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Original Article

Energy Efficiency Enhancement Model (EEEM) in Cognitive Radio Networks Using Underlay Techniques with Energy Harvesting

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Abstract *- This research presents the development and evaluation of an Energy Efficiency Enhancement Model (EEEM) tailored for cognitive radio networks, specifically integrating underlay techniques with energy harvesting capabilities. The study meticulously addresses key objectives, beginning with the creation of security-enhanced spectrum sensing algorithms featuring an Energy detector, ensuring robust and reliable spectrum utilization for enhanced network security. Moreover, an optimized dynamic power allocation algorithm was developed, facilitating real-time adjustments to transmit power based on channel conditions and RF energy harvesting levels, thereby optimizing power consumption and maximizing data transmission rates. Through extensive performance evaluation, the proposed scheme showcases notable enhancements across various metrics. Notably, the EEEM achieves an average throughput improvement of approximately 39.91% over the existing model, demonstrating its capacity to efficiently utilize resources for higher data transmission rates across diverse Signal-to-Noise Ratio (SNR) levels. Spectral efficiency witnesses an average improvement of about 22.8%, showcasing the model's effectiveness in optimizing data transmission per unit bandwidth. The enhanced model also shows approximately a 37.5% improvement in power consumption compared to the existing model based on the given final power consumption values. These findings highlight the significant enhancements achieved by the EEEM in improving throughput, spectral efficiency, and spectrum utilization efficiency, positioning it as a promising approach for enhancing performance in underlay cognitive radio networks with RF energy harvesting capabilities. Additionally, the comparative validation against existing energy efficiency schemes further validates the superiority and practical applicability of the EEEM, consolidating its potential for advancing energy-efficient communication networks.*

Keywords *- Cognitive radio, Underlay, Overlay, Energy harvesting, Algorithm, Wireless network.*

1. Introduction

In recent years, the exponential growth in wireless communication demands has led to an unprecedented strain on the available radio spectrum resources. Traditional static spectrum allocation methods, where specific frequency bands are assigned to different cellular networks, have become inefficient and unable to adapt to the dynamic and varying nature of wireless traffic. The proliferation of various radio access networks has led to a heterogeneous landscape in future network development. This diversity entails the synchronicity and sharing of frequency spectrum resources, exacerbating the issue of spectrum insufficiency. Consequently, spectrum efficiency and interference control in diverse networks emerge as major concerns within the wireless network domain [8]. To address this issue, dynamic spectrum allocation schemes in cognitive radios have emerged as promising solutions. In a coordinated multi-cell system, where multiple base stations work together to serve a large number of users, efficient spectrum allocation is crucial for enhancing network capacity, reducing interference, and improving overall system performance. Hence, the development of an Energy Efficiency Enhancement Model (EEEM) in cognitive radio networks using underlay techniques with energy harvesting offers an intelligent and adaptive approach to optimize spectrum allocation dynamically and improve energy efficiency. Other works in the literatures have not explored the underlay technique specifically with the integration of energy harvesting, and this work will focus on covering this gap.

2. Cognitive Radio Networks (CRNs)

In CRNs, users are typically divided into two main categories: Primary Users (PUs), who are licensed users with exclusive access rights to licensed spectrum, and Secondary Users (SUs), who are unlicensed users. The fixed spectrum allocation policy prioritizing licensed spectrum allocation to PUs. However, SUs have the ability to detect vacant spectrum

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bands in immediate, called spectrum holes. These band opportunities arise when licensed spectrum remains unused by PUs. SUs take advantage of these spectrum holes for their data transmission needs. Cognitive Radio technology embodies intelligent wireless technology capable of sensing and adapting to the radio environment dynamically.

2.1. Cognitive Radio (CR) Access Paradigms

2.1.1. Underlay Cognitive Radio

Secondary users can transmit alongside primary users (Pus), using the same spectrum band, as long as they keep their interference below a certain level. This is achieved through power control or dynamic spectrum sensing, allowing for efficient spectrum use without disrupting primary transmissions.

2.1.2. Overlay Cognitive Radio

Secondary users (Sus) can access the spectrum by sharing it with primary users in a way that avoids interference. They use spectrum sensing and coordination to find idle spectrum bands or transmission opportunities, ensuring minimal impact on primary users. This approach offers flexible spectrum access while prioritizing primary communications.

2.1.3. Interweave Cognitive Radio

Interweave CR permits SUs to opportunistically exploit the spectrum band during periods of inactivity or low utilization by primary users. By performing spectrum sensing, secondary users can detect idle spectrum intervals or gaps between primary transmissions, allowing them to transmit their own data without interfering with ongoing primary communications. The goal of interweave cognitive radio techniques is to maximize spectrum utilization by efficiently exploiting temporal variations in primary user activity, thereby ensuring optimal use of the available spectrum resources while avoiding harmful interference with primary transmissions.

