

Comprehensive energy detection framework for intelligent spectrum sensing in cognitive radio networks

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ABSTRACT

Cognitive radio networks (CRNs) have emerged as a promising solution to mitigate the spectrum scarcity problem by allowing dynamic and opportunistic spectrum access. Despite popularity, conventional energy detection (ED) methods suffer from noise uncertainty, weak signal sensitivity, and threshold dependency, which degrades the detection accuracy under varying wireless environment. This paper introduces a comprehensive ED framework to address these limitations by developing a flexible evaluation platform for spectrum sensing in CRNs. The proposed framework is analytically modeled to assess various ED approaches and evaluated under diverse channel conditions, including variations in signal-to-noise ratio (SNR), number of unlicensed users (UU), Rice-K factor and noise distributions. The study employs Monte Carlo simulations to validate the detection performance in both centralized and decentralized CRN configurations. The framework introduces a reliable platform to benchmark ED techniques, in which Rice-K factor-based spectrum detection (RKD) method shows significant improvement in detection probability under low-SNR conditions and varying user densities. The distinctiveness appears in its unified analytical approach combining cooperative sensing architectures with channel-aware detection, enables systematic and scalable assessment of ED techniques. In future CRN deployments, this method can be expanded to facilitate advanced channel models and intelligent detection algorithms. It also provides a scalable and useful foundation for reliable spectrum sensing.

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1. INTRODUCTION

The exponential growth of wireless devices and applications has intensified the demand for radio spectrum, resulting severe congestion in licensed frequency bands [1], [2]. Therefore, the scarcity of available spectrum have driven the need for efficient spectrum utilization and effective radio spectrum management schemes [3]-[5]. Cognitive radio networks (CRNs) have emerged as a promising solution to address this spectrum scarcity problem where it allows unlicensed users (UU) to opportunistically access the under-utilized licensed spectrum bands. Spectrum sensing is a fundamental technique in CRN that helps identifying vacant spectrum slots without interfering with licensed users (LU) [6]. Among various sensing techniques, energy detection (ED) methods have gained more popularity due its simplicity, low computational complexity, and independence from prior knowledge of the signal structure.

Regardless of significant beneficial factors, conventional ED methods struggle with various limitations which include noise uncertainty, sensitivity to weak signals, and threshold dependency. These problems negatively impact the detection performance in spectrum sensing, exclusively in dynamic wireless environments in which noise and signal conditions vary. There exist several recent works, which have attempted to address these constraints in CRNs, yet it is observed that still these methods lack robust performance by means of spectrum sensing reliability under dynamic network and channel conditions which therefore remain unsolved till date [7]-[10]. However, recent investigation on the related studies shows the matter of fact that various works have been carried out to overcome these aforementioned limitations. Studies explored various strategies such as data-driven, algorithmic and hybrid methods to improve the performance of classical ED. In the similar line of research, Musuvathi *et al.* [11] attempted to enhance ED performance using a K-nearest neighbour (KNN)-based classifier. Despite its robust performance under noise variations, it incurs expensive training overhead and dependency on labelled datasets. Lorincz *et al.* [12] also designed an evaluation algorithm for ED in cognitive radio MIMO-OFDM systems. The study offers valuable insights into multi-antenna and multi-carrier environments but restrict their scope in centralized evaluation metrics. On the other hand the authors Bani and Kulkarni [13] presented a hybrid approach combining matched detection (MD) with ED. The outcome shows that the method improved detection probability yet suffered from additional computational complexity and prior knowledge assumptions. The analysis on these works collectively outlines the current efforts being practiced in improving the spectrum sensing and detection performance in CRN. However, it also lays a motive that there is a need to design a cost-effective, flexible, and unified analytical framework that is well-capable of analysing and benchmarking ED methods under varied channel and user conditions. It is also noticed that existing approaches primarily emphasize on improving individual ED methods in segregation whereas very limited focus is laid on formulating unified assessment and benchmarking.

