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A Channel Ranking And Selection Scheme Based On Channel Occupancy And SNR For Cognitive Radio Systems

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A CHANNEL RANKING AND SELECTION SCHEME BASED ON CHANNEL OCCUPANCY AND SNR FOR COGNITIVE RADIO SYSTEMS

by

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This thesis, submitted by Adnan Quadri in partial fulfillment of the requirements for the Degree of Master of Science from the University of North Dakota, has been read by the Faculty Advisory Committee under whom the work has been done and is hereby approved.

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This thesis meets the standards for appearance, conforms to the style and format requirements of the Graduate School of the University of North Dakota, and is hereby approved.

Grant McGimpsey,

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Adnan Quadri

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TABLE OF CONTENTS

LIST OF FIGURES

Figure Page

LIST OF TABLES

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ABSTRACT

Wireless networks and information traffic have grown exponentially over the last decade. Consequently, an increase in demand for radio spectrum frequency bandwidth has resulted. Recent studies have shown that with the current fixed spectrum allocation (FSA), radio frequency band utilization ranges from 15% to 85%. Therefore, there are spectrum holes that are not utilized all the time by the licensed users, and, thus the radio spectrum is inefficiently exploited. To solve the problem of scarcity and inefficient utilization of the spectrum resources, dynamic spectrum access has been proposed as a solution to enable sharing and using available frequency channels. With dynamic spectrum allocation (DSA), unlicensed users can access and use licensed, available channels when primary users are not transmitting. Cognitive Radio technology is one of the next generation technologies that will allow efficient utilization of spectrum resources by enabling DSA. However, dynamic spectrum allocation by a cognitive radio system comes with the challenges of accurately detecting and selecting the best channel based on the channel's availability and quality of service. Therefore, the spectrum sensing and analysis processes of a cognitive radio system are essential to make accurate decisions. Different spectrum sensing techniques and channel selection schemes have been proposed. However, these techniques only consider the spectrum occupancy rate for selecting the best channel, which can lead to erroneous decisions. Other communication parameters, such as the Signal-to-Noise Ratio (SNR) should also be taken into account. Therefore, the spectrum decision-making process of a cognitive radio system must use

techniques that consider spectrum occupancy and channel quality metrics to rank channels and select the best option. This thesis aims to develop a utility function based on spectrum occupancy and SNR measurements to model and rank the sensed channels.

An evolutionary algorithm-based SNR estimation technique was developed, which enables adaptively varying key parameters of the existing Eigenvalue-based blind SNR estimation technique. The performance of the improved technique is compared to the existing technique. Results show the evolutionary algorithm-based estimation performing better than the existing technique. The utility-based channel ranking technique was developed by first defining channel utility function that takes into account SNR and spectrum occupancy. Different mathematical functions were investigated to appropriately model the utility of SNR and spectrum occupancy rate. A ranking table is provided with the utility values of the sensed channels and compared with the usual occupancy rate based channel ranking. According to the results, utility-based channel ranking provides a better scope of making an informed decision by considering both channel occupancy rate and SNR. In addition, the efficiency of several noise cancellation techniques was investigated. These techniques can be employed to get rid of the impact of noise on the received or sensed signals during spectrum sensing process of a cognitive radio system. Performance evaluation of these techniques was done using simulations and the results show that the evolutionary algorithm-based noise cancellation techniques, particle swarm optimization and genetic algorithm perform better than the regular gradient descent based technique, which is the least-mean-square algorithm.

Chapter 1

INTRODUCTION

1.1. The problem of inefficient spectrum utilization

As demand for advanced wireless technologies continues to grow, the load on frequency bands for wireless communication is also increasing. Initially, the problem of accommodating the increasing load was mainly identified as a physical scarcity of the spectrum but an in-depth analysis showed the result is also due to inefficient utilization of the radio spectrum. Research findings in [1-4] suggest that indeed in a specific location and time some frequency bands are heavily used while few are partially occupied and remaining bands are left unused. Under the fixed spectrum allocation policy, it was found that spectrum utilization only ranges from 15% - 85% in the United States [5]. Figure 1 [6] illustrates the inefficient utilization of spectrum resources. As seen from the figure, few frequency bands are heavily used, some are less used, while remaining ones are left idle.

A large number of licensed spectrum remains underutilized by the licensed or primary users (PUs), and cannot be accessed by potential radio spectrum users, secondary users (SUs). In order to address both spectrum scarcity and inefficient utilization of licensed spectrum, dynamic ways to share unoccupied channels can be employed. Unlike fixed spectrum allocation, dynamic spectrum sharing, also known as opportunistic spectrum sharing, enables sharing the channels between PUs and SUs. To pave the path to dynamic spectrum access by enabling spectrum sharing and reuse, Cognitive Radio (CR) technology stands to be a promising solution.

1.2 Cognitive Radio Technology

Cognitive Radio is an intelligent wireless communication technology, which will enable wireless radio systems to be aware of its surrounding radio frequency environment and adapt to any changes by reconfiguring communication parameters [7-8]. Amid active licensed users of frequency bands a cognitive radio detects the presence of available spectrum and is able to use the unoccupied licensed channels without interfering with PUs operations. Cognitive Radio technology is actively pursued as a next generation communication technology through the IEEE 802.11 standards that provide SUs the scope to use TV white space or available licensed TV spectrum [9].

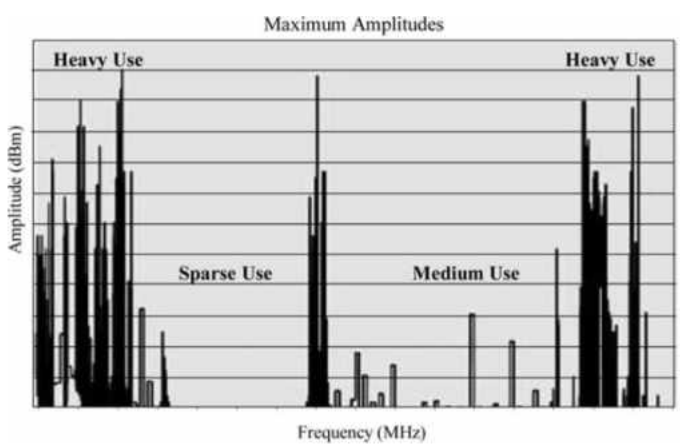

Figure 1. Spectrum Utilization [6]

Objectives of CR are to ensure faster and reliable communication at any time and location, and to efficiently utilize spectrum resources. Briefly, a cognitive radio cycle involves the three processes of sensing, deciding, and taking actions. To complete the cycle, a cognitive radio system goes through the three following phases of operation:

1) Spectrum Sensing

2) Spectrum Analysis

3) Spectrum Decision

During the first phase, a cognitive radio system performs spectrum sensing to determine available frequency bands for data communication. The processes of spectrum sensing involves sensing frequency channels, collecting sufficient signal samples during the scanning, and determine if the sensed channels are free or occupied. Examples of the sensing techniques include energy detection, cyclostationary feature-based detection and matched filter [9]. These sensing techniques have been studied and improvements were proposed to have both narrowband and wideband sensing. While in narrowband sensing one frequency channel is sensed, wideband sensing allows sensing one or more frequency bands. Example of the wideband sensing includes 1-bit and multi-bit compressive sensing techniques [11-13]. Similarly, other techniques were proposed that aims to reduce uncertainties involved in the accurate detection of available frequencies, much of which is discussed in the next chapters.

After spectrum sensing, which determines the availability of frequency channels, in the spectrum analysis phase a CR system evaluates the sensed channels. During this phase, several communication parameters are taken into account that provides information on the quality of channels. Some of these parameters that enables characterizing a channel are bit error rate (BER, signal-to-noise ratio (SNR), channel capacity, modulation scheme, received power and many more [14].

Once spectrum analysis is performed, spectrum decision making process takes into account the result of spectrum sensing and analysis to select the best available channel for data communication by the CR system. This is the last and most important step of the CR operation as this step ultimately fulfills the objective of cognitive radio technology; efficient utilization of radio spectrum resource while maintaining the quality of service of the communication [9].

One of the most important conditions imposed on the operation of a CR system is that its data communication under no circumstances can interfere with the licensed primary user's communication. To meet the stringent requirements and simultaneously provide standard data communication services, a CR system must be able to recognize the best options among several choices. In the next section, spectrum decision-making process of a CR system is further discussed and the problem with existing techniques is stated.

1.3 Problem Statement and Thesis Objectives

Radio spectrum decision-making process is an essential step of the cognitive radio operation as the decision making process enables CR systems to improvise and adapt to changing radio frequency environment accordingly. Based on the findings of spectrum sensing and analysis, the decision is made on which available channel could be the best one to establish data communication. Primarily, spectrum occupancy is determined either instantaneously or for a short period of time using the sensing techniques mentioned in the previous section. Information on the spectrum occupancy rate is essential for cognitive radio systems as it cannot interfere, and must vacate the channel when needed by the primary user (PU). Using statistical inference based techniques, such as Bayesian inference [15], occupancy rates can be estimated for a longer period of time, which reduces uncertainty in the occupancy measurement process. However, spectrum occupancy alone cannot verify if an available channel is the best one for data communication by the secondary user [16]. Subsequently, the CR system then performs spectrum analysis by gathering information on the channel quality of service.

To enhance the decision-making capabilities of CR systems, combined information on channel condition and its occupancy rate are necessary to develop a more accurate understanding of the adjacent radio frequency environment. Simultaneously, to select from a range of options provided by the decision-making process, a ranking mechanism or score based channel selection process is required to select the best channel. Ranks can be assigned to the list of channels by evaluating their usefulness in terms of channel condition parameters, such as signal-to-noise ratio (SNR), and spectrum occupancy rate. Utility models can characterize the channel condition parameters and occupancy, respectively. These models can then be used to estimate channel utility. Channel with the largest utility value is ranked highest and the rest of the channels follow with decreasing ranks.

This thesis aims to develop a utility-based channel ranking technique for cognitive radio systems that will take into account factors impacting communication channels, such as noise and occupancy, to evaluate the usefulness or utility of the available channels and assign ranks accordingly. This thesis also aims to develop evolutionary algorithm-based noise cancellation techniques to improve CR systems.

To achieve these goals, the flowing objectives were set and met:

1. Improve SNR estimation technique using an evolutionary algorithm-based estimation.

2. Investigate the suitability of mathematical functions for utility-based channel ranking.

3. Investigate the efficiency of noise cancellation techniques for CR systems.

1.4 Thesis Contributions

The contributions of the thesis are:

1. An evolutionary algorithm-based SNR estimation technique.

2. A utility-based channel ranking scheme that takes into account SNR and Spectrum Occupancy.

3. An evolutionary algorithm-based noise cancellation technique.

One of the existing SNR estimation techniques is improved by using evolutionary algorithm-based estimation. The evolutionary algorithm, particle swarm optimization is used to improve an existing non-data aided Eigenvalue-based SNR estimation techniques. The use of evolutionary algorithm enabled the Eigenvalue-based technique to adaptively change few of its operational parameters, such as the number of signal samples, Eigenvalues, and distribution size. Performance evaluation of the proposed technique is provided and compared with that of the existing technique. This research work on optimized SNR estimation technique was published and presented at IEEE, 7th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, Nevada, 2017.

To enhance the radio spectrum decision-making process, a utility-based channel ranking technique is proposed that takes into account SNR and spectrum occupancy rate to model channel utility. The utility-based channel ranking technique allows a cognitive radio system to more accurately list down useful channels, as opposed to usual occupancy rate based channel ranking. Utility modeling of SNR and spectrum occupancy rate is provided and the channel utility is defined as a function of the two parameters. The results are discussed, where the utility-based channel ranking is compared to the occupancy-based ranking. This research work was presented as poster during the Graduate Research Achievement (GRAD) day, organized by School of Graduate Studies, University of North Dakota, and was chosen as one of the finalist posters. The work also appears in the Cornell University digital library, arXiv.

Finally, the thesis contributes to the improvement of one of the existing noise cancellation techniques that get rid of noise induced from several sources, such as path loss, fading, non-linearity at radio front end, thermal noise, and noise from adjacent radio nodes. Several adaptive filtering techniques, including two evolutionary algorithm-based noise cancellation techniques, are implemented and tested. The improved noise cancellation techniques can be used to denoise signals during the spectrum sensing phase. Simulation results show better performance of evolutionary algorithm-based noise cancellation techniques over the traditional ones. This work was published and presented at the IEEE Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, New York, 2016.

The above mentioned thesis contributions were published and presented in the following conferences and digital libraries:

1. A. Quadri, M. R. Manesh, N. Kaabouch, "Noise cancellation in cognitive radio systems: A performance comparison of evolutionary algorithms," 2017 IEEE 7th Annual

Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, 2017, pp. 1-7.

2. A. Quadri, M. R. Manesh, N. Kaabouch, "Denoising signals in cognitive radio systems using an evolutionary algorithm based adaptive filter," 2016 IEEE 7th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, NY, 2016, pp. 1-6.

3. M. R. Manesh, A. Quadri, S. Subramaniam and N. Kaabouch, "An optimized SNR estimation technique using particle swarm optimization algorithm," 2017 IEEE 7th Annual Computing and Communication Workshop and Conference (CCWC), Las Vegas, NV, 2017, pp. 1-6.

4. A. Quadri, "A Review of Noise Cancellation Techniques for Cognitive Radio." arXiv preprint arXiv:1801.01111, 2018.

1.6 Thesis Organization

The thesis is organized as follows. In chapter 2, SNR estimation techniques are discussed. Classification of noise estimation techniques is provided and the estimation process is outlined. Finally, an evolutionary algorithm-based estimation is proposed and simulation results are discussed. Chapter 3 presents a utility-based channel ranking technique for cognitive radio systems. At first, the cognitive radio cycle is briefly reviewed and techniques used in each phase of the CR cycle are outlined. Channel ranking mechanisms are discussed and the utility-based ranking is proposed. Subsequently, four mathematical functions are provided and their suitability to model the channel utility is investigated. Results are then provided and the proposed ranking technique is compared with the existing occupancy rate-based ranking.

In chapter 4, noise cancellation techniques are classified and their differences are discussed. The steps involved in noise cancellation are outlined and two evolutionary algorithm-based techniques are developed. The simulation results are analyzed and the performances of the evolutionary algorithm-based techniques are compared with the traditional filtering technique using several performance evaluation metrics.

Chapter 2

NOISE ESTIMATION

This chapter discusses the importance of signal-to-noise ratio (SNR) estimation in communication and the need for adaptive techniques to better estimate noise in next generation communication technologies. The following chapter is organized as follows.

Section 2.1 discusses the importance of SNR estimation in communication systems followed by section 2.2 which presents classification of these techniques. Section 2.3 narrows the focus of the chapter on non-data aided and proposes the use of evolutionary algorithm for better SNR. The section also discusses the steps involved in SNR estimation for both of these techniques. Section 2.4 provides results from simulations and analyzes the performance of the techniques discussed in the previous section. Finally, the chapter is concluded by providing synopsis of the findings.

2.1 Noise Estimation in Cognitive Radio Systems

Signal-to-noise ratio (SNR) estimation is an important process in the current and future wireless communication systems [17]. Noise may originate from several sources, such as path loss, fading, non-linearity at radio front end, thermal noise, and from adjacent radio nodes to distort transmitted signal. The SNR may vary depending on the changing noise power of these sources. SNR estimation is usually employed in various techniques such as diversity combining, mobile assisted handoff, power control, adaptive coding/decoding and modulation, as well as channel assignment in cognitive radio networks [18-20]. Specifically, in the field of cognitive radio, the knowledge of signal-to-noise ratio (SNR) is important since it affects the probabilities of detection and false alarm of spectrum sensing techniques [21]. Estimating this parameter can help the cognitive radio system identify the available channels and estimate their usage levels [22-24]. However, with the presence of the prevailing channel coding techniques, systems are able to work in very low SNR regime which makes SNR estimation a challenging task.