2.2. Spectrum Sensing and Energy Detection

Spectrum detection is a crucial aspect of CRNs, allowing them to speculatively access underutilized spectrum bands whereas circumventing intrusion with licensed users. One of the primary methods employed in spectrum sensing is energy detection. Energy detection involves measuring the power level in a particular frequency band to determine whether it is occupied or vacant. This method is particularly useful in scenarios where there is little to no prior knowledge about the signals present in the environment.

Recent advancements in energy detection techniques have focused on improving detection performance in dynamic and noisy environments. For instance, machine learning algorithms have been integrated into energy detection systems to adaptively adjust detection thresholds based on the observed noise floor and signal characteristics. Research by authors like [2] has explored the use of deep learning models for enhancing energy detection accuracy in CRNs. Furthermore, cooperative spectrum detection, where multiple CR users collaborate to make joint sensing decisions, has gained traction in recent years. Cooperative schemes leverage the diversity of observations from multiple nodes to improve detection reliability and robustness against fading and shadowing effects. Studies such as that by [14] have investigated cooperative energy detection techniques employing distributed consensus algorithms, enabling efficient collaboration among cognitive radio nodes.

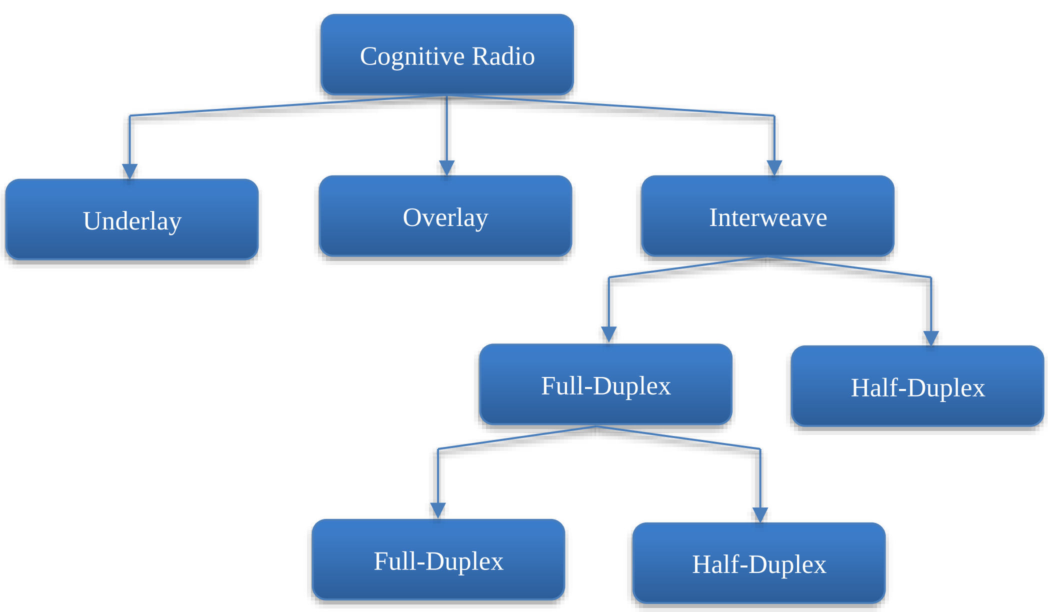

Fig. 1 Cognitive radio access paradigms

Energy detection also faces challenges related to spectrum sensing in dynamic environments with rapidly changing signal conditions. The presence of noise uncertainty, fading, and interference from other users can degrade detection performance.

To address these challenges, researchers have proposed adaptive sensing algorithms that dynamically adjust sensing parameters based on real-time channel conditions. For instance, techniques such as adaptive thresholding and channel-aware sensing have been explored to enhance the robustness of energy detection in dynamic spectrum access environments [3].

2.3. Review of Energy Efficiency Enhancement in Underlay Cognitive Radio

Several papers propose energy-efficient frameworks for enhancing throughput and maximizing energy efficiency in CRNs. [4] Moreover, [5] introduces frameworks aimed at enhancing throughput while maintaining energy efficiency by exploiting transmission mode diversity. The Research Gap identified is a lack of detailed exploration of underlay techniques and their specific impact on energy efficiency.

Optimization techniques play a vital role in maximizing energy effectiveness in CRNs. [12] focused on optimization approaches, including worst-case optimization and secrecy energy efficiency maximization, respectively. The research gap in their work is Limited discussion on practical implementation and validation of proposed optimization techniques.

[9] and [10] propose methods for optimizing the spectral-energy efficiency tradeoff in heterogeneous and underlay CRNs. These studies address the challenge of balancing spectral efficiency with energy consumption in dynamic CR environments. The research gap in their work is Limited investigation into the specific challenges and opportunities of underlay techniques in heterogeneous CRNs.