Therefore, this study aims to bridge this gap by introducing a robust analytical framework which is well-capable of integrating both centralized and decentralized sensing with a Rice-K factor-based enhancement for robust spectrum sensing [14]-[20]. The proposed framework is analytically designed in such a way in which it can establish a structured modelling environment to systematically evaluate various ED methods while considering both licensed and UU. Also, it employs an auxiliary processing unit for statistical analysis and dynamic channel conditions. It therefore allows cooperative decision-making and statistical evaluation capabilities while improving the detection accuracy and reliability of spectrum sensing yet reduces the computation burden on the system. In this proposed work, two distinct contributions are exhibited, firstly it offers a unified analytical framework to systematically validate ED techniques under centralized and decentralized CRN configurations. Secondly, it also employs a Rice-K factor-based spectrum detection (RKD) method that outperforms traditional eigenvalue-based ED method by considering channel fading characteristics. Therefore, it clearly shows improvement in detection robustness even under low-signal-to-noise ratio (SNR) conditions.

The extensive experimental evaluation further subjected to evaluate the detection efficiency in terms of varying SNR levels and different populations of unlicensed (cognitive) users. The crucial findings further outline that the proposed method consistently achieves superior detection accuracy across both low and high SNR conditions. Also, its performance significantly improved with the increasing number of cognitive users. It therefore ensures robust and scalable spectrum sensing in CRNs. This holistic methodology not only helps bridging these gaps in the existing approaches but also provides a lightweight analytical foundation for future intelligent spectrum sensing via adaptive threshold management and learning-based decision strategies meant for next-generation wireless networks. In contrast to the existing system that exclusively focus on isolated improvements, the proposed analytical method offers a unified platform that integrates centralized and decentralized sensing with channel aware Rice-K factor enhancement. This allows the systematic validation of ED methods under realistic and diverse CRN conditions. The manuscript is organized as follows. Section 2 talks about the analytical foundation and provides conceptual idea correspond to the proposed evaluation framework for spectrum sensing in CRNs. Further section 3 also discusses the experimental results along with a comparative performance analysis in contrast to existing approaches. Finally, section 4 concludes the key findings and the potential directions for future research.

2. METHOD

The primary motive of the proposed work is to design and implement a novel analytical and comprehensive ED framework for the purpose optimizing spectrum sensing in CRN-based wireless environments. Here the framework utilizes an abstractive numerical modelling approach to deal with noise uncertainty, weak signal sensitivity, and threshold dependency issues which are inherent in conventional ED approaches. The critical research findings from the above survey show the immense popularity of ED methods for spectrum sensing in CRNs. It has to be noted that the core objective of ED methods is to determine whether a given frequency band is engaged by a LU or is available for service to an UU [21]-[24].

The analytical design of this proposed ED framework therefore resolves the existing constraints of ED approaches by introducing an extensive evaluation model which is capable of diversely analysing the detection energy. Therefore, it provides a robust solution for spectrum sensing in CRNs. Figure 1 further demonstrated the block-based schematic architecture of the framework for comprehensive ED in CRNs. It has to be noted that during the design and evaluation of signal modelling, statistical analysis, and cooperative sensing, all simulation parameters and detection configurations are consistently applied across methods to approve fair and reproducible evaluation.

