1. INTRODUCTION

1.1 Cognitive Radio Technology

There is a discernible lack of usable spectrum as a result of the cellular services' explosive expansion throughout the continents. In response to the growing need for more bandwidth, communication experts and spectrum regulators are trying to find practical solutions. According to studies, a majority portion of the licensed spectrum is still in sufficiently utilised in different frequency bands and during specific times. Cognitive radio technology has emerged as a optimistic solution to this dilemma. This groundbreaking technology offers a significant shift in the way wireless systems are designed by enabling more efficient and dynamic spectrum usage. Cognitive radios are capable of sensing their environment, adapting to changes in real time, and sharing spectrum resources in a flexible manner. Such systems provide the ability to use radio spectrum more effectively, making it possible to accommodate growing demands without the need for additional spectrum allocation. In addition to cognitive radio, cooperative communication and networking is another advancing technology. It allows wireless devices to connect with each other by sharing communication duties or processing signals collectively. This cooperation enables new forms of space diversity, which helps to mitigate the negative influence of channel fading and enhance the reliability and performance of wireless networks. Together, these technologies offer innovative approaches to resolving the challenges of spectrum scarcity while enhancing the overall efficiency and resilience of wireless communication systems [1].

1.2 Definition of Cognitive Radio (CR)

Mitola and Maguire described "radio etiquette" as the set of frequency bands, air interfaces, protocols, and temporal and geographical patterns that control radio spectrum usage in their pioneering book. Software-defined radio (SDR) technology, which is similar to having a car with an engine that can be customised, is the foundation of cognitive radio. However, by including an extra layer of intelligence, CR goes one step further. It continuously observes its environment, assesses what’s happening—like detecting signals or interference—and modifies its behavior accordingly. If the present frequency becomes too congested, this may include finding an entirely new one to use or altering the way it communicates (modulation schemes). The ultimate goal of cognitive radio is to ensure reliable communication independent of location or spectrum congestion, while also making the most use of the limited radio spectrum by detecting and taking advantage of gaps that would otherwise be squandered [2]. Cognitive radio is essentially a very intelligent, self-aware communicator that is always learning, adjusting, and figuring out how to keep you connected in a congested and dynamic wireless environment.

Cognitive radio (CR) technology does not primarily aim to expand the availability of spectrum resources but rather focuses on enhancing their efficient utilization. It enables users to intelligently identify and access underutilized spectrum through a process known as spectrum sensing, which detects the presence or absence of licensed users. Once available bands are identified, CR systems perform spectrum management to select the most suitable channel based on current conditions. Furthermore, CR facilitates spectrum sharing, allowing multiple users to coordinate and access the available spectrum in an organized and non-interfering manner. A key feature of CR is its ability to support spectrum mobility, which ensures that secondary users can seamlessly vacate a channel when a licensed (primary) user becomes active, thereby maintaining interference-free communication. Through these capabilities, cognitive radio plays a critical role in maximizing the utility of existing spectrum resources in dynamic wireless environments [3].

Wireless networks based on point-to-point or point-to-multipoint topologies (cellular networks) are given a new paradigm by cooperative communications. Cooperative communication allows users or nodes in a wireless network to collaborate through resource sharing and dispersed transmission and processing. Instead of transmitting information solely from the originating user, collaborating users also participate in relaying the information. This new approach offers significant improvements in capacity and multiplexing gains within wireless networks. Moreover, it provides a form of spatial diversity that mitigates the negative impacts of severe fading. In the next chapter, we will explore how cooperative communication can enhance spectrum sensing decisions through collaboration among cognitive radio users, leading to more accurate and reliable spectrum management [4].

The utilization of the radio spectrum has increased dramatically in recent years due to the surge in demand for wireless devices. The wireless communication industry is changing quickly as a result of this increase in demand. But the quick development of these technologies has also brought about a problem: there is less space for new applications as the radio frequency gets more saturated. A novel strategy known as dynamic spectrum access (DSA) was created to deal with this problem. DSA makes it possible to use the spectrum more intelligently and adaptably, guaranteeing that it can accommodate users' expanding demands.

The foundation of DSA is cognitive radio (CR), a technology that enables users to access the spectrum intelligently. The DSA policy permits secondary users (SUs), who do not have priority, to use the same spectrum resources as main users (PUs), who own the primary rights to the spectrum. Here, cognitive radio is crucial because it can detect "empty" or underutilised spectrum gaps and enable effective use of them. This lessens waste and helps the spectrum reach its full potential. Cognitive radio can function in three primary ways, which are sometimes called paradigms: underlay, overlay, and interweave. When the primary users aren't actively using the spectrum, CR users swiftly fill in to use it. This is known as the interweave paradigm. This prevents primary and secondary users from interfering with one another. The overlay paradigm has a more cooperative stance, allowing CR users to utilise a portion of the spectrum while simultaneously assisting primary users, frequently by employing sophisticated methods to reduce interference. Finally, in the underlay paradigm, CR users share the same frequency bands as primary users but only transmit at very low power levels to ensure they don't disrupt the primary users' signals. This is like whispering in a crowded room so you don't disturb others. Each of these paradigms has its own strengths, but they all share a common goal: to make the most of the limited radio spectrum while ensuring that everyone—primary and secondary users alike—can communicate effectively. By using cognitive radio and dynamic spectrum access, we can create a more efficient and flexible wireless world, where the spectrum is shared fairly and used wisely [5].

This study examines the consequences of interference and the spectrum efficiency of underlay CR transmission while observing the larger spatial footprint of parallel transmission. Few studies have used underlay transmission to evaluate spectral efficiency (SE), despite the fact that underlay CR transmission has been thoroughly investigated. Underlay CR transmission over Rayleigh fading channels increases capacity. The SE analysis was evaluated using the Rayleigh fading scenario. System-level capacity is studied using a CR network with an average interference power (AIP) constraint. Under fading conditions, a CR gearbox is used to increase capacity. These experiments demonstrated the benefits of spectrum sharing with a primary receiver interference restriction. Nevertheless, the spatial component of radio waves is often overlooked in these investigations. We must take into account the impacted regions that result in radio transmission interference; this idea is called area spectral efficiency (ASE).

In wireless communication, one of the key ways to measure how effectively the spectrum is being used is through a metric called Area Spectral Efficiency (ASE). When we look at cognitive radio (CR) systems operating in the underlay mode—where secondary users (SUs) share the spectrum with primary users (PUs) at low power levels—we evaluate their performance using Global Area Spectral Efficiency (GASE), especially over challenging environments like Rayleigh fading channels. What we've found is that CR systems can actually improve spectral efficiency (SE) compared to traditional point-to-point (P2P) transmissions, but only if the distance between interfering links is much greater than the distance of the intended communication link. If not, the overall SE and energy efficiency (EE) can take a hit. Interestingly, if the density of secondary transmitters isn't set correctly, the underlay CR system might perform worse than a simple P2P transmission. This is because having too many SUs increases energy consumption, especially during spectrum sensing and identification. On the flip side, higher throughput—meaning more data being transmitted—tends to improve energy efficiency. To tackle this, researchers have focused on cooperative spectrum sensing (CSS), which reduces the number of SUs needed for sensing, thereby cutting down on energy use. To further boost energy efficiency, it's recommended to optimize the detection threshold in CSS and test it across different fading channel conditions. In short, while cognitive radio offers great potential for better spectrum use, it's a balancing act. Getting the most out of it requires careful tuning of system parameters, like the number of secondary users and detection thresholds, to ensure both spectral and energy efficiency are maximized [6].

A generalized fading distribution is frequently used to describe different fading circumstances when wireless communication involves small-scale signal variations. The α-μ fading distribution is one such model that accounts for the impacts of non-line-of-sight (NLOS) situations and multipath fading. Here, α represents the non-linearity of the propagation environment, while μ indicates how multipath waves cluster together. This distribution is versatile and can be applied to both small-scale and large-scale fading scenarios, making it highly useful for real-world networks where fading is often non-homogeneous.

Another fading model, η-μ, is used when the primary user (PU) signal shows progressive oscillations alongside NLOS components. The α-μ distribution has recently drawn a lot of interest for studying cognitive radio networks, especially in cooperative spectrum sensing (CSS) and energy harvesting systems. Researchers have developed closed-form mathematical methods to calculate outage probabilities in α-μ fading environments and have explored its impact on CSS networks using both soft and hard decision rules [7].

Additionally, advanced analytical models based on contour integrals and Bayesian energy detectors have been proposed to improve spectrum sensing in generalized fading environments, especially for single secondary users (SUs). Recent studies have also focused on optimizing CSS networks over generalized fading conditions, ensuring better performance and reliability in diverse wireless communication scenarios. These advancements highlight the importance of tailored fading models in designing robust and efficient cognitive radio systems [1].

2. LITERATURE REVIEW

The analysis of energy detection-based spectrum sensing in fading environments is pivotal for enhancing the reliability and efficiency of cognitive radio systems. Nallagonda, Prathyusha, and Ranjeeth (2022) focus on the generalized α−μ fading model to study its effects on spectrum sensing performance, emphasizing its application in environments with non-linear and non-Gaussian interference. Their work is significant for understanding complex fading channels like η-μ environments, which are crucial for characterizing real- world propagation scenarios in wireless communication. While the α−μ model offers significant flexibility, it does not fully capture non-line-of-sight (NLOS) conditions with asymmetric in-phase and quadrature components—scenarios often encountered in urban and indoor environments. To address this, the η−μ fading model has been proposed in the literature as an alternative that characterizes such conditions more accurately. The η−μ model, originally introduced by Yacoub, models the envelope of a signal as a result of multipath waves clustered in two components with unequal power. It includes several classical models as special cases and is suitable for environments with varying degrees of scattering and power imbalance. Despite its relevance, limited research has been conducted on analyzing energy detection performance under η−μ fading, especially when considering practical imperfections such as channel errors. This presents a critical research gap. To bridge this gap, the present work extends the analytical framework developed for the α−μ model to the η−μ fading scenario. By addressing the presence of channel errors, this study provides valuable insights into designing robust spectrum sensing systems that can operate efficiently in challenging conditions [8].

