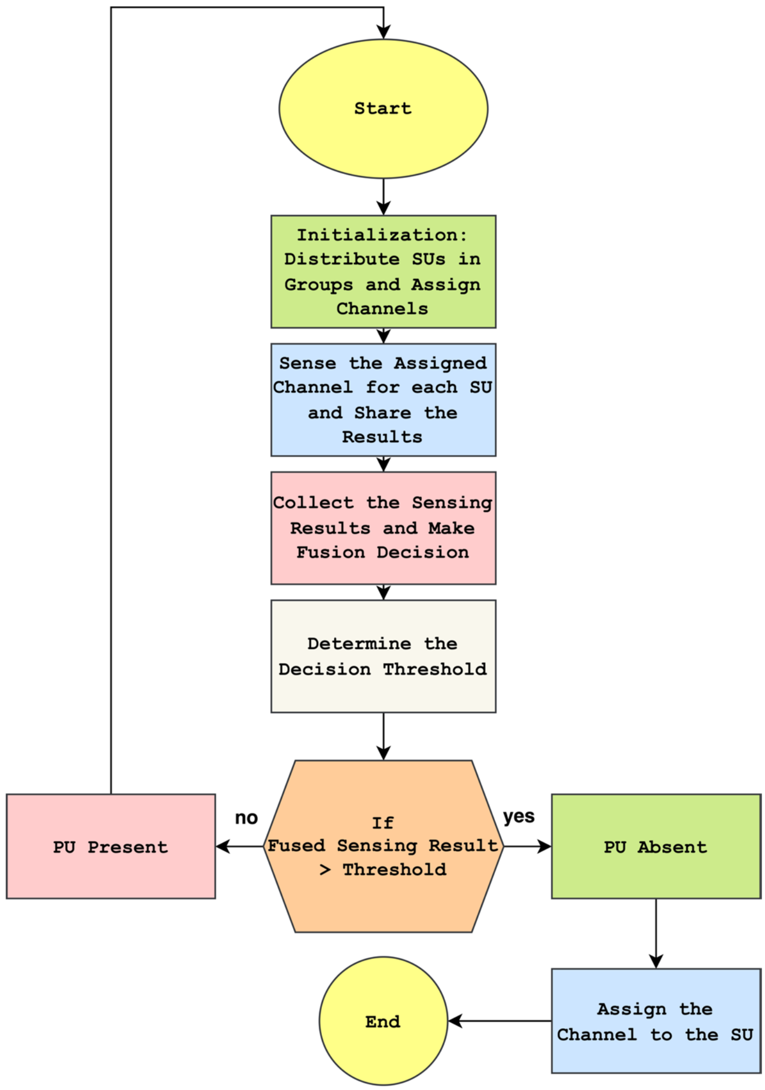

Fig. 5 Flowchart of the proposed ECOM model phases' sequence. Flowchart of the proposed model algorithm

channels, resulting in an energy consumption of E_{nc} per SU. The energy consumed for sensing a single channel is denoted by E_s.

In collaborative spectrum sensing, SUs cooperates by sharing their sensing results to collectively make decisions about the PU activity in each channel.

The fusion center receives the sensing results from all N SUs and applies fusion techniques to make a final decision. Let us denote the collaborative decision for channel c as D_c. D_c is determined based on the fusion of sensing results Z_c from all N SUs. Various fusion techniques can be used, such as majority voting or weighted averaging.

The energy consumed for collaborative spectrum sensing per SU, denoted by E_{cs}, can be expressed as:

$$E_{cs} = E_f + E_s \tag{7}$$

Algorithm 1 The pseudo-code of the proposed model implementation

Inputs:
Number of Requests (Packets)
Signals to Noise Ratio
Number of SU (K)
Number of PU
Start:
For each iteration(Request)
Initialization:
-Initialize the sensing groups and assign channels to SUs.
-Initialize decision threshold and other parameters.
Energy-Efficient Scheduling:
For each SU in the group
Set Time-Division manner ()
Schedule SUs to perform sensing
If SUs (Actv) →sense actively
Else
SUs → low-power or sleep mode.
End If
Adjust the scheduling dynamically based on PU activity patterns and traffic load.
End For
Local Spectrum Sensing Process
Sense the assigned channels
For Each Channel (C)
Generate binary sensing results (Z_c).
if (Z_c) indicating the presence (1) → PU+1
if (Z_c) indicating the absence (0) → PU
End For
Result Sharing Process
For each SU in the group
Share their individual sensing results (Z_c) with other SUs
End For
Fusion and Decision-Making
for each channel (DD_c).
Collect sensing results ($Z_c$from all SUs in the group
Apply fusion techniques
Combine the sensing results.
Decide (presence or absence of PU signals)
End For
Threshold Determination
Set the decision threshold based on the fused sensing results
Collaborative Decision:
For each channel (c)
If (fused sensing result > decision threshold)
Set D_c= 1 (PU signal present)
Else
Set D_c= 0 (PU signal absent)
End For
Iterative Refinement:
Update (sensing decisions) based on new feedback from other SUs:
Share (updated sensing results) from other SUs
Improve (accuracy and reliability)
End for

where E_f represents the energy consumed for fusion and decision-making processes. Now, let us compare the energy consumption between non-cooperative and collaborative spectrum sensing techniques.