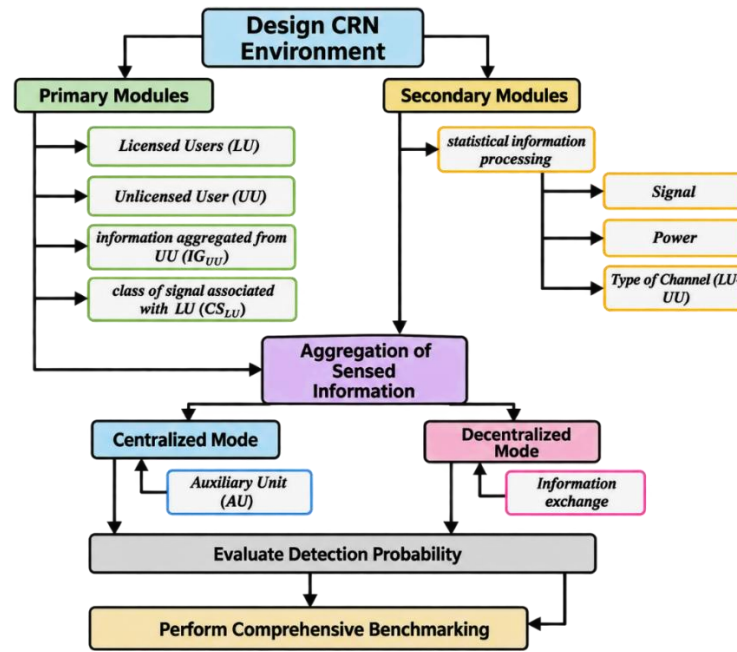


Figure 1. Framework for comprehensive ED in CRN

2.1. Baseline cognitive radio network environment design

The CRN environment in the proposed analytical evaluation framework consists of two modules which are primary module and secondary module respectively. The primary module consists of LU, UU, information aggregated from UU (IG_{UU}), and class of signal associated with LU (CS_{LU}). LU: transmitters with Gaussian or QPSK signal classes (CS_{LU}). UU: secondary users sensing the spectrum. Information aggregated from UU (IG_{UU}): functional module to collect sensing data from UUs. Auxiliary unit (AU): responsible for statistical analysis and final decision-making.

Here the investigation is carried out on standard QPSK or Gaussian class of signal associated with LUs. The environment also considers secondary module which is responsible statistical information processing related to received signal quality, power variations, and type of communication channel between LU and UU. The system also considers reference probability of outliers to ensure the accuracy of ED evaluation. All sensed information aggregated by UUs is updated to AU, which applies statistical analysis to make spectrum occupancy decisions. AU acts as the central processing entity responsible for aggregating sensing information from UUs and performing statistical decision-making in centralized mode. In decentralized mode, UUs collaboratively exchange sensing information and perform distributed decision-making without AU involvement. The proposed system functions in both centralized and decentralized mode to determine the detection probability. The detection framework is modeled as a binary hypothesis test where hypothesis-0 denotes the absence of LU signal, while hypothesis-1 denotes LU presence. The proposed Rice-K spectrum sensing model embeds the Rice-K factor into this hypothesis structure, which enhances the detection robustness under low SNR by accounting for line-of-sight (LOS) and multipath fading effects.

2.2. Signal and noise modelling in cognitive radio networks

The LU signal S is modeled for both Gaussian and QPSK modulation which is shown. Where μ is mean signal amplitude, σ^2 is noise variance, and n is number of samples collected per UU. The noise variance is computed using (2). The baseline framework assumes additive white Gaussian noise (AWGN), while the fractional

noise variation parameter models practical uncertainty in receiver noise power caused by channel and hardware variations. Non-Gaussian noise environments are beyond the scope of the present study and are considered for future work. Here, ρ_n refers to fractional noise variation. Also, the received power at UU is estimated using (3). Here ρ_p refers to the fractional variation of the received power relative to its mean. Here, $f(\cdot)$ denotes the generalized received-power estimation function accounting for channel attenuation and power fluctuations.

$$S = 1/n \sum_{i=1}^n X_i, X_i \sim \mathcal{N}(\mu, \sigma^2) \quad (1)$$

$$\sigma_n^2 = \sigma_{\text{avg}}^2 (1 + \rho_n) \quad (2)$$

$$P_{\text{Rx}}^{(i)} = f(m, \rho_p, P_{\text{Rx}}, \text{avg}) \quad (3)$$

2.3. Cooperative sensing modes

The framework evaluates spectrum sensing under two modes which are centralized mode and decentralized mode. Centralized mode: in this mode presence of AU acts as a fusion center, aggregating sensing information from UUs to decide spectrum occupancy. Decentralized mode: absence of AU, UUs exchange sensed information among neighbors and make local decisions collaboratively.

