DECISION MAKING TECHNIQUES FOR COGNITIVE RADIOS

MUBBASHAR ALTAF KHAN
830310-P391
maks023@gmail.com

&

SOHAIB AHMAD
811105-P010
asho06@student.bth.se

This report is presented as a part of the thesis for the Degree of Master of Science in Electrical Engineering.

Blekinge Institute of Technology
March 2008
ACKNOWLEDGMENT

It is our pleasure to express our thanks to Tommy Hult, Blekinge Institute of Technology our supervisor for the research. Without his moral support and guidance the progress in this research would not have been possible. We personally thank him for coordinating the research and providing us with timely and valuable tips and suggestions towards the task.

We extend our sincere thanks to our family members especially our parents and all our friends who helped us towards our task during the research.
ABSTRACT

Spectrum scarcity is one of the biggest challenges that the modern world is facing. The efficient use of available licensed spectrum is becoming more and more critical with increasing demand and usage of the radio spectrum. Different researches show that the usage is not uniform throughout the licensed spectrum rather it is heavy in certain parts of the spectrum and has portions that are utilized inefficiently. Some researchers even claim that more than 70% of the licensed frequency band is not in use, most of the time. So, there is much room for work yet in the unutilized parts or the inefficiently utilized parts of the spectrum, to overcome the spectrum scarcity problem.

Different researches are in progress and ways are being found to efficiently utilize the available licensed spectrum. One of the ways is the use of “Cognitive Radio”, according to this; the already licensed spectrum can be used more efficiently by introducing artificial intelligence, the decision-making to be specific, in the radio. This enables the radio to learn from its environment, considering certain parameters. Based on this knowledge the radio can actively exploit the possible empty frequencies in the licensed band of the spectrum that can then be assigned to other processes in such a way that they don’t cause any interference to the frequency band that is already in use. This makes the efficient usage of the available licensed spectrum possible.

The users that are allocated the licensed frequency bands of the spectrum are the primary users and the users that are allocated the empty frequencies within the licensed frequency band, according to their requested QoS specifications, are known as the secondary users or the cognitive users. They are called as the secondary users as they utilize the unused spectrum resources only, on non-interfering basis, with the primary users.

This thesis will focus on the implementation of different spectrum allocation techniques for these secondary users, based on Genetic Algorithms and an evaluation of the performance of these techniques using Matlab coding.

This research will focus on the decision-making process mainly, with an assumption that the radio environment has already been sensed and the QoS requirements for the application have been specified either by the sensed radio environment or by the secondary user itself.
# Nomenclature

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>AC</td>
<td>Alternating Current</td>
</tr>
<tr>
<td>BER</td>
<td>Bit Error Rate</td>
</tr>
<tr>
<td>BPSK</td>
<td>Binary Phase Shift Keying</td>
</tr>
<tr>
<td>CR</td>
<td>Cognitive Radio</td>
</tr>
<tr>
<td>CSM</td>
<td>Cognitive System Monitor</td>
</tr>
<tr>
<td>DB</td>
<td>Decibel</td>
</tr>
<tr>
<td>DSP</td>
<td>Digital Signal Processor</td>
</tr>
<tr>
<td>EM</td>
<td>Electromagnetic</td>
</tr>
<tr>
<td>FCC</td>
<td>Federal Communications Commission</td>
</tr>
<tr>
<td>FPGA</td>
<td>Field Programmable Gate Array</td>
</tr>
<tr>
<td>G.As</td>
<td>Genetic Algorithms</td>
</tr>
<tr>
<td>GMSK</td>
<td>Gaussian Minimum Shift Keying</td>
</tr>
<tr>
<td>GP</td>
<td>Genetic Programming</td>
</tr>
<tr>
<td>KHz</td>
<td>Kilo Hertz</td>
</tr>
<tr>
<td>LISP</td>
<td>List Processing</td>
</tr>
<tr>
<td>MAC</td>
<td>Media Access Control</td>
</tr>
<tr>
<td>MHz</td>
<td>Mega Hertz</td>
</tr>
<tr>
<td>PER</td>
<td>Packet Error Rate</td>
</tr>
<tr>
<td>PHY</td>
<td>Physical Layer</td>
</tr>
<tr>
<td>QAM</td>
<td>Quadrature Amplitude Modulation</td>
</tr>
<tr>
<td>QoS</td>
<td>Quality of Service</td>
</tr>
<tr>
<td>QPSK</td>
<td>Quadrature Phase Shift Keying</td>
</tr>
<tr>
<td>RF</td>
<td>Radio Frequency</td>
</tr>
<tr>
<td>RKRL</td>
<td>Radio Knowledge Representation Language</td>
</tr>
<tr>
<td>SBR</td>
<td>Signal to Noise Ratio</td>
</tr>
<tr>
<td>SDR</td>
<td>Software Defined Radio</td>
</tr>
<tr>
<td>TSP</td>
<td>Travelling salesman Problem</td>
</tr>
<tr>
<td>WCGA</td>
<td>Wireless Channel Genetic Algorithm</td>
</tr>
<tr>
<td>WSGA</td>
<td>Wireless System Genetic Algorithm</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>TABLE 4.1</td>
<td>37</td>
</tr>
<tr>
<td>TABLE 4.2</td>
<td>38</td>
</tr>
<tr>
<td>TABLE 4.3</td>
<td>39</td>
</tr>
<tr>
<td>TABLE 4.4</td>
<td>40</td>
</tr>
<tr>
<td>TABLE 4.5</td>
<td>41</td>
</tr>
<tr>
<td>TABLE 4.6</td>
<td>41</td>
</tr>
<tr>
<td>TABLE 4.7</td>
<td>42</td>
</tr>
<tr>
<td>TABLE 4.8</td>
<td>53</td>
</tr>
<tr>
<td>TABLE 4.9</td>
<td>53</td>
</tr>
<tr>
<td>TABLE 4.10</td>
<td>54</td>
</tr>
<tr>
<td>TABLE 4.11</td>
<td>54</td>
</tr>
<tr>
<td>TABLE 4.12</td>
<td>55</td>
</tr>
<tr>
<td>TABLE 4.13</td>
<td>55</td>
</tr>
<tr>
<td>TABLE 4.14</td>
<td>55</td>
</tr>
<tr>
<td>TABLE 4.15</td>
<td>55</td>
</tr>
<tr>
<td>TABLE 4.16</td>
<td>56</td>
</tr>
<tr>
<td>TABLE 4.17</td>
<td>57</td>
</tr>
<tr>
<td>TABLE 4.18</td>
<td>59</td>
</tr>
<tr>
<td>TABLE 4.19</td>
<td>60</td>
</tr>
<tr>
<td>TABLE 4.20</td>
<td>60</td>
</tr>
</tbody>
</table>

# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>FIGURE 2.1</td>
<td>18</td>
</tr>
<tr>
<td>FIGURE 2.2</td>
<td>18</td>
</tr>
<tr>
<td>FIGURE 4.1</td>
<td>43</td>
</tr>
<tr>
<td>FIGURE 4.2</td>
<td>62</td>
</tr>
<tr>
<td>FIGURE 4.3</td>
<td>63</td>
</tr>
<tr>
<td>FIGURE 4.4</td>
<td>63</td>
</tr>
</tbody>
</table>
Contents

ACKNOWLEDGMENT .................................................................................................................................. 2
ABSTRACT .................................................................................................................................................. 3
NOMENCLATURE ...................................................................................................................................... 4
LIST OF TABLES ......................................................................................................................................... 5
LIST OF FIGURES ....................................................................................................................................... 5
CONTENTS ............................................................................................................................................... 6
CHAPTER 1 ............................................................................................................................................... 9
INTRODUCTION ......................................................................................................................................... 9
1.1. SPECTRUM EFFICIENCY TASKS OR COGNITIVE TASKS .......................................................... 10
1.2. RESEARCH CONTEXT ..................................................................................................................... 11
1.3. RESEARCH OBJECTIVES .............................................................................................................. 11
1.4. THESIS OUTLINE .......................................................................................................................... 13
CHAPTER 2 ............................................................................................................................................... 14
LITERATURE REVIEW ............................................................................................................................ 14
2.1. BACKGROUND AND HISTORY OF COGNITIVE RADIOS ....................................................... 15
2.2. CHARACTERISTICS OF COGNITIVE RADIOS ........................................................................... 16
2.2.1. COGNITIVE CAPABILITY ....................................................................................................... 17
2.2.2. RE-CONFIGURABILITY ............................................................................................................. 19
CHAPTER 3 ............................................................................................................................................... 23
GENETIC ALGORITHMS (AN OVERVIEW) ............................................................................................. 23
3.1. SOME OTHER OPTIMIZATION TECHNIQUES .............................................................................. 23
3.2. WHY GENETIC ALGORITHMS .................................................................................................... 24
3.3. METHODOLOGY OF GENETIC ALGORITHMS ........................................................................... 25
3.3.1. OUTLINE FOR THE GENETIC ALGORITHMS ...................................................................... 25
3.3.2. CHROMOSOME DEFINITION .................................................................................................. 26
3.3.3. THE SEARCH SPACE ............................................................................................................... 27
3.3.4. THE FITNESS FUNCTION ......................................................................................................... 27
3.3.5. OPERATIONS IN GENETIC ALGORITHMS ............................................................................ 27
3.3.6. THE CROSSOVER AND MUTATION OPERATIONS .................................................................. 28
3.4. GENETIC ALGORITHMS IN THE RADIOS .................................................................................. 29
### 3.4.1. CHROMOSOME DEFINITION FOR THE RADIO

3.4.2. FITNESS FUNCTION DEFINITION FOR THE RADIO

3.4.3. FITNESS EVALUATION FOR THE RADIO

3.5. THE MULTI-CRITERIA OPTIMIZATION

3.5. THE DECISION-MAKING

### CHAPTER 4

**RESEARCH METHODOLOGY**

4.1. THE CHROMOSOME

4.1.1. THE FREQUENCY

4.1.2. THE POWER

4.1.3. THE BIT ERROR RATE

4.1.4. THE MODULATION SCHEME

4.1.5. THE CHROMOSOME STRUCTURE

4.2. THE FIRST POPULATION CHROMOSOMES GENERATION

4.3. THE FITNESS FUNCTION

4.3.1. FITNESS OF THE FREQUENCY GENE

4.3.2. FITNESS OF THE POWER GENE

4.3.3. FITNESS OF THE BER GENE

4.3.4. FITNESS OF THE MODULATION GENE

4.3.5. TOTAL FITNESS

4.4. METHOD 1

4.4.1. SELECTION

4.4.2. CROSSOVER

4.4.3. MUTATION

4.4.4. FITNESS CALCULATION

4.4.5. NEW POPULATION GENERATION

4.5. THE OPTIMAL SOLUTION

4.6. METHOD 2

4.6.1. ELITISM

4.6.2. CROSSOVER

4.6.3. MUTATION

4.7. MATLAB RESULTS

4.8. CONCLUSIONS & BEHAVIOR OF G.A.S
4.9. FVISION IN FUTURE

REFERENCES
Chapter. 1

Introduction

Electromagnetic radiation (EM), the disturbance in space that propagates by itself in the space has both electric and magnetic field components that oscillate in perpendicular to each other in phase and to the direction of energy. It carries both energy and momentum. The EM spectrum is the range of all possible EM radiations. The EM spectrum or simply “Spectrum” of an object is the radiated frequency distribution of EM radiation from that object. The spectrum range covers wavelengths equivalent to the size of an atom to thousands of kilometers and extends from the radio frequencies to gamma radiations. The spectrum is thus infinite and continuous in nature.

Our concern in this research is with the radio frequency (RF). The RF range of 3Hz to 300 Ghz corresponds to the frequency of alternating current (AC) signals that are used to detect radio waves. The radio spectrum is used for wireless communication purposes, where transmission and reception of signals at the antennas are involved. With an increasing demand and usage, the radio spectrum is becoming saturated in terms of its allocation. A need, therefore, is being felt for the efficient use of the available spectrum. This available spectrum has both licensed and unlicensed frequency bands. An immense research is being carried out in order to make the efficient use of the spectrum possible and the idea of Cognitive Radio is one of the ways to achieve this efficiency in the spectrum utilization. This idea, of cognitive radios, exploits the reality that the frequency band assigned to the licensed users is never utilized completely by them; rather it is heavy in certain parts and has the portions that are not utilized efficiently. The Cognitive Radio exploits these unused or empty frequencies in the spectrum. These unused frequencies are sensed using spectrum sensing techniques and then made available to the other users. The users that are allocated the licensed frequency bands of the spectrum are the primary users where as the users that are allocated the empty frequencies within the licensed frequency band, according to their requested QoS specifications, are known as the secondary users or the cognitive users. They are called as the secondary users as they utilize the unused spectrum resources only, on non-interfering basis.

