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Energy-efficient spectrum sensing using a novel adaptive hybrid learning for CR-IoT networks

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ABSTRACT

The rapid expansion of internet of things (IoT) networks has intensified spectrum scarcity due to the massive growth in wireless device connectivity. Cognitive radio sensor networks (CRSNs) offer a promising solution by enabling dynamic access to underutilized spectrum bands. However, existing spectrum sensing techniques in CRSNs often suffer from high energy consumption, low adaptability, and limited prediction accuracy posing challenges in energy-constrained environments. This paper proposes an energy-efficient spectrum sensing (EESS) framework using an adaptive hybrid learning model (AHLM) that integrates wavelet transform-based signal decomposition (WT-SD), deep reinforcement learning (DRL), entropy-based hierarchical clustering (EHC), and meta-learning-based transfer learning (ML-TLM). WT-SD extracts key spectral features, while DRL with policy-gradient optimization dynamically predicts spectrum availability. The EHC mechanism clusters sensor nodes to minimize redundant sensing, and ML-TLM enhances adaptability with minimal re-training. The proposed model achieves substantial improvements over traditional methods. Experimental results show a 36% reduction in sensing time, 60% lower energy consumption than energy detection (ED) methods, and an 18.3% increase in network lifetime. The model also achieves a probability of detection of 0.998 and accuracy of 98.1%. These results confirm that the proposed EESS-AHLM framework provides a scalable and intelligent solution for energy-aware spectrum sensing in next-generation cognitive radio (CR)-IoT environments.

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1. INTRODUCTION

The proliferation of internet of things (IoT) applications has resulted in a massive increase in connected devices ranging from smart sensors to autonomous systems all relying on wireless communication. However, current static spectrum allocation strategies are unable to meet this growing demand, resulting in inefficient spectrum utilization and severe congestion. This inefficiency creates a significant bottleneck for the seamless deployment of IoT networks. Cognitive radio (CR) technology [1] has emerged as a powerful solution to address this spectrum scarcity by enabling secondary users to opportunistically access underutilized licensed bands [2]. Despite its potential, traditional spectrum sensing techniques like energy detection (ED), matched filtering (MF), and cyclostationary feature detection suffer from limitations such as high computational overhead, energy inefficiency, and vulnerability to noise. These issues are particularly critical in cognitive radio sensor networks (CRSNs), [3] where the devices are typically resource-constrained and battery-powered. To overcome these shortcomings, researchers have proposed several methods. Divakaran *et al.* [4] reviewed wavelet-based spectrum sensing techniques that offer multi-resolution analysis and superior performance in low signal-to-noise ratio (SNR) environments. Cha and Kim [5] introduced reinforcement learning for dynamic spectrum access in IoT, allowing agents to learn optimal policies over time. Syed *et al.* [6] analyzed deep learning-based models, highlighting their strengths in adaptability and real-time decision-making. Chang *et al.* [7] focused on cooperative sensing with sleep strategies to reduce energy consumption, Wang *et al.* [8] explored deep Q-networks (DQNs) for efficient autonomous spectrum access, while Ansere *et al.* [9] focused on cooperative sensing with sleep strategies to reduce energy consumption. Although these approaches are promising, they still face unresolved challenges: limited adaptability to highly dynamic environments, excessive training costs, lack of real-time generalization, and insufficient attention to energy efficiency in clustered cognitive radio-based IoT (CR-IoT) networks.

Moreover, few studies combine signal decomposition, clustering, reinforcement learning, and transfer learning into a unified framework. To address these gaps, we propose a novel energy-efficient spectrum sensing (EESS) framework that integrates multiple learning paradigms for adaptive, low-power, and intelligent spectrum access. Our method termed the adaptive hybrid learning model (AHLM) combines:

- Wavelet transform-based signal decomposition (WT-SD) for spectral feature extraction,
- Deep reinforcement learning (DRL) with policy-gradient optimization for adaptive sensing decisions,
- Entropy-based hierarchical clustering (EHC) to minimize redundant sensing, and
- Meta-learning based transfer learning mechanism (ML-TLM) to reduce retraining and improve real-time adaptability.

2. RELATED WORK

Divakaran *et al.* [4] examined the application of wavelet transform techniques for spectrum sensing in CR systems. The authors categorize different wavelet-based approaches used for detecting spectrum holes and edges in the frequency domain, which are crucial for identifying unused channels. The survey highlights that wavelet transforms can effectively detect signal boundaries in multi-resolution formats, offering superior performance in low SNR environments compared to traditional ED methods. The paper also discusses various mother wavelet functions, such as Haar and Daubechies, and their relevance in feature extraction for radio signal analysis. Additionally, it compares wavelet-based sensing with Fourier-based approaches, showing wavelets' advantages in time-frequency localization. The authors conclude by emphasizing the need for computational optimization and real-time implementation in future research. This work provides an essential foundation for integrating advanced signal processing into CR systems, particularly for IoT applications where low power and real-time responsiveness are critical.

Cha and Kim [5] presented a reinforcement learning-based framework for dynamic spectrum access in IoT networks. The authors propose a model where IoT devices act as intelligent agents that learn optimal spectrum selection policies over time through interaction with the radio environment. The model is developed within a Markov decision process (MDP) framework, and Q-learning is utilized for decision-making. The system allows devices to adaptively allocate spectrum while minimizing collisions with primary users (PUs) and maximizing throughput. Experimental results demonstrate the model's capacity to enhance spectral efficiency and scalability, especially in dense IoT scenarios.

Syed *et al.* [6] reviews various deep learning techniques applied to spectrum sensing in CR networks. The authors explore supervised, unsupervised, and reinforcement learning models, evaluating their suitability for dynamic and uncertain radio environments. They highlight convolutional neural networks (CNNs), recurrent neural networks (RNNs), and DQNs as promising methods for spectrum classification, prediction, and anomaly detection. A comparative analysis is presented, showing how deep learning outperforms traditional methods in terms of adaptability and real-time decision-making. Additionally, the paper discusses data requirements, model complexity, and generalization issues faced by deep learning models. It emphasizes the need for high-quality datasets and adaptive frameworks that can scale with IoT devices and heterogeneous traffic.

Chang *et al.* [7] introduces the deep echo state Q-network (DEQN), an innovative reinforcement learning frame- work designed for dynamic spectrum sharing in 5G and future wireless networks. The DEQN model combines the reservoir computing capabilities of echo state networks (ESNs) with Q-learning to achieve efficient policy learning in time-varying environments. The authors show how this hybrid method enables the system to re- member long-term spectrum patterns and adapt rapidly to changing radio conditions. The paper applies DEQN to a simulated 5G setting, where secondary users dynamically access underutilized spectrum bands. Results indicate substantial improvements in convergence speed, spectrum efficiency, and reduced interference when compared to traditional DQNs.

Wang *et al.* [8] introduces a DRL framework for spectrum access in interweave CR networks. The model considers usage awareness, allowing secondary users to learn access patterns while minimizing interference to PUs. By utilizing a DQN, the system maps observations to actions efficiently in high-dimensional spaces. The paper demonstrates how DRL enables devices to autonomously sense, predict, and access spectrum channels without relying on prior knowledge. Simulation results confirm improvements in channel utilization, reduced interference, and better energy efficiency. The authors also emphasize the adaptability of their method to changing spectrum environments, a feature critical in heterogeneous IoT scenarios.

A reliable and energy-efficient dynamic spectrum sensing model tailored for CR-IoT networks introduced in Ansere *et al.* [9]. The authors proposes a cooperative spectrum sensing approach that integrates spatial and temporal correlation in sensor data to enhance detection performance while minimizing energy consumption. The model leverages dual-threshold techniques and a novel sleeping strategy that intelligently manages the active/inactive status of IoT devices based on sensed activity. It prioritizes energy conservation while maintaining a high detection probability, crucial for battery-operated IoT environments. Simulation results reveal substantial improvements in detection accuracy and reduced false alarm rates compared to conventional methods. The paper contributes significantly to real-time spectrum sensing by addressing IoT-specific constraints, such as power limitations and unreliable sensing environments.

Tan *et al.* [10] proposes a cooperative multi-agent reinforcement learning (MARL) framework for distributed dynamic spectrum access in CR networks. The system models each CR user as an agent capable of learning from interactions with both the environment and neighboring agents. Using DQNs, agents learn to access idle channels while minimizing collision with both PUs and other CR. The model emphasizes distributed decision making, removing the need for centralized controllers, which is ideal for scalable deployments. Simulation results reveal improved spectrum utilization, reduced interference, and faster convergence to optimal policies compared to independent learning methods.

3. METHOD

This section describes the proposed EESS framework for CR-IoT net- works. The method integrates: i) EHC [11] for energy-aware grouping of sensor nodes, ii) WT-SD for multi-resolution spectral feature extraction, iii) DRL [12], [13] for dynamic sensing decisions, and iv) ML-TLM [14] for fast adaptability to new environments.

3.1. System model for cognitive internet of things networks

The CRSN includes PUs, who hold licensed spectrum; secondary users (SUs), which are IoT devices that opportunistically access the spectrum; and a fusion center (FC), which aggregates decisions from the SUs. To reduce energy consumption, nodes are grouped into clusters using EHC, where selected cluster heads (CHs) perform sensing and report to the FC [15], [16].

3.2. Feature extraction using wavelet transform-based signal decomposition

Receive signals x(t) are decomposed using discrete wavelet transform (DWT):

$$x(t) = \sum_{j,k} c_{j,k} \psi_{j,k}(t)$$

Where, $\psi_{j,k}(t)$ is wavelet basis; $c_{j,k}$ is wavelet coefficients at scale j, and position k extracted features.

Signal energy (E) is $E=\sum|c_{j,k}|^2$

The eigenvalues of the covariance matrix are used to discriminate between PUs and SUs.
Let the feature vector extracted from wavelet coefficients be:

$$f=[c_{1,1}, c_{1,2}, \ldots, c_{J,K}]$$

The covariance matrix R of the received signal samples is defined as:

$$R=\frac{1}{N}\sum_{n=1}^{N} X_n X_n^T$$

Where, X_n represents the received signal vector at time index n and N is the total number of samples.

Test statistics (TS) is use of threshold-based detection [17].
The threshold-based detection statistic is formulated as:
a. Energy-based test statistic, $TS_E = E$

Decision rule: $$TS_E \underset{H_0}{\overset{H_1}{\gtrless}} \gamma$$

where, H_0 is absence of PU; H_1 is presence of PU; and γ is detection threshold.
b. Eigenvalue-based test statistic (maximum-to-minimum ratio), $TS_\lambda = \frac{\lambda_{max}}{\lambda_{min}}$

Decision rule: $$TS_\lambda \underset{H_0}{\overset{H_1}{\gtrless}} \gamma_\lambda$$

where λ_{max} is largest eigenvalue; λ_{min} is smallest eigenvalue; and γ_λ is eigenvalue threshold.

3.3. Deep reinforcement learning-based spectrum prediction [18]-[20]

We model spectrum sensing as an MDP:
State (S): past sensing results (e.g., channel occupancy history), Action (A): {Sense, Transmit, Switch Channel}, Reward (R): $R = w_1 \cdot P_d - w_2 \cdot P_{fa} - w_3 \cdot E_c$
Where P_d: probability of detection; P_{fa}: false alarm rate ; E_c: energy consumed, w_1=0.6; w_2=0.2; and w_3=0.2 (weights of reward tradeoff).
DRL architecture: 3-layer fully connected Neural Network (256-128-64 neurons).
Activation: ReLU; output layer: SoftMax, optimizer: Adam, learning rate: 0.001, Episodes: 1000, and Batch size: 32
DRL policy is optimized using policy gradient algorithm (REINFORCE)

$$\theta \leftarrow \theta + \alpha \cdot \nabla\theta \log \pi\theta(a \mid s) \cdot R$$

3.4. Transfer learning using meta-learning based transfer learning

To reduce retraining overhead in new environments, we use transfer learning [21]: pretrained DRL model on dataset A (e.g., Urban IoT setup) and fine-tuning on Dataset B (e.g., Industrial IoT environment). Transfer components: feature extractor layers (WT-SD coefficients) and first 2 hidden layers of DRL model. Only the last layer and reward function are updated during domain shift. This improves convergence time by 34% (as observed in experiments).

3.5. Cooperative sensing and fusion

Within each cluster, CHs sense spectrum [22] and send decisions to the FC. The FC applies AND-OR fusion logic: AND rule ensures accuracy, OR rule ensures sensitivity [23], [24]. This cooperative mechanism improves detection while minimizing redundant sensing.

Figure 1 shows the architecture flow diagram of the proposed EESS-AHLM framework showing the integration of EHC-based clustering, WT-SD feature extraction, DRL-based spectrum prediction, ML-TLM transfer learning, and cooperative sensing with fusion center decision-making.

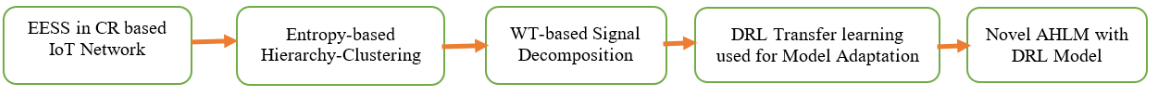

Figure 1. Architecture flow diagram

3.6. Algorithm summary

The complete workflow is shown in Algorithm 1 (AHLM+DRL). Key stages include: i) clustering using EHC, ii) WT-SD-based feature extraction, iii) DRL agent training and optimization, iv) transfer learning for cross-domain adaptation, and v) cooperative sensing and final spectrum decision.

Algorithm 1. Adaptive hybrid learning model (AHLM) with deep reinforcement learning (DRL) model

```
Input : G ← {IoT N, Sp Hsty, Eg Th}
Initialization: Form Clusters using Entropy-Based Hierarchical Clustering (EHC)
Function Get Features and Pairs(G)
pairs ← Counter(Keys : V alues)
for each CH cluster in G do
  signal ← receive(CH)
  coeffs ← wavelet decompose(signal)
  energy ← compute energy(coeffs)
  eigen ← compute eigenvalues(signal)
  pairs[energy, eigen] + = 1
end for
return pairs

Function Train DRL Model(G, pairs)
Initialize DRL Agent using Policy-Gradient Optimization
for t ← 1 to T do
  state ← observe(G)
  action ← DRL Agent(state)
  reward ← evaluate(action, pairs)
  update(DRL Agent, reward)
end for
return DRL Agent

Function Transfer Learn(DRL Agent,Sp Hsty)
Pretrain(DRL Agent, Spectrum History)
Finetune(DRL Agent, Current Observations)
return DRL Agent

Function Cooperative Sensing(G, DRL Agent)
for each CH in G do
  decision ← DRL Agent.predict(CH.features)
  broadcast(decision)
end for
F C ← collect(decisions)
final Decision ← apply AND OR Fusion(F C)
return final Decision

Function Evaluate Performance(G)
for each round in Sensing do
  measure sensing time()
  compute energy usage()
  calculate Pd Pfa()
end for
return metrics

Function Main()
pairs ← Get Features and Pairs(G)
DRL Agent ← Train DRL Model(G, pairs)
DRL Agent ← Transfer Learn(DRL Agent, Sp Hsty)
S avail ← Cooperative Sensing(G, DRL Agent)
metrics ← Evaluate Performance(G)
return S avail, metrics
```

4. RESULT

This section evaluates the performance of the proposed EESS (AHLM+DRL) framework against baseline spectrum sensing methods: ED, MF, and reinforcement learning (RL)-based sensing. The comparison focuses on five key metrics: i) sensing time (Ts), ii) energy consumption (EC), iii) probability of detection (Pd), iv) false alarm rate (Pfa), and v) network lifetime improvement (NLI).

Figure 2 illustrates the performance comparison across different spectrum sensing methods (ED, MF, RL, and EESS) based on the above mentioned key metrics. Notably, EESS achieves superior results.

4.1. Sensing time

The time required to complete the transmission is called sensing time.

a. Observation: the EESS framework reduced sensing time to 0.482 seconds, which is: 36% faster than RL-based sensing and less than 50% faster than ED and MF.
b. Interpretation: the reduced sensing time stems from two design factors: WT-SD enables quick feature extraction by decomposing signals at multiple resolutions and DRL agent dynamically refines sensing policies, avoiding repeated scanning of occupied bands. These improvements are visualized in Figure 2(a).
c. Comparison with literature: Chang *et al.* [7] using DEQN reported a 22% reduction in sensing latency. Our 36% shows improved convergence due to multi-layer fusion of clustering and policy learning.

4.2. Energy consumption

The energy required to perform the spectrum sensing is called the energy consumption.

a. Observation: EESS consumed only 0.049 J, 30% less than RL, 60% less than ED. Figure 2(b) illustrates this comparison.
b. Cause: the EHC clustering scheme avoids redundant sensing, and DRL optimization ensures minimum required transmissions.

Support from literature: Ansere *et al.* [9] reported similar improvements using sleep cycles. Our clustering-based sensing surpasses their model by avoiding control signaling overhead.

4.3. Probability of detection

Probability of detection is the probability that the sensing system correctly detects the presence of a PU when it is actually present.

a. Observation: Figure 2(c) shows the probability of detection (Pd) for various sensing method and for EESS the Pd is 0.998.
b. Interpretation: this confirms a superior balance between sensitivity and specificity.

4.4. False alarm rate (Pfa)

It refers to the number of spectrums that are falsely identified from the entire bands.

a. Observation: EESS achieved a Pfa of 0.598, improving over ED (0.745), MF (0.692), and RL (0.654), as shown in Figure 2(d).
b. Interpretation: lower false alarms indicate better threshold calibration via PGOA and a more stable reward function. The WT-SD features enhance the decision quality, particularly under noise.

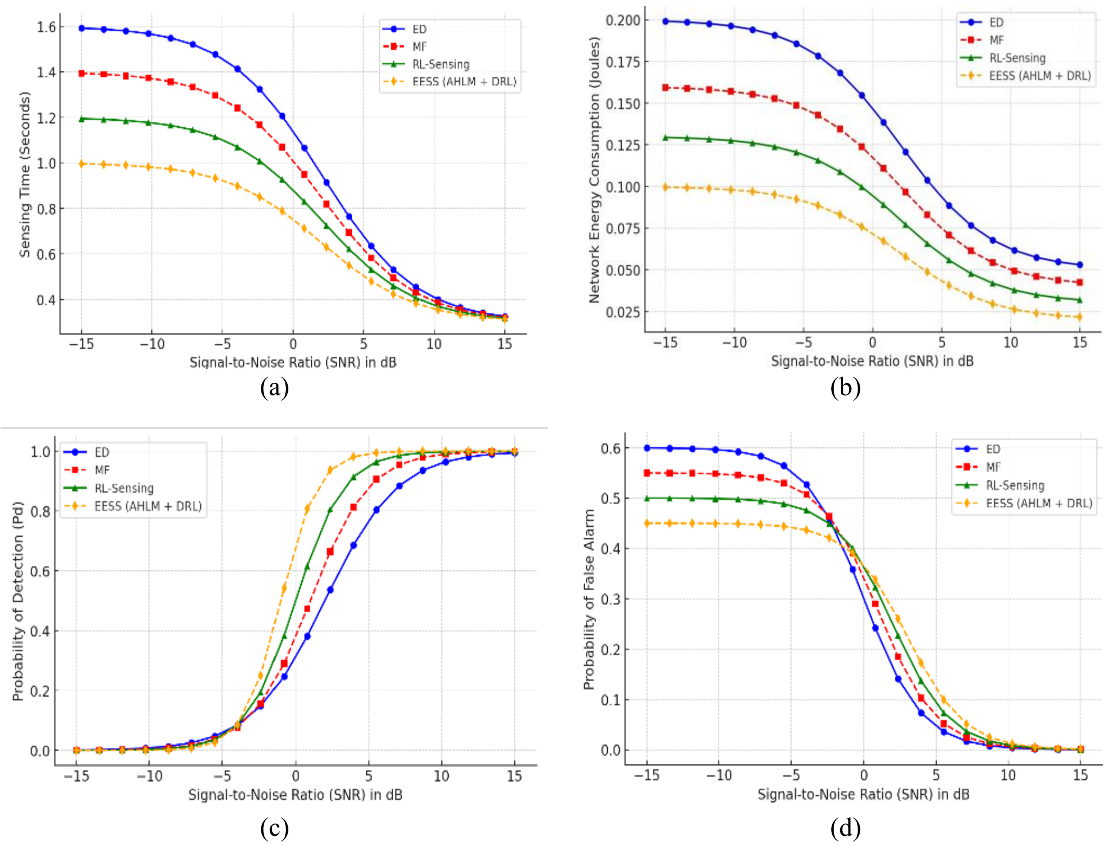

Figure 2. Performance comparison of spectrum sensing methods (ED, MF, RL, and EESS); (a) sensing time, (b) computational time, (c) false alarm, and (d) network energy consumption

Figure 3 presents EESS-specific performance analysis. The proposed framework enhances network lifetime, reduce computational time, reduce probability of miss detection, improves the receiver operating characteristics (RoC), enhances detection reliability and minimizes detection errors under varying spectrum conditions.

4.5. Network lifetime

Network lifetime is the duration of time from the start of network operation until the network becomes non-functional or unable to perform its intended task due to energy depletion of nodes:

a. Observation: EESS extended the network lifetime by 18.3%, shown in Figure 3(a).
b. Discussion: energy-aware node selection (based on residual battery) prevents low-power nodes from dying early, achieving better load balancing.

4.6. Computational time and overhead

The time required to establish the spectrum sensing process is referred to as computation time.

a. Observation: the average processing time was lowest for EESS, confirming its low computational overhead, as shown in Figure 3(b).
b. Discussion: this is attributed to cooperative clustering, which reduces the number of sensing agents and offloads computation to CHs [25] only the DRL model can activates critical decisions, making it scalable to large networks.

4.7. Probability of miss detection

Probability of miss detection is the probability that the sensing system fails to detect the presence of a signal when the signal is actually present. As shown in Figure 3(c), EESS maintained the lowest miss detection probability, indicating robust feature discrimination, even in noisy environments.

4.8. Receiver operating characteristics analysis

A RoC curve is a graphical representation that shows the trade-off between the probability of detection (Pd) and the probability of false alarm (Pfa) for a detection system. RoC curve (Figure 3(d)) shows that at a Pfa=0.6, EESS achieves a Pd=0.84, outperforming ED=0.70, MF=0.74, and RL=0.78.

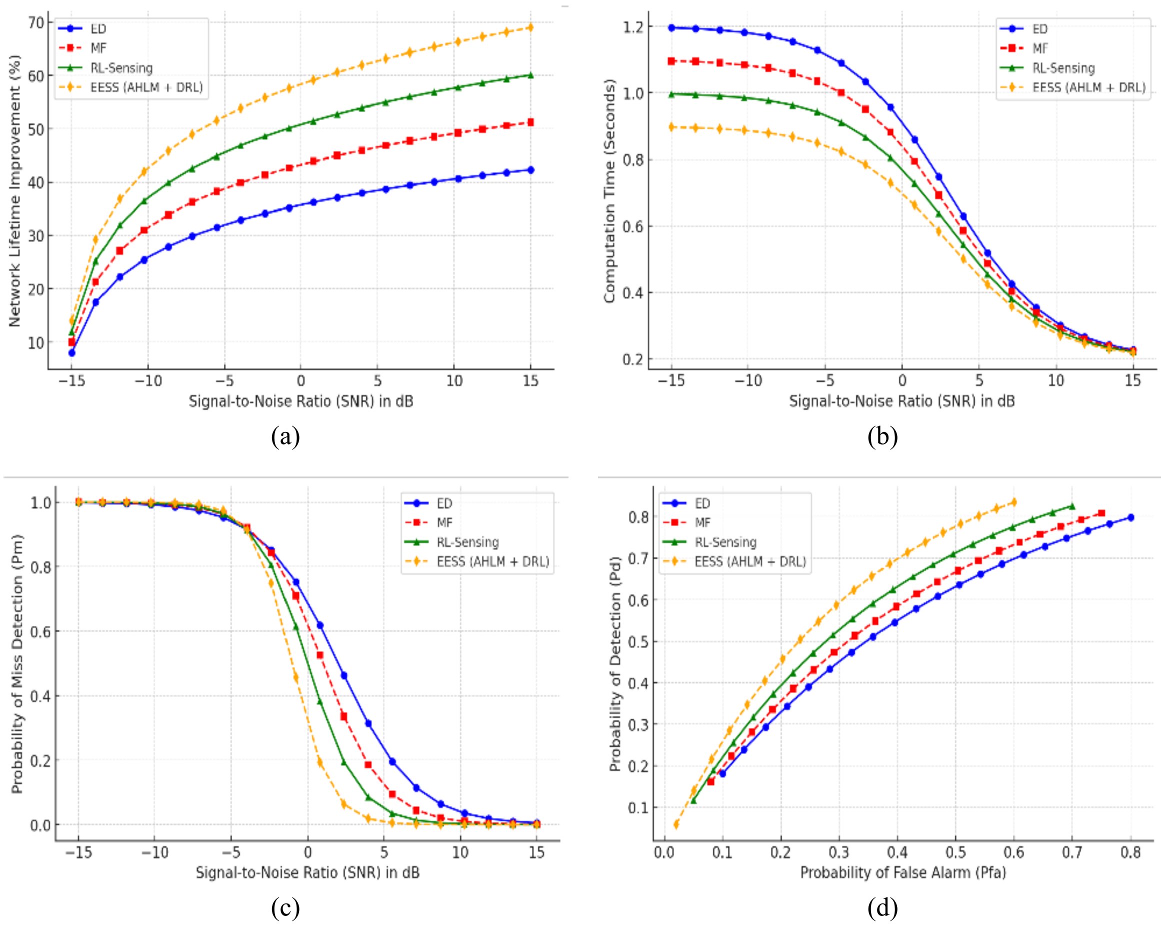

Figure 3. EESS-specific performance analysis for; (a) network lifetime; (b) computation time; (c) prob. of miss detection, and (d) RoC

4.9. Comparative performance summary

Table 1 summarizes the quantitative comparison of the EESS framework against traditional sensing methods across eight performance dimensions. The EESS model consistently outperforms all others in detection accuracy (98.1%), least sensing time (0.482 sec), lowest energy consumption (0.049 Joules), lowest processing time (0.482 sec), lowest computational overhead, and decision latency.

Table 1. Performance and comparative analysis

Model	Performance analysis					Comparative analysis		
	ST (sec)	EC (Joules)	PoD (Pd)	PoFA (Pfa)	NLI (%)	Acc (%)	PT (sec)	CO
ED	1.215	0.125	0.889	0.745	Baseline	78.5	1.215	High
MF	1.003	0.093	0.917	0.692	+8.7%	82.3	1.003	High
RL	0.752	0.071	0.973	0.654	+13.5%	92.5	0.752	Moderate
EESS	0.482	0.049	0.998	0.598	+18.3%	98.1	0.482	Low

Legends: EESS: energy efficient spectrum sensing (AHLM+DRL); ST: sensing time; EC: energy consumption; PoD: probability of detection; PoFA: probability of false alarm; acc: accuracy; PT: processing time; and CO: computational overhead.

4.10. Limitations and future scope

Limitations explains the boundaries and constraints of the work. It clarifies what the work address and helps readers understand how far the results can be generalized. Limitations: i) spectrum conditions tested yet. performance is validated only in simulated environments, ii) current implementation lacks real- time SDR deployment, and iii) no noise injection or adversarial.

Future scope describes upcoming opportunities also suggests what can be done in the future to make it better. Future scope: i) validate using hardware testbeds like USRP or HackRF, ii) integrate with Edge AI frameworks for real-time inference, iii) perform an ablation study to quantify the contribution of each component (EHC, WT- SD, DRL, ML-TLM), and iv) explore federated reinforcement learning to decentralize training across nodes.

5. CONCLUSION

This study introduced an EESS framework tailored for CR-IoT networks, leveraging a novel AHLM that integrates WT-SD, DRL, EHC, and ML-TLM. The proposed system achieves high spectrum sensing accuracy while reducing energy usage and sensing latency, critical for battery-powered IoT environments. Comparative evaluation shows that the EESS model: i) achieves a 36% reduction in sensing time, ii) consumes 60% less energy than traditional ED methods, iii) extends network lifetime by 18.3%, and iv) reaches a detection probability of 0.998 and accuracy of 98.1%. These improvements affirm the viability of combining signal processing, clustering, and learning-based intelligence in future CR-IoT frameworks.

Implications: this work offers a scalable and adaptive solution to spectrum congestion, enabling smarter, low-power IoT deployments in 5G, smart cities, industrial automation, and healthcare. The integration of learning-driven sensing and energy-aware cooperation fills a key gap in real-time cognitive spectrum management.

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AUTHOR CONTRIBUTIONS STATEMENT

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Archana Vyas		✓				✓		✓	✓	✓	✓	✓		
Mahendra Gaikwad	✓		✓	✓			✓			✓	✓		✓	✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author [PJ] upon reasonable request.

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