ENERGY DETECTION AND MACHINE LEARNING BASED SPECTRUM SENSING TECHNIQUES FOR QPSK BASED BASE-BAND AND PASS-BAND COGNITIVE RADIO SYSTEMS

by

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Dedication

I dedicate my all of research work to all researchers of the cognitive radio family

Acknowledgement

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Abstract

The number of applications and high-speed services are increasing at high speed due to the recent revolution in the wireless communication world. According to FCC 2002 report the licensed bands are underutilized by 15%-85%. Many applications are designed for operation in unlicensed bands. Cognitive radio proposed by J.Mitola is a solution to this problem. The cognitive radio is an intelligent, self-aware and self-managed radio. It can sense the communication environment and can adapt new parameters to improve QoS .It can avoid the possible interference by primary users. In this thesis four 802.16(d) systems are considered as primary users and 802.11(g) systems are considered as the secondary users. The cognitive radio based systems have a spectrum sensing and decision making device. The spectrum of the primary user is sensed on the basis of energy detection techniques (Welch periodogram) . The performance of a Welch periodogram based detector is good up to an SNR of -25dB. Below this, performance is poor. The idea of SVM was proposed by V.N.Vapnik. The SVM is working basically on the supervised statistical learning principle. SVM is basically designed for the solution of classification and regression problems. In this research a Support Vector Machine (SVM) based detector senses the spectrum and detects the spectrum holes at low SNR values with a high confidence level. The decision about the selection of the best spectrum hole is also done. On the basis of this information the cognitive devices can select a new spectrum band and can enjoy the spectrum flexibility. Fuzzy logic is basically used for the solution of control problems. In current research the fuzzy logic is used for the signal detection and hole selection by considering the time constraints. The signal detection and decision making is done by considering the 802.22 standard. This thesis is combining the statistical signal processing and machine learning concepts for the designing and improvement of future cognitive radio based networks.

Kurzfassung (Abstract German)

Die Anzahl der Anwendungen und Services in der kabellosen Kommunikationswelt ist stetig im Steigen. Aufgrund der wenig genutzten Frequenzbereiche sind jedoch die Übertragungsgeschwindigkeiten und -kapazitäten stark eingeschränkt. Laut dem FCC 2002 Report werden 15-85% der lizenzierten Frequenzbänder nicht genutzt. Viele der neuen Anwendungen hingegen werden im unlizenzierten Frequenzbereich betrieben. Das "Cognitive Radio"-Prinzip von J. Mitola kann als Lösung dieses Problems dienen.
Das Cognitive Radio ist ein intelligentes und autonomes Kommunikationsgerät. Es kann seine Umgebung wahrnehmen und neue Parameter adaptieren, um die dienst qualitatQuality of Service (QoS) zu verbessern. Des Weiteren kann es die möglichen Störungen und Interferenzen von Primary Users vermeiden. In dieser Arbeit werden die vier 802.16(d)-Systeme als Primary Users, die 802.11(g)-Systeme als Secondary Users bezeichnet. Die auf dem Cognitive Radio-Prinzip basierenden Systeme umfassen Funktionen zur Frequenzabtastung und Entscheidungsfindung. Das Frequenzspektrum des Primary Users wird mithilfe von Energy-Detection-Verfahren (Welch-periodogramm) abgetastet. Detektoren, welche auf dem Welch-periodogramm basieren, weisen eine gute Effizienz bis zu -25dB Signal/Rausch-Abstand (SNR) auf - liegt der SNR-Wert jedoch darunter, verlieren diese an Güte.

Zur Entscheidungsfindung wird die Idee der Support Vector Machine (SVM) von V. N. Vapnik aufgegriffen. Die SVM arbeitet hauptsächlich auf dem kontrollierten Statistical-Learning-Prinzip. Mithilfe der SVM können Klassifizierungs- und Regressionsprobleme gelöst und eingeordnet werden. Der in den Untersuchungen verwendete SVM basierende Detektor durchsucht das Spektrum und detektiert Frequenzlöcher scheint auch bei niedrigen SNR-Werten mit hohes konfidenz zu detektieren. Dabei wird die Auswahlentscheidung des Frequenzloches ebenfalls getroffen. Auf Basis dieser Informationen können die kognitiven Geräte ein neues Frequenzband auswählen und dadurch die Spektrumflexibilität nutzen. Um regeltechnische Probleme zu lösen, kommt Fuzzy Logic zum Einsatz. In den vorgelegten Ergebnissen wird Fuzzy Logic zur Signalerkennung und Lochauswahl unter Berücksichtigung von Zeiteinschränkungen verwendet. Die Signalauswahl und Entscheidungsfindung berücksichtigt des Weiteren den 802.22 Standard. Diese Doktorarbeit verbindet die statistische Signalverarbeitung mit Konzepten des Machine Learning, um zukünftige auf Cognitive Radio basierende Netzwerke entwerfen und verbessern zu können.

Acronyms

ACF	Autocorrelation function
API	Application programming interface
AWGN	Additive white Gaussian noise
BER	Bit error rate
BICA	Biologically inspired cognitive architecture
B_c	Coherence Bandwidth
C_{awgn}	Capacity of the additive white Gaussian noise channel
CAF	Cyclic autocorrelation function
CDMA	Code Division Multiple Access
CR	Cognitive Radio
CE	Cognitive Engine
DARPA	Defense advanced Research Program Agency
DTFT	Discrete time Fourier Transform
DFT	Discrete Fourier Transform
DSB_AM	Double side band amplitude modulation
DPSK	Differential phase-shift keying
E_b	Energy per received bit
ETSI	European Telecommunication standard Institute
FBSE	Filter bank spectrum estimation
FCC	Federal Communication commission
FDMA	Frequency Division Multiple Access
FFT	Fast Fourier Transform
f_m	Doppler shift
ISI	Inter-Symbol Interference
LOS	Line of Sight
MTSE	Multi-taper spectrum estimation
MUD	Multi User Detection
No	Power spectral density of white Gaussian noise
NP	Neyman Pearson criterion
OODA	Observer-orient-Decide –Act
OFDM	Orthogonal Frequency Multiplexing

OFDMA	Orthogonal frequency division multiple access
OSCR	Open source Cognitive Radio
OWL	Web Ontology Language
P_b	Probability of bit error
Pe	Error probability
P_D	Probability of detection
P_{FA}	Probability of false alarm
P_m	Probability of miss detection
PCA	Principal Component analysis
PCN	personal Communication Networks
PCS	personal communication systems
P_s	Probability of Symbol error
PSD	power spectral density
PU	Primary user
PSK	Phase Shift Keying
QPSK	Quadrature Phase Shift keying
ROC	receiver Operating Characteristic
R_{SU}	Bit rate of SU
SCA	software communication architecture
SCC	Spectral Coherence Coefficient
SCF	Spectral Correlation function
SDR	Software defined radio
S/I	Signal- to- Interference ratio
SNR	signal to noise ratio
SINR	Signal to interference pulse noise
SPTF	Spectrum Policy Task force
SNR_{PU}	Signal to noise ratio at PU
SRM	Structural risk Minimization
SSB-AM	Single side band amplitude modulation
SVD	Single Value Decomposition
SVM	Support Vector Machines
STFT	Short time Fourier transforms
SVD	Single value decomposition

SU	secondary user
SS_{PU}	signal strength receiver SU from the Pu
T_c	Coherence time
τ_d	Delay spread
TV	Television
UTC	Unified theory of Cognition
VS	Versus
W	Band width
WG	Working group
WRAN	Wireless regional area networks
w_L	Window function
XG	next Generation
γ	threshold level

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1 Introduction

1.1 Overview of Cognitive Radio Systems

Radio spectrum is the most valuable source in wireless communication. In most cases the shortage of spectrum is a spectrum access problem. The Cognitive Radio and Cognitive Radio Networks are transforming the static spectrum allocation based communication systems into dynamic spectrum allocation [1]. Cognitive radios must have the ability to check and sense the environmental conditions and can change its parameters according to the requirements to get the optimized performance at the individual nodes or to all systems [2]. This chapter covers the basis and origin of software defined radio, cognitive radio, cognitive radio network, cognitive cycle, cross layer design, performance metrics and the concept of cross layer design. This chapter also covers the different network paradigms. The performance metrics explain the node and network level performance measurements.

Wireless communication creates a revolution in our lives. The mobile communication is the most successful wireless service. New wireless devices are offering a better data rate and new and useful services. Normally, mobile communication systems operate at a frequency less than 3.5 GHz [3]. With the increase of the mobile services, the bandwidth requirements are also increasing. For the new services the bandwidth availability is a problem. Currently the spectrum is utilized in a static way. There are two types of the bandwidth allocation, one is the licensed band allocation and the 2nd are ISM bands, which can be utilized by any user. The new wireless applications and devices are basically designed for the unlicensed bands, e.g. last mile broadband wireless access, health care, wireless PANs/LANs/MANs and cordless phones are working in unlicensed bands. According to FCC 2002 report, the licensed bands are underutilized and the ISM bands are over utilized [4]. This situation is creating the spectrum scarcity. According to FCC report the licensed band spectrum are underutilized. The spectrum usage lies in between 15-85%. This situation occurs due to static spectrum allocation policy adopted by the governments worldwide. Due to this policy, the spectrum bands are vacant temporarily. These vacant spectrum bands are known as the spectrum hole or white spaces. The holes are available at particular time or in particular locations. In 1992 Joe Mitola presents the idea of Software Defined Radio [5]. Software Defined Radio (SDR) is a programmable device which has the ability of multichannel and multicarrier communication. The SDR has the ability to change its parameter and quality of service (QoS) by programming according to demand. The solution of this problem was suggested by Mr. J.Mittola during his PhD at KTH Sweden. The Cognitive Radio is a spectrum agile system which has the ability to sense the communication environment dynamically and it can intelligently adapt the communication parameters (carrier frequency, bandwidth, power, coding schemes and modulation scheme etc.) [6].

The idea of a fully Cognitive Radio presented by J. Mitola et.al is still practically not possible. The hierarchical model is presented in which spectrum is accessed and bandwidths are adopted by secondary users with priority of the primary users. Normally unlicensed users are considering as secondary users. The Cognitive Radios (Secondary users) are allowed to coexist with the primary users if they can maintain a minimum level of interference. The RF bands operated at the frequency <3.5 GHZ ,Cellular bands and fixed wireless access bands with a center frequency 2.5 GHz and 3.5 GHz are the potential candidates for Cognitive Radio deployment [3]. In the United States, FCC allowed the dynamic access of the UHF TV bands by the Cognitive Radio devices. The Cognitive Radio operation depends upon the spectrum sensing information regarding activity, channel conditions, codebooks, messaging to other nodes, modulation schemes, noise variance and decision about the spectrum parameter adaptation.

1.2 Spectrum Scarcity and Spectrum Utilization

According to the FCC's report published in 2002, the licensed spectrum is utilized in between 15%-85% [4]. The reason of this varying underutilization of the licensed spectrum is the policy of static allocation. Currently the devices are operated according to the fixed spectrum assignment policy. The demand of the radio spectrum is increasing dramatically specially for the Mobile Radio Communication. The current static allocation policy is the root cause of the inefficient spectrum utilization and spectrum scarcity .In unlicensed bands congestion is increasing rapidly. The ISM bands are overcrowded due to WLAN, Bluetooth, cordless phones, microwave ovens and other devices. In this situation of inefficient RF spectrum utilization and spectrum scarcity, the scientists and engineers want to design new systems which can sense the spectrum, detect spectrum holes and can utilize the spectrum more efficiently. This paradigm shift must also reduce the interference among the users. The limited availability of the spectrum is the basic reason behind heavy cost and limited applications.

1.3 Software Defined Radio

The idea of Software Radio was first time designed and implemented by Garland Texas division of E-Systems in 1984[7].In 1988 Helmuth Lang and Peter Hoeher designed first transceivers on the basis of software radio at German Aerospace Research Establishment (DFVLR). This transceiver was designed for satellite modem [8]. The idea of Software Defined Radio (SDR) was proposed in 1992 by J. Mitola [5]. Software defined radio is a reconfigurable radio [9]. In SDR all radio functions can be performed on the programmable chips. The radios can be reprogrammed and they can act as multi-transceivers. Due to their re-programmability, they are easy to design and cheaper [10].

The physical layer parameter of the radio can be modified by changing the software. The traffic and control information are fully programmable in SDR. In SDR the new and different protocols can be implemented due to reprogramming ability of the SDR. SDR radios are multi-functional, provide global mobility, compactness and they are efficient in power consumption [11]. As the radio functions are implemented with the help of software so they can be easily upgraded and runtime reconfiguration is possible. The Software defined radio based networks have a layered architecture [12]. Speak easy, JTRS, Wireless Information system, SDR-3000, Spectrum Ware and Chariot are few important projects completed on the basis of Software Defined Radio technology [13].

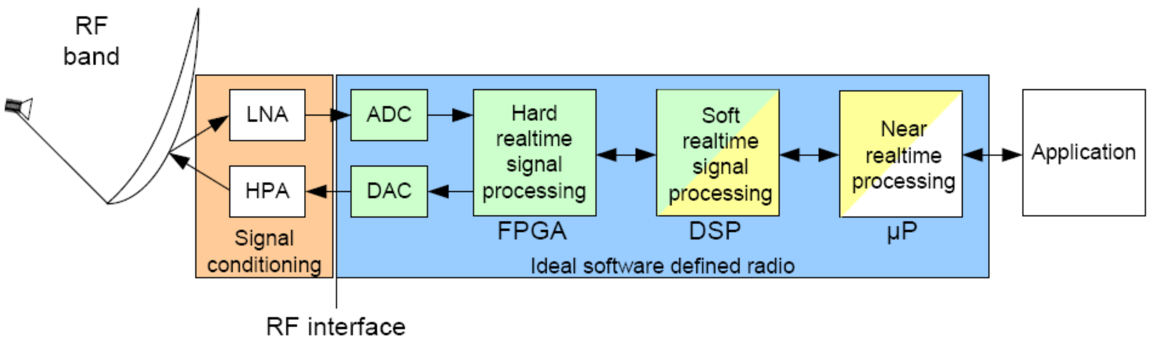


Figure1.1: Software defined radio [11]

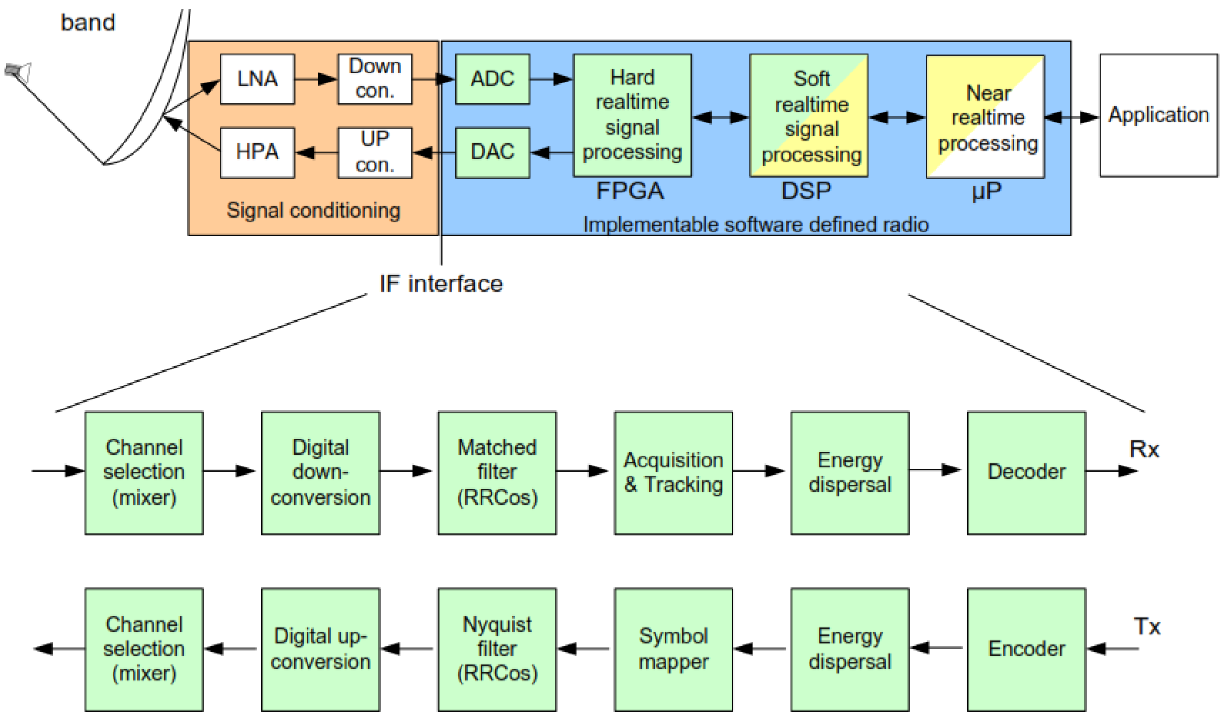


Figure1.2 Implementable SDR mapped on transceiver functions [11]

1.4 Cognitive Radios

The Cognitive Radio architecture was based on simple Observe-Orient-Decide-Act (OODA) loop frame work [14]. Cognitive Radios are self-aware and intelligent devices which can sense the changing environmental conditions and can change its parameter like frequency, modulation techniques, coding techniques and power etc., according to the changing statistical communication parameters to maximize the utilization of available spectrum resources and to ensure the QoS [15]. In Mitola's architecture prediction was done at planning stage. Self-awareness enables the Cognitive Radio to learn from the networking environment. Cognitive Radios can learn and make the decision about the adaptation of their operating parameters and change the transmission and receiving parameters to maximize the QoS. Operations of the cognitive Radio are controlled by the Cognitive Engine.

1.4.1 Cognitive Cycle

The Cognitive Engine works according to the cognitive cycle [14, 15]. The cognitive engine performs the tasks of sensing, analysis, learning and decision making. Cognitive Radio networks consist on two types of users. First type of users, are the primary (licensed) users (Pus) and the second type of users are known as the secondary users (SUs). Licensed users are allocated higher priority for the usage of the frequency spectrum [16]. Secondary users can change their communication parameters in an adaptive way [17]. The secondary users can transmit the information using the primary spectrum when spectrum holes are available [16]. The idle primary licensed spectrum is known as the spectrum hole. The secondary users can utilize the spectrum hole and try to reduce the problem of spectrum scarcity and underutilization of the licensed spectrum. The cognitive cycle is shown figure below

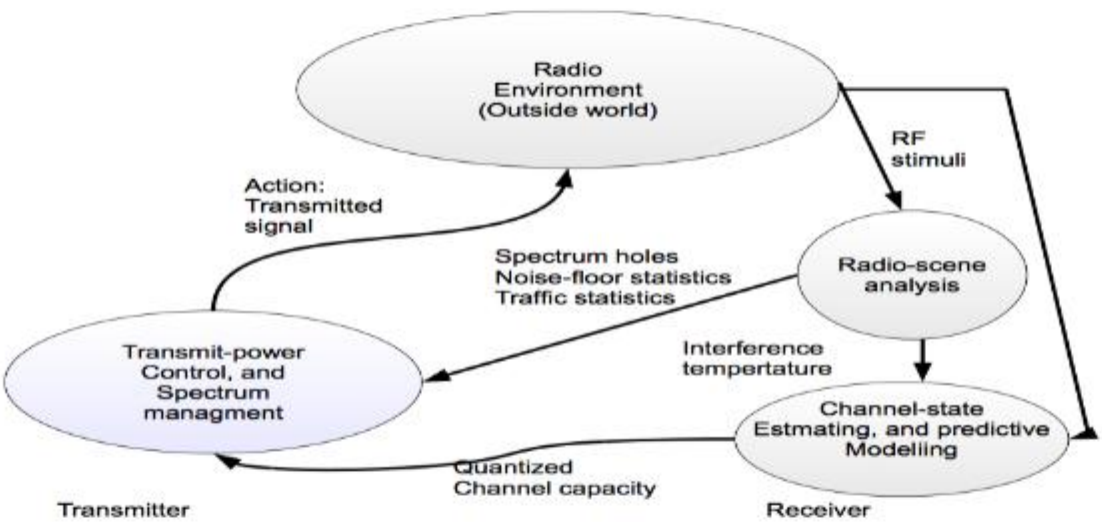


Figure 1.3 Cognitive radio cycle [14, 15]

The spectrum sensing devices sense the spectrum and detect the spectrum holes. The spectrum holes are temporarily unused spectrum of licensed users or filled by the low power interferers. The holes are referred as *gray or white spaces*, secondary users have the equal priority of spectrum utilization. The important functions of cognitive cycle are

***Spectrum sensing*:** Means to sense the primary user spectrum and find the spectrum holes.

Spectrum sharing: Coordinates with the other nodes and updates the spectrum information and adapts it in real time.

Spectrum Management: Selects the best available frequency band and then reduces the in band interference.

***Spectrum Mobility*:** The system continuously monitors the users and whenever the primary user wants to use the spectrum then vacates the spectrum. Different Machine Learning techniques like

Autocorrelation kernel function based SVM, Fuzzy logic or Neural Networks train the spectrum sensing devices and help in the prediction of spectrum holes in a supervised, unsupervised or semi-Supervised learning way.

Learning Process: Deals with the different machine learning techniques like SVM, Fuzzy logic or Neural Networks. These techniques are used for the training of cognitive engine, so that it can do the decision and can do online updating.

Decision Phase**:** During this phase CR must be able to do the decision about the adaptation of the communication parameters. For efficient spectrum sensing, parameters adaptation can be improved by different machine learning techniques.

1.5 Cognitive Radio Networks

The Cognitive Radio (CR) based communication is subdivided into *under lay, overlay and interweave paradigms.* The *underlay and overlay paradigms* are based on various *spectrum sharing* models. The Interweaver model is an example of a spectrum *agile opportunistic spectrum access* model [18].

The *underlay paradigm* is the most promising technique. In this technique the interference for the primary user is maintained below certain threshold level. In this paradigm the CR users need the information of channel gainto the licensed users. The smart power allocation algorithms or multiple antenna techniques are used for this purpose. This technique is also used in spread spectrum based ultra-wide band systems (UWB). In this technique the main hurdles are: requirements of perfect channel state information from the Cognitive Radio transmitter to the primary receivers, maintenance of interference noise temperature below an acceptable threshold level [19].

In the *overlay paradigm* the cognitive user and primary users are communicating simultaneously. The cognitive users apply the dirty paper coding in order to reduce the interference effect. The information is exchanged through messaging. The cognitive user needs the mechanism of messaging from the PU. Overlay model based CR devices can transmit at any required available power [19].

The *Interweaver paradigm* is the latest technique in Cognitive Radio Communication. This model is also known as spectrum agile opportunistic spectrum access model. In this technique the CR must know the exact location of spectrum holes in time, space and frequency coordinates [19].

The key point in performance of CR devices and networks are power efficient and computationally less complex spectrum sensing techniques. Spectrum sensing and the intelligent decision of the spectrum parameter adaptation play a vital role in interference mitigation and the efficient spectrum utilization in CR based communication devices. In this research spectrum sensing techniques and machine learning techniques for the efficient decision making are conducted for the improvement of the Interweaver paradigm for future Cognitive Radio devices.

1.5.1 Cognitive Radio Network Frameworks

The unified theory of cognition (UTC) is the key component behind the designing of the Cognitive Radio Networks [20]. Much cognitive architecture is designed on the basis of UTC. In cognitive architectures, the intelligent entities react with the inputs [19]. In cognitive environment knowledge representation and learning are important features.

UTC can be divided into simple and high complexity models

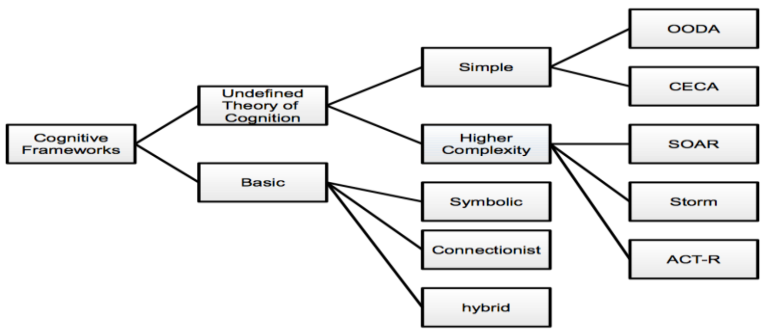


Figure 1.4 Classification of Cognitive Frame Works [19]

1.5.1.1 Simple Model

Observer-Orient-Decide-Act (OODA) and Critique-Explore-Compare-Adapt loop (CECA) are the example of simple models.

1.5.1.1.1 Observer-Orient-Decide –Act (OODA) Model

OODA was proposed by John Boyd for the decision making to explain the behavior of Cognitive Radio. OODA is a simple model in which the whole process is done on the basis of continuous feedback used [19].It is a reactive system based approach. It is commonly used in decision making in fighter pilot combat or cognitive nodes on the basis of observed environment [19, 21]. Mitola's radio was also designed by following the OODA architecture. Military Intelligence Cognition Systems are also developed on the basis of OODA loops. The OODA loop cannot describe a goal-oriented command decision process

1.5.1.1.2 Critique-Explore-Compare-Adapt Loop (CECA)

CECA is used to study the context of command and control on the OODA loop. CECA is a highly complex, conceptual model used for the initial plain of action [22]. The CECA model is started with the creation of conceptual model.

1.5.1.1.3 High Complexity Model

High complexity models are based on the UTC philosophy [23]. Some high complexity models are given below.

1.5.1.1.3.1 SOAR Cognitive Engine

SOAR was developed in 1983. The SOAR cognitive engine is used for the solution of open ended problems. In this architecture radio senses the environment and then decides the parameters intelligently. Open source Cognitive Radio is designed on the basis of the SOAR approach. OSCR enables the engine to integrate with software communication architecture (SCA). The OSCR based network has the information about modulation type, signal constellations and coding schemes. SOAR-based engines are very complex. OSCR links multiple applications programming with a single cognitive engine. The main task of OSR is to maximize the capacity of the noisy channels [24]. This structure is based on state operators [25].This engine is difficult to implement on a single radio. It is a biologically inspired model developed in Michigan as an extension of the SOAR Cognitive architecture [24].

1.5.1.1.3.2 Storm Cognitive Framework

Storm is the extension of the SOAR cognitive architecture. Storm was designed to develop a biologically inspired architecture. Due to complexity, it is not implemented on any practical platform [24, 26].

1.5.1.1.3.3 ACTR Model

ACTR was developed by Carnegie Mellon University by studying the Human Psychology [24, 27]. Some programming language is used to model this architecture. In this framework accuracy and performance time are the main metrics. ACTR is used to model the Cognitive Radio tasks.

1.6 Examples of Cognitive Radio Architecture

1.6.1 Mitola's Cognitive Radio Architecture

This radio was designed on OODA architecture. Its details are given below

1.6.1.1 Case Based Reasoning Cognitive Engine (CBR)

In this model the primary user (PU) has the priority of occupancy of the spectrum. The engine includes sensing, learning and decision making processes. The CBR based engines have different modules and their interfaces. IEEE 802.22 standard [29, 30] is operated on the base of the CBR model. CBR does the learning and decisions on the basis of historical record and environmental learning. CBR is implemented with the help of modular approach with interfaces. Constraint and Policy Engine (CnPE), multi-objective optimizer, case based reasoned (CBR), radio environment map, spectrum manager (SM) are few important primary modules [26]. The fuzzy logic based spectrum sensing and decision making also follow the CBR based approach.

1.6.1.2 Public Safety Cognitive Radio

The cognitive networks are also designed for public safety purposes [28]. Adhoc networks are one example of this type of cognitive radio based networks. These types of networks have a control and user domain. These networks have inner and outer loops. The outer loops have information recognition and behavioral adaptation. The inner loop consists of learning by tracking success and failure in the data base. In public safety networks applications a selfish approach is applied. In the selfish approach one node has the priority over the other nodes.

1.6.1.3 Open Source Cognitive Radio (OSCR)

The OSCR project was designed for the integration of CE with multiple software communication architecture (SCA) [24]. OSCR also enables the connection of multiple radios with a single cognitive engine with the help of an application programming interface (API) [24]. The OSCR links a multiple radio application programming interfaces (API) with a single cognitive engine.

1.6.1.4 Defense Advanced Research Program Agency (DARPA) Next Generation (XG) Program

DARPA's XG radio program is based on ontological reasoning on an SDR platform. It is a policy driven radio. This program is designed to make a strategy for unused spectrum. The main task is to avoid the interference of hidden users. In this program two ontological reasoning engines are suggested, one for policy and the other for waveform. The spectrum occupancy is provided by the dynamic spectrum access (DSA) capability. The white space probability tables are present at all nodes. These tables are updated at the fusion nodes. The XG uses the Web Ontology Language (OWL) [21]

1.6.2 IEEE 802.22 WRAN (Wireless Regional Area Networks): First Wireless Standard

The 802.22 was proposed in November 2004 [39]. It was the first Cognitive Radio based world wide effort to define a novel wireless air interface for the PHY and MAC layers [29, 30]. This standard was developed by the IEEE 802.22 Working Group (WG) [29]. The basic task of the Working Group was the development of PHY and MAC layers for CR based wireless regional area network (WRAN) [29]. The standard enables the unlicensed devices to operate in the Television (TV) band spectrums [30]. The basic task was the sensing and detection of the incumbent signal, so that interference due to incumbent users can be avoided and spectrum can be obtained by frequency reuse [29]. The dynamic spectrum management and radio environment characterization was designed also [29].

Adaptive modulation: Typical spectrum efficiency is 3 bits/sec*Hz (e.g., 64-QAM with ¾ code rate) OFDM type modulation to counter increased multipath due to less directional antennas at VHF and low UHF [29].

OFDMA on the return link allows scaling of the user terminal transmit power to the transmitted data rate [30].

1.6.3 Open Research Issues

Tighter coupling with true research, more proactive approach for prediction, development of new tools for fast prototyping, adaptation of selfishness approach with respect to applications are the open research issues with respect to the cognitive frame work and architecture [10].

1.6.4 Novel Algorithms for Cognitive Networks

The novel based algorithms are basically bio-inspired networks. The examples of these algorithms are Ant colony algorithm (ACO), fish algorithm, Particle Swarm Optimization (PSO) algorithm and Grey analysis. The algorithms are designed by studying the behavior of animals (fish, birds, ants). These algorithms are especially useful in the large distributed networks.

1.7 Cross Layer Design

For all above tasks, the CR based networks work on the basis of cross layer design. By the combination of information from Physical and MAC layers the CR senses the environment. The decisions are made on the basis of these 'meters'. On the basis of these 'knobs' (writeable parameters) the parameters of the Physical and MAC layer settings are changed to adapt according to the changing situation. The optimum performance of the CR networks can be obtained by the cooperation and exchange of information in between of the Physical, MAC and application layers [19]. Present protocols designed for the Physical and Mac layers for static spectrum allocation cannot be used for the CR based networks. For CR based networks the Mac layer protocols must have the ability to utilize the information from the Physical layer. It will help the MAC layer in assigning the resources to radio nodes. The decisions will be done on the basis of information provided by the Physical layer [31]. All the layers are used for the extraction of information from the physical layer and maximize the QoS for the applications.

1.7.1 Physical Layer

The main task of the Physical layer in CR networks is to sense the channel to check the presence of a primary user [31] and to find the spectrum hole. The best way of hole detection is the decision about the presence or absence of primary users' signals [33, 34]. The Physical layer also measures the amount of interference during the channel occupancy by the secondary user. The Physical layer also shapes the transmitter waveform to avoid intolerable interference to meet the QoS requirements [33, 34]. The spectrum sensing techniques are subdivided into parametric versus non-parametric techniques [19].

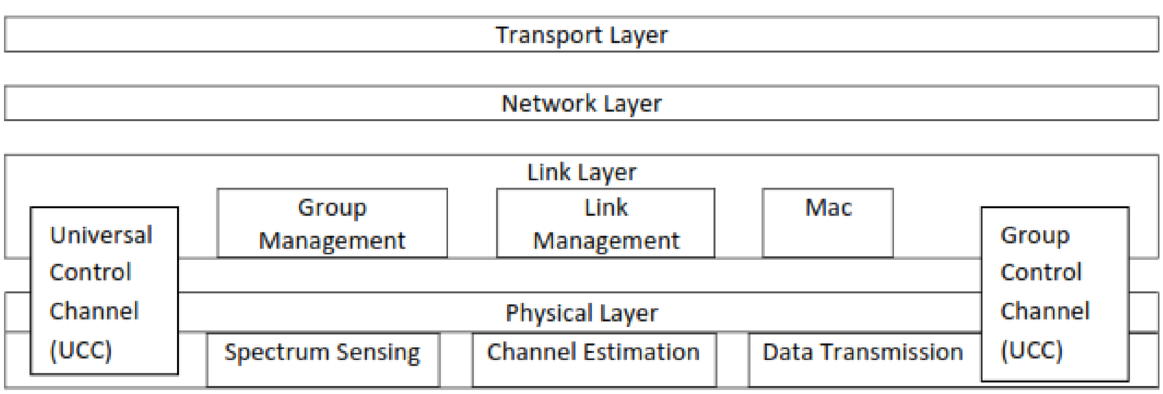


Figure 1.5 General OSI stack for the Cognitive radio based networks [34]

1.7.2 MAC Layer

The MAC layer uses the T_{on} and T_{off} information for the decision about switching of a new channel. It also works for the distribution of information among the other secondary nodes in the network [34] .It also manages the admission control and scheduling of different applications

NET	Determine Buffer Size
NET	Determine the Gain and particular Transmission strategy and application characteristics
PHY	Ton. Toff and Channel availability

Figure 1.6 Functions done at different levels in Cognitive Radio Networks [34]

1.8 Performance Metrics

The performance metrics appropriate the dynamic spectrum access and sharing has significant effects on various radio communication fields [36, 37]. The formalizing of the performance metrics will help in the research, comparison and advancement of the Cognitive Radio algorithms. The performance metrics are examined at the node, network and application levels [38]. The performance evaluation is a big challenge in the designing of CR networks and devices. The important step in CR design is the selection and establishment of effective performance metrics. The performance metrics will help the integration of the existing wireless networks with the CR based paradigm. The performance metrics help the regulators to establish the basics for regulating and certifying CR. The regulators ensure the non-generation of harmful interference. The vendors need performance, benchmarks for the approval testing during the production and development of the CR networks [3]. The performance benchmark helps the service providers in the deployment and maintenance of CR network and spectrum trading/subleasing [3]. The CR technologies cannot operate without performance metrics and benchmarking methods. The performance metrics must be selected carefully and they must enable the CE to give the proper response in changing environment and they must have the dynamic situation for utility functions [3].