Ghasemi and Sousa (2007) expand on this by presenting collaborative spectrum sensing in fading channels, showcasing how cooperation among users can mitigate the adverse effects of fading, improve detection accuracy, and enhance opportunistic spectrum access. This collaborative approach is particularly useful for η-μ fading channels, where diverse fading characteristics can be better handled through shared sensing data. The study assumed classical fading conditions (such as Rayleigh and log-normal shadowing) and showed that cooperation significantly enhances detection probability while reducing false alarms. However, the authors acknowledged that fading can still severely impact performance, particularly in non-line-of-sight (NLOS) environments. To address this, the η−μ fading model offers a more generalized and realistic representation. This model accounts for the presence of two multipath clusters with unequal powers in the in-phase and quadrature components, making it highly suitable for NLOS conditions. However, limited work has been done to extend energy detection analysis to η−μ fading channels, especially under conditions involving channel estimation errors or varying detection thresholds [9].

Urkowitz's (1967) seminal work on energy detection serves as the foundation for these advanced analyses, offering a theoretical framework for detecting unknown signals in noise. The relevance of his work extends to modern applications involving complex fading models like η-μ, where the randomness of channel conditions poses significant challenges. Urkowitz's model assumes that the signal to be detected is deterministic but unknown, and that the noise is Gaussian with known statistical properties. Under these idealized conditions, the energy detection problem was elegantly modeled as a binary hypothesis test, and the key performance metrics were expressed using the Marcum Q-function and the incomplete gamma function. This analysis laid the groundwork for the use of ED in radar and, more recently, in cognitive radio (CR) systems [10].

Digham, Alouini, and Simon (2007) build on this by deriving critical performance metrics for energy detection in fading channels, including probabilities of detection and false alarms. Their contributions are particularly applicable to η-μ fading scenarios, where precise performance evaluation is crucial for system design and optimization. Their work demonstrated that fading has a significant impact on detection performance—degrading it considerably compared to the AWGN case—and emphasized the need for incorporating accurate channel models in detection analysis. Although their study focused primarily on Rayleigh and Nakagami-m models, it paved the way for later research to consider more generalized and flexible fading models [11].

Bhandari and Joshi (2018) explore the integration of cognitive radio technology in 5G networks, focusing on dynamic spectrum access and efficient spectrum utilization. The study highlights the importance of spectrum sensing in enabling 5G networks to adapt to heterogeneous environments, including η-μ fading conditions, which are common in urban and dense deployments. Building upon the practical insights from Bhandari and Joshi's work, the present study explores the application of the η−μ fading model in the context of energy detection for cognitive radios, offering a more accurate representation of 5G environments characterized by non-line-of-sight (NLOS) propagation, multipath clustering, and unequal signal components. By enhancing the underlying mathematical framework of energy detection with the $\eta-\mu$ model, this work contributes to the development of more adaptive and reliable spectrum sensing systems suited for next-generation wireless networks [12].

The collective contributions of these studies provide a solid foundation for understanding spectrum sensing in η-μ fading environments. These findings are instrumental in designing cognitive radio systems capable of dynamic spectrum management, enhancing the reliability of communication in varying channel conditions, and supporting advanced applications. However, most existing models fall short in capturing the complexities of non-line-of-sight (NLOS) and asymmetric multipath environments typically encountered in modern wireless systems. This gap motivates the current work, which leverages the $\eta-\mu$ fading model—a more generalized and flexible statistical representation—to provide a deeper and more realistic analysis of energy detection performance in cognitive radio networks. By incorporating channel errors and practical impairments, this study aims to enhance the theoretical foundation and practical reliability of spectrum sensing in next-generation communication systems.

3. OBJECTIVE OF THE PROJECT

This project aims to address some of the most significant issues facing contemporary wireless communication, especially as we enter the 5G and beyond period. In order to satisfy the increasing needs for quicker, more dependable connectivity, the emphasis is on boosting overall system performance, optimizing dynamic spectrum management, and better utilizing available frequency bands. Implementing Cognitive Radio (CR) technology, which enables more intelligent and adaptable use of the radio spectrum, is at the core of this endeavour. The project intends to facilitate the smooth sharing of both licensed and unlicensed spectrum by utilising dynamic spectrum access (DSA) and sophisticated spectrum sensing techniques. Making sure secondary users (SUs), such as networks or devices without main access, may utilize available spectrum without interfering with primary users (PUs), who possess the licensed rights, is crucial in this situation. The project's goal is to optimize spectrum efficiency while preserving the quality of service for all customers by creating plans for SUs to opportunistically utilize unused spectrum gaps. To put it briefly, the goal is to build a wireless ecosystem that is more intelligent and flexible in order to meet the expectations of the connected world of the future.

Key areas of focus will include the creation of adaptive algorithms capable of detecting spectrum gaps in real-time and optimizing spectrum usage. The project aims to enhance performance indicators such as throughput, latency, and reliability to ensure smooth communication in 5G networks. The difficulties presented by dense user populations, the Internet of Things' (IoT) enormous connectivity demands, and the requirement for ultra-reliable low-latency communication (URLLC) will also be covered. These issues are all critical to the effective implementation of 5G technology.

In order to increase device battery life and lower the network's overall energy consumption, the project will also investigate energy-efficient spectrum detecting and transmission methods. Detection thresholds and spectrum management techniques will be optimized to reduce interference between primary and secondary users. In order to further improve system performance, the research will also investigate how Cognitive Radio may be integrated with 5G enablers including massive MIMO, beamforming, and millimeter waves (mm Wave).

The application of artificial intelligence and machine learning to enhance spectrum sensing, allocation, and mobility management decision-making will be investigated. Another top objective is making sure the CR framework is scalable, since this will be required to accommodate the growing connectivity requirements of 5G networks and prepare the system for the development of 6G. In the end, this project will contribute to the advancement of cognitive radio systems' role in enhancing 5G networks' sustainability and performance while opening the door for further advancements in wireless communication technology.

4. COGNITIVE RADIO

Here, we will explore the concept of spectrum sensing, the challenges it presents, the various methods employed for spectrum sensing, and the different architectures used in Cognitive Radio (CR) systems. Our focus will be primarily on cooperative spectrum sensing and the various possible architectures, as our work specifically centers around one of these architectures. Additionally, we will review several fusion rules and discuss the concept of censoring as a technique to enhance performance in the presence of fading.

An essential part of Cognitive Radio (CR) communications is spectrum sensing. By detecting accessible spectrum, also known as spectrum gaps, it allows the CR system to adjust to its surroundings. Determining whether Primary Users (PUs) are sending data inside the CR's range is the most accurate way to assess spectrum availability. The inability to physically measure the communication channel between the primary transmitter and its receiver, however, is a major obstacle for CR systems.

Due to this limitation, most spectrum sensing algorithms are designed to detect signals transmitted by primary users based on the local observations made by the CR. These algorithms generally depend on the CR’s ability to monitor its environment and analyze received signals to determine if a channel is occupied or available. By detecting primary signals, CR systems can avoid interfering with primary users while efficiently utilizing unused spectrum for secondary (unlicensed) users. This enables dynamic spectrum access, ensuring spectrum resources are used optimally without disrupting the operation of licensed spectrum users.

4.1 Challenges

Spectrum sensing in Cognitive Radio networks is impacted by a variety of sources of uncertainty, such as device and network-level uncertainties and channel randomisation. For spectrum sensing to function consistently, especially under the most severe conditions, these uncertainties require a higher detection sensitivity. To ensure accurate detection and avoid interference that could emerge from these various uncertainties, this enhanced sensitivity is necessary.

4.1.1 Channel Uncertainty

Channel uncertainty occurs when factors like as fading or shadowing make it difficult for cognitive radios (CRs) to accurately detect signals from principal users (PUs). A poor signal in these circumstances does not always indicate that the primary system is outside the interference range of the secondary user. On the other hand, physical barriers such as buildings or geography may block or significantly reduce the signal. This ambiguity complicates spectrum sensing since CRs must differentiate between a faded or darkened primary signal and actual unused spectrum. Higher detection sensitivity is required to accurately determine spectrum availability due to the primary user's unclear received signal power. Extreme fading can make it difficult for a single cognitive radio that uses local sensing to reach the necessary sensitivity within the permitted sensing time (Tp), which would lower the accuracy of detecting spectrum occupancy. Unintentional interference with the principal users may result from this.

The Hidden Terminal Problem is one of the main problems related to channel uncertainty. This issue arises when shadowing or severe multipath fading prevents a CR from detecting a PU. In this case, the CR might incorrectly assume that the spectrum is free and attempt to use it, causing interference with the PU. The interference arises because the CR believes the channel is idle, when it is actually being used by the primary user.

4.1.2 Hidden Terminal Problem

One of the biggest challenges in spectrum sensing, particularly in cognitive radio (CR) networks, is the Hidden Terminal Problem. Imagine a scenario where a CR device is blocked by obstacles or experiences heavy signal fading, making it unable to detect an active primary user (PU) on the channel. In such cases, the CR might wrongly assume the channel is free and attempt to use it, even though the PU is still transmitting. This can lead to unwanted interference and disrupt communication. The problem gets trickier when cognitive radios are "hidden" from each other due to obstacles in both the sensing and reporting channels. For example, if CR3 is blocked in the sensing channel and CR1 is blocked in the reporting channel, the information CR3 receives—and the data CR1 sends—might be inaccurate. This can cause CR3 to mistakenly believe the channel is available, even though CR1 is actively using it. Such errors in spectrum sensing can lead to inefficient spectrum use and increased interference, making it a critical issue to address in CR networks.