1 In non-cooperative spectrum sensing, each SU senses all M channels individually, resulting in an energy consumption of:

$$E_{\text{nc}} = N * M * E_s \tag{8}$$

2. In collaborative spectrum sensing, each SU only performs sensing on a fraction of the M channels, reducing the energy consumption. Let us assume each SU senses a fraction of channels denoted by α, $0 < \alpha < 1$. Therefore, the number of channels sensed per SU is α^*M.

The energy consumed for sensing in the collaborative scheme, denoted by E_{cs}, can be expressed as:

$$E_{\text{cs}} = N * (\alpha * M) * E_{\text{s}} = \alpha * E_{\text{nc}} \tag{9}$$

As $\alpha < 1$, the energy consumed in collaborative spectrum sensing, E_{cs}, is less than the energy consumed in non-cooperative spectrum sensing, E_{nc}. This reduction in energy consumption is achieved by distributing the sensing load among SUs and avoiding redundant sensing on all channels. By employing collaborative spectrum sensing, the cognitive radio network can achieve energy savings compared to non-cooperative sensing, leading to improved energy efficiency and prolonged network lifetime.

5 Experimental setting

In our investigation, the Network Simulator 2 (NS2) is used to setup the network and compare the cooperative and non-cooperative sensing models. The features of the CRN used by the NS2 simulator are: network nodes numbers = 5, 10, 15, 20, 25, the available channels in each node is 5, the propagation is two ray ground, the antenna is omnidirectional, the radio type is 802.11b, the MAC type is 802.11, the network protocol is IPV9, and the CBR properties is 512 bytes. The simulation results of the cooperative and non-cooperative sensing models in terms of energy consumption and throughput have shown enhancements for the cooperative approach compared to the non-cooperative approach.

6 Results and discussion

In this section, we will show the experimental setting used to produce this study results and conclusion, and we will discuss and analyze the results.

6.1 Energy consumption results discussion

The cooperative sensing model demonstrated in the proposed ECOM model section reduced the energy consumption compared to the non-cooperative models. This reduction can be attributed to the following factors:

- Distributed sensing: In the cooperative model, the sensing is distributed among multiple SUs, allowing each SU to sense a fraction of the channels. This avoids redundant sensing on all channels and reduces overall energy consumption.
- Fusion and decision-making: By fusing the sensing results from multiple SUs, the cooperative model achieves more accurate and reliable decisions about PU activity. This reduces the need for repeated sensing attempts, leading to energy savings.

Table 1 Energy consumption (mw) when varying number of requests

Number of packet requests	Q-DSV	Q-learning	ECOM
5	0.100032	0.208268	0.04459
10	0.200069	0.908332	0.099009
15	0.300096	0.608396	0.13559
20	0.900128	0.80896	0.18109
25	0.50016	1.00852	0.22659

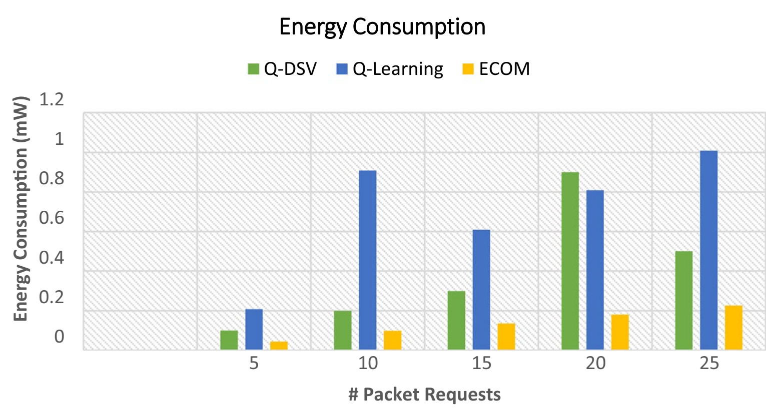

Fig. 6 Energy consumption in mW for the proposed model. The result of the energy consumption for the proposed model compared to two other models

- Energy-efficient scheduling: The cooperative model employs energy-efficient scheduling, where only a subset of SUs actively sensing at a given time, while others enter a low-power or sleep mode. This further contributes to energy savings in the network.