The CR performance metrics are sub-divided into two categories:

Node level performance metrics (node score card) as shown in below table

The functionality of the CR node is evaluated on the basis of four domains [38]. These domains are

1) Cognitive Functions.

2) Overall Node Performance.

3) Node Complexity.

4) Technical Maturity.

Network level performance metrics (network score card) are also measured in the following four domains [38]:

1) Cognitive Functions.

2) Overall Network Performance.

3) Network complexity.

4) Technical Maturity.

1.9 Motivation

The solution of the spectrum scarcity is the *dynamic spectrum sensing and change of new parameters adaptively* according to the demand of a changing environment by ensuring the minimum level of QoS. The researchers in the field of Cognitive Radio are trying to solve this problem by designing the 802.22, 802.15h and WRAN standards [29]. These standards are the steps towards the solution of the spectrum scarcity problem. In these standards the adaptation of the parameters of the TV bands and Wi-Fi bands are included. The knowledge of different disciplines is used for the designing of Cognitive Radios and networks. The main problem is still the effective decision making to mitigate the interference offered by the primary users. The interference problem is less serious in case of TV bands, but it will become a serious issue especially when the simultaneous communication of the both primary and secondary users will take place. In this thesis, spectrum sensing techniques are proposed for 802.16d as primary users and 802.11g as secondary users. In this case, as the 802.16d devices can communicate at any time and have the prior communication priority, so the problem of interference must be addressed. The solution of this problem is effective, low cost and computationally less complex spectrum sensing by using classical Non-Parametric Statistical Signal Processing based spectrum sensing techniques or machine learning based spectrum sensing techniques. The spectrum sensing is basically a problem of statistical signal processing. In this thesis statistical learning theory is also applied. The sensing is done at the Physical Layer and the decision making process needs the utilization of MAC layer and messaging at the Network Layer. When there are more than one cognitive radios and sensing centers than cooperative spectrum sensing entities, data fusion centers and dynamic routing are required in a distributive way. A bridge in between different disciplines is required. J. Mitola presents the idea of agent based learning in Cognitive Radio networks .Unfortunately, most of the research is concentrating on the statistical signal Processing or cross layer design aspects. Few of them are working on machine learning based spectrum management and resource allocation [39]. This research is a small effort to make a bridge between statistical signal processing and machine learning by using these techniques for spectrum sensing. The results show that spectrum sensing is improved with the help of Support Vector Machines [39] and Fuzzy Logic Controllers FLCs.

Welch periodogram is a non-parametric spectrum sensing technique and it does not need any prior knowledge about the signal. The performance of these detectors is poor at low SNR. At low SNR, the probability of miss detection (P_m) and probability of false alarm are high, and the probability of detection is reduced. The performance improvement needs more time and computational power. The machine learning based spectrum sensing devices work on the basis of Statistical Learning Theory. These concepts are implemented here with the help of Support Vector Machines (SVM) and Fuzzy Logic Controllers FLCs. SVM is a supervised learning technique. SVM is basically used for the pattern recognition, feature detection, classification and the solution of regression problems in the field of vision and the speech recognition [40]. In this thesis the Autocorrelation Kernel is used for the signal detection by using SVM at very low SNR.

1.10 Problem Description

The cognitive radio is a future approach for the efficient spectrum utilization. For the proper working of cognitive radio based systems, it is necessary to decide whether the Primary user licensed spectrum is occupied or vacant. The robust and efficient spectrum sensing algorithms are the necessary component in the Cognitive radio technology. The criteria for the robustness and efficiency of the spectrum sensing algorithms and techniques are the preventing of hidden terminal problem, interference and the provision of reliable and robust detection performance at low SNR values. The spectrum hole detection and decision about the best hole selection is the main task of Cognitive Radio Cycle. For the spectrum hole sensing various signal processing techniques are used. In this research Welch periodogram based spectrum sensing Autocorrelation Kernel function based spectrum sensing techniques and Fuzzy logic based spectrum sensing techniques are applied. These techniques are applied for the AWGN channel for the Gaussian distribution based random data. There are two detection criterions one is Bayesian Criterion and the other is the Neyman Pearson Criterion. In the current thesis, the Neyman Pearson criterions is considered .In spectrum sensing the decision about the presence of the signal is done with the help of Statistical Signal Processing and Statistical Learning concepts. If the signal is not present at the specific frequency then the hole is present and the Cognitive Radio device can communicate by using these vacant frequency bands. The other problem arises when more than one spectrum holes are available. In this case, it is necessary to select best hole which is available for the longer time and where the chances of the interference are minimum. Statistical signal processing techniques have poor performance at low SNR or they are computationally more complex. The Support vector machine is working on the basis of statistical learning theory. Support Vector Machines are supervised learning technique which is mainly used for the pattern recognition, feature detection in the classification and regression problems in the field of Vision and speech recognition fields. The autocorrelation kernel method is normally used for feature detection on the basis of classification. In this thesis, the autocorrelation kernel is used for the spectrum sensing at very low SNR values. The machine senses the spectrum up to 89% accurately. The fuzzy logic was defined by Mr. Zaedh in 1969. The fuzzy logic based principles are used for the solution of control system problems. In this thesis, the spectrum sensing and decision about the selection of best spectrum hole is done with the help of Fuzzy logic. The decision about the best hole selection is done on the basis of the previous statistical band utilization record by considering the time constraints. The MAT LAB results are compared with the Mamdani’s model. The difference between the results is 4.1%, which is up to acceptable level. The spectrum sensing techniques are used to verify the following two hypotheses

H0: W (n) noise only, the spectrum hole is present

H1: W (n) + S (n) signal is present Spectrum hole are available

The decision is done on the basis of threshold γ. If the PSD of the signal is< γ, then Ho will be satisfied and if the PSD> γ, then the H1 hypothesis will be satisfied. The Block diagram of the problem is given in figure 3.1

1.11 Thesis Division

The whole thesis is divided in the five chapters**.** The short description about the contents in these chapters is given below**.**

Chapter 1 deals with the concepts of SDR, cognitive radio, cognitive networks, and cognitive cycle. The concepts of cross layer network design, present cognitive standard (IEEE 802.22), cognitive frame works and performance metrics are also discussed in this chapter.

The *Chapter 2* is dedicated for the background of spectrum sensing techniques. In this chapter basics of detection and estimation theories are discussed. In detection theory, the idea of Bayesian and Neyman-Pearson detection criterion are discussed. In this chapter different data distributions are discussed. Furthermore the performance metrics for the detection devices is discussed. Short description of Quadrature Phase Shift Keying (QPSK) and Modulation techniques are given in this chapter. Also, in the end of this chapter, propagation effects on wireless channels are discussed. The characteristics of AWGN and fading channels are discussed in detail.

Chapter 3 deals with different classical, non-classical, parametric and non-parametric spectrum sensing techniques. The simulation results of the spectrum sensing with the help of Welch periodogram technique at various frequencies levels for both baseband and pass-band spectrum for AWGN channel are addressed. The Welch periodogram successfully detected the 400 MHz signals down to an SNR<-25 dB.

Chapter 4 discusses the concepts of Machine Learning, Support Vector Machines, Autocorrelation Kernel and Mercer Theorem. The Autocorrelation kernel is used and the spectrum is sensed with the help of linear prediction methods. The SVM based spectrum sensing device works on the basis of supervised learning concepts. The detector identifies four transmitters successfully. This chapter also discusses the simulation results for the Autocorrelation Kernel for the baseband and pass-band spectrums. The simulation results showed the signal detection at low SNR Values. This technique is computationally more complex as compared to the energy based spectrum sensing, but they show the better performance at low SNR. This technique faces only a disadvantage that it needs the prior knowledge about the signals and it needs the certain time for training. But after the completion of the training it shows the better performance.

Chapter 5 discusses the concept of the Fuzzy Logic. The Fuzzy Logic is a rule based technique. It is normally used for the solution of control system problems. In this chapter the spectrum sensing and best hole selection are done by considering the time constraints. The MATLAB simulation results and the results from the Mamdani model are compared. The difference is 4.1%, which is acceptable.

In the final conclusion, future work and the list of research papers are given.

1.12 Contributions

The main contribution of this thesis is the Autocorrelation Kernel, Fuzzy Logic and Welch periodogram based spectrum sensing for AWGN channel at very low SNR. The spectrum was successfully sensed up to 400 MHz by a Welch periodogram based signal detection device down to SNR<-25 dB. The Autocorrelation Kernel based SVM detector successfully detected the base-band and pass-band signals at low SNR values. SVM needs extra time for training the data, but after training the machine does not need extra time and computational power. The autocorrelation Kernel function based detection can provide a way for the detection of noise buried RF signals.

This thesis is a ray of light for the solution of the spectrum sensing with the combination of the concepts of Statistical Signal Processing and Statistical Learning Theory.

The few papers are already accepted in valuable research journals and will be published soon. The other papers are under progress and hopefully will be accepted in various scientific journals.

References

[1] Jose Luis Rojo-alvarez, Manel Martinez-Ramon, Jordi Munoz-Mari, Gustavo Camps-Valls, Carlos Cruz and Anibal R Figueiras-Vidaö,"Sparse Deconvolution Using Support Vector Machines",EURASIP Journal on Advances in Signal Processing 2008

[2] Danijela Cabric, Shridhar Mubaraq Mishra, Robert W. Brodersen, "Implementation Issues in Spectrum Sensing for Cognitive Radios,"38th Asilmoar Conference on Signal, Systems and Computers,2004, Volume 1,pp:772-776

[3] Andreas F.Molisch, Larry J.Greenstein, Mansoor Shafi" Propagation Issues for Cognitive Radio," Proceedings of the IEEE issue 5,volume 97,No 5,May 2009,pp.787-804

[4] Federal Communication Commission(FCC)," spectrum policy task force, Report of the spectrum efficiency Working Group", ET Docket no. 02-135, November 15,2002

[5] Joe mitola et al.,"The Software Radio Arcitecture," IEEE Communication Magzine, May 1995, pp.26-38

[6] Seung-Jun Kim, Georgios B Giannakis "Rate Optimal and Reduced–complexity Sequential Sensing Algorithms for Cognitive OFDM Radios",43rd annual Conference on Information Science and Systems, CISS 2009,pp 141-146,EURISAP journal on Advances in Signal Processing 23rd August,2009

[7] P.Johnson, "New Research Lab leads to Unique Radio Receiver," E-Systems Team, May 1985, Vol.5, No.4, pp.6-7

[8] P.Hoeher and H.Lang,”Coded-8PSK Modem for Fixed and Mobile Satellite Services Based on DSP,” Proceddings of First International Workshop on Digital Signal Processing Techniques applied to Space Communications, ESA/ESTEC, Noordwijk, Netherlands, Nov.1988,ESA wpp-006,January 1990,pp.117-123

[9] Klaus Moessner, Didier Bourse, Dieter Greifendorf, Joerg Stammen,”Software Radio and Reconfiguration Management”, Elsevier Computer Communications, vol.26, 2003, pp.26-35

[10] Gerald youngblood, “A Software-Defined Radio for the Masses, Part 1,2,3,4”,jul/Aug 2002,pp.1-31

[11] Wolfgang Kogler, Wilfried Gappmair,Kogler,”Course Notes: Software-Defined Radio”,TUGraz, Austria

[12] J.Mitola III, “Software Radios Survey, Critical Evaluation and Future Directions”, IEEE AES System Magazine, April 1993, pp.13/15 to 13/23, pp.25-36

[13] “First International Workshop on Software Radio,” Greece 1998

[14] J.Mitola et al.,”Cognitive radio: An Integrated Agent Architecture for Software Defined Radio,” Doctor of Technology, Royal Inst. technol. (KTH) Stockholm, Sweden 2000

[15] Simon Haykin, “Cognitive Radio: Brain–Empowered Wireless Communication”, IEEE Journal on Selected Areas in Communications, Vol. 23, No.2, Feburary 2005, pp.201-220

[16] Ying-Chang Liang, Yonghong Zeng, Edward C.Y.Peh, Anh Tuan Hoang, ”Sensing Throughput Tradeoff for Cognitive Radio Networks”, IEEE Transactions on Wireless Communications, Vol. 7, Issue.4, April 2008,pp.1326-1337

[17] D.D.Ariananda, M.K.Lakshanan, H.Nikookar,” A Survey on Spectrum Sensing Techniques for Cognitive Radio”,2nd International Workshop on Cognitive Radio and Advanced Spectrum Management 2009 (CogART) 18-20 May 2009,pp.74-79

[18] Hang Su, Xi Zhang, ”Design and Analysis of A Multi-Channel Cognitive MAC Protocol for Dynamic Access Spectrum Networks”, IEEE Military Communication Conference (MILCOM),2008,16-19 Nov 2008,pp.1-7

[19] Ashwin Amna, Jeffrey H.Reed, ”Survey of Cognitive Radio Architectures,” Proceedings of the IEEE South East Conference (south east conf),18-21 March 2010,pp.292-297

[20] Allen Newell, “Unified Theories of Cognition,” Harward University Press, 1994

[21] John Boyd Compendium, [online].Available hhtp://www.d-n-i.net/dni/john-r-boyd

[22] David J.Bryant, “Modernizing our Cognitive Model,”9th International Command and Control Research and Technology symposium, 2004, pp.1-14

[23] Pat Langley and Dongkyu Choi,”A Unified Cognitive Architecture for Physical Agents,” Twenty National Conference on Artificial Intelligence, Boston, 2007, pp.1-6

[24] Soar, 2008. [Online] Available: hhtp://sitemaker.umich.edu/soar/home

[25] J.Lehman, J.Laird, P.Rosenbloom, “A gentle Introduction to SOAR, an architecture for human cognition,”2006

[26] J.Laird, ”Extending the Soar Cognitive Architecture,” Artificial General Intelligence Conference,2008

[27] “Welcome to ACT-R,” 2009.[online].Available:http://act-r.psy.cmu.edu/.

[28] B.Le, F.A.G.Rodriguez, Q.Chen,B.P.Li, F.ge, M.Elnainay, T.W.Rondeau and C.W. Bostian,”A Public safety Cognitive Radio Node,” in 2007 SDR forum Technical conference Denver,CO,2007,

[29] carlos Cordeiro,Kiran Challapali and Dagnachew Birru,Sai Shankar N. “IEEE 802.22:An Introduction to the First Wireless Standadrd based on Cognitive Radios,”

[30] A.He, J.Gaeddert, K.K.Bae, J.H.Reed and C.H.park, ”Development of a Case-Based Reasoning Cognitive Engine for IEEE 802.22 WRAN applications.”2007

[31] J.Reed, C.Bostian, “Understanding the Issues in Software Defined Cognitive Radio,” in Dyspan, Dublin, Ireland, 2006

[32] FCC, “Establishment of an Interference Temperature Metric to quantify and manage interference and to expand available unlicensed operation in certain fixed, mobile and satellite frequency bands,” ET Docket No.03-237, FCC 03-289

[33] Ian F.Akyildiz, Won-Yeol Lee, Mehmet C.Vuran, Shantidev Mohanty ,”Next Generation/Dynamic Spectrum Access/Cognitive Radio Wireless networks: A Survey “,Science direct, Computer Networks,Volume 50,Issue 13,15 September 2006,pp.2127-2159

[34] Sai Shankar N, “Squeezing the Most Out of Cognitive Radio: A Joint MAC/PHY Perspective,”International Conference on Acoustics,Speech and Signal Processing,15-20 April 2007,pp.1361-1364

[35] Danijela Cabric, Shridhar Mubaraq Mishra, Robert W. Brodersen, “Implementation Issues in Spectrum Sensing for Cognitive Radios”,38th Asilmoar Conference on Signal, Systems and Computers,2004,Vol. 1,pp.772-776

[36] A Goldsmith, “Performance of Cognitive Radios: Myths and Realities,” BWRC Cognitive Radio Workshop Nov.2004

[37] W.Krenik, A.M. wyglinski and L.E. Doyle, “Guest Editorial-Cognitive Radios for Dynamic Spectrum Aaccess,”IEEE communication Magzine.Vol.45, May 2007,PP.64-65.

[38] Youping Zhao, Member IEE; Shiwen MAO, Member IEEE, James O.Neel, Member IEEE and Jeffery H.Reed, fellow IEEE “Performance Evaluation of Cognitive Radios: Metrics, Utility Functions and Methodology,” Invited Paper,Under review for proceedings of the IEEE-Special Issue on Cognitive Radio ,pp.1-15

[39] Richard,c.Bermudez,J.C;Honeine,p. “On line Prediction of Time Series Data with Kernel”, IEEE Transactions on Signal Processing, Vol. 57, Issue.3,pp.1058-1067

[40] Georgios Goudelis, Stefanos Zafeiriou, Anastasios Tefas, Ioannis Pitas, “Class-Specific Kernel-Discriminant Analysis for Face Verification”, IEEE Transactions on Information Forensics and Security,vol.2,No.3,September 2007,pp.570-587

2 Background

The understanding of many important concepts is required for the spectrum sensing in Cognitive Radios. Several ones are discussed here.

2.1 Signal Detection Theory

The detection theory is the key component in the decision about the presence or absence of the signal. It plays a vital role in the designing of electronic signal processing devices and wireless communication systems. These systems decide the occurrence of an event and then they extract the information about that event. The two main components of the detection theory are the 'detection and decision'. The knowledge about the statistics of the signal and the probability distribution functions are required in the detection theory. It is difficult to directly predict the presence of the information signals at the receiver end due to the presence of noise and other signal distortion factors. The performance of the detector is checked on the basis of the statistical performance metrics. The detectors are designed to work in the noisy environment [1].

The detection theory plays a vital role in communication and signal processing systems, e.g. the first step in the operation of radar, sonar, mobile radios, speech processing, image processing systems, biomedical instruments, astronomy and the seismology etc. is the signal detection. In radar, the 1st task is the signal detection and the 2nd task is the information extraction [2, 3].

The decision about the presence or absence of a signal is the simplest detection problem [4]. The detection theory is also known as the hypothesis testing theory. There are two types of the hypothesis testing problems: binary hypothesis detection and multiple hypothesis detection problems. The speech recognition belongs to the binary hypothesis problem. The current research problem is the example of binary hypothesis. The problem can be represented as [5]

$$H_0 = W[n] \qquad [2.1]$$

$$H_1 = X[n] + W[n] \qquad [2.2]$$

Where X[n] represent the information signal and the w[n] represents the noise signal [6]. The presence of the signal or spectrum hole is decided on the basis of threshold value γ. If the value of the received signal will be less than γ then it will be noise (the spectrum hole is present) and in the case when the signal value is greater than the threshold value γ [7] than it will be an information signal (spectrum hole is absent). $\boldsymbol{H_0}$ represents the null hypothesis and the H_1 represents the alternative hypothesis [2].

There are two simple classical testing approaches. These simple and classical hypothesis approaches are *Neyman-Pearson* theorem and *Bayesian theorem* or *Bayesian approach*. The *Bayesian approach* is based on minimizing loss. The loss function is established for each possible outcome and for possible decision. In the Bayesian approach of hypothesis, for testing prior probabilities are assigned [1]. The conditional likelihood ratio is compared to the threshold. The Bayesian approach can be implemented for M-ary detection problem, M ≥2 [8]. The communications and pattern recognition systems follow the Bayesian approach. In this approach, the probability of error **Pe** is defined as

$$\mathrm{Pe} = \mathrm{P}(H_0|H_1)\mathrm{P}(H_1) + \mathrm{P}(H_1|H_0)\mathrm{P}(H_0) \qquad [2.3]$$

The *maximum likelihood detector* (ML) is an example of Bayesian approach. A *ML dete*ctor has the equal prior probabilities. In a ML detector the threshold is represented as

$$\frac{\mathrm{P}(\mathbf{x}|H_1)}{\mathrm{P}(\mathbf{x}|H_0)} > \frac{\mathrm{P}(H_0)}{\mathrm{P}(H_1)} = \gamma \qquad [2.4]$$

The detector which has the maximum aposteriori probability and which minimizes the P_e for any given value of the prior probability is known as the *maximum aposteriori* (MAP) detector. The MAP converts into Maximum Likelihood (ML) detector in case of equal prior probabilities.

The *Neyman-Pearson* approach is used basically for the binary detection problem. The Neyman-Pearson theorem is defined as: '*Detector that maximizes the probability of detection for a given probability of false alarm is the likelihood ratio test'*. In this approach tests are reduced to the comparisons of ratios of probability density or probability mass. These ratios are known as likelihood ratio test. The value of threshold γ is found from the false alarm constraint [2, 9]. The *Neyman-Pearson* theorem is represented as

$$\mathrm{L(x)} = \mathrm{P}(\mathrm{x}; H_0)/\mathrm{P}(\mathrm{x}; H_1) > \gamma \qquad [2.5]$$

In the Neyman–Pearson approach, the decision function is used to maximize the probability of detection. Signal detection in sonar and radar follow the *Neyman-Pearson* criterion approach. In our current research problem *Neyman-Pearson approach* is adopted [1, 3 and 10].

The performance of a detector is normally expressed with the help of three quantities, *probability of* false alarm P_{FA}, *probability of detection* P_D and *probability of miss detection* P_m [2, 3 and 11]. In the Neyman-Pearson theorem there are three possibilities of signal detection. The possible error in the detection are termed as

a) $P(H0, H1)$ Is known as the Probability of false alarm (P_{FA}) [12]. It represents the situation when the noise is present and the detector shows the presence of the signal. It is also known as the type II error. Normally its value is up to 10^{-8} [2]. For a binary detection problem $P_{FA} = Q(\gamma)$ **[**2]. The equation 2.6 represents the values of the P_{FA}.

$$P_{FA} = P(H_1, H_0) = P_r\{x[0] > \gamma; H_0\} = \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-1}{2}t^2\right) dt = Q(\gamma) \qquad [2.6]$$ and

b) Type I error represents the situation when the detector decides $\boldsymbol{H_1}$ but H_0 is true. It is represented by $P(H_1, H_0)$ Probability of miss detection (P_m) explain the situation when the information signal is present, but the detector shows the presence of noise (spectrum hole) [2, 13].

c) $\mathrm{P}(H_1; H_1)$ Represents the probability of detection (P_D) [14]. The detector exactly represents the presence of the signal for the situation when the signal is present [13]. For the binary detection problem P_D can be represented mathematically as $P_D = Q(\gamma - 1)$. Mathematically it is represented by

$$P_D = P(H_1, H_1) = P_r\{x[0] > \gamma; H_1\} = \int_{\gamma}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-1}{2}(t-1)^2\right) dt = Q(\gamma - 1) \qquad [2.7]$$

The performance of a detector can be represented by the region of convergence (ROC) graph. This graph represents the relation between P_{FA} and P_D at various SNR values [2].

The performance of a detector depends upon the selection of the two hypothesis H_0 and H_1.It also depends upon the selection of probability density functions P(X [0]; H_0) and P(X [0]; H_1) [8]. The optimal detector minimizes the $P(H_0; H_1)$ [10].

The *Neyman-Pearson* Theorem based detector represents the mapping from possible data values to the decision in case of data sets. Mathematically it can be represented with the help of critical region R_1 [2]

$$R_1 = \{x: decide\ H_1\ or\ reject\ H_0\} \qquad [2.8]$$

In this case the P_{FA} can be represented with the help of significance level (size of the test) α as given below [2]

$$\int_{R_1} P(x; H_0) dx = \alpha \qquad [2.9]$$

The basic task of the *Neyman-Pearson* based detector is the maximization of the P_D at any given value of $P_{FA.}$ The P_D is known as the power of the test. It can be represented mathematically [2]

$$P_D = \int_{R_1} P(x; H_1) dx \qquad [2.10]$$

The region where the value of P_D is is known as the *best critical region*. The performance of NP detector can be represented with the help of a plot between P_D and P_{FA}. This plot represents the performance summary of the detector. The curve drawn in the plot is known as *Receiver Operating Characteristics* (ROC). Each point on the ROC curve represents a value of (P_{FA}, P_D) for the given value of the threshold γ.

It must be remembered that the value of threshold must be $\gamma > 45^0$ [2]. In the Figure 2.1 the ROC for the given value of γ is shown

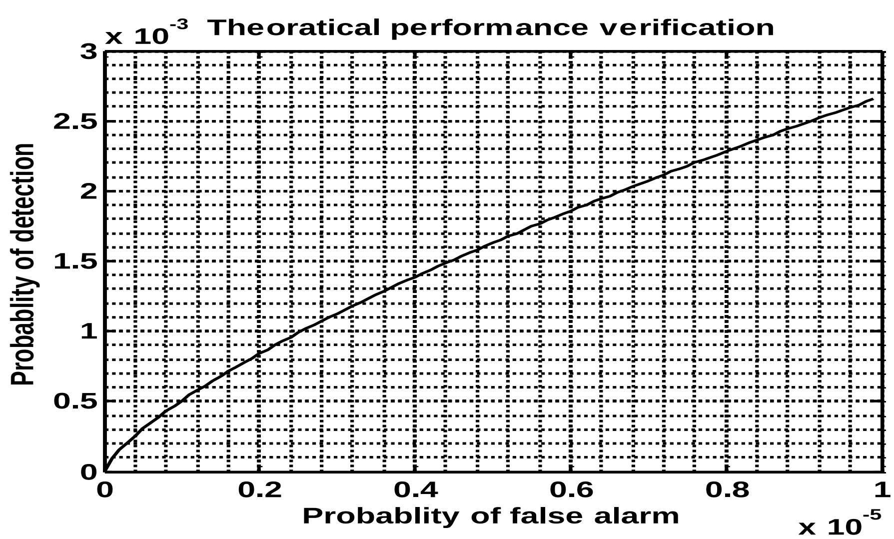


Figure 2.1: ROC for a Welch periodogram detector

The spectrum sensing techniques can be subdivided into local and cooperative spectrum sensing techniques. In local spectrum sensing techniques, decision about the presence of a primary user is done on the basis of local spectrum sensing measurements. While in cooperative spectrum sensing techniques, users within a group share their local spectrum sensing measurements and on the basis of this information, they decide the presence or absence of the primary users in a centralized or distributed fashion. Information fusion centers play a vital role in the decision process.

The signals are detected on the basis of various properties. One of these properties is *covariance* and *correlation*. The covariance can be defined as [8]

$$Cov[X,Y] = E[(X - E[X])(Y - E[Y])] = E[XY] - E[X]E[Y] \qquad [2.11]$$

The correlation coefficient is the normalized value of the correlation between two random variables X and Y. The correlation coefficient is define as

$$\rho_{\boldsymbol{XY}} = \frac{\boldsymbol{Cov[X,Y]}}{\sqrt{\boldsymbol{var[X]}}\sqrt{\boldsymbol{var[Y]}}} \qquad \textbf{[2.12]}$$

for a perfectly correlated variables i.e. $X = \pm Y$

The value of the correlation coefficient is $\boldsymbol{\rho_{XY}} = \pm 1$ and for the uncorrelated variables $\boldsymbol{\rho_{XY} = 0}$. In case of wireless communications, the signals are modulated carrier waves. These carrier waves can exhibit the built in periodicity [8]. This built-in periodicity can be used for the detection of the noise buried signal. These techniques are especially useful in case of time varying or frequency dispersive fading channels.

In Cognitive Radio networks the basic and the essential task is the detection of the spectrum holes and the decision about the busy or idle state of the channel. If the channels are vacant then it is necessary to decide which channel will be best. The selection of the best channel is done on the basis of the channel occupancy history. The channel which is idle most of the time will be best channel. The spectrum detection is the crucial aspect in the CR based systems. The spectrum sensing is done at the physical layer [15, 16].

2.2 Probability Density Functions (PDF)

The ability of numerical or analytical determination of the probability density function of the data samples effect the performance of a detector. If enough knowledge about the PDF is available then an optimal detector can be designed easily. In case when the PDF is not completely known, then the designing of an optimal detector becomes a difficult task. Some important probability density functions relevant to the research are explained below.

2.2.1 Gaussian Probability Density Function

The Gaussian distribution is also known as normal PDF**.** For a scalar random variable it can be represented as [2, 8, and 10]:

$$P(x) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left[\frac{-1}{2\sigma^2}(x-\mu)^2\right] \qquad where\ -\infty < x < \infty \qquad [2.13]$$

Where μ is known as the mean and σ^2 is known as the variance of x. Where $X_i \sim \mathcal{N}(\mu, \sigma^2)$. In case of $\mathcal{N}(0,1)$, the PDF have the bell shape.

The CDF for μ=0 and σ^2=1 can be represented as

$$\varphi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-1}{2t^2}\right) dt \qquad [2.14]$$

and the right tail probability is defined as $Q(x) = 1 - \varphi(x)$ where

$$Q(x) = \int_{x-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-1}{2t^2}\right) dt \qquad [2.15]$$

Where $Q(x)$is a monotonically decreasing complementary cumulative distribution function of a Gaussian random variable with zero mean and unit variance [17].

The multivariate Gaussian PDF of (n, 1) of random vector x is

$$P(x) = \frac{1}{(2\pi)^{n/2}\det(C)} exp\left[\frac{-1}{2}(x-\mu)^T C^{-1}(x-\mu)\right] \qquad [2.16]$$

Where C is the covariance matrix and it is positive definite and its value is

$$C = E[(x - E(x))(x - E(x))^T] \qquad [2.17]$$

It must be remembered that the value of odd order joint moments are zero for μ=0 and even order moments are the combination of 2nd order moments. In our present research problem we consider the sample distribution as Gaussian distribution.

It must be remembered that normal distribution satisfies the closure property under summation. Another important fact about normal distribution is the *Central Limit Theorem*. The *Central Limit Theorem* [18] is stated as, '*for any distribution, the sum of n independent random variables approaches to the normal distribution*.' If $X_i \sim D(\mu_i, {\sigma_i}^2)$, where $i = 1,2,3, \dots \dots \dots, n$ then

$$\sum_i X_i \sim \mathcal{N}(\mu, {\sigma_i}^2) where\ \mu = \sum_i \mu_i\ and\ \sigma^2 = \sum_i {\sigma^2}_i \qquad [2.18]$$

2.2.2 Chi Square (Central) Distribution

A chi squared probability distribution function with ν>1 degree of freedom is [2, 8 and 10]

$$P(x) = \begin{cases} \frac{1}{2^{\frac{\nu}{2}}\tau\left(\frac{\vartheta}{2}\right)} x^{\frac{\nu}{2}-1} exp\left(\frac{-1}{2}x\right) & where\ x > 0 \\ 0 \quad \text{where } x < 0 & \end{cases} \qquad [2.19]$$

The Chi-square distribution becomes Gaussian when the value of ν is large. The Chi-Square PDF arises as the result of $x = \sum_{i=1}^{n} x_i^2\ if\ \ \chi_i \sim \mathcal{N}$ (0, 1) where χ_i independently identical data (iid). In this research problem the output of the squared device without any data follows the Chi- squared data distributions.

2.2.3 Chi Square (Non- Central) Distribution

The sum of the square of iid Gaussian random variable with non-zero mean will be Non Central Chi-Square distribution [2, 8 and 10]. For the large value of ν it will convert into a Gaussian distribution. The Chi Squared (non-central) distribution occurs for $X = \sum_i^\nu x_i$ and $X_{i\sim}\mathcal{N}(\mu_i, 1)$ with ν degree of freedom [2, 19]. Its non-centrality parameter is $\lambda = \sum_{i=1}^{\nu} \mu^2{}_i$ [2] . In Integral form it can be represented as

$$P(\mathrm{x})=\{\frac{1}{2}(\frac{x}{\lambda})^{\frac{\nu-2}{4}}\ exp\left[\frac{-1}{2}(x+\lambda)\right]I_{\frac{\nu}{2}}-1\left(\sqrt{\lambda x}\right)\ where\ x>0 \qquad [2.20]$$

$$P(x) = \{0\ \ where\ x < o \qquad [2.21]$$

Where I(r) is the modified *Bessel function* of order and first kind [2, 20]. The value of $I_r(u) is$

$$I_r(u) = \frac{(\frac{1}{2}u)^r}{\sqrt{\pi}\Gamma(r+\frac{1}{2})}\int_0^{\pi} \exp(u cos\theta) sin^{2r}\theta\, d\theta \qquad [2.22]$$

In this thesis the output of the squared device (in case of data) is Chi-Squared (non-central) distribution [21].

2.2.4 Rayleigh PDF

The Rayleigh PDF is achieved in the case when the data is arranged in the form of $x = \sqrt{x_1{}^2 + x_2{}^2}$ where $x_1\ and\ x_2$ are independent and have the Gaussian PDF with zero mean represented as $x_1 \sim \mathcal{N}(0, \sigma^2)$ and $x_2 \sim \mathcal{N}(0, \sigma^2)$ and their PDF is given as[2,8,10]

$$P(x) = \begin{cases} \frac{x}{\sigma^2}\exp\left(\frac{-1}{2\sigma^2}x^2\right) & x > 0 \\ 0 & x < 0 \end{cases} \qquad [2.23]$$

2.2.5 Rician PDF

The Rician PDF is achieved in the case when the data is arranged in the form of

$x = \sqrt{x_1{}^2 + x_2{}^2}$ where $x_1\ and\ x_2$ are independent distributions and have with zero mean represented as $x_1 \sim \mathcal{N}(\mu_1, \sigma^2)$ and $x_2 \sim \mathcal{N}(\mu_2, \sigma^2)$ and their PDF is given as [2]

$$P(x) = \begin{cases} \frac{x}{\sigma^2}\exp[\left(\frac{-1}{2\sigma^2}(x^2+\alpha^2)\right)]I_0\left(\frac{\alpha x}{\sigma^2}\right) & x > 0 \\ 0 & x < 0 \end{cases} \qquad [2.24]$$

Here $\alpha^2 = \mu_1{}^2 + \mu_2{}^2$ and the value of $I_0(u)$ for $r = 0$ can be represented as

$$I_0(u) = \int_0^{2\pi} \exp(u cos\theta)\, d\theta \qquad [2.25]$$

The spectrum sensing and detection can be subdivided into direct and indirect methods. The power spectrum is directly estimated from the signal [24]. The direct methods are also known as the frequency domain approach. [2]

2.3 Multiuser Detection

The main task of the multiuser detection (MU) is the achievement of minimum error probability. A Matched Filter is also used for [25] optimum signal detection. The optimum detector must know about the signals and the signal correlations, the timing and amplitude of the signals, noise level. This information helps in the determination of bit error rate (BER). *Individually optimum* detector and *jointly optimum detector* are two possible approaches for the optimum detection. The *jointly optimum detector* [26] approach is a comparatively robust approach and provides the better results. Multiuser (MU) detection technique can be applied for the solution of non-orthogonal multiple access problems. For example, MU can be applied for CDMA, cross talk, Multipath TDMA and magnetic recording problems [27].