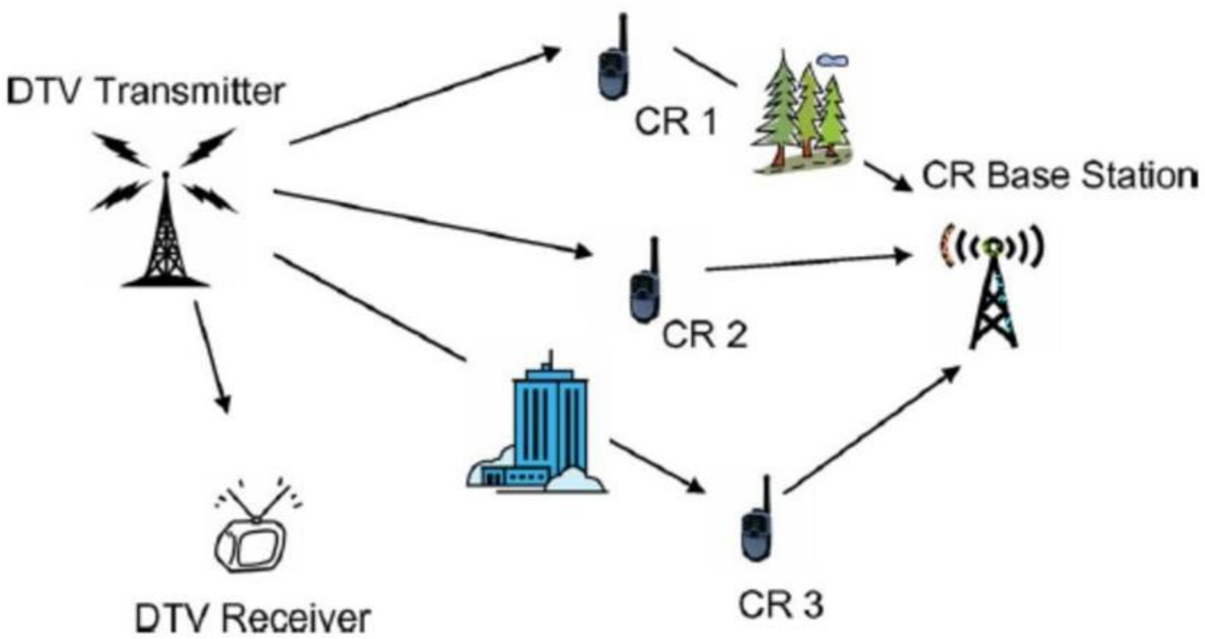

Figure 4.1 HIDDEN TERMINAL PROBLEM

One well-known spectrum sensing issue, particularly in cognitive radio (CR) networks, is the Hidden Terminal Problem. It occurs when a CR device cannot detect an active primary user (PU) on the channel due to significant signal fading or obstructions like buildings. In such cases, the CR might mistakenly think the channel is free and try to use it, even though the PU is still transmitting. This can lead to interference and disrupt communication for both the PU and the CR.

The problem becomes more complicated when CR devices are "hidden" from each other due to obstacles in both the sensing and reporting channels. For example, if CR3 is blocked in the sensing channel and CR1 is blocked in the reporting channel, the information CR3 receives—and the data CR1 sends—might be inaccurate. This can cause CR3 to wrongly assume the channel is idle, even though CR1 is actively using it. Such errors in spectrum sensing can lead to inefficient spectrum use and increased interference.

This issue is especially problematic when relying on a single CR device to detect primary users, as it increases the risk of missing important signals. To tackle this, techniques like cooperative spectrum sensing can be used. In this approach, multiple CR devices work together, sharing their sensing data to create a more accurate picture of the spectrum. By collaborating, they can reduce the chances of interference and improve the overall reliability of spectrum sensing, ensuring a smoother experience for both primary and secondary users.

4.1.3 Noise Uncertainty

Understanding the noise power is crucial for precise signal detection in cognitive radio networks, but this is frequently easier said than done. Measurement of noise power is not always straightforward in real-world situations because of things like calibration mistakes or variations in thermal noise brought on by temperature changes. Spectrum sensing is a challenging operation because of these uncertainties, particularly when energy detection is used. For instance, a weak primary signal may have a Signal-to-Noise Ratio (SNR) so low that it is nearly impossible to tell it apart from the noise. Because the fundamental signal is effectively "lost" in the noise, it becomes extremely difficult to identify. However, there’s a potential solution: feature detectors. Unlike energy detection, which struggles with noise uncertainty, feature detectors focus on identifying unique characteristics or patterns in the signal itself. This allows them to tell the difference between the actual signal and the noise, even when noise levels are unpredictable or constantly changing. Because of this, feature detectors are much more robust in challenging environments, offering a more reliable way to detect primary signals and avoid interference. In short, while noise uncertainty poses a significant challenge, feature detectors provide a smarter, more resilient approach to spectrum sensing.

5. AGGREGATE-INTERFERENCE UNCERTAINITY

The inclusion of additional secondary systems in several technical sectors complicates spectrum sensing. This is because many cognitive radio networks (CRNs) sharing the same licensed frequency range may cause disputes and interference. One of the primary challenges is the uncertainty around aggregate interference, which arises from the unknown total of secondary systems, their locations, and the possible methods in which they could interact. Even if the primary system is outside the immediate range of interference, the combined effect of multiple secondary systems can still cause significant disruption. This uncertainty forces secondary systems to use more sensitive detectors, as they need to detect and avoid interfering with primary systems that may be farther away. However, there's a potential workaround: energy detection. By enabling nearby CRNs to detect each other and coordinate their use of the spectrum, they can avoid overlapping on the same band at the same time. This helps reduce aggregate interference and, in some cases, allows for less stringent detection sensitivity requirements. In essence, while the growing number of secondary systems complicates spectrum sensing, smart coordination and detection techniques can help manage interference and keep the spectrum running smoothly. Alternatively, system-level coordination among different CRNs can help manage aggregate interference at the cost of increasing complexity and implementation expenses. For example, secondary systems can moderate access and manage interference with a common control channel, which standardizes communication and coordination. However, this approach may reduce the cost benefits typically associated with spectrum sensing solutions.

Despite these challenges, the need for system-level coordination may be relaxed by adjusting detection sensitivity during initial deployments, allowing spectrum sensing to continue operating effectively without resorting to costly coordination. By balancing sensitivity and coordination, cognitive radio networks can efficiently manage interference while minimizing operational costs.

6. ENERGY DETECTION

Energy detection is the optimum technique to apply if the CR users are unaware of the nature of the primary user signal. In our work, we deal with conventional energy detectors.
Conventional energy detector
A bandpass filter, a squaring device, an integrator, and a threshold comparator make up a traditional energy detector. The conventional energy detector is depicted in Fig. 5.1.

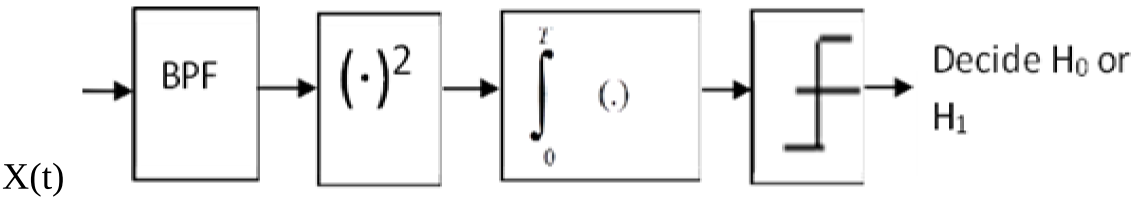

Figure 6.1 BLOCK DIAGRAM OF CONVENTIONAL ENERGY DETECTOR

The following notations will be used in the subsequent analysis.

- s(t)   : Signal Waveforms
- n(t)   :Noise waveform modeled as a zero-mean white Gaussian random process
- N01 : One-sided noise power spectral density
- $E_s = \int_0^t S^2(t)\,dt$
- γ = E_S/N_{01} : Signal-to-noise ratio(SNR).
- $\overline{\gamma}$: SNR(Average).
- W: One-side band width (Hz), i.e. positive bandwidth of low-pass(LP signal).
- M = TW : Time band width product.
- f_c : Carrier frequency.
- P_d : Probability of false alarm.
- P_m =1-P_d : Missed detection probability.
- H_0 : Hypothesis 0 represented the scenario where no signal is transmitted.
- H_1 : Hypothesis 1 represents the scenario where no signal is transmitted.
- N(μ,σ^2) : A Gaussian variate with mean μ and variance σ^2.
- X_a^2 : Central chi-square variate with **a** degrees of freedom.
- $X_a^2(\beta)$: A non-central chi-square variate with **a** degree of freedom and non-centrality parameter β.

6.1 Energy Efficiency

Energy detection is a widely used technique for spectrum monitoring in cognitive radio networks, especially in environments where fading affects signal strength. To evaluate the efficacy of this strategy in fading environments, simulations are used to analyze important performance measures like detection probability, false alarm probability, and detection delay. These metrics help evaluate the precision and reliability of energy sensing in real-world scenarios. In this study, we examine the energy detection performance in generalized fading channels using a cooperative spectrum sensing (CSS) network based on energy detection. We derive analytical formulas for detection probability under two fading models: α-μ and η-μ, while also considering errors in the reporting channel (R-channel). Additionally, we assess the system's overall performance by evaluating metrics like energy efficiency (EE), total error rate (TER), and network utility function (NUF) for both fading scenarios. By analyzing these factors, we aim to provide a clearer understanding of how energy detection performs in challenging fading environments and how it can be optimized for better reliability and efficiency in cognitive radio networks.

