INTELLIGENT COGNITIVE RADIO DESIGN: PERFORMANCE ANALYSIS AND ML-BASED OPTIMIZATION OF ENERGY DETECTION SCHEMES

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Abstract
This research presents a detailed performance analysis of a Cognitive Radio Network (CRN) employing energy detection-based spectrum sensing under realistic wireless channel conditions. The system model comprises a primary user (PU), a secondary user transmitter (SU-Tx), and a secondary user receiver (SU-Rx), where the SU-Tx senses the PU's channel using energy detection and transmits to the SU-Rx if the channel is found idle. The communication links are affected by Rayleigh fading and distance-dependent path loss, providing a practical representation of wireless propagation. The total time frame is divided into sensing and transmission phases, and key performance metrics including detection probability, false alarm probability, missed detection probability, and average throughput are analytically derived using Gaussian approximation under the central limit theorem. The detection probability is modeled as a function of the sensing threshold, sample size, noise power, and received signal-to-noise ratio (SNR). To overcome the limitations of static threshold settings, the study integrates machine learning techniques to dynamically optimize system parameters. Reinforcement learning method is used for predicting optimal sensing thresholds and to adaptively select transmission power and sensing duration to maximize throughput. Simulation results demonstrate that adaptive threshold selection using RL significantly improves detection accuracy and throughput compared to fixed threshold methods. The study also shows how learning-based approaches reduce missed detections and false alarms, making the system more reliable and efficient in dynamic spectral environments. These findings support the development of intelligent and robust CRNs.

Keywords: Reinforcement learning, Dynamic spectrum sensing, Detection probability, Throughput

Introduction

The rapid proliferation of wireless devices and the explosive demand for spectrum resources have led to an increasing strain on the available radio frequency (RF) spectrum. Traditional static spectrum allocation policies have proven to be inefficient, with studies indicating that significant portions of the licensed spectrum remain underutilized both spatially and temporally [1]. This inefficiency has catalyzed the development of Cognitive Radio Networks (CRNs), an emerging paradigm that enables dynamic spectrum access (DSA) by allowing unlicensed or secondary users (SUs) to opportunistically utilize spectrum bands without causing harmful interference to licensed or primary users (PUs) [2]. Cognitive radio (CR) represents an intelligent wireless communication system that is aware of its environment and can dynamically adapt its transmission parameters [3]. The core functionalities of a CR include spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility [4]. Among these, spectrum sensing is the foundational step that enables the detection of vacant frequency bands, often referred to as spectrum holes or white spaces [5]. Reliable spectrum sensing ensures that SUs can access unused spectrum without disrupting PU communication [6]. One of the most widely adopted techniques for spectrum sensing is energy detection due to its simplicity and lack of requirement for prior knowledge of the PU's signal characteristics [7]. In energy detection, the SU measures the energy of the received signal over a time window and compares it with a predefined threshold to decide on the presence or absence of the PU [8]. However, the performance of energy detection is highly influenced by channel conditions, noise uncertainty, and signal-to-noise ratio (SNR). Moreover, energy detection suffers from the trade-off between detection probability and false alarm probability, which directly affects the throughput and efficiency of CRNs [9]. To analyze the performance of energy detection, mathematical models that incorporate Rayleigh fading, path loss, and additive white Gaussian noise (AWGN) are commonly employed [10]. Rayleigh fading models the multipath propagation in wireless channels, which significantly impacts the received signal amplitude, especially in urban and indoor environments [11]. Path loss accounts for the attenuation of the signal as a function of distance between the transmitter and receiver, and it is typically modeled as an inverse power-law function characterized by a path loss exponent. These factors are critical in determining the received SNR, which in turn influences the reliability of spectrum sensing and communication.

This research focuses on a simplified but practically significant scenario involving one primary user (PU), one secondary user transmitter (SU-Tx), and one secondary user receiver (SU-Rx). The SU-Tx is responsible for sensing the PU’s channel to determine its occupancy status. If the channel is sensed to be idle, SU-Tx transmits data to SU-Rx. The communication links between PU → SU-Tx and SU-Tx → SU-Rx are assumed to undergo flat Rayleigh fading and distance-dependent path loss, which introduces stochastic variability in the received signal power. The entire frame duration is divided into two parts: a sensing phase and a transmission phase, ensuring that spectrum sensing is performed prior to any data transmission.