2.4 Performance Metrics

The different performance metrics are used for the measurement of performance of the spectrum sensing devices. For a particular problem, the required spectrum sensing technique is selected on the basis of performance criterion like speed and accuracy, computational complexity of the estimation of the spectrum [28, 29]. It is not possible to attain the time and frequency resolution simultaneously. So, the tradeoff between speed (time resolution) and accuracy (frequency resolution) is achievable [24]. Actually due to uncertainty problem, it is not possible to achieve high spectrum sensing speed with great accuracy (time frequency tradeoff) [25, 26 and 27]. The good time resolution is required for the location of time domain discontinuities. Time resolution is compromised for the frequency resolution.

In some cases the duty cycle is considered as the performance metric. So, the spectrum sensing technique will be selected on the basis of spectrum sensing speed and accuracy. The accuracy depends upon the frequency resolution, leakage and variance of the estimated power at each frequency band [24]. The bias or leakage depends upon the side lobe level [24]. The high side lobe creates the spillover in the neighboring frequencies and reduces the accuracy of the estimated power [24]. The variance is the result of the variations in the estimated power in a specific frequency band. Computational complexity is an important performance metric. The simplicity and less computational power consumption determine the possibility for the usage of the spectrum sensing device for the solution of a particular spectrum sensing problem. So, we can say that for a given problem, the best spectrum sensing (hole detection) technique will offer a tradeoff between time frequency resolution with minimum computational complexity.

The coherent detection devices behave well for the detection of the signals with low SNR but they need perfect information about the signal properties. For example in pilot based detection the matched filter need the prior information about the pilot signals [30]. Non-coherent based signal detection techniques do not need the prior information but there detection performance is poor at low SNR [25]

The cooperative spectrum sensing is the efficient way of increasing the performance of network. In cooperative spectrum sensing, the sensing is done at node level. The sensing results of each node are combined at the fusion center by using different data fusion rules [31]. The majority decision rule improves the detection probability [32]. The majority decision rule is an efficient and reliable decision rule which can provide the optimum detection ability.

The time domain spectrum estimation approach is also known as the indirect approach. Autocorrelation function based spectrum estimation is the example of the indirect spectrum estimation in the time domain [2]. The performance of these detection techniques is checked on the basis of their performance at the lower SNR.

2.5 Estimation Theory

The 2nd step of spectrum decision process is the estimation. The process of extraction of parameter values which gives some data is known as the estimation. The basic task of the estimation theory is to provide the foundations for the information extraction. The parameter is a global characteristic of the population. The probability theory establishes the base for estimation theory. During the estimation process the information can be processed in summation or pooling way [4, 3 and 27].

The estimator can be linear or non-linear. The sample mean and average based estimators are the examples of linear estimators. Linear estimators have the low variance and they can be used for the calculation of potentially better estimate of the true value of X. The linear estimator does not need the prior information. The Bayes' rule establishes the basis of the estimation theory [3]. It can be defined as

$$P(X|Z) = \frac{P(Z|X)P(X)}{P(Z)} \qquad [2.26]$$

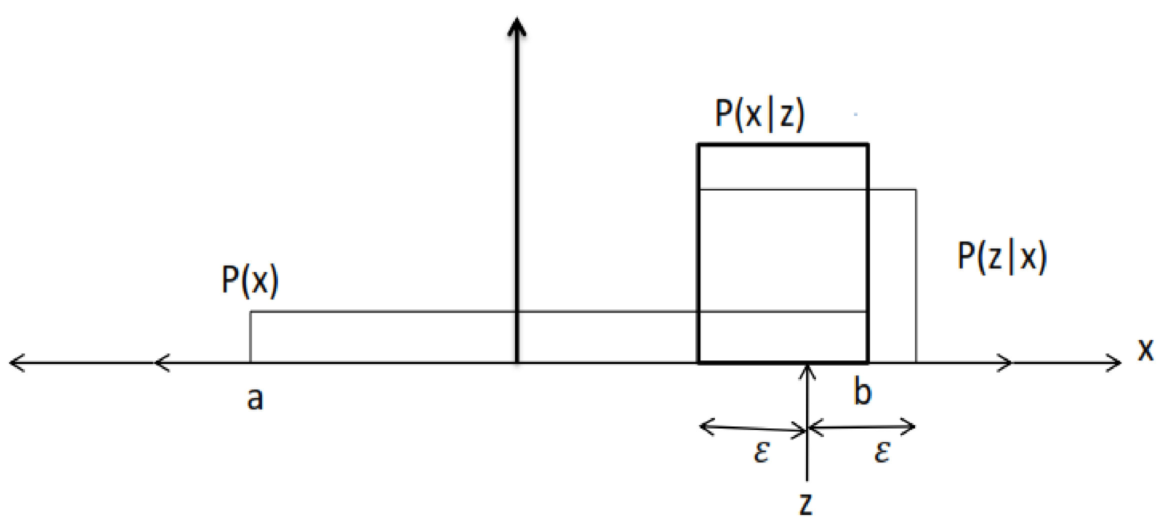


Figure 2.2 Combination of Prior Information p(x) with a measurement P (z|x) to calculate the Posterior [10].

The goal of the spectrum estimation is the description of the power contained over frequency in a signal [33]. The description is done for the finite data set. Power spectrum estimation is useful for the detection of noise buried wideband signals. The PSD $S_x(e^{j\omega})$ shows the power contents of the signals in an infinitesimal frequency band [33]. The *power spectral density (PSD) for a stationary random process* $x(n)$ *is the discrete Fourier transform of the correlation sequence* $r_x(n)$ [34]. It can be written as

$$S_x(e^{j\omega}) = \sum_{n=-\infty}^{+\infty} r_x(n) e^{-j\omega n} \quad where - \pi < \omega \leq \pi \qquad [2.27]$$

The equation 2.27 shows that the PSD of a signal represents the power content in an infinitesimal frequency band.

The value of the $r_x(n)$ is given by [35]

$$r_x(n) = E[x^*(m)x(m+n)] \qquad [2.28]$$

The integration of the PSD over a particular frequency band$[\omega_1, \omega_2]$ where $0 \leq \omega_1 < \omega_2 \leq \pi$ is equal to the average power of the signal for that particular band [3, 36]. It can be mathematically represented as

$$P(\omega_1, \omega_2) = \int_{\omega_1}^{\omega_2} S_x(e^{j\omega}) d\omega \qquad [2.29]$$

The asymptotic or high SNR assumption is useful in estimation problems. High SNR helps in accurate estimations.

$\boldsymbol{P}$ $\boldsymbol{p}$

The spectrum estimators used for wideband spectrum estimation are subdivided into parametric and non-parametric spectrum estimators [37].

The *parametric spectrum estimation* methods are based on some model [37]. The performance of the estimator is highly dependent on the model. If the model is inaccurate then the performance of the spectrum estimator will be poor and vice versa. In this method, the PSD is estimated from the signal which is assumed to be the output of the white noise driven linear systems [38]. The PSD can be determined by estimating the parameters (coefficients) of the linear system which is hypothetically responsible for the signal generation [38]. The parametric methods show the better performance as compared to the classical non-parametric methods in case of short data length signals. Yule-Walker autoregressive (AR) method, Burg methods and autoregressive moving average (ARMA) methods are examples of parametric methods.

The *non-parametric spectrum estimation* methods are not based on some model or assumption about the power spectrum shape. In this method, the PSD can be directly estimated from the signal itself without any prior knowledge [38]. Periodogram method, Welch periodogram, Multi-taper spectrum estimation and estimator-correlator methods are the few examples of non-parametric spectrum estimation approaches [38].

2.6 Modulation Techniques

Various modulation techniques are used in analog and digital communications. In this research the QPSK is used. The information signal is transmitted with the help of baseband signals. For the transmission through the wireless channels, different modulation techniques are used. The modulation techniques are named with respect to the variations in the characteristics of the signals [39]. The modulation techniques are subdivided into

Amplitude modulation (AM)

*Frequency modulation (*FM)

Phase (Angle) modulation (PM)

In AM the amplitude is varied. In frequency modulation, frequency of the carrier signals is varied. Phase is varied in case of phase modulation.

2.7 Propagation Through Wireless Channels

The performance of the communication devices depends upon the condition of the channels and propagation mechanism. The radio waves are propagated as travelling electromagnetic waves through space. The energy of the signals exists in the form of mutually perpendicular electric and magnetic fields [41]. Radio communication becomes complex especially in urban areas due to multipath propagation [36, 41]. The power of the transmitted signals is degraded due to channel impairments [36,41]. The performance of communication systems highly depends upon these impairments [41]. For example, the great hurdle in the success of optical wireless communication is the heavy attenuation due to rain or fog situations. A lot of research is done just in order to overcome the attenuation which reaches up to multiple of 10 dBs. The effect becomes especially important in case of wireless communications. The multipath propagation happens due to reflection and diffraction of the signals. It is difficult to establish the models for the obstacles like tunnels, underground passages and indoors due to their complex structures. The Rayleigh model can be used for the random environmental structures [36, 41]. The waveguide theory or Rician model can be used to solve the problems of line-of-sight propagation paths. The important propagation attributes are diffraction, reflection and scattering [42].

2.7.1 Reflection

Reflection is the bouncing back of the signal from the smooth surfaces. In case of reflection the angle of incidence is equal to the angle of reflection [43]. In case of reflection, the medium's intrinsic impedance, angle of incidence and electric field polarization [41] affect the amplitude and phase of the reflected waves.

2.7.2 Scattering

The Scattering effect occurs due to the collision of the signals with a rough surface or with an object whose size is as small as the wavelength of the signal. In scattering, the energy is spreading in all directions. Scattering can be done due to the objects like lamp posts, furniture and so on.

2.7.3 Diffraction

In this phenomenon the radio waves are bending towards or away from their original path when they are entering from one medium to another and vice versa**.**

In undisturbed line of sight (LOS) [45] links only the free-space loss has to be taken into account. It is defined as follow [36]

$$L_p = 20\log\left(\frac{4\pi d}{\lambda}\right)\ free\ path\ loss\ measured\ in\ dB \qquad [2.30]$$

2.8 Fading Channels

The performance of the communication devices depends upon the condition of the channels. The power of the transmitted signals is degraded due to channel impairments. The performance of communication systems highly depends upon these impairments. The effect becomes especially important in case of wireless communications. The fluctuations in the amplitude and phase occur due to multipath incoming waves at the receiver which results in the form of fading of the signals.

The *long- term or slow fading* have longer period and signal power [18, 36, 41 and 46] attenuation values around the mean value [41]. Slow fading is the average of signal power over larger distance between transmitter and receiver of the order of few kilometers (5 to 40 wavelengths) [18, 36, 41 and 46]. Normally *Rician distributions* are used for PDF [47].

In case of short term or fast fading signal power fluctuates rapidly due to local multipath. The short term fading is observed for a distance about a distance which is approximately equal to ½ λ. Fast fading is random and the rapid fluctuations in it occurs due to movements of receiver, transmitter and surrounding objects. The statistical properties are used for the determination of the system performance. In this case, *Rayleigh distribution* is used for the approximation of PDF [18, 48].

The slow and fast fading is separated on the basis of small area average or sector average [49]. The average within small areas due to shadowing caused by buildings is varying in a random manner. This effect can be represented by *lognormal distribution* and is known as the *Shadow effect* or *log normal fading*. In general the receiver power is expressed as

$$P_r = P_0(\frac{d_0}{d})^{\gamma} \qquad [2.31]$$

$$where\ P_0 = power\ at\ refernce\ distance\ d_0$$

$$d_0 = refernce\ distance(1m\ for\ indoor\ and\ 1\ km\ for\ outdoor\ environment)$$

$$\gamma = \text{path loss component, values are varying from 2 (free space) to 5 (urban environment)}$$

The received power for non-LOS case can be expressed as $\frac{d}{d_0}$

$$P_r(d) = 10\log[P_0(\frac{d}{d_0})] + 10\,\gamma\log(\frac{d_0}{d})\ [dB_m] \qquad [2.32]$$

The Doppler shift exists due to relative motion of transmitter and receiver [18, 41 and 50]. The value of maximum Doppler shift f_m is expressed as $f_m = \frac{v}{c/f}$ Where f= carrier frequency. The received signal is the product of signal component subjected to long term fading $m(t)$ and the signal component is subjected to short time fading $r(t)$ [41] and it can be expressed as

$$S(t) = m(t).r(t) \qquad [2.33]$$

2.8.1 Characteristics of Wireless Communication Channels

The characteristics of a wireless channel is quite different from wired channels due to *shadowing and multi path fading, Doppler Effect, delay spread and time dispersion* [18, 36, 46, 47, and 48]. *Time dispersion* in a mobile channel happens due to spread of symbol timing in the modulation symbol and produces the distortion. *Time dispersion* happens due to *frequency selective fading.* In this case, the frequency components spend different time to reach the receiver which results in the form of production of different attenuation levels [41] due to constructive and destructive interference [18, 36]. Frequency selective channel affects a portion of overall channel bandwidth at a given bandwidth [18, 41].

Doppler shift takes place due to the relative motion of the transmitter or receiver or both. It produces the shifting or spreading of frequency components which can be explained with the help of frequency dispersion. For *coherence time* (T_c) *,* the channel attenuations are assumed to be kept constant and the channel impulse response is relatively correlated or invariant. The value of *coherence time* (T_c) is equal to the inverse of *Doppler spread* [41, 51]

The value of c*oherence time* is

$$T_c \approx \frac{1}{2\pi f_m} \text{where } f_m = \frac{v}{\lambda} \text{ is max. Doppler spread} \qquad [2.34]$$

Doppler spread measures the rate of change of channel characteristics and it also calculate the rate of occurrence of the fading [41]*. Fast fading* takes place in case when the changes in the channel are faster than the symbol rate. When symbol rates are faster than the rate of changes in channels, then *slow fading* takes place. τ_d is the *rms* delay for multipath delay [41].

The attenuation is kept constant and frequency components behave identically over a frequency range known as the *coherence bandwidth.* The phenomenon that two frequency components have strong potential for amplitude correlation can be used to classify the channel fading [41]. The channel fading can be classified into *flat fading or frequency selective fading* [18, 41and 52]. The *coherence bandwidth* B_c between two frequency envelopes [52] is represented as

$$B_c \approx \frac{1}{2\pi\tau_d} \qquad [2.35]$$

Time dispersion takes place in case of *band-limited channels* or in a case when *coherence bandwidth* is less than modulation bandwidth [41]. Inter-symbol-interference (*ISI*) occurs due to time dispersion. For ISI, the bit error rate (BER) increases and energy of one symbol spills over to another symbol [17, 56]. B_c sets the upper limit for the transmission rate without any equalizer. The flat fading will takes place when *frequency components separation* $> B_c$ [52].

When, $B_c < B_w$, the channel acts as frequency selective channel. In case of a frequency selective channel, the frequency components are affected non-identically. The rule of thumb is

$$T_c = 0.423/f_m \qquad [2.36]$$

The communication system parameters of cellular systems are designed with the help of propagation path loss models [24]. The selection of channel model affects the performance of the wireless network due to its interference prediction ability [18, 41and 46]. The example of few of these models is

1. Hata/Oskumara model is the empirical model used in Europe and North America [54,55]
2. Cost 231 models were proposed by the *European Telecommunication standard Institute* (ETSI) for the use in *Personal Communication Networks/Personal Communication Syst*ems (PCN/PCS) [41].
3. IMT-200 model was proposed by *International Mobile Telecommunication-2000* (IMT-2000) for outdoor to indoor, pedestrian environment, indoor office environment and vehicular environment [41].

2.9 Noise in Communication Systems

Unwanted signals in electrical systems are known as noise. Noise limits the correct symbol decision [18]. Noise can be subdivided into *natural* or *man-made noise.* The sources of natural noise are *thermal or Johnson noise, atmosphere, sun and other galactic noise* [56]. The example of man-made noise is switching transients or spark plug ignition. Often different techniques for example shielding, filtering, selection of optimum receiver and proper modulation techniques are used for the reduction of noise effects. Thermal noise is described as a Gaussian random process. The value of Gaussian random process $n(t)$is characterized with the help of Gaussian probability density function as given below [54, 55 and 56]

$$p(n) = \frac{1}{\sigma\sqrt{2\pi}} \exp[\frac{-1}{2}\left(\frac{n}{\sigma}\right)^2 \Big] where\ \sigma^2 is\ the\ variance\ of\ n(t) \qquad [2.37]$$

Gaussian distribution is used for the system noise model due to the *central limit theorem* [57].

2.9.1 White Noise

White Gaussian noise channel is most commonly used for simple channel modeling. The two-sided power spectral density $G_n(f)$of thermal noise (white noise) [58] is the same (flat) for all communication frequencies [18] i.e.; equal amount of noise power bandwidth-up to 10^{12} Hz. It can be denoted as

$G_n(f) = \frac{N_0}{2}\ \ W/Hz\ \ for -\infty \leq f < \infty$, where $N_0 = noise\ power\ spectral\ density$

If N_o is uniform, then the noise is known as *white noise* [47]. The Inverse Fourier Transform of the noise power spectral density is equal to the autocorrelation function of white noise [36]. It can be represented as

$$R_n(\tau) = \mathcal{F}^{-1}\{G_n(f)\} = \frac{N_0}{2}\delta(\tau) \qquad [2.38]$$

The average power of white noise is ∞ due to its ∞ bandwidth [57]:

$$P_n = \int_{-\infty}^{\infty} \frac{N_0}{2} df = \infty \qquad [2.39]$$

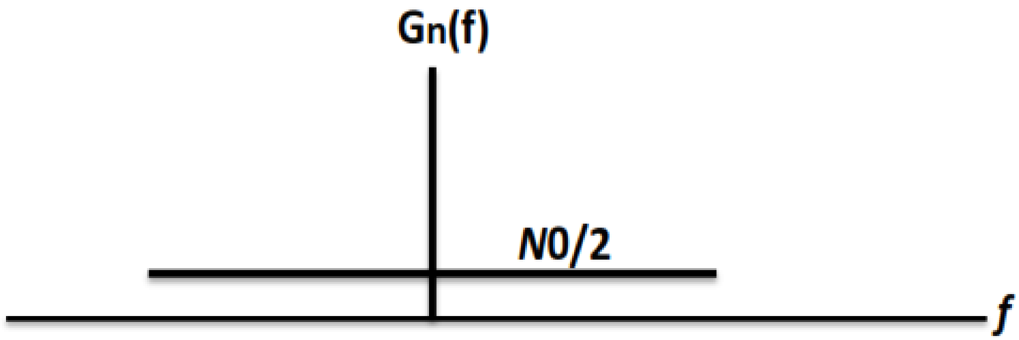


Figure 2.3 Power spectral density of white noise [15]

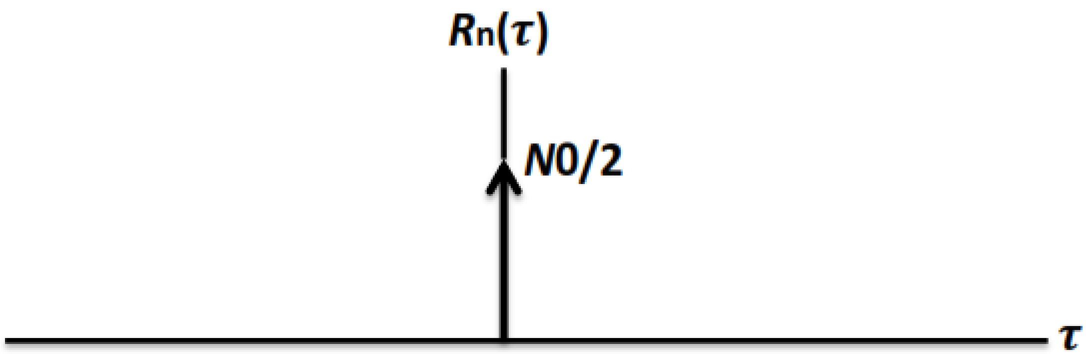


Figure 2.4 Autocorrelation function of white noise [15]

It must be remembered that white noise is decorrelated from the time-shifted version. The above discussed model is also known as additive white Gaussian noise (AWGN). AWGN noise affects each transmitted symbol independently and the noise is superimposed on the signal [59]. In this thesis, AWGN noise buried signals are considered.

References

[1] Klaus Kainrath, "The fundamentals of detection theory"

[2] Steven M. Kay, "Fundamentals of Statistical Signal processing Volume II detection Theory," Prentice Hall PTR, Upper saddle River, NJ 07458

[3] Steven M.Kay, "Fundamentals of Statistical signal Processing Estimation theory," Prentice Hall PTR, Upper saddle River,NJ 07458

[4] Huang Jianhua, Zhou Junan, Liu Yujia Huang Shi Gu, Huang Yijun, Lai Guanlong,"National Science Council subsidies thematic research project Orthogonal frequency division multiplexing wireless communications advanced technology and in extra-wide Frequency system applications" - Subproject 4:

Multi-band Orthogonal Frequency Division Multiplexing Workers ultra-wideband communication interference suppression technology, ”Projectnumber:NSC-96-2219-E-007,-005, Executionperiod:94,August1997,July31,2010

[5] Jian Liang huang,”Adaptive MIMO systems with channel state information at transmitter,” PhD Thesis, stockholm,sweden,2009

[6] Gosan Noh, Jemin Lee, Hano wang, seungJin you, Daesik Hong, “A new spectrum sensing scheme using cyclic prefix for OFDM-Based Cognitive Radio systems,” IEEE Vehicular technology conference, Singapore, VTC spring 2008,11-14 May 2008

[7] Fabio aioli, Alessandro sperduti Fabio, “Multiclass Classification with Multi-prototype Support vector Machines,” Journal of Machine Learning Research 6 (2005), 5th May, Published 5/05,PP.817-850

[8] Todd K. Moon, Wyne C. Stirling,”Mathematical Methods and Algorithms for Signal Processing”

[9] Kwang-Cheng Chen, Peng-yu chen, neeli Prasad,Ying-Changliang, sumei sun, “Trusted Cognitive radio networking, Wireless Communications and Mobile Computing, ”Wireless Communications and Mobile Computing, Volume 10,issue 4,Apri 2010, PP.467-485

[10] Ian reid , Hillary Term, “Estimation 1”

[11] Wei Zhang, Ranjan K.Malik, Hauz Khas, khaled Ben Lataief,“Cooperative spectrum sensing Optimization in Cognitive Radio Networks,” IEEE international conference on Communications,2008,ICC ’08,19-23 May 2008,pp.3411-3415

[12] Ying-Chang Liang, Yonghong Zeng, Peh,E.C.Y, Anh Tuan Hoangsensing -Throughput tradeoff for Cognitive Radio Networks, IEEE transactions on Wireless Communications, April 2008,volume 7, issue:4 pp.1326-1337

[13] Giusepp Avellone, Maristella Frazzetto, Ettore Messina,”On the acquisition ambiguity for Galileo Boc (n, n), Modulated signals,” IEEE International Conference on Communications,2007, ICC’07,24-28 June,pp.4438-4443

[14] Luca Bixio, Marina Ottonello, Mirco Raffetto, and Carlo S. Regazzoni ,”Review Article Comparison among Cognitive Radio Architectures for Spectrum Sensing,” Hindawi Publishing Corporation, EURASIP Journal on Wireless Communications and Networking, Volume 2011, Article ID 749891, PP.18 pages

[15] lancer Hester, Ahmad , D. Riedley, “Cognitive radio networks: Not your father's Wireless network”

[16] Jun Ma; Geoffrey Ye Li, and Biing hwang (FRED) juang ,”Signal Processing in Cognitive Radio, To share frequencies without constantly monitor for the presence of licensed users and to continuously adjust the spectrum of their transmitted signal,” IEEE proceddings,vol.97,No.5,May 2009,pp.805-823

[17] Seung –Hwan Lee and Yong-Hwan Lee, “Hard decision Combining-based Cooperative Spectrum Sensing in Cognitive Radio systems,”

[18] Marvin K.Simon,Mohamed Slim Alouini,Digital Communicationover fading channels A unified approach to performance analysis,A wiley-Interscience publication,John wiley &sons,INC.

[19] J.Baumeister Numerische Methoden der Finanzmathematik,WiSe 2009/10,15 April

[20] Vinayak Dutt,"Statistical Analysis of Ultrasound Echo Envelope," PhD Thesis, Submitted to the Mayo Graduate school

[21] Maja Loncar, Rolf Johannesson,Irina Bocharova, Boris Kudryashov, Estimating the List Size for BEAST-APP Decoding, Proceedings of International Symposium on Information Theory,4-9 September 2005,pp.1126-1130

[22] Abraham,D.A."Efficacy analysis of the power –law detector for non-Rayleigh distributed reverberation in active Sonar systems, "proceedings of IEEE Aerospace Conference, 2001, vol. 4, pp.1739-1748

[23] Dr.daniel C.Bukofzer,"Performance of Delay and Multiply spread Spectrum Receivers Operating in the presence of Modulated digital Signals Interference," International Symposium on Spread Spectrum techniques and applications,24-26 sept.1990,pp.87-95

[24] Arianada D.D, Lakshman,M.K, Nikookar.H, "A Survey on Spectrum sensing techniques for Cognitive radio," Second International Conference on Cognitive radio and advanced spectrum management, CogART 2009

[25] Sergio Verdu , "Multiuser Detection", Cambridge University Press

[26] T. J. Lim, "Optimum Multiuser Detection", Notes for ECE1530S 2002/2003, Part III

[27] S. Ulukus, R. D. Yates, "Optimum Multiuser Detection is Tractable for Synchronous CDMA Systems Using M-Sequences," IEEE Communications Letter, Vol. 2, No. 4, April 1998

[28] Dilip. S Aldar, "Centralized Integrated Spectrum Sensing for Cognitive Radios," International Journal of Computer Science & Communication, Vol. 1, No. 2, July-December 2010, pp. 277-279

[29] Georgios Goudelid, Stefanos zafeiriou,Anastssios Tefas and Ioannis Pitas, "Class-specific Kernel Discriminant Analysis for Face verification," IEEE Transactions on Information Forensics and Security,Vol.2.No.3,September 2007,pp.570-587

[30] Danijela Cabric, Artem Tkachenko and Robert W. Brodersen,"Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection Spectrum"

[31] D.cabric, S.M.Mishra,and R.Brodersen, "Implementation issues in spectrum sensing for cognitive radios".Proc. of the 38th Asilomar Confernce on signals, systems and Computers,Pacific Grove,CA;PP.772-776,Nov.2004

[32] SoYoung Lee, Eun Cheol Kim, Seho Park, Hoi Yoon Jung,Myung Sun Song,Chang-Joo Kim and Jin Young Kim, "Efficient Performance Decision Rule for Spectrum Sensing Performance Improvement in Cognitive Radio

[33] Meng wang,Jie Yang,Guo-Ping Liu,Zhi-Jie Xu and Kuo-Chen Chou, "Weighted Support Vector machines for predicting membrane protein types based on pseudo-amino acid composition," protein Engineering, Design & selection,2004,vol.17,no.6,pp.506-516

[34] Guofeng wang, Zhigao Luo,Xuda Qin, Yonggang Leng, Taiyong wang, “Fault identification and classification of rolling elements bearing based on time varying autoregressive spectrum,” Mechanical Systems and Signal Processing 22 (2008) 934–947

[35] Qinghua Hu, Lei Zhang, Degang Chen, Witold Pedrycz, Daren Yu, “Gaussian Kernel Based Fuzzy Rough sets; Model, Uncertainty Measures and Applications,”

[36] Bernard Sklar “Digital Communications Fundamentals and applications”, 2nd edition .PP171-176,30-33,951-1000

[37] Guofeng wang,Zhigao Luo,Xuda qin,Yonggang Leng,Taiyong wang,“Fault identification and classification of rolling element bearing based on time varying autoregressive spectrum,” Mechanical Systems and signal processing 22(2008),pp.934-947

[38] Alan V.Oppenheim, Ronald W.Schafer and John R.Buck, “Discrete-Time Signal Processing,”2nd edition, published by Pearson Education

[39] Simon Haykin, “Communication systems”, 4th edition pp.90-100,345-361

[40] Christopher A.Weed,Melba M.Crawford,Amy L.Neuenschwander, “Roberto Gutierrez, Classification of LIDAR Data Using a Lower Envelope Follower and Gradient based Operator,” IEEE international symposium Geoscience and Remote science, IGARSS ’02,Volume 3,pp.1384-1386

[41] Vijay K. Grag “Wireless Communications and Networking. Chapter 3 Radio Propagation and Propagation path loss models” October 2007,pp. 47-84

[42] Clarke, R. H. “A Statistical Theory of Mobile Radio Reception.” Bell System Technical Journal,Volume 47*,* July–August 1968: 957–1000

[43] “Coverage prediction for mobile radio systems operating in the 800/900 MHz frequency range,”IEEE Transactions on Vehicular technology, Feb.1988, volume: 37, Issue: 1, pp.3-72

[44] Clark, R.H. “A Statistical theory of Mobile radio Reception,” Bell system Technical, Journal 47, July-August 1968, PP. 957-1000

[45] HanzoL. And Stefanov J. “The pan eropean digital cellular Mobile radio Systems-Known as GSM. Mobile Radio Communications.” R.Steele, Ed., Chapter 8, London: Prentech press 1992

[46] Andreas F. Molish, “Wireless Communication,”2nd edition, Willy, IEEE

[47] Sampei,Seiichi, “Applications of Digital Wireless technologies to Global wireless communications,” Upper Saddle river,NJ: Prentice Hall,1997

[48] Lecours M,Chouinard I Y, Delisle G.Y and Roy J, “Statistical Modeling of the received Signal Envelope in a Mobile radio channel”. IEEE transactions Vehicular technology, Vol.VT-37, 1988, pp.204-212

[49] Bertoni, H.L. “Radio Propagation for modern wireless systems”. Upper saddle river, NJ

[50] K.V.S.Hari, “Channel Models for wireless communication systems,” International series in operation research Management Science, 2011

[51] Chirag S.Patel, “wireless Channel Modeling, Simulations and Estimation,” PhD thesis

[52] Sklar B, “Rayleigh fading Channels in Mobile Digital Communication Systems partI: Characterization.” IEEE Communication Magzine, Vol. 35, no.9, Septémber 1997, pp. 136-146

[53] Weisssberger M.A. “An Initial Critical Summary of Models for Predicting the Attenuations of Radio waves”, ESD-TR-81-101, Electromagnetic compatibility Analysis Center, Annapolis, MD, July 1982

[54] Hata, M. “Empirical formula for Propagation Loss in Land Mobile radio services” .*IEEE transactions vehicular technology*,Vol.29,no.3,1980

[55] Okumura, Y. “Field strength and its Variability in VHF and UHF land Mobile Radio Service” .review Electronic Communication lab 16,no.9-10,1968

[56] Johnson, J.B., “Thermal agitation of electricity in conductors,” Physics. Rev. Vol.32, July 1928, pp.07-109

[57] Papoulis, A., “Probability random Variables and Stochastic Processes,” MCGRAW-Hill Book Company, New York, 1965

[58] William C. Headly, “Classification and parameter Estimation of Asynchronously received PSK/QAM modulated signals in Flat-fading channels,” Master’s thesis, Virginia Polytechnic Institute and State University April 30, 2009

[59] Incorporating Equatorial Environmental conditions in an appropriate Technology, American Society for Engineering Education, 2007

3 Spectrum Sensing Techniques in Cognitive Radios

3.1 Introduction

J.Mitola presented the idea of SDR and Cognitive radio for the solution of spectrum scarcity problem [1, 2, 3, 4, 5 and6] for the solution of spectrum scarcity problem. There are many signal processing operations in the background of the Cognitive Radios [5, 7, 8 and 9]. One of these operations is the spectrum sensing. Signal detection theory is used for the separation and recognition of information from the noise-buried signals. The spectrum sensing (primary user detection in licensed spectrum) is the most important task and fundamental problem in Cognitive Radio based systems and networks. Cognitive Radio based networks have two types of users. One type of the users are known as the primary users and the other are known as the secondary users. The primary users are licensed users and the secondary users are the cognitive users (unlicensed users) [3, 5]. The primary users have the priority of spectrum usage [3, 5]. While the cognitive user have the opportunistic nature of the spectrum usage [3, 5], cognitive users can use the primary user's frequency when the spectrum holes (primary users are not communicating) are available. Various Parametric and Non parametric Spectrum Sensing techniques are used for the spectrum hole detection. In this chapter various techniques are reviewed and discussed. Welch periodogram is a non-parametric, computationally less complex and fast spectrum sensing technique. The energy detection, Autocorrelation Estimator Correlator, Filter bank, MTSVD [3, 8] based spectrum sensing techniques are discussed here. These sensing techniques need a small amount of prior information about the source signal and the propagation channels. The practical challenges in spectrum sensing are the presence of interference noise due to the primary user signals. Welch periodogram works on the basis of Barlett windowing. In this chapter the Welch periodogram is successfully applied for the baseband and passband signal detection for the signals propagating through an AWGN channel in cognitive radio systems and networks. The detector detects the 4 signals successfully up to SNR=-30 dB. The performance of the detector was checked for various SNR values and for various frequencies. With the help of available computational power, the Welch periodogram detector can detect the signals up to 400 MHz. The real-time and low complex spectrum sensing techniques are required. The solution of these challenges is theoretically analyzed on the basis of test statistics and the simulation results are shown in this chapter.