6.2 ED-CSSN Model

Figure 1 depicts a cooperative spectrum sensing (CSS) network with multiple secondary users (SUs), a fusion centre (FC), and a single main user (PU), all of which have a large number of antennas. The method, which ensures accurate and efficient spectrum sensing, consists of three key steps. In order to determine whether the PU signal is there or not, each cognitive radio (CR) device first does an independent spectrum scan. After sensing is finished, the CRs send the information they have gathered to the FC over a specific reporting channel. To determine whether the spectrum is available, the FC lastly examines the aggregated data from each CR. This collaborative path enhances the reliability of spectrum sensing, especially in challenging environments where factors like fading, interference, or hidden terminal problems might affect individual CRs. By leveraging multiple SUs with multiple antennas, the network can achieve more robust and accurate detection, ensuring efficient spectrum utilization while minimizing interference with the primary user.

Ultimately, FC decides regarding PU by utilizing the fusion rule.

The detection and false alarm probabilities are designed as P_d and P_f correspondingly, and their expressions for AWGN are provided in [5,6] as

$$P_d = Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) = \exp(-\gamma)\sum_{n=0}^{\infty}\frac{\Gamma(u+n, \lambda/2)}{n!\Gamma(u+n)} \tag{1}$$

$$P_f = (\mathrm{Y} > \lambda \mid \mathrm{H}_0) = \frac{\Gamma\left(\mathrm{u}, \frac{\lambda}{2}\right)}{\Gamma(\mathrm{u})} \tag{2}$$

Here λ as detection threshold, γ as instantaneous S-channel SNR, $\Gamma(.)$ is the gamma, $Q_u(.,.)$ is known to be Marcum Q-function of u^{th} order and $\Gamma(.,.)$ is gamma functions where they are incomplete.

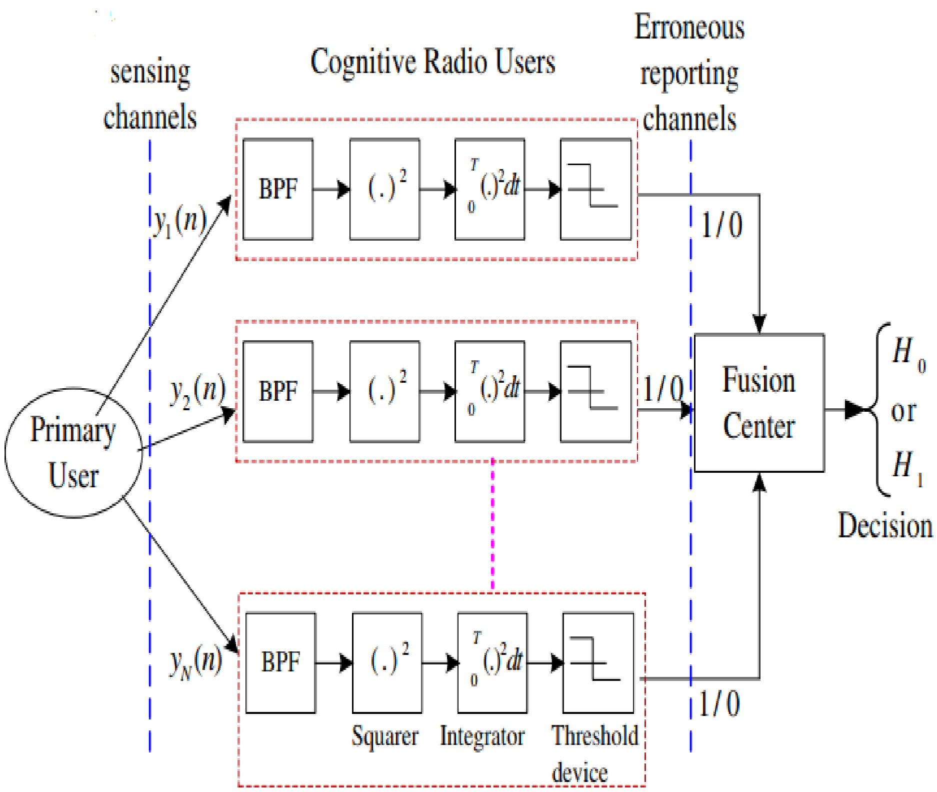

Figure 6.2 THE PROPOSED ED-CSS NETWORK.

7. ARCHITECTURES OF COGNITIVE RADIO NETWORKS

Two different types of architectures are possible for Cognitive Radio Networks (CRNs) with each CR employing spectrum sensing.

1. Centralized sensing networks using cooperative spectrum sensing.
2. Distributed sensing networks using collaborative spectrum sensing.

7.1 Centralized Sensing Networks:

In centralized sensing, a central fusion center plays a key role by collecting spectrum sensing data from multiple cognitive users. Once the data is gathered, the fusion center analyzes it to determine whether the spectrum is available for use. Based on this analysis, it either directly controls the traffic of the cognitive users or shares the combined results with them so they can adjust their actions accordingly. This centralized approach ensures sensing data with one another before sending it to the fusion center, fostering collaboration. In the other approach, users send their data directly to the fusion center without exchanging information among themselves. Both methods aim to improve the accuracy and reliability of spectrum sensing, but the choice between them depends on the network's design and requirements. By leveraging centralized sensing, cognitive radio networks can make smarter, more informed decisions about spectrum availability, reducing interference and optimizing resource use.

(a) Partially Cooperative Network

Every CR user independently senses the spectrum and sends the fusion centre its sensing data. In this case there is no sharing of information amongthe CR users, that is why it is called as partially cooperative network.
coordinated and efficient spectrum usage. Centralized sensing can be further divided into two categories, depending on how cognitive users interact with each other.

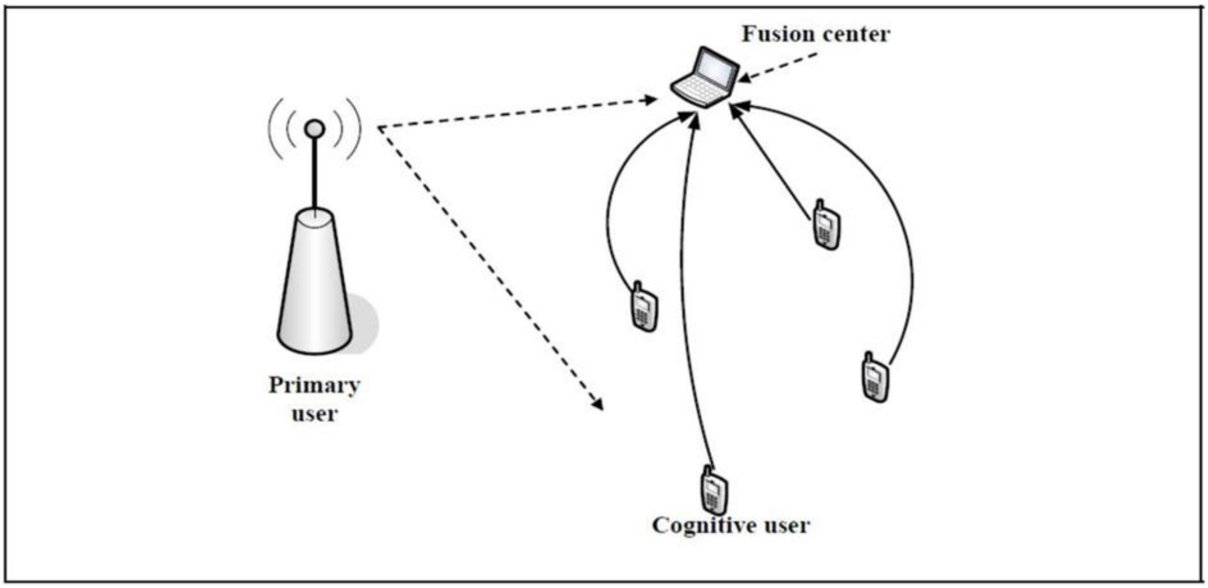

Figure 7.1 PARTIALLY COOPERATIVE NETWORK

(b) Totally Cooperative Network

In this approach, sensing information is mutually transmitted by cognitive users, who then convey it to the fusion centre. In this case, information is shared between CR users and FC users. It is referred regarded as a completely cooperative network for this reason.