These secondary users actually create “Virtually unlicensed frequency bands” in the licensed frequency bands of the spectrum. Once detected, the characteristics of these “Virtually unlicensed frequency bands” are estimated. The cognitive radio then adapts its parameters according to the detected spectrum characteristics and secondary user’s QoS (Quality of Services) requirements.

This idea can more specifically be defined as a SDR (Software Defined Radio)
or smart radio that has the intelligence built in it to sense the environment and change its transmission and reception parameters, to utilize these virtually unlicensed frequency bands, on non-interfering basis with the licensed users of the spectrum. It has also to keep in view the needs and requirements of the application that is going to use these virtually unlicensed frequency bands. Once having done the allocation, the next issue is reallocation. Reallocation is necessary in case of detection of a primary user in the present allocated virtually unlicensed frequency band. The reallocation is basically done in order to avoid the interference that may occur among the co-existing users in the same spectrum. Care must be taken while reallocating, as it should not affect the ongoing communications while we reallocate the spectrum. This is achieved by the provision of a fair scheduling among the co-existing users in the same spectrum. So, this as a whole makes the spectrum to be dynamically accessible, at the real time.

The following steps and subtasks can explain this whole process more explicitly.

**1.1. Spectrum efficiency tasks or cognitive tasks:**

Cognitive tasks can be divided into the following subtasks.

- **Spectrum sensing:**

  It detects the empty frequencies in the licensed spectrum. These empty frequencies create virtually unlicensed frequency bands within the licensed frequency bands of the spectrum. This is done by the mutual coordination that exists among the participating radios. Each of the radios coordinates by reporting its spectrum usage. The spectrum distribution is carried out on the basis of calculation of certain parameters. After this sensing process these whole frequency bands are available to be used by the secondary users unless a primary user is detected in the same frequency band.

- **Spectrum policy or spectrum management policy:**

  Once detected the empty frequencies in the spectrum, the QoS of the application are considered, i.e. the secondary user that is to use these empty frequencies, and the best available spectrum that meets these QoS is selected among these empty frequencies and is assigned to the secondary user.
• **Spectrum Reallocation:**

  If in case a primary user is detected in the same frequency band allocated to the secondary user. The secondary user should be reallocated another frequency band in the spectrum to avoid interference that may occur with the primary user’s frequency band, otherwise. This transition should take place in such a way that it does not affect the ongoing communications. Hence care must be taken while reallocation, in order to maintain a seamless communication during the transition.

• **Spectrum sharing:**

  During the whole cognitive process, a fair scheduling is required between the primary and the secondary users. This is necessary to avoid the interference that may occur between them. Defining holding times for the users that have been allocated the frequency band can do this scheduling. This promises for fair scheduling among the co-existing users that share the spectrum.

1.2. **Research Context:**

  Cognitive radios are emerging as one of the ways for efficient utilization of the available spectrum. Due to the allocation of the available spectrum to the licensed (primary) users, the spectrum is becoming more and more saturated. Also, the number of the unlicensed (secondary) users trying to access the spectrum is increasing enormously. The ground reality is that the licensed users do not use the whole of the spectrum at all instances of time, so the idea is that sensing the empty frequencies in the licensed frequency bands and thus defining virtually unlicensed frequency bands, within the already licensed frequency bands, can accommodate some other users. This makes the efficient utilization of the available spectrum possible. To achieve this Cognitive Radios can be used, that can allocate these virtually unlicensed frequency bands, dynamically at real time by changing their parameters keeping in view the QoS requested by the secondary user or simply the application, without interfering with the primary users.

1.3. **Research Objectives:**

  An immense research is being carried out relating to the cognitive radios. Certain techniques have been developed to allocate these virtually unlicensed frequency bands to the secondary users. This particular thesis will focus on the implementation of different spectrum allocation techniques for secondary user, based on some Genetic Algorithms and an evaluation of the performance of these techniques using Matlab coding.
This research will focus on the decision-making process mainly, with an assumption that the radio environment has already been sensed and the QoS requirements for the application have been specified either by the sensed radio environment or by the secondary user itself.

The aims and objectives of our research are as follows:

- Develop the basic understanding of the concept and working of Cognitive Radios.
- Study the characteristics (parameters) of Cognitive Radios’ and the applications that are used in secondary user system.
- Study different techniques for optimization.
- Evaluate different techniques and methods for decision making for spectrum allocation.
- Spectrum allocation techniques for secondary user based on Genetic Algorithms.
- Performance evaluation of the spectrum allocation techniques, using Matlab toolbox.

This particular work will allow a more intensive access to and use of spectrum than possible with the traditional, hardware-based radio systems. It will help in effective use of the spectrum as well as dynamic spectrum management and spectrum allocation schemes in the wireless communication systems, in future. There is still a lot of work to be done in this regard. This research work would be an attempt towards better utilization of the spectrum.

With the increasing number of mobile users in today’s communication world, the cognitive radios are supposed to make sure that all the users get access to the spectrum. The users’ QoS requirements should also be met while they are allowed the dynamic access to the spectrum. The Cognitive radios at the same time are also supposed to make sure the interference avoidance between the primary and the secondary users, while the primary users keep changing their licensed frequency band utilization over real time.
1.4 Thesis Outline:

**Chapter 1:**
An introduction to the concept of cognitive radios, the context, scope and objectives of the research

**Chapter 2:**
Literature overview with a brief history of cognitive radios, along with the opportunities that the cognitive radios can provide, in order to exploit the intermediate opportunities towards the efficient utilization of the spectrum in the future.

**Chapter 3:**
Literature review of the concept of the Genetic Algorithms, particularly their use in the Cognitive radios to carry out their decision-making process.

**Chapter 4:**
The methodology of this research, i.e. the focus is on what would be our considerations and possible assumptions in this concept, in order to pursue our research for the explanation of the decision-making in the cognitive radios.

Also, we shall discuss the conclusions that can be drawn from the research work and some of the directions in which the concept of cognitive radios can be extended in future, towards the goal.

The references for the research are included at the end, along with the Matlab code used in the decision-making process for the cognitive radios.
Chapter. 2

Literature Review:

This chapter gives a brief overview of the current work that is going on the Cognitive Radios and the advancements made in the concept.

Due to the spectrum scarcity the software defined radios are the most popular these days. The term “Software defined” implies the fact that the use of hardware is kept as little as possible and the most of the signal processing is done using the software. Cognitive radio S.D.R., is one of the newer versions of the software defined radios, that has achieved a significant amount of improvement over services offered by existing wireless networks. The basic characteristic of the “Cognitive radio” is that it can change its parameters at real time, considering the QoS requirements of the application. This feature enables the Cognitive Radio to be able to utilize the available spectrum efficiently. The cognitive radio S.D.R. is based on software embedded in a mobile device that can change its operating functionalities according to the environment, as the mobile user moves from one place to the other.

Cognitive Radio is more intelligent and adaptable than just Software Defined Radio. It is designed to be aware of and be sensitive to the changes in its surroundings. Thus it learns from its environment and performs functions that best serve its user.

The activities of The Federal Communications Commission (F.C.C.) over the past few years have raised the importance of cognitive radios to overcome the spectrum sacristy issues. This is our main concern in this research. The F.C.C. is reviewing its policies regarding the usage of licensed frequency bands by the unlicensed users [1], for efficient utilization of the spectrum. In the notice given in may 2004 in which the FCC proposed to allow unlicensed radio transmitters to operate in the broadcast television spectrum at locations where that spectrum is not being used. The operation under Part 15, of the notice is subject to the condition that the device does not cause harmful interference to authorized services, and that it must accept any interference received. The current Part 15 rules provide substantial flexibility in the types of unlicensed devices that can be operated. However, the rules prohibit the operation of unlicensed devices on certain frequencies, including almost all of the frequency bands used for broadcast television service.

“The FCC should allow unlicensed use of unused TV frequency band spectrum, when and if the technology is ready.”[2].

In view of the possibility of this change the feature of the Cognitive Radio S.D.R. mentioned above acquires a great deal of importance, in the future of the
wireless technologies and the spectrum usage. The main reason for that is due to the fact that the Cognitive Radios provide an opportunity to the unlicensed users, commonly known as the secondary users of the spectrum to utilize the empty frequencies in the already licensed frequency bands, of the primary users. The Cognitive Radios use these empty frequencies to identify virtually unlicensed frequency bands in the licensed frequency bands of the primary user. So, these virtually unlicensed frequency bands are now available to be used by the secondary users. It assigns the best possible frequency band in the spectrum to the secondary user, keeping in view the QoS requested by it. As mentioned earlier the Cognitive Radio is sensitive to the changes in its environment it changes its parameters to fulfill the QoS requested by the secondary user. The main idea during this procedure is to avoid its interference with the primary user’s frequency band.

So, the Cognitive Radio now provides the users, both primary and the secondary with sharing of the spectrum. Also, the Cognitive Radio must ensure that it frees the spectrum resource for the primary user if it is detected in the virtually unlicensed frequency band identified by it earlier. In case of detection of a primary user it should vacate the spectrum for the primary user and should move to a better virtually unlicensed frequency band, maintaining a seamless communication along with that, in order to avoid its interference with the primary user’s frequency band. So, a proper scheduling mechanism is required during this process so that it can satisfy both primary and the secondary users.

Thus the key tasks in Cognitive Radios can be identified as, sensing the RF environment and based on that designing a decision-making module for the spectrum allocation. This decision-making depends upon the current network traffic, QoS requirements of the secondary user and the information collected through RF environment sensing.

2.1. Background and History of cognitive radios:

The Cognitive Radios can formally be defined, as [3] “A Cognitive Radio is a radio that can change its transmitter parameters based on interactions with the environment in which it is currently operating.”

The Cognitive radios do not have the history of a century; rather the development of cognitive radio is still at a conceptual stage. As discussed earlier the Cognitive Radio is an emerging technology, for the efficient use of the limited available spectrum. Nevertheless, as we look to the future, we see that cognitive radio has the capacity to make a significant difference to the way the radio spectrum can be accessed, with much improved utilization. Indeed, given its potential, the cognitive radio can justifiably be described as a “disruptive, but unobtrusive technology”. Disruptive as it can make a great difference in the
technology. Unobtrusive as it attracts with its solution for utilization of the already licensed frequency bands efficiently.

A brief history of the Cognitive Radio is given below.

Cognitive radio is not a single technology to be very explicit. It resulted from many technologies coming together to result in the Cognitive Radio technologies, due the verity that exists among its applications. For example, the development of digital signal processing (DSP), development of math and signal processing tools and source coding of voice, image and data etc.

If we were particularly specific to SDR, the roots of SDR design go back to 1987, when Air Force Rome Labs (AFRL) funded the development of a programmable modem as an evolutionary step beyond the architecture of the integrated communications, navigation, and identification architecture (ICNIA). This historical development is represented by the [figure 2.2], given below.

Coming back to the Cognitive radios again, the term “cognitive radio” was first used and defined by Joseph Mitola III in an article published in 1999. [4] He described, the way a cognitive radio could enhance the flexibility of personal wireless services, through a new language called the “Radio Knowledge Representation Language” (RKRL). The idea of RKRL was further expanded in Mitola’s doctoral dissertation, presented at the Royal Institute of Technology, Sweden, in May 2000 [5]. This dissertation presents a conceptual overview of cognitive radio as an exciting multidisciplinary subject.

As mentioned earlier, the FCC published a report in 2002, aimed at the changes in technology and the profound impact that those changes would have on spectrum policy. This report set the stage for a workshop on cognitive radio, held in Washington DC, in May 2003. The papers and reports presented at that Workshop are available at the Web page listed under [6]. This Workshop was immediately followed by a Conference on Cognitive Radios, held in Las Vegas, NV, in March 2004 [7].

2.2. Characteristics of Cognitive Radios:

According to the definition of the Cognitive radios given in the section 2.1, the Cognitive Radios can be categorized as having the following characteristics.
2.2.1. **Cognitive Capability:**

The cognitive capability refers to, sensing of the RF environment, by the Cognitive radio. In sensing of the RF environment the unused part in the spectrum (referred to as empty frequencies) are specified. There are different techniques used for this purpose. It includes power measurements, modulation schemes and scheduling mechanisms. It is not that easy as has been specified here, it involves very complex real time measurements and decision making to achieve the target. Nevertheless, we sense the RF environment and specify the empty frequencies in the licensed frequency band in such a way that there is no interference to other users, after their allocation to the secondary users.