The early work in the detection theory [10, 11, and 12] was done by radar researchers. Peterson, Birdsall, Fox, Wilson P. Tanner, David M. Green, and John A Swets play an important role in the development of the signal detection theory. Spectrum sensing and estimation can be divided into various categories. The spectrum estimation devices are sub-divided on the basis of *classical direct and indirect* spectrum estimation techniques [13]. *Direct spectrum estimation* techniques are basically lying in the category of *frequency domain approach* [13]. In this technique, the power spectrum is directly estimated from the signal [13]. While *indirect spectrum estimation* techniques are in the category of *time domain approach* [13]. The example of indirect method is the spectrum sensing on the basis of cross correlation (autocorrelation) function. The power spectral density can be calculated from the autocorrelation function with the help of Discrete Fourier Transform (DFT).

Spectrum estimation methods are also subdivided into parametric and non-parametric categories [14]. The parametric approach is also known as the model-based approach. The autoregressive (AR) model, moving average model or auto regressive moving average (ARMA) models are the few examples of this approach [8, 15, 16 and 17]. The signal parameters are estimated on the basis of observed signals with the help of derived model. Parametric estimators have the higher degrees of detail [18]. The parametric model based estimators have few drawbacks. In the case of nonsufficient and inaccurately described signals, the results of the estimators are less meaningful and accurate.

The non-parametric methods do not need any assumption about the power, shape and other signal parameters [18]. The non-parametric methods find the power spectrum estimation without any prior knowledge of the respective stochastic approach [18].

There are three main and commonly used spectrum sensing approaches. These approaches are

Energy Detector

Matched Filter

Cycostationary Feature Detection

3.2 Problem Statement

The basic problem in the cognitive radio is to determine whether the channel is vacant or busy. The primary users have the priority of spectrum usage. The secondary users can use the spectrum bands when they are not used by the primary user. The idle frequency bands are known as the spectrum holes. So, the main problem is to decide about the idle or busy state of the channel [10, 19]. For this purpose the Binary Hypothesis mechanism is used [10]. *H1 (alternative hypothesis)* shows the presence of the primary signal and *H0 (null Hypothesis)* shows the empty signal or presence of the spectrum hole [8, 17]. The system model is discussed here for the FFT based (windowing based) energy detection device. In this case

$$H_0 = x[n] = W[n] \qquad n=0, 1, 2,\ldots,N-1 \qquad [3.1]$$

$$H_1 = x[n] = S[n] + W[n] \qquad n=0, 1, 2,\ldots,N-1 \qquad [3.2]$$

S[n]: zero-mean Gaussian process with known covariance

W[n]: white Gaussian noise (WGN) with $\mathcal{N}(0, \sigma^2)$ independent of s[n] [20]

The detection problem is to distinguish between these two hypotheses [44]. In this thesis, various techniques were used to distinguish between the above two hypothesis

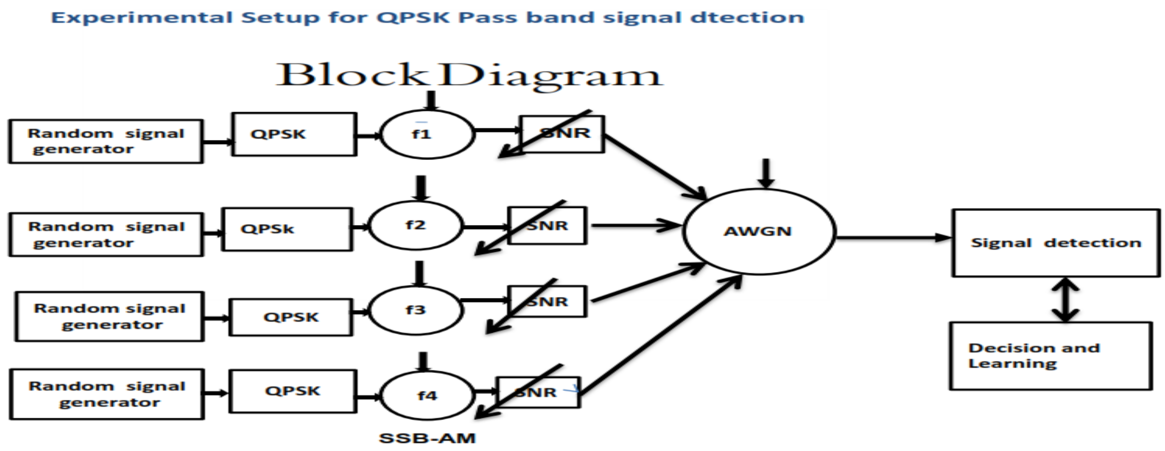


Figure 3.1 Experimental set up for QPSK based signal detection

In this research problem four random signals were generated in MATLAB. The QPSK modulation scheme was applied on the signals. SSB-AM modulation scheme was used to propagate the signals at high carrier frequencies. The signals of different SNR values were propagated through the AWGN channel. At the receiver end, the signals were detected with the help of a detector. In this thesis these signals are detected by Welch periodogram, autocorrelation kernel based Support Vector Machines (SVM) detector and Fuzzy logic based detector. The selection of the best spectrum hole was done by SVM and Fuzzy logic detector. The Welch periodogram detector successfully detects the signals up to 400 MHz down to SNR 0-30dB. The SVM detector successfully detects the signals at low SNR values. The fuzzy logic detector selects the best spectrum hole in time varying environment. The theoretical details, simulation results, advantages and disadvantages of each scheme will be discussed in the remaining chapter

3.2.1 Neyman-Pearson (NP) Theorem

Definition: *the likelihood ratio test (LRT) to maximize the probability of detection* (P_d) *at any given probability of false alarm* (P_{FA}) [10] .H1 is related to the source signal distribution and H_0 relates to the noise distribution [10, 20]. The Neyman Pearson based spectrum sensing detector decides H1 if the likelihood ratio exceeds to the threshold value [10, 20] then

$$L(X) = \frac{P(X;H_1)}{P(X;H_0)} > \gamma \qquad [3.3]$$

will represent the information signals [10, 20]. We must remember that the LRT based detection needs the knowledge about channel and noise distributions. Here received data vector is

$$X=[x\,[0]\ x\,[1],\ldots,x\,[N-1]]^T \quad .$$

In this case Gaussian PDF [10,20] will be

$$P(X;H_1) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}\exp[\frac{-1}{2\sigma^2}(X-S)^T(X-S)] \qquad [3.4]$$

$$P(X;H_0) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}}\exp\left[\frac{-1}{2\sigma^2}X^TX\right] \qquad [3.5]$$

So, the likelihood ratio will be [10, 20]

$$l(X) = lnL(X) = \exp[\frac{-1}{2\sigma^2}[(X-S)^T(X-S) - X^TX]] > \gamma \quad [3.6]$$

It must remembered that the inequality cannot be changed by taking the logarithm due to the monotonically nature of the process [10, 20], so that

$$l(X) = \ln L(X) = \frac{-1}{2\sigma^2}[\frac{-1}{2\sigma^2}(X-S)^T(X-S) - X^TX] > ln\gamma \quad [3.7]$$

After some algebraic operations, the inequality will be [10, 20]

$$\frac{1}{\sigma^2}X^TS - \frac{1}{2\sigma^2}S^T\,S > ln\gamma \quad [3.8]$$

The signal energy is represented by the 2nd term [10, 20], now

$$X^TS > \sigma^2 ln\gamma + \frac{1}{2}S^TS \quad [3.9]$$

In this case, the alternative hypothesis H_1 will be decided with the help of new threshold γ' [20, 21]

$$T(X) = X^TS = \sum_{n=0}^{N-1} X[n]S[n] > \gamma' \quad [3.10]$$

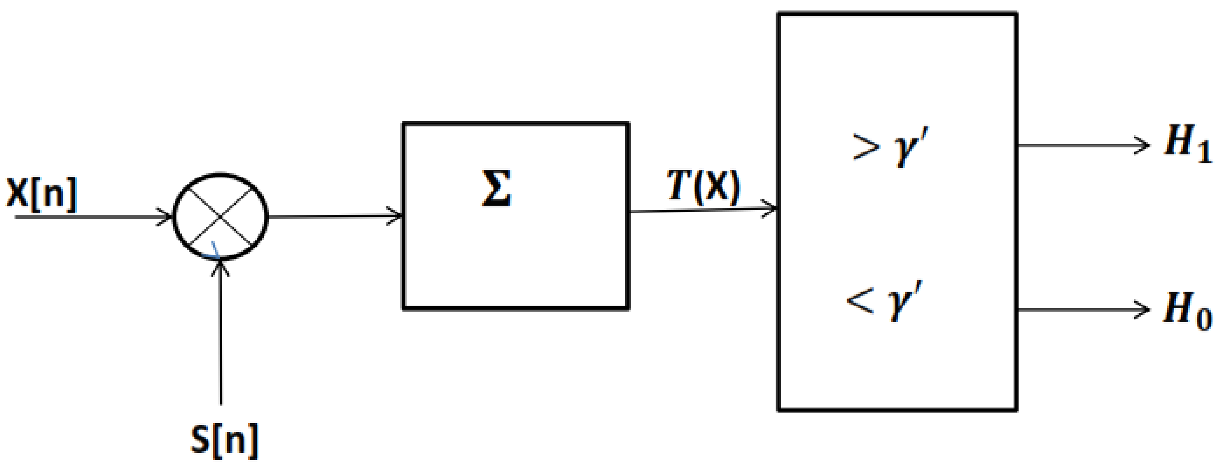


Figure 3.2 Received signal is correlated with replica signal [10]

X^Ts is the projection of X on to S [20]. This is the *Neyman-Pearson* criterion for the deterministic signals. It is known as correlator or replica correlator [10, 20 and 21]. This equation represents the correlation between X[n] and replica of S[n]. T(X) and γ' *are* used to satisfy the desired value of P_{FA} *where* $P_{FA} = \alpha$. The above equation is derived from the linear vector space theory and represents the projection of X on to S [10, 22]. Schwarz inequality shows the higher values for the parallel vectors and has the 0 value for the orthogonal vectors [10, 20]. The estimator-correlator can remove orthogonal signal noise components and the parallel components (information signals) can be observed [20]. We must remember that the LRT based detection needs the knowledge about channel and noise distributions.

3.3 Energy Detector for Random Signals

The Energy Detection based spectrum sensing technique is a non-coherent, non-parametric and suboptimal spectrum sensing (detection) technique [23]. The energy detector is a most common spectrum sensing technique due to its low implementation and computational complexities [10, 20, 24, and 25]. In this technique, the prior information about the signal shape is not required. It is the most generalized, easy to implement technique which can be implemented to any type of signal. In many cases the energy detector is used for the PU detection [21, 26, 27and 28]. The energy detector needs minimum information like signal bandwidth and carrier frequency. In energy detector, the low pass filter is used to remove the out-of-band noise and adjacent interference [10]. The Analog to digital Converter (A/D) is used to convert the analog signals into processable digital signals. In the energy detector, the square law device is used to compute the energy of the signal. Due to non-flexibility, the periodogram detector is used for the detection of narrowband signals and sine waves. The details of the periodogram will be discussed further.

In the case of zero mean, white Gaussian signals in WGN Channel, the energy detector is the NP detector [10, 20]. The problem statement regarding to the random signals are represented by equation 3.1 and eq.3.2

The detection problem is to distinguish between these null and alternative hypotheses [10, 20, 23, 24 and 26]. In this research problem, the energy detector will follow the *Neyman-Pearson criterion*. According to the *Neyman-Pearson (NP*) criterion, the detector can decide that the H_1 hypothesis is satisfied if the likelihood ratio is greater than threshold value γ [10, 20].

$$L(X) = P(X;H_1)/\, P(X;H_0) > \gamma \qquad [3.11]$$

For the signal s[n] as WGN with variance σ^2_s is independent of S [10, 20]. Under any hypothesis, the received data vector X is distributed according to Gaussian PDF [20]. The variance will change when the signal s[n] will be present [20]. So,

$$X \sim \begin{cases} \mathcal{N}(0, \sigma^2 I) \quad under\ H_o \\ \mathcal{N}(0, (\sigma_s + \sigma^2) I) \quad under\ H_1 \end{cases} \qquad [3.12]$$

Where $CS=\sigma^2_s I$ is the covariance matrix [22]. It can be written as [10, 20]

$$P(X;H_1) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp[\frac{-1}{2\sigma^2}(X-S)^T(X-S)] \qquad [3.13]$$

and $$P(X;H_0) = \frac{1}{(2\pi\sigma^2)^{\frac{N}{2}}} \exp\left[\frac{-1}{2\sigma^2} X^T X\right] \qquad [3.14]$$

The decision criterion for the H_0 [20] is $T(X) = X^T X = \sum_{n=0}^{N-1} X^2\,[n] > \gamma'$ [3.15]

The decision criterion for the H_1 [20] is $T(X) = X^T X = \sum_{n=0}^{N-1} X^2\,[n] < \gamma'$ [3.16]

Where T(X) represent the test statistics [20].

When the data is not added then the distribution will become the Chi–square distribution and in case of data addition the distribution becomes the Non-chi-square central distribution [10]. The diagram of the energy detection based sensing device is

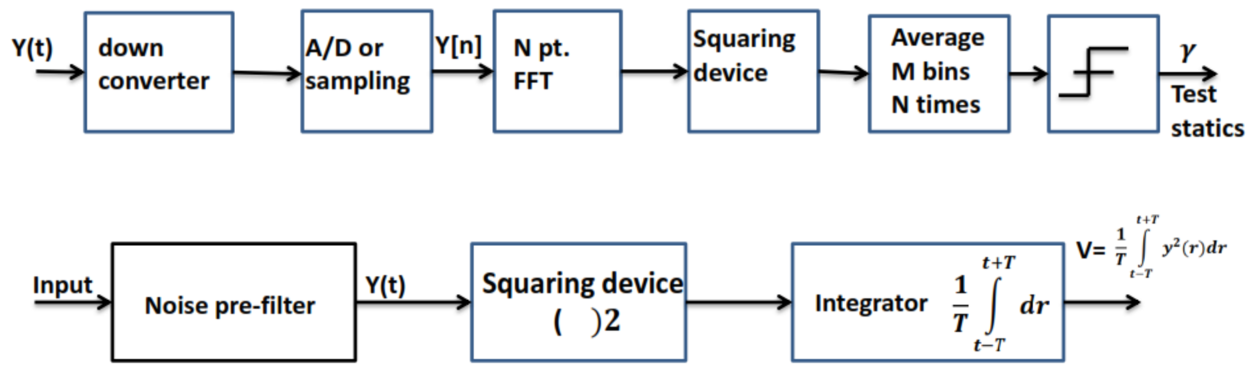


Figure 3.3 Energy detector based spectrum sensing devices [28]

It must remembered that for Rs = σ_s^2 I, the estimator correlator is reduced to energy detector (ED). The energy detector has two degrees of freedom. The frequency resolution can be increased by the increase of FFT size. Increase in frequency resolution improve the detection performance and improve the signal energy estimation, but this increase in the FFT size needs more time for processing [15,21,28]. In the case of fixed FFT size, the energy detector has comparatively low computational complexity [28]. The performance of the energy detector also depends upon the number of samples [29]. If the numbers of samples are not limited, then theoretically the energy detector can meet any required value of P_D and P_{FA}. The minimum number required for any desired value of P_D and P_{FA} is calculated as

$$no\ of\ samples = 2[Q(P_{FA}) - Q^{-1}(P_D)SNR^{-1} - Q^{-1}(PD)]^2 \qquad [3.17]$$

The sensing time scale for the energy detector is $O\left({}^{1}/_{SNR^2}\right)$. The sensing time scale is improved in case of sine wave detection.

Disadvantage

1. The energy detectors need less processing power.

2. The energy based detector cannot detect the signal below $SNR_{wall,}$ where SNR_{wall} is the minimum amount of SNR for detectable signals.

3. The performance of the energy detector suffers from the noise power uncertainties [13, 21 and 28].

4. The energy detector can only determine the presence of the signals. It cannot differentiate between the signal types.

5. The simulation results show that the energy detector performance is poor at SNR <-30dB.

Estimator correlator, periodogram and Welch periodogram are the few examples of energy detectors.

3.3.1 Estimator- Correlator

In case of Gaussian distribution, The LRT becomes the estimator correlator. For the WSS Gaussian random process based signal detection propagating through WGN channels, PSD detectors can be used as approximate estimator-correlator for large data records N. Estimator correlator is the generalized energy detector for the signals with arbitrary covariance matrices C_s.

The problem statement regarding to the random Signals is represented in equation 3.1 and 3.2. The decision criterion for the signal is represented by equation 3.11

For the signal s[n] as WGN with Covariance matrix Cs, the data distribution will be [20]

$$X \sim \begin{cases} \mathcal{N}(0, \sigma^2 I) & under\ H_o \\ \mathcal{N}(0, \mathrm{Cs} + \sigma^2 I) & under\ H_1 \end{cases} \qquad [3.18]$$

After some algebraic manipulations and matrix inversion lemma [20] , the criterion for the occurrence of the H1 will be [20]

$$T(X) = X^T \hat{s} = \sum_{n=0}^{N-1} X[n]s[n] > \gamma'' \qquad [3.19]$$

$$\widehat{where}\ \ s = C_s(C_s + \sigma^2 I)^{-1} X$$

and if the noise signal occurs then we can say that the channel is vacant and the spectrum hole is available. Here $T(X)$ is the test statistics in quadratic form [20]. The diagram for the estimator-correlator is given below

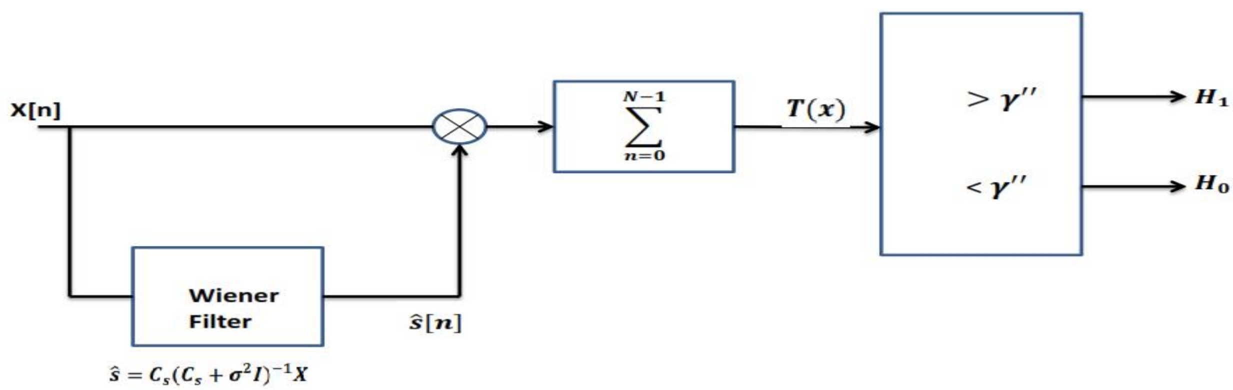


Figure 3.4 Estimator-correlator for the detection of a Gaussian random signal in WGN [10]

The detector is known as the *estimator-correlator* because the detector correlates the received data vector X with the estimated signal $\hat{S}$ [20]. $\hat{S}$ is known as *Wiener filter estimator* of the signal because the estimated signal is produced after filtering through the wiener filter [10,20]. It must remembered that an estimator-correlator detector needs the knowledge about the source signal covariance matrix and the noise power [20, 22] .

3.3.2 Window Function

The window function is used for the spectrum analysis [15]. The window function multiplied by the time waveform reduces the effects of spectral spreading [15, 30]. The FFT is used for the spectrum analysis for the calculation of cyclic extension of the time waveform [15, 30]. The non-cyclic time waveform results in the form of spectral spreading [15]. The window function is reducing these transients [15, 23 and 30]. The power spectrum can be calculated by using the window function [30]

$$P(s) = 20\log_{10}(|FFT(S(t).w(t))|) - 20\log_{10}\left[\tfrac{N}{2}\right] + w_L \quad [3.20]$$

Where $w(t)$ is the window function and $w(L)$ is the window loss function, N is the number of samples in S (t) and P(s) is the power spectrum measured in dB [15, 28 and 30]. The performance of a window function can be determined with the help of side lobe power and the transition function. There is a tradeoff between the side lobe power and the transition width of the window function [15, 30]. The leakage in the window function is measured with the help of *equivalent noise bandwidth (NEB)* [15, 30]. The rectangular window is a simple but non popular window [15, 30]. Non rectangular windows can provide more details about the signals but they have more leakage effect [15]. The quality of windows is explained with a tradeoff between *high resolutions* versus *high dynamic range* windows [15]. The leakage is used to define the metric "*Scalloping Loss*" [15].

3.3.3 Periodogram

Short Time Fourier Transform (STFT) provides the information about the time and frequency [15, 18]. The tradeoff between the speed and accuracy can be compromised by changing the dimension of the window [15, 18]. If the window used is of small size then the estimation needs less time. It also results in the form of larger main lobes of the window kernel [15, 18]. This larger window kernel will result in poor frequency resolution. If the window size will be increased then for sample collection more time will be required which results in better frequency resolution. The STFT suggests the same window size for all sample collection. The STFT of a signal X[n] is defined as [15]

$$X[n,\lambda] = \sum_{-\infty}^{\infty} x[n+m]W[m]e^{-j\lambda m} \quad [3.21]$$

Where $W[m]$ is window sequence. In this case a one dimensional sequence $x[n]$ is converted into two-dimensional function of discrete time variable n and continuous frequency variable λ. STFT is periodic with period 2π. Equation 3.22 can be consider as DTFT of the shifted signal $x[n+m]$[15].

The STFT is the key concept behind the periodogram spectrum sensing. The periodogram is used for the estimation of the power spectral density of a signal [15]. It is the energy based spectrum sensing method. The idea of the periodogram was proposed by Arthur Schuster in 1898 [7]. Periodogram based spectrum sensing is a non-parametric spectrum sensing approach. The periodogram based spectrum estimation is considered as the output of several filters banks where each point in the power spectrum estimation is considered as the output of the respective filter. Practically, the periodogram is computed with the help of FFT from a finite length digital sequence. The use of a raw periodogram is not a good technique for spectral estimation [15, 31]. The problems in raw periodogram are spectral bias and the variance at the desired frequency. Sharp truncation of the sequence is the basic reason of spectral bias. The bias problem can be reduced with the help of multiplication of the finite data sequence with some window function. The multiplication of the window function truncates the sequence gradually. Normally the rectangular window is used which results in the form of Dirichlet Kernel. The Dirchhlit Kernel is explained by the size of the side lobes and the width of the main lobe [18]. The width of the main lobe depends upon the frequency resolution of the power spectra [18]. The size of the side lobes [18] depends upon the ratio between minimum and maximum spectral power [18]. The rectangular window based spectrum estimators face the problem of leakage. The periodogram based estimators are biased estimators. The time and frequency resolution is not achievable simultaneously. So, the tradeoff between speed (time resolution) and accuracy (frequency resolution) is achievable [18]. The periodogram or STFT cannot be tuned into time frequency varying radio environment. They compromise on the frequency resolution [15]. The variance problem can be reduced by smoothing the periodogram [15]. The first step in implementation of a periodogram is the calculation of the FFT of the signal [15]. Then the squaring takes place and the last step is the division by the number of samples N.

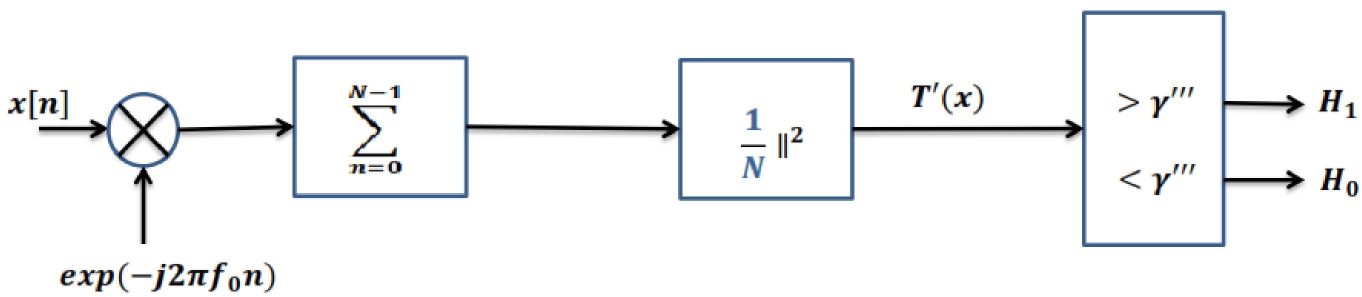


Figure 3.5 Periodogram detector [20]

3.3.4 The Barlett Window

The Barlett window is used for the improvement of the performance of the periodogram method. Barlett window [15, 32 and 33] is an energy based spectrum sensing method. In this method, averaging process can reduce the power variance [15, 18 and 33]. For the averaging process, the samples are divided into several segments and the average of the each segment takes place [15, 18 and 33]. By the increase of the number of the segments, the variance is decreased and vice versa [15, 33 and 34]. The decrease in the number of samples in each segment results in the form of larger bias and less frequency resolution [15, 33 and 34]. Barlett's method is one of the window function based smoothing mechanism [8, 15]. It is used for smoothing the discontinuities at the beginning and at the end of the tapering function [8, 15]. The Barlett's method based Periodogram consist on the following steps [15, 33]

1. The N point data segment is split up into K data points. The length of each data point is M.

2. The periodogram for each segment is computed with the help of DFT (not divided by M). The result of the periodogram is squared and divided by M.

3. Take the average of K data segments.

The Bartlett window is defined as [15, 33]

$$\omega(n) = \frac{2}{M}\left(\frac{M-1}{2} - \left|n - \frac{M-1}{2}\right|\right) \qquad [\ 3.22]$$

The Barlett method was improved by the *Welch periodogram* method [34]. The Welch-periodogram method uses the overlapping window. The Welch periodogram is an energy based spectrum estimation method .It is a spectral density estimation approach. The power of a signal at different frequencies can be estimated by Welch periodogram method [15, 34]. In this technique, the segment overlap takes place. The arbitrary window is applied on the data segments which improve the spectrum estimation performance. The presence of the signal is shown by the lobes. In this method, the signal is transformed from time domainto frequency domain [15, 34]. Fourier transform (FFT) is used to estimate the power spectrum [15, 34]. The Welch periodogram reduces the noise in the estimated power spectra [7, 15 and 34]

The procedure of the Welch periodogram method is written below

1. The data is split into L data segments and the length of each data segments is M. The signal is split into overlapping segments [20]. The overlapping is defined by the factor D [15, 34].If D=M/2, the overlap will be 50% and if D=0, the overlap will be 0% [15, 34]. This situation happened in Barlett's method [33].
2. The individual L data segments are windowed. The windowing makes the Welch periodogram an improved periodogram method [15, 34]. The periodogram is calculated by DFT and then its square magnitude is computed. In the end, the individual periodograms are averaged. The end result is shown by frequency bins versus PSD graph. The performance of the detector can be shown by the ROC curve [10]. In this thesis, the spectrum sensing of base-band and pass-band signals on AWGN channel with the help of the Welch periodogram detector was done. The periodogram detected the signals up to -30 dB well. At SNR<-30dB, the signal detection is not possible with the help of this technique. This technique performed well and was effective with respect to time efficiency and flexibility of spectrum sensing. The Welch periodogram detector was slowed down for wide band signal detection at 40 MHz and the processing time is increased.

3.4 Matched Filter

Matched filtering is a generic spectrum sensing technique [26]. A Matched filter technique is used for pilot detection [15, 18]. In this technique the SNR is maximized. The secondary user must have full prior knowledge about the signal characteristics [35, 36] e.g.; order, modulation type, packet format, pulse shaping [37] pilot, preamble, synchronization words, training sequence and spreading codes etc. For example analog TV signals have narrow band pilots for the audio, video carriers [38]. CDMA schemes have pilot channels and paging channels and the OFDM based systems [38] have fixed preamble for the packet acquisition. The information about the pilot signal is used for the timing, carrier synchronization and channel equalization operations are done for coherent detection. Matched filter is an optimum and coherent spectrum sensing techniques. So, it is computationally less complex. For desired probability of detection O(1/SNR) samples are required at lower SNR. In a Matched filter less time is required for detection. Matched filter based detection faces a disadvantage that for each primary wave different receivers are required. For the same modulation technique and different frequencies, filter banks can be used. It must be remembered that LRT becomes a matched filtering detector in case of Gaussian distribution based noise and deterministic source signals**.** In short, pilot detector is an optimal detector with minimum time for detection but it needs the perfect synchronization**.** In case of lack of information about the pulse, the detector based on matched filtering can be used as an optimal detector [39, 40].

3.5 Correlogram

Correlogram is a well-known approach for the spectrum estimation. In this approach the autocorrelation function is determined [18]. The power spectral density can be calculated from the Fourier transform (FT) of this autocorrelation function [15, 18]. The value of the PSD depends upon the exact value of the autocorrelation function Rxx(k). The Fourier transform of the autocorrelation function is equal to the PSD of the signal [15,35]. The length is considered as infinitely long for the measurement of the autocorrelation. The performance of the correlogram technique can be improved by using the rectangular window. The Improved version of the *correlogram* is the *Blackman-Tukey* method [15]. In this method, the estimated autocorrelation value is calculated and then the suitable window function w(k) is applied [15, 18]. Then the Fourier transform is applied which results in the PSD [15, 18]. The *Blackman–Tukey* method can be considered as *smoothing periodogram* method [15, 18]. In this method the periodogram is convolved with the selected window kernel.

3.5.1 Cyclostationary Feature Detection

Normally, the transmitted data is taken as a stationary random process [10, 15 and 18]. Transmitted data is modulated on sinusoidal carrier wave [15, 41 and 42]. The cyclic prefix is introduced (in case of OFDM) and code or hoping sequence (in case of CDMA) [18]. All of these additions introduce the built-in periodicity. This builtin periodicity introduces cyclostationarity features [15, 56]. These spectral correlation features help in signal detection and correlation [43, 44 and 56]. The built-in periodicity helps the non-coherent detection of the signals. The periodicity is generated intentionally in order to estimate the parameters like pulse timing, direction of arrival and carrier phase. The random noise mixed in signals can be detected on the basis of these periodic parameters [57]. The random signals can be detected on the basis of autocorrelation and power spectral density [45, 57]. The correlation function is also known as cyclic spectrum function [15, 35 and 46, 56]. The spectrum correlation function is a two dimensional transform. If cyclic frequency =0 then PSD can act as spectral correlation 52[58]. Cyclic autocorrelation function (CAF) and spectral correlation function (SCF) are two key functions are typically utilized for the cyclostationary feature analysis [4, 15,35,41,46 and 47, 58]. CAF is used in time domain analysis and it can be expressed as [15, 35, 41, 46 and 47]

$$R_x{}^{\alpha} = \lim_{T\to\infty} \frac{1}{T}\int_{\frac{-T}{2}}^{\frac{T}{2}} x(t+\tfrac{\tau}{2})x(t-\tfrac{\tau}{2})e^{-j2\pi\alpha t}dt \qquad [3.23\ ]$$

The spectral correlation function is obtained from the Fourier transform of CAF. The SCF can be written mathematically as [15, 35 and 46]

$$S_x{}^{\alpha}(f) = \int_{-\infty}^{+\infty} R_x{}^{\alpha} e^{-j2\pi\alpha t} d\tau = \int_{-\infty}^{+\infty} \lim_{T\to\infty} \frac{1}{T} \int_{\frac{-T}{2}}^{\frac{T}{2}} x(t+\frac{\tau}{2}) x(t-\frac{\tau}{2}) e^{-j2\pi\alpha t} e^{-j2\pi f\tau} \mathrm{dt}$$

$$= \lim_{T\to+\infty} S_{xT}{}^{\alpha}(t,f) \qquad [3.24]$$

Where α represents the cycle frequency [28], f is known as the spectral frequency [15, 35 and 46] and $S_{xT}{}^{\alpha}(t,f)$ is known as the cyclic periodogram of $S_x{}^{\alpha}(f)$ [4] where

$$S_{xT}{}^{\alpha}(t,f) = [X_T\left(t, f+\frac{\alpha}{2}\right). X^*{}_T(t, f-\frac{\alpha}{2}]/T \qquad [3.25]$$

The spectral coherence coefficient (SCC) is the correlation coefficient of the spectral correlation function (SCF) between frequency components $f \pm \alpha/2$. The SCC values are in a range from 0 to 1 when α=0. The value of SCC can be calculated as [4, 5]

$$C_x{}^{\alpha}(f) = \frac{S_x{}^{\alpha}(f)}{\sqrt{S_x{}^{0}(f+\alpha/2).S_x{}^{0}(f-\alpha/2)}} \qquad [3.26]$$

3.5.1.1 Signal Feature Extraction

The spectral correlation function is estimated from a finite number of samples [15, 35, 43 and 46]. Time domain averaging and frequency domain smoothing which are used for the estimation of spectral coefficients [15, 35, 43 and 46]. Spectral correlation estimation can be expressed as [4, 5]

$$S^{\alpha}(f)_{\Delta f} = \frac{1}{M} \sum_{n=\frac{M-1}{2}}^{n=\frac{M+1}{2}} \frac{1}{\Delta t} X_{\Delta t}\left(t, f+\frac{\alpha}{2}+nF_s\right). X^*{}_{\Delta t}\left(t, f-\frac{\alpha}{2}+nF_s\right) \qquad [\,3.27]$$

Where the frequency increment is represented by $F_s = \frac{1}{(N-1)T_s}$ and the cyclic sampling interval is represented T_s and $N = \frac{\Delta t}{T_s}$ represents the sample length. Remember that $\Delta f = M.F_s$ is the width of the data tapering window $W_{\Delta t}(kT_s)$.In this case the value of [3]

$$X_{\Delta t}(t,f) = \sum_{k=0}^{N-1} W_{\Delta t}(kT_s). X(t-kT_s) e^{-j2\pi f(t-kT_s)} \qquad [3.28]$$

The spectral correlation magnitude surface for different types of signals can be calculated from SCF [15, 35, 43 and 46]. The features *f* and *energy* can be calculated from equations 3.25, 3.26, 3.27 and 3.28.