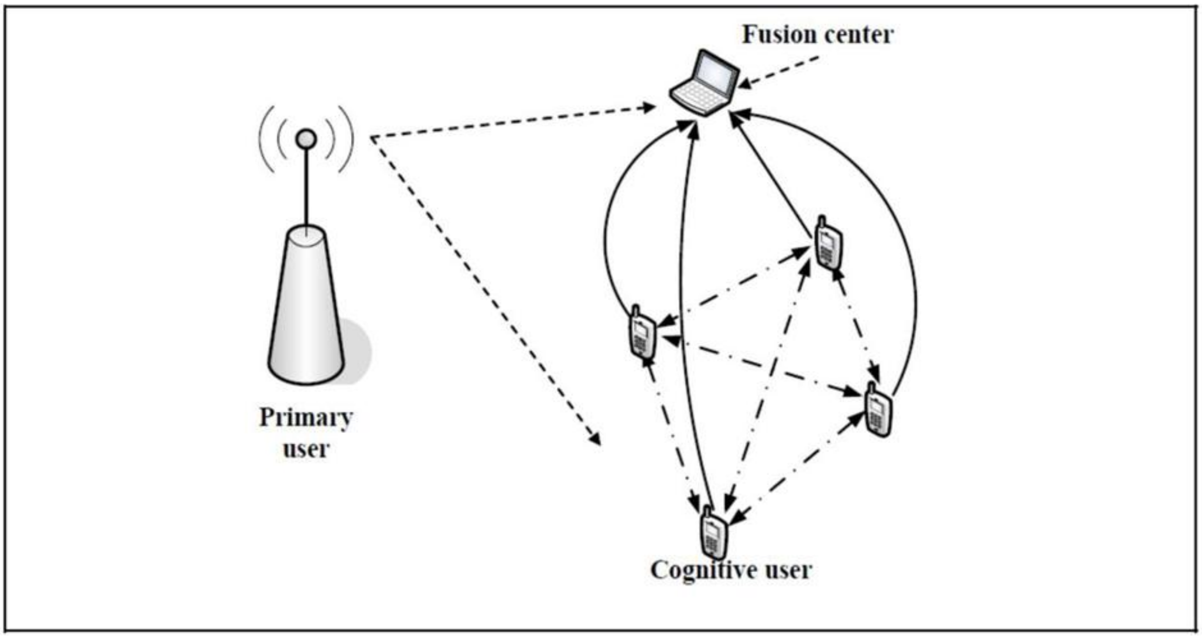

Figure 7.2 FULLY COOPERATIVE NETWORK

7.2 Distributed Sensing Networks:

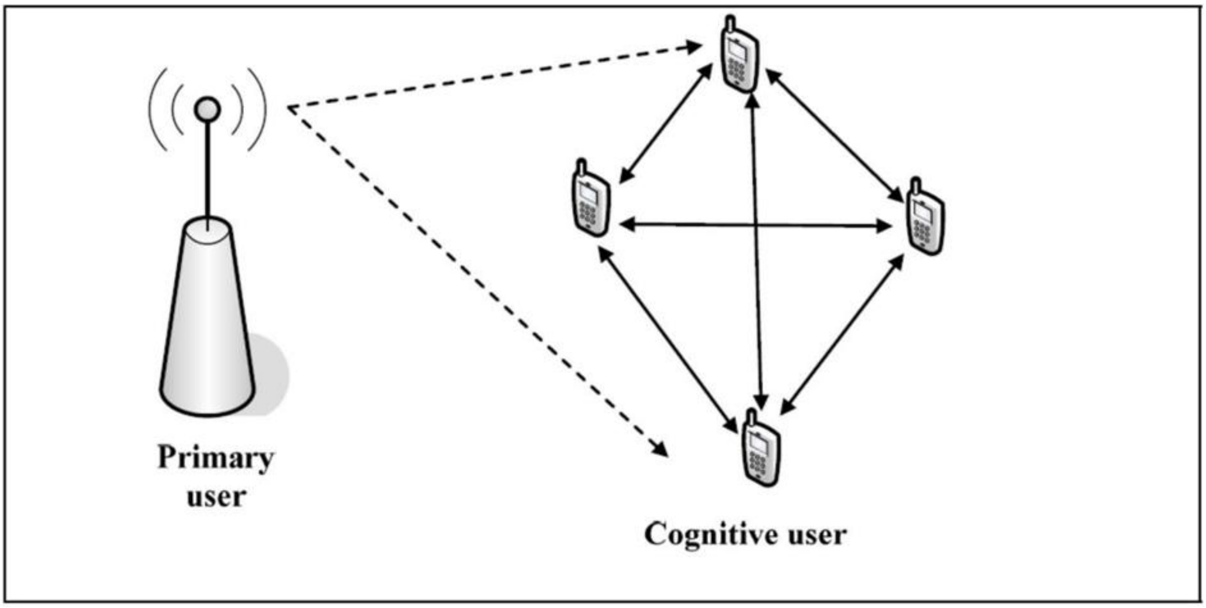

Figure7.3 DISTRIBUTED SENSING NETWORK

In distributed sensing, cognitive users exchange information with one another but independently make decisions about which parts of the spectrum they can access. This approach offers advantages, as it eliminates the need for a central backbone infrastructure, allowing for more flexibility and scalability in spectrum management. Among the above architectures described we mainly focus on partially cooperative networks of centralized sensing in our subsequent sections.

7.3 Cooperative Spectrum Sensing

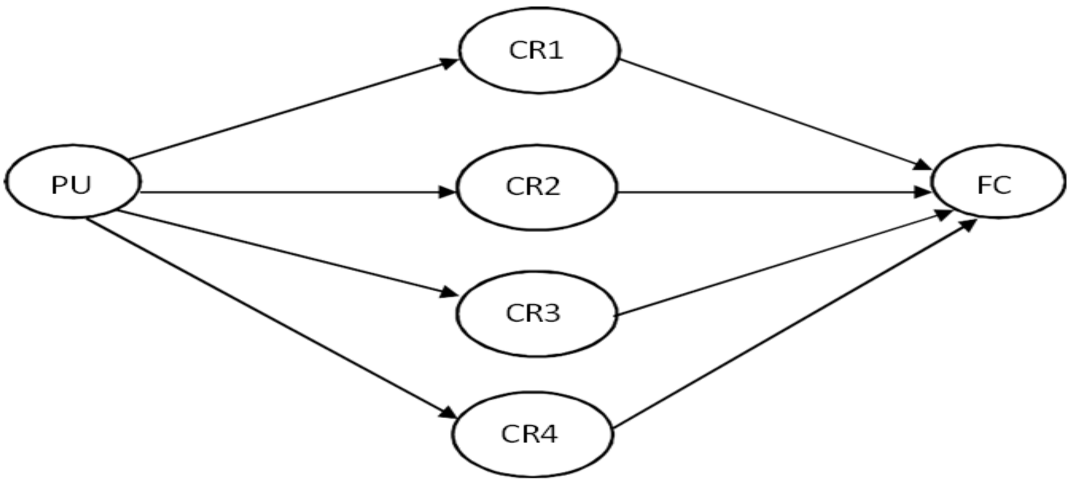

Figure 7.4 BLOCK DIAGRAM OF COOPERATIVE SPECTRUM SENSING

Cooperative spectrum sensing implements the following steps in a network consisting of one Primary User (PU), four Cognitive Radios (CRs), and a Fusion Center (FC):

• Local spectrum sensing is carried out independently by each CR, which then produces a binary decision indicating whether the primary user is active or not.

• These individual conclusions are then transmitted to a centralized receiver, known as the FC.

• Here the final decision regarding existence or nonexistence of PU, the Fusion Centre compiles the findings from each CR.

As a data fusion rule for cooperative networks, each participant cognitive radio (CR) in the cooperative spectrum sensing technique mentioned above makes a choice based on its local observation and then sends a single bit of its binary judgement to a shared receiver. The process of combining these 1-bit evaluations at the common receiver using fusion logic is called decision fusion, or hard decision together. Sending the real observation values to the shared receiver instead of the 1-bit option is another method for cooperative spectrum sensing. It's called "soft decision combining," and it usually works better than "hard decision combining" Soft decision combining works well, but sending 1-bit decisions requires a low-bandwidth control channel. The reporting channels in the CRs and the receiver, however, may dim and shade in real-world scenarios, which could reduce the conveyed sensing data's accuracy. For instance, due to fading and noise, a CR reporting the presence of a principal user (PU) with a value {1} may be misinterpreted by the common receiver as indicating no PU existence. As a result, problems with the reporting channels may negatively impact cooperative spectrum sensing's overall effectiveness.

7.4 Fusion rules

Various rules can be used on the censored data collected at the fusion centre. Those rules are listed as under. Here u1, u2, u3,…uN represent the decisions sent by 'N'CRs to a fusion centre (FC) where 'N' is the number of CRs and u0 is the final decision taken by FC.

1. AND logic:

Fusion centre takes decision in favour of H1 if all CR decisions are in favour of H1. This can be expressed as follows.

2. OR logic:

According to this rule fusion centre's final decision will be in favour of H1 even if atleast oneof all the CRs decision is in favour of H1.

Majority logic:

As per this logic the decision will be in favour of H1 if the majority of the CRs decisions are in favour of H1 and it will be H0 if majority of the CRs are in favour of H0. FC takes a random decision when half of the CR decisions are in favour of H1 and the remaining half of the CR decisions are in favour of H0. This can be explained by the following equation.

7.5 $\alpha - \mu$ Fading Channel

PDF expression for α-μ fading is;

$$f_\gamma(\gamma) = \frac{\alpha\mu^\mu}{2\Gamma(\mu)\bar{\gamma}}\left[\frac{\gamma}{\bar{\gamma}}\right]^{\frac{\alpha\mu}{2}-1}\exp\left(-\mu\left[\frac{\gamma}{\bar{\gamma}}\right]^{\frac{\alpha}{2}}\right) \tag{3}$$

The following expression is used to determine the P_d expression for any fading channel.

$$P_d(\gamma) = \int_0^\infty Q_u\left(\sqrt{2\gamma}, \sqrt{\lambda}\right) f_\gamma(\gamma)\, d\gamma \tag{4}$$

Equation (3) can be substituted into equation (4), yielding the following P_d final expression under the α-μ fading channel:

$$P_d = \sum_{n=0}^{\infty}\frac{\Gamma(u+n,\lambda/2)}{n!\Gamma(u+n)}\int_0^\infty \frac{\alpha\mu^\mu\gamma^n}{2\Gamma(\mu)\bar{\gamma}}\left[\frac{\gamma}{\bar{\gamma}}\right]^{\frac{\alpha\mu}{2}-1}\exp\left(-\gamma-\mu\left[\frac{\gamma}{\bar{\gamma}}\right]^{\frac{\alpha}{2}}\right)d\gamma \tag{5}$$

The above equation can be further arranged as;

$$P_d = \frac{\alpha\mu^\mu}{2\Gamma(\mu)\bar{\gamma}}\sum_{n=0}^{\infty}\frac{\Gamma(u+n,\lambda/2)}{n!\Gamma(u+n)}\int_0^\infty\left[\frac{\gamma}{\bar{\gamma}}\right]^{\frac{\alpha\mu}{2}+n-1}\exp\left(-\gamma-\mu\left[\frac{\gamma}{\bar{\gamma}}\right]^{\frac{\alpha}{2}}\right)d\gamma \tag{6}$$