Since, the most of the spectrum has already been assigned, the most important challenge is to share the licensed spectrum without interfering with the transmission of other licensed users as illustrated in [Figure 2.1 and Figure 2.2], [8]. The cognitive radio enables the usage of temporally unused spectrum, which is referred to as the empty frequency thus creating a virtually unlicensed frequency band, to be allocated to the secondary users on non-interfering basis with the primary users.

Once it has allocated the spectrum to the secondary user it has to make sure, to vacate the spectrum for the primary user in case of its detection. If the current assigned frequency band to the secondary user is also used by some licensed user, the cognitive radio moves to another empty frequency or stays in the same frequency band, altering its transmission power level or modulation scheme to avoid interference as shown in, the same figure 2.1. This is done to share the spectrum between the primary and the secondary user, on non-interfering basis. So, a fair spectrum scheduling is also required between the primary and the secondary users to share the spectrum in such a way that no interference takes place. These decisions for the spectrum scheduling are taken in real time, to provide fair scheduling among the users in order to avoid interference.

In other words, the cognitive capability of a cognitive radio enables real time interaction with its environment. This interaction helps to determine the appropriate communication parameters in order adapt to the dynamic radio environment. The radio analyzes the spectrum characteristics and changes the parameters at real time to provide a fair scheduling among the users that share the available spectrum.
Figure 2.1.] explains the procedure, identifying the allocated spectrum, the empty frequencies and the dynamic access to the spectrum, along with a plot, along the time, power and frequency axes.

Figure 2.2.] Shows the tasks required for the adaptive operation in the spectrum, referred to as, the cognitive cycle.

In the following subsections we provide an overview of the three main steps for the cognitive cycle: i.e., spectrum sensing, spectrum analysis, and spectrum decision.
• **Spectrum sensing:**

A cognitive radio identifies from the information available in the spectrum, the empty frequencies and the portions of the spectrum that are in use, by sensing the spectrum.

• **Spectrum Analysis:**

Once identified the empty frequencies, their characteristic are determined, in order to make the allocation of the best possible frequency band among them, to the secondary user, according to the QoS requested by it. This includes the determination of the data rate, the transmission mode, and the bandwidth of the transmission.

The Cognitive Radio can then change its parameters according to the spectrum analysis carried out in the above manner to allocate it to the secondary user.

• **Spectrum Decision:**

On the basis of the above spectrum analysis, the decision for the allocation of the best possible frequency band to be assigned to the secondary user is taken. This spectrum decision lies among the identified empty frequencies in the spectrum sensing process.

Once the operating spectrum frequency band is determined, the communication can be performed over this spectrum frequency band. However, there is still the dynamic spectrum access part to be considered for scheduling purpose, as the radio environment changes over time and space, the cognitive radio should keep track of the changes of the radio environment, at real time. If the current spectrum band in use becomes unavailable, the spectrum mobility function is performed, it must vacate the spectrum for the primary user, and move to a better virtually unlicensed frequency band, maintaining the on going communications along with a fair scheduling among the users and spectrum sharing by them, in such a manner that no interference is observed among them. Any environmental change during the transmission such as primary user appearance, user movement, or traffic variation can trigger this adjustment.

2.2.2. Re-configurability:

Re-configurability implies to the feature of the Cognitive Radios that allows the change in the parameters according to the changing the radio environment. As mentioned earlier, the Cognitive Radio can adjust its operating parameters for the transmission, without any modifications on the hardware components. This
enables the cognitive radio to adapt easily to the dynamic radio environment. There are several reconfigurable parameters that can be incorporated into the cognitive radio as [3] explained below:

• **The Carrier frequency:**

A cognitive radio is capable of changing its carrier frequency. Based on the information about the radio environment; it determines the most suitable operating frequency and performs the dynamic communication over that selected frequency.

• **The Modulation scheme:**

A cognitive radio also reconfigures the modulation scheme that is adaptive to the user requirements and channel conditions. The modulation scheme selection depends upon the application. For example, for delay sensitive applications like VOIP, the modulation scheme that enables the higher spectral efficiency is selected, as the data rate is more important than the error rate, for these types of applications. Similarly, for the loss-sensitive applications like TCP enabled applications, modulation schemes with low bit error rate are selected, as the error rate is important for these applications.

• **Transmission power:**

Controlling the power constraints, in the Cognitive Radio, can reconfigure transmission power. The cognitive radio provides with dynamic power configuration. This provides with an efficient use of the available power, as it enables the radio to reduce the power of the transmitter to a lower level to save power if higher power is not necessary for a certain operation. It increases the efficiency as it can accommodate more users by allocating lower powers to the users that do not ask for a higher power for their operation. Hence more number of users can share the spectrum, using dynamic power configuration. Also, a lower power helps to decrease interference among the users sharing the spectrum.

• **Communication technology:**

A cognitive radio can also be used to provide interoperability among different communication systems.

These transmission parameters of a cognitive radio can be reconfigured not only at the beginning of a transmission, for the spectrum allocation when the empty frequencies have been identified, but also during the transmission, when
the radio environment changes, i.e. the dynamic allocation. So, the cognitive radio is switched to a different frequency band, according to the spectrum characteristics by reconfiguring these parameters.

In order to describe the dynamic nature of Cognitive Radios, each empty frequency in the spectrum should be characterized considering not only the time-varying radio environment and but also the primary user activity and the spectrum band information such as operating frequency and bandwidth. Hence, it is essential to define some other parameters such as interference level, channel error rate, path-loss, link layer delay, and holding time that can represent the quality of a particular spectrum band as follows:

• **Interference:**

  Some spectrum bands are more crowded compared to others. Hence, the spectrum band in use determines the interference characteristics of the channel. From the amount of the interference at the primary receiver, the permissible power of a user can be derived, which is used for the estimation of the channel capacity.

• **Path loss:**

  The path loss increases as the operating frequency increases. Therefore, if the transmission power of a user remains the same, then its transmission range decreases at higher frequencies. Similarly, if transmission power is increased to compensate for the increased path loss, then this results in higher interference for other users.

• **Wireless link errors:**

  Depending on the modulation scheme and the interference level of the spectrum band, the error rate of the channel changes.

• **Link layer delay:**

  To address different parameter changes like path loss, wireless link error, and interference, different types of link layer protocols are required at different spectrum bands. This results in different link layer packet transmission delay.

• **Holding time:**

  The activities of primary users can affect the channel quality of the spectrum. Holding time refers to the expected time duration that the user can occupy a
licensed frequency band before getting interrupted. Obviously, the longer the holding time, the better the quality would be.

- **Channel capacity:**

  The channel capacity can be derived from the parameters explained above, is the most important factor for spectrum characterization. Usually SNR at the receiver has been used for the capacity estimation. However, since SNR considers only local observations of users, it is not enough to avoid interference at the primary users. Thus, spectrum characterization is focused on the capacity estimation based on the interference at the licensed receivers.
Chapter 3

Genetic Algorithms (An Overview):

*Genetic algorithm (GA)* is a technique based on evolutionary computation to find the approximate solutions to the optimization problems. Genetic algorithms are inspired by Darwin's theory of evolution and the best or simply the survivor among the available pool is an evolved solution. The history of evolutionary computation goes back to 1960s when Rechenberg first described it in his work "Evolution strategies". To be particular to the G.A.'s, they were invented and developed by John Holland that lead to his book "Adaption in Natural and Artificial Systems" that was published in 1975. The evolutionary computation may involve techniques like inheritance, mutation, selection and crossover to provide for the best possible optimization. In 1992 John Koza introduced "Genetic Programing" (G.P.).

3.1. Some Other Optimization Techniques:

The goal in case of optimization problems is to achieve an optimum solution but the problem is that the search may get complicated and one may not know where to look for the solution or where to start with. There are many methods that can help finding a suitable solution but the solution might not be the best one. Some of these methods are hill climbing, tabu search, simulated annealing and the genetic algorithms. The solutions found using these methods are often considered as good solutions as it is not always possible to define the optimum.

Game theory that is also at a nascent stage and is used for interactive decision situations provides analytical tools to predict the outcome of complex interactions among the rational entities based on perceived result. It works on predictions of probabilities but demands for a precise knowledge of the total number of nodes, but the dynamic nature of real networks one doesn’t even have the knowledge of what nodes do enter or leave the network and at real time. Also, the definition of a steady state and fear form an undesirable drift with increasing number of nodes may cause worries and may make the implementation of Game theory concept in the cognitive radios very complex.

Another approach in the race is fuzzy logic but it offers sever limitations that cause its value in the dynamic nature of the wireless environment, to taper. It permits the approximate solutions to be found in the face of uncertain inputs. Its logic for approximation does not have an evolutionary ability to allow it to change well in time with the environment encountered at real time. [13]
Yet another approach is the neural networks that are well recognized as an AI technique but it doesn’t offer with reliability in terms of surety that it will play within a set of operational constraints. Most of the neural networks require for an extensive training to replicate the observed behaviors and usually behave in unexpected manner when introduced to a totally new problem to solve. [13]

3.2. **Why Genetic Algorithms:**

Genetic algorithms have applications in many fields nowadays, like computer science, engineering, economics, chemistry, physics, mathematics and bioinformatics and many other fields.

Since their introduction, the G.A.’s have been used to solve difficult problems like, Non deterministic problems and machine learning as well as for the evolution of simple programs like evolution of pictures and music. The main advantage of G.A.’s over the other methods is their parallelism. G.A.s travel in a search space that uses more individuals for the decision-making and hence are less likely to get stuck in a local extreme like the other available decision-making techniques.

Genetic Algorithms have the ability to converge very quickly on a specific solution, have a wide range of solutions to address the unknown environments, can be implemented on semiconductor devices and enable integration with wireless technologies. Also, the biological model for the G.A.’s provided rapid prototyping using DSP or FPGA. These are some of the advantages of using G.A.’s in the cognitive radios. The others are their chaotic search capability and flexibility along with their ability to be implemented on a vector based co-processor. It provides with a wireless channel genetic algorithm (WCGA) to sense the wireless environment, a wireless system genetic algorithm (WSGA) to adapt to the radio along with a Cognitive System Monitor (CSM) based on metagenetic algorithm to monitor and change the behavior of the system, in the cognitive radios. All these provisions work continuously in a cyclic process for the decision-making. A distributed memory can be used to understand the pattern and utilize the information in the past for the current decision-making.

The G.A.s are very easy to implement and can be reused to solve other problems. Once you have implemented a basic G.A. you just add a new object i.e. just another chromosome and using the same encoding scheme just change the existing fitness function and you can solve another optimization problem. However some problems might find implementation of the encoding scheme and the fitness function to be very difficult.
The disadvantage of using G.A.s lies in the computational time. G.A.s can be slower than the other available methods at times. But the availability of the option to control the number of generations and terminate a longer run at any stage and faster and faster computers these days, enable to ignore this factor. To have a clear idea about the use of G.A.s we list some of their applications:

[16]
- Nonlinear dynamical systems - predicting, data analysis.
- Designing neural networks, both architecture and weights.
- Robot trajectory.
- Evolving LISP programs (genetic programming).
- Strategy planning.
- Finding shape of protein molecules.
- TSP and sequence scheduling.
- Functions for creating images.

3.3. Methodology of Genetic Algorithms:

The evolutionary computation starts from the selection of some randomly generated population of individuals (known as chromosomes) that exhibit certain characteristics, and follows them through the generations. The fitness of every individual in a population at a generation is evaluated based on the stochastic calculations and mutating them, thus giving rise to a new population, with a hope that the new population will be better than the old one. The fitter the solutions, the more chances they have to be reproduced in the next generation of solutions. An iterative algorithm is then followed to continue the process from generation to generation, until some condition like a maximum number of generations have been reached or the optimum solution has been found. This may or may not give a particular satisfactory solution.

Genetic algorithms require the definition of two basic actions.
1. A genetic representation of the solution domain.
2. A fitness function to evaluate the solution domain.

3.3.1. Outline for the Genetic Algorithms:

1. **Start**: Generate a random initial population of $n$ chromosomes that consists of the available solutions for the problem.
2. **Fitness**: Emulate the fitness of each of the chromosomes in the initial population.
3. **New population**: Reproduce, according to the following steps until the next generation completes.
• **Selection:** Select two chromosomes that have the best fitness level among the current population.