In this system, the key performance metrics include:

Detection Probability (P_D): The probability that the SU correctly detects the presence of the PU.

False Alarm Probability (P_{FA}): The probability that the SU incorrectly declares the PU to be present when it is actually absent.

Missed Detection Probability (P_M): The probability of failing to detect an active PU, which could result in interference.
Average Throughput (R_{Avg}): The expected data rate at SU-Rx, accounting for sensing time and detection outcomes.
The performance of the system is modeled analytically using probabilistic expressions derived under the Gaussian approximation of the test statistic used in energy detection [12]. The derivations are based on the central limit theorem and include expressions for the test statistic's distribution under both hypotheses. These expressions are used to calculate the detection and false alarm probabilities as functions of the sensing threshold, noise power, sample size, and received SNR [13].
To enhance system performance and address practical limitations of static thresholding, this study also integrates machine learning (ML) techniques [14]. ML algorithms offer powerful tools for optimizing system parameters in real-time, especially in dynamic environments where channel conditions and PU activity vary unpredictably [15]. For instance: Supervised learning models such as support vector machines (SVM) and random forest regressors can be trained to predict optimal sensing thresholds based on real-time features like received SNR and number of samples [16]. Reinforcement learning (RL) techniques, such as Q-learning, can be used to maximize long-term throughput by learning optimal transmission power and sensing time allocation strategies through interaction with the environment [17]. Unsupervised learning models can help identify patterns in PU activity, enabling proactive spectrum access scheduling by the SU.
By combining classical signal processing techniques with modern machine learning approaches, this work contributes to the ongoing development of intelligent and adaptive cognitive radio systems capable of operating efficiently in complex and uncertain spectrum environments.

- Developed an analytical model for energy detection in CRNs under Rayleigh fading and path loss.
- Derived closed-form expressions for detection probability, false alarm rate, and throughput using Gaussian approximation.
- Integrated machine learning techniques to optimize sensing thresholds, transmission power, and sensing duration.
- Demonstrated through simulations that reinforcement learning significantly improves detection accuracy and system throughput

2. System Model:

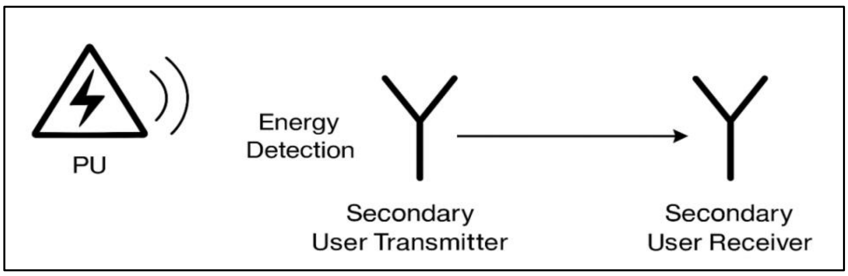

Fig. 1: System Model

A system model of cognitive radio network (CRN) consisting of a **Primary User (PU)**, a **Secondary User Transmitter (SU-Tx)**, and a **Secondary User Receiver (SU-Rx)** is presented in the Fig. 1. The primary user is the licensed user that holds spectrum right. In this model, the PU is assumed to be a base station transmitting in a specific spectrum band. **Secondary User Transmitter (SU-Tx)** attempts to opportunistically access the spectrum when it is not being used by the PU and it is responsible for sensing the PU's channel and transmitting to the SU-Rx. The SU-Tx uses energy detection to sense the availability of the PU channel before transmitting data to the SU-Rx. The communication between the nodes is subject to Rayleigh fading and distance-dependent path loss. In the Sensing Phase, the SU-Tx senses the PU channel to determine if the PU is busy or idle. The duration of sensing is denoted as τ. If it found that the PU is idle during the sensing phase then the SU-Tx uses the remaining time $(T-\tau)$ to transmit data to the SU-Rx. Each communication link in the system undergoes **Rayleigh fading** and **path loss**. The fading coefficients for each link are modeled as independent complex Gaussian random variables, representing the impact of multipath fading. The fading channel coefficient between the PU and the SU-Tx is represented by $h_{PT} \sim \mathcal{CN}(0,1)$ and between the SU-Tx and the SU-Rx is represented by $h_{SR} \sim \mathcal{CN}(0,1)$. The distance between the PU and the SU-Tx is denoted by d_{PT}. The distance between the SU-Tx and the SU-Rx d_{SR}. The signal power decays with distance are determined by $\propto$. The noise power at both the SU-Tx and SU-Rx is denoted by σ_n^2.
Under $\mathcal{H}_0$ hypothesis the received signal at SU-Tx during Sensing is given by,