Substituting $\left(\frac{\gamma}{\bar{\gamma}}\right)^{\frac{\alpha}{2}} = x$ => $d\gamma = \frac{2}{\alpha}\bar{\gamma}x^{\frac{2}{\alpha}-1}dx$, we can obtain as;

$$P_d = \frac{\mu^\mu}{\Gamma(\mu)}\sum_{n=0}^{\infty}\frac{\Gamma(u+n,\lambda/2)\bar{\gamma}^{n}}{n!\Gamma(u+n)}\int_0^\infty x^{\mu+\frac{2n}{\alpha}-1}\exp\left(-\mu x+\bar{\gamma}x^{\frac{2}{\alpha}}\right)dx \tag{7}$$

Using

$$\int_0^\infty x^{p-1}\exp\left(-qx+rx^s\right)dx = \left(2\Pi\right)^{\frac{1-s}{2}} s^{p-1/2}q^{-p}$$
$$G_{1,s}^{s,1}\left[\frac{\left(q/s\right)^s}{r}\,\Big|\, \begin{matrix} 1 \\ p/s,\ldots..\left(p+s-1\right)/s \end{matrix}\right] \tag{8}$$

By contrasting equations (7) and (8), we can formulate it as

$$p=\mu+\frac{2n}{\alpha}, q=\mu, r=\bar{\gamma}, s=2/\alpha$$

Following simplification, the α-μ fading channel's final expression for P_d is as follows:

$$P_d = \frac{\mu^\mu}{\Gamma(\mu)}\sum_{n=0}^{\infty}\frac{\Gamma\left(u+n,\lambda/2\right)\bar{\gamma}^{-n}}{n!\,\Gamma\left(u+n\right)}\left(2\pi\right)^{(1/2-1/\alpha)}\left(2/\alpha\right)^{\mu+2n/\alpha-1/2}\mu^{-\mu-2n/\alpha}$$
$$G_{1,\frac{2}{\alpha}}^{\frac{2}{\alpha},1}\left[\frac{\left(\frac{\mu\alpha}{2}\right)^{\frac{2}{\alpha}}}{\bar{\gamma}}\,\Big|\, \begin{matrix} 1 \\ \frac{\alpha\mu+2n}{2},\ldots.\frac{\alpha\left(\mu-1\right)}{2}+\left(n+1\right) \end{matrix}\right] \tag{9}$$

7.6 $\eta-\mu$ Fading Channel

The envelope of η-μ fading involves of two components (in-phase and quadrature) and it is given as;

$$r^2=\sum_{i=1}^{p}\left(x^2+y^2\right) \tag{10}$$

Analytically η and μ are calculated as;

$$\eta=\frac{\sigma_x^2}{\sigma_y^2}$$
$$\mu=\frac{E^2(\mathrm{r}^2)}{2\,\mathrm{V}(\mathrm{r}^2)}\left[1+\left(\frac{H}{h}\right)^2\right] \tag{11}$$

Where

$$h=\left(2+\eta^{-1}+\eta\right)/4$$
$$H=\left(\eta^{-1}+\eta\right)/4 \tag{12}$$

For η-μ fading, CDF and PDF expressions are given as;

$$f_{\gamma}(\gamma_s)=\frac{\sqrt{\Pi}h^{\mu}}{\Gamma(\mu)}\left[\frac{\mu}{\overline{\gamma_s}}\right]^{\mu+\frac{1}{2}}\left[\frac{\gamma_s}{H}\right]^{\mu-\frac{1}{2}}\exp\left(-\frac{2\mu h\gamma_s}{\overline{\gamma_s}}\right)\tau_{\mu-\frac{1}{2}}\left(\frac{2\mu h\gamma_s}{\overline{\gamma_s}}\right) \tag{13}$$

$$F_{\gamma}(\gamma_s)=\frac{\sqrt{\Pi}}{\Gamma(\mu)}\sum_{j=0}^{\infty}\frac{H^{2j}g\left(2\mu+2j,\frac{2\mu h\gamma_s}{\overline{\gamma_s}}\right)}{j!\Gamma\left(\mu+j+\frac{1}{2}\right)2^{2\mu+2j-1h^{\mu+2j}}} \tag{14}$$

where

$$g(a,y)=\int_0^y t^{a-1}\exp(-\mathrm{t})\,\mathrm{dt}$$

denotes lower incomplete gamma function.

The expression for η-μ fading channel is computed using by substituting eq. (14) in eq. (9), final equation of P_d under η-μ fading channel is calculated as;

$$P_{d,j}^{\eta-\mu}=A\sum_{v=0}^{\infty}\frac{\Gamma\left(\mu+v,\frac{\lambda}{2}\right)}{\Gamma(\mu+v)v!}\int_0^{\infty}\gamma_s^{v+\mu-\frac{1}{2}}\exp\left(-\left[1+\frac{2\mu h}{\overline{\gamma_s}}\right]\gamma_s\right)\left(\frac{2\mu h\gamma_s}{\overline{\gamma_s}}\right)\tau_{\mu-\frac{1}{2}}d\gamma_s \tag{15}$$

were

$$f_{\gamma}(\gamma_s)=\frac{\sqrt{\Pi}h^{\mu}}{\Gamma(\mu)}\left[\frac{\mu}{\overline{\gamma_s}}\right]^{\mu+\frac{1}{2}}\left[\frac{1}{H}\right]^{\mu-\frac{1}{2}} \tag{16}$$

Using [9], finally, we get;

$$P_{d,j}^{\eta-\mu}=\frac{\sqrt{\Pi}h^{\mu}}{\Gamma(\mu)}\left[\frac{\mu}{\overline{\gamma_s}}\right]^{2\mu}\sum_{v=0}^{\infty}\frac{\Gamma\left(\mu+v,\frac{\lambda}{2}\right)}{\Gamma(\mu+v)v!}\left[1+\frac{2\mu h}{\overline{\gamma_s}}\right]^{-(v+2\mu)}$$
$$\frac{\Gamma(2\mu+v)}{\Gamma\left(\mu+\frac{1}{2}\right)}{}_2F_1\left(\frac{v+2\mu+1}{2},\frac{v+2\mu}{2};\mu+\frac{1}{2};\left(\frac{2\mu Hh\gamma_s}{2\mu h+\overline{\gamma_s}}\right)^2\right) \tag{17}$$

7.7 Energy Efficiency

a) Analysis of Fusion Rules

The following are the formulas for the OR-Rule's missed detection (Q_m) and false alarm (Q_f);

$$Q_{f,OR} = 1 - \left(1 - P_f\right)^N \tag{18}$$

$$Q_{m,OR} = \left(P_m\right)^N \tag{19}$$

For AND-Rule The Q_f and Q_m expressions are given in [30-31] as;

$$Q_{f,AND} = \left(P_f\right)^N \tag{20}$$

$$Q_{m,AND} = 1 - \left(1 - P_m\right)^N \tag{21}$$

Here with an error rate (r) the total error rate (TER) (Z) expression is computed as;

$$\begin{aligned} Q_f &= 1 - [(1 - P_f)(1 - r) + rP_f]^N \\ Q_m &= [P_m(1 - r) + r(1 - P_m)]^N \end{aligned} \tag{22}$$

$$Z(p, \lambda, N) \cong Q_f + Q_m \tag{23}$$

b) Energy Efficiency Calculations

As per average channel throughput (C_{avg}) value is computed as follows;

$$\begin{aligned} T_{P,\chi}\left(N\right) = P\left(H_1\right)\left(1 - Q_{m,\chi}\right)t_p + P\left(H_0\right)\left(1 - Q_{\mathrm{f},\chi}\right)t_s \\ + P\left(H_1\right)Q_{m,\chi}\left(\overline{t_p} + \overline{t_s}\right) \end{aligned} \tag{24}$$

t_s and t_p are the throughputs of secondary and primary user values.

The following formula can be used to determine the total energy: [29];

$$\begin{aligned} E_{C,\chi}\left(N\right) = P\left(H_1\right)\left(1 - Q_{m,\chi}\right)\left[N\left(e_1 + e_2\right) + e_p\right] + P\left(H_1\right) \\ Q_{m,\chi}\left[N\left(e_1 + e_2\right) + e_p + e_s\right] + \left(1 - Q_{f,\chi}\right)P\left(H_0\right) \\ \left[N\left(e_1 + e_2\right) + e_2\right] + p\left(H_0\right)Q_{fe}\left(N\right)L\left(e_1 + e_2\right) \end{aligned} \tag{25}$$

In this setup, it's assumed that each cognitive radio (CR) node consumes e_1 amount of energy to perform the spectrum sensing operation and e_2 energy to transmit the sensing data to the

fusion center (FC). On the other side the primary user (PU) uses e_p energy to transmit its information, while the CR nodes consume e_s energy when transmitting their own data. These energy values help model the overall energy consumption of the network, providing insights into how efficiently the system operates and where improvements can be made to optimize energy usage.
The EE value can be calculated using [29] as;

$$E_{F,\chi} = \frac{T_{P,\chi}}{E_{C,\chi}} \tag{26}$$

where χ may represent an AND-Rule or an OR-Rule.

The EE formulation for the OR-Rule is ;

$$E_{F,\mathrm{OR}} = \frac{T_{P,\mathrm{OR}}}{E_{\mathrm{C,OR}}} \tag{27}$$

$$N_{OR}^{*} = \left\lceil \frac{\ln\left(\frac{P_f\left(\alpha_2 - P\left(H_0\right)\rho_{OR}e_s\right)}{\left(1-P_m\right)\left(\alpha_1 + P\left(H_1\right)\rho_{OR}e_s\right)}\right)}{\ln\left(\frac{P_m}{1-P_f}\right)} \right\rceil \tag{28}$$

where ρ_{OR} is a positive number that can be calculated as follows: 0≤ρ≤1;

$$\rho_{OR,AND} = \left| \frac{P_m\alpha_1 - \left(1-P_f\right)\alpha_2}{2\left(P\left(H_1\right)P_m e_s - P\left(H_0\right)e_s\left(1-P_f\right)\right)} \right| \tag{29}$$

The EE formulation for the AND-Rule is;

$$N_{AND}^{*} = \left\lceil \frac{\ln\left(\frac{P_m\left(\alpha_1 + P\left(H_1\right)\rho_{\mathrm{AND}}e_s\right)}{\left(1-P_f\right)\left(\alpha_2 + P\left(H_0\right)\rho_{AND}e_s\right)}\right)}{\ln\left(\frac{P_f}{1-P_m}\right)} \right\rceil \tag{30}$$

where N_{AND} is a positive value that may be computed using equation (30), and it varies from 0≤N≤1.