• **Crossover:** Crossover the two selected chromosomes considering the crossover probability, to form the offsprings for the next generation. If this operation were not performed the offspring would be the exact copy of the parent chromosomes.

• **Mutation:** Mutate the new offspring at each defined mutation point, considering the mutation probability and place it in the new population.

4. **End Condition:** Repeat the above steps until certain condition (maximum no of population or the desired optimum has been reached), has been met. [14]

Implementation of the above outline for the G.A.’s is not that straightforward, rather certain factors how to create the chromosomes and which encoding to use to perform the G.A. operations on them. Also, the selection of parents and definition of criteria i.e. the fitness function definition are some issues to be addressed. We discuss these factors in the following sections.

3.3.2. **Chromosome Definition:**

One of the standard representations of a solution domain is an array of bits (other representations may also be used), essentially having the same size, throughout in order to have a uniformity, to facilitate the operations to be performed on them, like the crossover operation. Variable length representations may also be used, but certain operations like crossover would get too complex in that case.

A representation for the chromosome must provide the information about the solution that it represents. The most popular of all representations is the binary string. Where each bit in the string can represent the chromosome characteristics or the whole string cumulatively can do this. The use of integer or real number representations for the chromosomes can also be useful. This will be explained further as we move towards our decision-making process.

This genetic representation is commonly known as chromosome definition for a genetic algorithm. We select some of the parameters that contribute for the basic structure of the chromosome. These parameters are the essential components, without which the chromosome structure definition would be incomplete. An initial population of these chromosomes is generated randomly, that provides a pool of chromosomes that are the possible solutions to the optimization problem. These chromosomes are then transferred from generation to generation and certain operations like selection, crossover and mutation are performed at each
generation. These processes actually act as filters for a population of chromosomes that enable the best or at least the better ones among a population of chromosomes to be transferred to the next generation, according to their qualification for a satisfaction level of a defined fitness test.

3.3.3. The Search Space:

Looking to find a solution that is the best among the others, in a space of all feasible solutions i.e. the search space (the state space). Each of the points in the search space represents a possible solution that can be marked by its value (the fitness value). [14] So looking for a solution in the search space can also be viewed as looking for the some extreme value i.e. a minimum or maximum value and this is what optimization is all about. The G.A. methodology might lead to the generation of some other points in the search space, of course the possible solutions as it proceeds with the evolutionary process.

3.3.4. The Fitness Function:

A fitness function is defined over the genetic representation to measure its quality. This fitness function definition varies from problem to problem. The fitness function is applied to every individual in a population based on the stochastic calculations. Each individual is mutated and the fitness of the solution would contain the best of the individuals among the current population, according to the defined fitness function, to give rise to the new population in, an iteration. The fitness function actually filters out the individuals with a lower fitness level at the current generation and transfers only those to the next generation that satisfy the defined fitness function. This enables the presence of individuals with a higher fitness level to be transferred to the next generation while filtering out the ones that deviate too far away from the optimization solution. This fitness function is applied at every generation, to a specified number of generations.

Once specified the genetic representation and the fitness function the GA performs other functions like, initialization of a population of solutions and then reproducing it from generation to generation by repeatedly applying the mutation, crossover, inversion and selection operations.

3.3.5. Operations in Genetic Algorithms:

As demonstrated in the above outline for genetic algorithms, the operations in the Genetic algorithms, i.e. the crossover and mutation are the most important for the decision-making process. These two operations are performed considering the probability for these operations to occur, i.e. how often the two operations will be performed.
If there is no crossover operation on the parents, the offspring would be exact copies of the parents otherwise the offspring would contain the parts of both parent’s chromosome and a crossover probability of 100% would cause all the offspring be made by the crossover operation. Similarly a crossover probability of 0% would yield the whole new generation be made from exact copies of the chromosomes from the old population but this does not mean that the whole new generation is the same as the old one, rather crossover is done in a hope that the new chromosomes will contain good parts of the old chromosomes to result in better chromosomes in the new generation. These good parts are essential to survive in the next generation.

Also, the mutation probability implies, how often the parts of the chromosomes would be mutated. The offspring are generated immediately after the crossover or simply, directly copied without any change, if there is no mutation operation. If the mutation occurs, one or more parts of the chromosome would be changed. A mutation probability of 100% would result in change of the whole chromosome and a mutation probability of 0% means no change in the chromosome. Mutation attempts to prevent the G.A. to fall in local extremes but it should not occur much often as it can convert G.A. to a random search and the mutation rates are usually set low.

Population size definition is yet another factor to be taken care of while using G.A.’s. i.e. the number of chromosomes to be included in a single generation. If there are too few chromosomes in a generation, the G.A. might not be able to explore the whole search space for the optimum solution and a selection of too many chromosomes for a generation might make the decision-making process too slow. Researches prove that after a certain limit a large population size selection would prove to be useful as it makes it unable to solve the problem faster than the moderate sized populations.

3.3.6. The Crossover and Mutation operations:

Once defined the chromosome structure and the fitness function, the G.A. then performs certain operations to increase the number of solutions in its pool. These operations like crossover and mutation operations are performed in a defined standard way. It’s the user that has the privileges to define both the crossover and the mutation rates.

If a crossover occurs on two of parents to create an offspring, a set of random crossover points is selected in the chromosomes. These crossover points separate the chromosomes into parts with reference to the parametric values; this may split the individual genes for example a frequency gene in two. In such a
case the higher of the two frequency values will be preserved in one of the off
springs and the lower in the other. The crossover rates are normally set high, to
increase the probability for the occurrence of the operation.

Mutation operation then follows the crossover operation. The mutation operation
is performed on some or all of the bits of the chromosome. For each gene a
random value is generated; if this value is less than the mutation probability
defined by the user according to its specified mutation rate, one of the bits in the
gene is inverted. Mutation rate is usually kept low as it can have a huge effect on
the structure and fitness of the offspring produced, as a result. If the fitness of the
gene is still not improving then the mutation rate can be increased in order to
achieve the required optimization.

3.4. Genetic Algorithms in Radios:

The radios using the genetic algorithms require to be represented in the above-
mentioned way in order to be able to use the genetic algorithm and come up with
an optimization. Representing the radios in the above-mentioned genetic terms
actually allow them to accommodate the genetic algorithms in them and evolve
as Cognitive Radios. This enables the cognitive radios to adapt themselves to
the constantly changing RF environment, at the real time.

The Genetic algorithms approach used for the optimization of the decision-
making module in the radio, as they are well suited to the multi-objective
functions due to their convergence behavior towards the optimized solution and
help the radios in adaptation for the decision-making process. Apart from this, the
genetic algorithms also provide the optimization in decision making with multiple
advantages. They provide with flexibility in problem analysis, as long as the
chromosome and the objective functions are defined properly. Also, the
convergence behavior of the genetic algorithm is really helpful in our application,
i.e. the Cognitive Radios. The genetic algorithms may have a long convergence
time for an optimal solution but normally do not take much time to give very good
solutions.

The use of genetic algorithms in the radios involves the following actions.

3.4.1. Chromosome Definition for the Radio:

As mentioned earlier, the very first step in the design of a genetic algorithm is
the definition of the chromosome structure that is followed by the development of
a fitness (or objective) function in order to determine the fitness of a population of
chromosomes. The chromosome definition must represent the radio’s behavioral
traits for the decision-making process to achieve the required optimization. There
can be many possible traits that can be considered in this regard but we shall consider only some of the basic traits for the radio in this research. Some of the possible traits that can be considered are the occupied bandwidth, spectral efficiency, power consumption and data rate. These traits will be explained further in this report.

The chromosomes in the genetic algorithms would be represented as simple vectors of data structures with different data types defining their genes. These genes and chromosomes may have different representations. In this research we shall represent the genes and the chromosomes in terms of arrays of bits. We shall use the minimum number of bits for the sake of simplicity. A radio chromosome may have different genes representing its structure, but for the sake of simplicity we shall consider only a few basic ones in this research (four in total), namely frequency, power, bit error rate and the modulation schemes. All these four genes shall be discussed further in the research report in detail, in the coming sections.

3.4.2. Fitness Function definition for the Radio:

The chromosome definition is followed by the definition of a fitness function that serves for the analysis of the fitness for a population of these chromosomes. We shall define a fitness function based on the performance parameters of the current ratio channel. Each of the genes representing the chromosome will be analyzed for its fitness by the defined fitness function according to its associated weight. This associated weight will represent the relative importance that the user has assigned with each definition.

The Pareto front [12] therefore will move such that the optimal solution provides the most efficient performance for the user’s QoS requirements under combinatorial constraints. This multi-objective decision-making procedure according to our defined fitness function comes up with a solution that provides the best performance without wasting the spectrum resources. This implies that the solution will be obtained on the user preferences i.e. the application that the user has to run on the identified virtually unlicensed frequency band. This will prohibit the wastage of the spectrum resources, as it considers the QoS and Qoe requirements specified by the secondary user or the application itself. For example, allocating a 100Mbps link with a 30 dB carrier to noise ratio for a user to just send a mail would be a sheer wastage of the allocated resources. So, the definition of the fitness function should be able to handle these issues and that makes it very critical, for the best optimization in our decision-making process.

The fitness evaluation functions designed would reflect the current quality, both at the PHY and the MAC layer of the current channel, it would include the mean
transmitting power, data rate, BER, packet error rate (PER), spectral efficiency, bandwidth, interference avoidance, packet latency and packet jitter and many more, to provide for the current QoS requirements, but for the sake of simplicity at this level we shall focus only on a few of them in this research as mentioned in the previous section.

Another attribute of the GA is “The dynamic fitness definition and evaluation”, where the weight of assigned to the fitness of each individual gene can be adjusted dynamically, but any fitness function that does not fulfill the requirements for the current radio channel might not be used. Actually a database of all the fitness functions is maintained and fitness for each individual can dynamically be weighed and added into the fitness evaluation for a particular QoS requested by the user. This involves some higher-layer intelligence to evaluate the radio and the network performance.

### 3.4.3. Fitness Evaluation for the Radio:

As mentioned earlier the fitness functions are defined individually considering the current user’s QoS specifications. These fitness functions are applied on a randomly selected population of chromosomes in a multi-objective decision-making process with the use of stochastic processes. This implies to the existence of a trade-off among the parameters for a particular channel. This is analyzed by the corresponding weights assigned by the user to each of them. This is actually very useful in our decision-making process and provides with a verity of solutions for the best optimization of a problem. For example, for loss sensitive applications the BER would have a higher weight than the data rate in its fitness function, due to its importance indicated by the user application in its QoS specifications. Similarly, a higher wattage assigned to the data rate than the BER, by the user will be beneficial in case of time sensitive applications. So, the weight associated with each of the fitness functions enables a relative measurement among different parameters and the one with higher weight in a particular channel would pass the fitness test.

So, an evaluation of the fitness of the randomly generated population of chromosomes is carried out in multiple dimensions and the ones that survive these fitness tests are passed to the next generation as a reproduction of the current one. This actually serves to be a filtering process, carried out at each generation that results in an optimized solution at the end of the evaluation by the G.A., This is described as the Pareto front [12].

The G.A.s may result in long and tedious calculations for the optimal solution in some cases but the diversity of the solutions in the selected population allows multiple (some of them turn out to be very good) solutions to be tired at each
Decision Making Techniques For Cognitive Radios

generation. This prevents the G.A. to get stuck, at any stage during the decision-making process. This implies that even though the G.A.s may not come up with and exact solution in some cases but they do provide the closest possibility among the pool of solutions. This will be discussed in more detail in the coming sections.

3.5. Multi-Criteria Optimization:

The multi-criteria optimization or the multi-attribute optimization is a process of analyzing multiple conflicting objectives subject to certain constraints. Multi-criteria optimization problems are found in various fields, where maximization or minimization of some functions is required and a trade-off exists among the objectives. Generally, there is no single solution to a multi-criteria optimization problem, as maximizing one of the objectives to a certain extent can affect the other objectives in the same problem. So, we usually have more than one solution as the optimized result. Then we can pick up the best among them that suits our particular case. This gives the best optimization for the problem.