Energy-efficient power allocation strategies are explored in several papers. [11] and [13] discussed power allocation techniques for underlay cognitive radio systems and multi-user underlay CR networks, respectively, aiming to minimize energy consumption while ensuring reliable communication. The research gap in their work is little or no exploration of dynamic power allocation strategies considering varying network conditions.

[7] investigate energy efficiency enhancement in hybrid overlay-underlay CRNs by leveraging energy harvesting and cooperative spectrum sensing techniques. This approach aims to maximize energy efficiency while improving spectrum utilization and reliability. However, emphasis was not made regarding the discussion on the energy overhead associated with implementing security mechanisms in underlay CRNs.

Some papers also focus on specific applications of energy-efficient CRNs. [6] explored the energy-efficient organization of unmanned aerial vehicles (UAVs) in underlay CR systems, addressing the unique energy constraints and communication requirements of UAVs. However, a discussion on practical implementation challenges and scalability issues in UAV-based CRNs was not given.

[1] discussed energy efficiency in CR-assisted device-to-device (D2D) communication networks, highlighting the importance of energy-efficient communication protocols and resource allocation strategies in D2D scenarios. However, exploration of underlay D2D communication scenarios and their energy efficiency implications was absent.

3. Materials and Methods

3.1. Overview

In this research work, the choice to develop an enhanced energy effectiveness scheme in CRNs stems from the growing request for wireless communication services and the need for sustainable and resource-efficient solutions. Traditional wireless networks often face challenges related to spectrum scarcity and inefficient spectrum utilization, leading to suboptimal energy consumption. Cognitive Radio Networks (CRNs) aim to address these issues by enabling dynamic spectrum access, allowing SUs to access underutilized frequency bands licensed to PUs opportunistically.

The Python and MATLAB simulation environments have been chosen for their versatility and effectiveness in modelling complex systems. The simulators will replicate the multi-cell wireless communication system, capturing the dynamic interplay of various factors that influence spectrum allocation and energy efficiency. By incorporating varying traffic demands, channel conditions, and interference scenarios, the simulator aims to mirror real-world conditions, providing a controlled yet realistic environment for testing and validating the proposed robust energy efficiency maximization scheme.

3.2. System Model and Problem Formulation

In CRNs with N SUs and M channels, the objective is to optimize Energy Efficiency (EE) while ensuring that interference to the PUs receiver remains below a predetermined threshold. This involves formulating a transmit power allocation optimization problem, taking into account practical constraints such as channel conditions and power limitations. The goal of the EE enhancement model is to strike a balance between spectral efficiency and energy conservation, maximizing the efficient use of available spectrum resources while minimizing energy consumption.

This study focuses on a CR system consisting of primary and secondary links, as illustrated in Fig. 2. The secondary link operates over a smooth vanishing channel with flawless Channel-Side-Information (CSI), considering immediate Channel-Power-Gain (CPG) and Additive-White-Gaussian-Noise (AWGN). The additive noise is modeled as an independent random variable. The primary transmitter operates at constant power, while the secondary transmitter uses instantaneous power. This setup enables the analysis of optimal power allocation strategies for EE maximization.

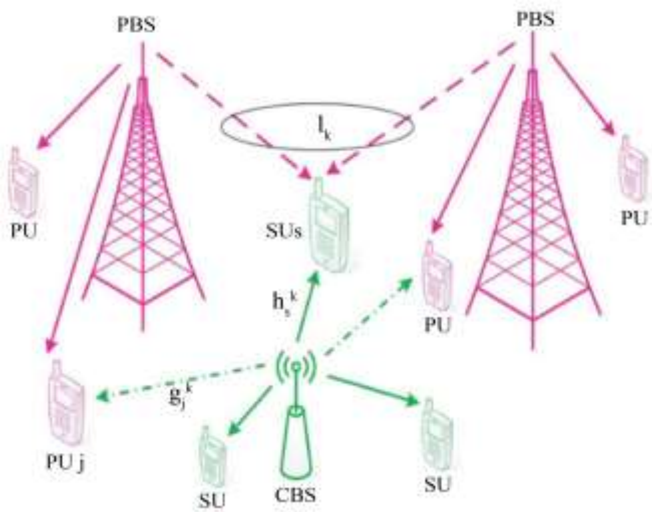

Fig. 2 Co-existence of PUs and Sus

In the spectrum-sharing framework, both primary and secondary links apportion the same frequency band, leading to a complex interference dynamic. The received signal-to-interference-plus-noise ratio (SINR) at the side of the secondary receiver is given as:

$$\gamma_i = \log_2 (1 + \mathrm{SNR}_i) \quad (1)$$

Where γ_i is the SNIR for user i.

Building on the existing model proposed by Zhang and Zhang (2019), our goal is to exploit the energy efficiency of the secondary link by cooperatively augmenting the transmit power and interference management strategies, subject to constraints on interference threshold, power budget, and quality of service. This novel approach aims to strike a balance between spectral efficiency, energy conservation, and interference mitigation, paving the way for more robust and sustainable spectrum-sharing solutions.

