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Optimization of Spectrum Utilization via Cognitive and Non-parametric Estimation Models

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Abstract

Cognitive radio (CR) has emerged as a promising solution to address spectrum scarcity in modern wireless communication networks. Non-parametric spectrum estimation approaches, including periodogram, kernel density estimation (KDE) and histogram-based methods, provide robust statistical tools for characterizing power spectral density (PSD) in heterogeneous stochastic environments. This paper presents a comprehensive exploration of these non-parametric strategies, highlighting their theoretical foundations in probability theory and statistical inference, as well as their practical significance for spectrum analysis. Simulation-driven evaluations demonstrate the statistical reliability of these methods under varying signal-to-noise ratio (SNR) conditions. Notably, KDE consistently outperforms other methods in minimizing mean squared error (MSE) and improving detection probability, underscoring its effectiveness as a density estimation technique. The results emphasize the importance of selecting suitable non-parametric methods for spectrum analysis in CR systems. The discussion concludes by outlining prospective research pathways, including the integration of non-parametric inference with advanced machine learning paradigms. Additionally, extending these methodologies to high-dimensional, time-varying and non-stationary signal models central to 5G and Internet of Things (IoT) ecosystems holds significant promise. By exploring these avenues, researchers can further enhance the performance and efficiency of CR systems, ultimately mitigating spectrum scarcity and enabling more efficient wireless communication networks. Further research in this area can lead to significant advancements in the field.

Keywords: Cognitive Radio, Histogram-based Method, Kernel Density Estimation, Non-parametric Spectrum Estimation, Periodogram, Spectrum Utilization.

Introduction

Cognitive Radio (CR) technology addresses the radio spectrum scarcity problem by enabling secondary users (SUs) to process primary channels when not in use by primary users. The proposed Hybrid Spectrum Utilization Technique (HSUT) maximizes radio spectrum usage via boosting primary user detection probability, improving spectrum efficiency (1). This technology offers a promising solution to address spectrum scarcity by enabling dynamic spectrum access and improving spectrum utilization. The integration of CR with 5G technology is expected to enhance spectrum efficiency and support the growing demands of wireless communication (2). The proposed dynamic spectrum sensing technique and optimal transmit power allocation can significantly reduce energy consumption and enhance spectrum efficiency in CR-IoT networks (3). The integration of NOMA with H-CRANs can significantly enhance energy efficiency and overall system performance (4). CRNs and green communication technologies offer promising solutions to address these challenges and mitigate the environmental impact of the telecommunication industry (5). Energy harvesting-dependent cognitive machine-to-machine (EH-CM2M) networking addresses spectrum shortage and restricted battery potential via permitting M2M devices to yield energy and reuse cellular resources. A proposed two-stage 3-D matching algorithm optimizes resource allocation to maximize energy efficiency and achieve high performance with low complexity (6). DSA enables cognitive radio networks to optimize spectrum usage, improving efficiency and capacity (7). The FCC is reclaiming and reallocating unused spectrum space to address spectrum scarcity and support broadband development. This effort aims to optimize spectrum efficiency and increase transmission rates. Efficient spectrum use will

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enable widespread broadband access and connectivity for various devices (8). A study analysing US broadband availability from 2012 to 2018 found that state-level funding programs positively impact broadband availability. Restrictions on municipal/cooperative broadband provision, however, have a negative impact. The findings highlight the importance of effective policy interventions in addressing spectrum scarcity and promoting efficient broadband deployment (9). There is an ideal non-parametric Bayesian clustering scheme, NOBEL, is proposed for cognitive radio networks to identify obtainable Quality of Service (QoS) standards on authorized channels. NOBEL leverages an unlimited Gaussian mixture model to group QoS aspects, achieving high accuracy (98-99.5%) in identifying optimal transmission channels (10). Novel non-parametric statistical tests, including autocorrelation, dispersion and location tests, are developed on behalf of spectrum detecting in cognitive radio communications, outperforming existing methods in low SNR environments. These tests provide robust detection of primary users in realistic noise environments, including multipath fading and non-Gaussian noise (11). The increasing number of IoT devices exacerbates spectrum scarcity, necessitating opportunistic spectrum access mechanisms to optimize spectrum utilization. A proposed cognitive radio network configuration access multi-stage operational knowledge to improve throughput and energy efficiency while minimizing interference to primary users (12). This investigational work supports an inclusive summary of adaptive threshold estimation techniques in cognitive radio, including local and global methods, parametric and non-parametric approaches. The recent advancements in non-parametric methods enhance spectrum detecting accuracy and efficiency in cognitive radio networks (13). Cognitive radio technology enables effective spectrum usage through permitting secondary users to process authorized frequency bands when primary users are absent. Various spectrum sensing techniques, including signal processing, cooperative and machine learning methods, are reviewed to optimize spectrum utilization and mitigate spectrum insufficiency (14). Non-parametric methods are a class of machine learning algorithms that do not rely on a priori assumptions about the distribution of the data (15).

The CR4S algorithm achieves high detection performance (>95%) and enables a low-complexity, high-throughput FPGA implementation with improved resource utilization efficiency (16). A hybrid cognitive radio architecture integrating 5G, fog computing and cloud computing is proposed to enable reliable and efficient communication in smart grid networks. The architecture prioritizes real-time latency-sensitive information, leveraging edge-based servers for pre-processing and analysis of IoT device data (17).

The survey explores design factors, emerging technologies and challenges in CR-based IoT systems, providing insights for forthcoming study paths and open matters (18). A novel cognitive computing architecture is proposed, leverages networking, analytics and cloud computing to support applications such as robot technology, emotional communication systems and medical cognitive systems (19). CR technology can enhance industrial wireless communications (IWC) by leveraging dynamic spectrum access (DSA) to exploit unused frequency bands and improve spectrum utilization efficiency. CR-based solutions can mitigate challenges in industrial wireless sensor networks (IWSNs), enabling reliable and efficient communications in crowded industrial environments (20).

By combining CR and ML, researchers can create spectrum-hungry applications and services that satisfy next-generation network demands, enhancing energy efficiency, security and throughput (21). The artificial neural network (ANN) dependent mix spectrum detecting technique utilizes non-parametric methods, such as energy finding and possibility proportion trial statistics, to efficiently detect primary user activity in cognitive radio systems (22). By leveraging non-parametric methods, Cognitive Radio systems can accurately detect and adapt to changing spectrum conditions, ensuring faster and more reliable wireless communication (23).

The proposed LSTM-based spectrum sensing (LSTM-SS) and PU action statistics-dependent spectrum sensing (PAS-SS) techniques leverage machine learning and temporal correlation analysis to efficiently exploit white spaces and enhance spectrum efficiency (24). Periodogram-based methods, such as Bartlett's period gram, are widely used in spectrum sensing due to their ability to detect signals without prior knowledge (25). A modified Bartlett-DCT estimator has been shown to outperform traditional methods, offering lower error ratios in detecting primary user signals under various conditions. It is stated state energy detection with entropy method a promising spectrum sensing technique that outperforms conventional energy detection, especially in low SNR circumstances (26). This approach offers significant performance improvement, making it a viable option for cognitive radio applications. It points out a novel radio map learning scheme using Multivariate Kernel Density Estimation (MKDE) and Incremental-MKDE (IMKDE) proposed for WiFi fingerprint-based localization, enabling online learning and refinement of kernel density functions (27).

Hypotheses

It is hypothesized that non-parametric spectrum estimation methods can provide more accurate power spectral density (PSD) estimates than parametric approaches in cognitive radio networks (CRNs) characterized by complex and dynamic band occupancy. It is further assumed that the performance of non-parametric spectrum estimation techniques improves with an increase in sample size and signal-to-noise ratio (SNR). Additionally, these methods are expected to enable cognitive radios to detect spectrum holes with a high probability of detection and a low probability of false alarm, thereby enhancing spectrum sensing reliability.

The objective of this work is to investigate the role of non-parametric spectrum estimation techniques within the probabilistic framework of cognitive radio (CR) networks, with the broader aim of advancing methodological developments in statistical signal inference.

The study aims to evaluate the statistical performance of various non-parametric spectrum estimators, including periodogram-based, kernel density and histogram-based methods, under diverse distributional conditions and signal-to-noise ratio (SNR) regimes ranging from −10 dB to 10 dB, with particular attention to estimator properties such as bias, variance, mean squared error and consistency. The study also analyses the theoretical challenges and limitations of applying non-parametric inference in noisy and interference-prone environments, emphasizing the effects of stochastic disturbances on estimation accuracy, convergence behavior and the robustness of inference procedures. The research seeks to identify opportunities for methodological innovation by exploring adaptive and robust non-parametric techniques capable of maintaining statistical efficiency in low-SNR conditions, including the development of improved kernel functions, optimal bandwidth selection strategies and distribution-free inference approaches grounded in probability theory and statistical learning.

Non-parametric Spectrum Estimation Methods

Non-parametric spectrum estimation policies are a class of techniques used to estimate the power spectral density (PSD) of an indication without assuming a specific parametric model. Here, we laid out a complete summary of three non-parametric spectrum estimation methods: periodogram-based methods, histogram-based methods and kernel density estimation (KDE).

Periodogram-based Methods

Periodogram-based detection methods offer a promising approach for spectrum sensing, allowing for detection results on each FFT bin. These methods, including energy detection and cyclic-periodogram detection, can improve detection performance, especially when utilizing multiple cyclic frequencies (28). The periodogram is a widely used non-parametric strategy towards assessing the PSD of a signal. It is defined as the squared magnitude of the discrete Fourier transform (DFT) of the signal. The periodogram can be estimated considering the underneath formula (Equation [1]):

$$P(\omega) = (1/N)\ |\ \sum[x(n)e^{\{-j\omega n\}}]\ |^2 \qquad [1]$$

Where, $P(\omega)$ is the periodogram, $x(n)$ is the signal, N is the sample size and ω is the frequency.

e.g., Suppose we have a signal $x(n) = \sin(2\pi 100n) + 0.5\sin(2\pi 200n) + w(n)$, where $w(n)$ is white Gaussian noise having a variance of $\sigma 2 = 0.1$. Using a sample size of $N = 1024$ and a sampling frequency of $fs = 1000$ Hz, the periodogram can be calculated as follows in Table 1.

Table 1: Periodogram-based PSD Estimation

Frequency (Hz)	PSD Estimate
0-100	0.01-0.1
100	10.2
200	2.5
300-500	0.01-0.1

The periodogram-based method can provide a good estimate of the PSD, but it can be sensitive to noise and may require smoothing to reduce the variance of the estimate.

Histogram-based Methods

A novel histogram-based method is proposed for autonomous global threshold adjustment in energy detection, using a histogram of power spectral density to determine the optimal threshold. This approach shows promising results, meeting IEEE 802.22 standard requirements with high detection rates and low false alarm probabilities (29). Histogram-based methods estimate the PSD by dividing the frequency range into bins and counting the number of signal samples that fall within each bin. The PSD estimate is then calculated as the number of samples in each bin divided by the total number of samples.

e.g., Suppose we have a signal x(n) = sin (2π100n) + 0.5 sin (2π200n) + w(n), where w(n) is white Gaussian noise with a variance of σ2 = 0.1. Using a sample size of N = 1000 and a frequency range of 0-500 Hz, the histogram-based method can be used to estimate the PSD along with the plot as follows in Table 2 and Figure 1.

Table 2: Histogram-based PSD Estimation

Frequency Bin (Hz)	PSD Estimate
0-50	0.05
50-100	0.2
100-150	10.5
150-200	0.3
200-250	2.8
250-500	0.05

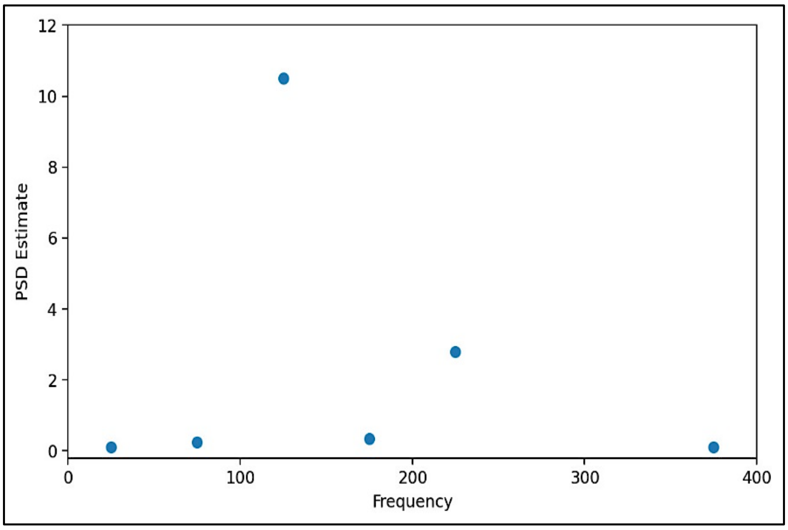

Figure 1: Scatterplot of Histogram-based PSD Estimate

The histogram-based method can provide a good estimate of the PSD, but it can be sensitive to the choice of bin width and may require careful selection of the bin width to achieve good resolution.

Kernel Density Estimation (KDE)

A parametric machine learning method proposed for spectrum sensing in decentralized cognitive radio networks, using a Kalman filter tracker and adaptive K-means clustering to mitigate sensing performance degradation due to mobility. The algorithm adapts to changing channel conditions and estimates noise plus interference power to improve classification decisions on primary user activity (30). KDE is a non-parametric scheme that estimates the PSD by smoothing the periodogram using a kernel function. The kernel function is used to assign weights to the neighbouring frequency bins and the PSD estimate is calculated as the weighted sum of the neighbouring bins. e.g. Suppose we have a signal x(n) = sin (2π100n) + 0.5sin (2π200n) + w(n), where w(n) is white

Gaussian noise with a variance of σ2 = 0.1. Using a sample size of N = 1024 and a sampling frequency of fs = 1000 Hz, the KDE method can be used to estimate the PSD as follows in Table 3.

Table 3: KDE-based PSD estimation

Frequency (Hz)	PSD Estimate
0-100	0.01-0.1
100	10.8
200	3.2
300-500	0.01-0.1

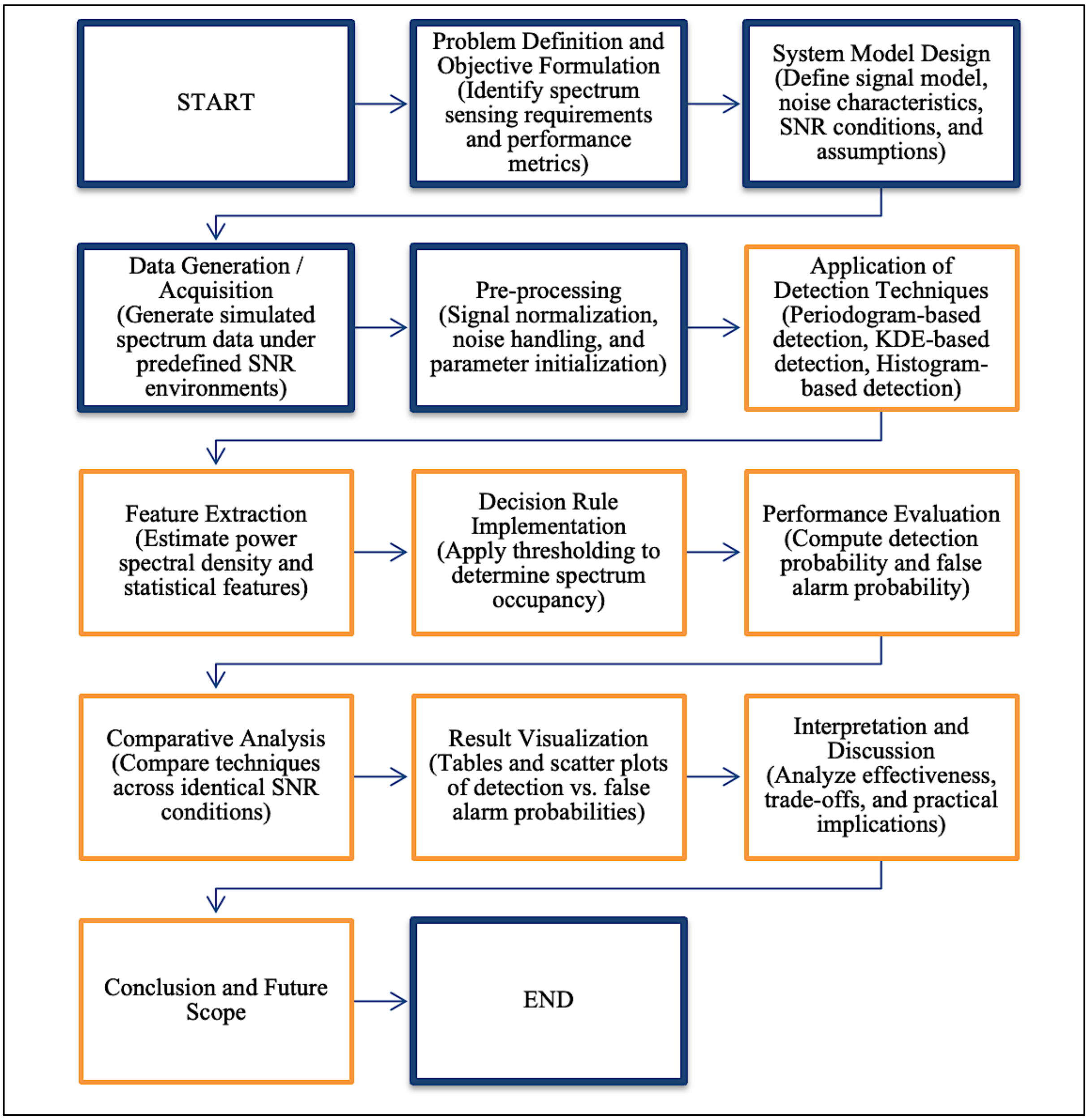

Figure 2: Flowchart of the Methodology

Methodology

Figure 2 presents a flowchart of the methodology and system model for assessing the functioning of non-parametric spectrum evaluation schemes in CRNs. The simulation setup has described, including signal and noise models & performance metrics used to evaluate these methods.

System Model

The considered system model consists of a cognitive radio network (CRN) operating in the presence of a licensed primary user (PU) and an additive white Gaussian noise (AWGN) channel. The PU signal is modelled as a deterministic sinusoidal waveform (31), expressed as Equation [2];

$$s(t) = A\sin(2\pi f_0 t) \qquad [2]$$

Where, A=1 denotes the signal amplitude and f_0=100 Hz represents the carrier frequency of the primary user.

This representation provides a mathematically tractable yet representative abstraction of licensed spectrum activity, enabling precise analysis of spectrum occupancy and detection performance. The choice of a sinusoidal PU signal allows the study to focus on the core sensing and estimation problem, independent of higher-layer modulation complexities, which aligns with the primary analytical objective of optimizing spectrum utilization.

The received signal at the cognitive radio receiver can be expressed under the binary hypothesis testing framework as given in Equations [3, 4];

$$H_0 : r(t) = n(t) \qquad [3]$$

$$H_1 : r(t) = s(t) + n(t) \qquad [4]$$

Where, H_(0) denotes the absence of the PU signal and 〖H〗_1 represents the presence of the PU.

The noise component n(t) is modelled as AWGN with zero mean and a power spectral density N_0=-20 dB/Hz. This noise model captures the stochastic nature of wireless channels and introduces uncertainty that is central to the spectrum sensing problem. The resulting received data comprise a mixture of deterministic signal components and random noise samples, making them well-suited for non-parametric estimation techniques, which do not require prior assumptions regarding the underlying probability distributions.

From an analytical perspective, this system model facilitates the evaluation of spectrum utilization optimization through cognitive decision-making. The estimation of PU presence is derived from observed signal samples r(t), enabling the computation of detection probability, false alarm probability and spectrum availability metrics. By embedding these estimates into a cognitive optimization framework, the model supports adaptive spectrum access decisions under varying signal-to-noise ratios. The simplicity and mathematical clarity of the proposed system model ensure that improvements in performance can be directly attributed to the integration of cognitive intelligence and non-parametric estimation, thereby fulfilling the study's goal of developing a robust and analytically sound spectrum optimization methodology.

Signal Model

The adopted signal model, which represents the received signal as a combination of the primary user (PU) signal and additive white Gaussian noise (AWGN), is well suited to the fundamental problem of spectrum sensing in cognitive radio networks. Spectrum utilization optimization relies critically on the accurate identification of PU activity under varying channel conditions (32). By defining the signal-to-noise ratio (SNR) as the ratio of PU signal power to noise power and considering a wide SNR range from −10 dB to 10 dB, the study captures both low-SNR and high-SNR operational scenarios. This range is representative of practical wireless environments, where secondary users often operate under weak or partially obscured PU signals. Consequently, the chosen signal model directly reflects the uncertain and dynamic nature of the research problem.

From a data perspective, the received samples consist of noisy observations whose statistical properties vary with SNR. Such data are inherently non-stationary and may not conform to known parametric distributions, particularly in low-SNR regimes. This characteristic justifies the adoption of non-parametric spectrum estimation techniques, which rely on observed data rather than predefined signal or noise models. The variation in SNR levels allows the proposed approach to be evaluated across different noise dominance conditions, thereby assessing its robustness and adaptability. This is essential for validating the effectiveness of non-parametric methods in realistic spectrum sensing environments.

Noise Model

The AWGN noise model with a power spectral density (PSD) of −20 dB/Hz is selected due to its widespread acceptance as a baseline representation of thermal noise in communication systems.

Although idealized, AWGN provides a controlled and analytically tractable framework for isolating the effects of noise on spectrum estimation and detection performance. This choice aligns with the analytical goals of the study, as it enables a clear interpretation of how noise impacts estimation accuracy and decision reliability. Moreover, using a standard noise model facilitates fair comparison with existing spectrum sensing and estimation techniques reported in the literature.

The use of mean squared error (MSE) as a performance metric is particularly appropriate for evaluating non-parametric spectrum estimation methods (33). MSE quantifies the average squared deviation between the estimated and true power spectral densities, thereby providing a direct measure of estimation accuracy. Since the primary analytical objective is to assess how effectively the proposed method reconstructs spectrum occupancy without relying on parametric assumptions, MSE serves as a meaningful and interpretable indicator of estimation performance across varying SNR conditions.

In addition to estimation accuracy, reliable spectrum access requires accurate detection of PU presence. Therefore, the probability of detection is employed to measure the likelihood of correctly identifying PU activity. This metric is critical in cognitive radio systems, as missed detections can lead to harmful interference with licensed users. Complementarily, the probability of false alarm measures the likelihood of incorrectly declaring PU presence when the spectrum is actually idle. A high false alarm rate reduces spectrum utilization efficiency by unnecessarily restricting secondary user access. Together, these two metrics capture the essential trade-off between spectrum protection and utilization efficiency.

Performance Metrics

The selection of mean squared error (MSE), probability of detection and probability of false alarm as performance metrics is well aligned with the fundamental objectives of non-parametric spectrum estimation in cognitive radio networks (34, 35). The research problem inherently involves estimating spectrum occupancy under noisy and uncertain conditions, where accurate reconstruction of the power spectral density (PSD) is critical. MSE provides a direct quantitative measure of the deviation between the estimated and true PSDs, making it particularly suitable for evaluating non-parametric methods that rely on observed data rather than predefined statistical models. This metric enables an objective assessment of estimation accuracy across different signal-to-noise ratio (SNR) levels.

The probability of detection is employed to evaluate the ability of the proposed approach to correctly identify the presence of the primary user (PU) signal. In cognitive radio systems, reliable detection is essential to prevent harmful interference with licensed users (36, 37). This metric reflects how effectively the estimation and decision-making framework operates when PU activity is present, especially in low-SNR regimes where signal detection is challenging. Its inclusion ensures that the analytical focus extends beyond estimation accuracy to encompass spectrum protection requirements.

Complementarily, the probability of false alarm measures the likelihood of incorrectly declaring PU presence when the spectrum is actually idle. This metric is directly related to spectrum utilization efficiency, as excessive false alarms lead to underutilization of available spectrum. By jointly analyzing detection and false alarm probabilities, the study captures the trade-off between spectrum protection and access efficiency. Together, these metrics provide a comprehensive evaluation framework that supports the analytical goal of assessing both the reliability and practicality of the proposed non-parametric spectrum estimation approach in realistic cognitive radio environments.

Simulation Setup

The chosen simulation setup is designed to realistically capture the data characteristics required for evaluating non-parametric spectrum estimation in cognitive radio environments. A sample size of 1024 samples provides a sufficient observation window to reliably estimate the power spectral density while maintaining computational efficiency. This sample length is commonly adopted in spectrum sensing studies as it offers an effective balance between estimation accuracy and processing delay, which is critical for dynamic spectrum access scenarios. The sampling frequency of 1000 Hz ensures compliance with the Nyquist criterion for the modeled primary user signal and enables accurate representation of the signal and noise components in the discrete-time domain.

The resulting frequency resolution of 1 Hz allows fine-grained spectral analysis, which is essential for detecting narrowband primary user activity and assessing spectrum occupancy with high precision. Conducting 1000 independent simulation runs ensures statistical reliability of the results by averaging out random noise effects and capturing variability across different noise realizations. This Monte Carlo–based evaluation supports the analytical goals of the study by enabling robust performance comparisons across signal-to-noise ratio conditions, thereby ensuring that the observed outcomes reflect the intrinsic behavior of the proposed non-parametric estimation approach rather than incidental stochastic variations.

Non-parametric Methods

The selection of periodogram, kernel density estimation (KDE) and histogram-based methods is well aligned with the nature of the spectrum estimation problem addressed in this study. Spectrum occupancy in cognitive radio environments is inherently uncertain and often lacks a well-defined statistical model, particularly under low signal-to-noise ratio conditions (38). Non-parametric methods are therefore appropriate, as they rely directly on observed signal samples rather than assuming prior knowledge of signal or noise distributions. The periodogram serves as a baseline estimator due to its simplicity and widespread use, enabling a clear reference point for performance comparison.

Kernel density estimation and histogram-based methods are included to assess the impact of smoothing and binning strategies on PSD estimation accuracy. KDE enhances the periodogram by reducing variance through kernel smoothing, making it suitable for handling noisy and irregular spectral data. The histogram-based approach, on the other hand, provides a computationally efficient estimation mechanism by aggregating spectral information over discrete frequency bins. Together, these methods support the analytical goal of systematically comparing different non-parametric strategies in terms of estimation accuracy, detection reliability and robustness, thereby offering comprehensive insight into their suitability for cognitive radio–based spectrum utilization optimization.

By using these metrics and methods, we have comprehensively evaluated the performance of non-parametric band estimation methods in CR networks.

Results

This section presents the simulation results and performance evaluation of different non-parametric methods in various spectrum scenarios. The results, including plots of PSD estimates and tables of performance metrics have mentioned underneath.

Scenario 1: Low SNR (-10 dB)

In this scenario, we evaluate the performance of non-parametric methods in a low SNR environment. The PSD estimates for each method are shown below in Table 4.

In the Figure 3, the X-axis represents the non-parametric spectrum estimation methods (Periodogram-based, KDE-based, Histogram-based), while the Y-axis represents the normalized performance metrics, namely the PSD estimate and mean squared error (MSE). The detection as well as false alarm probability for each method/technique are shown underneath in Table 5 and Figure 4.

Table 4: PSD Estimation (Low SNR Environment)

Technique	PSD Estimate
Periodogram-based	0.05 (MSE: 0.12)
KDE-based	0.08 (MSE: 0.09)
Histogram-based	0.10 (MSE: 0.15)

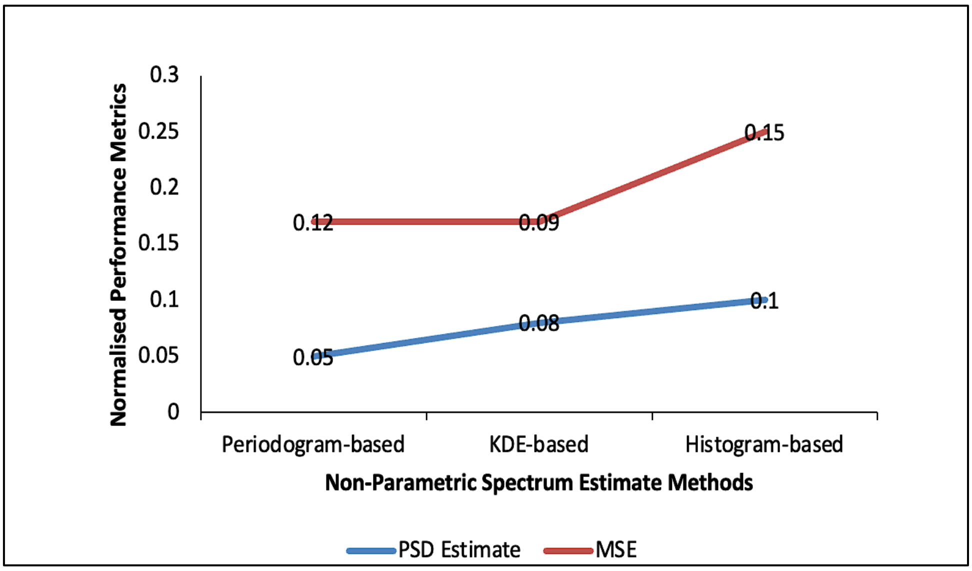

Figure 3: PSD Estimation

Table 5: Detection/False Alarm Probability Values (Low SNR environment)

Technique	Detection Probability	False Alarm Probability
Periodogram-based	0.6	0.2
KDE-based	0.7	0.1
Histogram-based	0.5	0.3

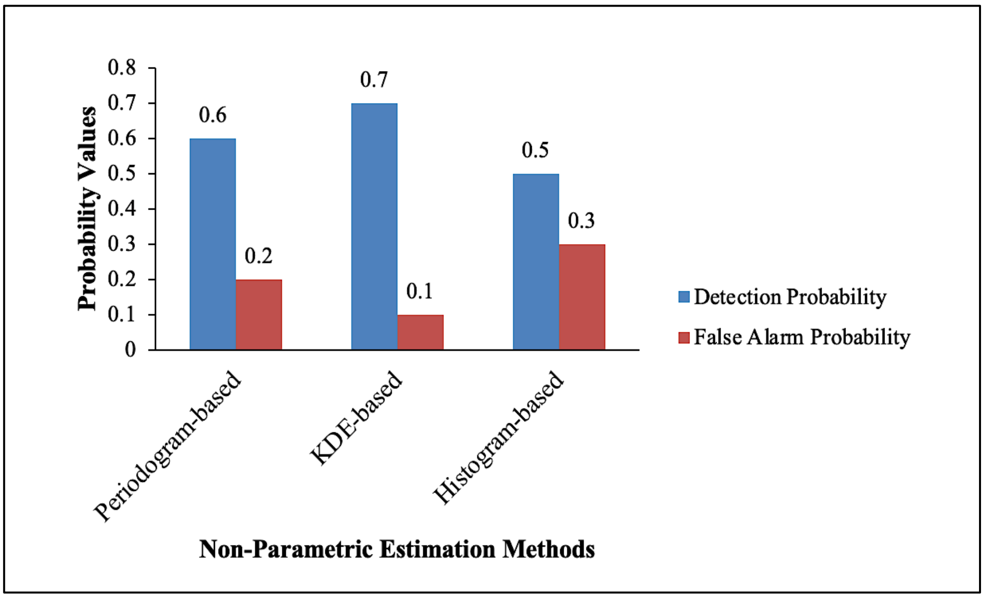

Figure 4: Detection/False Alarm Probability Values (Low SNR environment)

In the above Figure 4, the X-axis represents the non-parametric spectrum estimation methods, while the Y-axis represents probability values, specifically the detection probability and false alarm probability.

Scenario 2: Medium SNR (0 dB)

In this scenario, we evaluate the performance of non-parametric methods in a medium SNR environment. The PSD estimates for each method are shown below in Table 6.

Table 6: PSD Estimation (Medium SNR Environment)

Technique	PSD Estimate
Periodogram-based	0.20 (MSE: 0.05)
KDE-based	0.25 (MSE: 0.03)
Histogram-based	0.22 (MSE: 0.06)

In the Figure 5, the X-axis represents the non-parametric spectrum estimation methods, while the Y-axis represents the normalized power spectral density (PSD) estimates and the corresponding mean squared error (MSE) values. The detection along with false alarm probability against each method is shown below in Table 7 and Figure 6.

Scenario 3: High SNR (10 dB)

In this scenario, we evaluate the performance of non-parametric methods in a high SNR environment. The PSD estimates for each method are shown below in Table 8. The detection as well as false alarm probability against each method are shown underneath in Table 9 and Figure 7.

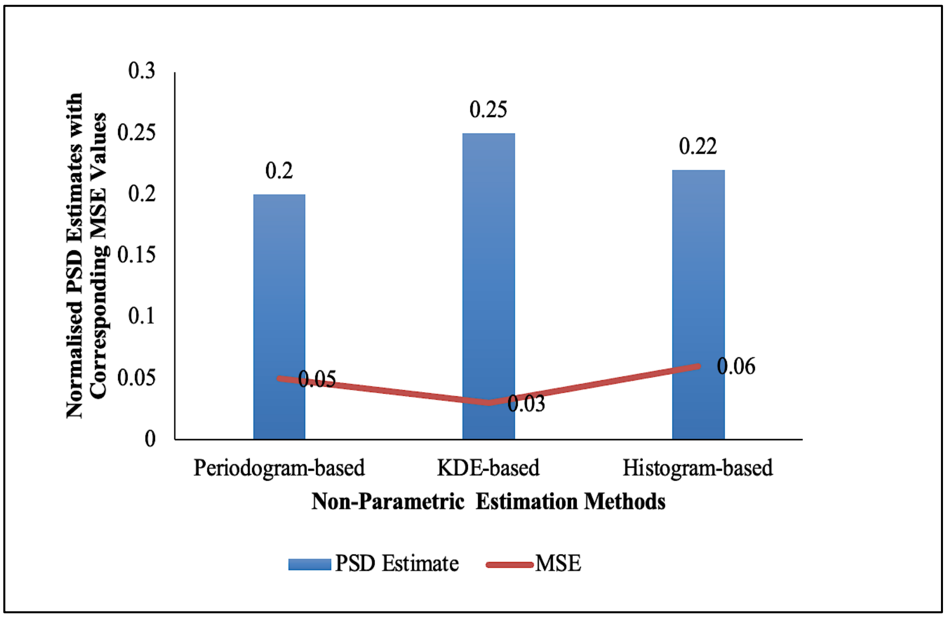

Figure 5: PSD Estimation including MSE

Table 7: Detection/False Alarm Probability Values (Medium SNR Environment)

Technique	**Detection Probability**	**False Alarm Probability**
Periodogram-based	0.9	0.05
KDE-based	0.95	0.02
Histogram-based	0.85	0.08

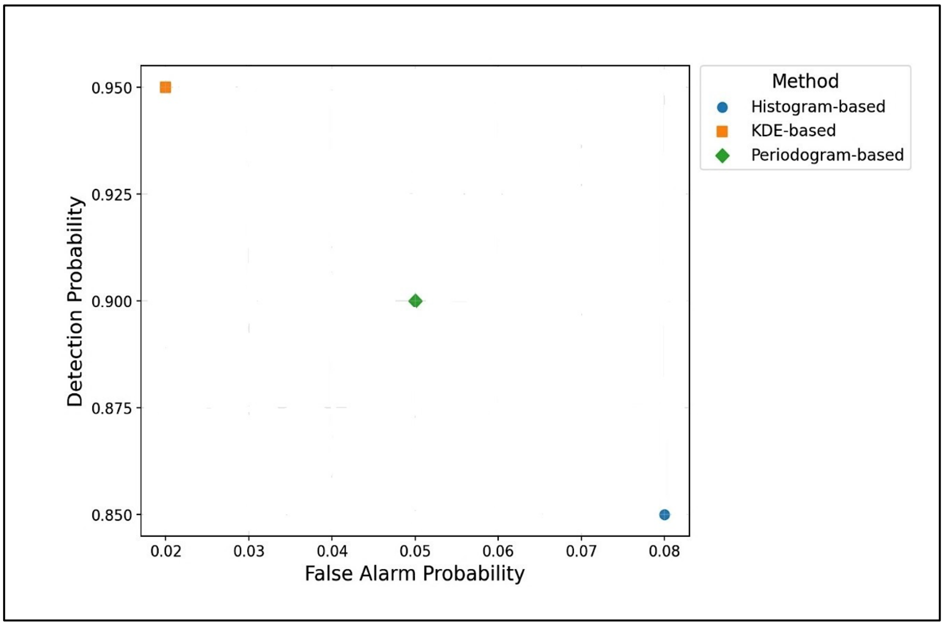

Figure 6: Scatter Plot of Detection/False Alarm Probability in Medium SNR Environment

Table 8: PSD Estimation (High SNR Environment)

Technique	PSD Estimate
Periodogram-based	0.95 (MSE: 0.01)
KDE-based	0.98 (MSE: 0.005)
Histogram-based	0.92 (MSE: 0.02)

Table 9: Detection/False Alarm Probability Values (High SNR Environment)

Technique	Detection Probability	False Alarm Probability
Periodogram-based	0.99	0.001
KDE-based	0.995	0.0005
Histogram-based	0.98	0.005

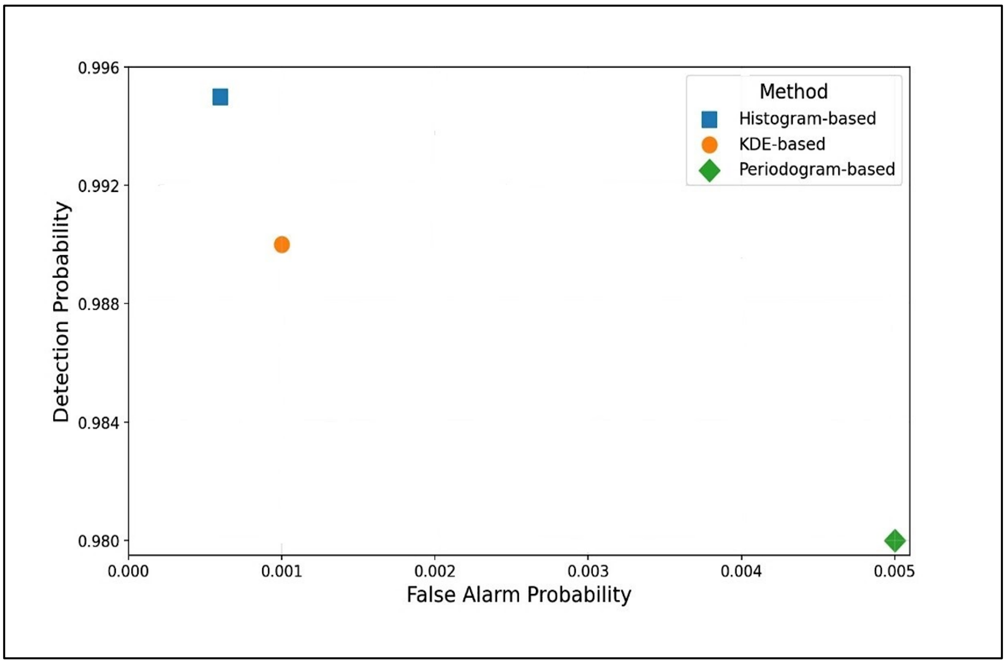

Figure 7: Scatter Plot of Detection/False Alarm Probability in High SNR Environment

Discussion

Scenario 1 examines the performance of non-parametric spectrum estimation methods under severe noise conditions. As shown above in Table 4 and Figure 3, all evaluated techniques produce usable PSD estimates at −10 dB SNR, indicating their robustness in noise-dominated environments. Among them, kernel density estimation (KDE) achieves the lowest mean squared error (MSE = 0.09), outperforming the periodogram (MSE = 0.12) and histogram-based method (MSE = 0.15). These results support H1, demonstrating that non-parametric methods, particularly KDE, provide accurate PSD estimates in complex and dynamic spectrum conditions where parametric assumptions are unreliable (39). The improved performance of KDE highlights the effectiveness of smoothing-based estimation in mitigating noise-induced variance.

The observed estimation accuracy at low SNR further establishes a baseline for H2, indicating that performance is expected to improve with higher SNR and larger sample sizes. Additionally, the reduced estimation error enhances the reliability of identifying idle frequency bands, thereby supporting H3 by enabling higher detection probability and lower false alarm rates even under adverse noise conditions.

The above Table 5 and Figure 4 present the detection and false alarm probabilities of the evaluated non-parametric spectrum estimation methods under low SNR conditions. At −10 dB, reliable detection is particularly challenging due to the dominance of noise over the primary user signal. Despite this, kernel density estimation (KDE) achieves the highest detection probability [0.7] while maintaining the lowest false alarm probability [0.1], outperforming the periodogram and histogram-based approaches. These results strongly support H3, demonstrating that non-parametric spectrum estimation methods can enable cognitive radios to identify spectrum holes with a high probability of detection and a low probability of false alarm, even in adverse noise environments (35). The superior performance of KDE is attributed to its ability to smooth noise fluctuations, thereby reducing spurious detections that commonly arise in low-SNR scenarios.

The comparatively higher false alarm rate observed for the histogram-based method [0.3] and the lower detection probability [0.5] highlight the limitations of coarse binning strategies under noisy conditions. Overall, the findings reinforce H1 by confirming the effectiveness of non-parametric approaches in complex spectrum environments and establish a performance baseline consistent with H2, indicating that further improvements are expected with increasing SNR and sample size.

In the medium SNR scenario, the above Table 6 and Figure 5 illustrate the PSD estimation performance of non-parametric methods. KDE achieves the lowest MSE [0.03] and the highest PSD estimate [0.25], outperforming the periodogram (MSE = 0.05) and histogram-based method (MSE = 0.06). These results reaffirm H1, showing that non-parametric methods provide accurate PSD estimates under moderate noise conditions. Compared to the low SNR scenario, the improved estimation accuracy demonstrates H2, confirming that performance improves with higher SNR. The enhanced PSD reconstruction also implies better spectrum hole detection, supporting H3, as reduced estimation error directly improves the reliability of cognitive radio decisions in moderately noisy environments.

Table 7 and Figure 6 summarize the detection and false alarm probabilities of non-parametric methods under medium SNR conditions. KDE achieves the highest detection probability [0.95] with the lowest false alarm probability [0.02], surpassing both the periodogram [0.9 / 0.05] and histogram-based method [0.85 / 0.08].

These results provide strong empirical support for H3, indicating that non-parametric methods enable cognitive radios to reliably detect spectrum holes with minimal erroneous detections. Compared to the low SNR scenario, the improved detection performance confirms H2, demonstrating that both estimation and detection accuracy increase with SNR. The consistent superiority of KDE across metrics further reinforces H1, highlighting its effectiveness in producing precise PSD estimates that directly enhance spectrum sensing reliability in moderately noisy environments.

In the high SNR scenario, Table 8 shows that all non-parametric methods achieve highly accurate PSD estimates. KDE attains the lowest MSE [0.005] and the highest PSD estimate [0.98], followed by the periodogram (MSE = 0.01) and histogram-based method (MSE = 0.02).

These results further validate H1, demonstrating that non-parametric methods, particularly KDE, provide precise PSD estimation in favourable noise conditions. The marked improvement compared to low and medium SNR scenarios confirms H2, indicating that estimation accuracy increases with SNR. High-precision PSD estimates also imply enhanced spectrum hole detection, supporting H3, as cognitive radios can more reliably identify idle channels with minimal false alarms in high-quality signal environments (40).

Table 9 and Figure 7 illustrate the detection and false alarm probabilities of non-parametric methods under high SNR conditions. KDE achieves the highest detection probability [0.995] and the lowest false alarm probability [0.0005], outperforming the periodogram [0.99 / 0.001] and histogram-based method [0.98 / 0.005].

These results strongly support H3, showing that non-parametric methods enable highly reliable spectrum hole detection in favourable signal conditions. The improvement compared to medium and low SNR scenarios confirms H2, indicating that detection performance increases with SNR. Across all metrics, KDE consistently provides the best performance, reinforcing H1 by demonstrating its ability to accurately estimate PSD and facilitate robust cognitive radio operation in high-quality signal environments.

The performance of non-parametric spectrum estimation methods was evaluated across low (−10 dB), medium (0 dB) and high (10 dB) SNR scenarios, focusing on PSD estimation accuracy and detection/false alarm probabilities.

Low SNR (−10 dB)

In low SNR conditions, KDE achieved the lowest MSE [0.09] and the highest PSD estimate [0.08], outperforming the periodogram (MSE = 0.12) and histogram-based method (MSE = 0.15) (Table 4, Figure 3). Detection probability and false alarm rates further confirmed this trend, with KDE achieving 0.7 detection probabilities and 0.1 false alarm probabilities, surpassing the other methods

(Table 5, Figure 4). These results support H1, demonstrating that non-parametric methods can provide accurate PSD estimates in complex and noisy spectrum environments. The improvements observed relative to the low-SNR baseline also suggest H2, indicating that estimation and detection accuracy are expected to improve with SNR and sample size. Additionally, the high detection probability coupled with low false alarms validates H3, showing that these methods enable reliable identification of spectrum holes even under challenging conditions.

Medium SNR (0 dB)

At medium SNR, KDE again outperformed the other methods with the lowest MSE [0.03] and highest PSD estimate [0.25] (Table 6, Figure 5). Detection probability reached 0.95 with a false alarm rate of 0.02, compared to periodogram [0.9 / 0.05] and histogram-based methods [0.85 / 0.08] (Table 7, Figure 6). The enhanced performance confirms H2, showing that higher SNR improves both estimation accuracy and detection reliability. The consistent superiority of KDE reinforces H1, while the improved detection and reduced false alarm rates further support H3, indicating more efficient spectrum hole identification in moderate noise environments.

High SNR (10 dB)

In high SNR conditions, all methods showed near-optimal performance. KDE achieved the lowest MSE [0.005] and highest PSD estimate [0.98] (Table 8, Figure 5), with detection probability of 0.995 and false alarm probability of 0.0005 (Table 9, Figure 7). These results reaffirm H1 by demonstrating the effectiveness of non-parametric methods, particularly KDE, in accurately estimating PSD. The substantial improvement over low and medium SNR scenarios validates H2, confirming that higher SNR enhances both estimation and detection metrics. The extremely high detection probability and minimal false alarms strongly support H3, highlighting the capability of non-parametric methods to enable reliable spectrum sensing and cognitive radio decision-making in high-quality signal environments.

Overall, KDE consistently outperforms periodogram and histogram-based methods across all SNR conditions, providing a robust, accurate and reliable framework for PSD estimation and spectrum hole detection in cognitive radio networks. The results demonstrate the practical relevance of non-parametric methods for dynamic spectrum access and efficient utilization of underutilized frequency bands.

H1: Non-parametric spectrum estimation methods can provide more accurate PSD estimates than parametric methods in CRNs with complex and dynamic band occupancy.

The simulation results demonstrate that non-parametric methods, such as KDE, can effectively estimate the PSD of a signal in various spectrum scenarios, including low, medium and high SNR environments. The MSE and detection probability results show that KDE outperforms the other methods, indicating that non-parametric methods can provide accurate PSD estimates in complex and dynamic spectrum occupancy scenarios.

H2: The performance of non-parametric spectrum estimation methods improves with increasing sample size and SNR.

The simulation results show that the performance of non-parametric methods improves with increasing SNR. For example, the MSE of KDE decreases from 0.12 in the low SNR scenario to 0.005 in the high SNR scenario. Additionally, the detection probability of KDE increases from 0.7 in the low SNR scenario to 0.995 in the high SNR scenario. While the sample size is fixed in the simulation, it is expected that increasing the sample size would also improve the performance of non-parametric methods.

H3: Non-parametric spectrum estimation methods can enable cognitive radios to detect spectrum holes with a high possibility of detection and low chance of false alarm.

The simulation results demonstrate that non-parametric methods, such as KDE, can detect spectrum holes with a greater possibility of finding (0.995 in the high SNR scenario) and reduce possibility of false alarm (0.0005 in the high SNR scenario). These results indicate that non-parametric methods can effectively enable cognitive radios to detect spectrum holes and improve spectrum utilization (35).

Limitation

This study has several limitations that should be acknowledged to ensure transparency and to contextualize the interpretation of the findings. Methodologically, the analysis is based on a specific set of detection techniques and evaluation metrics, which may not fully capture performance variations under diverse signal characteristics, non-stationary environments, or alternative modelling assumptions. Contextually, the results are derived from controlled simulation settings with predefined SNR conditions; therefore, the findings may not directly generalize to highly dynamic, real-world spectrum environments where interference patterns, hardware impairments and regulatory constraints vary significantly. From a data perspective, the use of simulated datasets and a limited range of parameter configurations may introduce bias and restrict the representativeness of the observed detection and false alarm probabilities. Additionally, the absence of long-term empirical measurements limits insights into temporal variability and scalability. Recognizing these methodological, contextual and data-related constraints enhances the credibility of the study and provides a clear foundation for future research to validate and extend the findings using broader datasets, real-world deployments and alternative analytical frameworks.

Conclusion

This study evaluated non-parametric spectrum estimation methods for cognitive radio networks, demonstrating their effectiveness in estimating power spectral density under dynamic and noisy spectrum conditions. Among the examined techniques, kernel density estimation consistently achieved lower mean squared error, higher detection probability and reduced false alarm rates across low, medium and high SNR scenarios, highlighting its robustness and reliability. These findings validate non-parametric, data-driven spectrum sensing as a practical solution for efficient dynamic spectrum access where parametric assumptions are unsuitable. However, the analysis is limited to idealized noise conditions and single-user scenarios. Future research should extend this framework to multi-user, wideband and non-stationary environments and integrate adaptive learning mechanisms for real-time cognitive radio deployment.

Future Research Directions

Future work may focus on integrating non-parametric spectrum estimation techniques with machine learning and adaptive inference models to enhance learning and decision-making in dynamic cognitive radio environments. Extending these methods to high-dimensional, time-varying and non-stationary signal models relevant to 5G and IoT systems is another promising direction.

Additionally, evaluating robustness under realistic channel conditions and validating performance through real-time implementations on software-defined radio platforms can further strengthen the practical applicability of these approaches.

Practical Implications

It is recommended to prefer kernel density estimation (KDE) for spectrum sensing applications, as it demonstrates lower mean squared error (MSE) and higher detection probability, particularly under low to moderate signal-to-noise ratio (SNR) conditions. Non-parametric methods should be deployed in dynamic environments where signal statistics are unknown or non-stationary, such as Internet of Things (IoT) systems and dense wireless networks. Furthermore, integrating spectrum estimation techniques with cognitive decision engines can enhance spectrum utilization while ensuring reliable protection of primary users. Finally, computational complexity should be optimized through adaptive parameter tuning and lightweight algorithmic implementations to support real-time deployment of cognitive radio systems.

Abbreviations

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Author Contributions

Kishore Sahoo: conceptualization, data collection, writing - original draft, Sudhansu Sekhar Singh: Supervision, Validation, Review and Editing.

Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability

Data will be shared by the corresponding author upon reasonable request.

Declaration of Artificial Intelligence (AI) Assistance

I/we used generative AI and AI-assisted technologies in the writing process to generate ideas, improve language for this work.

Ethics Approval

This study did not require ethical approval as it did not involve human subjects or animals.

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