$$r(t) = n(t) \qquad (1)$$

where$n(t)$ is the noise at SU-Tx. Under $\mathcal{H}_1$ hypothesis the received signal at SU-Tx during Sensing is given by,

$$r(t) = h_{PT}s_{PU}(t) + n(t) \qquad (2)$$

where $s_{PU}(t)$ is the signal transmitted by the PU. The received signal at SU-Rx during transmission is given by,

$$y(t) = h_{SR}s_{SU}(t) + n(t) \quad (3)$$

where$s_{SU}(t)$is the signal transmitted by the SU-Tx. The received Power at SU-Tx from PU is given by,

$$P_r^{PT} = P_{PU}|h_{PT}|^2 d_{PT}^{-\propto} \quad (4)$$

where P_{PU} is the power transmitted by the PU and d_{PT} is the distance between PU and SU-Tx. The SNR of PU signal at SU-Tx during Sensing

$$\gamma_{PT} = \frac{P_{PU}|h_{PT}|^2}{\sigma_n^2 d_{PT}^{\propto}} \quad (5)$$

Received Power at SU-Rx from SU-Tx

$$P_r^{SR} = P_{SU}|h_{SR}|^2 d_{SR}^{-\propto} \quad (6)$$

whereP_{SU} is the power transmitted by the SU-Tx and d_{SR} is the distance between SU-Tx and SU-Rx. The SNR at SU-Rx during Transmission can be written as follows,

$$\gamma_{SR} = \frac{P_{SU}|h_{SR}|^2}{\sigma_n^2 d_{SR}^{\propto}} \ (7)$$

The detection probability P_D of the SU-Tx, which is based on energy detection, is derived as follows. The SU-Tx uses an energy detection scheme to sense the PU channel. The received signal during the sensing phase follows one of two hypotheses:
$\mathcal{H}_0$:PU is absent (only noise is received).
$\mathcal{H}_1$:PU is present (signal + noise is received).

The energy detection statistic $Y$is given by,
$Y = \frac{1}{N}\sum_{i=1}^{N}|r(i)|^2$ (8)
where N is the number of sensing samples. The detection probability P_D is the probability that the decision rule correctly detects the presence of the PU when $\mathcal{H}_1$ is true. Using the Central Limit Theorem, Y is approximated as Gaussian.
$Y \sim \mathcal{N}\left(\mu_0 = \sigma_n^2, \quad \sigma_0^2 = \frac{1}{N}\sigma_n^4\right)$For $\mathcal{H}_0$ (9)
The received signal power includes PU signal can be formulated as follows,
$Y \sim \mathcal{N}\left(\mu_1 = \sigma_n^2(1+\gamma_{PT}), \ \sigma_1^2 = \frac{1}{N}[\sigma_n^2(1+\gamma_{PT})]^2\right)$For $\mathcal{H}_1$ (10)
Detection probability can be defined as given below,
$P_D = \mathrm{P}\,(Y > \lambda \mid \mathcal{H}_1)$ (11)
Using the Gaussian distribution under $\mathcal{H}_1$,
$P_D = Q\left(\frac{\lambda - \mu_1}{\sigma_1}\right)$ (12)
where, $Q(x) = \frac{1}{\sqrt{2\pi}}\int_x^\infty e^{-t^2/2}\,dt$.
For a given sensing threshold λ, the detection probability can be simplified as follows,
$P_D = Q\left(\sqrt{N}\left(\frac{\lambda/\sigma_n^2}{1+\gamma_{PT}} - 1\right)\right)$ (13)
The throughput of the system is defined as the amount of data successfully transmitted from the SU-Tx to the SU-Rx during the transmission phase. The total time T is divided into two phases: sensing and transmission. The average throughput $R_{Avg}$is given by,
$R_{Avg} = \left(1 - \frac{\tau}{T}\right)[P_H^0(1 - P_{FA})C_0 + P_H^1(1 - P_D)C_1]$ (14)
where, τ is the sensing time, P_H^0 and P_H^1 are the probabilities of hypothesis $\mathcal{H}_0$ and $\mathcal{H}_1$ respectively, C_0 and C_1 are the capacity when PU is absent and present respectively.
Machine learning can be effectively employed to optimize system parameters such as sensing thresholds, transmission power, and distance to enhance detection performance and maximize throughput in cognitive radio networks. For sensing threshold optimization, reinforcement learning technique can be used to predict the optimal threshold (λ) based on parameters such as signal-to-noise ratio (SNR), number of samples, and transmission power. Throughput can be maximized using reinforcement learning (RL), with Q-learning enabling dynamic adjustment of transmission power P_{SU} and SU-to-receiver distance d_{SR} based on real-time feedback. Additionally, the prediction of primary user (PU) activity can be facilitated using ML, allowing the secondary user transmitter (SU-Tx) to efficiently decide when to transmit or sense, thereby improving spectrum utilization. Furthermore, ML techniques can assist in