2.4. Statistical test parameterization

The proposed framework evaluates different ED-based sensing methods along with its proposed contribution where it has incorporated a channel-aware adaptive RKD modelling which is built upon an enhanced eigenvalue-based ED modelling which is specifically adapted for Rician fading channels. It basically belongs to hybrid ED family as it integrates eigenvalue-based ED baseline and further embeds the Rice-K factor (K) into the test statistic. In a Rician fading channel, the received signal experiences both deterministic LOS component and a random scattered component. The relative strength of these two is captured by the Rice-K factor K which is defined using (4). Here, P_{LOS} refers to the power of the direct LOS path and P_{NLOS} refers to the power of scattered multipath components. A higher K implies a stronger LOS component while K=0 reduces the Rayleigh fading case. In the proposed framework, the RKD is modelled using (5), where $\lambda_{\text{max}}(R)$ refers to the maximum eigenvalue of the sample covariance matrix R, σ_n^2 is the estimated noise variance, and K embeds the channel's fading characteristic directly into the detector.

$$K = P_{\text{LOS}} / P_{\text{NLOS}} \quad (4)$$

$$\varepsilon_{\text{RKD}} = \lambda_{\text{max}}(R) / \sigma_n^2 * K \quad (5)$$

Here, embedding effectively scales the test statistic according to the channel's LOS-to-scattered power ratio. Unlike existing ED methods that assume uniform fading, the proposed RKD approach dynamically adapts its threshold based on the Rice-K factor (K). This offers several advantages. Here, incorporation K ensures that the weak signals masked by noise variability still can be distinguished, thus improving the probability of detection (δ_e) under low-SNR regimes. Since real-world wireless channels often experience both LOS and multi fading, the inclusion of K makes the detection model more practical and accurate compared to detectors assuming only Gaussian and Rayleigh fading channels. Here, the additional multiplication with K introduces negligible overhead, as eigenvalue decomposition is already performed for competing methods (maximum eigenvalue detection (MED) and maximum-minimum eigenvalue detection (MMED)). Here, the proposed RKD approach achieves improved detection accuracy without significantly increasing the computational complexity. Here, the UU estimates the Rice-K factor based on the observed signal fading pattern. So, if there is a strong LOS (large K), the detector becomes more confident in identifying LU presence. If the environment is heavily scattered with small K, the detector reduces sensitivity to avoid false alarms. Here, UU also compares ε_{RKD} with a threshold φ_{RKD} if $\varepsilon_{\text{RKD}} > \varphi_{\text{RKD}}$, then LU is present means busy channel else LU is absent. If LU is present in that case UU waits and do not transmit whereas if LU is absent UU transmits safely on that channel.

The decision threshold φ_{RKD} is determined empirically to satisfy the target false alarm probability ($P_{\text{fa}} = 0.1$). The Rice-K factor is assumed to be known or estimated using standard moment-based estimation techniques. Each UU processes 200 samples per sensing interval to ensure statistically reliable estimation of the received signal energy, while 2000 Monte Carlo runs provide stable estimates of detection probability across random channel realizations. The Rice-K factor (K=2) represents a moderate LOS environment commonly adopted in CRN performance evaluation. The computational complexity of the proposed RKD method remains comparable to eigenvalue-based ED approaches, as the inclusion of the Rice-K factor introduces a simplified scaling operation with negligible additional overhead.

2.5. Cooperative spectrum sensing

In order to ensure the appropriateness of evaluation of ED, the scheme also considers an attribute of reference probability of outliers. All the sensed information aggregated by the UU is updated to a processing unit known as AU, which applies statistical analysis on the spectrum information for undertaking decision-making. The assessment of the signal is also performed on reduced value of signal quality in baseline CRN environment. This assessment is further resumed for both centralized and decentralized channel of wireless CRN communication where the former is characterized by presence of AU and latter is characterized by absence of AU. Basically, AU is responsible for detecting the spectrum (in form of energy) from the spectrum information obtained collectively from UU. Each UU performs exchanging of their sensed information in decentralized channel between adjacent UU and available UU permitted to undertake ultimate decision. Finally, an extensive test environment is set which is capable of benchmarking the outcome of proposed system with multiple existing approaches. In centralized mode, the AU serves as the primary decision-maker, collecting spectrum information from all participating UUs, computing energy features, and determining spectrum occupancy. On the other hand, in decentralized mode, the AU is absent. Here, each UU exchanges its sensed information with adjacent UUs. The decision making responsibility is distributed among the UUs themselves, where a consensus or majority voting mechanism determines the final spectrum availability status.