2.2 Classification of Signal-to-Noise Ratio Estimation Techniques

SNR estimation methods can be classified into two categories: data-aided and non-data aided approaches. Data-aided estimation techniques require the information about the properties of the transmitted data sequences (pilot). These techniques are normally able to provide an accurate estimate of SNR. However, in time varying channels, they need to employ larger pilot information to enable the receiver to track the channel variations. This type of approaches leads to excessive overhead imposing undesired capacity loss to the system [25]. On the other hand, non-data aided algorithms estimate the SNR without impacting the channel capacity. These techniques do not need any knowledge of the transmitted data sequence characteristics. Techniques of this type use methods such as extracting and analyzing the inherent characteristics of the received signal to estimate the noise and signal powers. Examples of data aided and non-data aided methods are those described by Pauluzzi et al [26], such as split symbol moment estimator, maximum likelihood estimator, squared signal to noise variance estimator, second and fourth order moment estimator, and low bias algorithm negative SNR estimator.

One of the non-data aided methods is a technique based on the Eigenvalues of the covariance matrix formed from the received signal samples that was proposed by Hamid et al. [27]. This method initially detects the Eigenvalues as in [28-31] and employs the minimum descriptive length (MDL) criterion to split the signal and noise corresponding to Eigenvalues. It is a blind technique in the sense that it does not have any knowledge of the transmitted signal and noise, and SNR is merely estimated based on the received signal samples. Furthermore, since this method is based on sub-spaced decomposition of the signal, it requires less processing time and is more accurate. However, this technique is highly dependent on: 1) the number of received samples, 2) the number of Eigenvalues, and 3) the Marchenko-Pastur distribution size.

The selection criteria of these parameters is based on a number of factors such as type of application, channel condition, and hardware limitation. It is obvious that this estimator could be more efficient if an algorithm can dynamically optimize these parameters according to particular situations. One possible solution is the use of evolutionary optimization algorithms such as particle swarm optimization (PSO) and genetic algorithms. These techniques, as the name implies, mimic the pattern of biological evolutions and evolve and iterate repeatedly to find the optimum solution of an objective function corresponding to a specific situation. Some of these algorithms, such as the genetic algorithm, are application-dependent and require selecting appropriate initialization values to converge at a steady rate [32-33]. However, PSO algorithm does not rely on a specific single variable initialization and is less complex.

2.3 Non-data Aided and Evolutionary Algorithm Based Noise Estimation Techniques

In this section, we first describe the original Eigenvalue-based SNR estimation technique described in the previous section. The estimation technique involves computation of two distributions, namely Marchenko-Pastur and empirical, from Eigenvalues of the received signal and calculation of goodness of fitting between these two distributions. We show that the goodness of fitting requires to be optimized to provide more accurate estimate of SNR. Next, we describe the PSO algorithm and how this algorithm optimizes the goodness of fitting.

2.3.1 SNR Estimation Method Using Eigenvalue Based Covariance Matrix

To produce the received signal, a binary phase shift keying (BPSK) modulated signal with carrier frequency of 2.4 GHz is generated and added with additive white Gaussian noise (AWGN) with zero mean and standard deviation, σ_z^2. Therefore, the received samples are comprised of both noise components, $\boldsymbol{Z}$, and signal components, $\boldsymbol{S}$. It is necessary to determine the noise power i.e. noise variance, σ_z^2, in order to estimate the SNR. For this purpose, we need to apply the SNR estimation method to the received signal samples. To do so, N received signal samples, $x[n]$, are obtained and stored in an array as shown by:

$$[x[0], x[1], x[2], \dots, x[N-1]] \tag{1}$$

A value known as the smoothing factor is chosen and denoted as L. An $L \times N$ dimension matrix is formed, where each row of the matrix is comprised of L time-shifted versions of the received signal samples $x[n]$, as shown by:

$$\boldsymbol{X} = \begin{pmatrix} x_{1,1} & \cdots & x_{1,N} \\ \vdots & \ddots & \vdots \\ x_{L,1} & \cdots & x_{L,N} \end{pmatrix} \tag{2}$$

where $x_{i,j}$ is the received signal vector sample, L is the number of Eigenvalues and N is the length of the received signal vector. Similar to the approach in [28], the sample covariance matrix is computed as the product of matrix, $\boldsymbol{X}$ and its Hermitian transpose averaged over N samples which is given by:

$$\widehat{\boldsymbol{R}}_x = \frac{1}{N}\boldsymbol{X}\boldsymbol{X}^H \tag{3}$$

The Eigenvalues of the resultant $L \times L$ matrix are computed and sorted in descending order to form an L-element array. The descending order sort is performed based on the MDL criterion which implies that the first M Eigenvalues represent the transmitted signal component and the remaining $L - M$ Eigenvalues represent the noise component. The array of Eigenvalues is shown below:

$$[\lambda_1, \lambda_2, \dots, \lambda_M, \lambda_{M+1}, \dots, \lambda_L] \tag{4}$$

The value of M is estimated using the MDL criterion as given by:

$$\widehat{M} = \underset{M}{argmin}\left(-(L-M)N\log\left(\frac{\theta(M)}{\phi(M)}\right) + \frac{1}{2}M(2L-M)\ logN\right) \tag{5}$$

where $0 \leq M \leq L - 1$ and,

$$\theta(M) = \prod_{i=M+1}^{L} \lambda_i^{\frac{1}{L-M}} \tag{6}$$

$$\phi(M) = \frac{1}{L-M}\sum_{i=M+1}^{L} \lambda_i \tag{7}$$

and $\widehat{M}$ is the estimated value of M. After M is estimated, the array of Eigenvalues is split up based on the noise group and transmitted signal group as given below:

$$\lambda_{Signal} = [\lambda_1, \lambda_2, \dots, \lambda_{\widehat{M}}] \tag{8}$$

$$\lambda_{Noise} = [\lambda_{\widehat{M}+1}, \lambda_{\widehat{M}+2}, \dots, \lambda_L] \tag{9}$$

To estimate the noise power σ_z^2 using the array λ_{Noise}, two values σ_{z1}^2 and σ_{z2}^2 are calculated as follows:

$$\sigma_{z1}^2 = \frac{\lambda_L}{(1-\sqrt{c})^2} \tag{10}$$

$$\sigma_{z2}^2 = \frac{\lambda_{\widehat{M}+1}}{(1+\sqrt{c})^2} \tag{11}$$

where $c = L/N$. In random matrix theory, the Marchenko-Pastur law provides the probability density function of singular values of large rectangular random matrices [34]. In this case, the matrix $\boldsymbol{X}$ is the rectangular random matrix whose entries $x_{i,j}$ are independent and identically distributed random variables with mean zero and variance σ^2. A set of K linearly spaced values in the range $[\sigma_{z1}^2, \sigma_{z2}^2]$ is generated and denoted as π_k, where $1 \leq k \leq K$. The Marchenko-Pastur density of the parameters $(1-\hat{\beta})c$ and π_k where $\hat{\beta} = \frac{\widehat{M}}{L}$ is given by:

$$MP_d = MP\left((1-\hat{\beta})c, \pi_k\right) = \frac{\sqrt{\left(\nu - \left(\pi_k\left(1-\sqrt{(1-\widehat{\beta})c}\right)\right)^2\right) * \left(\left(\pi_k\left(1+\sqrt{(1-\widehat{\beta})c}\right)\right)^2 - \nu\right)}}{2*\pi*\pi_k^2*(1-\widehat{\beta})c*\nu} \tag{12}$$

where

$$\left(\pi_k\left(1-\sqrt{(1-\hat{\beta})c}\right)\right)^2 \le \nu \le \left(\pi_k\left(1+\sqrt{(1-\hat{\beta})c}\right)\right)^2 \tag{13}$$

The empirical distribution function of the noise group Eigenvalues, λ_{Noise}, is computed by:

$$E_d = F_n(t) = \frac{\text{number of sample values} \le \text{t}}{\text{n}} = \frac{1}{n}\sum_{i=1}^{n} 1_{\lambda_{Noise}(i) \le t} \tag{14}$$

where $n = L - \widehat{M} + 1$.

Both the arrays (MP_d and E_d) are compared and a goodness of fitting ($D(\pi_k)$) is used to find the best estimate of π_k, thereby estimating the value of the noise power σ_z^2. The goodness of fitting is given by:

$$D(\pi_k) = \|E_d - MP_d\|_2 = \sqrt{\sum(E_d - MP_d)^2} \tag{15}$$

From the array of values of $D(\pi_k)$, the index of the minimum value of $D(\pi_k)$ is obtained and the corresponding value of the array π_k for the obtained index is the estimate of noise variance $\widehat{\sigma_z^2}$ which is given by:

$$\widehat{\sigma_z^2} = \underset{\pi_k}{argmin}\left(D(\pi_k)\right) \tag{16}$$

Once the noise power has been estimated, the signal power can be calculated as the difference between the total received signal power and the estimated noise power. The total received signal power is given by:

$$\widehat{P_t} = \left(\frac{1}{NL}\sum_{j=1}^{L}\sum_{i=1}^{N}\left|x_{i,j}\right|^2\right) \tag{17}$$

Therefore, the SNR $\hat{\gamma}$ is given by:

$$\hat{\gamma} = \frac{\widehat{P_s}}{\widehat{\sigma_z^2}} = \frac{\widehat{P_t} - \widehat{\sigma_z^2}}{\widehat{\sigma_z^2}} \left(\frac{1}{NL\widehat{\sigma_z^2}} \sum_{j=1}^{L} \sum_{i=1}^{N} \left| x_{i,j} \right|^2 \right) - 1 \tag{18}$$

As mentioned earlier, the goodness of fitting, ($D(\pi_k)$), is used to find the best estimate of π_k, from which the value of the noise power, σ_z^2, can be estimated. A precise look at (15) reveals that the goodness of fitting is a measure of how close MP_d and E_d are to each other. To further clarify the concept, we evaluated these two distributions for L of 10 and 100 against different values of v, which is multiple variations of K linearly spaced range of noise variance, while keeping SNR at -15 dB as shown in Figure 2. Different values of L result in different E_d and MP_d curves which might be closer or farther to each other. Since the index of the minimum value of $D(\pi_k)$ is used to estimate the noise power as in (16), PSO algorithm can be applied to minimize $D(\pi_k)$, as an objective function, to provide the closest MP_d and E_d.

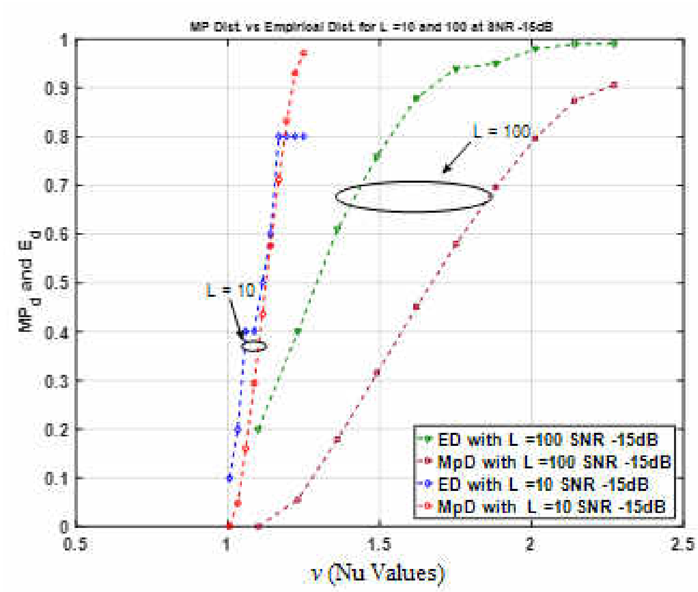

Figure 2. Marchenko-Pastur and Empirical distribution

2.3.2 SNR Estimation Method Using Particle Swarm Optimization

Particle swarm optimization (PSO) algorithm was first proposed by Kennedy and Eberhart in [35]. The concept of the algorithm is based on behavior of swarm of birds and fishes. It is an iterative algorithm and consists of several particles, each of which has two parameters: position and velocity. Position of a particle takes on the values of the parameter that needs to be optimized. The velocity of a particle identifies how much the particle changes its position. Each particle operates according to its own knowledge as well as other particles' information. In every iteration, the position of a particle that provides the best value of objective function is shared among all other particles. After enough iteration, the algorithm converges to an optimal solution.

In this work, we use (15) as the objective function which is a function of *L, N* and *K*. Due to hardware limitations, we set the number of samples, *N*, to a fixed value. We will show that *K* does not significantly affect the output and hence, at this stage, we use the PSO to only optimize the value of *L*. To this end, the steps of algorithm are defined in the following.

1) The algorithm begins with initializing *M* number of particles each of which has a position value in the range of 10 to 200 which accounts for number of Eigenvalues, *L*. The position and velocity of the i^{th} particle at iteration *j* is denoted by p_i^j and v_i^j, respectively. The velocity of all particles are set to zero for initialization.

2) We evaluate the goodness of fitting related to each particle as $D_{p_i^j}(\pi_k)$ and store the minimum value of each $D_{p_i^j}(\pi_k)$.

3) The smallest of these values are selected and the particle position corresponding to it is denoted as $P_{best,j}$. We define the GP_{best} as the global best position among all iteration. If $P_{best,j} \leq GP_{best}$, the value of GP_{best} is replaced by $P_{best,j}$.

4) We update the velocity of the particles by:

$$v_i^j = v_i^{j-1} + c_1 r_1 \left(P_{best,j} - p_i^{j-1}\right) + c_2 r_2 (GP_{best} - p_i^{j-1}) \tag{19}$$

where c_1 , c_2 are learning coefficients and, r_1, r_2 are uniformly distributed random numbers within the range of 0 and 1.

5) We update the position of the particles to get new positions by $p_i^j = p_i^{j-1} + v_i^j$

6) If the stopping criteria are satisfied, the algorithm stops working. Otherwise, it repeats from step 2.

When the minimum $D(\pi_k)$ is found, it is given to (16) to get the noise power from which the SNR can be calculated. A flowchart summarizing the proposed PSO-based estimation technique is shown in Figure 3. As shown, each particle in PSO algorithm is assigned with an L value and then it is passed to SNR estimation algorithm to estimate the SNR value. The $D(\pi_k)$ values obtained by all particles are compared and the minimum value is identified. This process is repeated until a maximum number of iteration is satisfied and the value of L leading to smallest $D(\pi_k)$ is utilized for SNR estimation.