Multi-criteria optimization has much to do with the decision-making in order to get an optimized solution. The reference [12] provides with a brief overview of the concept of multi-criteria optimization. A generalized form of the multi-criteria optimization problem can be represented as follows.

\[
\min/\max(y) = [f_1(x), f_2(x), \ldots, f_n(x)]
\]

Subject to:
\[
x = [x_1, x_2, x_3, \ldots, x_m] \in X
\]
\[
y = [y_1, y_2, y_3, \ldots, y_n] \in Y
\]

Where there are \( n \) dimensions to consider in the search space and \( f_n(x) \) defines the mathematical function to evaluate dimension \( n \). Both \( x \), the set of input parameters, and \( y \), the set of dimensions, may be constrained to some space; \( X \) and \( Y \). \( EX \) and \( EY \) represent the functions for the spaces \( X \) and \( Y \), respectively. The optimal solutions to the above problem are a set of Pareto points. Where improvement in one of the objectives may worsen the others. So, there exists a trade-off among the individual genes.

In over research the Pareto points move in such a way that the optimal solution provides the most efficient performance for the user’s requested QoS under the radio domain and the regulatory constraints. A point here should be noticed that there should not be any wastage of the radio resources while decision-making. A higher QoS than requested by the user would be wastage of the resources and should not be allocated.
3.6. The Decision-Making:

The unused or the inefficiently utilized spectrum bands that are spread over a wide frequency range in the RF environment may include both unlicensed and the licensed frequency bands. The empty frequencies detected in the frequency band may show diverse characteristics due to the time-varying radio environment and some parameters like frequency and the bandwidth. It's the radio that should decide the best spectrum band to meet the QoS requirements available throughout the spectrum bands. The following discussion will further elaborate the decision-making in the radio.

The focus in this research is the spectrum management in the cognitive radio; with an assumption that the user specifies the QoS requirements itself or the radio’s sensing environment provides this information. The receiver in the cognitive radio receives the RF environment and then the radio involves itself in the decision-making process to accommodate a new user requesting the spectrum allocation in that environment. It considers the user’s QoS requirements as the modulation scheme, channel coding, power consumption and data rate. It also has the information about the channel conditions, the network interactions and the radio environment such as the empty frequency bands, transmission and reception power for a specific application and the amount of interference that would be produced with the induction of the new user in that environment, with the primary users already using the spectrum.

The sensor gives the spectrum status as an input to the spectrum allocator and a spectrum test is performed. If the user gets satisfied with the frequency band it takes no further action and terminates the process, otherwise the appropriate frequency bands are selected and certain spectrum decisions are taken. This spectrum test must comply with the regulations of the spectrum allocations and tend to minimize the interference with the other users. These regulations are considered in the decision-making process to meet the QoS requirements of the secondary (new) user.

One of the most important factors that should be considered during the decision-making about the allocation of the empty frequencies is that the primary user should always be preferred if it needs that particular frequency band, over the secondary user.

There are two available techniques to implement the decision-making process.
1. Use of G.A.s that provide for a good convergence and suite well with the multi-criteria environment.
2. Use of expert systems that provide with an ability to learn at each iteration.
but have a great chance to give a very bad decision at the beginning of the decision-making process.

The following Chapter in the research will elaborate the development of the decision-making algorithm based on the genetic algorithm approach, along with an analysis of the techniques used in the research. Further these techniques will also be evaluated using the Matlab coding.
Chapter 4

Research Methodology:

This research focuses on the spectrum management and mobility issues in the cognitive radios, with an assumption that the sensing information is provided as an input either from the radio environment or the secondary user itself specifies the QoS requirements specifications to the radio. The Cognitive Radio receives the RF environment at its receiver and involves itself in a decision-making process to accommodate a new user requesting the spectrum allocation. This requires a decision-making considering certain factors, such as the secondary user’s requirements as parameters like, its modulation scheme, channel coding, data rate and power consumption etc. The user or the application that needs the spectrum to carry out its communications specifies its QoS requirements to the cognitive radio that also gets the information about the RF environment from a sensing module. This enables the decision-making process to make a comparison between the user’s specifications against the available pool of the solutions received from the RF environment. Thus, this sensed information from the environment serves as the initial population for the genetic algorithm. We shall generate random values that will serve as the initial population information received from the RF environment and then take the decision for allocation as an optimization and come up with the best solution after a comprehensive process described in the following sections.

We shall just consider a few parameters only, in order to maintain the simplicity in the research. These are the frequency bands, the modulation scheme, power and BER. It is a simplified case, some other parameters such as data rate, spectral efficiency, interference; system-to-noise ratio etc can be introduced in the research at the advanced stages.

There are a number of approaches towards the solution to this problem. For instance we could have a probabilistic approach, in which we could consider the amount of time a certain frequency band is free or the power availability of a band, at most of the time for transmission or we could specify the transmission power for a majority of the applications that would use the cognitive radios, or we could considerer the number of times a certain modulation scheme is in use for a specific application etc.

Another possible approach can be the use of genetic algorithms that compare the user QoS requirements to a number of available solutions in the pool and then the best-optimized solution can be taken among that. The genetic algorithms use the concept of biological characteristics such as chromosomes and genes. Functions like crossover and mutation are applied on these
chromosomes to get the next population of the solutions. There is a possibility that the new pool of solutions may be better than those in the original population or they may be even worse than the original set of solutions.

The genetic algorithm approach begins with the definition of the structure of a chromosome. We intend to keep the size of the chromosome as small as possible or it can make the selection process for the best solution among the pool very complex and too slow. In this research we shall focus on the genetic Algorithm approach and shall develop on it in the following sections.

4.1. The Chromosome:

Before we get started with the definition of the chromosome structure we must have the information and understanding of the genes of the chromosome that will constitute its structure. The genes in this particular research would be the individual parameters that will be considered for the decision-making process. These genes are basically a part of the solution.

In order to keep the things simple we shall start with the consideration of just a few parameters (four in total). These four parameters are mentioned below.

1. Frequency
2. Power
3. Bit error rate
4. Modulation techniques

The following sections would focus of the explanation of the above-mentioned four parameters in detail. We shall keep ourselves specific by focusing on the way they are used in a chromosome, without going in detail with the generalized view.

4.1.1. The Frequency:

Any application that is able to transmit and receive requires a particular frequency band to communicate. The frequency band that we shall consider for this particular research would range form 0-10MHz. There is no theoretical reason for the selection of this particular band. The step size to consider would be 10KHz. So, if a frequency band of 10KHz is available for each of the application during a transmission period, we can calculate the number of users that can be accommodated in this interval. The step size of 10 KHz gives a total of 1000 available frequency bands. So, a total of 1000 randomly generated chromosomes are possible in the initial population of pool of solutions for the decision-making process.
We shall see in the following sections that these frequency bands should be represented in terms of bits for the application of certain functions. This would help in carrying out certain operations during the decision-making process, like the mutation operation on certain defined chromosomes. The number of bits required to represent a 1000 frequency bands comes out to be 10, as a total of 10 bits can represent up to 1024 frequency bands that fulfills our requirement and can easily accommodate a total of a 1000 chromosomes, only. Also, there should be a check in the decision-making so that value no more than 10 bits for just a 1000 bands are selected, as that can result in a complete wastage of resources. Also, we shall convert it back to the decimal representation after the mutation operation has been done, as it is easier to manipulate the inputs and outputs in the decimal representation, after that.

This implies that each frequency band in the range of 0-10 MHz is represented in terms of an integer. The first frequency band of 10 KHz i.e. from 0-10 KHz would be given the Integer value of 0. The second band with the integer value of 1 that range from 11 to 20 KHz. Similarly after every step of 10 KHz the band would be assigned a new integer value in the order of the frequency bands in the selected spectrum. Therefore the last frequency band will have a range of 9.99 MHz to 10 MHz and would be represented by an integer value of 999.

So, the band ranging 0-10MHz with a step size = 10KHz, gives integer values ranging from 0 to 999, as provided by the following table 4.1.

<table>
<thead>
<tr>
<th>Integer value</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>......</th>
<th>999</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency Band</td>
<td>0-10KHz</td>
<td>11-20KHz</td>
<td>21-30KHz</td>
<td>......</td>
<td>9.99-10MHz</td>
</tr>
</tbody>
</table>

[Table 4.1] Representation of the frequency gene.

It can be observed that each band is of 10 KHz or .01 MHz and there are a total of 1000 frequency bands and one of these is allocated to each requesting application. The user specifies its desired frequency band as an integer value, within a range of 0-999. Therefore, an error message should be generated if the user specifies a value out of this range.

In the mutation operation these frequency bands should be converted into the corresponding binary representation. As each of these frequency bands needs 10 bits to represent, the frequency gene therefore will take 10 bits in the initial population of chromosomes, for the frequency part. This will be explained when we shall come to the mutation operation details, further in this research.
4.1.2. The Power:

One of the other important parameters that we shall consider for the chromosome structure definition is the power. This is the power required by application to provide for a good transmission, a power less than that may result in the transmission of a weak signal and might not be useful in most of the cases. The range of power values should be specified in such a way that allows the users to communicate easily without giving too many errors, as we know that increasing the power for a transmission of a signal increases the signal strength and hence increases the chances of a successful communication process. Also, increasing the power of a signal the chances of production of the number of errors decreases, as is desired of any communication system.

The power range varies from -30dBm to 30dBm with a step size of 1 dBm in between them. This gives a total of 61 values to be represented with an integer value. The lowest power range i.e. from -29dBm to -30 dBm with a step size of 1 dBm would be represented by the integer value “0”. Similarly with a step of 1 dBm the power would be represented by an integer value, in the increasing order. These integer values should also be converted to the corresponding binary representation during the mutation operation, as the mutation is applied on bit level only. The representation of these 60 values will require a total of 6 bits to enable the user to know whether the given input is with in the correct range or not. Here again a check is maintained to keep these values in the range from 0 to 60. An error message should be declared otherwise.

The power gene would be the second one in the order of our chromosome’s structure and a range from –30dBm to 30dBm with a step size of 1 dBm is represented in the corresponding integer values illustrated in the following table 4.2.

<table>
<thead>
<tr>
<th>Integer value</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>………</th>
<th>30</th>
<th>……………</th>
<th>59</th>
<th>60</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power (dBm)</td>
<td>-30</td>
<td>-29</td>
<td>-28</td>
<td>………</td>
<td>0</td>
<td>……………</td>
<td>+29</td>
<td>+30</td>
</tr>
</tbody>
</table>

[Table 4.2] Representation of the Power gene.

The user inputs an integer value that it wants to be mapped against its required power. For instance, if an application requires a power of 15 dBm for its communication, it must enter an integer value that has been mapped against this power value. i.e. 45 would be the value that has the corresponding value of 15 dBm mapped to it, according to the above table. This mapping of the actual values in the integer form makes the values for our decision-making process much simpler to manipulate.
4.1.3. The Bit Error Rate (BER):

Another parameter that we shall consider in our chromosome’s structure is the “Bit error rate” (BER) that represents the radio’s average number erroneous bits for a particular transmission. It is of great importance to know the BER as it works as a specification and depends upon certain applications. The reason that the errors occur is not that much significant when we consider the bit error rate. It depends on the application that requires the spectrum allocation that specifies this bit error rate. There are some applications (error sensitive applications) that require a low bit error rate for the transmission. These applications can sacrifice a high bandwidth for that, for example the VoIP applications. On the other hand there are applications that can compromise with a higher error rate but demand a high bandwidth (known as bandwidth sensitive applications), for example the video streaming applications.

As there are more chances of errors in the wireless communications than the traditional wired circuits, the applications need to have some procedure to reduce the occurrence of these errors, to the possible extent. The bit error rates can either be reduced by the use of certain coding schemes at the receiver and/or at the transmitter. Another way to reduce the bit error rates is to increase the transmission power of the device.

In this research we shall consider the bit error rates with in a range of $10^{-1}$ and $10^{-8}$. This range fulfills the requirements of the most of the mobile applications. The step size that we shall consider for the bit error rate would be $10^{-1}$. This will give us eight different values of BER. Each of these values would be represented by an integer value, in the same manner as done in the frequency and power cases, for the chromosome definition.

These values in decimal for BER would also be converted into their corresponding binary values for the mutation operation.

The following table 4.3. Illustrates the way these eight integer values are mapped against their corresponding BER values.

<table>
<thead>
<tr>
<th>Integer value</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>BER</td>
<td>$10^{-1}$</td>
<td>$10^{-2}$</td>
<td>$10^{-3}$</td>
<td>$10^{-4}$</td>
<td>$10^{-5}$</td>
<td>$10^{-6}$</td>
<td>$10^{-7}$</td>
<td>$10^{-8}$</td>
</tr>
</tbody>
</table>

[Table 4.3] Representation of the BER gene.
4.1.4. The Modulation Scheme:

Yet another, and the last of the four genes to be considered in our chromosome’s structure definition is the modulation gene. There are a total of four modulation schemes that will we shall consider in this particular research. They are BPSK, QPSK, GMSK, and 16QAM. So, to represent these four schemes we need just 4 integers. The following table 4.4 illustrates the way these four schemes are mapped to the integer values.