The AU, in the centralized setup, performs refined spectrum detection by statistically processing the received signal vectors and identifying outliers before energy computation. Conversely, in the decentralized setup, cooperativeness among UUs ensures the elimination of redundant or conflicting sensing data through local interaction and mutual verification. The dual-mode evaluation allows the proposed cooperative sensing framework to assess the reliability and consistency of detection accuracy under both structured and ad-hoc CRN conditions.

3. RESULTS

The proposed work implements a novel analytical comprehensive ED framework where it assess the performance of three different popular ED methods such as MMED [8], arithmetic-to-geometric mean (AGM) [9], and Hadamard ratio (HR) [10], along with the proposed spectrum detection method based on Rice-K factor. In the proposed evaluation framework, extensive Monte Carlo simulations were carried out over 2000 independent runs for each configuration. The use of 2,000 Monte Carlo runs ensures statistical stability of the obtained detection performance metrics. The sensing environment considered 1-2 LUs and 3-12 UUs with an average of 200 samples per UU and a Rice-K factor of $K=2$. Here, the probability of false alarm was fixed at 0.1, while the SNR was varied from (-25 dB to 5 dB). The empirical probability of detection is estimated for each competing algorithm including the approach of ED_Method_1 (MMED) [8], ED_Method_2 (AGM) [9], and ED_Method_3 (HR) [10]. The estimation of detection probability versus false alarm probability is illustrated in Figure 2.

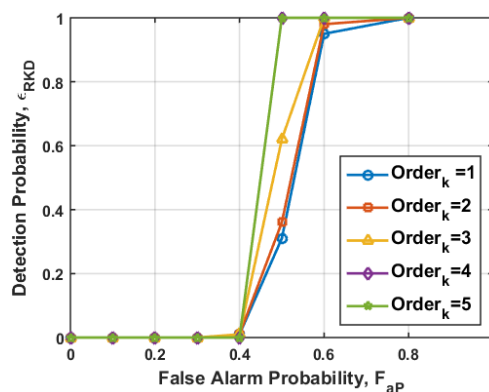


Figure 2. Estimation of detection probability versus false alarm probability

The analysis of classical ED model [25] in the proposed evaluation framework shows, that for classical ED all curves show very low detection probability, close to zero. This means that for very strict false alarm limits, the detector struggles to correctly identify the signal. Around $F_{ap}=0.4-0.6$, the detection probability rises sharply for all orders. This is a critical transition region, the point when the detector starts becoming effective. On the other hand ($F_{ap}>0.6$), detection probability saturates near 1 for all orders, that means that if more false alarms are allowed then the detection becomes nearly perfect for all orders. The critical analysis of the graph

also implies that classical ED with higher orders exhibit better detection probability. However, it allows more false alarms at the cost of more system complexity. It is observed that the thresholds appearing between ~ 0.4 to $0.5 F_{ap}$, the detection probability sharply rises which is a good indication for certain applications which have restricted tolerance up to that range. However, even though higher order improves detection probability but it resulted in computational complexity in many instances and poses energy requirements. This outcome clearly indicates a trade-off that exist between detection probability and false alarm rate. This is considered a fundamental characteristics of spectrum sensing systems.