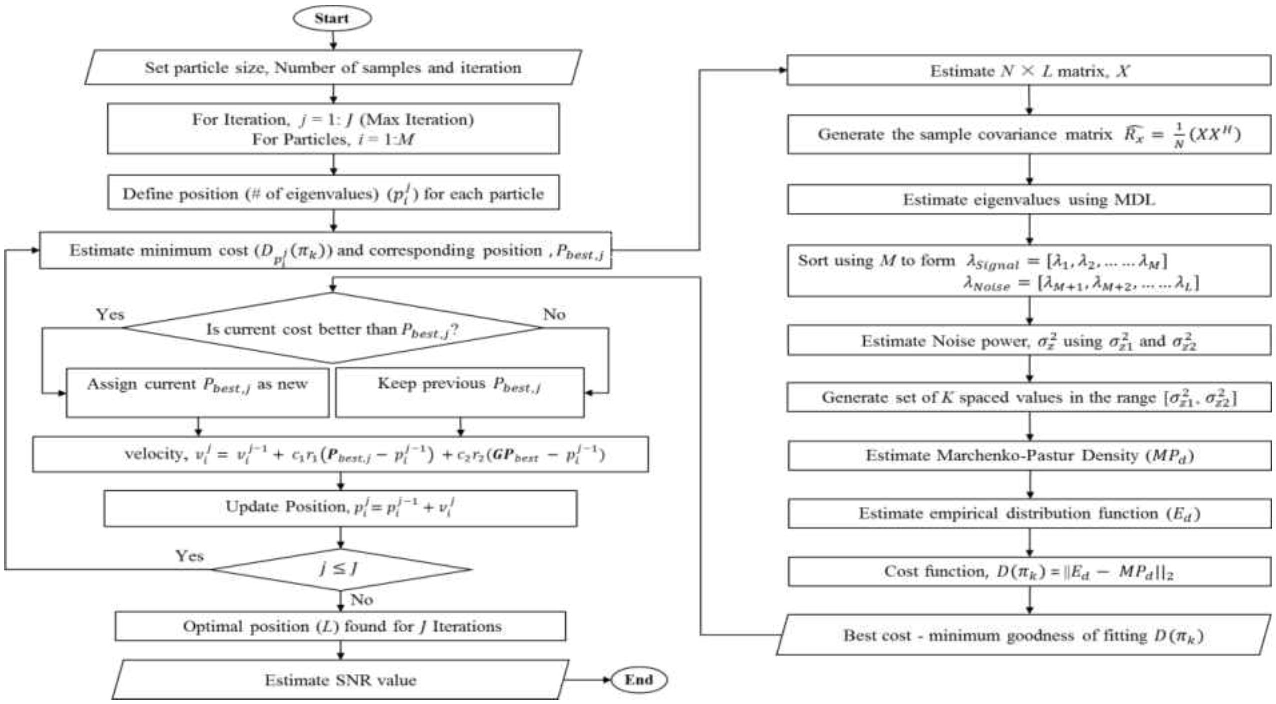

Figure 3. The flowchart of the PSO-based SNR estimation method

2.4 Results and Discussion

Using these mathematical formulations, the process of SNR estimation was implemented using GNU Radio and Python language. To assess the performance of the SNR estimator, initial experiments were performed by simulating a BPSK signal, fusing it with additive white Gaussian noise with mean 0 and standard deviation σ_z^2, and subjecting it to the SNR estimation technique. This experiment was performed to study how the three independent variables K (Marchenko-Pastur distribution size), L (smoothing factor/number of Eigenvalues), and N (number of samples) impact the estimated SNR value by measuring the normalized mean square error (NMSE). NMSE expresses the overall deviations between the true and estimated SNR values and is defined as:

$$\mathrm{NMSE} = \frac{1}{M_T}\sum_i \frac{(\gamma_i-\hat{\gamma}_i)^2}{E(\gamma)E(\hat{\gamma})} \; i = 1, \dots, M_T \tag{20}$$

where γ and $\hat{\gamma}$ denote the true and estimated SNR, respectively, M_T is the number of trials for each estimation method and $E(x)$ denotes the expected value of x which is expressed as:

$$E(x) = \frac{1}{M_T}\sum_i x_i \tag{21}$$

From this set of results, we understand which parameters we need to optimize using PSO. The values of *K*, *L* and *N* were varied and simulations were run for a specified number of iterations.

The impact of number of samples (*N*) and number of Eigenvalues (*L*) on NMSE are shown in Figure 4. It can be seen that by increasing the number of samples NMSE considerably drops. However, this increase will in turn increase the processing time of the SNR estimation. It is also observed that increasing the value of *L* improves the NMSE overall. However, if a target NMSE, for example 10^{-3}, is required, we have to either use higher number of samples (undesired) and lower number of Eigenvalues (desired) or vice versa. Therefore, there is a tradeoff between these two parameters which need to be optimized. This optimization is performed using PSO algorithm. Due to the high processing time, in this paper, we set the value of *N* to 3072 to have chosen a reasonable value which provides both relatively low NMSE and processing time.

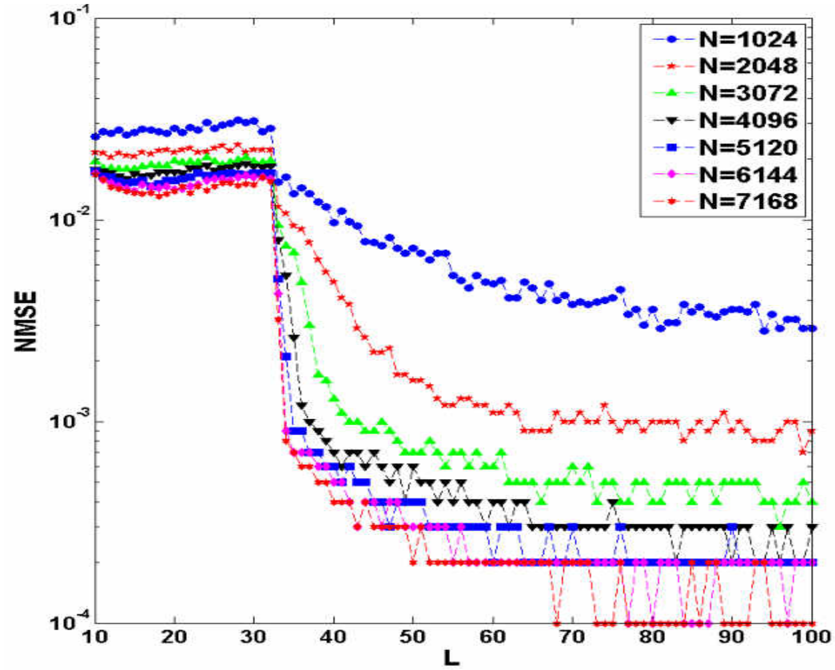

Figure 4. Impact of number of samples (*N*) on NMSE

Figure 5. shows the impact of Marchenko-Pastur distribution size (*K*) on the NMSE for different SNR values. The range of values of *K* in these experiments is 10 to 100 with a step of 1. The value of *L* and *N* in this figure are 40 and 3072, respectively. As can be seen, different values of *K* results in different NMSE values. In addition, depending on SNR of the received signal, there is a value for *K* which outputs the lowest NMSE. However, since the variation of values of *K* from 10 to 100 does not drastically change the NMSE, it can be exempted from optimization in this paper. In addition, it was noticed during the experiments that a higher value of *K* leads to a higher processing time in the estimation of the SNR. This is because of the complexity that arises in the implementation of the Marchenko-Pastur distribution.

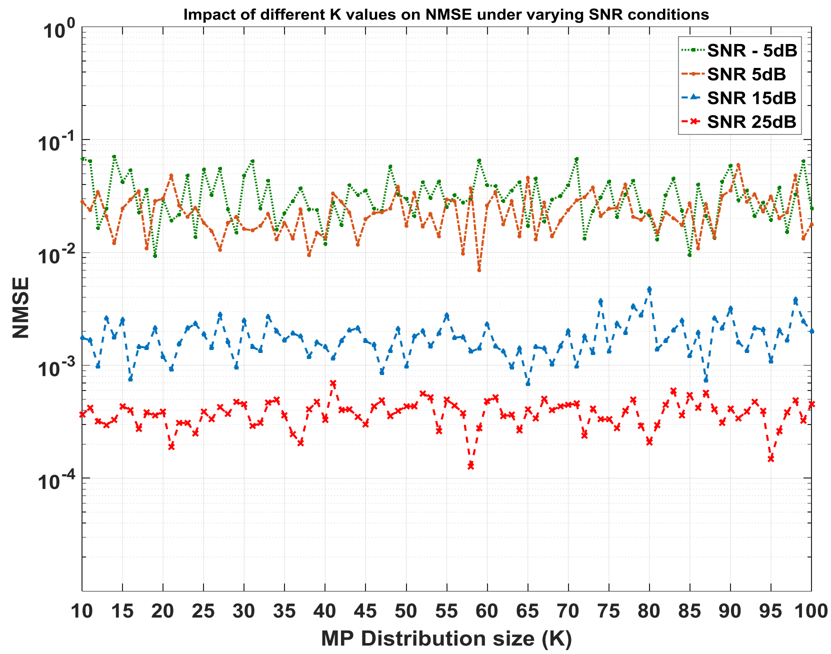

Figure 5. Impact of Marchenko-Pastur distribution size (K) on NMSE for different SNR values

Therefore, in order to choose a fixed value of K, it is ensured that the value is low so that it can approximately produce the same result as that of any higher value of K and at the same time making the process of SNR estimation consume least practicable amount of time. From this analysis, the optimum value of K is set to 10.

Figure 6 shows the impact of L on NMSE for different SNR values. In this figure, it is seen that up to SNR of 10 dB, NMSE is not significantly impacted with changes in the value of L. However, it is obvious from the curves wherein the SNR is 15 dB and greater that the range of values of the NMSE shows significant drop. It is notable that depending on the value of the SNR, NMSE varies for different number of Eigenvalues. Therefore, since different signals with different true SNR values will be the input to the SNR estimator, the value of L needs to be optimized to make sure the estimated SNR is as accurate as possible.

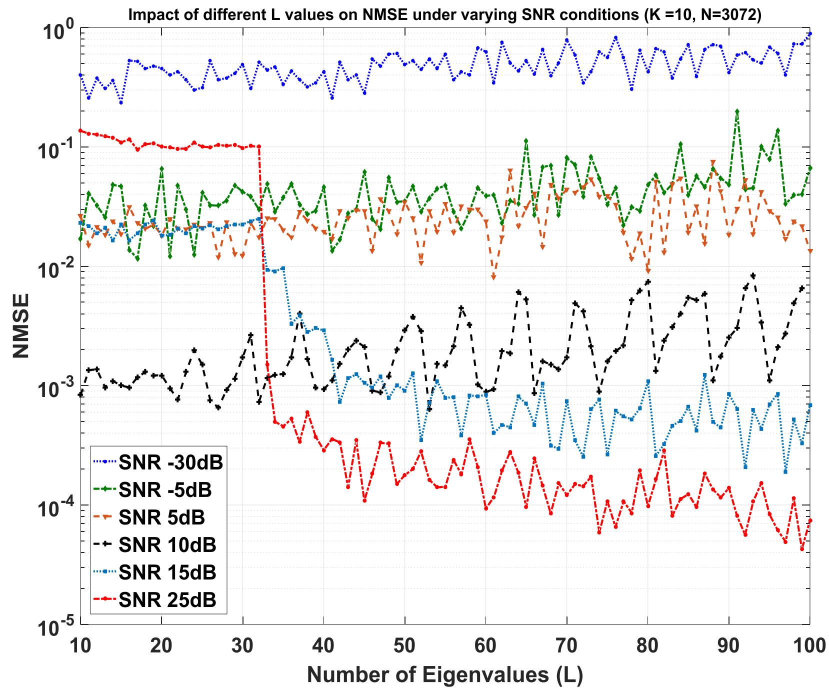

Figure 6. Impact of number of Eigenvalues (L) on NMSE for different SNR values

Figure 7 illustrates and compares the NMSE between the true and the estimated SNR for PSO-based SNR estimation and original SNR estimation methods. The PSO was used to optimize the value of the L. As can be seen, the NMSE for PSO-based method is smaller than that of original SNR estimation method which means the estimated SNR is closer to the actual SNR. It is because of the fact that PSO is able to select the best number of Eigenvalues that is required to estimate a particular SNR. In general, it is evident that the maximum improvement of 92% at SNR of 10 dB have been achieved using PSO-based SNR estimation method with respect to the one with no optimization at all.

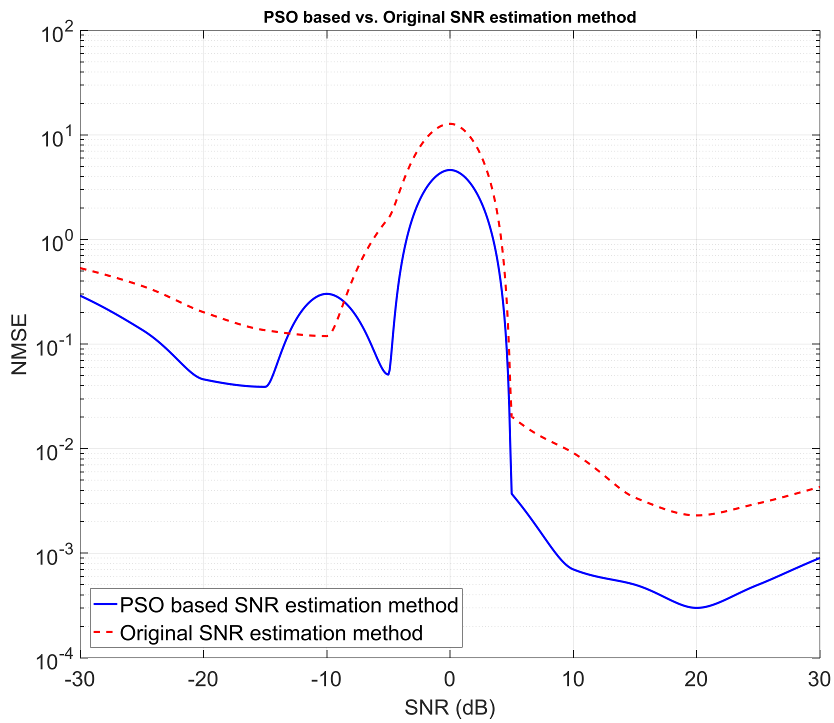

Figure 7. NMSE of the PSO-based SNR estimation method vs. original method

All the experiments investigated different variables affecting the performance of the system, such as N, K and L. It was found out that the Marchenko-Pastur distribution size (K) has the least impact on the NMSE. However, the results show that different K values results in different values of NMSE for various SNR values. On the other hand, it was shown that there is a tradeoff between number of samples (N) and number of Eigenvalues (L) and they have remarkable impact on NMSE. Therefore, we proposed to use PSO algorithm to optimize these parameters so that the performance of the SNR estimator is improved. We showed that the proposed PSO-based SNR estimation method provides better NMSE compared to the original technique.

2.5 Conclusions

In this chapter, importance of accurate noise estimation is acknowledged and several estimation techniques were presented. Subsequently, an improved SNR estimation method based on the computation of Eigenvalues of the covariance matrix of the received signal samples was studied. Different variables affecting the performance of the system, such as N, K and L were analyzed. It was found out that the Marchenko-Pastur distribution size (K) has the least impact on the NMSE. However, the results show that different K values results in different values of NMSE for various SNR values. On the other hand, it was shown that there is a tradeoff between number of samples (N) and number of Eigenvalues (L) and they have remarkable impact on NMSE. Therefore, we proposed to use PSO algorithm to optimize these parameters so that the performance of the SNR estimator is improved. We showed that the proposed PSO-based SNR estimation method provides better NMSE compared to the original technique.