Different modulated signals (e.g., BPSK, QPSK and QAM) have identical PSD function but have different spectral characteristics. The correlation based spectrum can be used for the spectrum sensing at lower SNR levels. The Fourier transform of the autocorrelation function [21,27,49,66] is equal to the power spectral density [15,35,46 and 48]. In DGPS devices, the location is calculated on the basis of the autocorrelation function based spectrum estimation.

As the noise signal has no correlation with WSS signal, while the modulated signals exhibits the spectral correlation due to signal periodicity. So, SCF can differentiate between the noise signal and modulated signals.

In this thesis the autocorrelation features are used for the signal detection. Autocorrelation kernel function was used in support vector machines based signal detector.

3.6 Other Spectrum Sensing Approaches

There are few other important spectrum sensing approaches such as Multi Taper Spectrum Estimation (MTSE) and Filter Bank Spectrum Estimation (FBSE) [15, 18 and 49]. MTSE performs better for small sample spaces [4, 13] and small number of samples. This technique is not useful for large sample sizes due to increasing computational complexities [4, 13]. FBSE has slower speed of execution in case of big window size. The FBSE is computationally less complex as compared to MTSE technique.

3.6.1 Wavelet Based Detection

This technique is commonly used for edge detection in the field of image processing. Wavelet based spectrum sensing technique for the dynamic spectrum access was first proposed by Tian and G.B.Giannakis [54]. They proposed edge detection in case of wideband channels for the spectrum sensing by measuring the PSD. The edges determine the boundary occupied bands and spectrum holes, which can be used for the detection of spectrum holes [49]. Wavelet based spectrum sensing technique has the excellent time frequency localization properties [16]. The time frequency localization property is used as a powerful tool for the analysis of the spectral structure and the identification of singularities and edges. In this technique, the wide frequency band is decomposed into elementary non-overlapping blocks of sub bands [18]. In each sub-band the power characteristics are smooth. There are discontinuities in the adjacent sub-bands. These local frequency irregularities characterize the sub bands [18]. These singularities and irregular structures can be analyzed by wavelet detection technique [18]. It can be used for the characterization of the edge of the signals and local regularity [55]. Intensities and location of the spectrum holes can be determined with the help of irregularities in the PSD [18]. The wavelet is convolved with the power spectrum density [16, 54 and 55]. The frequency boundaries are found by the 1st and 2nd order derivatives of convolution.

3.7 Simulation Results

3.7.1 Base Band Signal Detection by Welch Periodogram Detector

In the context of this work, signal detection is a binary problem. The Welch periodogram is an efficient, computationally less complex method for the signal detection. In this thesis, QPSK based base-band and pass-band signal detection is done. Four transmitters are detected in a centralized environment (as shown in Fig 3.1). Due to limited available computational power, the signals up to 400MHz are detected. The simulation results show that welch periodogram detector can detect the base-band signals up to SNR=-20dB. The baseband signals are communicated with the help of QPSK modulation technique. The simulation results at different SNR values are given below. In these simulation results power spectral density is shown along Y-axis. In MATLAB, spectrum.welch function calculate the PSD and represent it along y-axis in the form of power/frequency [dB/Hz].It must remember that the performance of the detector is dependent on the processing machines.

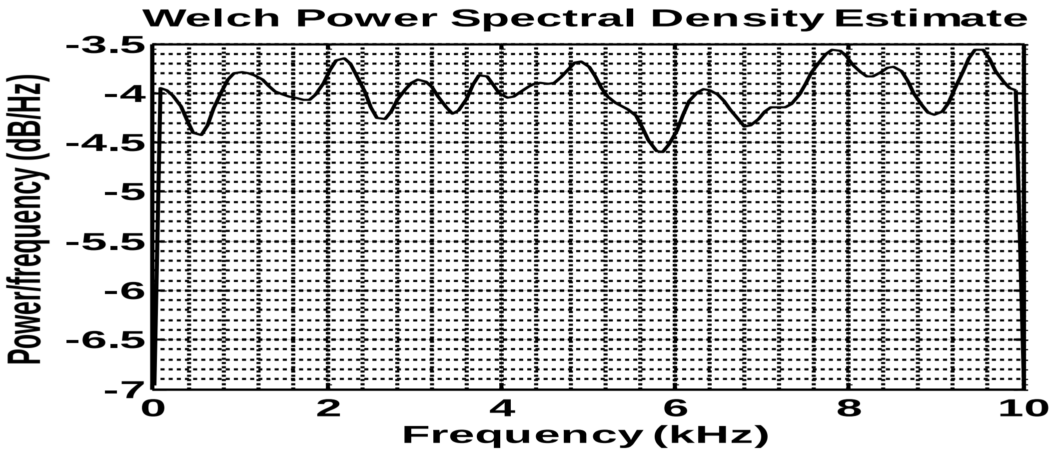


Figure 3.6 2, 3, 4 and 5 kHz baseband signals at -30 dB by Welch periodogram detector

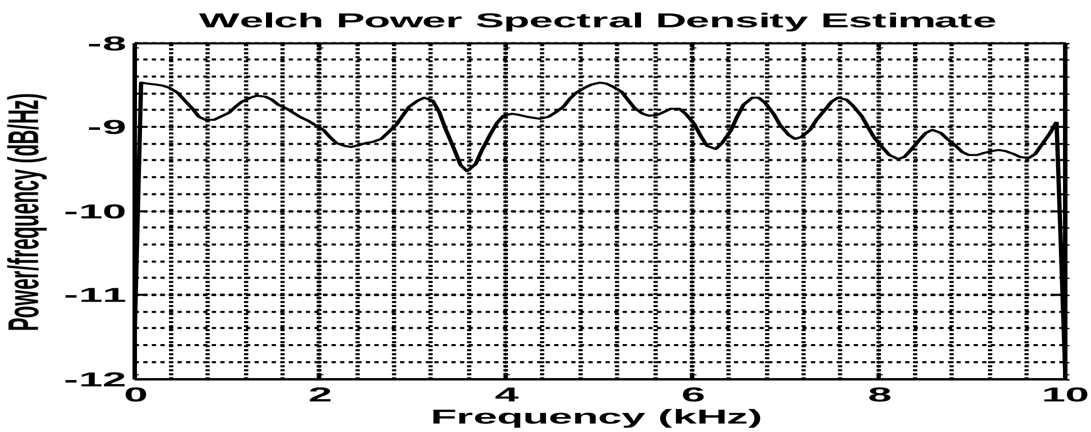


Figure 3.7 2, 3, 4 and 5 KHz baseband signals at -25 dB by Welch periodogram detector

The above simulation results shows that the baseband signal or signals cannot be detect at the SNR ≤-25 dB.

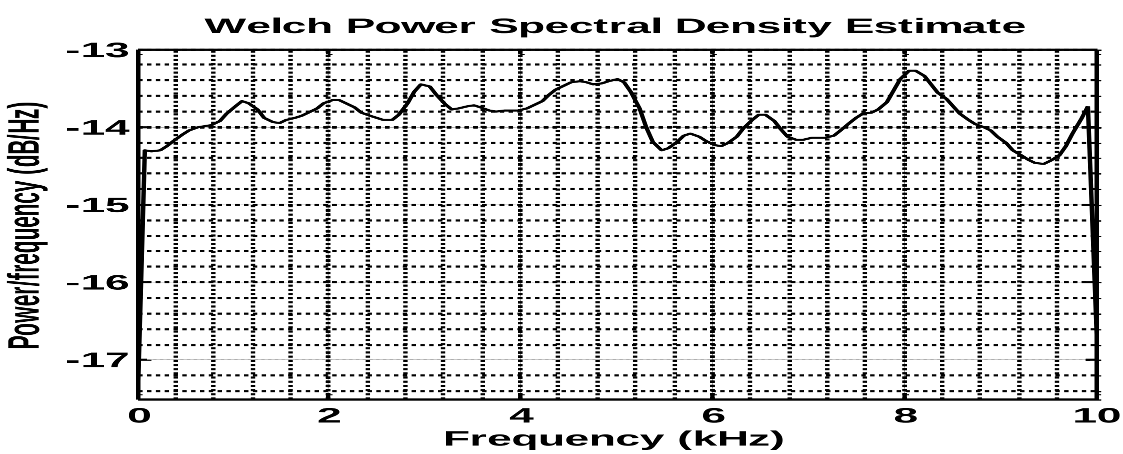


Figure 3.8 2, 3, 4 and 5 kHz baseband signals at -20 dB by Welch periodogram detector

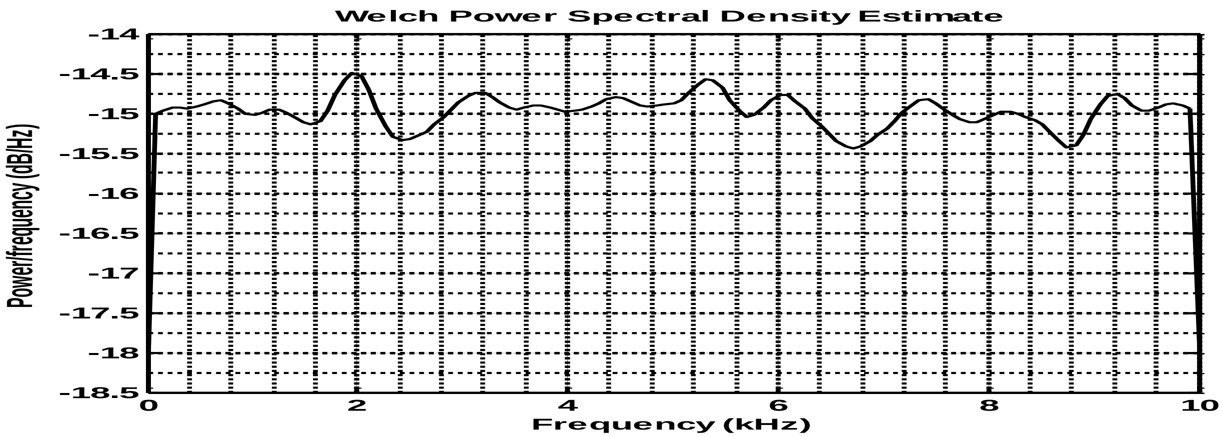


Figure 3.9 2 kHz baseband signals at -20 dB by Welch periodogram detector

The above simulation results show that the signal detection is not clear for four signals at SNR≤-20 dB. It must be remembered that the performance of the Welch periodogram detector is improved for single or two signals at SNR=-20dB. Especially the detection is clear and significant for the single baseband signal at -20 dB

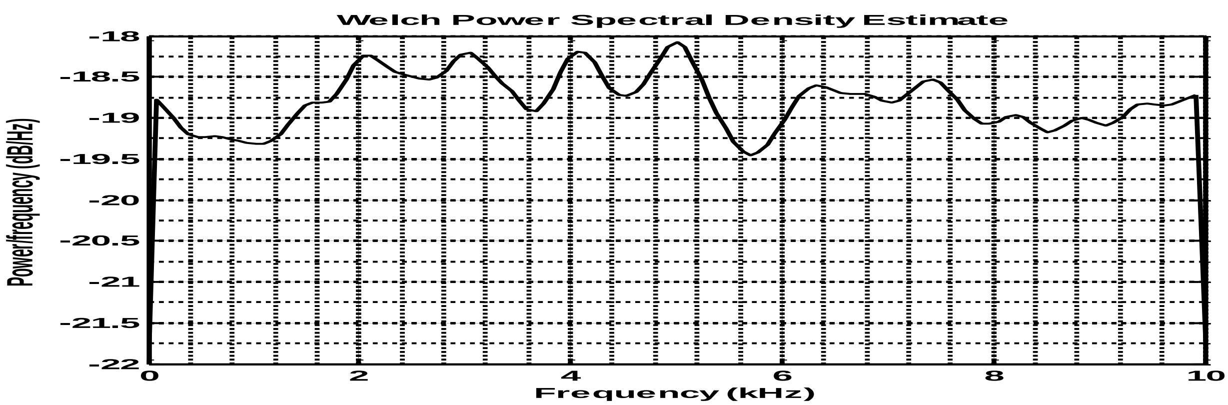


Figure 3.10 2, 3, 4 and 5 kHz baseband signals at -15 dB by Welch periodogram detector

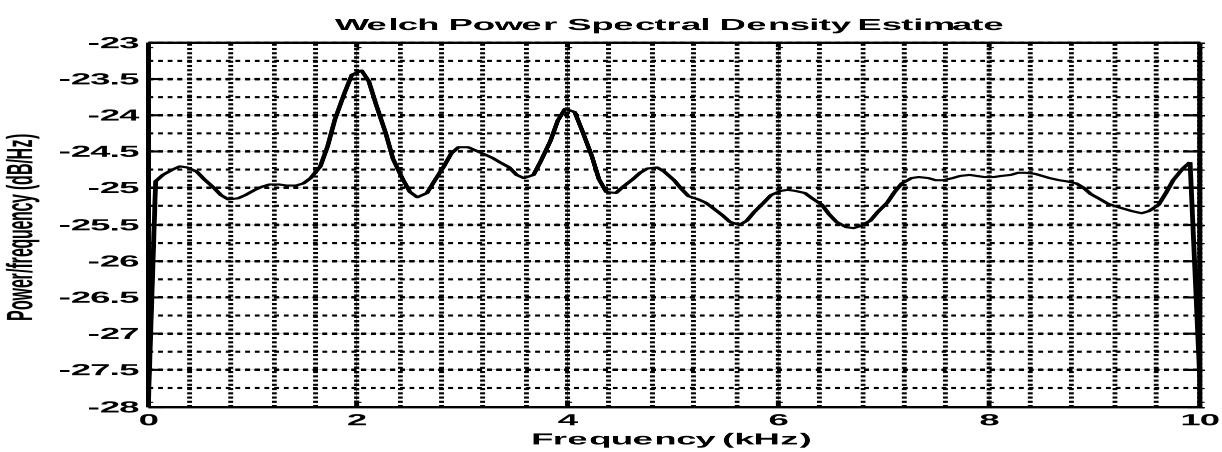


Figure 3.11 2, 4 kHz baseband signals at -15 dB by Welch periodogram detector

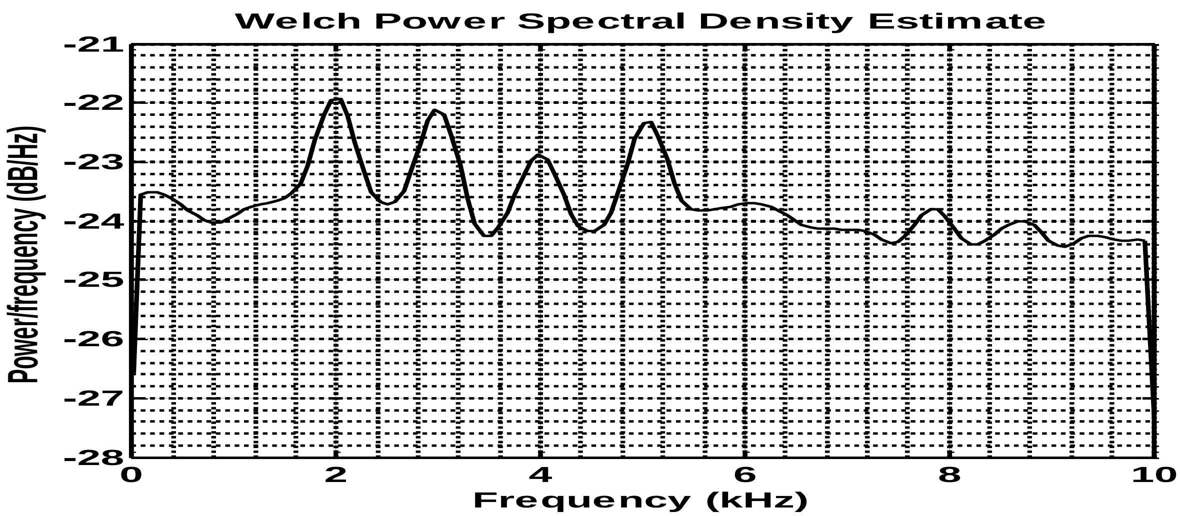


Figure 3.12 2, 3, 4 and 5 kHz baseband signals at -10 dB by Welch periodogram detector

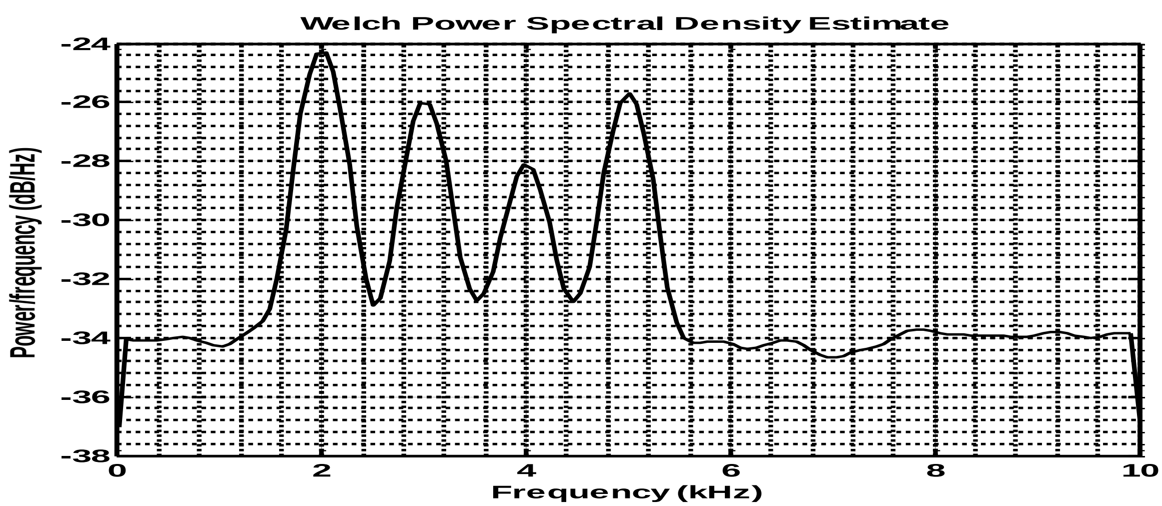


Figure 3.13 2, 3, 4 and 5 kHz baseband signals at 0 dB by Welch periodogram detector

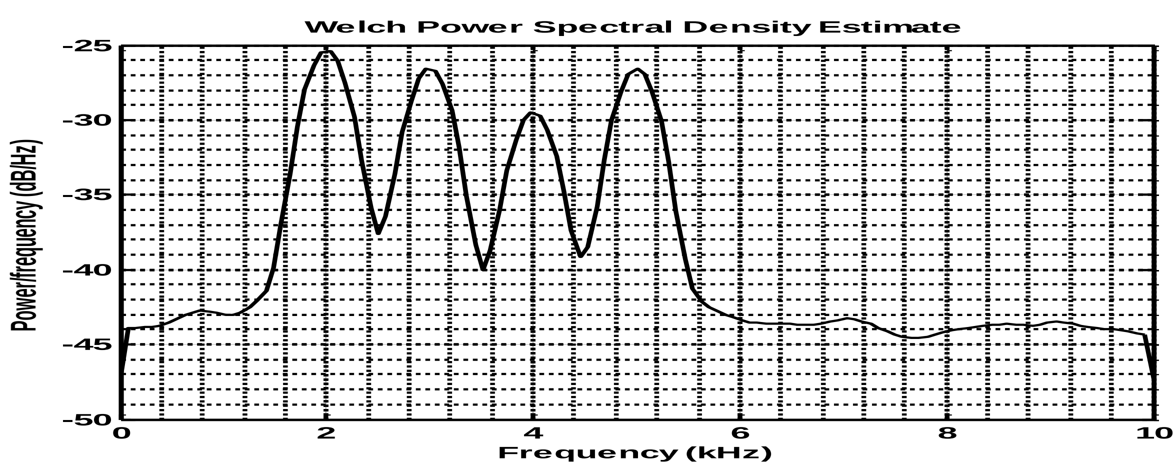


Figure 3.14   2, 3, 4 and 5 kHz baseband signals at 10 dB by Welch periodogram detector

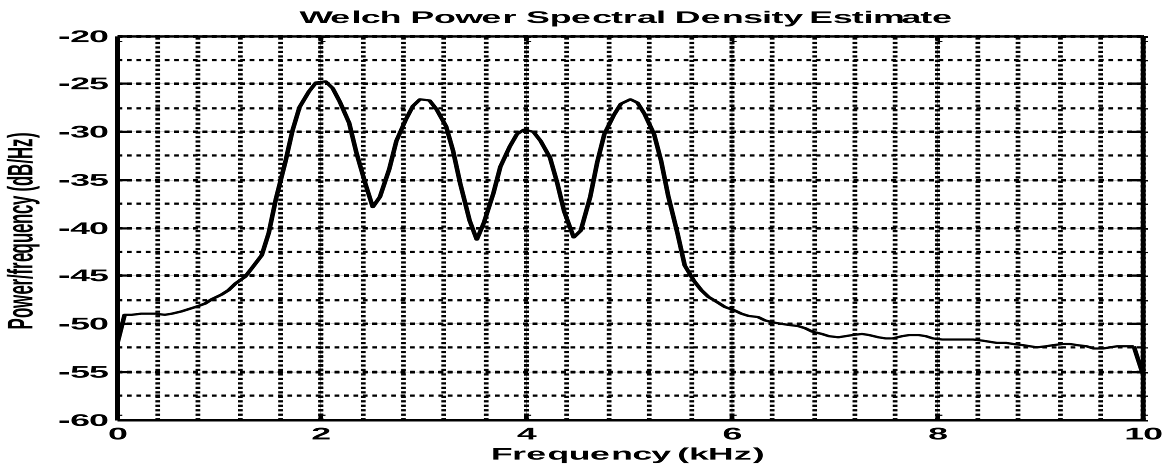


Figure 3.15 2, 3, 4 and 5 kHz baseband signals at 20 dB by Welch periodogram detector

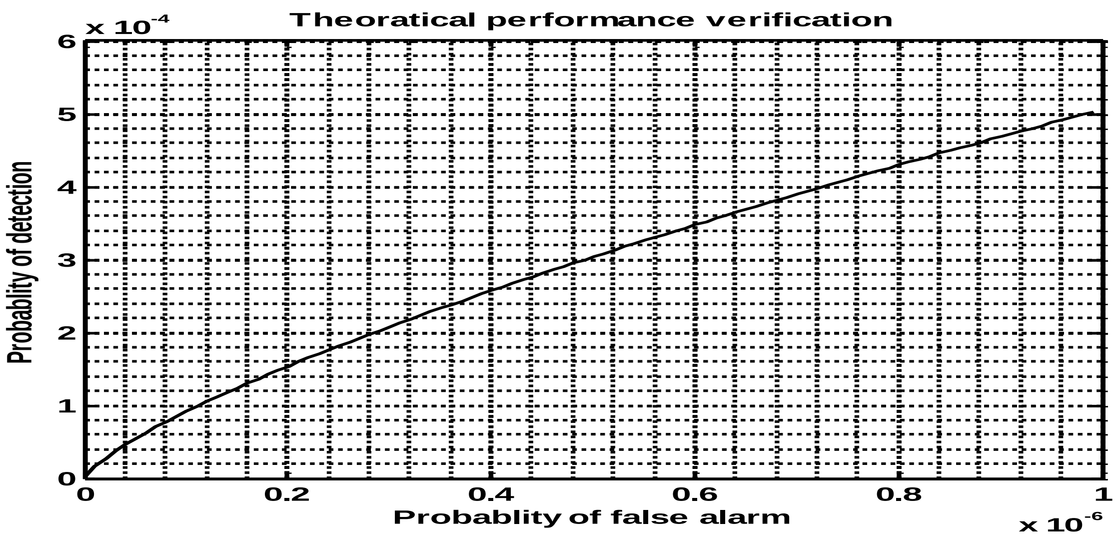


Figure 3.16 ROC curve for 2, 3, 4 and 5 kHz AWGN base-band baseband signals by welch periodogram detector

The above simulation results show that the Welch periodogram detector cannot detect the signals at SNR<-20dB. Even at -15dB the signals are not so much clear but at least they can be identified. For the SNR>-20dB, say at -15dB and above values, the signals can be detected correctly. The above simulation results show that the detector performance is improved for the single detector as compared to its performance for the detection of more than one transmitter. The detector is very simple, computationally less complex and fast and can detect the signal in a short interval of time. The deficiency of the signal detector is its poor performance at the lower SNR values.

3.7.2 Simulation Results for Pass-band Signal Detection by Welch Periodogram Detector

In this thesis the four transmitters are detected in a centralized way. Due to limited computational power, the signals are measured only up to 400 MHz frequency. If the heavy computational power is available, then this technique can be applied for the detection of the signals up to GHz frequency range.

The simulation results show that the detector performance is good up to -25dB. Below this SNR value, detector cannot detect the signal. Few important simulation results are shown and discussed below.

3.7.2.1 Simulation Results for 1.6, 1.7, 1.8 and 1.9 MHz AWGN Pass Band Signals by Welch Periodogram Detector

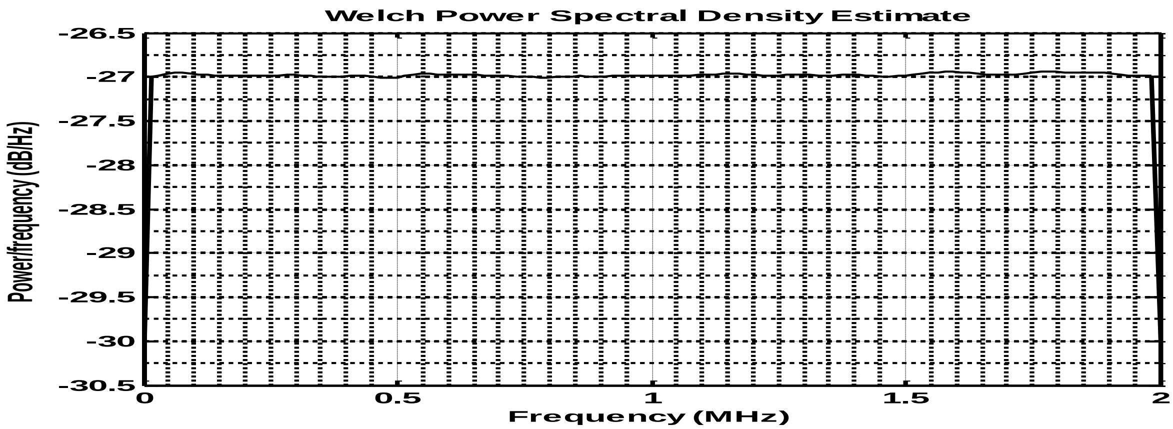


Figure 3.17 1.6, 1.7, 1.8 and 1.9 MHz AWGN pass-band signals at -30 dB by Welch periodogram detector

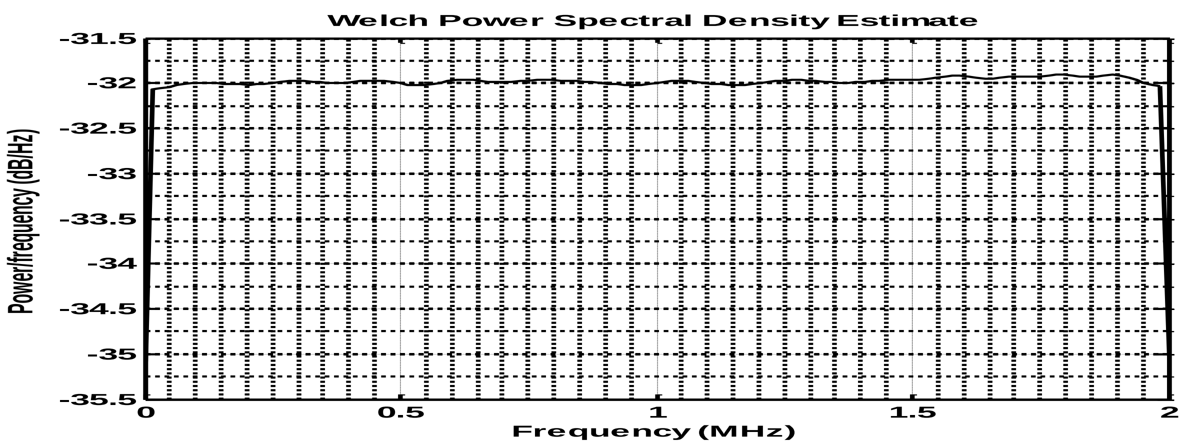


Figure 3.18 1.6, 1.7, 1.8 and 1.9 MHz AWGN pass-band signals at -25dB by Welch periodogram detector

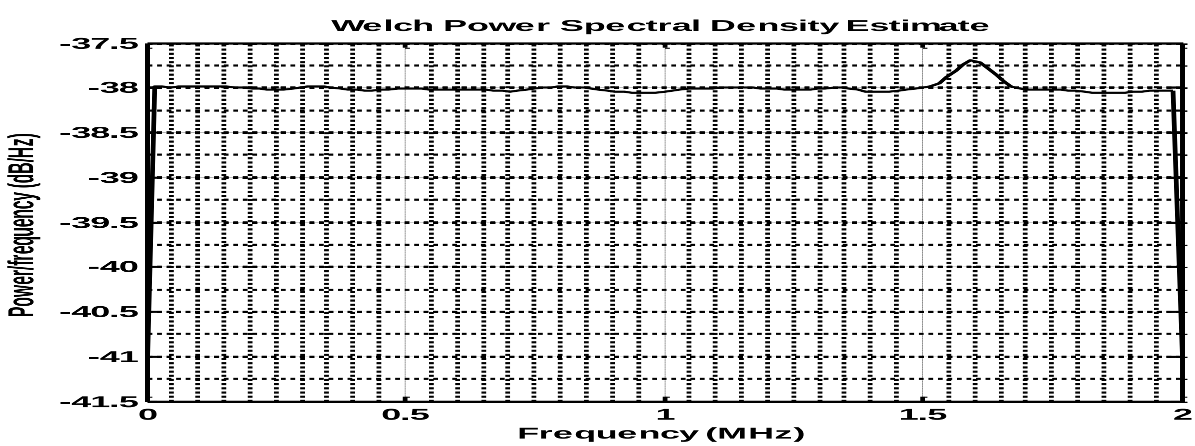


Figure 3.19 1.6 MHz AWGN pass-band signal at -25 dB by Welch periodogram detector

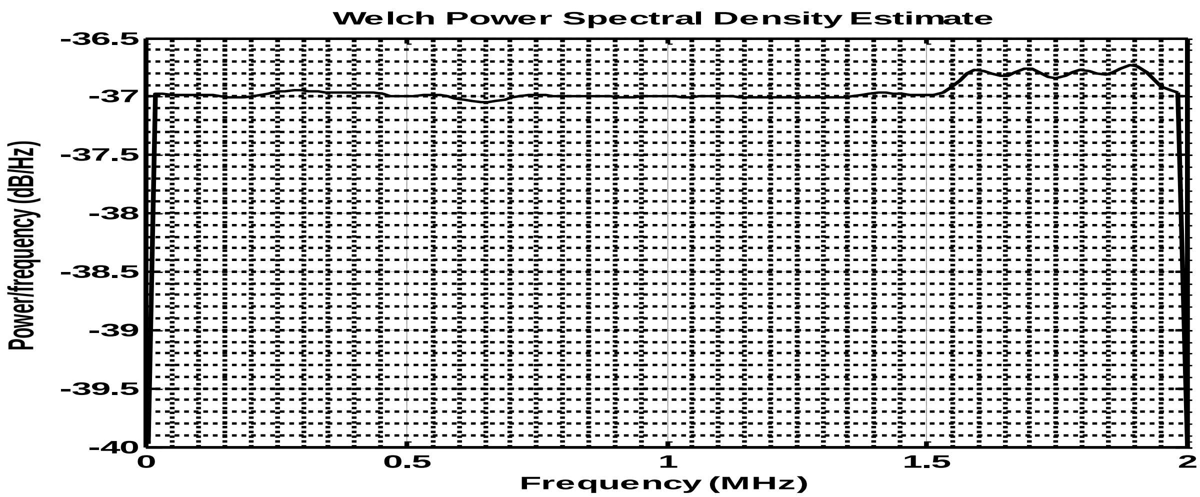


Figure 3.20 1.6, 1.7, 1.8 and 1.9 MHz pass-band signals at -20 dB by Welch periodogram detector

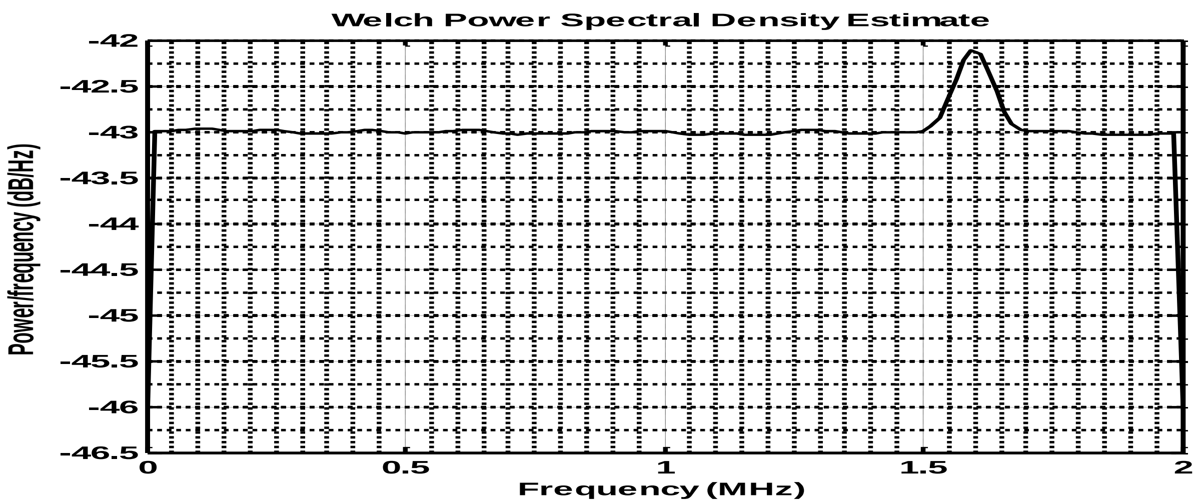


Figure 3.21 1.6 MHz AWGN pass-band signal at -20 dB by Welch periodogram detector