8. RESULTS AND DISCUSSION

Figures 5.7 to 5.10 show the results of MATLAB simulations used to assess energy efficiency (EE) under different scenarios of fading environment in α-μ. Here single antenna (M=1) at each CR and different fusion rules at the fusion centre (FC) are used to analyse EE for varying numbers of cognitive radios (N) and threshold values (λ) in Figures 5.7 and 5.8. The findings reveal intriguing patterns: when λ = 10, the EE value falls by 21.4% as N rises from 1 to 5 when the AND-Rule is applied. In contrast, the OR-Rule shows a 32.1% increase in EE under the same conditions. Further comparisons of EE values across different scenarios are presented in Tables 2 and 3, providing a detailed look at how various parameters impact performance. Additionally, Table 5.2 summarizes the key simulation parameters used in the study, offering a clear reference for understanding the setup and results. These findings highlight the importance of choosing the right fusion rule and threshold values to optimize energy efficiency in cognitive radio networks operating under α-μ fading conditions.

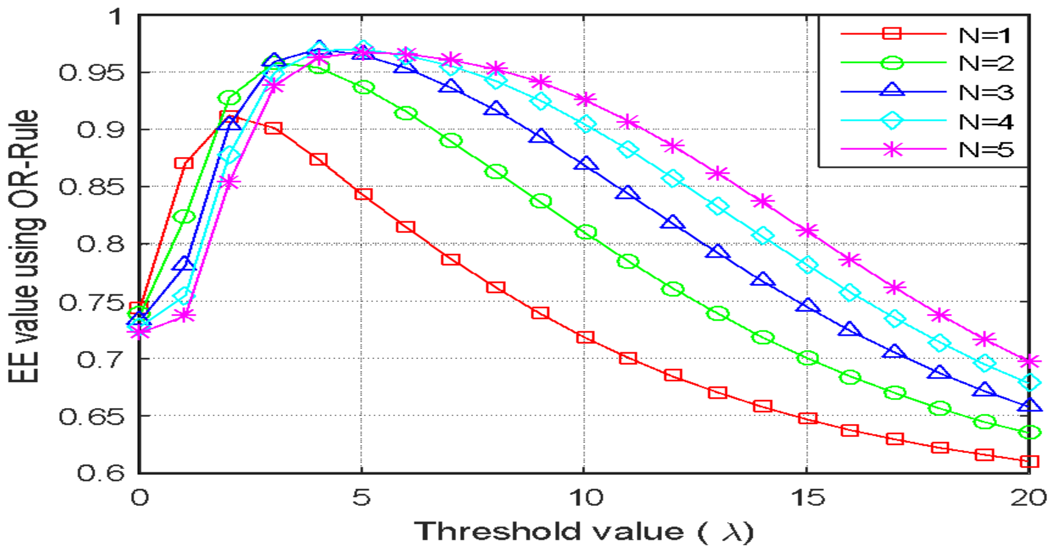

Figure 8.1 EE ANALYSIS FOR α-μ FADING WITH OR-RULE.

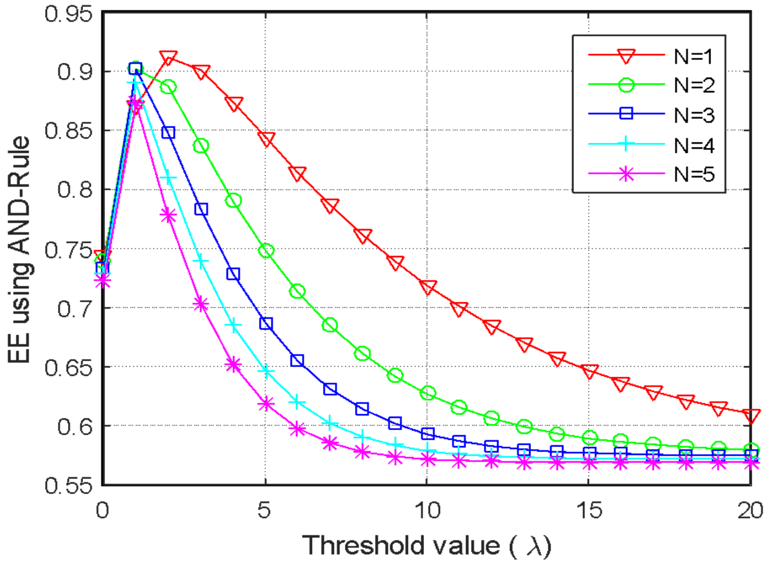

Figure 8.2 EE ANALYSIS FOR α-μ FADING WITH AND-RULE.

For a number of fusion algorithms, Figures 5.9 and 5.10 display the total error rate (TER), which is the sum of the likelihood of missed detection and false alarms (Q_m + Qf). The TER curve at starting approaches its lowest value as the threshold (λ) increases, and then it stabilises at higher λ values. It's interesting to note that using OR-Rule reduces the TER value by 64.6% as the number of cognitive radios (N) increases from 1 to 5. Additionally, for certain parameters such p=3, λ=20, and γ=5dB, the TER value decreases by 42.7%, illustrating the impact of parameter optimisation. Additionally, the data in Figure 5 shows that as N increases, the optimal threshold (λ_opt) falls lower and travels away from the origin. Likewise, Figure 6 illustrates that the curves tend to approach the origin as N increases, suggesting enhanced performance with more cooperative sensing. These findings show that the number of cognitive radios, threshold values, and fusion rules may have a significant influence on the precision and reliability of spectrum sensing in cognitive radio networks.

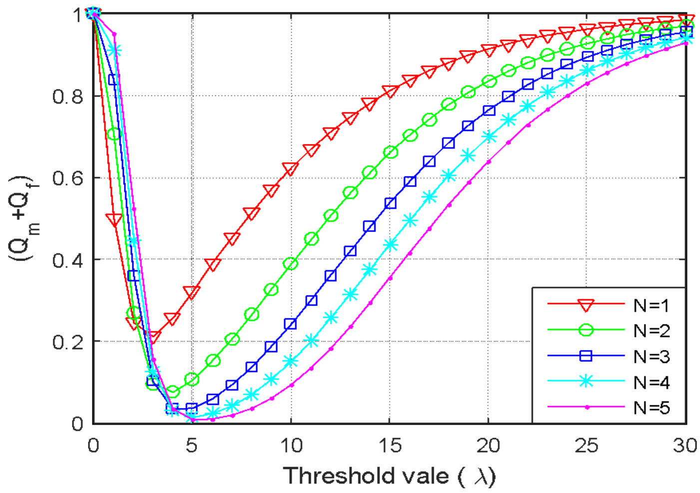

Figure 8.3 TER ANALYSIS FOR α-μ FADING WITH OR-RULE.

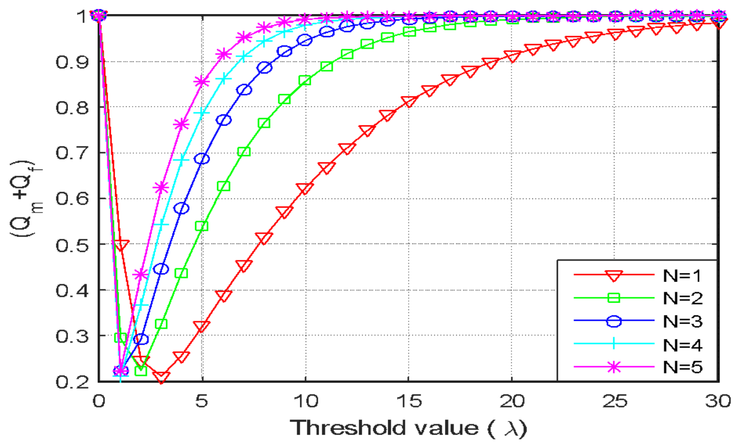

Figure 8.4 TER ANALYSIS FOR α-μ FADING WITH AND-RULE.

The simulations shown in Figures 5.11 to 5.14 are conducted in an η-μ fading environment, which models real-world signal fading conditions. Figures 5.11 and 5.12 focus on analyzing energy efficiency (EE) using the AND-Rule and OR-Rule for multiple secondary users (SUs). The results reveal interesting trends: as the number of SUs (N) increases from 1 to 5, the EE value rises by 43.1% when using the OR-Rule but drops by 32.6% when using the AND-Rule at a threshold (λ) value of 10. This highlights how the choice of fusion rules can significantly impact energy efficiency in fading environments. For a deeper comparison, Tables 4 and 5 provide a detailed analysis of EE values under the OR-Rule and AND-Rule in the η-μ fading environment. These tables help illustrate the trade-offs between the two fusion rules, offering insights into how different configurations affect performance. Overall, the findings emphasize the importance of selecting the right fusion rule and optimizing parameters like N and λ to achieve the best energy efficiency in cognitive radio networks operating under challenging fading conditions.