Chapter 3

UTILITY-BASED CHANNEL RANKING FOR COGNITIVE RADIO SYSTEMS

In this chapter, a utility-based channel ranking method is proposed, which takes into account signal-to-noise ratio (SNR) and the occupancy rate of sensed channels. This technique can enable cognitive radio systems to select the optimal channel for data communication. The rest of the chapter is organized as follows. Section 3.1 discusses the existing works related to the parameters to evaluate the quality of channels, the occupancy rate, and channel ranking mechanisms. Section 3.2 describes the methodology of the proposed ranking method. It explains the process of how a cognitive radio system performs spectrum sensing and ranks channels using the proposed utility-based channel ranking method. Simulation results are discussed in section 3.3, where the results of utility modeling of SNR and spectrum occupancy are illustrated as well as the results of the utility-based channel ranking. Finally, section 3.4 draws conclusions iterating the fundamentals of the proposed channel ranking method and simulation findings.

3.1 Background: Spectrum Sensing and Channel Quality Parameters

During the operation of a Cognitive Radio (CR) system, usually referred to as the cognitive cycle [36-37], one of the main steps is spectrum sensing, followed by spectrum analysis, and then spectrum decision making. A number of techniques to sense the radio spectrum has been proposed. These techniques can be classified into two categories: narrowband and wideband. Narrowband techniques aim to sense one frequency channel.

Examples of techniques include energy detection technique, cyclostationary features detection, matched filter detection. Energy detection based spectrum sensing [38-42] measures the energy of the received signal samples. The computed energy level of the signal is then compared to a predetermined threshold. If the energy of the signal is above that threshold, the primary user signal is considered to be present, which implies that the sensed signal is occupied or unavailable for data communication by secondary users. Energy detection is one of the simplest and primitive techniques used for spectrum sensing. However, this technique is inefficient in noisy environments and is not able to distinguish between signals and noise [21]. At low SNR values, energy detection with fixed threshold values usually fails to detect primary user signals. To improve this sensing technique, the authors of [39, 43] proposed ways to dynamically change the threshold and improve the detection of the PU signals.

Unlike energy detection, cyclostationary feature [43-48] detection performs better in low SNR conditions as the technique detects primary user signals based on the correlation of the signal with its shifted version. Because noise is uncorrelated, this technique is able to distinguish between signals and noise. However, cyclostationary feature detection is more complex to implement and requires a high number of samples [43, 49].

Matched filter detection [50 - 51] based signal detection requires prior knowledge of the PU signals. This technique uses pilot samples that are matched with samples of the received signal for the detection of the primary user. Although this technique does not require a large number of samples the need for prior knowledge of the PU signal is a major disadvantage.

Wideband spectrum sensing techniques aim at sensing a wide frequency range that include one or several bands. To perform wideband spectrum sensing, the spectrum is divided into several sub-bands that are sensed either sequentially or simultaneously using one of the aforementioned sensing techniques. Examples of these techniques include 1-bit compressive sensing and multi-bit compressive sensing approaches [12] [52-55].

The result of any sensing technique is 1 or 0. This result is used to estimate the occupancy, using one of the two techniques: Frequentist and Bayesian inferences [15] [24] [56-58]. In the case of the Frequentist inference [24], the probability of an event to occur is inferred based on the frequency of occurrence of the event, provided that the event is observed for many trials.

In the case of Bayesian inference, the probability of an event is inferred based on the previous observations and as well as the current ones. Bayesian inference is based on Bayesian Networks which are probabilistic models that handle uncertainty. In [56], the authors proposed a simplified Bayesian inference model for spectrum occupancy that takes into account both deterministic and measured variables. In [15], the simplified model is further improved by including random variables, such as the probability of detection and false alarm of the sensing technique.

Both the inference techniques aim to reduce uncertainties involved in channel occupancy measurement. However, Bayesian models allow the measurement of the occupancy in real time and take into consideration all or some of the variables that affect the occupancy, such as the characteristics of the sensing technique (detection, false alarm, and miss-detection probabilities), which increases the accuracy of the occupancy estimation compared to the Frequentist inference.

Other than spectrum occupancy, CR system must be able to analyze the condition of all the available channels using various other channel quality parameters. Some of the parameters include Signal-to-Noise Ratio (SNR), Signal-to-Interference Ratio (SINR), different types of delay associated with a channel, capacity of channels, and Bit Error Rate (BER) [14] [17] [59-62]. In [14][60], the authors discuss several BER estimation techniques and an estimation technique based on pilot samples is proposed, respectively.

Similarly, in addition to BER, SINR can also be used and may provide better information on channel condition as the parameter considers the impact of interference during communication. For instance, in [17], a Bayesian approach is used to estimate and model SINR. The proposed technique reduces uncertainty in the estimation and provides better real-time measurements. In [62], the authors proposed a sample covariance matrix based SNR estimation, where an evolutionary algorithm is used to improve the accuracy of estimation.

Once the spectrum sensing and analysis are performed, a CR system goes through the decision-making phase, when the best channel for transmission is selected. Channel ranking mechanisms assign ranks to the sensed channels, which enables the CR to efficiently utilize scarce radio spectrum while meeting certain communication requirements, such as quality of service, security, and latency.

Several mechanisms have been proposed, where channels are ranked based on the primary user activity and state predictions [16] [63-69]. In [64], a learning strategy for distributed channel selection in cognitive radio networks is proposed. The strategy considers different QoS requirements of CR systems/secondary users and means availability of channels in a network to determine the rank-optimal channels. Similarly, the authors of [16] [63] determine the best channel for communication by estimating the occupancy rate. In [11] [65 - 69], channel state prediction is performed by using predictive models and inference techniques, such as Bayesian inference. Based on the prediction of channel idle time and the accuracy of sensing, a secondary user then ranks the channels with the objective to use channels for a longer time.

Almost all the techniques discussed above use spectrum occupancy as a parameter to rank channels for data communication. Measuring spectrum occupancy alone is not enough and also does not indicate the quality of the sensed spectrum bands. However, SNR and spectrum occupancy rate together can be two QoS parameters that can be used to decide which channel is the most appropriate for data communication. Spectrum occupancy rate and SNR provide information on how readily available a channel is and how noisy is the radio frequency environment.

The process of selecting the best channel among the sensed channels requires assigning scores or ranking levels, which can be achieved by estimating the usefulness i.e. utility of the channel based on its SNR and occupancy. The next section outlines the process of modeling channel utility based on channel's SNR and occupancy rate. Some constraints and ideal scenarios that are considered to define the channel utility are also discussed in the following section.

3.2 Methodology: Utility-Based Channel Ranking

Utility modeling allows optimizing resource allocation, such as transmission power and modulation schemes of wireless communication systems by quantifying the usefulness of the resources [70]. Based on the usefulness of resources, ranking levels or scores can be assigned to indicate a preference for specific resources over the others. Therefore, utility-based modeling of communication parameters can help a CR system to decide the best course of action.

A utility model based channel access has been proposed by the authors of [71] to enable cognitive radio systems to access a channel that can be used for a longer period of time and maintain a reasonable throughput before it has to be handed back to the primary user. Similarly, the authors of [72] propose an opportunistic channel selection in IEEE 801.11 based wireless mesh network by employing a utility modeling of the mesh network’s load in different situations, which is then forwarded to a learning algorithm for the selection of the best channel. In [73-74], a utility-based resource allocation is applied to decide on the optimal transmission power allocation. Utility-based channel selection applied in the stated works depends on probabilistic models, which helps determine the future conditions of a channel by modeling collision probability, interference, and other metrics [75].

Some popular methods to design utility functions are the weighted-sum approach, linear-logarithmic or Cobb Douglas utility function, and constant-elasticity-of-substitution [76]. In the weighted-sum approach, the utility function is defined by summing multiple objectives, which is assigned with varying weights to dictate the preference for each objective. Similar to the weighted-sum approach, the linear-logarithmic utility assumes additivity but is found to be more useful as the logarithmic function is used to shape the utility.

In the case of channel ranking, the two parameters that are considered to determine the utility of a channel are SNR and spectrum occupancy, which are observed to show substitutive and complementary effects between each other. In cases where the utility function needs to reflect the substitutive effects, constant-elasticity-of-substitution (CES) utility function allows determining the degree of elasticity between two parameters and their relationship. In the next section, the use of CES utility function is described and utility modeling of SNR and spectrum occupancy is discussed.

The utility model for the sensed channels can be defined by combining the utility values of the corresponding SNR and occupancy of these channels. Before we delve into defining a utility function that takes into account the utility values of both SNR and occupancy of a channel, it is necessary to outline the preferences for most desirable channel conditions.

The following are four scenarios, where a channel usefulness or 'utility' can be defined based on its SNR and occupancy.

1. A channel would be undesirable/less useful if it has high occupancy rate and also high SNR. In this case, even with a good SNR, the channel is less reliable as it may be found occupied most of the time.
2. A channel with low SNR (beyond acceptable SNR level) but with low occupancy rate is also undesirable. For such channels, although the occupancy rate is low it is still undesirable as the occupancy measurements at low SNR condition tend to be unreliable, increasing the probability of false alarm.
3. A channel with high SNR but also with low occupancy rate is most useful/desirable channel. Here, SNR and occupancy rate exhibits substitutive effects, where we want SNR to take over and have more impact on the utility

calculation. As a result, such a channel will be defined with higher preference or utility.

4. A channel with low SNR (above acceptable SNR level) and intermediary occupancy rate (40 – 60 % occupancy rate) are also desirable. In such cases, it is convenient to have the occupancy take over and have the most impact on utility calculations for the channel.

   To acknowledge the substitutive and complementary effects of SNR and occupancy a utility function needs to be defined to allow one parameter to be substituted by the other.

The constant elasticity of substitution (CES) utility function [49], can be defined as:

$$U_{SNR,Occ} = ({w_{snr}}^{(1-\sigma)}{U_{SNR}}^{\sigma} + {w_{occ}}^{(1-\sigma)}{U_{Occ}}^{\sigma})^{1/\sigma} \tag{22}$$

Where, w_{snr} and w_{occ} are the weight factors for SNR and occupancy, respectively. U_{SNR} and U_{Occ} are utility values for SNR and spectrum occupancy, and σ determines the constant elasticity of substitution, $\rho = \frac{1}{1-\sigma}$.

The constant σ, which is the elasticity between the parameters SNR and occupancy, introduces the degree to which one parameter can substitute another one. This elasticity can be changed and based on the analysis of our application, a proper value of elasticity can be defined from case to case [76]. More details about the appropriation of elasticity and weight factor are discussed in the later section, where simulation results are provided and discussed. For now, it can be stated that the CES utility function enables us to substitute SNR for Occupancy and vice-versa as required, which finally allows us to define channel utility value based on its corresponding SNR and occupancy rate.

Some utility models are used to make hard decisions while others for soft decision-making purposes. Hard decision making refers to the binary representation of 1 for 'ON switch' and 0 for 'OFF switch', and soft decision making allows a transient period between 0 and 1. As shown in Figure 8, when the signal-to-interference ratio (SINR) is characterized by a utility modeling as in [50], the utility should be 0 to represent SINR beyond the acceptable level marked by the defined threshold. Any SINR value above the threshold will be perceived as a utility of 1 or highest utility as that kind of interference has no significant impact on the quality of service requirement of a communication system.

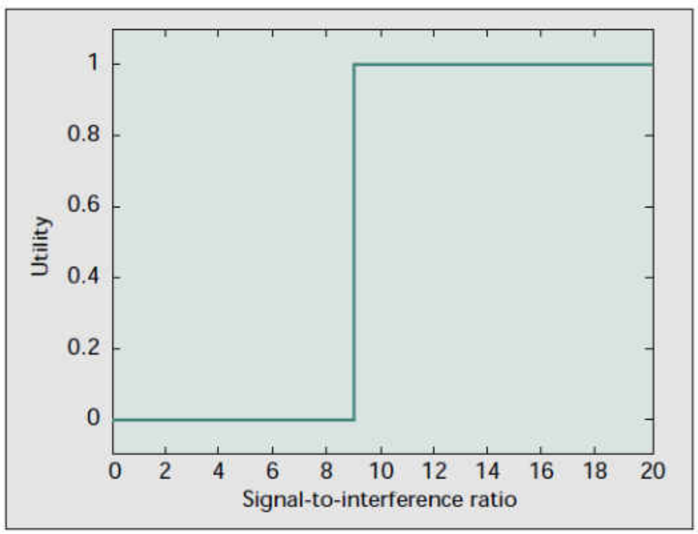

Figure 8. Utility modeling of SINR to determine Quality of Service [77]

In this work, several mathematical functions are applied to define a utility function that appropriately characterizes our preference for higher SNR and lower occupancy. At first, varying SNR starting from negative 30 dB to 30 dB is considered. Different functions are defined and the corresponding utilities are estimated for the considered range of SNR. In this case, the functions are defined to return utility values in the range of 0 to 100, where a utility value of 100 represents a preference for highest SNR conditions. To allow soft decision-making capabilities, sigmoid curve or logistic function appears to be useful as it renders utility values which represent high SNR, intermediate SNR values (SNR between 5 to negative 5 dB), and poor SNR conditions below negative 10 dB. The slope of the logistic function provides enough transient state to be able to make a soft decision by having a wide range of utility values for the considered range of SNR. Below are few utility functions that are used to represent SNR:

$$U_{SNR} = A/(1 + e^{-\alpha(X - X_o)}) \tag{23}$$

$$U_{SNR} = A(\frac{e^{\alpha X}}{1+e^{\alpha X}}) \tag{24}$$

$$U_{SNR} = X_{max}(1 + tanh(\alpha(X))) \tag{25}$$

$$U_{SNR} = \frac{1}{2} + \frac{1}{2}(\tanh(X/2)) \tag{26}$$

Where X_{max} represents the highest SNR value in the range of SNR values considered in the simulation, X_o is the SNR value considered to be the midpoint for the sigmoid curve, and α determines the steepness of the curve and A maximum value for utility. These four functions are continuous and render a utility between 0 and A, as SNR values range from $X_{min}$to X_{max}. The utility model from these functions all appear to be 'S' shaped as logistic functions should be, which allows us to define wide ranges of utility values representing SNR in dB. Utilizing the symmetry property of logistic functions, same but reversed equations can be used to represent the utility of spectrum occupancy, where Y is occupancy rate, Y_{max} is a constant that is the highest occupancy rate, and Y_o is the occupancy rate considered to be the midpoint for the sigmoid curve. As lower occupancy is preferred, reversed sigmoid curve provides higher utility for low occupancy and lower utility for high spectrum occupancy rates.

3.3 Results & Discussion

Figure 9 illustrates the previously defined utility functions for a fixed range of SNR values from -20dB to +20 dB. MATLAB is used as the platform to implement the simulations. For the experiments, $\boldsymbol{\alpha}$ that determines the steepness of the curve is defined to be 0.1 for the hyperbolic *tan* function and 0.2 for the logistic functions. Maximum value for a utility, $\boldsymbol{A}$ is defined to be 100, so that the utility values are in the range of 0 to 100. $\boldsymbol{X_{max}}$, which is the highest SNR value in the fixed range of SNR values, comes up to be 20 dB for this experiment. Subsequently, $\boldsymbol{X_o}$ that is the midpoint of the range of SNR is 0 dB, in this case. As seen from Figure 9, the 'S' shape of (23), the logistic function, allows to define the higher utility values for high SNR conditions and lower utility values for low SNR conditions. However, function 26 renders a utility model that is appropriate for the case of hard decision making, as the utility values see a sharp rise and fall for any SNR values above and below -5 and 5 dB. Excluding function 26 from consideration, rest of the simulation illustrating utility values over occupancy will narrow down the choice of the most accurate utility function to model both occupancy and SNR for a given channel. The same utility functions are then used to model the utility for the spectrum occupancy rate, which ranges from 0 to 1. Figure 10 illustrates the utility values over occupancy for each of the four utility functions. For this simulation, α that determines the steepness of the curve is defined to be 5 for all the utility functions except for function 5, which is defined to have a steepness of 0.5. Maximum value for the utility $\boldsymbol{A}$ is defined to be 100. As seen in the figure, the 'S' shape is not retained anymore by both functions 2 and 5, the logistic and hyperbolic *tan* functions. This is due to the range of occupancy values being under 1.