The Figure 3 further shows comparison of the detection probability among proposed RKD and three popular conventional ED methods over varying SNR levels of distributions. It is observed that all methods exhibit improved detection with increasing SNR; however, the proposed RKD method consistently outperforms MMED, AGM, and HR, particularly under low-SNR conditions (below -10 dB). This improved detection indicates that RKD is more robust against fading-induced energy fluctuations, making it particularly suitable for spectrum sensing in dynamic wireless environments. RKD improves low-SNR detection because the Rice-K factor models the relative strength of the LOS and scattered multipath components, enabling more reliable discrimination between weak primary-user signals and background noise than conventional eigenvalue-based ED methods. At 0 dB, the Rice-K factor method accomplishes near-perfect detection earlier than the baseline approaches. This clearly implies faster convergence and better robustness of the proposed method. Overall, the proposed ED method demonstrates superior performance where it also ensures optimal trade-off between accuracy and reliability, making it more suitable for artificial intelligence-driven cognitive sensing in dynamic and noisy environment.

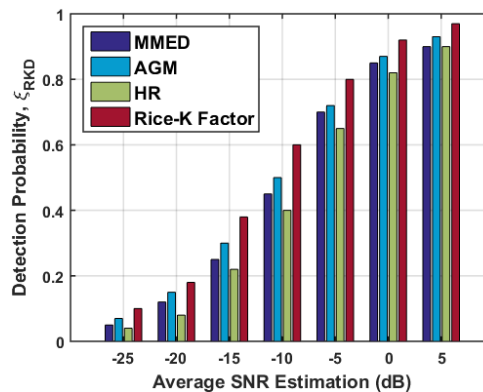


Figure 3. Detection probability versus SNR showing superior low-SNR performance of RKD compared to MMED, AGM, and HR methods

The proposed RKD method achieves approximately 25%-40% higher detection probability in low-SNR regions (< -10 dB), demonstrating its superior capability in detecting weak signals under noise uncertainty compared to MMED, AGM, and HR methods. The improved performance of the RKD method is attributed to the incorporation of the Rice-K factor, which captures the relative strength of LOS and multipath components. This enables more accurate discrimination of signal presence under fading and noise uncertainty, particularly in low-SNR conditions. The enhanced performance is attributed to the incorporation of the Rice-K factor, which captures the relative strength of LOS and multipath components, therefore improves the discrimination of weak primary-user signals from background noise.

Figure 4 compares the detection probability for three ED methods and the proposed Rice-K factormethod across varying number of UU (from 3 to 12). It clearly shows that as the number of UUs increase, the probability of detection consistently rise in the case of Rice-K factor. The Rice-K factor performs comparably to ED method 1, ED method 2, and ED method 3, showing its potential as a viable detection method, especially for higher number of UU (9-12). These findings implies that the proposed RKD method maintains reliable detection performance under increasing network density and also demonstrates its suitability for scalable cognitive radio applications where cooperative sensing improves resilience against channel impairments and interference. The increase in detection probability with a higher number of UUs is due to cooperative sensing, where spatial diversity and information improve robustness against channel variations and noise. The proposed framework is scalable to larger CRNs, as cooperative sensing mechanisms can be extended to a higher number of users. Although communication overhead increases with the number of cooperative users, the RKD computation itself remains lightweight because only a single Rice-K factor scaling operation is performed after eigenvalue decomposition. In conclusion, the proposed Rice-K factor presents a strong,

competitive approach for detection in CR environments, offering a promising alternative to traditional ED methods. Although evaluated with up to 12 UUs, the cooperative sensing architecture can be extended to larger CRNs which comprises of hundreds of UUs. Future work will also investigate communication overhead and distributed fusion strategies for such large-scale deployments.

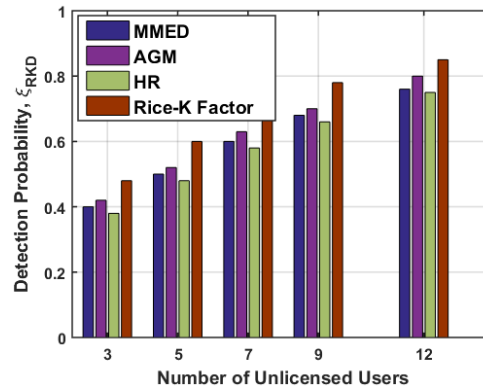


Figure 4. Detection probability versus number of UUs highlighting scalability advantage of the proposed RKD method