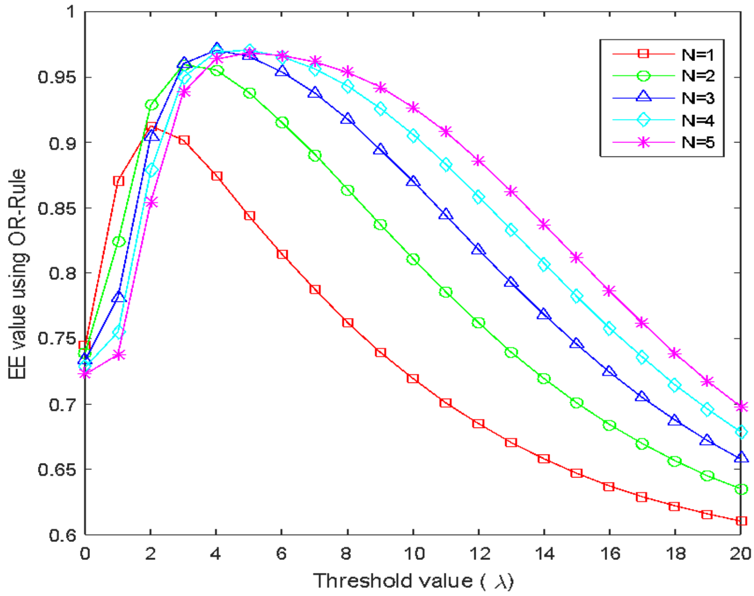

Figure 8.5 EE ANALYSIS FOR η-μ FADING WITH OR-RULE.

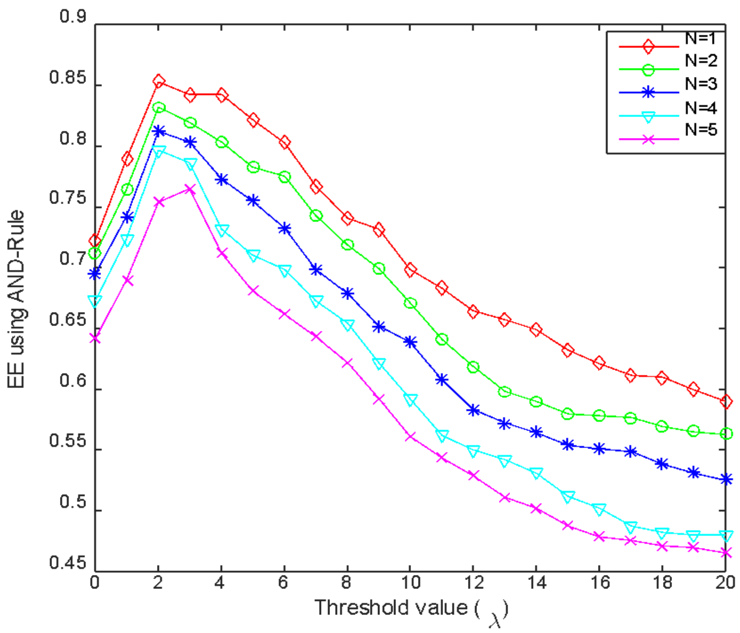

Figure 8.6 EE ANALYSIS FOR η-μ FADING WITH AND-RULE.

The curves for Total error rate (TER) as shown in Fig.5.13 and Fig.5.14 using various fusion rules at FC under η-μ fading environment. Initially, TER curve reaches to least value, later it rises with λ, and at higher λ values, it becomes constant. For a case, N =1 to N =5, TER value falls by amount 43.2% with OR-Rule and it falls by a 31.6% at p=3, λ=20 and γ=5dB.

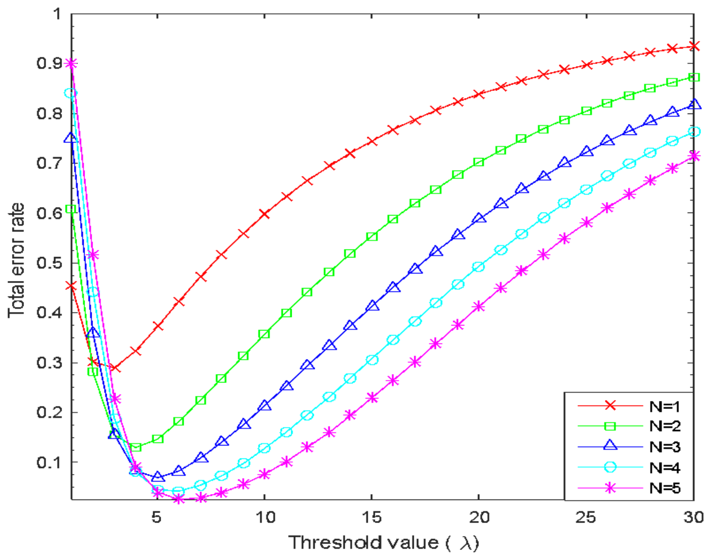

Figure 8.7 TER ANALYSIS FOR η-μ FADING WITH OR-RULE.

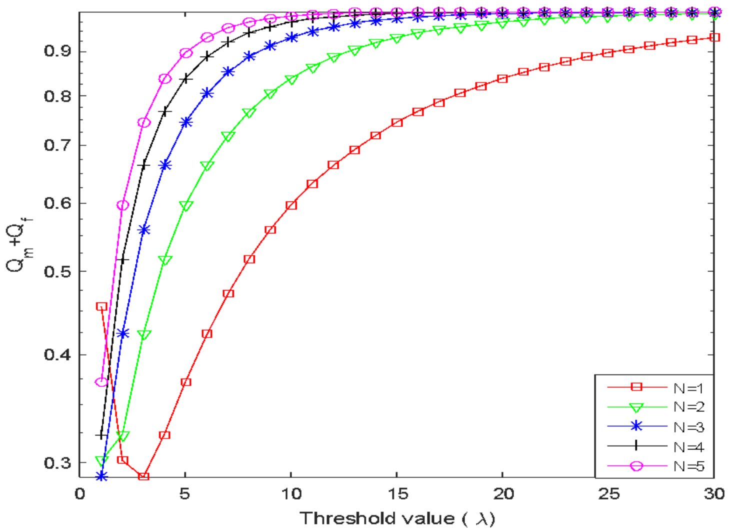

Figure 8.8 TER ANALYSIS FOR η-μ FADING WITH AND-RULE.

9. CONCLUSION

In this work, we used the GASE technique to investigate parallel CR transmission over Rician fading channels utilising the underlay paradigm. In particular, we have focused on improving the SE value while taking into account the spatial characteristic of CR transmission. First, we computed conventional P2P transmission to demonstrate the GASE approach. Additionally, a new theoretical definition for GASE was developed by utilising the underlying CR transmission. Additionally, we have used simulation data and analytical discoveries to illustrate the asymptotic GASE performance. When compared to the conventional approach, this study also shows that the GASE enhances SE and limits interference. Lastly, utilising the GASE performance metric, it is found that CR parallel gearbox with the underlying paradigm yields a higher SE value. The analysis of an ED-based CSS network in fading scenarios, specifically in the α-μ and η-μ directions, is another main topic of this research piece. Through the application of many fusion rules, the PU at an FC is identified. For the phenomenon of both fadings, the likelihood of detecting expression is first given. Throughput, TER, energy efficiency, and NUF performance have also been assessed using mathematical methods. Furthermore, an optimisation study of the EE value is conducted.

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ANNEXURE

#Code for “Total Error Rate (TER)”

```
clc;
clear all;
close all;
lambda = 0:1:100; %thres value
%N=1:1:10;
SNRdB=10;
snr=10^(SNRdB/10);  %snr to linear scale
q=0.01;
p=2; %ene dec scheme
M=3; %SU
N=3; %CR invloved in FR
for SS=1:length(lambda
rr(SS)=((lambda(SS))^(2/p));
Pf(SS)=1-((1-exp(-rr(SS)))^M);
%marcum PD on Fading envi
K=0;
D2=2/((1+snr)); %def depen parameter on SNR
Pm1(SS)=marcumq(sqrt(2*K),((lambda(SS))^(1/p))*sqrt(D2*(1+K)));
%Pm1(SS)=marcumq(sqrt(D2*snr),((lambda)^(1/p(SS)))*sqrt(D2));
Pm(SS)=(1-Pm1(SS))^M;
Qm(SS)=[(Pm(SS)*(1-q))+(q*(1-Pm(SS)))].^N;
Qf(SS)=1-[((1-Pf(SS))*(1-q))+(q*Pf(SS))].^N;
end
Total=Qm+Qf
semilogy(lambda,Total,'r*-');
```

#Code for "Energy Efficiency (EE)"

```
clc;
clear all;
p=2;
L=5;
snrdb=10;
SNR=10^(snrdb/10);
X=((2^(p/2))/L);
Y=((sqrt(pi))*gamma(((2*p)+1)/2))-(((gamma((p+1)/2))^2));
Z=gamma((p+1)/2)*sqrt(pi);
W=X*(Y/Z); %normalizes the equ
A=L*((gamma((p+1)/2))^2);
B=A/Y;
C=((1+SNR)^(p/2))*W;
lamda=0:0.5:50;
u=10;
for z=1:length(lamda)
%pf(z)=(gammainc(B,lamda(z)./W));
%pd(z)=(gammainc(B,lamda(z)./C));
pf(z)=(gammainc(lamda(z)./2,u,'upper'));
pd(z)=marcumq(sqrt(2*SNR),sqrt(lamda(z)),u);
pm(z)=1-pd(z);
pe=0;
pfe(z)=(pf(z)*(1-pe))+((1-pf(z))*pe);
pde(z)=(pd(z)*(1-pe))+((1-pd(z))*(pe));
M=4;
%n=M-2;
n=2;
k=1+n;
Qd=0;
Qf=0;
for l=k:1:M
Qd1(z)=Qd+(factorial(M).*(pde(z).^l)*((1-pde(z))^(M-l))/(factorial(l)*factorial(M-
l)));
```

```
Qf1(z)=Qf+(factorial(M).*(pfe(z).^l)*((1-pfe(z))^(M-l))/(factorial(l)*factorial(M-l)));
Qm(z)=1-Qd1(z);
end
Qd=Qd1;
Qf=Qf1;
Cavg(z)=(11.5)+((1.5).*Qd(z))-(7*Qf(z))
end
plot(lamda,Cavg,'r-*')
% % semilogy(lamda,U,'m-*')
grid on
hold on
```

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