<table>
<thead>
<tr>
<th>Modulation Scheme</th>
<th>Integer Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>BPSK</td>
<td>0</td>
</tr>
<tr>
<td>QPSK</td>
<td>1</td>
</tr>
<tr>
<td>GMSK</td>
<td>2</td>
</tr>
<tr>
<td>16 QAM</td>
<td>3</td>
</tr>
</tbody>
</table>

[Table 4.4] Representation of the Modulation gene.

So, in order to represent just four modulation schemes in binary we shall need only two bits. Note that this binary representation will be required for the mutation operation as that can be performed on the bit level, only. After mutation they are converted back to the decimal notation, as in the other genes.

It is the application that provides its requirements for the modulation scheme that it will use, as was the case with all the other genes. The cognitive radio, by its decision-making process, can then provide with the best possible match from the pool of solutions available to it. It maintains a trade-off among all the genes in the chromosome’s structure according to the corresponding weight assigned to each of them by the user itself.

4.1.5. The Chromosome Structure:

The above-mentioned four genes all together define our chromosome’s structure. The order of their representation in the chromosome structure is the same as the order in which they are explained in this report. The whole structure of the chromosome and the order of each of the genes can be explained with the help of the following table 4.5.
As the above table explains, the frequency band is the very first gene in the chromosome structure and can have any value between 0-999. The power gene follows the frequency gene in the order and can have any value between 0-60. The third gene in the chromosome structure is the BER gene and can have any value between 0-7. The last gene in the order of the chromosome structure is the modulation gene that can have a value between 0 and 3.

The user or the application specifies its requirements to the cognitive radio as a chromosome and asks for an optimized solution that fulfills these requirements. The optimized solution also has the same structure as that of the chromosome.

The representation of these four parameters in a chromosome requires 21 bits in total, i.e. $10 + 6 + 3 + 2 = 21$ bits.

As mentioned earlier the conversion from the decimal to the binary system is necessary as the mutation operation is carried out at the bit level. The corresponding binary representation of the above chromosome will look as follows. Table 4.6.

<table>
<thead>
<tr>
<th>Gene</th>
<th>Binary representation</th>
<th>Number of Bits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency (F)</td>
<td>29 28 27 26 25 24 23 21 20</td>
<td>10</td>
</tr>
<tr>
<td>Power (P)</td>
<td>25 24 23 22 21 20</td>
<td>6</td>
</tr>
<tr>
<td>Bit Error Rate (BER)</td>
<td>22 21 20</td>
<td>3</td>
</tr>
<tr>
<td>Modulation Scheme (M)</td>
<td>21 20</td>
<td>2</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>21</strong></td>
</tr>
</tbody>
</table>

[Table 4.6] Bit wise representation of the chromosome.

### 4.2. The First Population Chromosomes Generation:

Once the chromosome structure has been defined the next issue of concern is the generation of the very first population chromosomes. This is done randomly and there are no particular rules about the size limitations in the first population of the chromosomes. To begin with, we can start with the generation of an initial
population of 100 chromosomes. This population size can be increased if the results are not satisfactory, in the provided solution set.

This randomly generated first population of chromosomes then undergoes a number of operations like selection, crossover and mutation, during the fitness tests in the decision-making process and results in the next generation of chromosomes.

These first population chromosomes are not only selected randomly but also have random values for each of the gene specified in these chromosomes. So, this randomly generated first generation population has diversity among the solutions provided in it. Some of these solutions may be the good ones while the other ones may be the worst solutions. In order to increase the possibility of good solutions in the next generation we apply the fitness function to this initial population and perform operations like selection, crossover and mutation.

The initial population of the chromosomes can be illustrated with the help of the following Table 4.7.

<table>
<thead>
<tr>
<th>Chromosome No.</th>
<th>Frequency</th>
<th>Power</th>
<th>BER</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>F1</td>
<td>P1</td>
<td>B1</td>
<td>M1</td>
</tr>
<tr>
<td>2</td>
<td>F2</td>
<td>P2</td>
<td>B2</td>
<td>M2</td>
</tr>
<tr>
<td>3</td>
<td>F3</td>
<td>P3</td>
<td>B3</td>
<td>M3</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>99</td>
<td>F99</td>
<td>P99</td>
<td>B99</td>
<td>M99</td>
</tr>
<tr>
<td>100</td>
<td>F100</td>
<td>P100</td>
<td>B100</td>
<td>M100</td>
</tr>
</tbody>
</table>

[Table 4.7] Initial population Generation.

Before performing operations like crossover and mutation there is a need for the definition of a fitness function. This fitness function is basically responsible for the generation of the next generation population chromosomes. This fitness function checks for the fitness of the chromosomes in the initial population of 100 chromosomes and passes the fittest of them to the next generation population.

A rough algorithm for the whole decision-making process can be plotted as shown in the following figure 4.1.
[Figure 4.1.] The flow diagram of the process of decision-making.
4.3. The Fitness Function:

Once having the structure of the chromosome been defined and having generated the first generation population of the chromosomes, we move to next step, i.e. the fitness evaluation of each chromosome in the population. This first population of chromosomes has a diverse pool of solutions to meet the specified QoS requirements of the user or the application. Some of these solutions may exactly satisfy the QoS required while others may just get close to those specifications. So, we can choose among this pool on the basis of the trade-off conditions mentioned earlier. The important thing to notice here would be that some of these solutions might prove to be the worst of all. So, there is a need for the definition of a test for these chromosomes individually such that the possibility of the transfer of the chromosomes leading to worst solutions, to the next generation can be minimized.

It is quite necessary to completely identify and define a fitness function according to the genes of the chromosomes, before we move forward because without this we shall not be able to perform the operations such as, selection, crossover, and mutation, in order to move to the next generation population. So, the next generation population of chromosomes is not possible without the definition of a fitness function. This is also obvious from the fact that it is the fitness function that enables us to select the best of the solutions and then apply the crossover and mutation operations on these solutions to have an optimum solution. So, in the absence of a fitness function we would not be able to get optimal solutions.

In order to have something to start off with we can define the simplest of the possible fitness functions, i.e. a fitness function that is equally dependent on all the four parameters, defined above, as its genes. Although this might not be the practical case in communication systems, as a change in any of these four parameters affects the other parameters (genes) in reality, yet theoretically it provides us with the simplicity. All the four parameters will have an equal weight i.e. 25% each, for this particular case.

The given user's QoS requirements are compared against the population of chromosomes. Their fitness is calculated as the cumulative sum of the individual fitness of each gene (parameter) according to the procedure described in the following sub-sections.

4.3.1. Fitness of The Frequency Gene:

The fitness of the frequency gene is calculated by just taking the absolute difference between the frequency band of the chromosome under consideration
and the frequency band requested by the user (application), as described by the following equation 4.1.

\[
\text{Difference} = \left| \text{(frequency band - QoS frequency band)} \right| \quad (4.1)
\]

We can specify by ourselves the number of frequency bands that we shall consider, for the fitness calculation, on either side of the frequency band requested by the application. Let us generalize this consideration to an integer variable “p”, where “p” can have any value up to 999. Where the limit 999 refers to the maximum range the frequency gene can have, as described in the sections above.

If the absolute difference calculated above is less than this specified value of “p”, we further use the following equation 4.2 in the fitness calculation of the frequency gene.

\[
\text{Fitness of frequency gene} = \frac{x \cdot |\text{frequency band - QoS frequency band}|}{p} \quad (4.2)
\]

The above equation provides for the calculated fitness of the frequency gene. The variable “x” in the equation is the associated weight that we assign to each of the genes in a chromosome. For example in our case considered above, “x” having a value of 25 implies that the frequency gene counts for 25% of the total fitness of the respective chromosome. So, we can vary the assignment of weight by changing this value of “x” according to its respective participation of the gene in the total fitness calculation for the chromosome.

If the equation 4.2 above results in an absolute value that were greater than the specified value of “p”, then this value of “x” itself would have been fitness of the frequency gene, given by the following equation 4.3.

\[
\text{Fitness of frequency gene} = x \quad (4.3)
\]

The more the fitness of the frequency gene would be, the less suitable solution it would be. So, it gets fitter with the value of fitness of the frequency gene approaching to zero. This can be explained by the following example, more explicitly.

Let the user specifications of the QoS for the frequency band is 850, with a weight of 25% for the frequency gene in the total fitness, as considered in our case. This implies that “x” has a value of 25. Also, let us consider a value of 300 for “p”. The fitness of two of the chromosomes, one with a frequency band of 712 and the other with a value of 345, in their frequency genes, is required.
The fitness of each of the frequency genes would be calculated as follows.
The frequency gene with a frequency band of 712 would result in following calculations.

\[
\text{Difference} = |712 - 850| = 138, \text{ which is less than the specified } p = 300.
\]

So, we move to equation 4.2,

Fitness of the frequency gene = \([25 \times 138]/300\) = 11.5

For the other case, with its frequency gene having a frequency band of 345, the fitness calculation would be done as follows:

\[
\text{Difference} = |345 - 850| = 505, \text{ which is greater than } p = 300
\]

So, the fitness of the frequency gene would be the value of “x” itself and equation 4.3 would be used, in this case. i.e.

Fitness of the frequency gene = 25.

So, comparing the above two results, the value of the fitness function in the second case is higher than that in the first one and leads to a worse result i.e. far from the desired solution. So, it clarifies that the solution gets closer to the desired results as the value of the fitness of the frequency gene approaches to zero.

4.3.2. Fitness of The Power Gene:

The fitness of the power gene is also calculated in the same way, as for the frequency gene fitness calculation, i.e. we consider the absolute of the difference between the power value of the chromosome under consideration and the power requested by the user or application. The following equation 4.4 is used to calculate this difference.

\[
\text{Difference} = |(\text{power} - \text{QoS power})| \quad (4.4)
\]

Here also, we can specify by ourselves the number of power values that we shall consider on either side of the power requested by the user or the application. Let this be denoted by a variable “q”. Where the “q” can be any value between 0 and 60. Note that, the maximum value of 60 refers to the maximum range that the power gene can have, as described in the sections above.

Now if the difference calculated using the above equation 4.4 is less than our
specified value “q”, then we use the following equation 4.5 for the fitness calculation of the power gene.

\[
\text{Fitness of power gene} = \left[ \frac{y \cdot |\text{power - QoS power}|}{q} \right]
\]  

(4.5)

The variable \( y \) in the equation above is the associated weight that we assign to each of the genes in a chromosome. For example in our case, the value \( y = 25 \) implies that the power gene counts for 25% of the total fitness of the respective chromosome. So, we can vary the weight of each gene in the total fitness of a chromosome by varying the value of “y”.

If the difference in equation 4.4 were greater than the value of “q” then the value “y” itself would have been the fitness of the power gene, described by the following equation 4.6.

\[
\text{Fitness of power gene} = y
\]  

(4.6)

The more the value of fitness of the power gene, the less suitable the solution would be. So, there exists an inverse proportion between the value of the suitability of the solution and the value of the fitness of power. This can be explained by the following example more explicitly.

For example, a user asks for a power of 47, with \( q = 12 \) and a specification of \( y = 25 \), as its corresponding weight in the total fitness. We consider two chromosomes for the calculation of their fitness. One with power value of 54 and the other with 16.

For the power gene with the power value of 54, the fitness would be calculated in the following way:

\[
\text{Difference} = |54 - 47| = 7 \text{ that is less than } q = 12
\]

So, equation 4.5 would be used and the fitness of power gene is,

Fitness of power gene = \([25 \times 7]/12\) = 14.58

For the other chromosome with a power value of 16, the power fitness would be calculated in the following way:

\[
\text{Difference} = |16 - 47| = 31, \text{ which is greater than } q = 12
\]

So, equation 4.6 would be used and the fitness of power gene is
Fitness of power gene = 25

So, comparing the above two results, the value of the fitness function in the second case is higher than that for the first one and leads to a worse result i.e. far from the desired solution. So, it clarifies that the solution gets closer to the desired results as the value of the fitness of the power gene approaches to zero.