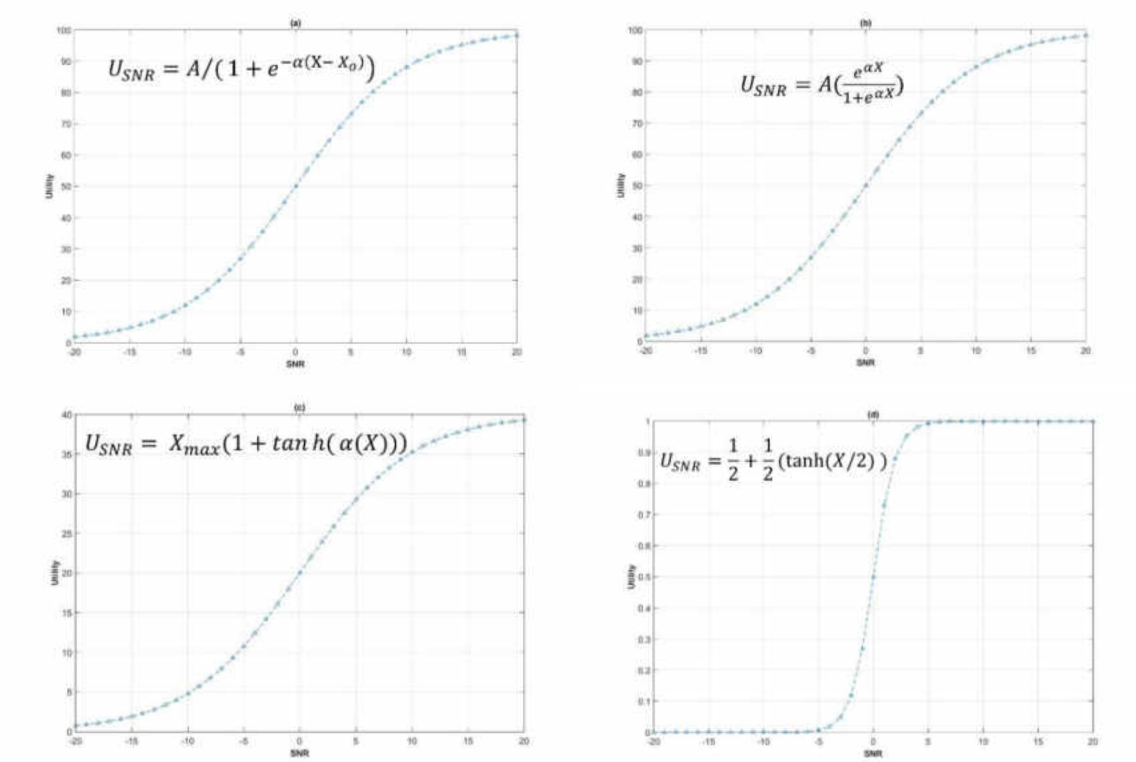

Figure 9. (a) Variant of the logistic function, (b) Logistic function, (c) Hyperbolic tangent function scaled by maximum SNR value, (d) Logistic function as a scaled hyperbolic tangent function

However, the utility modeling still characterizes the lower occupancy rates with higher utility values, which is desired in our case. When compared in Figure 10, functions (23), (24) and (25) renders similar utility model, where (23) and (24) have different maximum utility but similar steepness, (25) has a steeper descent and a maximum utility at 1. Figure 10(d), which is generated from function 26 renders utility values that follow a linear relationship between utility and corresponding occupancy.

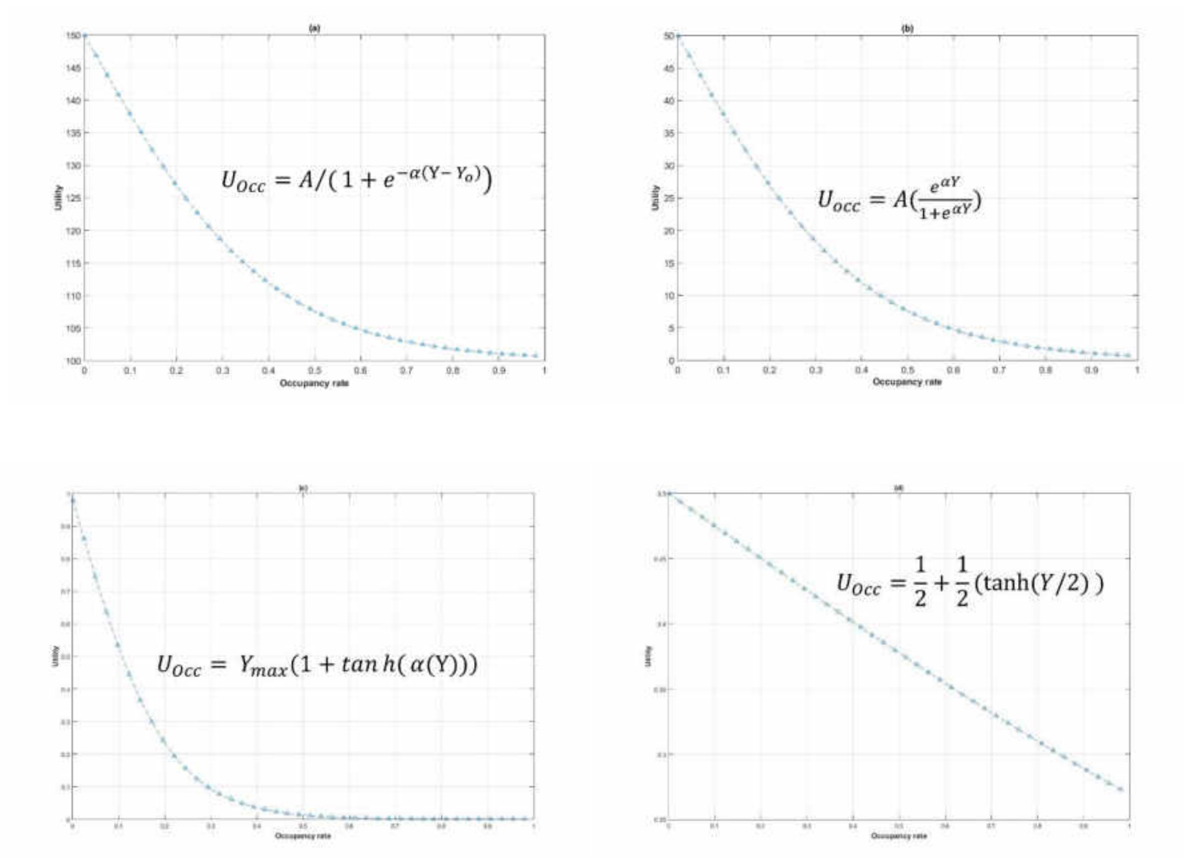

Figure 10. (a) Variant of the logistic function, (b) Logistic function, (c) Hyperbolic tangent function scaled by maximum SNR value, (d) Logistic function as a scaled hyperbolic tangent function

Based on the results of the previous experiments, Function 26 offers the most suitable utility model as it characterizes better SNR and occupancy with high utility values and reprimands degrading conditions with lower utility. This utility model, defined by the utility function 26, allows soft-decision making capabilities, where the transition from good to a worse condition doesn't follow steep descent. Once the utility for SNR and occupancy is estimated, constant elasticity of substitution defined in (22) is used to estimate the combined utility of the corresponding channel.

Table I and II provide the result of the utility based channel ranking and occupancy based channel preference. Table I shows the combined utility of all the sensed channels based on their corresponding utility value of SNR and occupancy. Channels are then ranked in a descending order based on their utility values. As seen from Table I, the highest ranked channel is the one with the highest utility value and has a reasonable SNR and occupancy rate compared to channels with lower utilities. When compared to the first channel in Table II, it is observed that the channel with the lowest occupancy is selected although the corresponding SNR is lower than that of the second channel in Table II. The utility based channel selection is able to recognize the two channels with the same occupancy rate but different SNR conditions, where ranked 1 channel in Table I has slightly better SNR.

Similarly, the yellow colored row in Table II shows the channel ranked 18 to be preferred when only the channel occupancy is considered. Red colored rows in Table II are the channels that should have been ranked low as they have bad SNR conditions. In Table I, the red colored channels are ranked 27 and 24 due to their degrading SNR values. From these two tables, it can be deduced that utility-based channel ranking and selection helps to recognize and perform a tradeoff between SNR and spectrum occupancy rate to prefer better channels than that of the occupancy based channel selection method. Therefore, it can be concluded that the utility-based method provides better means of decision-making for a CR system to select the best channels among all the sensed channels.

The utility-based channel ranking technique, proposed in this chapter is computationally simple compared to other channel ranking mechanisms, which involve the implementation of complex algorithms requiring a large number of iterations and multiple steps [78-82].

Table I: Utility-based channel ranking

Rank	Frequency (GHz)	SNR	Occupancy (%)	Combined Utility - $U(\gamma, Occ)$
1	2.462	12	1	94
2	2.437	19	6	93
3	2.437	8	1	89
4	5.765	11	9	84
5	5.765	17	12	84
6	2.462	8	6	83
7	1.88	17	14	82
8	2.462	18	15	81
9	1.88	17	15	81
10	2.412	13	16	77
11	5.765	12	16	76
12	1.88	7	13	73
13	2.462	19	24	71
14	2.412	8	28	59
15	2.437	5	24	58
16	1.88	-1	11	56
17	2.437	-2	10	54
18	1.88	-2	10	54

Table II: Occupancy based channel selection

Frequency (GHz)	SNR	Occupancy (%)	Ranked by Utility based ranking as
2.437	8	1	Ranked 3
2.462	12	1	Ranked 1
5.765	-17	1	Ranked 27
5.765	-12	5	Ranked 24
2.437	19	6	Ranked 2
2.462	8	6	Ranked 6
5.765	11	9	Ranked 4
2.412	-18	10	Ranked 34
2.437	-2	10	Ranked 17
2.462	-6	10	Ranked 22
1.88	-2	10	Ranked 18
1.88	-1	11	Ranked 16
5.765	17	12	Ranked 5
1.88	-9	12	Ranked 25
1.88	7	13	Ranked 12
1.88	17	14	Ranked 7
2.437	-17	15	Ranked 37
2.462	18	15	Ranked 8
1.88	17	15	Ranked 9

The CES function relies on two important QoS parameters, SNR and spectrum occupancy rate, which provide important information regarding the channel condition. The CES based utility function can also be used with channel quality metrics, such as Bit Error Rate (BER) and Signal-to-Interference Ratio (SINR) along with spectrum occupancy.

3.4 Conclusions

In this chapter, functions for channel ranking mechanism for cognitive radio systems are discussed. Simultaneously, several communication parameters that provide information on channel conditions are also studied and their impact on channel selection mechanisms is discussed. The utility modeling for two important channel condition parameters, SNR and spectrum occupancy is then provided. CES utility function is defined to model channel utility, which combines the utility values of channel's SNR and occupancy rate. Subsequently, the channel utility model is used to rank the sensed channels.

Simulations were performed for multiple frequencies, ranging from megahertz to gigahertz, with different corresponding SNR values and occupancy rates. Results indicate that the proposed utility-based channel ranking performs better with increased accuracy in ranking optimal channels for communication, compared to the usual occupancy-based channel selection, which is currently being employed by CR systems.

Chapter 4

NOISE CANCELLATION

In this chapter, we discuss the undesired impact of noise on a signal and present several adaptive filtering techniques to denoise communication signals. Subsequently, the performance evaluation of these filtering techniques are presented and compared using several evaluation metrics.

Rest of the chapter is organized as follows: Section 2.1 briefly discusses noise cancellation, Cognitive Radio systems, and proposes the use of evolutionary algorithm based adaptive denoising techniques for next generation communication technologies; Section 2.2 describes the state-of-the-art of several noise cancelling techniques; Section 2.3 discusses the methodology of a simulation setup and steps involved in cancelling noise using particle swarm optimization, genetic algorithm, and least-mean-square; Section 2.4 discusses simulation results, analyzes the performance of the simulated adaptive filtering techniques, and concludes by providing a comparison of the techniques.

4.1 Noise Cancellation in Cognitive Radio Systems

In any communication systems, data integrity can be impacted by several factors, including noise, multipath, and shadowing. The noise sources effecting signals can originate from several sources, including thermal noise, noise rooting from system non-linearity in the radio front end, and interference between co-located wireless nodes within

within a network [83-86]. In the case of signal distortion by noise, filters are employed in communication systems to retrieve the original transmitted signal. These filters are built using hardware components, which leads to costly and bulky systems that can only filter specific frequencies [87]. However, next-generation communication technologies will host reconfigurable hardware and will enable advanced digital signal processing. Therefore, filters for these advanced systems should be programmable and should have the ability to de-noise signals of any frequency.

A promising advanced communication technology is Cognitive Radio (CR) [36] [88-89]. A CR system operates with full-duplex communication and consists of a wideband transceiver that can configure its communication parameters according to the environment. However, these systems are impacted by additional system-induced noise sources. As a wideband transceiver, CR systems can sense multiple bands at the same time, resulting in interference-generated noise [90-91]. Similarly, in full-duplex communication, the CR receiver is saturated by noise when the co-located CR transmitter is transmitting on the same or close channel. In addition, noise from system non-linearity and thermal noise are also present in CR systems [92].

Traditional filters cannot adapt to changing frequencies and multiple bands. To that end, adaptive filters must be employed to de-noise a signal of any frequency by readjusting filter parameters during the operation. Several adaptive techniques for noise cancellation have been proposed, including search optimization algorithms [93-96].

4.2 Classification of Noise Cancelling Techniques

Briefly, in an adaptive filter, the received noisy signal is subjected to filtering and the filtered output is compared against a desired signal to compute the error. The task of the adaptive algorithm is to search for an optimal solution that minimizes the error (i.e., the global minima of the error surface). Broadly classified, adaptive filter algorithms can be divided into three categories: 1) Time-frequency analysis, 2) Matrix factorization, and 3) Adaptive filter-based techniques. Figure 11 illustrates the classification of adaptive filtering techniques.