adaptive power control and interference mitigation by learning from historical channel conditions and interference patterns.

3. Results & Discussion:

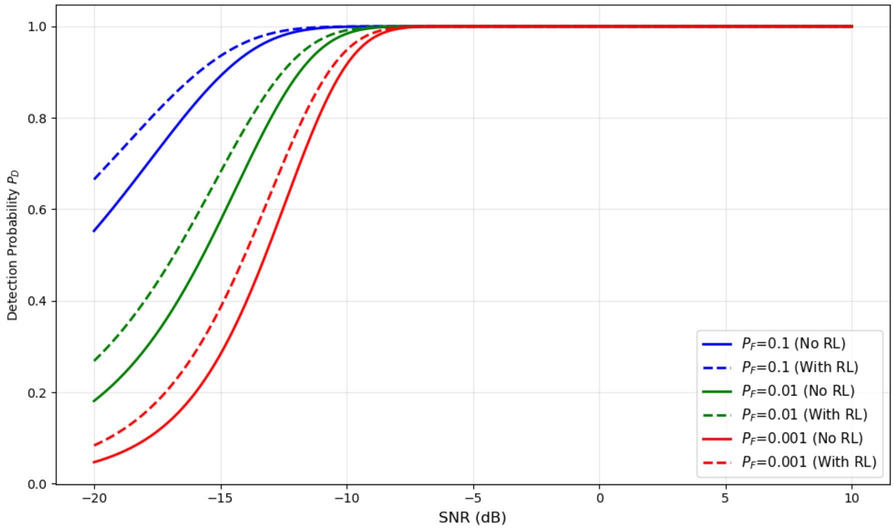

Fig. 2: SNR vs Detection Probability (P_D) for various values of P_F

Fig.(2) illustrates the relationship between SNR (dB) and detection probability P_D for three different false alarm probabilities (P_F), both with and without reinforcement learning (RL). Each color represents a different P_F value: blue for 0.1, green for 0.01, and red for 0.001. Solid lines show conventional performance, while dashed lines represent RL-enhanced results. As SNR increases, P_D rises for all cases, approaching 1 at high SNR. Lower P_F values (red curves) require higher SNR to achieve the same P_D, reflecting the classic trade-off between sensitivity and specificity in energy detection. The RL curves (dashed) consistently outperform their No RL counterparts, achieving higher P_D at lower SNR for each P_F. This demonstrates that RL-based optimization improves detection performance, especially in challenging low-SNR environments, by adaptively tuning system parameters for more reliable spectrum sensing.