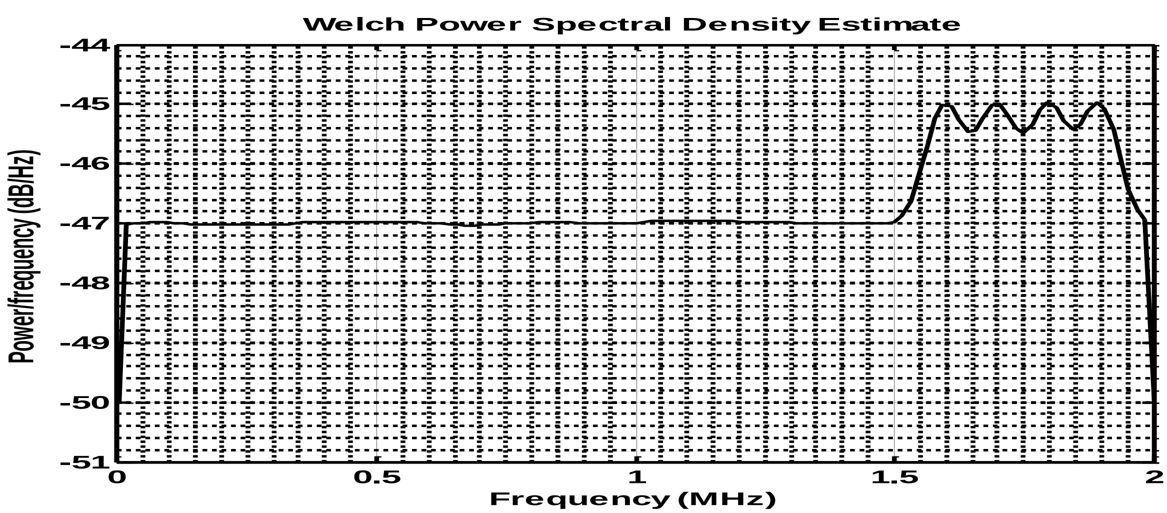


Figure 3.22 1.6, 1.7, 1.8 and 1.9 MHz AWGN pass-band signals at -10 dB by Welch periodogram detector

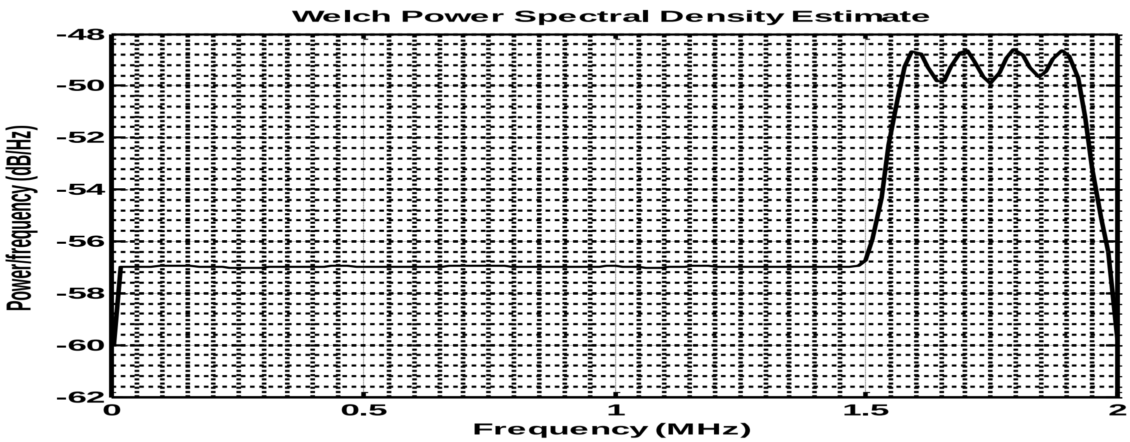


Figure 3.23 1.6, 1.7, 1.8 and 1.9 MHz AWGN pass-band signals at 0 dB by Welch periodogram detector

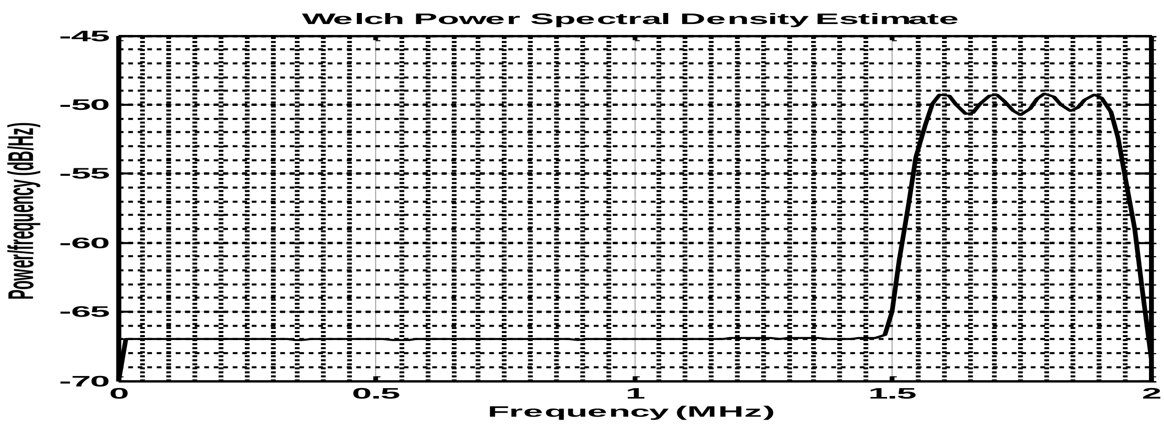


Figure 3.24 1.6, 1.7, 1.8 and 1.9 MHz AWGN pass-band signals at 10 dB by Welch periodogram detector

3.7.3 Simulation results for 100,200,300 and 400 MHz AWGN Pass-Band Signals by Welch periodogram Detector

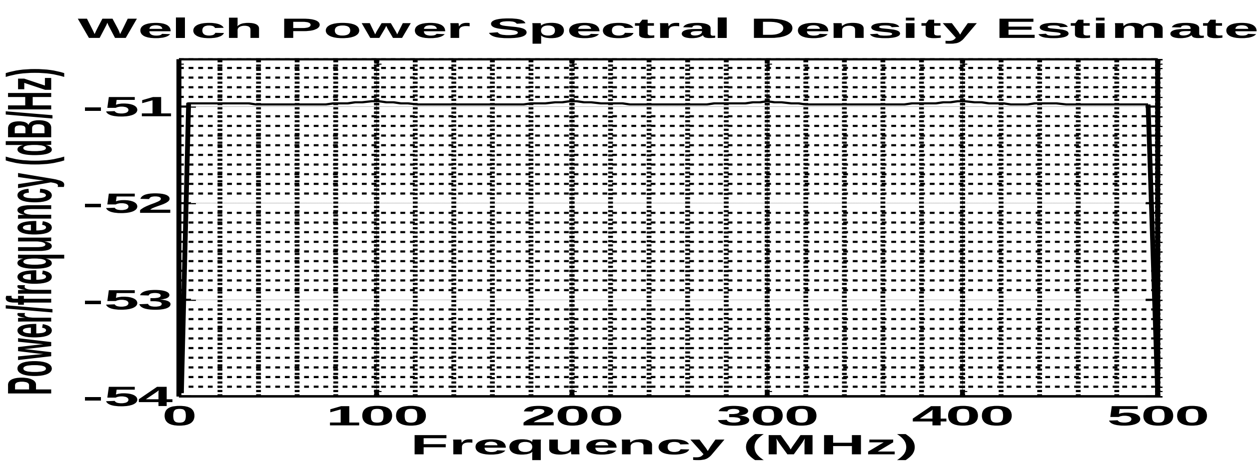


Figure 3.25 100,200,300 and 400 MHz AWGN pass-band signals at -30 dB by Welch periodogram detector

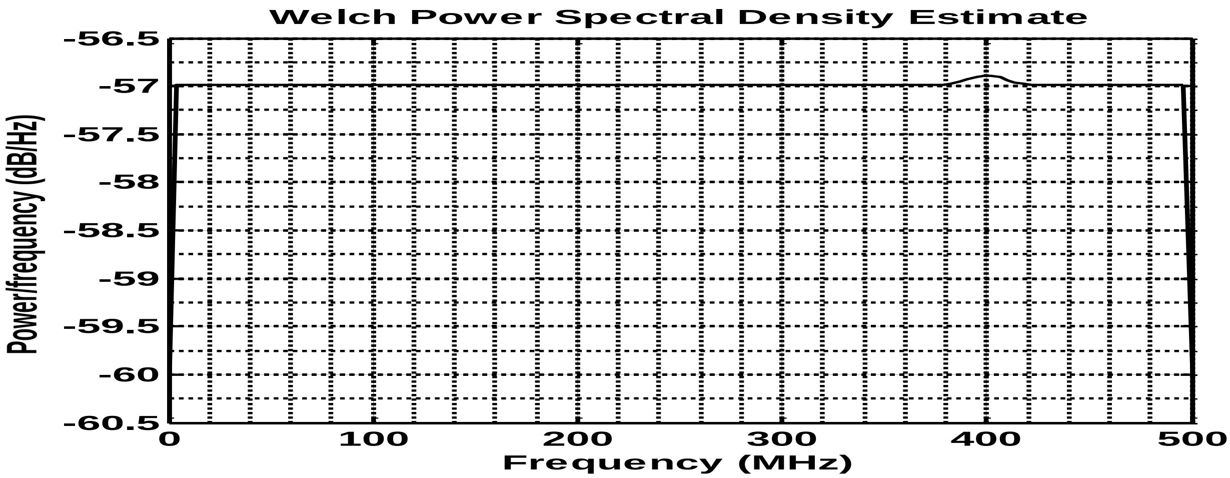


Figure 3.26 400 MHz AWGN pass-band signal at -30 dB by using Welch periodogram detector

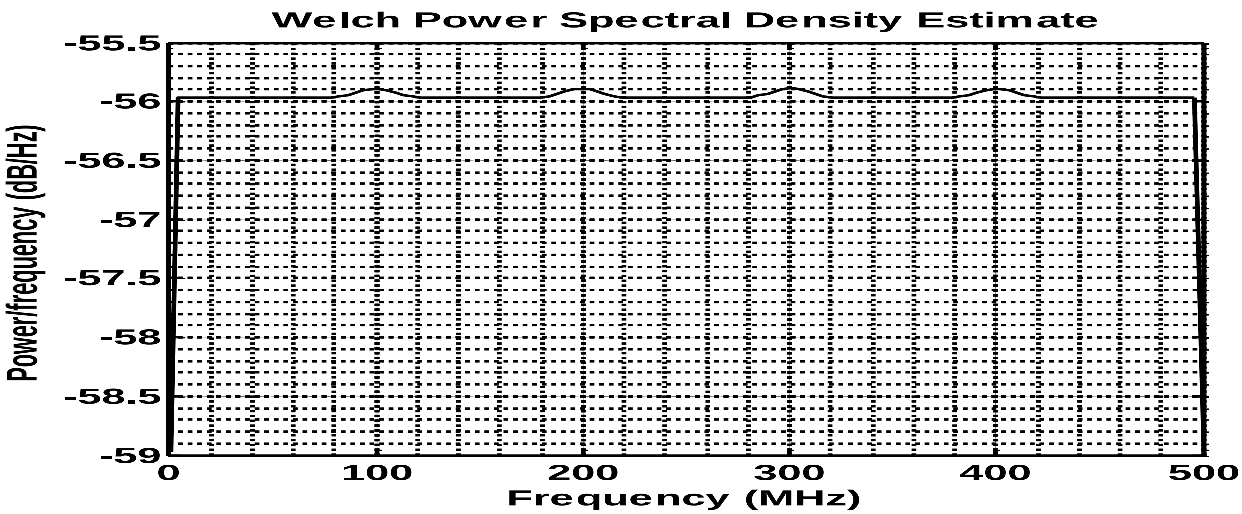


Figure 3.27 100,200,300 and 400 MHz AWGN pass-band signals at -25 dB by Welch periodogram detector

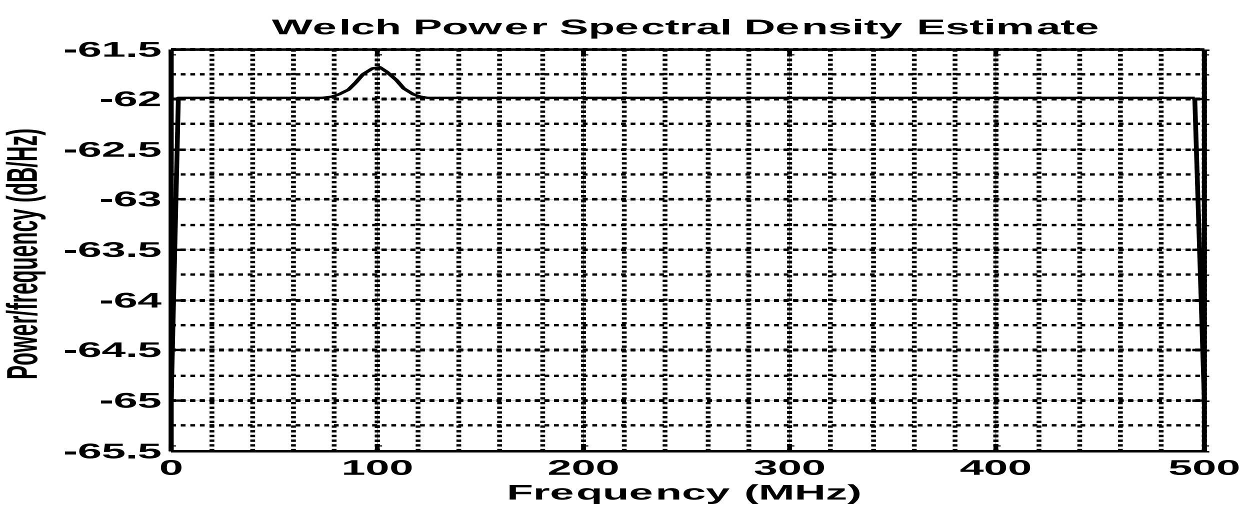


Figure 3.28 100 MHz AWGN pass-band signal at -25dB by Welch periodogram detector

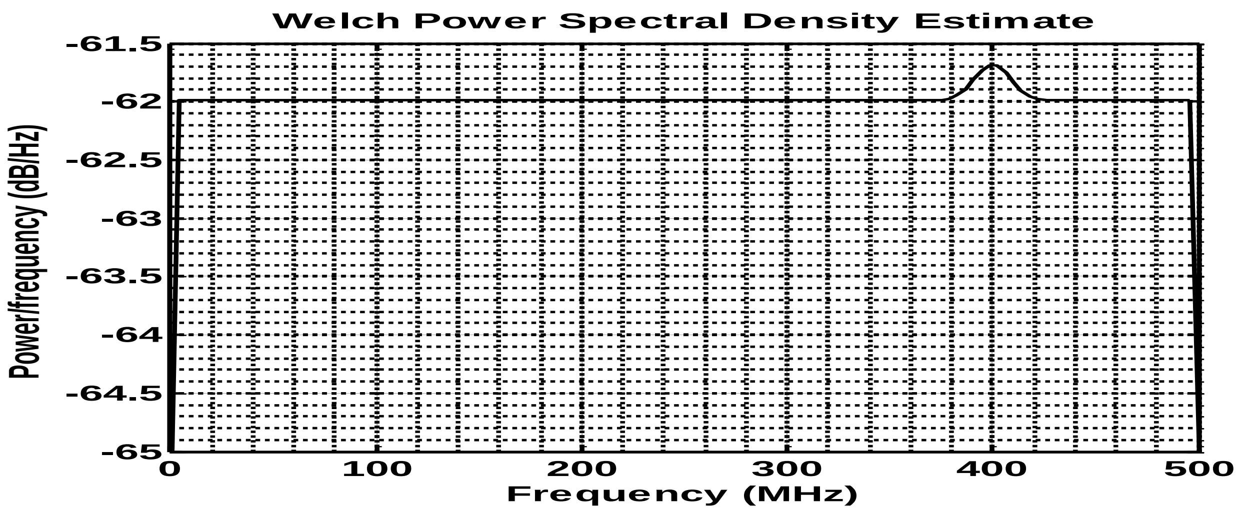


Figure 3.29 400 MHz AWGN pass-band signals at -25 dB by Welch periodogram detector

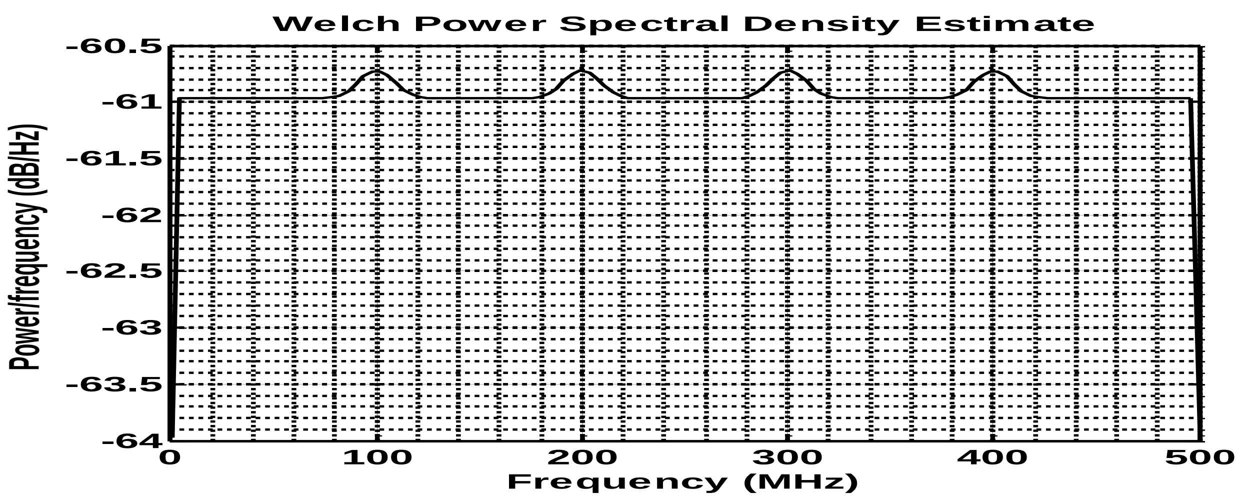


Figure 3.30 100,200,300 and 400 MHz AWGN pass-band signals at -20 dB by Welch periodogram detector

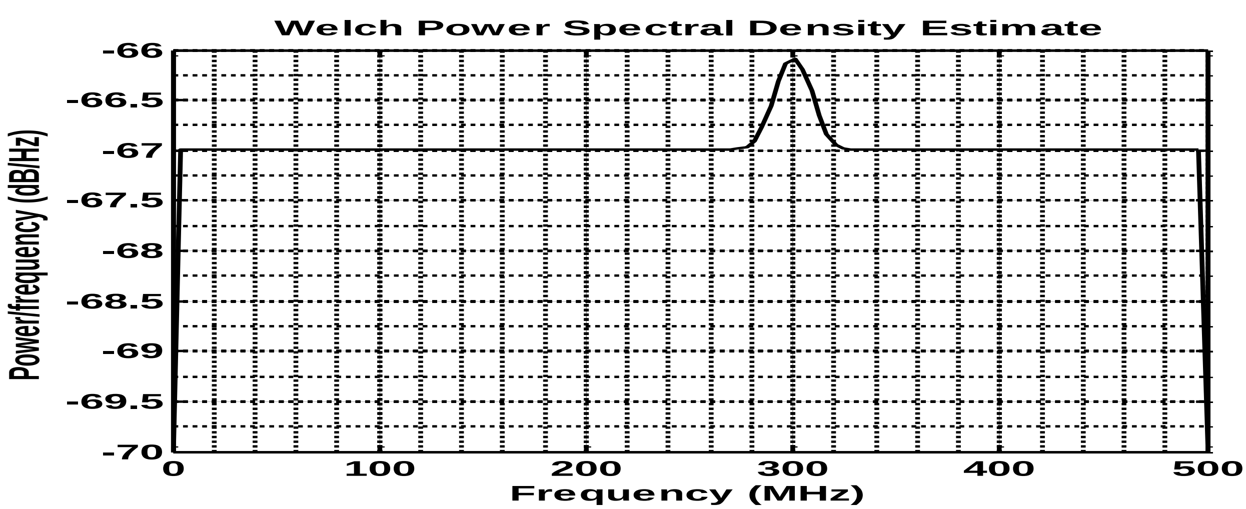


Figure 3.31 300 MHz AWGN pass-band signals at -20 dB by using Welch periodogram detector

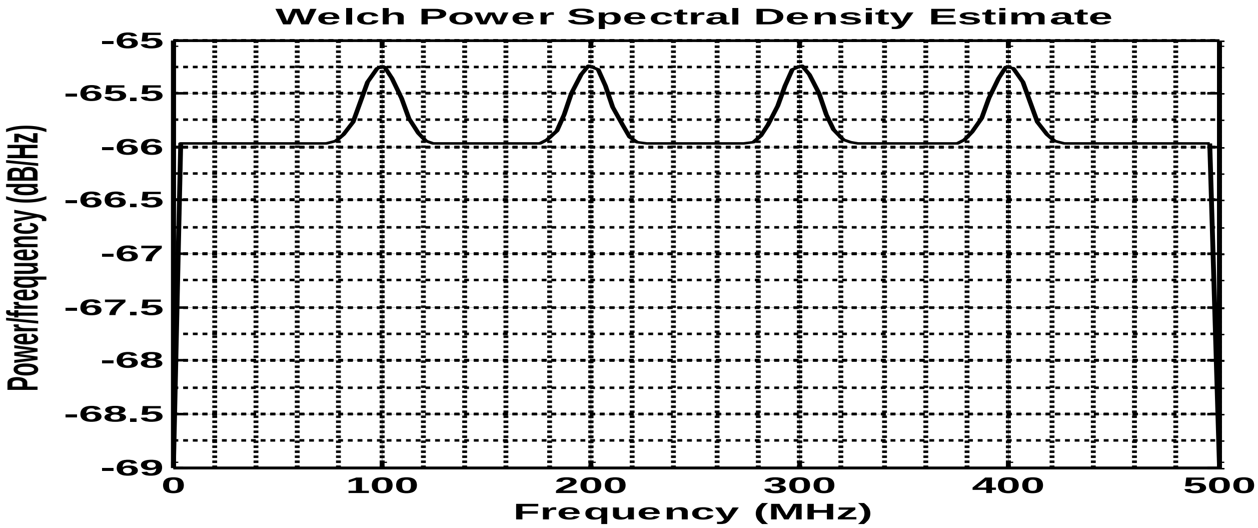


Figure 3.32 100,200,300 and 400 MHz AWGN pass-band signals at -15 dB by Welch periodogram detector

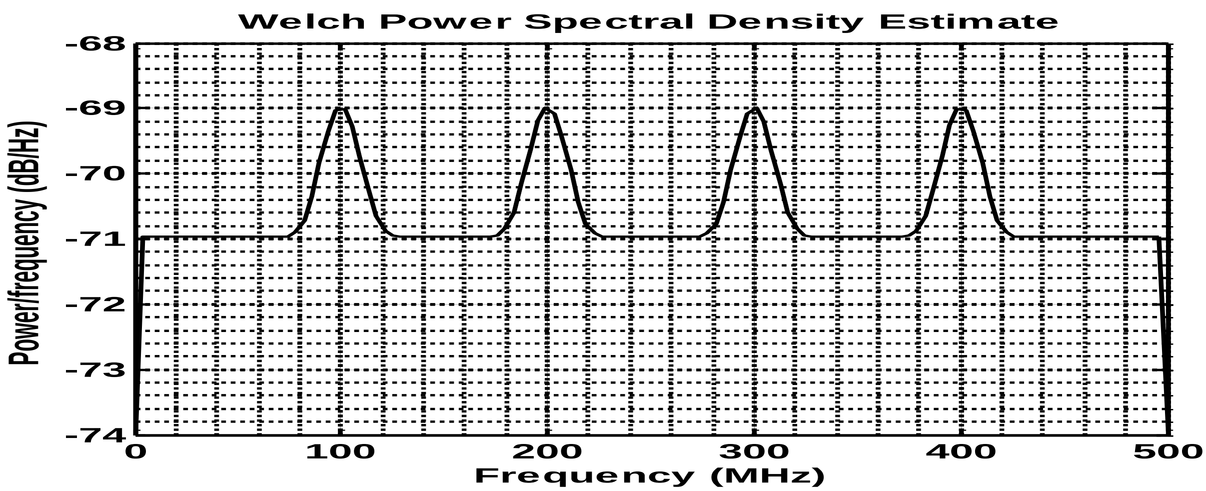


Figure 3.33 100,200,300 and 400 MHz AWGN pass-band signals at -10 dB by Welch periodogram detector

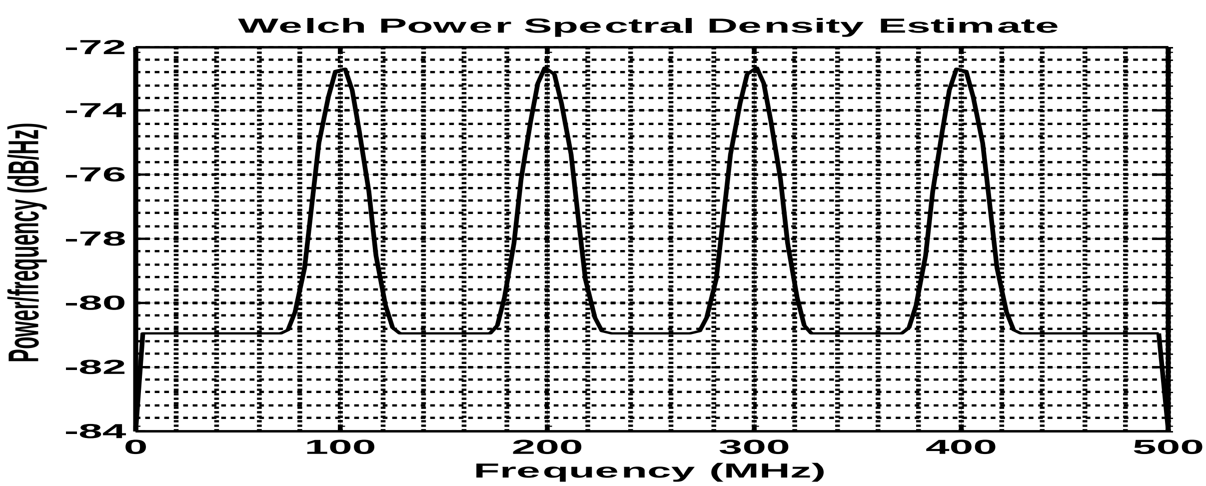


Figure 3.34 100,200,300 and 400 MHz AWGN pass-band signals at 0 dB by Welch periodogram detector

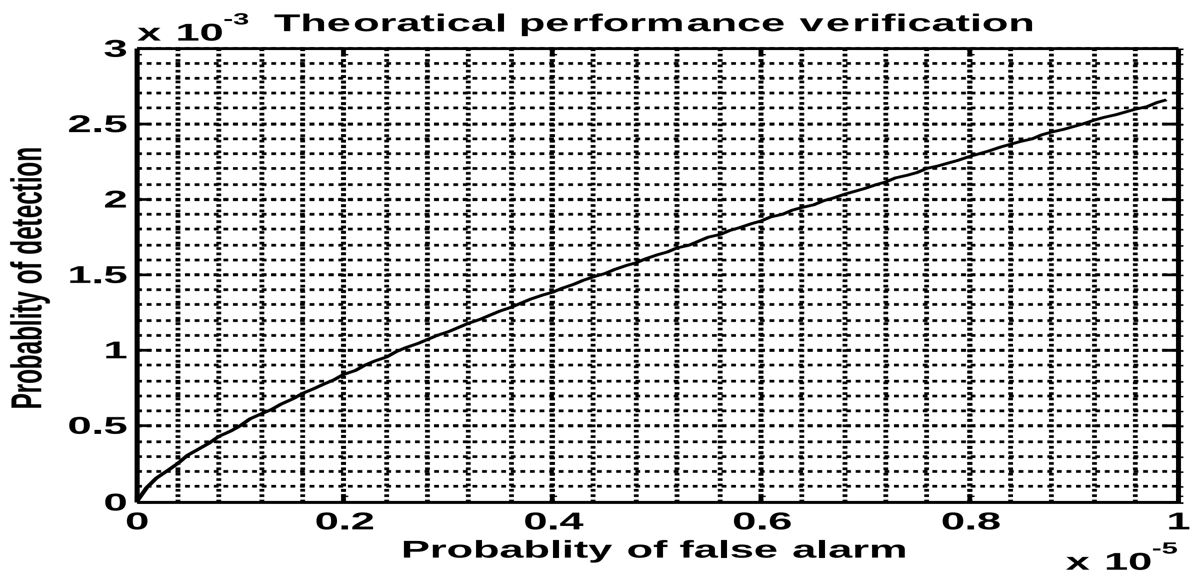


Figure 3.35 ROC of Welch periodogram detector for 100, 200,300 and 400 MHz AWGN pass-band signals

The above results show that the performance of the detector is very poor for four signals in centralized environment at-30dB. The above simulation results show that the signal detection up to 400 MHz frequency is reliable for the single and four signals at the SNR≥-25dB. At SNR =-30 dB, the detector can detect the signals successfully. But the performance is still poor. At SNR≤-30 dB, the signal detection is very poor and the improvement in the performance of the detector is required. The signal detection can be improved by the increase of SNR values. The above simulation results show that the Welch periodogram based signal detection is simple, computationally less complex and fast. The only problem is its poor performance at lower SNR values.

References

[1] Joe Mittola "The Software Radio architecture," IEEE communication Magazine , May 1995

[2] Gerald Youngblood, AC50G, "A software defined Radio for the Masses"

[3] Simon Haykin, "Cognitive Radio: Brain-Empowered wireless Communications", IEEE journal on Selected areas in Communications, vol. 23, No.2, Feburary , pp.201-220

[4] Klaus Moessener, Didier Bourse, Dieter Greifendorf, Joerg Stamen "Software Radio and Reconfiguration Management"

[5] Joseph Mitola III "Cognitive Radio an Integrated Agent Architecture for Software Defined Radio" Dissertation Doctor of Technology

[6] "Federal Communications Commission Spectrum Policy Task Force Report of the Spectrum Efficiency Working Group", November 15, 2002

[7] D. Cabric, S. M. Mishra, and R. W. Brodersen, “Implementation Issues in Spectrum Sensing for Cognitive Radios”, Proceedings of the Asilomar Conference on Signals and Systems, 2004

[8] I. Budiarjo, H. Nikookar, L.P. Ligthart, "Cognitive Radio Modulation Techniques", IEEE Signal Processing Magazine, Vol. 25, Page(s): 24-34, Nov 2008.

[9] Y. Hur, J. Park, W. Woo, K. Lim, C.H. Lee, H.S. Kim, and J. Laskar, “A Wideband Analog Multi-Resolution Spectrum Sensing Technique for Cognitive Radio Systems”, IEEE International Symposium Circuit and System, pp. 4090-4093, May 21-24, 2006.

[10] Steven M.Kay “Fundamentals of Statistical Signal Processing, Detection Theory”, 3rd edition

[11] J.G. Proakis and D. G. Manolakis, “Digital Signal Processing: Principles, Algorithms, and Applications,” Fourth Edition. Upper Saddle River, NJ: Prentice Hall, Inc, 2007.

[12] B. Porat, “A Course in Digital Signal Processing,” New York: John Wiley and Sons, Inc., 1996

[13] Danda B.rawat. “Signal Processing techniques for Spectrum Sensing in Cognitive Radio Systems: Challenges and Perspectives,”2009, First Asian Himalayas International Conference on Internet, 11/2009

[14] D. J. Thomson, “Spectrum Estimation and Harmonic Analysis”, Proc. IEEE, vol. 70, no. 9, pp. 1055-1096, September 1982

[15] Alan Oppenheim, Ronald W. Schafer, “Discrete time signal Processing, “Third edition

[16] M.K. Lakshmanan, and H. Nikookar, “A Review of Wavelets for Digital Wireless Communication”, Springer International Journal on Wireless Personal Communications, vol. 37, May 2006

[17] Klaus kainrath, “Advance Signal Processing: The Fundamentals of Detection Theory”, 26-11-2004, pp.1-18

[18] D.D.Ariananda, M.K.Lakshmanan, H.Nikookar (2009), “A Survey on Spectrum Sensing Techniques for Cognitive Radio”, Wireless VITAE'09, Aalborg, Denmark, pp. 74-79.

[19] Khalid Ben Letaief. “Cooperative Spectrum Sensing, Cognitive Wireless Communication Networks”, 2007

[20] Stefan Tertinek. ”Optimum Detection of Deterministic and Random Signals”, Report written for the Advance Signal Processing 1 SE, December 2004, pp.1-6

[21] Harry Urkowitz, “Energy Detection of Unknown Deterministic Signals,” Proceedings of the IEEE, Vol.55, No.4, April 1967

[22] Yonghong zeng, “A Review on Spectrum Sensing for Cognitive radio: Challenges and Solutions.” EURASIP Journal on Advanced in signal Processing, 2010

[23] D. Cabric, A. Tkachenko, R.W. Brodersen, “Spectrum Sensing Measurements of Pilot, Energy, and Collaborative Detection”, IEEE Military Communications Conference, October, 2006

[24] Sai Shankar N, Carlos Cordeiro, and Kiran Challapali Spectrum Agile Radios: Utilization and Sensing Architectures pp.160-169.In Proc.IEEE int. Symposiumon, New Frontiers in Dynamic Spectrum Access Networks, Baltimore Maryland, USA, Dublin Ireland ,Nov.2005, pp 160-169

[25] D.Cabric, A.Tkachenko, R.W.Brodersen,"Spectrum Sensing Measurements of Pilot, Energy and Collaborative Detection", proc. IEEE Military Communication Conf.Washington, DC,USA Oct.2006,pp1-7

[26] D. Cabric, A. Tkachenko, and R.W. Brodersen, "Experimental study of Spectrum Sensing Based on Energy Detection and Network Cooperation," *Proc. ACM Int.Workshop on Technology and Policy for Accessing Spectrum* (TAPAS), Boston, MA,Aug. 2006.