Time-frequency analysis based denoising techniques allow inspection of the noise-induced signal in both time and frequency domain. Examples of techniques under this category are empirical mode decomposition and wavelet-based denoising. Although based on the same method of analysis, the approaches for denoising a signal is different for the two time-frequency analysis-based techniques. Conceptualized since the late 1980's, wavelet transform allows signal processing for time-frequency analysis. Succinctly put, a mother wavelet is chosen, which is also referred to as a basis function and is the primary step to wavelet analysis of a received signal. Wavelets revolve around the basis function by using a shifted and dilated version of the function. Translation and dilation introduce enough components to the transformation to retain the main properties of the original signal. In [37], authors put forward two important properties of wavelets which are admissibility and regularity conditions. The first property, admissibility allows decomposition of a signal which can later be reconstructed without losing any of the components of the original signal. Such breakdown enables identification of noise which is spread over a large number of coefficients, unlike the main signal which usually is found in a small portion of wavelet dimensions [97 - 98]. More elaborate discussion on the wavelet properties can be found in [99 - 100]. In [101], a two-branch wavelet-based denoising is proposed, a technique which aims to locate noise singularities for the purpose of denoising and be able to reconstruct the original signal. Two-branch wavelet denoising goes through two stage of denoising in the first branch and the second branch is initiated only when it is found to be necessary thus reducing computational redundancy. During the first stage, Lipschitz exponent and wavelet transform modulus maxima is used for denoising. Details of the mentioned stage involve locating noise singularities at each scale to eventually remove the found modulus maxima. In [102], one of the methods for edge detection is based on wavelet transform modulus maxima, which is effective in locating singularities under high signal-to-noise ratio (SNR) and the other method is based on Multiscale wavelet product which enhances the multiscale peaks due to the edges and makes it convenient to detect noise-induced singularities. Several other application of wavelet-based noise mitigation may not have been introduced to cognitive radio technology yet but sparsely refers to the possibility of being effective once employed. For instance, in [103] wavelet-based denoising technique is tried to get better power delay profile estimates in indoor wideband environments. Work in [104] presents an estimation of TDOA – time difference of arrival for GSM signals in noisy channels using wavelet-based denoising technique. While [105] discusses composite wavelet shrinkage for the purpose of denoising low SNR signals, [106] proposes wavelet-based digital signal processing algorithms to encounter the high power nonstationary noise in infrared wireless systems.

Proposed by Huang et al [107], empirical mode decomposition (EMD) operates in an iterative process to generate several components of the original signal, which for a signal $f(t)$ can be defined as in [88]. The mono-component signals with amplitude $r(t)$ are called the Intrinsic Mode Function (IMF), which characterizes the intrinsic and reality information of the decomposed signal. The process by which EMD functions can be described well by an algorithm than mathematical theories as can be seen in [108 - 109]. To elaborate, EMD is an adaptive process which decomposes a multicomponent signals into several IMFs as mentioned previously [110]. In order to create the IMFs sifting process is employed where cubic spline interpolation locates the local maxima and minima to form an upper envelope and lower envelope. Subtracting the mean of these two envelopes from the original signal results in the formation of IMFs with certain characteristic properties. As the multicomponent signals are decomposed to several IMFs, denoising requires identifying the noise components so that they can be removed and the original signal can be reconstructed without noise contribution. Research in [88] refers to an implementation of EMD block in GNU Radio [111], an open source software that hosts signal processing packages [112]. Experimental setup in [88] aims to reduce noise contribution in received signals and improve the transmission bit error rate (BER). One prominent performance factor for the sifting process is the right estimation of when to stop the sifting process. Besides the stopping criterion determination right method of spline interpolation is also necessary to generate desired results from the EMD. Different spline interpolation methods are tried in [88] and results were compared to analyze the accuracy of the sifting process for EMD. Similar to [88], authors in [109] pointed out the possibility of erroneous outputs of EMD because of the convergence problems in sifting process and the correct choice of interpolation methods. Several other research works focused on the issue of implementing the right method of spline interpolation for the sifting process. In [113], an alternative to cubic spline interpolation, B-spline is introduced with no significant improvements. Iterating filters are considered in [114] to resolve the issue of a convergence problem. IMFs are analyzed based on their energy difference and is considered to be useful for differentiating purposes in [110]. With the replacement of cubic spline with a rational spline, work in [115] presents some promising results. In [116], authors present IMF threshold determination based denoising technique inspired by the threshold determination technique in wavelet-based denoising. Coherent with the threshold selection mechanism in wavelet, work in [116] suggests the use of the same principles with the only difference of applying the threshold to each sample of every IMF instead of applying the threshold to only reconstructed signals, which is the case in wavelet.

The second category, matrix factorization based denoising techniques, provides the means to perform signal space analysis. Examples of matrix factorization techniques are singular value decomposition and non-negative matrix factorization based denoising. Both singular value decomposition and non-negative factorization are capable of factorizing a huge or sparse matrix into smaller data sets, which allows easier inspection of a signal. Singular Value Decomposition (SVD) is one of the useful matrix decomposition methods that enables the factorization of a matrix. For a matrix A, SVD factorizes A into the product of a unitary matrix U, a diagonal matrix $\sum$, and another unitary matrix V^{H} [117].If matrix A is $m\ x\ n$ matrix, **U** will be the unitary matrix $m\ x\ m$, with non-negative real numbers $m\ x\ n$ diagonal matrix is $\sum$ and V^H is the $n\ x\ n$ unitary matrix. The $\sum_{i,j}$, of $\sum$ are the singular values of A and the left-singular vectors of A are the m columns of U while right-singular vectors are the n columns of V. SVD being numerically stable produces non-negative Eigenvalues which makes it a preferable choice over Eigen decomposition [117]. As discussed in the previous sections, signal processing to sense the availability of spectrum is one of the primary tasks of cognitive radio. Second order statistical data and covariance matrix are commonly used methods to analyze a set of data, in this case, which would be sensed spectrum. The above-mentioned matrix factorization technique opts to reduce the dimension of the sample covariance matrix retaining an important set of information which can be used to distinguish different components of a signal such as noise. In [118], the factorization technique – SVD is employed to detect noise anomalies in the 2.4 GHz band. It is notable to point out that SVD was employed instead of Eigen decomposition to differentiate the noise components in the signal. SVD's numerical stability and non-negative Eigenvalue output make it a desirable choice for data analysis. Non-negative factorization (NMF), also referred to as non-negative approximation, of matrix results in non-negative outputs which makes it easier to analyze the signal of interest [119-120]. NMF factorizes a matrix A into two matrices W and H, all of the three with a common property of having no negative elements. To elaborate, a matrix A made up of m x n matrix can be factorized into W, a m x p matrix and H as n x p matrix where p can be significantly lower than both m and n. H is the coefficient matrix that supplies with appropriate coefficients for the numerical approximation NMF provides with its multivariate analytical characteristics. To track the divergence of the factorized matrix A and the product matrix W, H different divergence function, also referred to as cost functions, can be defined for the purpose of introducing regulations. Keeping in mind this case-specific problem of SVD, authors in [118] employed NMF as the second technique for denoising purpose. Dimension reduction technique like NMF allows the creation of two non-negative matrices as outlined earlier in the section. Both the techniques are suitable for achieving noise cancellation by providing means to clearly identify the signal space from the noise space. In short, SVD and NMF are able to decompose the unprocessed signal to capture principal independent components which in turn spaces out the signal components making the dataset convenient to inspect. A clear overview of the importance of non-stationary noise removal in the context of cognitive radio is highlighted at the beginning of [118]. A performance evaluation along with the methodology to setup noise removal experiment is also discussed in [118].

The third category, adaptive filter-based techniques can be further divided in two categories, gradient descent based and non-gradient descent. Previous studies employed gradient-descent based search optimization algorithms, which initialize with a predefined guiding factor and follow the slope of the gradient to locate the desired minima of the error surface. Examples of these algorithms include least mean square (LMS) and its variants – normalized LMS (NLMS) [93], recursive least square (RLS) [94], and filtered x-LMS (FxLMS) [95]. However, these algorithms are only able to identify the local minima of a multimodal error surface and are highly dependent on the appropriate selection of their initialization variables [96]. For instance, LMS algorithm initializes with a step size variable that acts as the controlling parameter for the convergence of the algorithm. A larger step size value renders high steady state misadjustment, but smaller values decrease the convergence speed of the algorithm [121]. In addition, these gradient-descent based algorithms experience degrading performance for signals with random and non-linear noise [32].

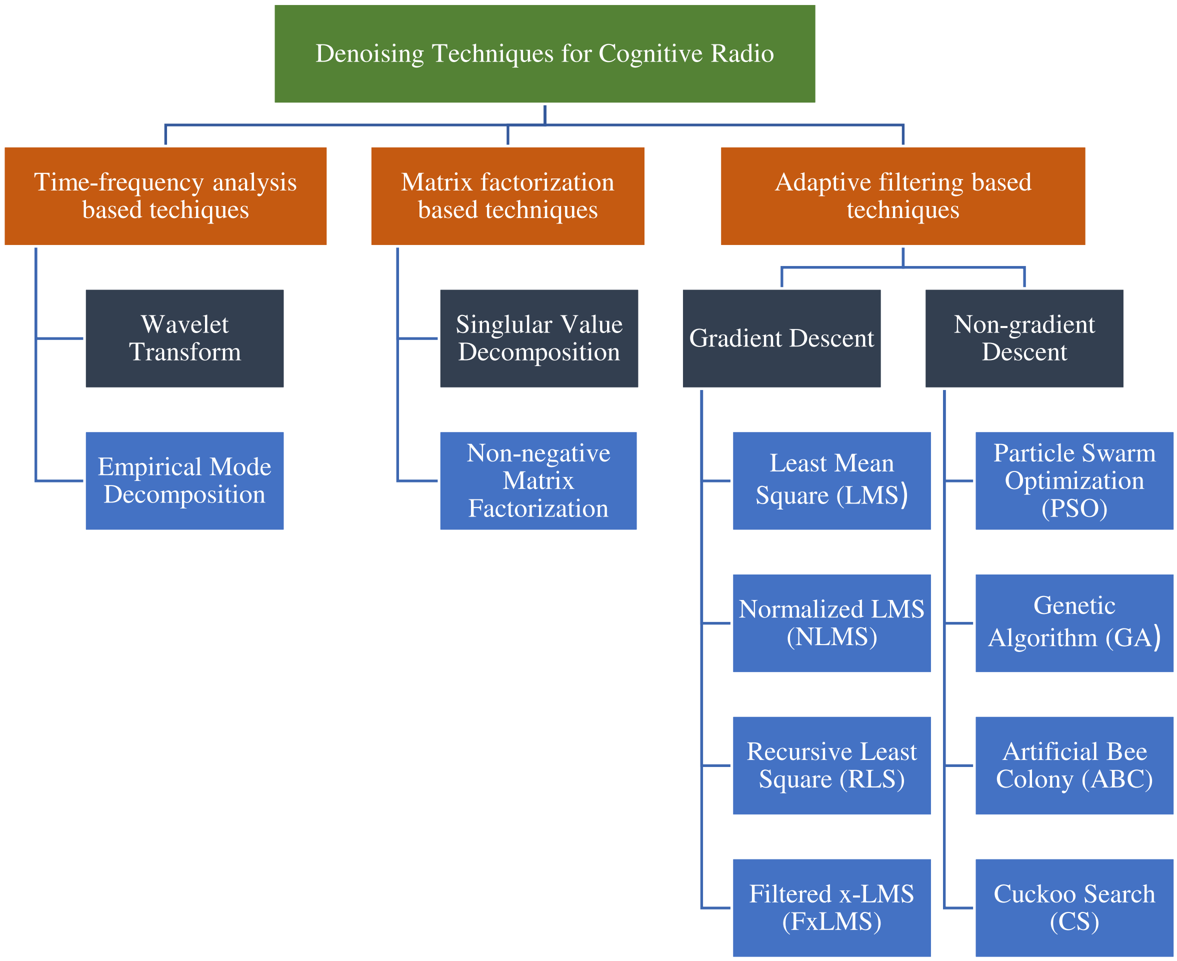

Figure 11. Classification of adaptive filtering techniques

To overcome the problem of locating global minima of an error surface, non-gradient algorithms, also known as global search optimization techniques, can be applied. Examples of such methods include genetic, artificial bee colony, cuckoo search, and particle swarm optimization algorithms. Some of these algorithms, such as the genetic algorithm, require selecting appropriate initialization values for the process of mutation and crossover to converge at a steady rate [122]. Often, appropriate values for the initialization of variables is found to be case-dependent and estimated through empirical observations. Several other research works proposed improved versions of these algorithms by applying self-adaptive methods of defining the initialization variables [123 – 125]. Particle swarm optimization (PSO) algorithm, on the other hand, does not rely on a specific single variable initialization, such as the step size in gradient algorithms, and is less complex [126]. Based on the focus of our work and implementation of evolutionary algorithm for other applications, such as noise estiamation, the rest of the chapter discusses use of evolutionary algorithm based adaptive filtering techniques for noise cancellation in Cognitive Radio systems.

4.3 Noise Cancellation using Adaptive Filtering Techniques

Figure 12 shows the block diagram of the proposed system. This system was implemented using MATLAB. Stream of information bits are generated and modulated using M-*ary* phase shift keying (M-PSK) modulation scheme to be transmitted as signal, $x(t)$. Two cases of received noisy signal, $r(t)$, are developed in the simulation by adding noise to the transmitted signal, $x(t)$. For the first case, additive white Gaussian noise (AWGN) is added to the transmitted signal. For the second case, in addition to the AWGN, nonlinear noise is added to the signal. Received noisy signal corrupted with both AWGN and nonlinear noise is referred to as random noisy signal throughout the rest of the paper. After the addition of noise, signal $r(t)$ is sampled at the receiver radio's front end and forwarded to the adaptive filter, where it goes through the process of noise cancellation by one of the three filtering techniques.

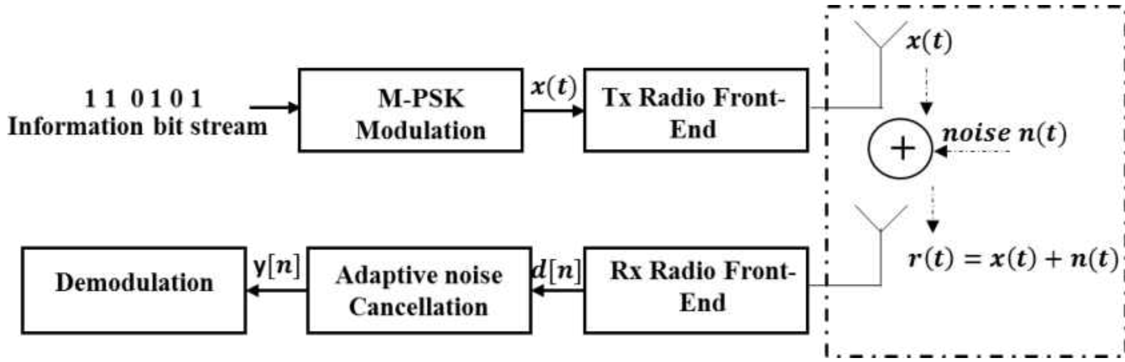

Figure 12. System Block Diagram

The adaptive noise cancellation block employs an adaptive line enhancer (ALE) as the adaptive filter instead of active noise control (ANC) based filtering system. As illustrated in Figure 13, an ALE based filtering system uses only one sensor and produces a delayed version of the received signal for noise cancellation. In ANC, a secondary reference sensor is required to estimate the noise in a noisy signal [93]. The received samples of noisy signal, $d[n]$, is fed to the ALE, which creates a delayed version, $\hat{y}[n]$ of the received samples, $d[n]$ by introducing a delay of , $Z^{-\Delta}$. The filtered output signal, $y[n]$ is estimated by updating weight coefficients $W[n]$, which is supplied by the GA/PSO/LMS of the adaptive filter. The output can be expressed as:

$$y[n] = \hat{Y}[n]W[n] \tag{27}$$

$$\hat{Y}[n] = [\hat{y}[n], \hat{y}[n-1], \dots, \hat{y}[n-L+1] \tag{28}$$

$$W[n] = [W_1, W_2, \dots, W_L]^T, \tag{29}$$

where, L is the adaptive filter order and T represents the transpose of the weight vector. To find the optimal weight solution for noise cancellation, the error, difference between the received samples and filtered output, is calculated and minimized. This error signal $e[n]$ is expressed as:

$$e[n] = d[n] - y[n] \tag{30}$$

The filtered output is then processed by the analog-to-digital converter and converted to baseband received bits for the purpose of demodulation. In the next section, an overview of PSO, GA and LMS is provided to describe the concept of the algorithms and the steps involved in each algorithm's adaptive filtering process.