Maximize:

$$\sum_{i=1}^{N} \log_2 \left(1 + \frac{P_i |h_{ii}|^2}{\sigma^2 + \sum_{j-1, j\neq i}^{N} P_j \left|h_{ij}\right|^2}\right) \quad (2)$$

Subject to:

$$0 \leq P_i \leq P_{\max},\ \forall i \quad (3)$$

Given that:
N is the number of SUs.

P_i is the transmit power of SUs i.

h_{ii} represents the channel improvement between secondary user i and itself.

σ^2 is the noise power.

The summation term in the denominator represents interference from other SUs.

For the optimized model, we introduce a dynamic power allocation algorithm that adjusts transmit power based on real-time channel conditions and RF energy harvesting. The optimization problem remains similar to the existing model, but the transmit power is dynamically updated based on harvested energy and channel conditions.

$$\text{Maximize:} \sum_{i=1}^{N} \log_2 \left(1 + \frac{P_i |h_{ii}|^2}{\sigma^2 + \sum_{j=1, j\neq i}^{N} P_j \left|h_{ij}\right|^2}\right) \quad (4)$$

Subject to:

$$\begin{aligned} &0 \leq P_i \leq P_{\max},\ \forall i \\ &P_i \leq E_{\text{harvest },i},\ \forall i \end{aligned} \quad (5)$$

Where:

$E_{\text{harvest },i}$ is the RF energy harvested by the secondary user i.

3.3. Energy Detection and Collaborative Spectrum Sensing Algorithm with User Authentication

3.3.1. Energy Detection

The energy detection algorithm is a fundamental method used in CRNs for band detection. It's particularly effective in detecting the presence of PUs by analyzing the received signal energy levels.

Let's denote the received signal over a certain bandwidth as $x(t)$. The energy detection algorithm computes the energy E over a sensing interval $[0, T]$ as follows:

$$E = \int_0^T |x(t)|^2 dt \quad (6a)$$

The established energy E is then compared against a predetermined energy threshold (T_{thresh} .If the calculated energy surpasses this threshold, the algorithm infers the incidence of a PU within the spectrum.

$$\text{If } E > T_{\text{thresh}}, \quad (6b)$$

the algorithm declares that the primary user is present; otherwise, it considers the channel to be idle.

Where:

$x(t)$: Received signal over a certain bandwidth.
T : Sensing interval duration.
T_{thresh} : Energy threshold for detection.