The reduced energy consumption is shown in Table 1 and illustrated in Fig. 6. The energy reduction translates to improved energy efficiency and prolonged network lifetime, making it a more sustainable and cost-effective solution.

6.2 Testing the throughput results discussion

ECOM model performance is evaluated by the network throughput when changing the number of packets. The cooperative sensing model showed improved throughput compared to the non-cooperative models. This enhancement can be attributed to the following factors:

- Enhanced spectrum utilization: By accurately detecting and utilizing available spectrum opportunities through collaborative sensing, the cooperative model ensures efficient allocation of resources. This leads to increased spectrum utilization and improved overall throughput for network.
- Reduced interference: The cooperative model minimizes interference by reliably detecting PU signals and avoiding interference-prone channels. This results in reduced collisions and improved overall network throughput.

Table 2 Throughput (b/s) obtained when varying number of requests

Number of packet requests	Q-DSV	Q-learning	ECOM
5	221.79	528.32	992.76
10	254.16	559.91	996.96
15	314.76	662.17	722.57
20	346.03	732.53	792.91
25	376.22	801.39	891.19

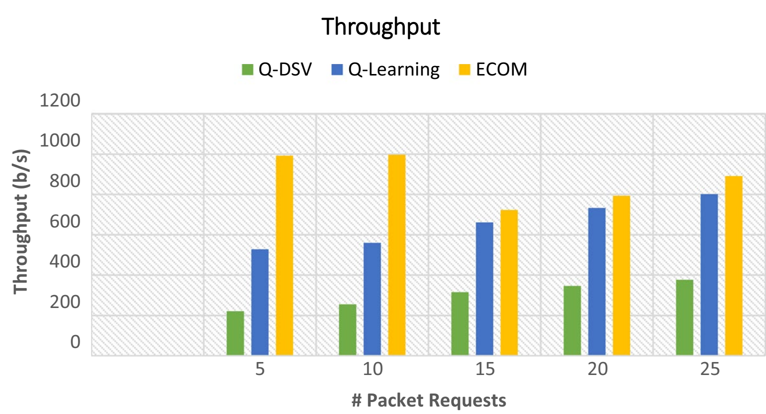

Fig. 7 Throughput in bps obtained by the ECOM proposed model. The result of the throughput for the proposed model compared to two other models

- Optimized channel assignment: In the cooperative model, channel assignment is performed considering channel characteristics and interference avoidance. This optimized assignment enables better channel utilization and higher throughput.

The throughput results are shown in Table 2 and illustrated in Fig. 7. The increased throughput in the cooperative model led to enhanced network performance, better utilization of available resources, and increased data transmission capacity.

Figure 6 demonstrates a notable improvement in total energy consumption with the proposed ECOM utilizing cooperative sensing compared to the non-cooperative sensing models. Additionally, Fig. 7 illustrates the enhancement of the throughput. When compared to the non-cooperative sensing model, ECOM using cooperative sensing achieves significantly higher throughput with substantial margins. These results emphasize the effectiveness and advantages of the collaborative sensing model, offering energy savings and increased throughput. Such findings make collaborative spectrum sensing a promising approach for future wireless communication systems.

6.3 Testing the probability of detection

The performance of the ECOM is assessed in this experiment by comparing it to two recent models, namely Q-DSV [21] and Q-learning [22]. Figure 8 showcases a comparison of the probability of detection versus the probability of false alarms for 10 secondary users at an SNR of − 5 dBs. Furthermore, Fig. 9 presents the ROC curve, providing a

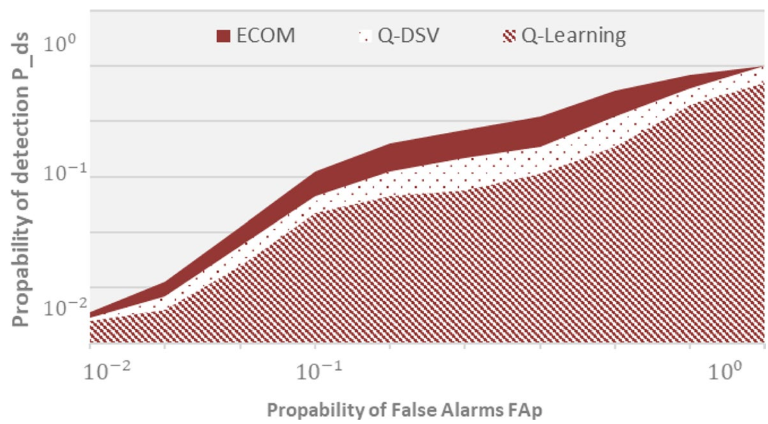

Fig. 8 ECOM's probability of detection vs probability of false alarms. A comparison of the probability of detection versus the probability of false alarms for 10 secondary users at an SNR of -5 dBs