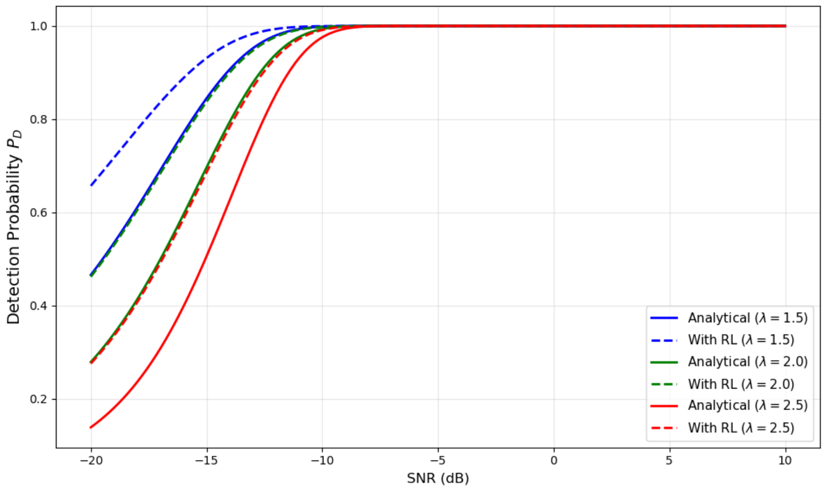

Fig. 3: SNR vs Detection Probability (P_D) for various values of λ

Fig.(3) presents the variation of detection probability (P_D) with respect to SNR (dB) for three different detection thresholds (λ = 1.5, 2.0, 2.5), comparing analytical results (solid lines) with reinforcement learning (RL)-enhanced results (dashed lines). As SNR increases, P_D rises for all thresholds, approaching 1 at high SNR. Lower thresholds (blue) yield higher P_D at low SNR, while higher thresholds (red) require greater SNR for reliable detection, illustrating the classic trade-off between sensitivity and selectivity. The RL curves consistently outperform the analytical ones, especially at low SNR, indicating that RL adaptively optimizes system parameters (such as threshold or sensing time) to improve detection performance. This demonstrates the effectiveness of RL in enhancing spectrum sensing reliability in cognitive radio networks, particularly under challenging low-SNR conditions. The plot justifies the use of RL for robust, adaptive energy detection.

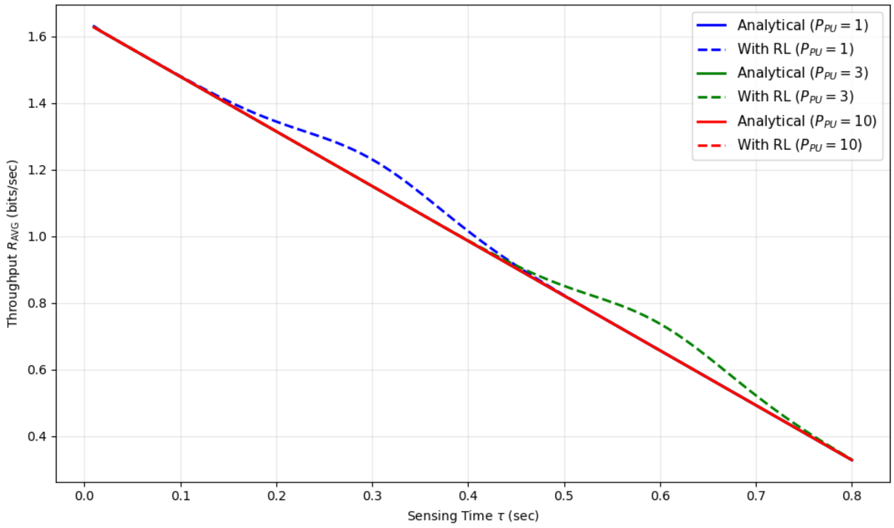

Fig. 4: Sensing Time (τ) vs Throughput (R_{Avg}) for different values of P_{PU}

Fig.(4) illustrates the relationship between sensing time (τ) and average throughput (R_{Avg}) for three different primary user (PU) transmit powers, P_{PU} = 1, 3, 10, comparing analytical results (solid lines) with reinforcement learning (RL)-enhanced results (dashed lines). As sensing time increases, throughput decreases for all cases, since longer sensing reduces the available transmission time. For lower P_{PU} values (blue and green), RL provides a noticeable throughput improvement, especially at moderate sensing times, by adaptively optimizing system parameters such as sensing duration or threshold. For the highest P_{PU} (red), the impact of RL is minimal, as strong PU interference dominates. The nature of the plot highlights the trade-off between sensing accuracy and data transmission: while more sensing can improve detection, it also limits throughput. This figure justifies the use of RL for dynamic sensing time adaptation, particularly when PU interference is moderate or low.