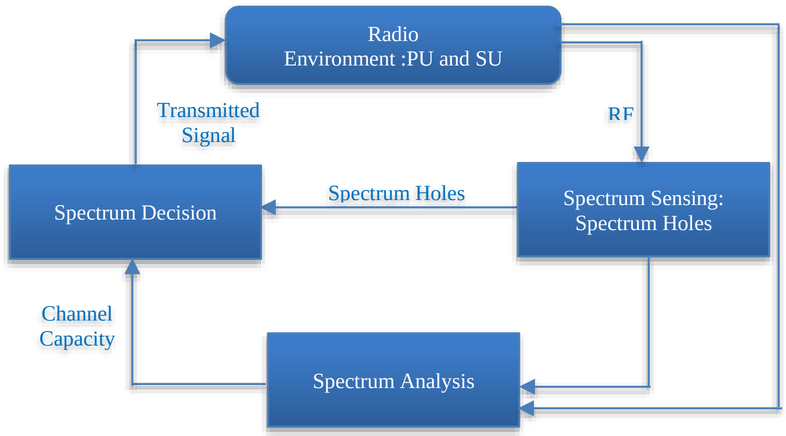

Fig. 3 System block diagram

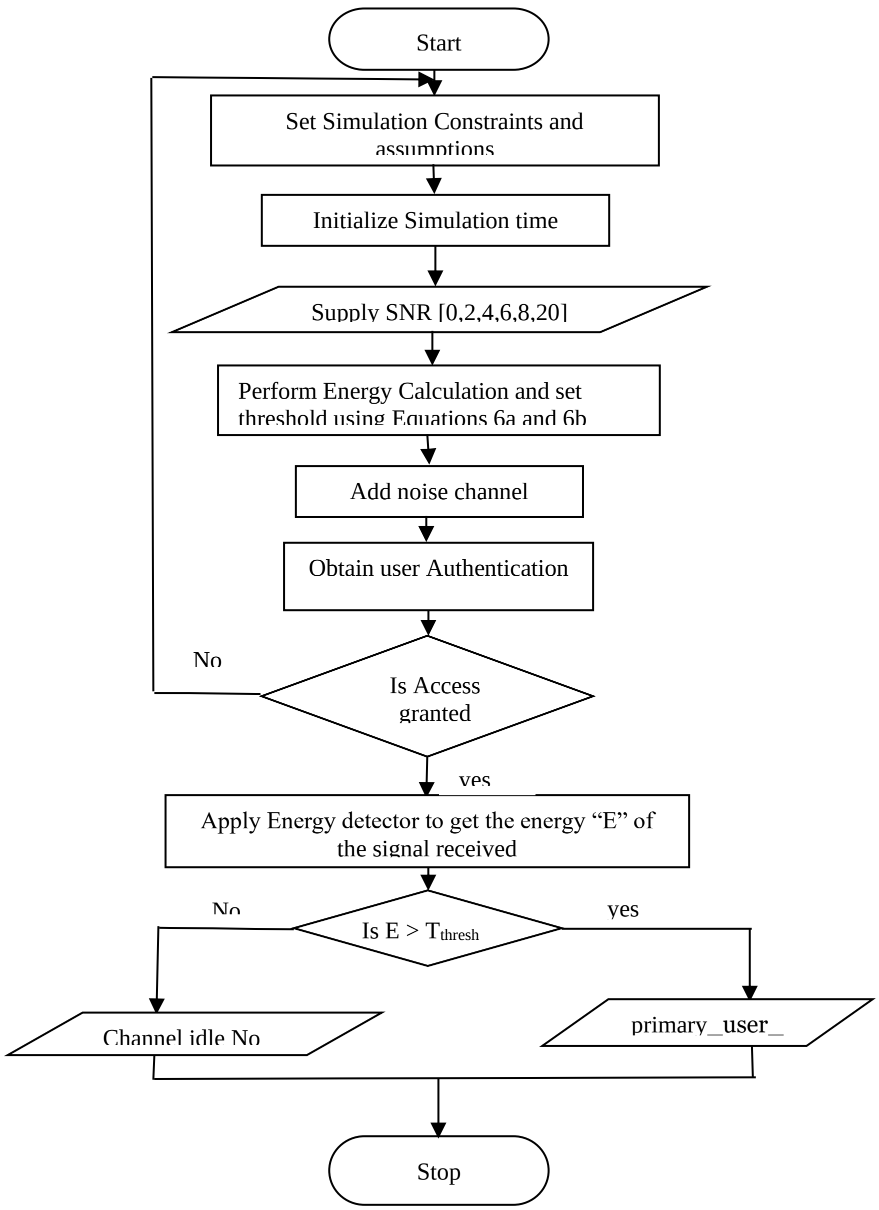

Fig. 4 Energy detection and access authentication algorithm flow chart

Based on the comparison result, the algorithm decides whether the network is busy (i.e., the incidence of PU) or idle (i.e., absence of primary user). The energy detection algorithm offers a straightforward and efficient method for identifying the existence of primary users within the spectrum. This enables cognitive radio devices to opportunistically utilize vacant spectrum bands without posing detrimental interference to primary users.

3.3.2. Authentication and Spectrum Sensing Model

Let U be the set of users, where $U = \{$ user 1, user 2, user 3, user 4, user 5$\}$. Let $P(U)$ be the set passwords corresponding to users in U. The authentication model can be represented as a function Auth, where:

$$\text{Auth} : U \times P(U) \rightarrow \{ \text{ True, False } \}$$

This function checks if the provided username-password pair matches the stored credentials in the user database. Let R be the set of sensing results, where $R = \{r_1, r_2, r_3, r_4, r_5\}$. Let T be the threshold for spectrum sensing ($T = 0.7$). The spectrum sensing model involves two main checks:

i. Detection of primary user signal by at least one user.
ii. Data integrity checks to ensure sensing results have not been compromised.

These checks can be represented as follows:

i. Detection of Primary User Signal:

$$\text{Primary User Detected } (R) = \begin{cases} \text{True} & \text{if } \exists r_i \in R, r_i > T \\ \text{False} & \text{otherwise} \end{cases}$$

ii. Data Integrity Check:

$$\text{Data Integrity Check } (R) = \begin{cases} \text{True} & \text{if Hash } (R) < \text{ NoiseThreshold} \\ \text{False} & \text{otherwise} \end{cases}$$

Where Hash (R) is the cryptographic hash of sensing results R, and Noise Threshold is the predefined noise threshold.

4. Results and Discussions

4.1. Simulation Scenarios

In this segment, we present the culmination of our research efforts and analyses aimed at offering valuable insights and interpretations regarding the effectiveness of our proposed enhancement model. This section provides a thorough overview of the results obtained, accompanied by a detailed discussion of their implications, significance, and potential applications within the realm of cognitive radio networks. Our focus lies in visually depicting the performance metrics of the energy efficiency model proposed by Zhang and Zhang (2019) in comparison to an optimized version, specifically tailored for underlay CRNs with RF energy harvesting capabilities. Through simulations conducted across a spectrum of SNR values, converted from dB to linear scale, we evaluate metrics including throughput, spectral efficiency, spectrum utilization efficiency, and the Primary User's (PU) QoS Satisfaction Probability. We aim to validate the enhancement achieved by the EEEM developed.