4.3.3. **Fitness of The BER Gene:**

The fitness of the BER gene is also calculated by considering the absolute difference. That is the difference between BER gene of the chromosome under consideration and the BER requested by the user (application). The following equation 4.7 is used to calculate the difference.

\[
\text{Difference} = |(\text{BER} - \text{QoS BER})| \tag{4.7}
\]

Here also, we can specify by ourselves the BER values that we shall consider on either side of the BER requested by the user or the application. Let this be denoted by a variable "r". Where “r” can be any value between 0 and 7. Note that, the maximum value of 7 refers to the maximum range that the BER gene can have, as described in the sections above.

Now if the difference calculated using the above equation 4.7 is less than our specified value “r”, then we use the following equation 4.8 for the fitness calculation of the BER gene.

\[
\text{Fitness of BER gene} = \frac{z \cdot |\text{BER} - \text{QoS BER}|}{r} \tag{4.8}
\]

The variable “z” in the equation above is the associated weight that we assign to each of the genes in a chromosome. For example in our case, the value \( z = 25 \) implies that the BER gene counts for 25% of the total fitness of the respective chromosome. So, we can vary the weight of each gene in the total fitness of a chromosome by varying the value of “z”.

If the difference in equation 4.7 were greater than the value of “r” then the value “z” itself would have been the fitness of the BER gene, described by the following equation 4.9.

\[
\text{Fitness of BER gene} = z \tag{4.9}
\]
The more the value of fitness of the BER gene, the less suitable the solution would be. So, there exists an inverse proportion between the value of the suitability of the solution and the value of the fitness of BER. This can be explained by the following example more explicitly.

For example, if a user asks for a BER of $10^{-5}$ and specifies 25% ($\alpha=25$) as the weight of the BER gene in the total fitness and the value of “$r$” as 3, and asks for the calculation of the fitness of two chromosomes, one with a BER value of 6 and the other with BER value of 1, in their BER genes.

The fitness for the BER gene having BER 6 would be calculated in the following way:

\[ \text{Difference} = |6 - 4| = 2 \text{ that is less than } r = 3 \]

So, equation 4.8 would be used and the fitness of BER gene would be,

\[ \text{Fitness of BER gene} = \frac{25 \times 2}{3} = 16.6 \]

The fitness for the BER gene having BER value of 1 would be calculated in the following way:

\[ \text{Difference} = |1 - 4| = 3 \text{, which is equal to } r = 3 \]

So, equation 4.9 would be used, in this case and the fitness of BER gene is

\[ \text{Fitness of BER gene} = 25 \]

So, comparing the above two results, the value of the fitness function in the second case is higher that leads to a worse result i.e. far from the desired solution. So, it clarifies that the solution gets closer to the desired results as the value of the fitness of the BER gene approaches to zero.

**4.3.4. Fitness of The Modulation Gene:**

The fitness of the modulation gene is calculated in a slightly different and simple way than that for the other three genes. It just compares the modulation gene of the considered chromosome and that of the QoS requested by the user (application). The following equation 4.10 is used to calculate the fitness of the modulation gene.

\[ \text{Difference} = |(\text{Modulation} - \text{QoS Modulation})| = 0 \quad (4.10) \]
But a fitness of 100% is achieved only if the difference calculated using the above equation is zero, otherwise the fitness itself becomes zero.

If the difference is zero then, the fitness of modulation gene = 100% and it perfectly fits to the modulation requested by the user in its QoS, otherwise we assign the fitness of the modulation gene its corresponding weighing factor “w” in the total fitness, illustrated in the following equation 4.11.

\[
\text{Fitness of Modulation gene} = \text{weighting factor (w)}
\]  

(4.11)

This can be explained by the following example.

Let's suppose that the user asks for a modulation of BPSK (with the integer value of 0, assigned in the sections above) and the chromosome has modulation gene of QPSK (integer value of 1, assigned in the sections above). As we have supposed equal weight for all four parameters, let the weight assigned to the modulation gene in total fitness be 25%, then

\[
\text{Difference} = |(2 - 1)| = 1
\]

So, the Fitness of the modulation gene = 25, as the difference is not exactly zero.

If it had matched the modulation technique requested by the user i.e. BPSK (integer value of 0), then the fitness would have been 100% and had resulted in a fitter result. So, the difference zero refers to the fittest modulation gene and becomes less fitter as it approaches to the corresponding weighing factor in total fitness, in contrast to the behavior of the other genes described above.

4.3.5. Total Fitness:

The Total Fitness is calculated by just summing up all the individual fitness values of the four genes of a single chromosome. A larger value of the total fitness would refer to a less fit chromosome whereas a smaller value would stand for a better solution. The Total Fitness of a chromosome is given by the following equation 4.12.

\[
\text{Total Fitness} = [\text{Fitness of Frequency gene} + \text{Fitness of Power gene} + \text{Fitness of BER gene} + \text{Fitness of Modulation gene}]
\]

(4.12)

To get the values of total fitness of the chromosomes we calculate them in percentages, using the following equation 4.13
Total Fitness(%) = 100 - [Fitness of Frequency band gene + Fitness of Power gene + Fitness of BER gene + Fitness of Modulation gene] \hfill (4.13)

So, in the comparison of the total fitness of the chromosomes in percentages, the higher the Total Fitness (%), the better the solution would be and vice versa.

The variables “x”, “y”, “z” and “w” described in the sections above are the corresponding weighting factors of the frequency gene, power gene, BER gene and the modulation gene, respectively. The sum of all the weighting factors of the four genes should be equal to 100. That is; \( w + x + y + z = 100\% \).

With all this background, we use two approaches for the decision-making that lead to the optimization for the best solution. Both these approaches discussed in the following sections just slightly differ from each other in their implementation part only, but both aim at the same goal, i.e. optimization for the best solution. We shall also include a working matlab code for both these methods along with the conclusions and generalized behavior of the G.A.s, in the research.
4.4. **Method 1:**

The procedure followed in this method basically involves the selection of the fittest of the available chromosomes among the available pool of solutions. Certain operations like, crossover and mutation are performed on these selected chromosomes. This results in an evolution of a new generation population of chromosomes and we choose the best of the chromosomes on the basis of their fitness values, according to our defined fitness function. The process is explained in detail in the following sub-sections.

4.4.1. **Selection:**

Selection involves the selection of the best offsprings within the pool of available chromosomes. This selection is done in accordance with our own defined fitness function, described in the previous sections. The “Roulette Wheel selection” method, also known as “Fitness proportionate selection” method is used for the selection purpose. It is basically a genetic operator generally used in the genetic algorithms for the selection of potentially useful solutions for recombination in the next generation. It associates a probability of selection with each individual chromosome, using the following equation 4.14.

\[
P(i) = \frac{f(i)}{\sum_{j=1}^{N} f(i)}
\]  

(4.14)

Where, \( P(i) \) is the associated probability of the individual chromosome among the pool, \( f(i) \) is the fitness of an individual \( i \) in the pool and \( N \) is the total number of chromosomes in the population.

So, the chromosomes with the highest probability value would be transferred to the next generation. This enables a mechanism that does not allow the transfer of the lower fitness value chromosomes to the new population of chromosomes. After each generation the fittest chromosomes are transferred to the new population until the new population reaches the maximum defined limit.

Once the fittest chromosomes among the pool have been selected, we can perform the operations like crossover and mutation (explained in the previous sections), as we move towards the optimization.
4.4.2. Crossover:

The next step after the selection of the fittest chromosomes available in the pool is, to perform the crossover operation. The crossover operation is performed on a pair of chromosomes, selected randomly. The operation is performed at the defined crossover points that define the junction of the genes in the chromosome structure. The following table 4.8 illustrates explicitly the range that the crossover points may exist.

<table>
<thead>
<tr>
<th>Gene</th>
<th>Range for the definition of crossover points.</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>0-999</td>
</tr>
<tr>
<td>P</td>
<td>0-60</td>
</tr>
<tr>
<td>BER</td>
<td>0-7</td>
</tr>
<tr>
<td>M</td>
<td>0-3</td>
</tr>
</tbody>
</table>

[Table 4.8] The range that crossover points may exist.

In a single iteration the crossover is performed randomly at one of these crossover points. The following table 4.9 illustrates a crossover point between two chromosomes, at the juncture of frequency and the power gene (highlighted in gray).

<table>
<thead>
<tr>
<th>Gene</th>
<th>Chromosome 1</th>
<th>Chromosomes 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>F</td>
<td>861</td>
<td>34</td>
</tr>
<tr>
<td>P</td>
<td>23</td>
<td>57</td>
</tr>
<tr>
<td>BER</td>
<td>5</td>
<td>2</td>
</tr>
<tr>
<td>M</td>
<td>1</td>
<td>3</td>
</tr>
</tbody>
</table>

[Table 4.9] Two chromosomes before the crossover.

This crossover point in the above table marks a point at which the crossover operation to be performed. The part of both the chromosomes after the crossover points (highlighted in green) is swapped with each other. This results in totally new combination with new values for each of the genes. The following table 4.10 illustrates the resulting combination after the crossover operation.
So, the crossover operation gives rise to new solutions in the solution space for the problem.

Usually, the possibility for the crossover operation to occur between two chromosomes is about 90%. This means that out of every 100 times the possibility for the crossover operation to occur is 90 times and whereas, there is a possibility of only 10 times out of 100 that the original chromosomes would not change and there would be no crossover. It is the user that decides for the crossover rates and can vary them.

4.4.3. Mutation:

The next step that follows the crossover is the mutation operation. The crossover operation did not need any conversion, i.e. the operation was performed on a randomly selected pair of chromosomes on the same decimal values of the genes. This is not the case with mutation operation. The mutation operation involves the conversion to corresponding binary values with consideration of only one chromosome at a time. In mutation, a randomly selected bit belonging to any of the four genes is inverted. The random selection of the bit indicates that it can be any of the bits from the total of 21 bits (explained in the previous sections), representing the chromosome. The following table 4.11 illustrates the detailed structure of the chromosome represented in binary format.

<table>
<thead>
<tr>
<th>Gene</th>
<th>Binary representation</th>
<th>Number of Bits</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>29 28 27 26 25 24 23 22 21 20</td>
<td>10</td>
</tr>
<tr>
<td>Power</td>
<td>25 24 23 22 21 20</td>
<td>6</td>
</tr>
<tr>
<td>Bit Error Rate</td>
<td>22 21 20</td>
<td>3</td>
</tr>
<tr>
<td>Modulation Scheme</td>
<td>21 20</td>
<td>2</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td></td>
<td><strong>21</strong></td>
</tr>
</tbody>
</table>

The mutation operation can be explained by considering an example. Let there be a chromosome with the following structure, table 4.12, in the decimal notation.
Let us assume that the randomly generated bit position to be mutated is 15.

Then the mutation operation on this chromosome would be performed in the following way.

First of all convert the decimal values, of each gene (in the same order) to their corresponding binary notations. The binary conversion in for this example would result in following bit pattern. Table 4.13.

<table>
<thead>
<tr>
<th>F</th>
<th>P</th>
<th>BER</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>678</td>
<td>34</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

[Table 4.12] Considered Chromosome Structure.

Where the 15\textsuperscript{th}, (falls in the power gene range) bit (in red font) is the one that will undergo the mutation operation. It falls in the power bit range. The mutation operation will just invert the 15\textsuperscript{th} bit. i.e. it is changed to “0”, in this case, generating the following bit pattern after the mutation process, as shown in the table 4.14.

<table>
<thead>
<tr>
<th>F</th>
<th>P</th>
<th>BER</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 0 1 0 0 0 1 1 0 1 0 0 0 1 0 0 1 1 1 0</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

[Table 4.13] Binary Representation of the Chromosome.

Where the “0” at the 15\textsuperscript{th} bit (in red font), indicates the inversion, after the mutation operation.

Now we can convert this resulting bit pattern back to decimal notation again. The Corresponding values in decimal notation after the mutation operation can be represented as follows. Table 4.15.

<table>
<thead>
<tr>
<th>F</th>
<th>P</th>
<th>BER</th>
<th>M</th>
</tr>
</thead>
<tbody>
<tr>
<td>678</td>
<td>32</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

[Table 4.15] Resulting chromosome after mutation.

Note that this is not the same chromosome as the original one, i.e. before the mutation operation. So, the mutation operation also, provides with new solutions
in the solution space for the problem. The selection procedure for the selection of chromosomes for the mutation operation is the same as that for the crossover operation.

The possibilities for the mutation operation to occur are not that high as that for the crossover operation. Usually it is between 2% to 5%. For example if the mutation possibility is 3% then it means that the possibility for the mutation rate to occur, is just three times out of every 100 times, on a chromosome. If the mutation is not performed then the chromosome remains the same.