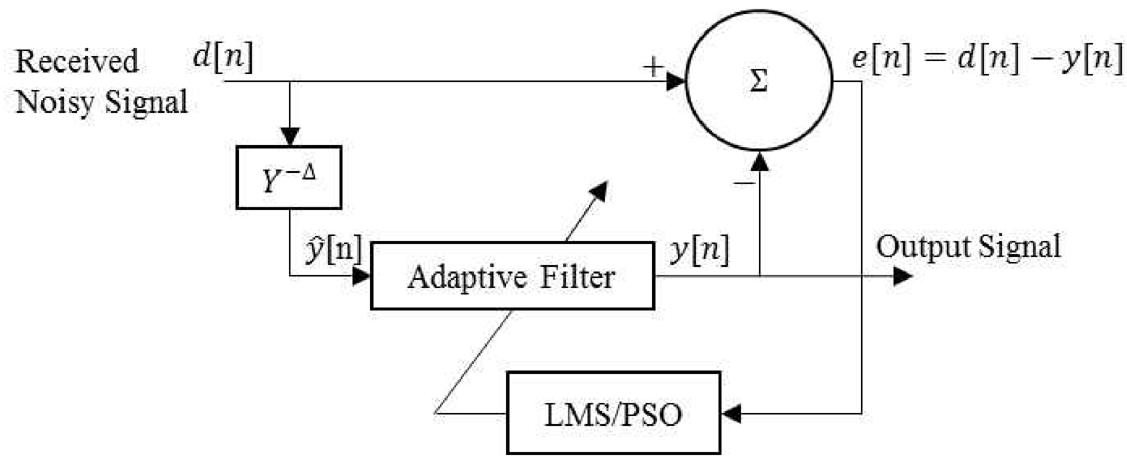

Figure 13. ALE Based Adaptive Filter

4.3.1 Noise Cancellation Using Genetic Algorithm (GA)

Genetic Algorithm is a global search optimization technique that can locate the global minima of a multimodal error surface. This algorithm mimics the biological evolution and follows the 3-step cycle: evaluation, selection, and reproduction [32] [122]. It starts with a set of population, P_{ga} (also referred to as chromosomes) and this set is then evaluated for its fitness to minimize the error over J generation. Once the evaluation steps are completed, the most fit chromosomes or parents are selected to mate.

In the last step, the selected chromosomes bear offspring and these children are used as the next set of population or parents for the next generation until maximum number of generation is reached or the global minima is located.

Precisely, for P_{ga} the number of population random solutions are generated as P_i= [P_1 , P_2, ..., P_L], where i = 1,…... , P_{ga}. The first set of solutions are then binary decoded and forwarded for fitness evaluation. The fitness or cost function is defined to minimize the error for the i^{th} solution in j^{th} generation. This fitness is expressed as:

$$f_{i,J} = \frac{1}{H}\sum_{n=1}^{H} \boldsymbol{e}_{i,J}[n]^2 \tag{31}$$

where $\boldsymbol{e}_{i,J}[n]$ is the error signal for the i^{th} population of J^{th} generation and H is the input samples to the filter. After the fitness is calculated, minimum fitness is stored as best fitness and portion β of the population $D = \beta. f$ parents are selected and passed into the next generation. Using the roulette wheel selection procedure D parents are mated to generate children, which then undergo crossover and mutation. The mutation rate impacts the convergence of GA – a too low mutation rate within a reasonable number of generation is not sufficient for the convergence of GA, whereas a high mutation rate may cause GA to diverge [32]. Similarly, crossover introduces genetic diversity and usually is set based on engineering experiences [122]. In this paper, the crossover and mutation rates are defined as P_c and P_m and are set to a value for which GA renders the lowest mean square error. In this work, simulations were performed to define the mutation and crossover rates, which are shown in the results section of this paper. Once the new set of population is generated it undergoes fitness re-evaluation and the best fit portion of the population is kept. As shown in the flowchart of Figure 14, the above mentioned processes continue until the maximum number of generation is reached or the optimal solution is found.

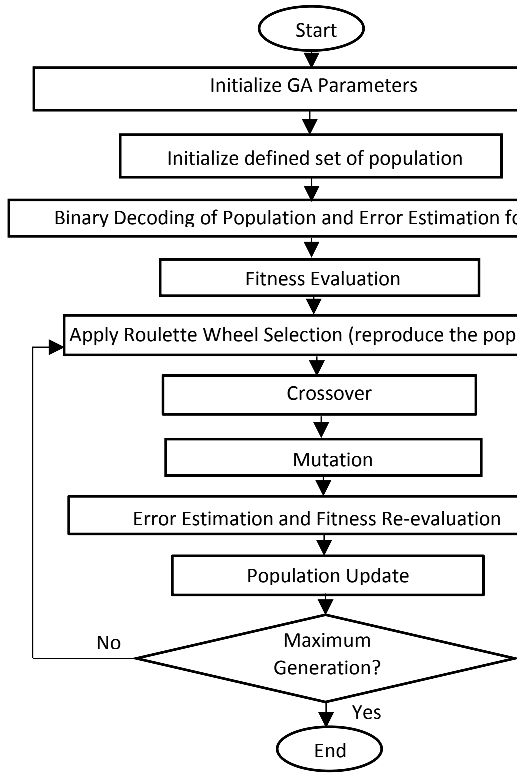

Figure 14. Flowchart for Genetic Algorithm

4.3.2 Noise Cancellation Using Particle Swarm optimization (PSO)

PSO algorithm is based on stochastic global optimization techniques. Motivated by the social interaction of bird flocking and fish swarms, PSO was proposed by James Kennedy and R.C. Eberhart in 1995 [95]. When in search for food, birds share their respective positions and update the flock with the information on the best food source within the search space. In the case of adaptive noise cancellation, similar search pattern is used in PSO with the objective of minimizing residual noise by locating best weight coefficients for the adaptive filter, which is analogous to finding the best food source or position. In order to cancel the noise, a cost function is defined that calculates the mean square error (MSE) between the received samples $d[n]$, and the filtered output $y[n]$.This cost function is defined as:

$$C_{i,k} = \frac{1}{H}\sum_{n=1}^{H} e_{i,k}[n]^2, \tag{32}$$

where $e_{i,k}[n]$ is the error signal for the i^{th} particle and k^{th} iteration and H is the input samples to the filter. Once the error is minimized by identifying the optimal solution or weight coefficients, PSO supplies the solution to the filter, which in turn produces the filtered output $y[n]$, as in (27). Precisely, PSO starts by defining a set of particles and their respective velocities where the initial velocities are set to be zero. Here, the weight coefficients are represented by the position vector that is initialized as *N* number of random solutions $w_i = [w_1, w_2, \ldots., w_L]$, where $i = 1, \ldots.. N$. The cost with the first set of particle positions is then calculated for maximum of *k* iterations and *N* particles. When the minimum value of the cost function is attained by PSO, the respective particle position for the minimum cost is set as the best cost, $P_{bestcost}$. Over *k* iterations, the velocity of each of the *N* particles is updated from the initial value of zero and is defined as:

$$v_{i,k} = v_{i,k-1} + c_1 r_1 (P_{bestcost,k} - w_{i,k-1})$$

$$+ c_2 r_2 (P_{globalbest,k} - w_{i,k-1}) \tag{33}$$

where, c_1 , c_2 are global and local learning coefficients, $w_{i,k-1}$, $v_{i,k}$ are the position and velocity, respectively, and r_1, r_2 are random numbers within the range of 0 and 1. For the i^{th}particle at k^{th} iteration, the position of the particle is updated using:

$$w_{i,k} = w_{i,k-1} + v_{i,k} \tag{34}$$

The local best position at k^{th} iteration is considered to be $P_{bestcost}$, and $P_{globalbest}$ is considered to be the global best position among the overall k iterations. As shown in the flowchart of Figure 15, the above processes are repeated by PSO until the maximum number of iterations are reached or a global optimum solution is found as the algorithm converges.

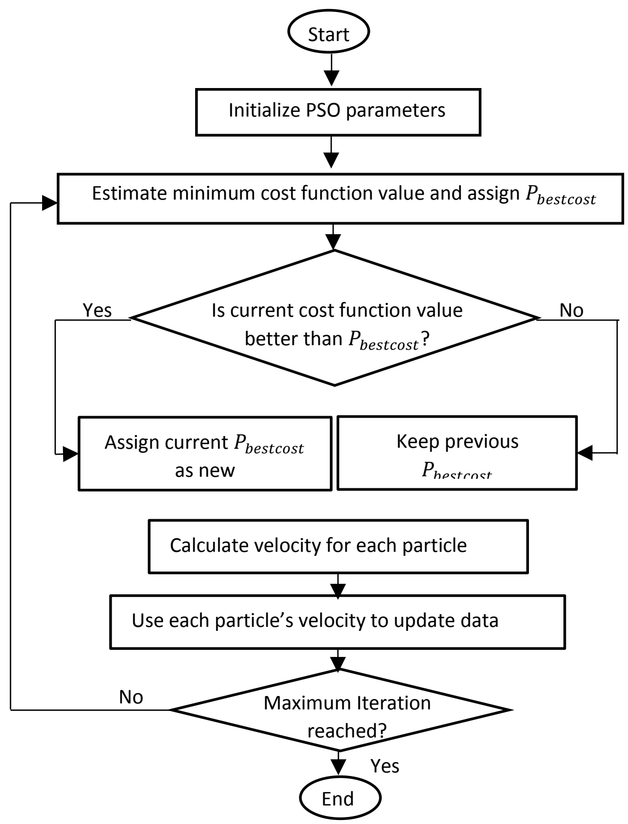

Figure 15. Flowchart for PSO

4.3.3 Noise Cancellation Using Least Mean Square (LMS)

LMS falls under the category of gradient descent algorithms, which when initialized with an assigned value it follows the negative of gradient to locate the desired local minima of an error surface. In the case of LMS, the step size, which can be considered as the guiding factor for the algorithm, controls the negative descent to reach the local minima. The process of updating weight coefficients using the LMS can be expressed as:

$$W[n+1] = W[n] + \mu e[n]\hat{Y}[n] \tag{35}$$

where, $W[n]$ is the weight vector and μ is the step size. Determining the appropriate step size is found to be an important performance requirement for LMS algorithm [96]. To minimize the error signal $\boldsymbol{e}[n]$, small step size is preferred to achieve the optimal convergence speed whilst maintaining a steady performance [96]. Once the optimal weights are found, the output signal is estimated by supplying the updated weight coefficients to the filter. Figure 16 shows the flowchart of the LMS algorithm.

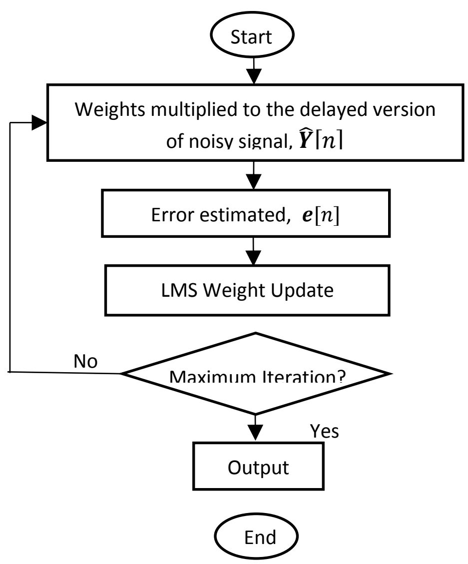

Figure 16. Flowchart for LMS

4.4 Performance Comparison of Noise Cancelling Techniques

The transmitted bit stream used in the simulations was generated to produce a signal of 10,000 samples, which was then modulated using M-PSK (with M=2) modulation scheme and transmitted over a carrier frequency of 2.4 GHz. Additive white

Gaussian noise and non-linear noise were simultaneously added to the transmitted signal. At the receiver, the noisy signal was filtered using one of the three algorithms. Two metrics, bit error rate (BER) and mean square error (MSE), are used to compare the performance of these algorithms. BER, which is the ratio of bit error and total number of transmitted bits during the studied period, can be formulated as:

$$BER = \frac{Number\ of\ Corrupted\ Bits}{Total\ Number\ of\ Transmitted\ Bits} \tag{36}$$

MSE is the difference between the noisy signal and the filtered output and estimates the average of squared error. It is defined as:

$$MSE = \sum_{l=1}^{H}(Noisy\ Signal\ - Filter\ Output)^2/H, \tag{37}$$

where, H is the length of the received signal.

Figure 17 illustrates the simulated random noisy signal generated to investigate one of the notable drawbacks of LMS. This figure shows additional noise induced frequencies besides the actual 2.4 GHz frequency. The spikes at lower frequency ranges are generated when the co-located CR antennas operate at the same time with the same frequency during full-duplex communication.

Figure 18 shows MSE as a function of number of iterations or samples for three different step sizes of the LMS algorithm. Results were obtained using fixed -2dB SNR and filter order of L =5 for three step sizes 0.001, 0.005, and 0.01. As one can see, MSE for all step sizes increases sharply within the first 300 iterations and then gradually decreases with increasing number of iterations.

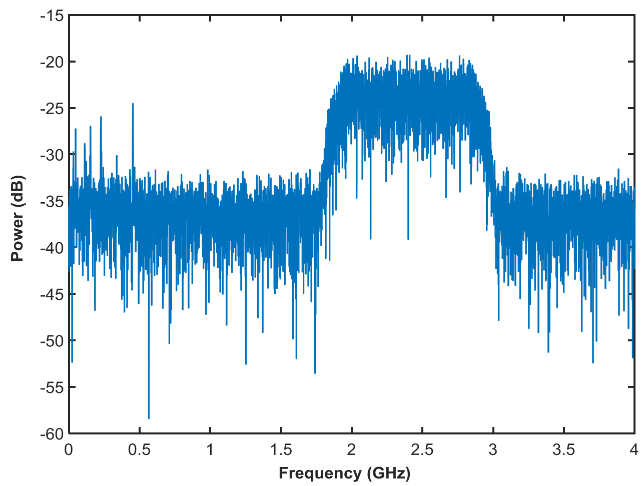

Figure 17. Received Noisy Signal Distorted by AWGN and Nonlinear Noise

MSE for step size of 0.01 is found to decrease at a faster rate and enables LMS to converge after about 5000 iterations. As step size decreases, LMS converges at a slower rate and the peak MSE increases. From these results, it can be said that the appropriate choice for step size impacts the performance of LMS.

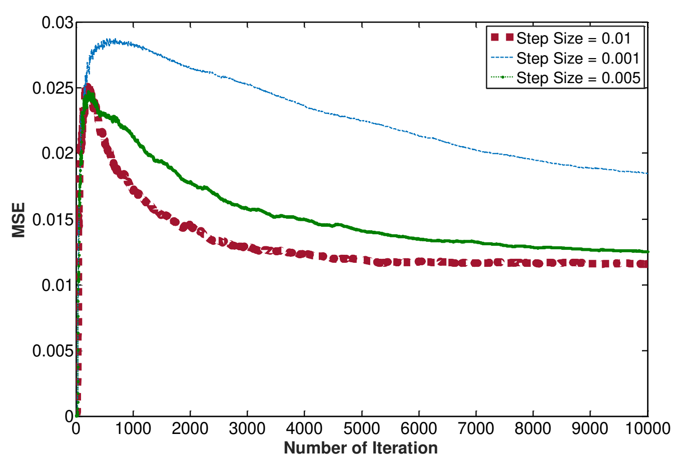

Figure 18. Impact of *Step Size* on LMS Convergence Characteristic

Figure 19 illustrates the impact of different number of population or particle sizes of GA and PSO on MSE values for both algorithms. The simulation was performed with a filter order of $L = 5$ and 200 number of iterations/generations for a fixed SNR condition of -5dB. As observed, MSE of GA is higher than that of PSO for all the considered sizes, but is almost similar to PSO for the population sizes 60, 90, 110, 140, and 150. In addition, for the first three population sizes, MSE values for GA are higher but gradually decrease as the population size increases.

After the population size of 30, GA renders more steady MSE values with population size of 110 achieving the lowest MSE among all sizes. However, MSE for PSO remains almost constant for all the particle sizes investigated in this simulation.

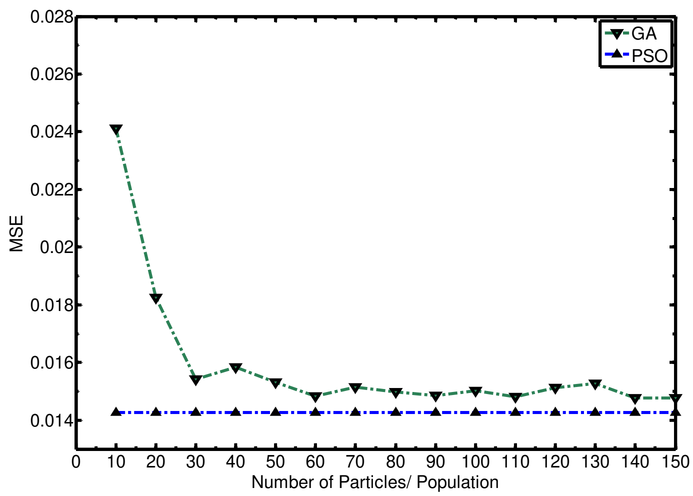

Figure 19. MSE for Different Population and Particle Sizes of GA and PSO

Therefore, for the next simulations optimal population size for GA is chosen to be 110 and for PSO particle size of 60. These optimal sizes are chosen considering factors such as computational complexity associated with iterating through large particle sizes and closest and lowest MSE values achieved by both the algorithms.

In Figure 20, MSE over varying probability of crossover is shown for two different SNR conditions, 5dB and -5dB. The results were obtained using the population size of 110 and 300 generations for SNR -5dB and 5dB. As one can see from this figure, MSE values do not vary for P_c in the range of 0 to 0.8 under both the SNR conditions of -5dB and 5dB. As expected, MSE is higher for both P_c and P_m under -5dB SNR as compared to 5dB SNR. MSE for P_c decreases after the probability of 0.8 for both SNR conditions and is found to be the lowest at the probability of 1. As for the probability of mutation under -5dB SNR, sharp decrease of MSE is observed in the range of 0 to 0.1 after which it does not vary significantly. For SNR conditions under 5dB. MSE of P_m gradually decreases within the range of 0 to 0.3 and stabilizes for the rest of the mutation rates. Probabilities of mutation of 0.6 (under 5dB SNR) and 0.45 (under SNR -5db) are found to have the lowest MSE values.

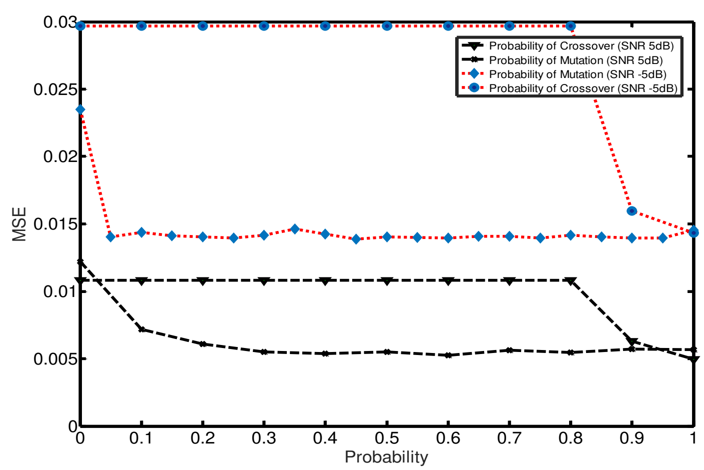

Figure 20. Effect of Crossover and Mutation Rate of GA on MSE

Figure 21 corresponds to MSE of GA, PSO, and LMS filtered signals for varying SNR conditions in the range of -10 dB to 10 dB. The simulation was performed on noisy signal distorted by AWGN and the results are obtained using a filter order L= 5, a population size of 110 for GA, optimal particle size of 60 for PSO, and a step size of 0.01

for LMS. As one can see, MSE values for all the three algorithms decrease as SNR increases, with GA and PSO having the lowest MSE values than those of LMS for all the SNR conditions. However, MSE decreases at a similar rate for GA and PSO till SNR of -2 dB. After -2dB SNR, the difference in MSE values between GA and PSO is found to increase indicating better performance of PSO than those of both GA and LMS algorithm. For all the SNR conditions, both GA and PSO outperform LMS.

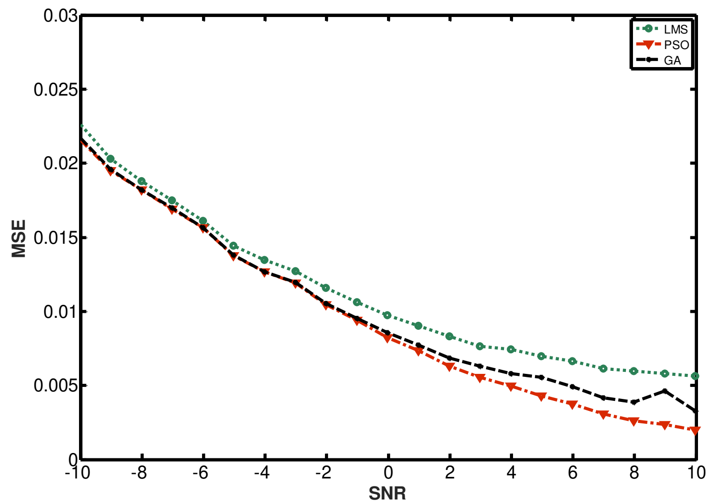

Figure 21. MSE for GA, PSO, and LMS under Varying SNR Conditions

Figure 22 show the performances of GA, PSO, and LMS, in filtering AWGN corrupted signals and random noisy signals. BER for all algorithms are calculated to compare their performances for a range of SNR from -10 to 10 dB. Figure 11 shows BER of AWGN distorted noisy signal under varying SNR conditions. The results are obtained using a filter order of L=5, step size 0.01, population of 110 for GA, and particle size of 60 for PSO. As can be seen, BER for all the algorithms decreases at a similar rate till -7 dB SNR. The difference in BER between the algorithms increases after -5dB SNR with PSO having the lowest BER followed by GA and then LMS. Both GA and PSO achieve zero BER at 1 dB and 3 dB SNR, performing significantly better than LMS.

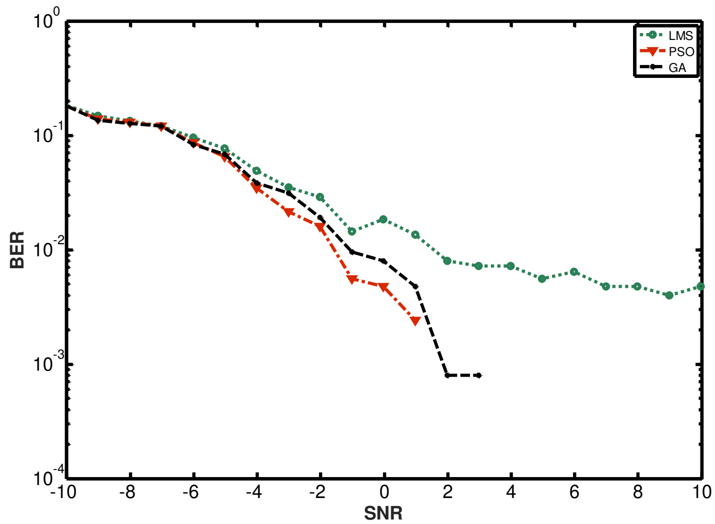

Figure 22. BER for GA, PSO, and LMS under Varying SNR Conditions

However, after 4 dB SNR, BER of GA is seen to fluctuate indicating degrading performance. Overall, PSO performs better than both GA and LMS for all the considered SNR conditions. In the case of GA, fixed control parameters (crossover and mutation rates) results in less efficient performance. The poor performance of LMS is mainly because of the increasing impact of non-linear random noise as SNR increases.

Table III outlines a general performance comparison of the 3 algorithms in terms of complexity, factors affecting their convergence rates, and optimization efficiency. In terms of computational complexity, GA and PSO are more complex than LMS. However, unlike PSO both GA and LMS require the selection of appropriate values for step size and control parameters in order to converge at an optimal rate. In terms of search optimization efficiency, GA and PSO being global optimization techniques are able to locate the global minima of a multimodal error surface. On the other hand, LMS being a local optimization technique fails to do as it can only locate local minima. Among the two global optimization techniques, GA has more steps than PSO, which increases the required processing time for GA to search for global minima. In addition, GA weight coefficients are kept in a binary-coded string format, referred to as chromosomes. These chromosomes go through crossover and mutation in every generation before they are updated. Whereas, in PSO particle position and velocity are updated at every iteration to search for the minimum cost and corresponding best solution.

Table III. Performance Comparison of Three Algorithms

Algorithm	**Complexity**	**Convergence**	**Optimization Efficiency**
PSO	Complex	Not affected by initialization variables	• Able to identify global minima • Requires less processing steps then GA
GA	Complex	Affected by Control Parameters e.g. – crossover and mutation rates	• Able to identify global minima • Requires more processing steps and iterations than PSO
LMS	Simple	Affected by initialization variables, e.g. step size	Only locates local minima of error surface

4.5 Conclusions

In this chapter, we have described the results of a comparison study of the performances of three algorithms: GA, PSO, and LMS. Detailed simulations were performed where practical communication systems and signals were modelled with Gaussian and non-linear random noise. BER and MSE were used as performance evaluation metrics to compare the efficiencies of the three algorithms. The results show that BER values of GA and PSO are significantly better than LMS in filtering the signal distorted by Gaussian noise. However, all the three algorithms show poor performance in the case of non-linear random noise with PSO outperforming the other two algorithms. MSE for different SNR conditions were also calculated and discussed and it was shown that MSE values for GA and PSO filtered signals are lower than that of LMS. In addition to the performance metrics, population size, crossover and mutation rate for GA, and effect of particle size for PSO were also investigated.

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Chapter 5

CONCLUSIONS

Next generation communication technology, cognitive radio, will enable efficient utilization of spectrum resources by sensing the availability of frequency bands used by licensed owners, the primary users. A cognitive radio is able to reconfigure its communication parameters to provide superior data communication services by sensing the radio spectrum, but without interfering with primary users' signals. By using spectrum sensing techniques, a CR system can detect the free channels. During the spectrum analysis phase, the condition of the channel can be analyzed and evaluated using channel quality metrics, including but not limited to, SNR, BER, and channel capacity. Finally, using the decision-making process a CR system decides which channel to use for transmission. The existing decision-making techniques only consider the presence/absence of the primary users or the occupancy rate of a channel for a longer period of time. However, these existing techniques do not consider other communication parameters that provide information on the channel quality. Therefore, the decision taken by the CR can be erroneous.

To address the problem, this thesis aimed at developing a channel ranking technique that considers two parameters, SNR along with spectrum occupancy rate, to model the 'usefulness' or utility of a channel. The utility-based channel ranking technique can be used periodically, after the spectrum sensing process. The technique then assigns ranks to the sensed channels according to their utility values, where the highest rank is assigned to the best channel. The utility-based channel ranking technique enhances the radio spectrum decision by taking into account quality of service metrics and ranks channels in an orderly fashion.

To develop and achieve the goals of this thesis, in chapter 1, SNR estimation techniques were studied and an improvement over Eigenvalue-based SNR estimation technique was proposed. The proposed technique employs the particle swarm optimization to adaptively change key parameters, such as the number of samples, distribution size, and Eigenvalues used by the existing technique. Performance evaluation has been done using simulations and the results show a better SNR estimation performed by the proposed technique.

In chapter 2, the utility-based channel ranking technique is described by defining a global utility function based on the utilities based SNR and channel occupancy rate. Different mathematical functions are investigated to characterize the utility of SNR and that of channel occupancy. Finally, a ranking table is provided with the utility values of sensed channels and the results are compared with those of the occupancy based channel ranking. The proposed technique is able to rank channels more accurately based on the channel quality and occupancy rate, whereas the occupancy-based ranking often assigns high ranks to poor quality channels with low occupancy rate.

In chapter 3, several noise cancellation techniques are investigated, which can be used to get rid of noise from the received signals during the spectrum sensing. Particle swarm optimization and genetic algorithm- based noise cancellation techniques were found to perform better than the gradient-descent based existing technique, least-mean-square.

In conclusion, the utility-based channel ranking enhances the radio spectrum decision capabilities of a cognitive radio system. The channel ranking technique considers more than one factor in the decision-making process of choosing the best channel for wireless communication. There are scopes to work more on the ranking techniques, which are discussed in the following section.

Future Directions

To pursue future scope of work for SNR estimation, Multi-objective Particle Swarm Optimization (MOPSO) algorithm can be employed to optimize all multiple key parameters of the Eigenvalue based SNR estimation technique. It is evident from the simulation results that both the parameters, number of received signal samples and Eigenvalues, impact the accuracy of SNR estimation. With MOPSO, the above-mentioned parameters can be optimized simultaneously, which can result in more accurate estimation of SNR.

For the utility-based channel ranking, as future works, other channel quality parameters can be used with channel occupancy. Bit Error Rate, channel capacity, and Signal-to-Interference and Noise Ratio are few of the parameters that can be used in the constant elasticity of substitution utility function to model the utility function. However, the utilities of these parameters have to be first modeled by using appropriate mathematical functions and then the channel utility can be defined as a function of these parameters.

Subsequently, a back propagation feedback method can be used which can train a reinforcement learning algorithm to identify which frequencies provide reliable communication and if their corresponding ranking was appropriately assigned. The reinforcement learning algorithm can be useful to update the elasticity of the channel utility function, which in turn can perform better channel modeling for accurate ranking.

There are also scopes to use machine learning methods for the purpose of channel ranking, where right models and learning algorithms can interpret and learn from the vast amount of data on radio frequency environment. Machine learning technique can take into account several communication parameters and characterize the communication channels based on previously collected training data set. The learning technique can primarily be online but after a certain amount of training, may also operate offline in cognitive radio nodes for instantaneous decision-making.

As future work for noise cancellation in cognitive radio systems, other sources of noise can be investigated, such as noise originating from co-channel interference. As cognitive radio systems may transmit and receive signals using the same frequency at the same time, noise can be generated from co-channel interference. Therefore, the performance of the existing noise cancellation techniques in getting rid of co-channel interference induced noise can be evaluated and improvements of the techniques can be researched.

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