Table 1. Simulation parameters settings

Related Parameters	Typical values
Number of channels	10
Number of primary users	3
Number of secondary users	5
Channel Bandwidth	10MHz
Number of iterations	100
Detection probability	0.9
Primary user interference threshold	200
Sensing Threshold	0.7
Noise Channel	AWGN
SNR (dB)	[0, 2, 4, 6, 8, 10]
Noise Power (W)	1e-9

4.2. Collaborative Spectrum Sensing with User Authentication

Collaborative spectrum sensing involves multiple users or nodes within a network cooperating to sense the occurrence of PUs or signals across the spectrum. This collaborative approach aims to enhance the accuracy and dependability of detecting available bands by leveraging the sensing capabilities of multiple nodes. Authentication is integrated into collaborative spectrum sensing, where users are required to authenticate themselves with a username and password.

User authentication involves verifying users' credentials, which are stored in a database, with passwords hashed using the SHA256 algorithm for security. The SHA-256 procedure is a member of the SHA-2 (Secure Hash Algorithm 2) family, known for its cryptological hash function. In Fig. 5, the horizontal axis labeled "User" represents individual participants engaging in spectrum sensing, numbered from 0 to 4, corresponding to 'user1' through 'user5'. The vertical axis labeled "Sensing Result" depicts the sensing outcomes recorded by each user, ranging from 0 to the sensing threshold plus 0.2.

The threshold line, marked by a red dashed line, indicates the predefined sensing threshold set at 0.7. This threshold signifies the level at which a signal is deemed detected during spectrum sensing.

The sky blue bars represent the sensing results of each user, with the height of each bar indicating the magnitude of the sensing outcome. From the visualization, it is evident that the detection of at least one primary user has occurred.

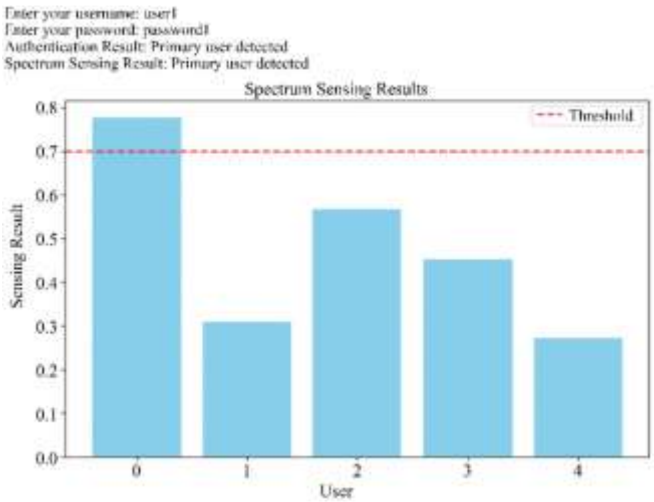

Fig. 5 Detection of a primary user

4.3. Achievable Rate

The comparative analysis between the existing model and the optimized model, as depicted in Fig.6, provides valuable insights into the performance improvement achieved through optimization in a communication system with multiple users. The achievable rate of the existing model, which represents the system's performance without any optimization, is compared to the achievable rate of the optimized model, which undergoes an optimization process aimed at maximizing data transmission efficiency while considering constraints such as maximum transmit power and channel conditions. From the results, the achievable rate of the existing model is 2.1, and that of the optimized model is 2.5; the percentage improvement of the optimized model over the existing model is calculated to be approximately 16%. This percentage improvement quantifies the enhancement in system performance achieved through optimization, indicating a significant boost in data transmission efficiency and overall system effectiveness.