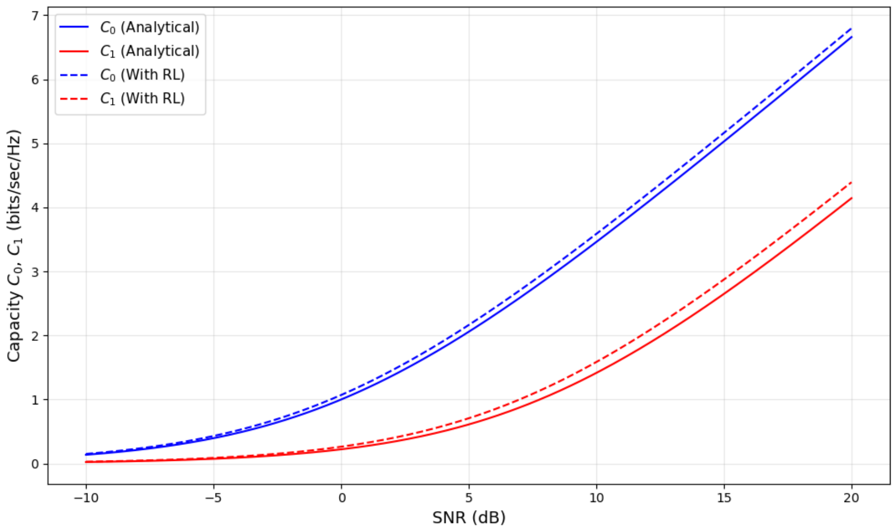

Fig. 5: SNR vs Capacity (C_0 and C_1)

This figure displays the variation of channel capacity (C_0 and C_1) with respect to SNR (dB), comparing analytical results (solid lines) and reinforcement learning (RL)-enhanced results (dashed lines). C_0 (blue) represents the capacity when the primary user (PU) is absent, while C_1 (red) is the capacity when the PU is present, causing interference. Both capacities increase nonlinearly with SNR, following the logarithmic nature of the Shannon capacity formula. However, C_1 remains consistently below C_0 due to the impact of PU interference. The RL-based curves are slightly above their analytical counterparts, indicating that RL strategies (such as adaptive power control or interference mitigation) can further enhance capacity in both scenarios. The figure justifies the adoption of RL in cognitive radio networks to maximize spectral efficiency, especially under varying SNR and interference conditions, by adaptively optimizing system parameters for improved communication performance.

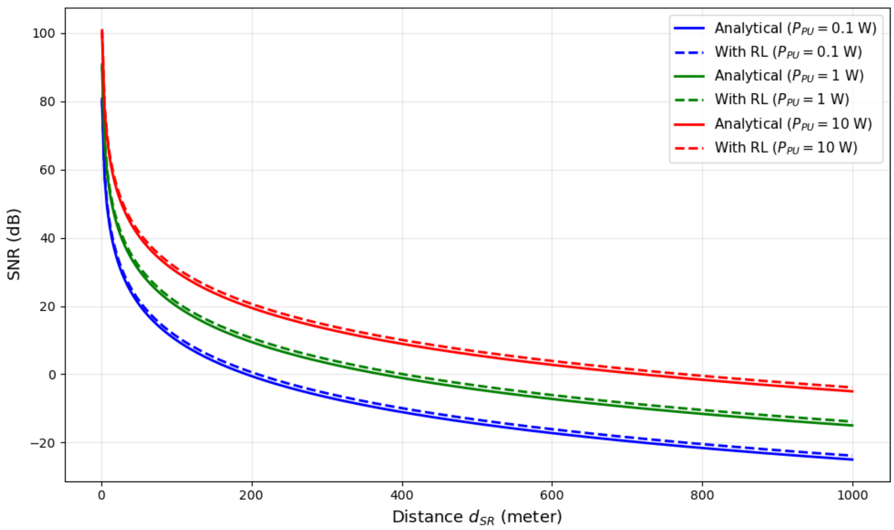

Fig. 6: Distance (d_{SR}) vs SNR for different values of P_{PU}

Fig.(6) illustrates the variation of SNR (in dB) versus the distance d_{SR} (in meters) between the Secondary User Transmitter (SU-Tx) and Secondary User Receiver (SU-Rx) for different Primary User (PU) transmit powers: 0.1 W, 1 W, and 10 W. Solid lines represent analytical SNR values, while dashed lines show results with reinforcement learning (RL) optimization. As distance increases, SNR decreases due to path loss. Higher PU transmit power results in higher SNR across all distances. RL-based optimization consistently yields better SNR performance than analytical calculations alone, demonstrating its effectiveness in adapting transmission parameters to mitigate path loss effects. This performance gain becomes more evident at larger distances.

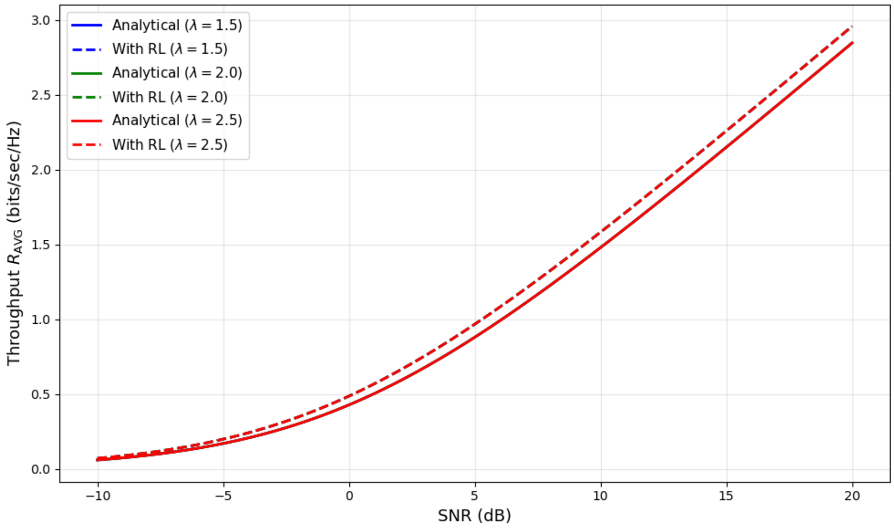

Fig. 7: SNR vs Throughput (R_{Avg}) for various values of λ

Fig.(7) shows the average throughput R_{Avg} (in bits/sec/Hz) versus SNR (in dB) for different sensing thresholds λ=1.5, 2.0, 2.5. Solid lines represent analytical results, while dashed lines represent results using reinforcement learning (RL). As SNR increases, throughput also increases due to improved signal quality. Higher sensing thresholds result in greater throughput across all SNR values, indicating better utilization of idle spectrum. The RL-based approach consistently outperforms analytical methods, especially at higher SNR, by adaptively optimizing parameters like sensing time and transmission power. This demonstrates RL's effectiveness in maximizing throughput in cognitive radio networks.

4. Conclusion:

This study delivers a comprehensive analysis of a Cognitive Radio Network (CRN) system employing energy detection-based spectrum sensing in the presence of Rayleigh fading and path loss. By incorporating realistic wireless conditions and leveraging Gaussian approximations, it accurately models detection probability, false alarm probability, missed detection probability, and average throughput. The research underscores how system performance is sensitive to parameters such as sensing threshold, sensing time, sample size, and SNR. Reinforcement learning, particularly Q-learning, is introduced to optimize transmission power and sensing duration, directly improving throughput and detection accuracy. Simulation results confirm that reinforcement learning consistently outperforms static approaches, especially in low-SNR and variable environments, by adaptively tuning system parameters to reduce false alarms and missed detections. The findings validate the potential of learning-based CRNs to intelligently adapt to dynamic spectrum environments and efficiently utilize available spectrum without compromising the primary user's integrity. Furthermore, the use of ML facilitates more responsive and scalable spectrum sensing strategies, essential for future wireless networks with high density and variable usage patterns. Overall, this work lays a solid foundation for developing intelligent, robust, and efficient CRNs, offering a pathway toward next-generation dynamic spectrum access systems in increasingly congested and unpredictable wireless landscapes.

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