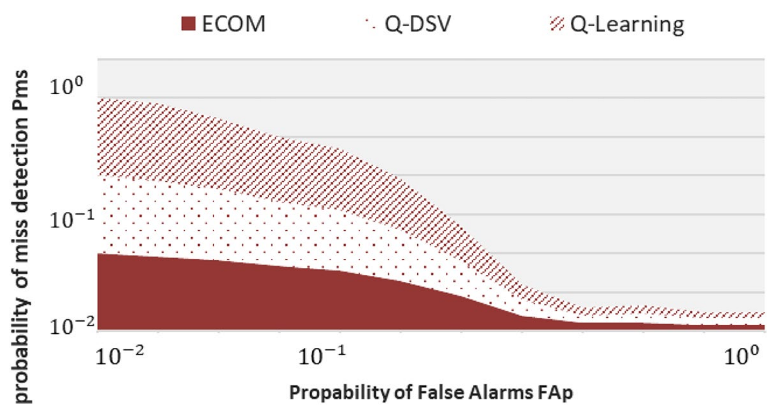

Fig. 9 ECOM's probability of false alarm vs. Probability of miss detection. Visual representation of how the different algorithms perform in terms of false alarms probability and missing detection probability

visual representation of how the different algorithms perform in terms of false alarms probability and missing detection probability.

7 Conclusions

This paper highlights the critical role of collaborative spectrum sensing in achieving energy consumption optimization in green cognitive radio networks. It serves as a valuable resource for researchers and network operators seeking to balance the increasing demand for wireless communication services. Energy-efficient CR networks not only benefit the environment, but also enhance the reliability and longevity of wireless communication infrastructure. The paper proposed an energy consumption optimization model (ECOM) for green CRN based on collaborative spectrum sensing. The collaborative spectrum sensing proved its role in optimizing the energy consumption in the green CRN. In addition, an energy-efficient scheduling algorithm is implemented in ECOM, in which the SUs' in the green CRN perform the sensing process can be scheduled in a time-division manner to reduce energy consumption. The results obtained demonstrated that ECOM outperforms other algorithms in signal detection. These experiments prove the favorable performance of ECOM when compared to other approaches not utilizing collaborative sensing. ECOM attains a high probability of detection (P_ds) while maintaining low probabilities of miss detection ($\mathcal{P}_{\Updownarrow\lceil}$) and false alarms ($\mathrm{FA}_{P}$). In addition, the simulation results and mathematical proof emphasize that ECOM demonstrates reduced energy usage and increased average effective throughput when compared to other recent models, thanks to the integration of the energy scheduling mechanism.

Abbreviations

CRN	Cognitive radio network
SU_s	Secondary users
PU_s	Primary users
ECOM	Energy consumption optimization model
GCRNs	Green cognitive radio networks
SNR	Signal-to-noise ratio
RSS	Received signal strength
FC	Fusion center
DIS	Distance
P_ds	Opportunity of finding a signal
FA	False alarms
$P_{\_\mathrm{mdp}}$	Missed detection
$P_{\_\mathrm{dsi}}$	The Possibility of signal
$\mathrm{FA}_{p\text{-}i}$	The Possibility of false alarm
$P_{\_\mathrm{mdi}}$	The possibility of miss detection
$P_{\_(\mathrm{Er}\text{-}i)}$	The probability of the total error
HDFS	Hadoop distributed file system
DSA	Dynamic spectrum access
RF	Radio frequency
SDR	Semidefinite relaxation
SINR	Signal-to-interference-plus-noise ratio
RL	Reinforcement learning
DSDV	Destination-sequenced distance vector
QoS	Quality of service
DQMN	Deep Q-learning multiple networks
CSS	Collaborative spectrum sensing
Z	The sensing result
C	Channel
D_c	The presence or absence of PU signals
E_{cs}	Energy consumed for collaborative spectrum sensing per SU
E_s	Energy consumed for sensing a single channel
E_f	Energy consumed for fusion and decision-making processes
E_{nc}	Energy consumed in non-cooperative spectrum sensing
NS2	Network simulation 2
MAC	Media access control
IPV9	Internet protocol version 9
CBR	Constant bit rate

Author contributions

SE participated in the sequence alignment and drafted the manuscript. AI participated in design of the paper and performed the simulation analysis and related work. AH participated in design and coordination and helped to draft the manuscript. All authors read and approved the final manuscript.

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Availability of data and materials

The corresponding author will provide the data used to support the study's conclusions upon request.

Declarations

Competing interests

The authors declare no competing interests.

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