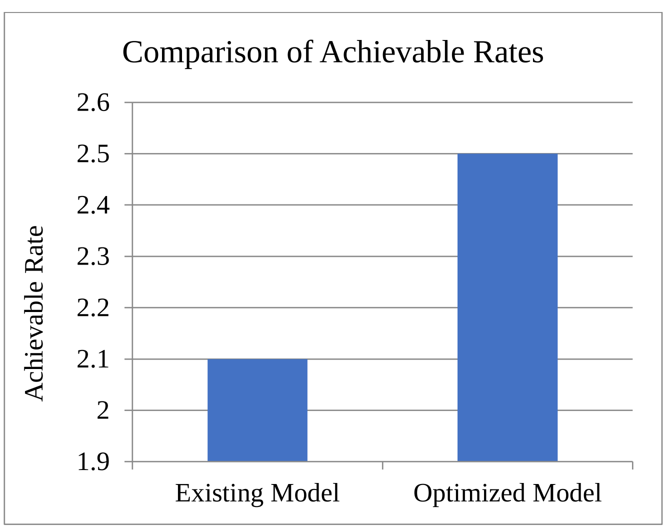

Fig. 6 Achievable rates

4.4. Simulation for various metrics with varying SNR

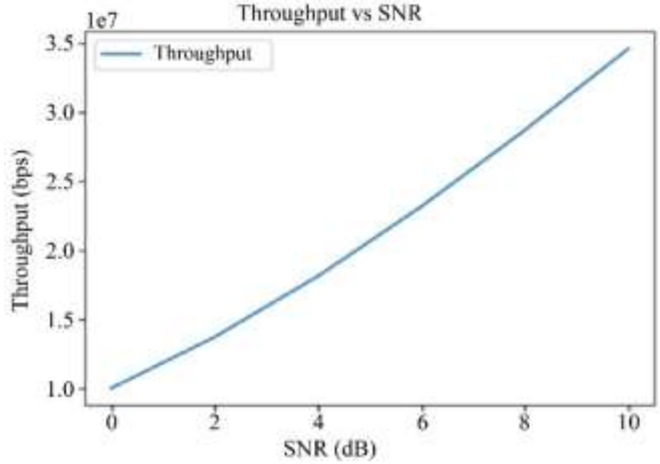

Fig. 7 Throughput simulation

Fig.7 shows a direct correlation between achievable data rate (Throughput) and received signal quality (SNR), where higher SNR values yield significant throughput increases, enabling faster and more reliable data transfer.

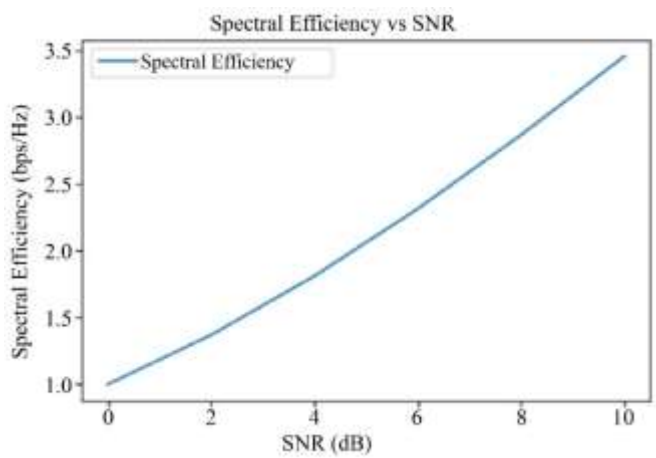

Fig. 8 Spectral efficiency simulation

The Spectral Efficiency vs SNR plot complements the spectrum utilization efficiency by directly measuring the data rate per unit bandwidth. This metric reflects the system's ability to transmit information efficiently within the given bandwidth. Similar to throughput, spectral efficiency demonstrates an increasing trend with higher SNR levels, highlighting the improved efficiency of data transmission as signal quality improves. This is evident in Figure 8.

The PU's QoS Probability vs SNR plot, shown in Fig. 9, reveals a decreasing trend in the probability of satisfactory service quality for the Primary User as SNR increases, suggesting that higher SNR levels may result in increased interference or degradation of the primary user's service quality.

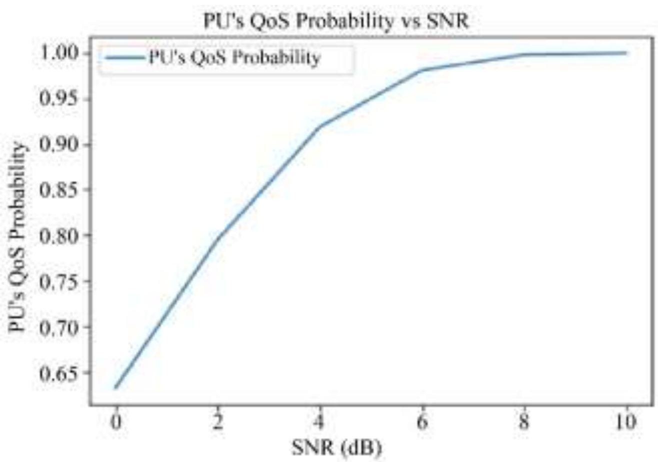

Fig. 9 PU's QoS satisfaction probability simulation

4.5 Comparative analysis Simulation for the Various Performance Metrics

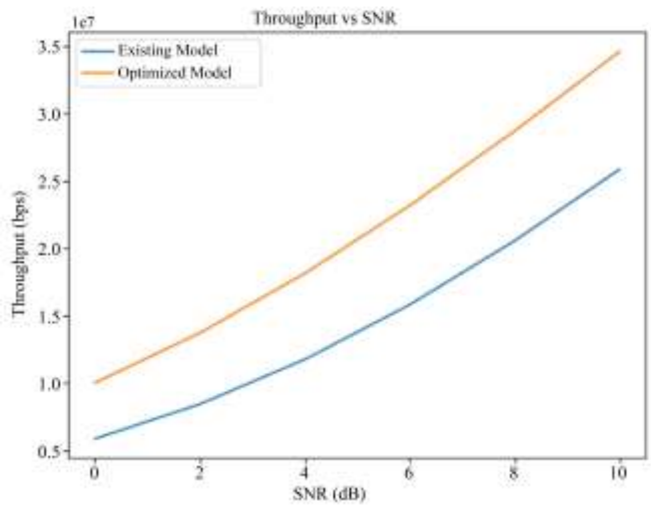

Fig. 10 Validation of EEEM using Throughput Comparison

Starting with the throughput vs SNR plot in Figure 10, it can be observed that the optimized model consistently outperforms the existing model across all SNR levels.