4.4.4. Fitness Calculation:

As the crossover and mutation operations resulted in the production of some new chromosomes in the solution space for the problem. We apply the same fitness tests, as in sections under 4.3, explained earlier in this research, to ensure the selection of the fittest chromosomes among the population.

4.4.5. The New Population Generation:

The operations defined above along with the fitness tests have been performed on each of the chromosomes in the initial population and the new chromosomes produced after these operations. The fittest chromosomes among them are transferred to a new set. This is the new generation population set. The size of this set is equal to the new generation population. The values in the genes for certain chromosomes would differ from those in the initial population. This is due to the operations performed during the process, explained in the sections above. For example, if the initial population in a certain case looked as shown in the following table 4.16.

<table>
<thead>
<tr>
<th>Chromosome No.</th>
<th>Frequency Bands</th>
<th>Power</th>
<th>BER</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>F34</td>
<td>P23</td>
<td>B5</td>
<td>M3</td>
</tr>
<tr>
<td>2</td>
<td>F861</td>
<td>P57</td>
<td>B2</td>
<td>M2</td>
</tr>
<tr>
<td>...............</td>
<td>...............</td>
<td>.......</td>
<td>......</td>
<td>..........</td>
</tr>
<tr>
<td>...............</td>
<td>...............</td>
<td>.......</td>
<td>......</td>
<td>..........</td>
</tr>
<tr>
<td>99</td>
<td>F456</td>
<td>P39</td>
<td>B4</td>
<td>M1</td>
</tr>
<tr>
<td>100</td>
<td>F589</td>
<td>P14</td>
<td>B1</td>
<td>M0</td>
</tr>
</tbody>
</table>

[Table 4.16] Initial population table.

The resulting new generation population after the operations defined in the above sections may look like the following table 4.17.
<table>
<thead>
<tr>
<th>Chromosome No.</th>
<th>Frequency Bands</th>
<th>Power</th>
<th>BER</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>F34</td>
<td>P16</td>
<td>B1</td>
<td>M0</td>
</tr>
<tr>
<td>2</td>
<td>F765</td>
<td>P57</td>
<td>B4</td>
<td>M1</td>
</tr>
<tr>
<td>……………</td>
<td>……………</td>
<td>………</td>
<td>……</td>
<td>……………</td>
</tr>
<tr>
<td>99</td>
<td>F646</td>
<td>P39</td>
<td>B2</td>
<td>M3</td>
</tr>
<tr>
<td>100</td>
<td>F589</td>
<td>P23</td>
<td>B3</td>
<td>M3</td>
</tr>
</tbody>
</table>

Table 4.17] The new generation chromosomes.

4.5. The Optimal Solution:

The above-mentioned steps in the process are repeated and a new population of chromosomes is generated at every generation and the fitness tests are performed on them. This process continues unless the maximum number of specified populations has been reached. After the application of the fitness test on the last population, the chromosome with the maximum fitness value among all is chosen. This is our desired optimized result. It may or may not exactly match the requested solution but it will definitely be the closest of all the available solutions in the solution set.

This completes our decision-making process, for this method. Now we shall move to the other method that we shall include in this research for the decision-making process.
4.6. Method 2:

The approach in this method is a bit different from the one adopted in the previous method. Most of the operations like crossover and mutation are the same as in the previous method, but they differ in the respect of their implementation. The main differences are that the “Roulette wheel selection” is not used anymore instead the concept of elitism is used for the selection in this method.

4.6.1. Elitism:

The word “Elitism” comes from the word “Elite” that means the ones with the most distinguished attributes. Elitism used here in our decision-making process selects the best among the population of chromosomes and transfers them to the next generation, using the defined fitness function. It actually copies a few of the best chromosomes to the new population before the other G.A. operations are performed on that population and can increase the performance of G.A. as it prevents the loss of the best possible solution. [15]

The number of chromosomes to be picked up to be transferred to the next generation after the Elitism operation is controlled by the user and can varied. But we shall consider the selection only two of the fittest chromosomes from a generation of population and transfer them to the next generation. This does not require the crossover or mutation operations. So, we have two fittest chromosomes among the population, just using Elitism.

4.6.2. Crossover:

The crossover operation is performed in the same manner as described for method 1, in the section 4.4.2. There is no difference in the operation but the only difference here in this method is with the meaning of the crossover rate. The crossover rate here in this method, stands for the number of chromosomes that will undergo the crossover operation, rather than the possibility that the operation will occur. So, a crossover rate of 90% in this method would mean that 90 chromosomes (45 pairs) out of every 100 among the population will undergo the crossover operation and would be transferred to the next generation.

4.6.3. Mutation:

Mutation operation is also performed in the same manner as in method 1, in section 4.4.3; but the difference here is the way it is implemented in this method. There is no difference in the operation but only the meanings of mutation rate are different. The mutation rate here in this method, stands for the number of
chromosomes that will undergo the mutation operation, rather than the possibility that the operation will occur. So, a mutation rate of 3% in this method would mean that 3 chromosomes out of 100 among the population would undergo the mutation operation and would be transferred to the next generation. The bit position for the mutation operation is chosen randomly even in this method.

The difference in this method is the random selection of chromosomes for the mutation operation, rather than the use of “Roulette Wheel” for the selection purpose, as in method 1.

The rest of the procedure after the mutation operation, that is fitness calculation, new population generation and getting an optimal solution at the end of the process are the same, as described in the subsections 4.4.4, 4.4.5 and 4.4.6 for method 1.

4.7. Matlab Results:

The QoS specifications are specified by the user (application) and include the four parameters (genes), mentioned earlier in the research. The specification by the user for decision-making should include the following four parameters.

User’s QoS frequency Band specification (F) for operation.
User’s QoS power specification (P) for operation during the communication.
User’s QoS Bit error rate (BER) specification.
User’s QoS Modulation scheme specification for communication.

The following QoS specifications in table 4.18 were given as an input and calculations were performed five times, using the same input. Both method 1 and method 2 use the same input specifications, to perform their calculations. Both these methods follow the methodology defined earlier in the report, to find the optimal solution. They take the QoS specifications as an input from the user and involve themselves in a decision-making process and evaluate the fitness of each chromosome in the solution pool at each generation. The optimal solution thus found by the G.A. might not match exactly the QoS specifications requested by the user but is the closest possible in the solution pool, for each gene. This behavior of the G.A. is due to the presence of multiple genes in the chromosome structure and trade-off that exists among them. This behavior of the G.A.s is explained in the next section in the report.

<table>
<thead>
<tr>
<th>Frequency</th>
<th>Power</th>
<th>BER</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>623</td>
<td>35</td>
<td>4</td>
<td>2</td>
</tr>
</tbody>
</table>

[Table 4.18] Input specifications to test the codes, for Method 1 and Method 2.
The corresponding outputs produced by method 1, for the above input are given in table 4.19.

<table>
<thead>
<tr>
<th>S #</th>
<th>Frequency</th>
<th>Power</th>
<th>Bit-Error Rate</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>427</td>
<td>34</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>789</td>
<td>37</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>782</td>
<td>45</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>648</td>
<td>44</td>
<td>3</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>603</td>
<td>49</td>
<td>3</td>
<td>2</td>
</tr>
</tbody>
</table>

[Table 4.19] Results for the input in table 4.18, using Method 1.

The corresponding outputs produced by method 2, for the above input are given in table 4.20.

<table>
<thead>
<tr>
<th>S #</th>
<th>Frequency</th>
<th>Power</th>
<th>Bit-Error Rate</th>
<th>Modulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>464</td>
<td>32</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>2</td>
<td>870</td>
<td>34</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>641</td>
<td>40</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>4</td>
<td>835</td>
<td>31</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>5</td>
<td>669</td>
<td>41</td>
<td>6</td>
<td>1</td>
</tr>
</tbody>
</table>

[Table 4.20] Results for the input in table 4.18, using Method 2.

Note that, the output or the optimal solution found by the G.A. is also a chromosome having the same structure as that of the input given to it, as QoS specification. Also, remember that, both the methods work using random values for each gene and can produce very different values for the chromosome structure each time they are run. Hence, they might not allocate the same values for each gene much often.
4.8. Conclusions & Behavior of G.A.s:

Each of the four parameters mentioned above contribute for the total fitness of the chromosomes, in accordance with their respective weights assigned to them by the user (application). This weight factor plays an important role in the selection process, discussed earlier. The genes allocated more wattage in the decision-making process will have higher fitness values than those with lower wattage, with increasing number of generations. Also, the user (application) enjoys the privileges to control the number of values that it considers on each side of its requested QoS specification, for each gene. Using the same seed for the initial population ensures the generation of the same population every time i.e. the experiments would be performed on the same population. If we keep the population size the same throughout our operation and vary the number of generations only, we can study the behavior of both individual fitness for each gene and the total fitness values in our operation. I.e. a study of the behavior of G.A.’s operation “Fitness Vs the Number of Generations” can be carried out.

The researches show that the fitness of the individual genes (frequency, power, bit-error rate and modulation in our case) increases with increase in number of generations, but this behavior is not always absolutely linear rather it would have dips at certain points. This behavior of the G.A.s is due to the presence of other genes in the chromosome structure that affect the decision-making process, to reach an optimal solution. If the behaviors of individual genes for the same experiment are compared, they show almost an opposite behavior to each other at the same instances against the number of generations. This is because of the fact that the optimal solution reached by the Genetic Algorithms may have to compromise for a lower value of an individual gene to have a better fitness value for another gene in the structure at the same instant and hence obtain a better overall fitness of the chromosomes. So, the G.A.s actually go for the closest possible values for each gene among the available pool of solutions. Also, the range for decision-making associated with each gene affects the decision-making process. A gene with a smaller range to choose (modulation gene in our case) would have a higher fitness value, while the one with a larger range to choose (frequency gene in our case) will enjoy a lower fitness value in the optimal solution found by the G.A.s, over the number of generations. This implies that although, the individual fitness values for the genes may not increase in the same manner, yet the total fitness values stay above 80% throughout the generations, to find the closest possible optimum values in the available pool of solutions.

The following figure, figure 4.2 represents the behavior of the G.A.s for the total fitness of the chromosome with increasing number of generations, to find the optimum.
The plot for total fitness for chromosomes versus the number of generations shows that despite of the existence of the trade-off and the difference in the range for the individual genes, the total fitness stays over 80% throughout the decision making process to find the optimum.

The following figures, figure 4.3 and 4.4 represent the trade-off relationships among the plots for the individual genes in the chromosome structure for method 1 and method 2, respectively. The plots are obtained using values from table 4.19 and table 4.20 for method 1 and method 2, respectively. The trade-off among the individual genes and the affect of the range in the genes that exist among them to reach an optimized solution are obvious in the plots.
Another factor that can affect the fitness values in the decision-making to find the optimum is the size of the initial population. If we increase the size of initial population and keep all other factors, e.g. the associated wattage to each gene in
the structure constant and analyze the individual fitness and the total fitness with increasing number of generations, we can study the behavior of the G.A.s for our decision-making process.

The researches show that the fitness values for chromosomes again increase with the increase in number of generations. These fitness values obtained by using a bigger initial population would have greater values than those with a smaller initial population size. So, it can be concluded that increasing the initial population size provides for better fitness values over the number of generations. This may also result in an increase in the computational complexity for the decision-making. So, the trade-off between the computational complexity and the initial population size should always be considered.

So, summarizing the above discussion, we can simply state that the fitness values for chromosomes increase either by increasing the size of the initial population or by increasing the number of generations, or both of them.

4.8. Vision in Future:

The aim of this research was to explain the decision-making process involved in the cognitive radios, mainly the use of G.A.s for the purpose. We considered only the case of a single user system capable of allocating all the parameters considered i.e. frequency, power, bit error rate and modulation, at a single time instant only, for the research. The allocation of these parameters to multiple users at the same time can be a possible extension of the research in future.

Also, in this particular research, there was no mechanism defined to vacate and reallocate another band in the spectrum to the secondary user if a primary user is detected in the same band. Hence, in future the research can be extended for this purpose as well. This may involve the definition of holding times for the bands allocated to the secondary users so that the primary users requesting the band should always be proffered, even after the allocation.

The parameters considered for fitness function in this research were independent of each other. Yet another possible future extension of the research can be the consideration of the interdependency among the parameters that exist in the fitness function. Also, we considered only four parameters for our fitness function i.e. frequency band, power, bit-error rate and modulation scheme only. In future some more parameters like data rate, spectral efficiency and signal to noise ratio etc. can also be added to the fitness function definition.
REFERENCES: