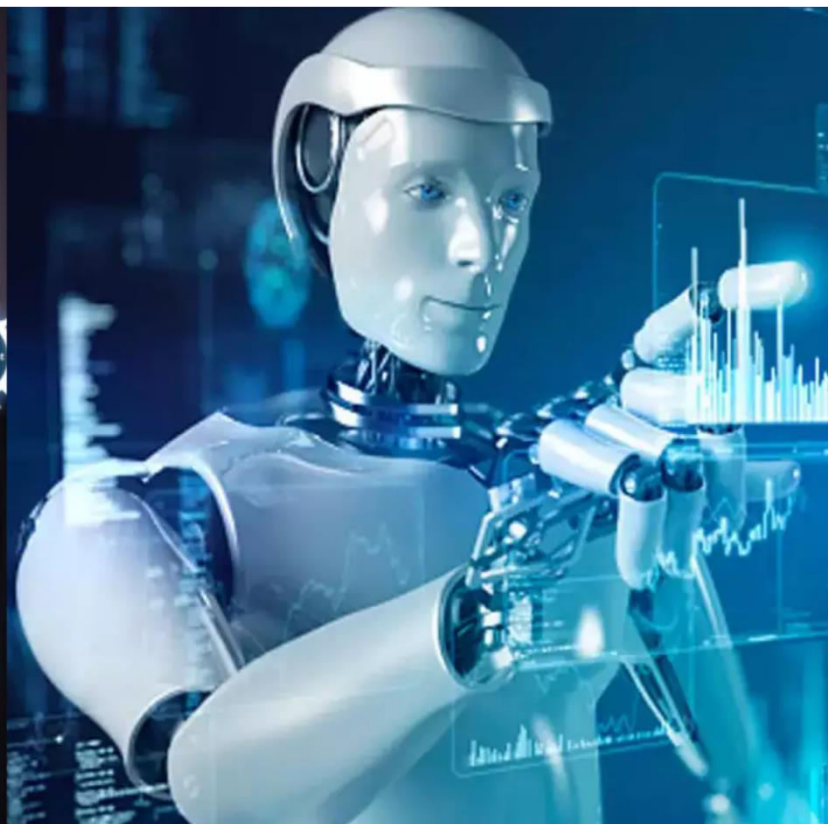




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BER and Spectrum Efficiency of Massive Cognitive Radio Networks using Sensing Approach

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ABSTRACT: With the explosive growth of wireless devices and services, the demand for efficient spectrum utilization has become increasingly critical. Cognitive Radio Networks (CRNs) have emerged as a promising solution to address spectrum scarcity by allowing unlicensed users, or secondary users (SUs), to opportunistically access underutilized licensed spectrum without interfering with primary users (PUs). Among the key performance indicators in CRNs, Bit Error Rate (BER) and spectrum efficiency play a vital role in evaluating communication reliability and bandwidth utilization. This paper presents a comprehensive review of how various spectrum sensing techniques impact BER and spectrum efficiency, particularly in large-scale or massive CRNs.

The study explores classical and advanced sensing approaches including energy detection, matched filtering, cyclostationary detection, and cooperative sensing. It also highlights recent trends involving machine learning and decentralized algorithms that enhance sensing accuracy in dense networks. The interplay between sensing accuracy, interference management, and BER is critically examined, along with the trade-offs between sensing time and spectral efficiency.

Furthermore, the paper discusses challenges associated with massive deployments, such as increased interference, dynamic spectrum availability, and the need for low-latency decision-making. This review aims to guide future research by emphasizing efficient spectrum access strategies that optimize both BER and spectrum efficiency in next-generation cognitive radio networks.

KEYWORDS: Massive System, Cognitive Radio, Compressive Sensing

I. INTRODUCTION

As CRNs evolve into Massive Cognitive Radio Networks (MCRNs)—featuring a high density of users and devices—the complexity of spectrum sensing, interference management, and performance optimization significantly increases. In such large-scale networks, two key performance metrics become particularly important: Bit Error Rate (BER) and Spectrum Efficiency (SE).

BER is a measure of the reliability of a communication link, representing the ratio of incorrectly received bits to the total number of transmitted bits. It reflects the quality of transmission and is influenced by factors such as signal-to-noise ratio (SNR), modulation scheme, interference levels, and sensing accuracy. In cognitive environments, a poor sensing decision (e.g., failing to detect a primary user) can result in interference that drastically increases the BER for both SUs and PUs.

On the other hand, Spectrum Efficiency (measured in bits/sec/Hz) indicates how effectively the available spectrum is being utilized. It is directly related to the throughput achieved in the network and is influenced by sensing time, access delay, bandwidth reuse, and adaptive transmission strategies. While increasing sensing accuracy can reduce BER, it often comes at the cost of reduced spectrum efficiency due to longer sensing times and lower transmission durations. This interplay introduces a challenging trade-off: improving BER performance through accurate sensing may lead to lower spectrum efficiency, while maximizing spectrum use could result in increased interference and higher BER.

Therefore, a critical goal in MCRNs is to strike a balance between communication reliability (low BER) and resource utilization (high SE), especially under dynamic and dense conditions.

From the above definition, the two major characteristics of CR can be defined as the cognitive capability and configurability. The cognitive capability refers to the ability of the radio component to capture (using techniques such as autonomous learning and action decision) or sense information (the temporal and spatial variations in the radio environment and the interference level generated to other users) from its surrounding radio environment. On the other hand, the configurability refers to the ability to enable the transmitter parameters to be dynamically programmed and modified according to the dynamics of radio environment.

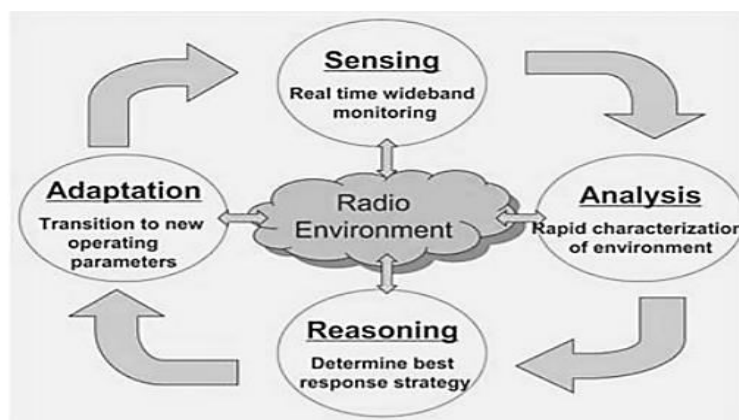


Figure 1: Cognitive Cycle

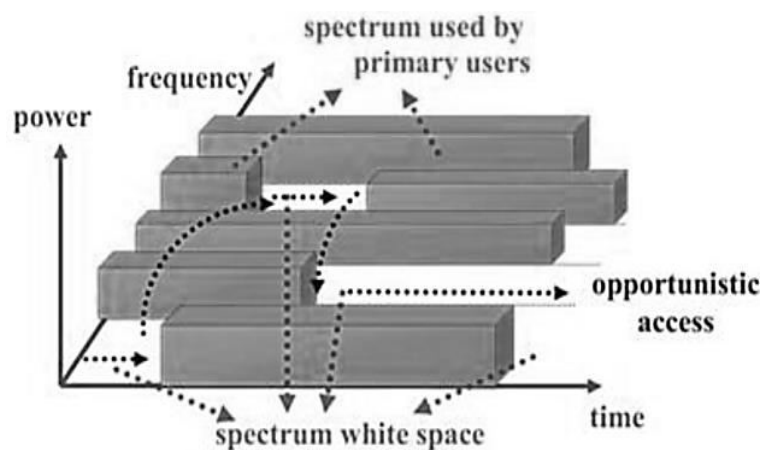


Figure 2: Opportunistic Usage of Spectrum Holes

Therefore, a CR enabled node in the network adapts dynamically to re configure several parameters such as the operating frequency (to take advantage of detected spectrum holes on different frequency bands), modulation and channel coding (to adapt to the requirements of application and the instantaneous conditions of channel quality), transmission power (to control the possible generated interference), and communication technology (to adapt to specific communication needs). Depending on the characteristics of the detected spectrum holes, as shown in Figure 1 and Figure 2, the CR enables to switch to different spectrum bands opportunistically [4], while the transmitter and receiver parameters are reconfigured accordingly.

II. CR NETWORK ARCHITECTURE

The possible architecture of a CR network as defined is shown in Figure 3. The components of such CR network architecture can be classified into two groups as primary network and secondary network (i.e. cognitive radio network). Primary network: A primary network is referred to an existing network infrastructure, where the nodes called primary users (PUs) have authorized license for exclusively accessing a certain frequency band. Examples of such networks include the cellular and the TV broadcast networks. Primary user (PU) activities are controlled through the primary base-stations in infrastructure based the primary network. Since the PUs have their priority in spectrum access, the operations of PUs should not be affected by any other unlicensed or secondary users.

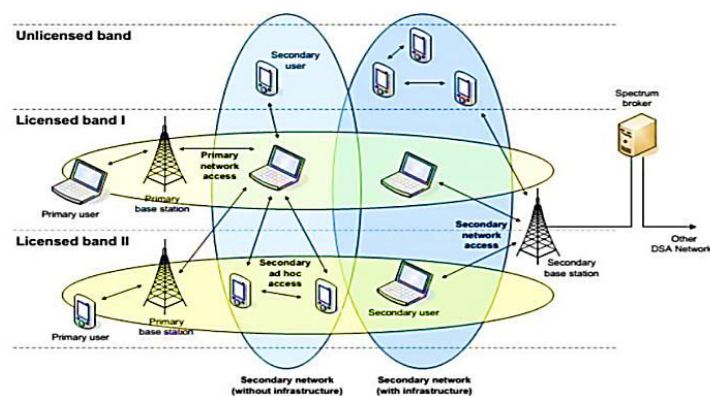


Figure 3: Cognitive Radio Network Architecture

Secondary network: A secondary or unlicensed network is referred to a network, with fixed infrastructure or based on ad hoc communication principle, without license to operate in a desired licensed band. Hence, to share the licensed spectrum band with primary networks, the additional functionalities are used by the nodes called CR users/secondary users (SUs). The infrastructure based secondary networks are equipped with a central entity called CR base station, which implements a single-hop connection to SUs. On the other hand, the secondary ad-hoc networks have no infrastructure backbone and a SU can communicate with other SUs through the ad-hoc connection on both licensed and unlicensed spectrum bands. Furthermore, secondary networks may include spectrum brokers, which can play a role in sharing spectrum resources among different secondary networks.

In the context of network architecture, the spectrum management functionalities are implemented by different entities. For instance, in infrastructure based architecture, the spectrum broker is responsible for coordinating the tasks of spectrum sensing, decision and management (sharing and mobility), while in ad-hoc architecture; CR nodes themselves are responsible for spectrum sensing, decision and management. The former requires a dedicated control channel whereas in infrastructure less architectures use of dedicated control channel is optional.

III. PROPOSED METHODOLOGY

When multiple CRs cooperate with each other in a network for the purpose of spectrum sensing, the process is called cooperative sensing. Fig. 4 illustrates a system model where CS is established for cooperative network. In a cooperative Cognitive Radio Network (CRN), there are more than one CR nodes, where each of them individually conducts CS to detect the existence of PU. According to the occupancy of spectrum by the PU, each of the CR nodes generates a local decision (binary or decision statistic). Among all the cognitive nodes, there are one CR node which acts as a common receiver called Decision Fusion Center or Cognitive Manager (CM). From Fig.4 each of the local decision is sent by the CR nodes to the Decision Fusion Center. Usually, the local decision is made by comparing the energy of the received spectrum with a predetermined threshold value. In order to minimize the control channel overhead, CRs only share their final 1-bit hard decisions (H_0 or H_1) rather than their decision statistics. It is the responsibility of the decision fusion center to gather the local sensing decisions from all the member nodes presenting in the CRN. For the final decision, the local decisions are combined by employing different hard decision fusion rules.

This signal is then passed through an Additive White Gaussian Noise (AWGN) channel. At the receiver end, the CP is removed and the signal is converted from serial to parallel to get the original, with FFT applied to each symbol for analysis in the frequency domain. After demodulation, the signal is cross correlated with that of a time-shifted local oscillator.

We implemented our circuit (Figure 4) in MATLAB software, with the main parameters described below. We generated a random binary signal in a serial manner. To analyse a signal in the time domain, we apply IFFT (Inverse Fast Fourier Transform) and convert it from parallel to serial OFDM signal to Add a cyclic prefix (CP), which helps avoid interference between OFDM symbols. We then feed this signal through an Additive White Gaussian Noise (AWGN) channel. At the receiver end, the CP is removed and the signal converted from serial to parallel to get the original, with FFT applied to each symbol for analysis in the frequency domain. After demodulation, the signal is cross correlated with that of a time-shifted local oscillator.

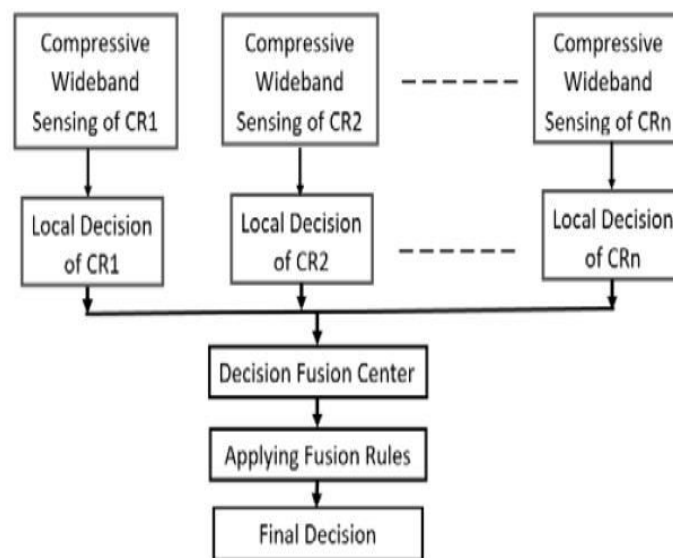


Figure 4: Design of MIMO-OFDM System using Compressive Sensing Cognitive Radio Network

SNR to determine whether the signal is absent or present; if the received signal is greater than the threshold value, there will be a detection, otherwise not:

$$\begin{aligned}
 H_0: y(t) &= n(t) & \text{PU is absent} \\
 H_1: y(t) &= h*s(t) + n(t) & \text{PU is present}
 \end{aligned}$$

IV. SIMULATION RESULTS

MATLAB simulations are performed for various combinations of transmitted and received antenna in massive MIMO system. Simulation experiments are conducted to evaluate the SNR verse bit error rate (BER) performance of the proposed compressive sensing 8×8 system is shown in figure 5. For different value of SNR, the implemented compressive sensing 8×8 system shows BER reduction performance.

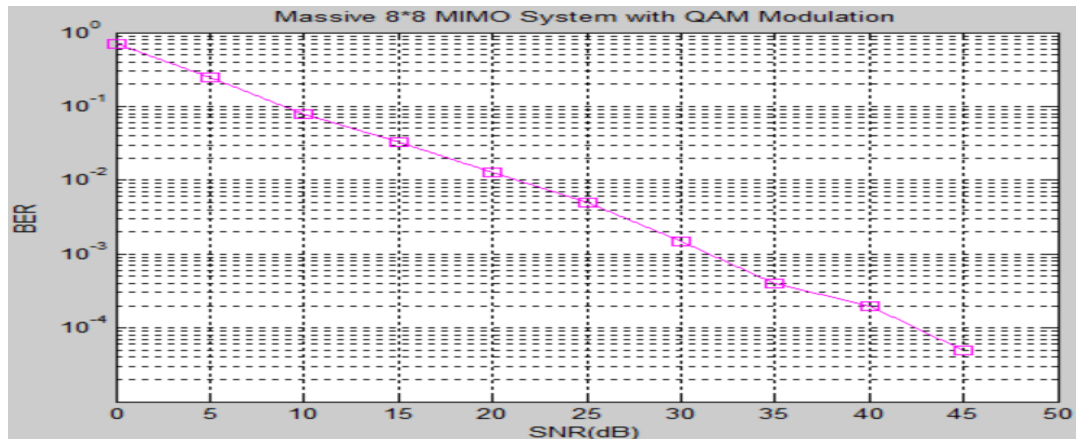


Figure 5: BER vs SNR for Compressive Sensing 8×8 System

The simulation covers an end-to-end system showing the encoded and/or transmitted signal, channel model and reception and demodulation of the received signal. It is assumed that the channel is known perfectly at the receiver for all systems. Then run the simulation over a range of E_b/N_0 points to generate BER results that allow comparing the 16×16 systems is shown in figure 6.

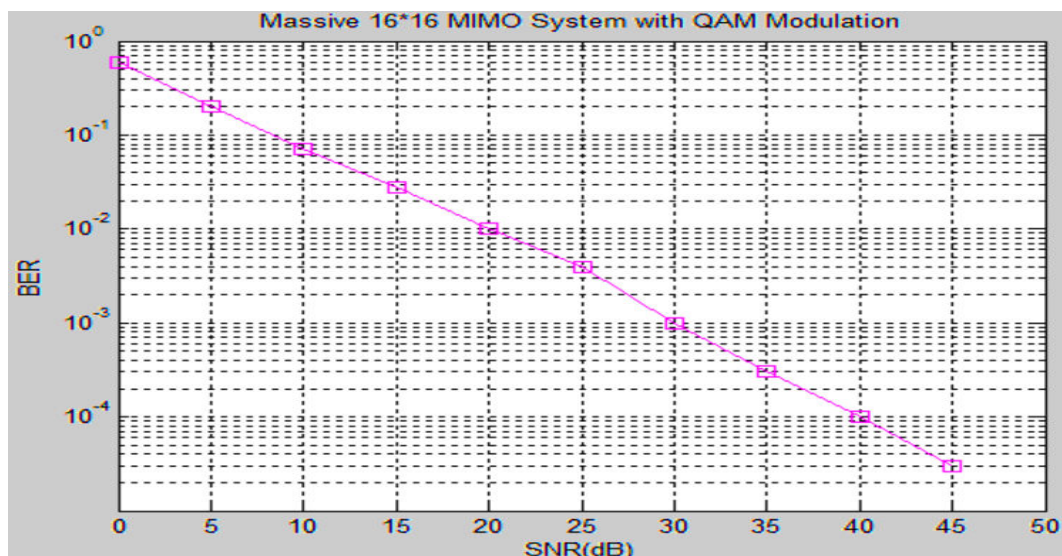


Figure 6: BER vs SNR for Compressive Sensing 16×16 System

Simulation experiments are conducted to evaluate the SNR verse relative mean square error performance of the proposed matched filter detection spectrum sensing 8×8 system is shown in figure 7. To analysis random binary generator signal, a signal in the frequency domain, an IFFT is applied to the signal and converted from parallel-to-serial for the addition of the CP, four transmitter antenna and four receiver antenna through an additive white Gaussian noise (AWGN) channel.

Figure 8 shows the relative mean square error (MSE) versus signal to noise ratio (SNR) graph for 16×16 massive MIMO system with 16-QAM modulation technique. As the SNR increase, the MSE value is decreased. The lowest value of MSE is achieved the case of implemented method. We have estimated the channel under additive white Gaussian noise (AWGN) channel condition. It is clearly that the increase the transmitter and receiver antenna than increase the MSE with the help of matched filter detection spectrum sensing system.

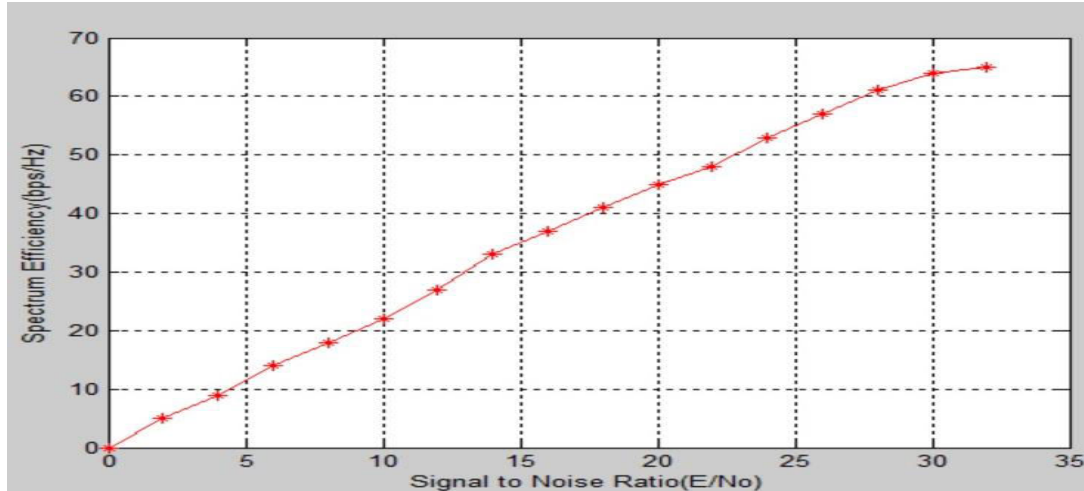


Figure 7: Spectrum Efficiency vs SNR for Compressive Sensing 8×8 System

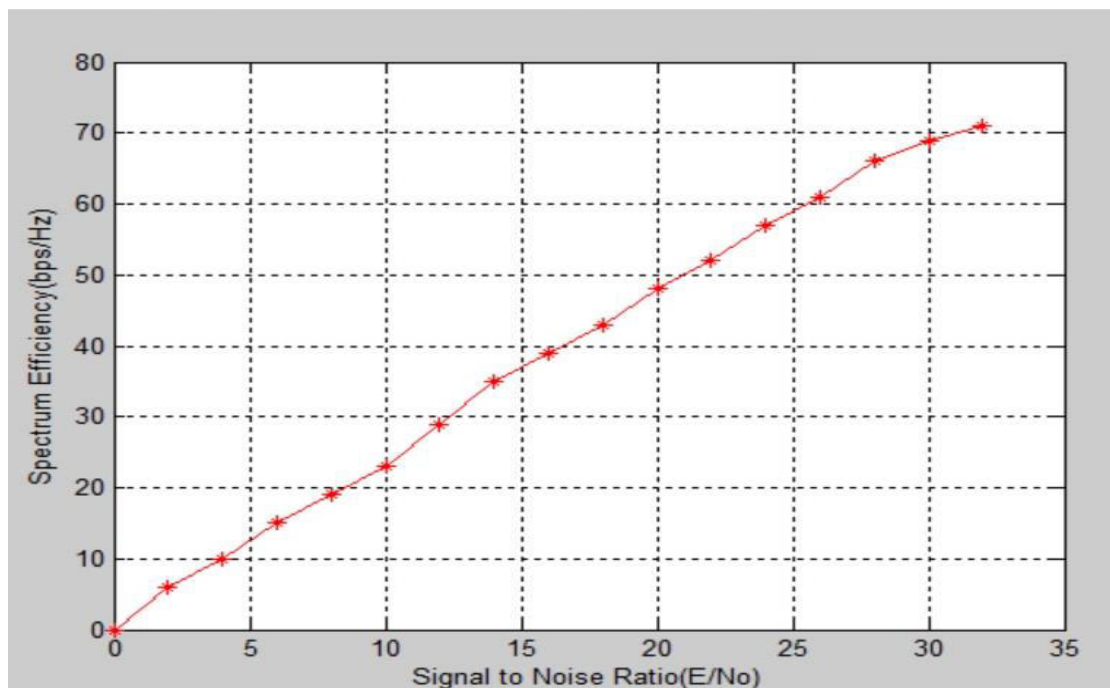


Figure 8: Spectrum Efficiency vs SNR for Compressive Sensing 16×16 System

V. CONCLUSION

Compressive sensing is known as an optimal method for detection of primary users when the transmitted signal is known. It is a linear filter designed to maximize the output signal to noise ratio for given input signal. It is obtained by correlating a known signal, with an unknown signal to detect the presence of the known signal in the unknown signal. This is equivalent to convolving the unknown signal with a time-reversed version of the signal. Convolution is at the heart of matched filters.

Convolution does essentially with two functions that it places one function over another function and outputs a single value suggesting a level of similarity, and then it moves the first function an infinitesimally small distance and

finds another value. The end result comes in the form of a graph which peaks at the point where the two images are most similar. The matched filter is the optimal linear filter for maximizing the Signal to Noise Ratio (SNR) in the presence of additive White Gaussian Noise. The performance of implemented method including wireless communication is better as compared to the previous technique algorithm

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