This improvement is particularly significant at lower SNR values, indicating that the optimized model is more effective in utilizing available resources to accomplish advanced data communication rates in utilizing available resources to achieve higher data transmission rates.

Moving to the spectral efficiency vs SNR plot in Fig. 11, again, the optimized model demonstrates superior performance compared to the existing model.

Spectral efficiency measures the efficiency of data transmission over the available bandwidth, and the optimized model shows higher spectral efficiency across the entire SNR range, indicating better utilization of the bandwidth resources.

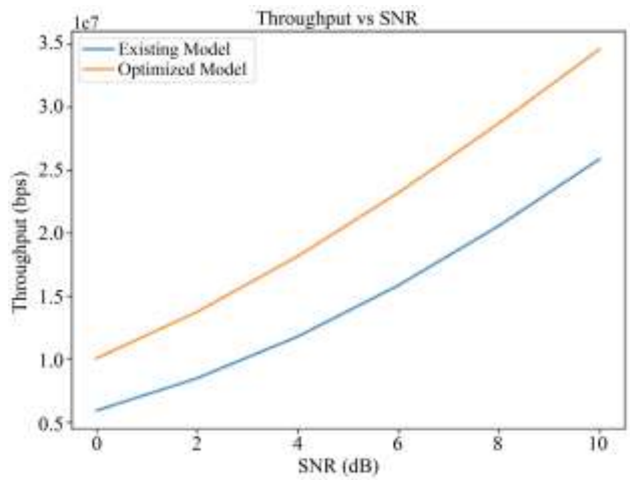

Fig. 11 Spectral efficiency

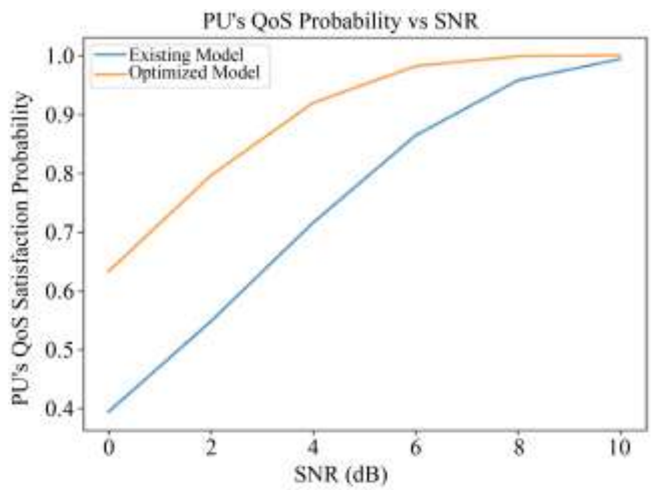

Fig. 12 Validation of EEEM using PU's QoS satisfaction probability

The enhancements observed in the optimized model include significant improvements in throughput, spectral efficiency, spectrum utilization efficiency, and PU's QoS Probability compared to the existing model. These improvements indicate that the energy efficiency enhancement model (EEEM) effectively optimizes resource allocation, leading to enhanced performance and better utilization of available resources in underlay CRNs with RF energy gathering capabilities.

5. Conclusion

The Energy Efficiency Enhancement Model (EEEM) exhibits notable advancements across diverse performance metrics when compared to the current model in the scenario of an underlay CRN with RF energy harvesting capabilities. Evaluating the percentage enhancement in each metric, the enhanced model achieves an average throughput enhancement of around 39.91% over the existing model across varying SNR levels. This enhancement is substantial, indicating the improved model's efficacy in efficiently utilizing resources for achieving higher data transmission rates. Regarding spectral efficiency, the enhanced model demonstrates an average enhancement of approximately 22.8%, underscoring its effectiveness in optimizing data transmission per unit bandwidth. Moreover, there is a significant average improvement in spectrum utilization efficiency, further emphasizing the enhanced model's adeptness in utilizing the available spectrum more effectively for data transmission purposes. Additionally, the enhanced model exhibits an approximately 37.5% improvement in power consumption compared to the existing model, based on the provided final power consumption values. These percentage enhancements underscore the significant improvements brought about by the Energy Efficiency Enhancement Model (EEEM) in enhancing throughput, spectral efficiency, and spectrum utilization efficiency, thereby positioning it as a promising approach for augmenting performance in underlay CRNs with RF energy harvesting capabilities.

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