Across all configurations, RKD exhibits improved detection performance while it maintains computational complexity comparable to MMED, AGM, and HR. Since eigenvalue decomposition dominates the computational cost of all competing methods, the additional inclusion of the Rice-K factor requires only a lightweight scaling operation after eigenvalue computation, which result in negligible execution overhead. Also, the average processing time per sensing interval remains practically unaltered while providing improved detection accuracy under low-SNR conditions. Average execution time per sensing interval remained comparable to MMED, AGM, and HR because RKD performs only a lightweight post-processing operation. Even though it is observed that the RKD method offers improved detection performance in simulated CRN environment, however still further validation considering diverse fading models and real-world datasets is envisioned to confirm its general applicability. It is quite clear that RKD significantly improves detection performance, however in many cases inaccurate estimation of Rice-K factor might slightly affected the detection accuracy under rapidly varying channels. Still, the computational burden associated with K estimation remains significantly negligible when compared with learning-based sensing methods. These characteristic features make this proposed RKD approach suitable for rapid and reliable spectrum access in IoT-enabled CRNs, 5G spectrum sharing, and vehicular cognitive radio environments. In comparison with ML-based sensing approaches including SVMs and deep neural networks, which rely on massive training data and higher computational resource requirements, RKD applies a lightweight analytical formulation which require no offline training. It also can maintain improved detection performance under low-SNR conditions.

4. CONCLUSION

The performance analysis of the classical ED model for spectrum sensing in CRN reveals that detection probability improves progressively with increasing energy order that confirms its inherent capability to enhance the sensitivity toward weak LU signals. The outcome also validates statistical consistency of the model and its robustness against moderate noise fluctuations. However, the classical ED model in the proposed framework still exhibits performance degradation under highly correlated fading and non-Gaussian interference environments, where conventional noise assumptions become less valid. To overcome these limitations, the proposed evaluation framework models Rice-K factor based spectrum detection scheme that extends the classical model by statistically modelling multipath fading environment using rice distribution. The main contributions of this work are summarized as follows: i) development of unified analytical framework for benchmarking ED methods, ii) integration of centralized and decentralized sensing, and iii) incorporation of a Rice-K factor-based detection mechanism for improved robustness. The proposed method demonstrates enhanced detection performance under low-SNR conditions. However, further validation across diverse fading models and real-world datasets is required for broader generalization. The comparative evaluation confirms that the proposed ED method achieves significantly higher detection probability under varying SNR and

increasing number of UUs when compared with the popular baselines establishing it as a more resilient and intelligent alternative for dynamic spectrum sensing in next-generation cognitive and AI-driven wireless networks. Moreover, this work highlights the importance of unified evaluation frameworks in addressing limitations of conventional ED methods.

The proposed RKD-based framework demonstrates improved robustness under noise uncertainty and low-SNR conditions, making it suitable for practical CRN deployments. The findings of this study can be applied in practical CRN deployments for improving spectrum sensing reliability in dynamic and low-SNR environments. The present work is limited to simulation-based evaluation under Rician fading. Validation using real-world datasets and additional fading environments remains an important direction for future research. Although the current study primarily considers Rician fading environments, future work will explore hybrid RKD frameworks which will incorporate machine-learning techniques for adaptive threshold estimation, additional channel models such as Rayleigh and Nakagami fading, real-world spectrum datasets, and software-defined radio testbed validation.

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Pushpa Yellappa	✓	✓	✓	✓	✓	✓		✓	✓	✓			✓	
Keshavamurthy		✓				✓		✓	✓	✓	✓	✓		

C : Conceptualization	I : Investigation	Vi : Visualization
M : Methodology	R : Resources	Su : Supervision
So : Software	D : Data Curation	P : Project administration
Va : Validation	O : Writing - Original Draft	Fu : Funding acquisition
Fo : Formal analysis	E : Writing - Review & Editing	

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 upon reasonable request.

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