[27] J. Baek, H. Oh, and S. Hwang, "Improved Reliability of Spectrunm sensing using Energy Detector in Cognitive Radio Systems," *10th International Conference on Advanced Communication Technology* (ICACT), Feb. 2008

[28] Harry Urkowitz, "Energy Detection of a random Process in Colored Gaussian Noise," IEEE Transactions on Aerospace and Electronic systems, Vol. AES-5, No.2, March 1969

[29] Guicai Yu, "Spectrum Detection Based Cyclostationarity in Spectrum Pooling System," WRI world Congress on Computer Science and Information Engineering, 03/2009

[30] Eric-Philip Lawrey, "Adaptive Techniques for Multiuser OFDM," PhD thesis, December 2001, pp.259-265

[31] Nani fadzlina Naim,"Offline Analysis of High frequency Digital Signal," 5th International Conference on MEMS NANO and Smart Systems,12/2009

[32] Steven M.Kay, stanley Lawrence Marple, JR.,"Spectrum Analysis-A Modern Perspective", Proceedings of the IEEE, Vol.69, N=.11, November 1981

[33] M.S. Bartlett, "Smoothing Periodograms from Time Series with Continuous Spectra", Nature (London), Vol.161, May 1948

[34] P. D. Welch, "The Use of Fast Fourier Transform for the Estimation of Power Spectra: A Method Based on Time Averaging Over Short, Modified Periodograms", IEEE Transactions on Audio and Electroacoustic, vol. AU-15, no. 2, pp. 70-73, June 1967.

[35] Prokas, j.g, "Digital Communications,"4th ed. McGraw-Hill 2001

[36] Tevfik Y¨ucek and H¨useyin Arslan, "A Survey of Spectrum Sensing Algorithms for Cognitive Radio Applications", IEEE Communications surveys & Tutorials,vol.11,no.1,First Quarter 2009, pp. 116-130

[37] F.Richard Yu, "Distributed Consensus –Based Cooperative Spectrum Sensing in Cognitive Radio Mobile Ad Hoc Networks," Cognitive Radio Mobile AD Hoc Networks, 2011

[38] I.Budiarjo. "Cognitive Radio Dynamic Access Techniques," Wireless Personnel Communications, 05/2008

[39] M. Davenport, M. Wakin, and R. Baraniuk, "Detection and Estimation with Compressive Measurements." Rice ECE Department Technical Report TREE 0610, November 2006

[40] J. Haupt and R. Nowak,"Compressive Sampling for Signal Detection," *IEEE Int.Conf. on Acoustics, Speech, and Signal Processing* (ICASSP), Honolulu, Hawaii, April 2007

[41] W.A.gardner, “Spectral Correlation of Modulated signals: part 1-analog Modulated signals, “IEEE transaction on communication, 1987, COM-35(6):584-594

[42] W.A.gardner, “Spectral Correlation of Modulated Signals: part II-Digital Modulation,” IEEE trans communication, 1987, COM-35(6):595-601

[43] Hao hu, junde song, Yujing Wang, “Signal Classification Based on Spectral Correlation Analysis and SVM is Cognitive Radio”,2nd International Conference on Advanced Information Networking and Applications

[44] William A.Gardner, “Signal Interception: A Unifying Theoretical Framework for Feature Detection, ”IEEE Transactions on Communications, Vol.36, NO.8, August 1988,pp.897-905

[45] Er. Vishakha sood, Er. Manwinder Singh, “Spectrum utilization by using Cognitive radio technology,”International Journal of Advanced Engineering Sciences and Technologies, Vol No.7, Issue No.2, pp.258-263

[46] Bernard Sklar, “Digital Communications Fundamentals and Applications,”2nd Edition

[47] Xinying He, “Signal Classification Based on Cyclostationary Spectral Analysis and HMM/SVM in Cognitive Radio,”International Conference on Measuring technology and Mechatronics Automation,04/2009

[48] Petr Sysel, “Enhanced Estimation of Power Spectral Density of Noise using the Wavelet Transform,” IFIP-Personel Wireless Communications, IFIP-the International Federation of Information processing, volume 245, 2007

[49] Mansi Subhedar and Gajanan Birajdar “SPECTRUM SENSING TECHNIQUES IN COGNITIVERADIO NETWORKS: A SURVEY” International Journal of Next-Generation Networks (IJNGN) Vol.3, No.2, June 2011, pp. 37-51

[50] B. Farhang-Boroujeny,”Filter Banks Spectrum Sensing for Cognitive Radios”, IEEE Transaction on Signal Processing, Vol. 56, pp. 1801-1811, May 2008

[51] Mengda Lin. “Progressive Decimation Filter Banks for Variable Resolution Spectrum Sensing in Cognitive Radios,”2010, 17th International Conference on Telecommunications, 04/2010

[52] B. Farhang-Boroujeny, “A Square-Root Nyquist (M) Filter Design for Digital Communication Systems”, IEEE Transaction on Signal Processing, vol. 56, no. 5, May 2008

[53] B. Farhang-Boroujeny and R. Kempter, “Multicarrier Communication Techniques for Spectrum Sensing and Communications in Cognitive Radios”, IEEE Communication Magazine, vol. 48, no. 4, April 2008

[54] Z. Tian and G. B. Giannakis, “A Wavelet Approach to Wideband Spectrum Sensing for Cognitive Radios”, Proceeding of International Conference on Cognitive Radio Oriented Wireless Networks and Communications, Greece, 2006

[55] H. Nikookar, “Short Course: Wavelets for Wireless Communication”, European Conference and Wireless Technology, Munich, Germany, October 9-12, 2007.

[56] Robert W. Bordersen, “Cycloststationary Feature Detector Experiments using Reconfigurable BEE2,”2nd IEEE International symposium on New Frontiers in Dynamic Spectrum Access Networks, 04/2007

[57] J.P.donohoe. “Stationary and Cyclostationary Random process models,” Proceedings of South East CON 94 SECON-94, 1994

[58] Lei Yang, zhe chen, Fuliang Yin, “Cyclo-Energy Detector for Spectrum Sensing in Cognitive Radio,” AEUE-International Journal of Electronics and Communications, Volume66, Issue 1,January 2012,pp.89-92

4 Support Vector Machines Based Spectrum Sensing

4.1 Introduction

In this chapter, the system design approach to meet the challenge of detecting very weak signals with machine learning technique is shown. The design space is diverse as it involves various types of primary user signals. The analysis of signal processing approaches helps in the identification of the regimes where these techniques are applicable. The goal of the research is to present a practical system design view of spectrum sensing functionality to improve the spectrum sensing results [1].

Support Vector Machines (SVM) works on the basis of Statistical Learning Theory concepts. Normally SVM is used for the solution of classification and regression problems. SVM is a type of detection technique. In this chapter SVM is used for the spectrum sensing problem at very low SNR values. This task is done with the help of a new SVM kernel known as the *Autocorrelation function (ACF) kernel*. It is a linear classifier and performs well for classification problems [2]. In this chapter, ACF kernel based detector detects the spectrum holes up to 89% confidence level for both base-band and pass-band communication signals for the frequency range up to 50 MHz at very low SNR values in AWGN Channel for the four signals. Spectrum sensing improve the spectrum efficiency and the interference [3, 4,5and 6].Recently spectral correlation analysis and feature detection is used for the communication parameter detection by using the Support Vector Machines [7, 8, 9 and10]. The signal classification approaches are based on patter recognition or decision theoretic approach.

Generally Support Vector Machines (SVM) is used for pattern recognition. SVM works on the basis of structural risk minimization principle. SVM have an advantage that can provide better generalization and improve performance for small number of training samples. SVM can be used for the signal classification. In this chapter, a new approach for the signal detection is implemented which is based on the combination of SVM based supervised learning and spectral correlation analysis [10]. The high performance at low SNR and better detection results are proved by simulations.

4.2 Machine Learning

The Machine Learning is branch of Artificial Intelligence. The computer algorithms allow computational machines to learn from the empirical training data sets which are collected from a set of sensors. This task oriented approach and process can be used for solving real-world problems. Machine Learning methods are usually categorized by their requirements over the types of data they can use.

The machine learning algorithms can be *supervised, unsupervised or semi-supervised* learning.

Supervised algorithms always need teachers to reveal the true interpretation of the data. Such interpretation is referred as the label of the data. The goal of these algorithms is to learn a mapping from the input data to the output given by the teachers [13]. Depending on the nature of the output, the algorithms can be subdivided into classification problems (where the output space is represented in discrete form) or the regression problem (where the output space is continuous).

Unsupervised learning algorithms do not need any teacher and they are operating slowly over the data samples themselves. Their basic task is to identify the similar patterns in their inputs and identify clusters of data samples. Unsupervised algorithms can be used to recognize the structure of data and recognize the organization between them.

There are many applications where the requirement for a teacher in supervised learning methods cannot be satisfied. For example, in few cases the true interpretation of data is either costly or require special measurements or it is a time consuming task [10]. In few cases, the true interpretation of the data requires the repeated efforts which are tedious for a human. However, the collection of large amount of unlabeled data samples requires less effort. In some cases, it is cheap to collect the unlabeled data samples. Due to these reasons, it is necessary in many cases to use the methods which need the minimum amount of supervision and they can learn from labeled and unlabeled data. The semi-supervised learning techniques full fill these requirements and deals with developing of the algorithms which can learn from both labeled and unlabeled data samples. The semi supervised algorithms can mix both unsupervised and supervised principles to fulfill and attain the specific tasks.

4.2.1 Support Vector Machines for Classification

SVM is a universal learning machine [12, 14 and 15]. It belongs to the category of supervised learning methods. The idea of SVM was initially proposed by *Vladimir Vapnik* [12]. Support Vector Machines are considered as the special case of *Tikhonov regularization* [16]. Regularization refers to the generalization of the model to previously unseen data and it is necessary to produce smooth decision functions thus, avoiding over fitting onto the training data [5]. SVM works on the basis of the principal of *Statistical Learning Theory*. The principal of Statistical Learning Theory used in SVM is known as *structural risk minimization principle* (SRM) [3]. The SVM can be used for the solution of classification problems. The SVM is known as non-probabilistic binary linear classifier. For the solution of classification problems, SVM based models assign the new data into one or another category. Different categories are divided by clear wide gaps and mapped into same space. Then decision about the belonging of the new data samples with any category is done. Let us consider the independent uniformly distributed data set $(\boldsymbol{x}_i, \boldsymbol{y}_i)$ where $i = 1, \dots \dots .., n$ and $\boldsymbol{x} \in \boldsymbol{R}^d and\, \boldsymbol{y} \in \{-1,1\}$ are labels. Our main task is the determination of a classifier which can separate the data and have smallest generalization error. For this task, hyperplane is an optimal choice. Hyperplane has the maximum margin between the two classes. It is formulated as quadratic optimization problem [12] which can be represented as [14]

$$min\left[\frac{1}{2}\|\boldsymbol{w}\|^2\right] \qquad [4.1]$$

Where $\boldsymbol{y}_i[\boldsymbol{w}.\boldsymbol{x}_i) + \boldsymbol{b}] - 1 \geq 0, i = 1,2,3, \dots \dots .., n$ are the conditions for the classification [2].By introducing the Lagrangian multiplier into each constraint, the resultant constraints will be

$$L(\boldsymbol{w},\boldsymbol{b},\boldsymbol{\alpha})=\frac{1}{2}(\boldsymbol{w}^{T}\boldsymbol{w})-\frac{1}{2}\sum_{i=1}^{n}\boldsymbol{\alpha}_{i}\{\boldsymbol{y}_{i}[(\boldsymbol{w}.\boldsymbol{x}_{i})+\boldsymbol{b}]-\mathbf{1}\} \quad [4.2]$$

The $\boldsymbol{w}$ can be removed with the help of a dual optimization problem which can be written as $\max_{\alpha}\boldsymbol{Q}(x)=\sum_{i=1}^{n}\alpha_{i}-\frac{1}{2}\sum_{i,j=1}^{n}\alpha_{i}\alpha_{j}\boldsymbol{y}_{i}\boldsymbol{y}_{j}<\boldsymbol{x}_{i},\boldsymbol{x}_{j}>$ [4.3]

$$\boldsymbol{where}\ \boldsymbol{\alpha_i}\geq\mathbf{0},\boldsymbol{i}=\mathbf{1},\mathbf{2},\mathbf{3},\ldots\ldots..,\boldsymbol{n}\ \boldsymbol{and}\ \sum_{i=1}^{n}\boldsymbol{\alpha_i y_i}=0 \quad [4.4]$$

The coefficients α_i $where\ i=1,2,3,\ldots\ldots..,n$ can be obtained by solving the dual optimization problem [17, 18]. These results in the form of a non-linear decision function can be written as

$$\boldsymbol{y}=\boldsymbol{sgn}\left[\sum_{i=1}^{N_s}\boldsymbol{\alpha_i y_i}\,\boldsymbol{k}(\boldsymbol{x_i},\boldsymbol{x})+\boldsymbol{b}\right] \quad [4.5]$$

Where $\boldsymbol{k}(\boldsymbol{x}_i,\boldsymbol{x})$ is known as kernel function and N_s are the number of support vectors. We can introduce the slack variable $\xi_i \geq 0$ in case of binary non-linear separable data which can relax the hard-margin constraints. It gives the minimization which can be represented as

$$\boldsymbol{min}\left[\frac{\mathbf{1}}{\mathbf{2}}\|\boldsymbol{w}\|^{2}+\boldsymbol{C}\sum_{i=1}^{n}\boldsymbol{\xi_i}\right]\ \boldsymbol{s.t}\ \ y_i[(\boldsymbol{w}.\boldsymbol{x}_i)+\boldsymbol{b}]-\mathbf{1}+\boldsymbol{\xi}\geq\mathbf{0};\boldsymbol{i}=\mathbf{1},\mathbf{2},\mathbf{3},\ldots\ldots..,\boldsymbol{n} \quad [4.6]$$

Where, $0\leq\alpha\leq\boldsymbol{C}$. The decision function can be calculated with the help of the above formula.

4.2.2 Kernel Methods

Basically, kernel methods belong to a class of algorithms which are used for the pattern analysis. Pattern analysis deals with the relation between the data. The example of these relations is classification, ranking, correlation and principal component's analysis (PCA). In this technique, data is mapped into a higher dimensional feature space ***H***. Each coordinate in the feature space belongs to at least one feature of the respective data item. In this way, the data is converted into a set of points in the Euclidian Space. This mechanism is also known as the Kernel trick.

The Kernel method works on the basis of the Kernel function [19, 20 and 21]. The performance of SVM mainly depends upon the support vectors and prior selection of the Kernel function. The Kernel function is the key component of Support Vector Machines [2]. Different kernels can produce different support machines [2]. The Kernel functions are calculated by the inner products in some feature space [22]. The inner products are calculated between the images of all data pairs in the feature space. Kernel methods are computationally less complex, cheaper, simple, statistically efficient and well founded processes. Many learning techniques, for example, Support Vector Machines, Fisher's Linear Discriminant Analysis (LDA), Principal Components Analysis (PCA) are working on the basis of Kernel algorithm. Normally Kernel algorithms are based on *Eigenvalues* or *Convex Optimization* problems.

The Kernel methods are commonly applied for the solution of the problems of Bioinformatics, Geostatic, Chemo Informatics, Cognitive Radio, text recognition and hand writing recognition fields. The problems in these fields are solved with the help of Kernel methods.

A Kernel algorithm is used for mapping the learning data (non-linear) into a higher dimensional feature space, in which the problem becomes linearly separable. In this case, the computational power of the linear machine is increased. The kernel provides an efficient way of dealing with non-linear algorithms. It reduces a non-linear algorithms into linear in some *feature space H,* which is non-linearly related to the input space. The kernel function computes the inner function in the feature space.

$$k(x, x') = < \varphi(x), \varphi(x') >$$

4.2.3 Conditions for Admissible Support Vector Machines Kernel

It must be remembered that a function can be considered as admissible Support Vector Machines kernel, if it satisfies the two conditions, Firstly, it must satisfy the *Mercer's Theorem* and secondly, the Fourier Transform must be non-negative (+ve definite) [9, 11]. These conditions are explained below.

4.2.3.1 Mercer Theorem

The Mercer theorem [4, 5] provides the conditions [8, 23] for admissible Support Vector Machine Kernel, which are given below

Let us consider $\boldsymbol{k} \in L(\boldsymbol{R}^d \times \boldsymbol{R}^d)$ for a symmetric real valued kernel where integral operator is given by [2]

$$\boldsymbol{T_k}: \boldsymbol{L_2}(\boldsymbol{R^d}) \rightarrow \boldsymbol{L_2}(\boldsymbol{R^d}) \quad [4.7]$$

and $(\boldsymbol{T_k f})(\boldsymbol{x}) \coloneqq \int_{\boldsymbol{R^d}} \boldsymbol{k}(;\boldsymbol{x})\boldsymbol{f}(\boldsymbol{x})\boldsymbol{dx}$ is positive for all $\boldsymbol{f} \in \boldsymbol{L}_2(\boldsymbol{R^d})$ and we can get from [2]

$$\int_{\boldsymbol{R^d} \times \boldsymbol{R^d}} \boldsymbol{k}(\boldsymbol{x};\boldsymbol{y})\boldsymbol{f}(\boldsymbol{x})\boldsymbol{f}(\boldsymbol{y})\boldsymbol{dxdy} \geq \boldsymbol{0} \quad [4.8]$$

The necessary and sufficient condition for translation invariant kernel [24, 25] is explained as

A translation invariant Kernel $\boldsymbol{k}(\boldsymbol{x}, \boldsymbol{x}') = \boldsymbol{k}(\boldsymbol{x} - \boldsymbol{x}')$ is an admissible support vector machine kernel [26] if Fourier Transform is non-negative [2, 27].

$$\boldsymbol{F}[\boldsymbol{k}(\boldsymbol{\omega})] = (\boldsymbol{2\pi})^{\frac{-d}{2}} \int_{\boldsymbol{R^d}} \mathbf{exp}\big(-\boldsymbol{j}(\boldsymbol{\omega}.\boldsymbol{x})\big)\, \boldsymbol{k}(\boldsymbol{x})\boldsymbol{dx} \quad [4.9]$$

4.2.3.2 Spectral Correlation Analysis

Many communication signals exhibit built-in 2nd order periodicities due to modulation, sampling, coding and multiplexing like operations. These cyclostationary properties are known as spectral correlation features (SCF) [10]. These features can be used for the signal recognition and detection. Basically, correlation is a matching process [14]. The cyclostationary processes have cyclical statistical properties with respect to the time [28]. The Auto Correlation Function (ACF) is a special type of correlation and an important function in statistical signal processing techniques [2]. It is the correlation between two samples $\boldsymbol{x}_i$ and $\boldsymbol{x}_j$ which are separated by a time lag $(\boldsymbol{i} - \boldsymbol{j})$ [2]. It shows the degree of correlation between two time samples of the same random process. ACF depends upon the relative time lag $(\boldsymbol{i} - \boldsymbol{j})$ for stationary signals [2]. It does not depend on the absolute time $\boldsymbol{i}$ [19]

The autocorrelation function of a random process can be defined as [2]

$$\boldsymbol{r}(\boldsymbol{i} - \boldsymbol{j}) = \boldsymbol{E}[\boldsymbol{x_i x_j}] \quad [4.10]$$

For a real valued energy signal $x(t)$, autocorrelation function can be defined as [14, 30]

$$\boldsymbol{R_x}(\boldsymbol{\tau}) = \int_{-\infty}^{\infty} \boldsymbol{x}(\boldsymbol{t})\boldsymbol{x}(\boldsymbol{t} + \boldsymbol{\tau})\boldsymbol{dt} \qquad \boldsymbol{for} - \infty < \boldsymbol{\tau} < \infty \quad [4.11]$$

The ACF shows how the signal is closely matched with its shifted version in time unit τ, here τ plays as the scanning or searching parameter. It must be remembered that the autocorrelation is the function of time difference between the signal and its shifted copy [14].

4.2.3.3 Properties of Autocorrelation Function

The ACF has the following important properties

The ACF is a symmetric function **i.e.;** $\boldsymbol{r\big(-(i-j)\big) = r(i-j)}$

ACF is symmetric in $\boldsymbol{\tau}$ about zero i.e; $\boldsymbol{R_x(\tau) = R_x(-\tau)}$ [30]

The maximum value of ACF occurs at origin $|R_x(\tau)| \leq R_x(0)\ for\ all\ \tau$ [30]

The PSD of the signal is equal to the Fourier transform (FT) of ACF i.e.; $R_x(\tau) = \Psi_x(f)$ [30, 31]

The energy of the signal is equal to the value of ACF at origin [14, 30] i.e.

$$R_x(0) = \int_{-\infty}^{\infty} x^2\,(t)dt$$

It must be remembered that it will show the *average power* in case of a power signal.

The autocorrelation function of real valued power signal power $x(t)$ is defined as [14, 30]

$$R_x(\tau) = \lim_{\mathrm{T}\to\infty} \frac{1}{T}\int_{-T/2}^{T/2} x(t)x(t+\tau)dt \qquad for -\infty < \tau < \infty$$

The Autocorrelation function of the periodic power signal $x(t) with\ period\ T_0$ is taken as time average over a single period T_0[30]. The ACF can be expressed as

$$R_x(\tau) = \frac{1}{T_0}\int_{-T_0/2}^{T_0/2} x(t)x(t+\tau)dt \qquad for -\infty < \tau < \infty$$

It must be remembered that the autocorrelation function of a real valued periodic signal can satisfies the above four properties [30].

In our research, 4 QPSK signals are transmitted as shown in figure 3.1.On the basis of this builtin periodicity the *triangle based autocorrelation function* is used for the spectrum sensing.

4.2.3.4 Auto Correlation SVM Kernel

The autocorrelation function satisfies the condition of admissible SVM Kernel [1].It is explained above that the autocorrelation function is symmetric. The autocorrelation function can satisfy the Mercer's theorem.

The Autocorrelation function can be decomposed as [2]

$$\boldsymbol{r(i-j) = E\big[x_i x_j\big] = \lim_{N\to\infty} \frac{1}{N}\sum_{k=1}^{N} {x_i}^k {x_j}^k \approx \frac{1}{N}\sum_{k=1}^{N}\sum_{k=1}^{N} {x_i}^k\, {x_j}^k = (\varphi(x_i).\,\varphi(x_j))} \qquad [4.12]$$

Where N is the total number of pulses of a signal. It must be remembered that $\forall\ \boldsymbol{f \epsilon L}_2(\boldsymbol{R}^d)$, so we get [2]

$$\boldsymbol{\iint_{R^d\times R^d} r(x,y)f(x)f(y)dxdy = \iint_{R^d\times R^d}(\varphi(x).\,\varphi(y))f(x)f(y)dxdy = \iint_{R^d\times R^d}(\varphi(x)f(x)dx)^2 \geq 0}$$

[4.13]

The above proof shows that the autocorrelation function satisfies the Mercer's Theorem.

Meanwhile, we know that the discrete time Fourier transform (DTFT) of the autocorrelation function is equal to the power spectrum of the random signal $\boldsymbol{x_i}$ [2] which can be represented as

$$\boldsymbol{F}[r(\boldsymbol{\omega})] = (\boldsymbol{2\pi})^{\frac{-d}{2}} \int_{\boldsymbol{R^d}} \mathbf{exp}\left(-\boldsymbol{j}(\boldsymbol{\omega}.\boldsymbol{x_i})\right) \boldsymbol{r}(\boldsymbol{x})\boldsymbol{dx} \qquad [4.14]$$

As we know that the power spectrum is a non-negative quantity[2]. So, the 2nd condition for admissible Support Vector Machines kernel is also satisfied. The above discussion proves that the autocorrelation function can be used as the admissible Support Vector Machine kernel [2] .

4.3 System Model

Basically, the process of classification is similar to the process of detection. Initially, the estimation and detection of the signal parameters are considered as the problem of Statistical Signal Processing. The performance of classical detection techniques is limited especially at low SNR values. In Cognitive Radio systems we need the computationally less complex, efficient and less power consuming and real- time sensing process. Along with the sensing it is necessary to do online adaptive decision about the selection of the best spectrum hole out of all available holes. The performance criteria for the best spectrum hole are the availability of the band for longer time so that the chance of interference due to primary users can be mitigated. The problem of interference mitigation becomes serious when the primary and the secondary users want to communicate simultaneously. In this thesis, different spectrum sensing techniques are applied. Here four transmitters are acting as primary users. While the signals are detected in a centralized environment with the help of a SVM detector, Kyouwoong Kim et.al, Shujie Hou et.al and Robert, Hao Hu, Marco di Felice, George Piewald, Tobias Renk, T:charles Clancy and many others suggests the Kernel based spectrum sensing in Gaussian and fading Channels. In the current research problem, four different QPSK based band-limited base-band and pass-band signals through an AWGN channel are investigated by using autocorrelation kernel function based SVM detector. The signals have the builtin periodicity. At the receiver end, the signals are sampled and processed. These processed signals are used for the classification. The signal classification is done by analysis and feature extraction with the help of a support vector classifier. A set of generated signals are used for training purposes and another set of signals are used for the testing purpose [32].This detection problem is a binary hypothesis problem. The system model is

$$H_0 = \mathrm{W}\ (t) \qquad [4.15]$$

$$H_1 = \mathrm{S}\ (t) + \mathrm{W}\ (t) \qquad [4.16]$$

Where the *Ho* is *null hypothesis* which represents the presence of noise only and the H_1 is known as the *alternative hypothesis* which shows the presence of the Information signal .In the current problem, the Neyman-Pearson criterion is considered for the decision in which $\gamma \underset{<H0}{\overset{>H1}{}}$, where γ represents the threshold value. The threshold is selected on the basis of desired value of P_{FA}. The whole system description is represented by the figure 3.1.

According to Neyman-Pearson criterion, the performance of a detector depends upon the value of the P_{FA} (probability of the false alarm) and P_D $(probabilty\ of\ detection)$ [33, 34]. The results of the cyclostationary feature detection techniques are improved with the help of triangular autocorrelation SVM Kernel. In the SVM detector P_{FA} represents the false positive rate and P_D represented by true positive rate.

4.4 Simulation Results

The baseband and pass-band signals are generated in MATLAB which is used as input to the SVM classifier [35]. In this simulation pass-band signals are detected. The transmission channel is modeled as non-line of sight (LOS) AWGN channel. The receiver and the transmitters are both in fixed positions. So, the Doppler shift $f_{ds} = 0.$ The signals are transmitted with adjustable SNR values = [-80:10:20] dB. The sampling frequency for the signals follow the Shannon's theorem [30]. The performance of the detector is decreased at the lower SNR values. The graph shows that the confidence level of the detector is up to a high confidence level. The performance of the detector depends upon the number of samples, resolutions, number of training sessions, frequency of signal to be detected and SNR range. All of these factors are shown with the help of simulation results given below.

4.4.1 Simulation Results for Pass-Band Communication Signals

The SVM detector is used here for the pass-band signal detection. In this thesis, autocorrelation Kernel function based SVM detector is used for the detection of four AWGN pass-band signals (shown in figure 3.1). The maximum performance of SVM detector is equal to AUC= 89%. These results can be improved by cross validation and by the increase of number of training samples (sessions). Also the ROC curve can be improved by the increase of SNR resolution (SNR step size). The caption shows the decision level about the presence of the signals. The confidence level >20% will show the presence of the signal. The simulations results show that the signal detection is possible at very low SNR values.

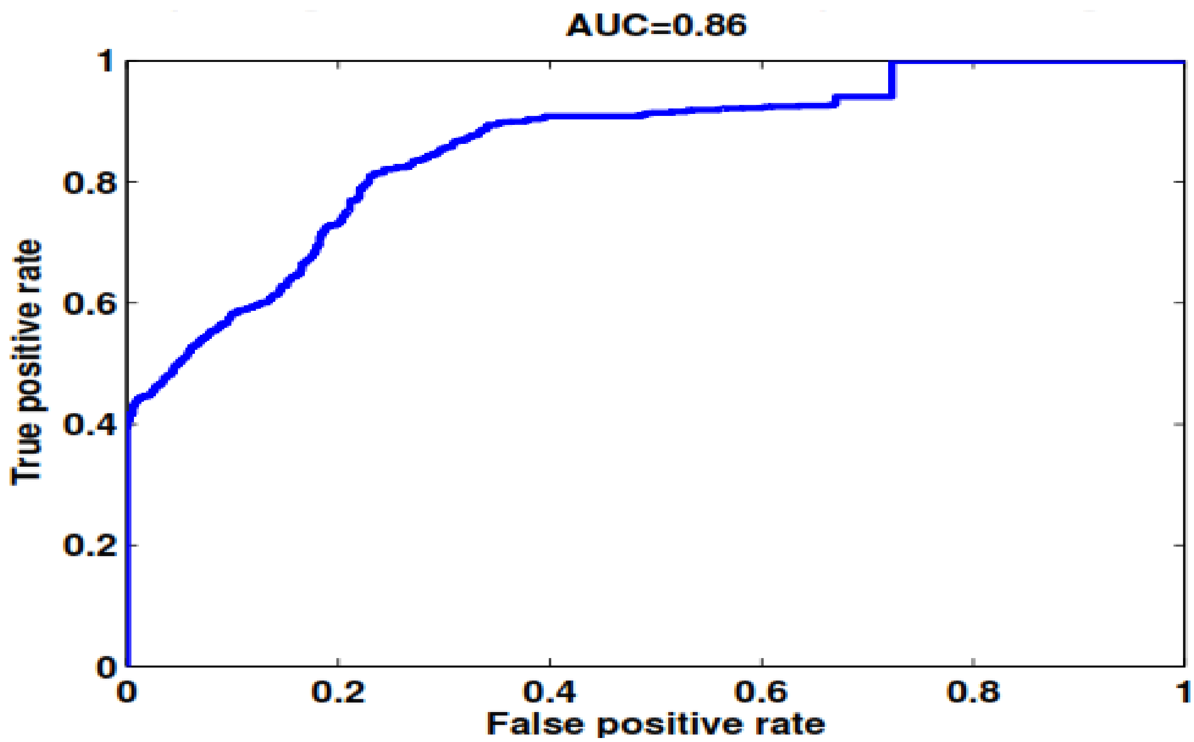


Figure 4.1 ROC for 20, 30, 40 and 60 kHz AWGN pass-band signals for SNR= [-40:10:40] by autocorrelation Kernel based SVM detector

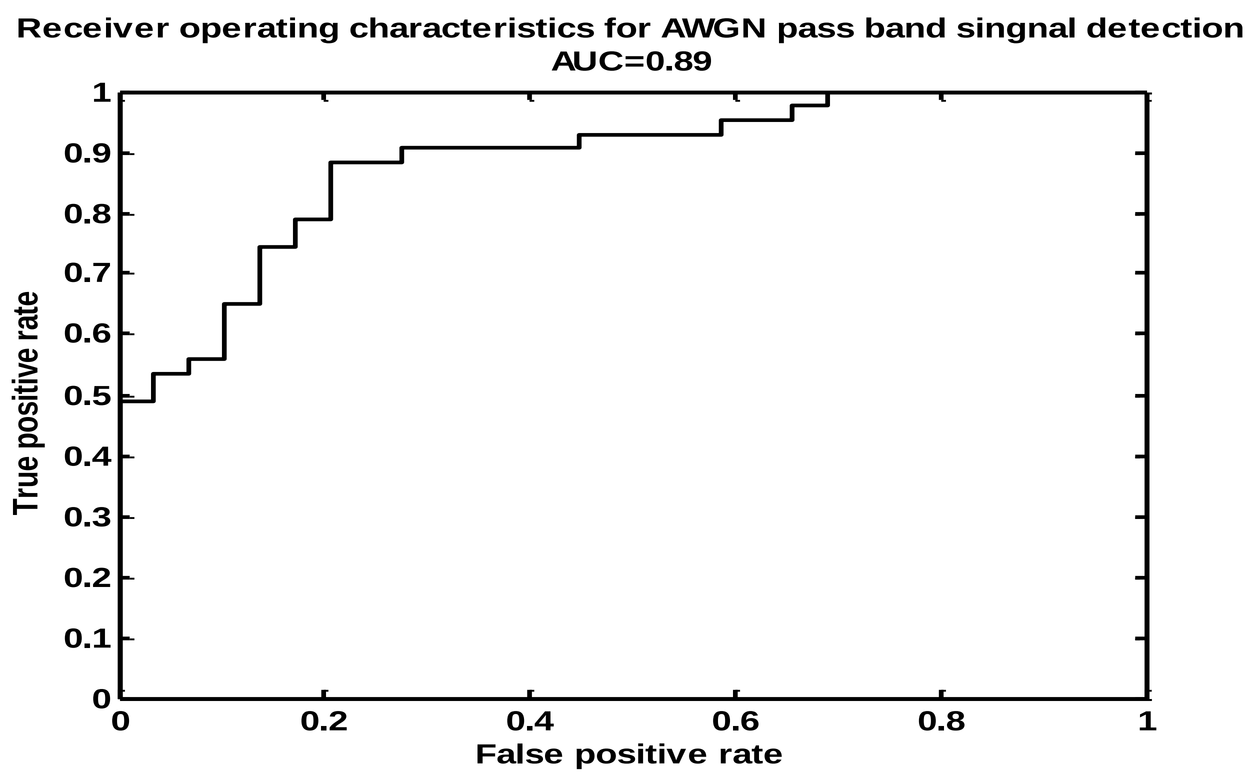


Figure 4.2 ROC for 20,30,40 and 60 kHz AWGN pass-band signals by autocorrelation Kernel based SVM detector for SNR= [-40:2:40]

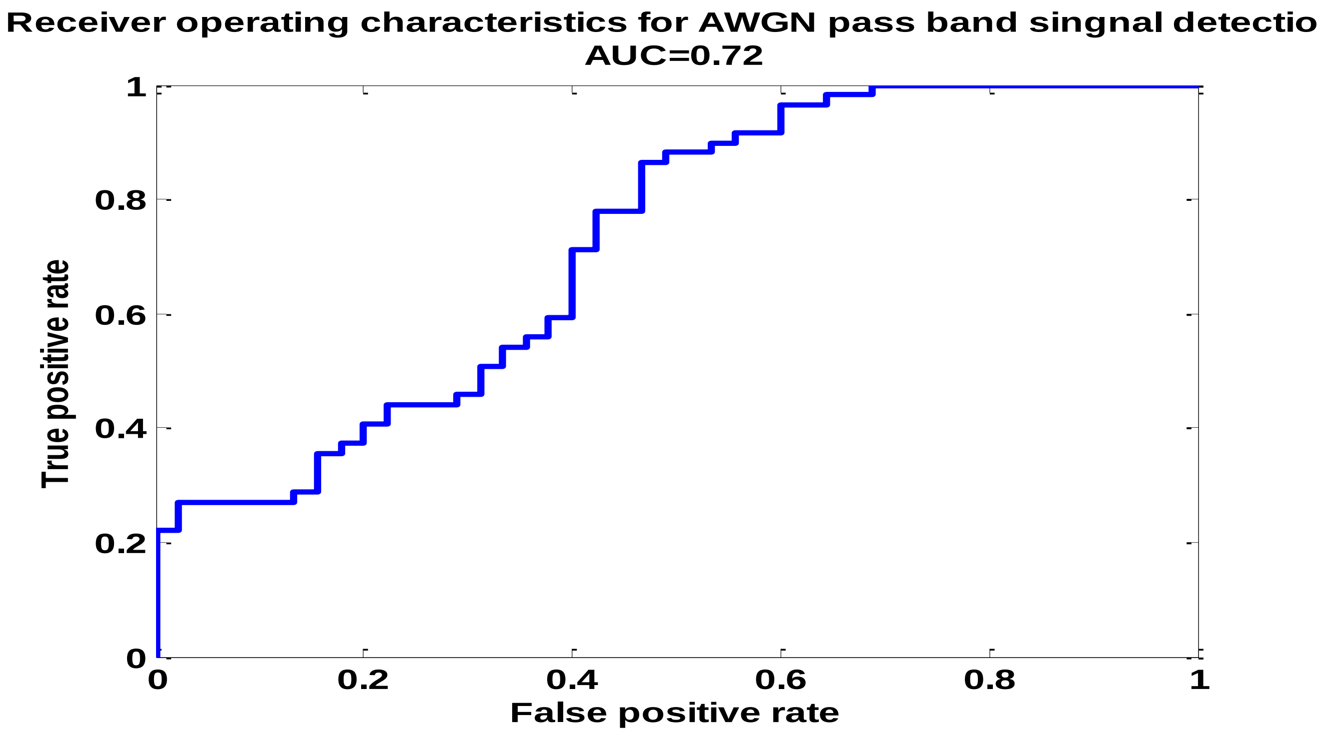


Figure 4.3 ROC for 20,30,40 and 60 kHz AWGN pass-band signals by autocorrelation kernel based SVM detector for SNR= [-80:10:40] after first training session

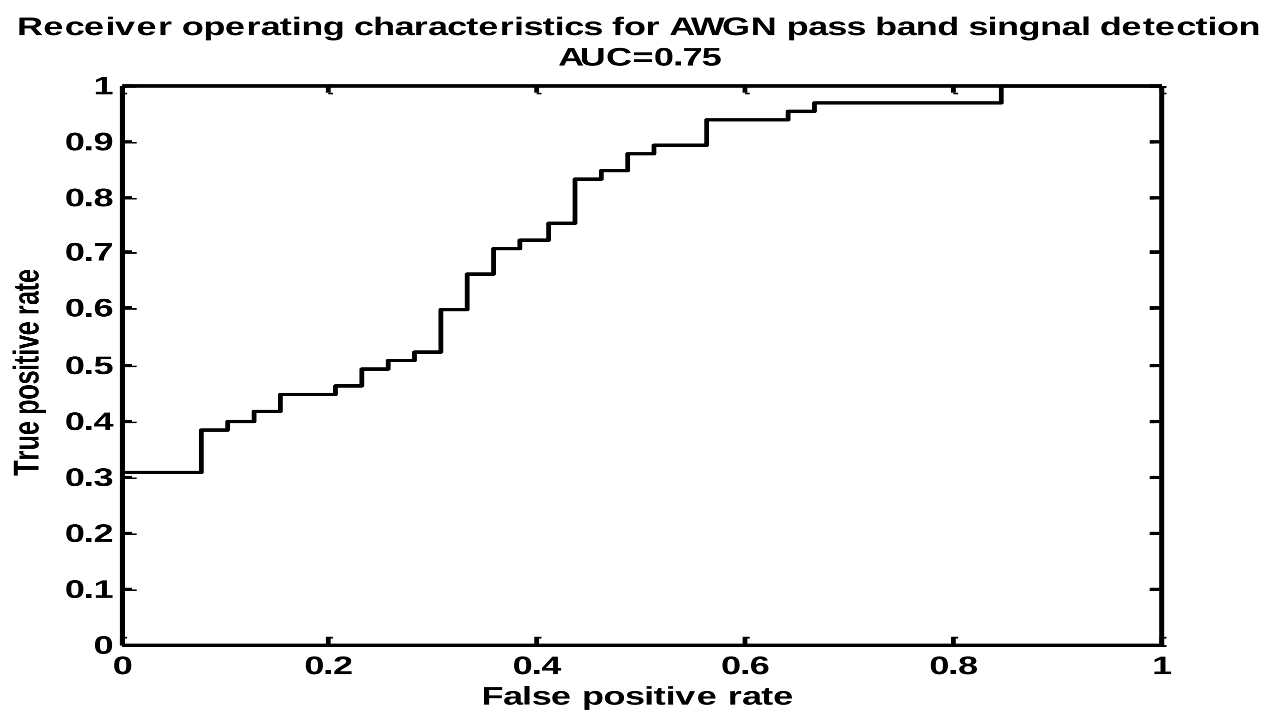


Figure 4.4 ROC for 20,30,40 and 60 kHz AWGN pass-band signals autocorrelation kernel based SVM detector for SNR= [-80:10:40] after second training session.

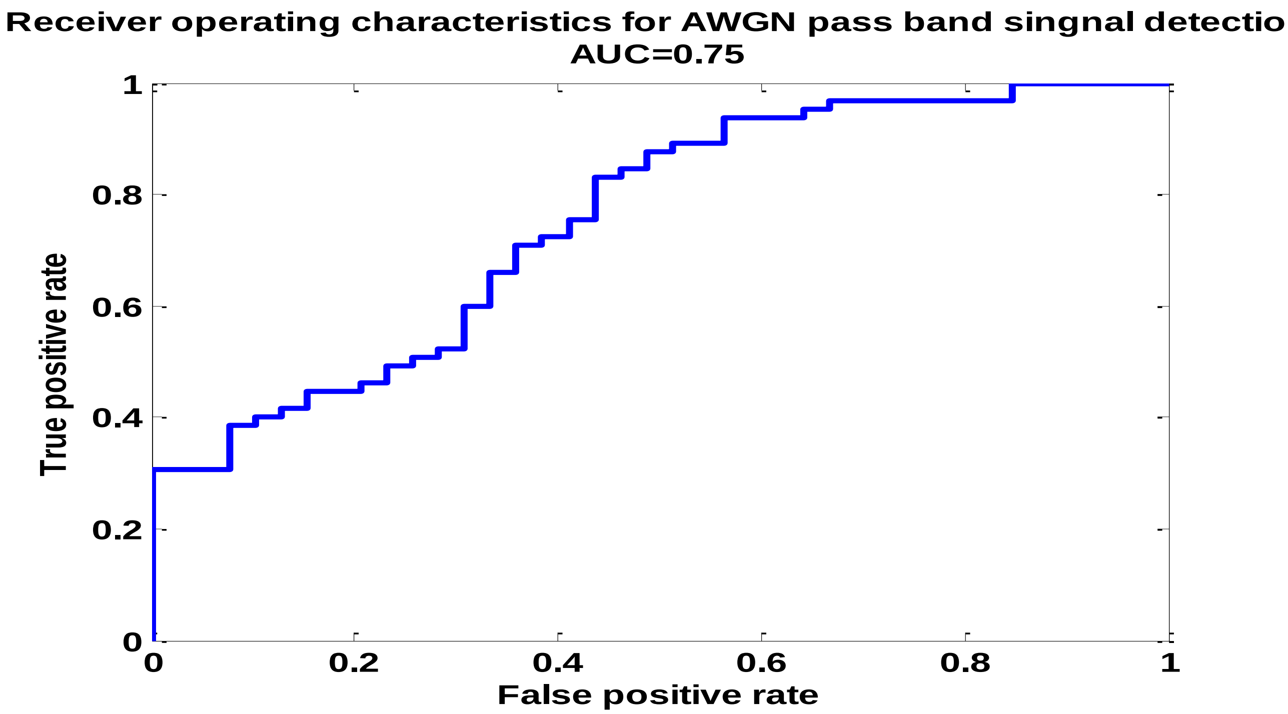


Figure 4.5 ROC for 200,300,400 and 500 kHz AWGN pass-band signals for SNR= [-80:10:20] by autocorrelation based SVM detector

The above simulation results show that the performance of the detector for AWGN pass-band signals depends upon the step size. The performance of the SVM detector will be improved by the decrease of step size. The above simulation result shows that AUC =86 for SNR step size=10 and simulation result shown by Figure 4.2 Figure 4.2 ROC for 20,30,40 and 60 kHz AWGN pass-band signals by autocorrelation Kernel based SVM detector for SNR= [-40:2:40]shows that it became AUC=89 for SNR step size=2 for the same SNR range =[-40:10:40]. The simulation results of Figure 4.3 ROC for 20,30,40 and 60 kHz AWGN pass-band signals by autocorrelation kernel based SVM detector for SNR= [-80:10:40] after first training session and Figure 4.4 ROC for 20,30,40 and 60 kHz AWGN pass-band signals autocorrelation kernel based SVM detector for SNR= [-80:10:40] after second training session. The performance is improved by the increase of the number of training sessions for the same SNR range and step size. The more training sessions, the better will be the detector performance. The simulation results show that the value of AUC becomes 72 to 75 after the 2nd training session for the same SNR range = [-80:10:40] for the 20, 30, 40 and 60 kHz pass- band signals. The training process initially need more time but in the end it will improve the net detector performance. The simulation results shown by Figure 4.5 confirms that the performance of SVM detector depends upon the frequency range of the signal .It is shown that the increase in the frequency range of the signals will decrease the performance of the detector for the same SNR range and step size.

4.4.1.1 20, 30, 40 and 60 kHz AWGN Pass Band Signal Detection for SNR= [-80:10:40] by Using Autocorrelation Kernel Function based SVM Detector

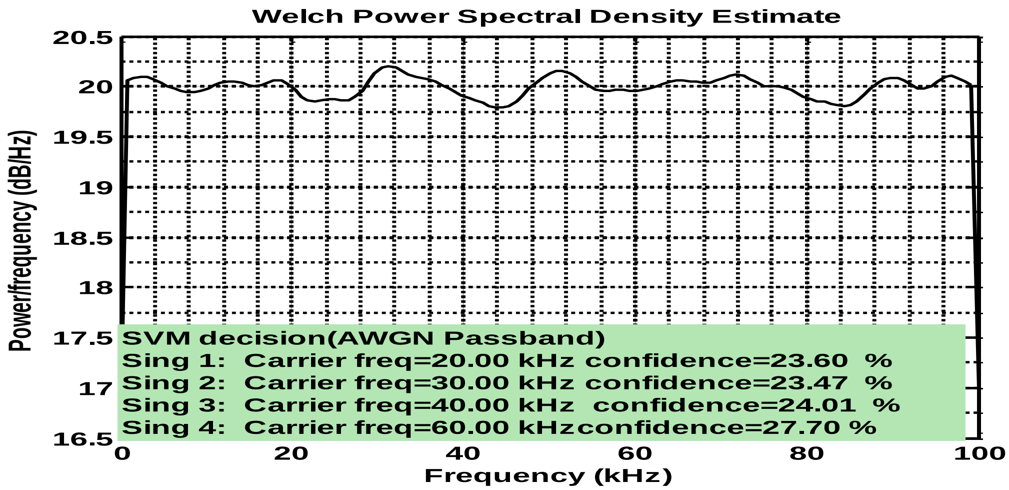


Figure 4.6 20, 30, 40 and 60 kHz AWGN Pass-band signals at -80 dB for SNR= [-80:10:40]

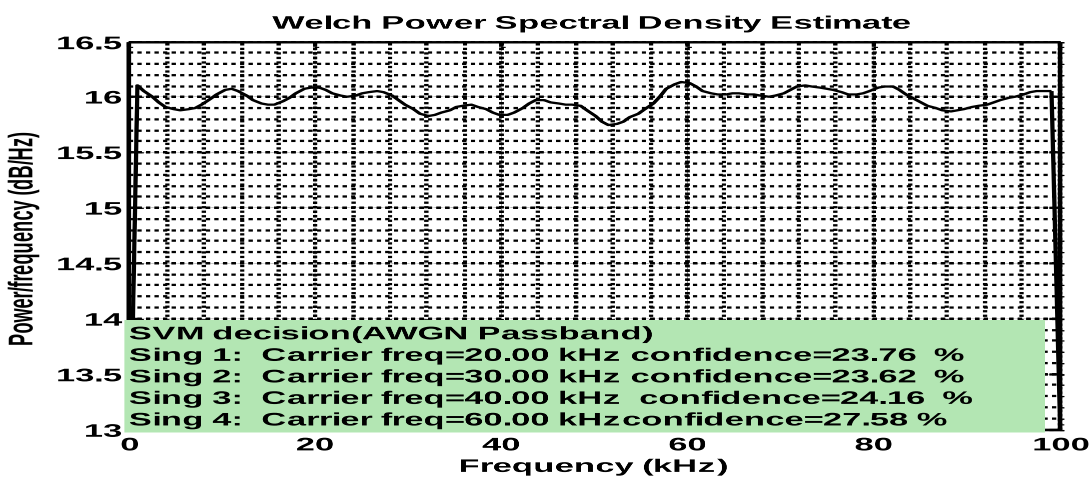


Figure 4.7 20, 30, 40 and 60 kHz AWGN pass-band signals at -70 dB for SNR= [-80:10:40]

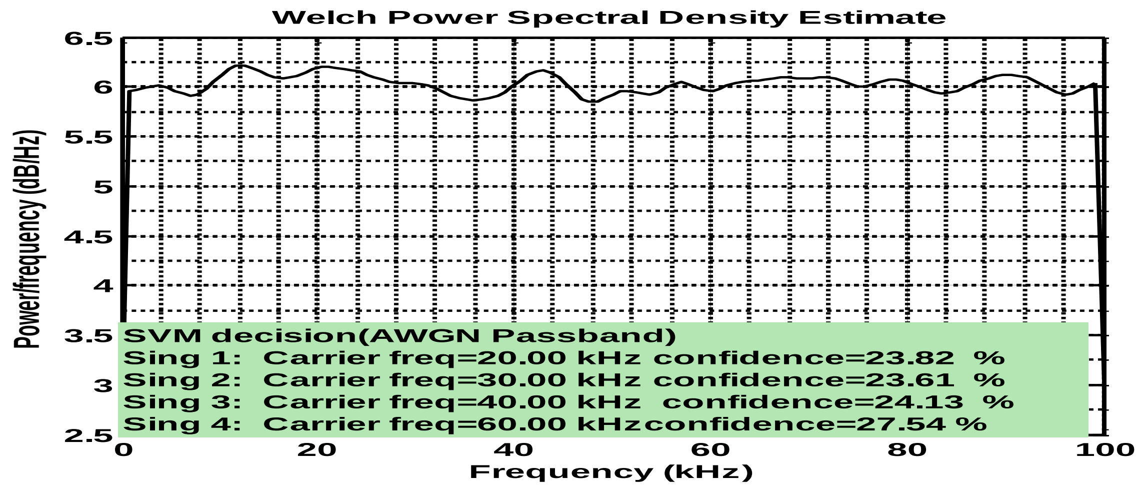


Figure 4.8 20, 30, 40 and 60 kHz AWGN pass-band signals at -60 dB for SNR= [-80:10:40]

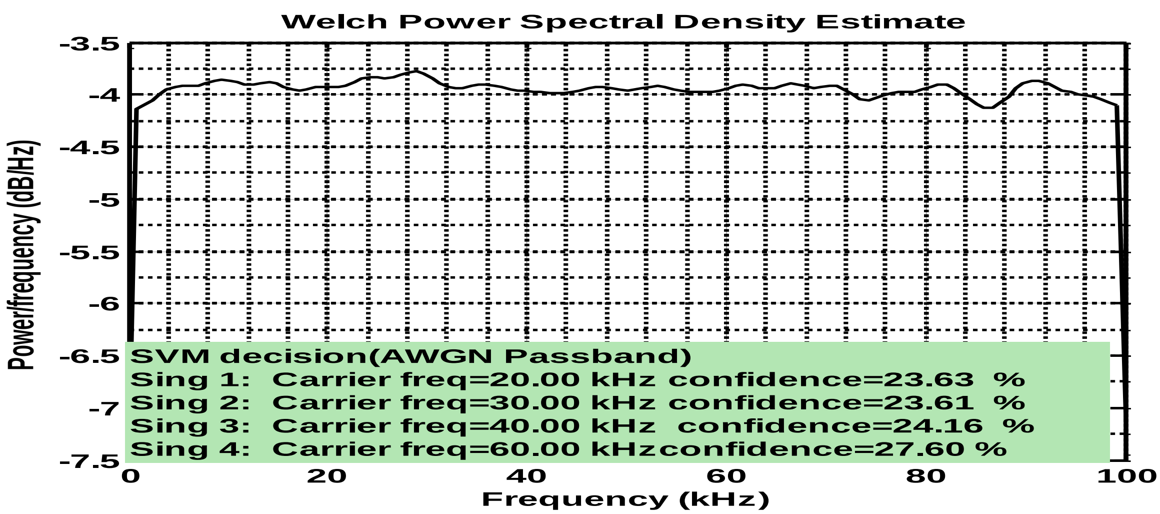


Figure 4.9 20, 30, 40 and 60 kHz AWGN pass-band signals at -50 dB for SNR= [-80:10:40]

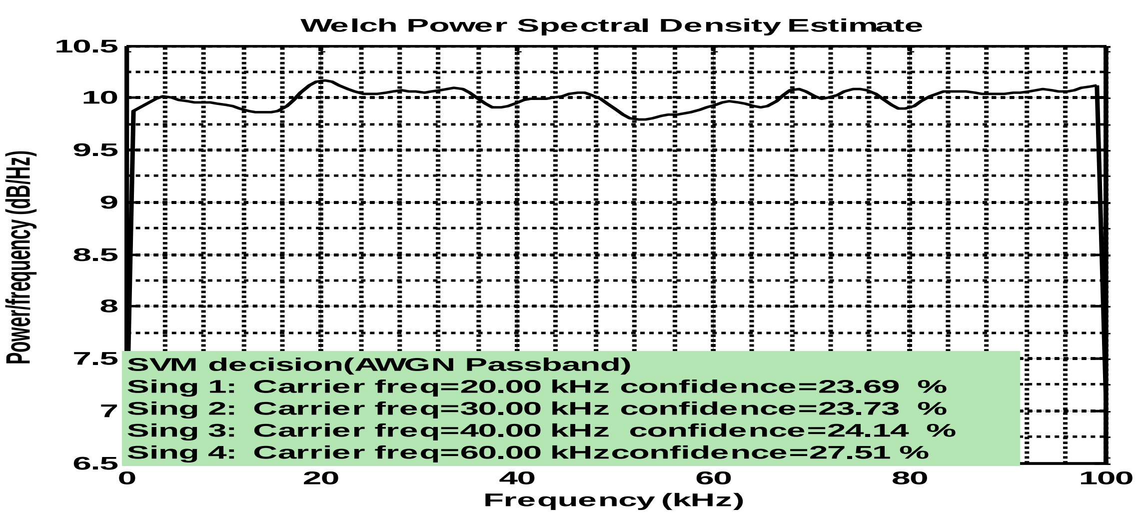


Figure 4.10 30 kHz AWGN pass-band signals at -50 dB for SNR= [-80:10:40]

Fig. 4.10 shows the detection of four signals, but only one was transmitted. This is a detection failure.

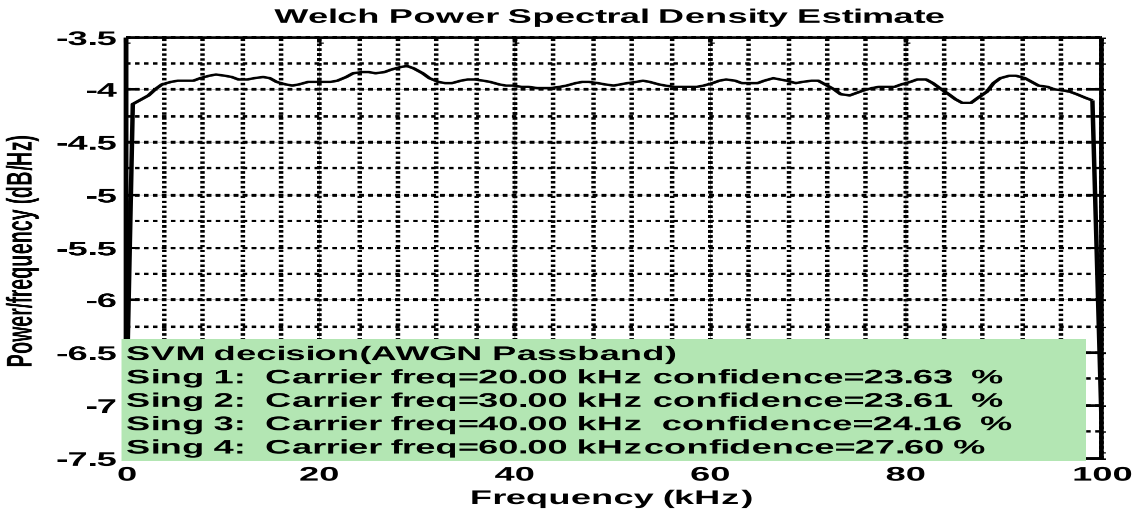


Figure 4.11 20, 30, 40 and 60 KHz AWGN pass-band signals at -40 dB for SNR= [-80:10:40]

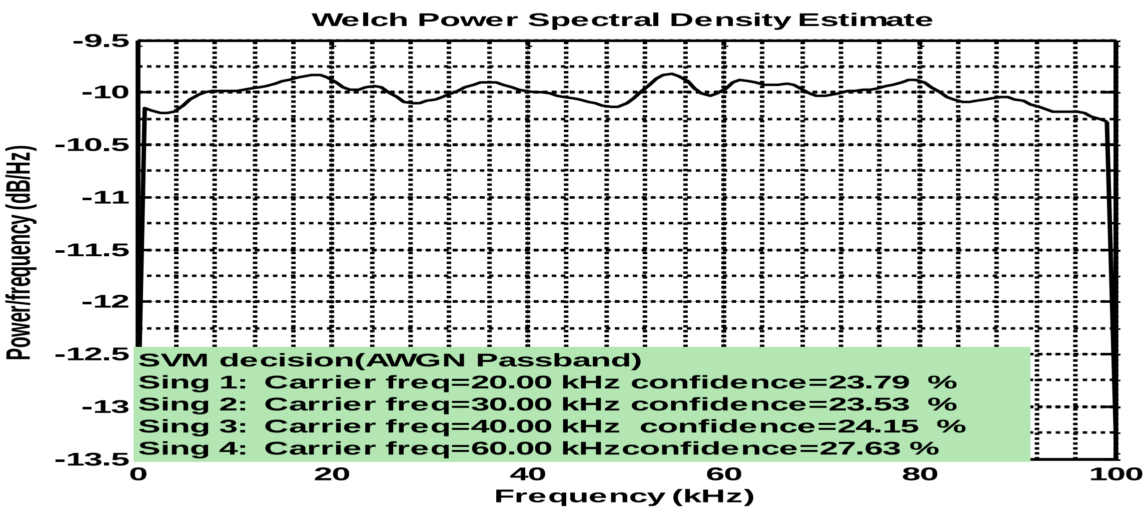


Figure 4.12 30 kHz AWGN pass-band signals at -40dB for SNR= [-80:10:40]

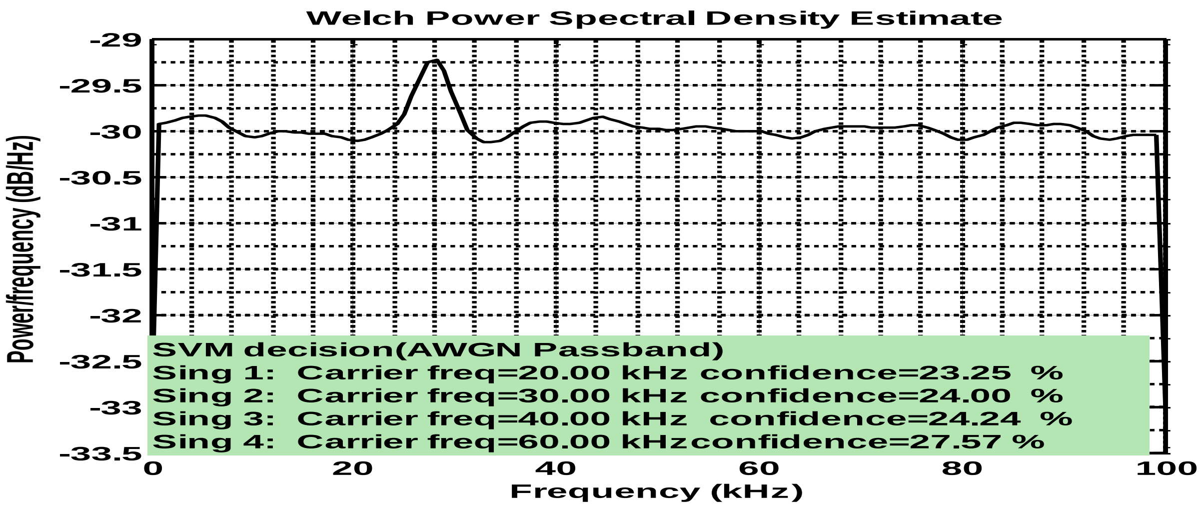


Figure 4.13 30 kHz AWGN Pass-band signals at -20 dB for SNR= [-80:10:40]

The SNR is high enough for reliable detection of a single signal by Welch periodogram. However, the SVM fails because it was trained for four signals

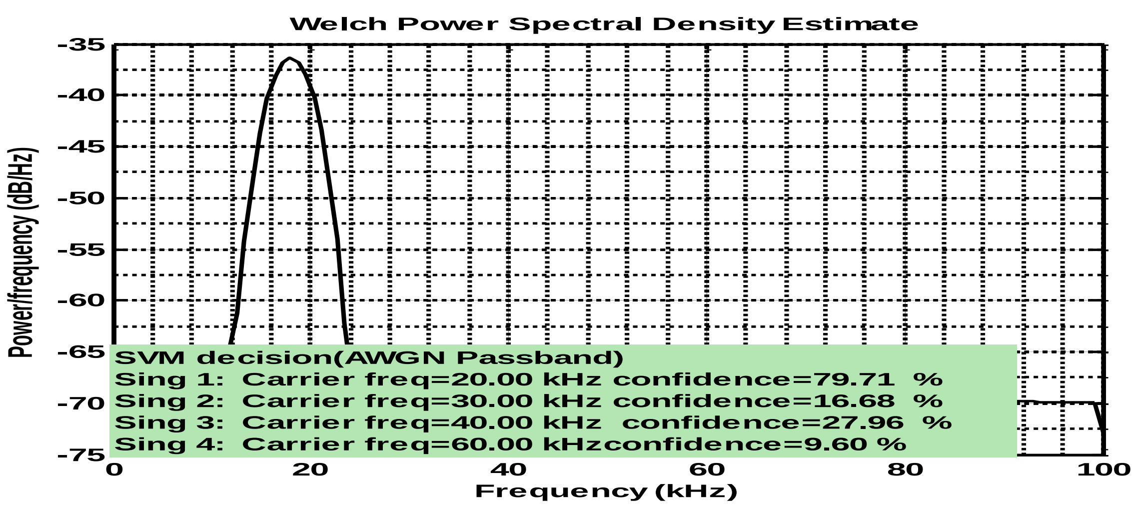


Figure 4.14 20 kHz AWGN pass-band signal at 10 dB for SNR= [-80:10:40]

In Fig. 4.14 20 kHz single strong signal (SNR=10 dB) was transmitted. The SVM detects it despite the fact it was trained for four signals. This needs further investigation.

The results suggest that the SVM detector may identify very low signals. However simulation will be needed to verify that the confidence level drops significantly below the threshold no carriers are present. In any case the combination of Welch periodogram and a SVM based detector could provide means to detect signals at low SNR levels reliably. This will be subject to future investigations

References

[1] Nawaf Hadhal Kamil , Deah J. Kadhim, Wei Liu, Wenqing Cheng, “Signal Processing Techniques for Robust Spectrum Sensing,” ETP International Conference on Future Computer and Communication,2009

[2] Rui Kong, Bing Zhang, “Autocorrelation Kernel Functions for Support vector Machines,” Third International Conference of Natural Computation2007, ICNC 2007, Volume 1, pp. 512-516

[3] J. Mittola III and G.Q.Maguire “Cognitive Radio Making Software Radio more Personal,” IEEE per.Commun. Vol. 6, no.4, 1999,pp.13-18.

[4] S. Haykin, “Cognitive Radio: Brain Empowered Wireless Communications,”Vol.23, no. 2, Feb.2005, pp.201-220,

[5] A.Sahai,n.Hoven and R.tandra *“*Some fundamental limits in Cognitive Radio*,”* In Alletron Conf. on Communication,Control and Computing,Oct.2004

[6] F.F:Digham, M.S: Alouini and M.K.Simon, “On the Energy detection of Unknown Signals over Fading Channels,” In Proc. IEEE ICC, Anchorage, USA, May 2003,pp.3575-3579

[7] Sadeghi, H.Azmi. “A Novel Primary User Detection Method for Multiple Antenna Cognitive Radio,” International Symposium on Telecommunication, IST 200827-28 Aug.2008, pp.188-192

[8] D.Cabric, S.M.Mishra and R.W.brodersen,”Implementation Issues in Spectrum Sensing for Cognitive Rdaios”, Proc. of the 38th Asilomar Conference on Signals, Systems and computers, 2004, pp 772-776

[9] H. Tang, “Some physical Layer Issues of Wide Band Cognitive Radio Systems,” In Proc. IEEE DySPAN 2005, November 2005, pp.151-159

[10] Hao hu, Junde song, Yujing Wang, “Signal Classification based on Spectral Correlation Analysis and SVM in Cognitive Radio”, 22nd international Conference on Advanced Information Networking and Applications ANIA, IEEE Computer Society,pp.883-887

[11] A.Fehske, J.D: Gaeddert, J.H.Reed, “A New Approach to Signal Classification Using Spectral Correlation and Neural Networks,” Proc. IEEE DySPAN 2005, November 2005, pp.144-150

[12] V.N:Vapnik, “The Nature of Statistical Learning Theory,” New York, Springer verlag,1995

[13] Marlize Barkhuizen ,Chris Aldrich, “Classification of process dynamics with Monte Carlo singular spectrum analysis,” European Symposium on Computer Aided process Engineering -14,volume 3,Issue 5,15 April 2006,pp.816-831

[14] N.Cristianini, J.Shawe-Tayor,” An Introduction to Support Vector Machines and Other Kernel-based Learning Methods”,Publishing House of Electronics Industry ISBN:9780521780193,Publication date: March 2000, 204

[15] Chintanu K. Sarmah,s Andhya samarasinghe, Don Kulasiri, Daniel Catchpoole,“A simple affymetrix Ratio-transformation Method Yields Comparable Expression Level Quantification with cDNA data,” International Journal of Biological and Life Sciences 8:3 2012,pp.157-162

[16] Lorenzo Rosasco, Tomaso Poggio “Stability of Tikhonov Rgularization”, 9.520 Class 7, 5March2012

[17] JOse’luise Rojo-A’lvarez, Manel Martinez Ramo’n, Jordi Munoz-Mari, Gustavo Camps- Valls, Carlo Cruz, Anibal R Figueiras-Vidal, “Sparse Deconvolution Using Support Vector Machines, “EURASIP Journal on Advances in Signal Processing , 3 April 2008

[18] Aylin Yener,Roy D.Yates,Sennur Ulukus,“CDMA multiuser detection: a nonlinear programming approach,” IEEE transactions on Communications,vol.50, No.6, June 2002,pp. 1016-1023

[19] Chritopher.J.C.Burges,‘‘A Tutorial on Support Vector Machine for Pattern Recognition, knowledge discovery and Data Mining,” Kluwer Academic Publishers,Boston,1998, 2 (2), 1998,pp.1-43

[20] K.R.Muller, S.Mika, G:Rätsch,Koji Tsuda and Bernhard Schkölp,“An Introduction to Kernel-Based Learning Algorithms”, IEEE Transactions on Neural Networks,Vol.12,No.2,March 2001,pp.181-201

[21] Jing Bai, Xue-Ying Zhang, Yue-ling Guo, “Speech recognition based on a compound kernel Support Vector Machine,”11th IEEE international conference of communication Technology, ICCT2008, 10-12 Nov.2008, pp.696-699

[22] Bernhard Schölkopf, Sebastian Mika, Chris J.C Burges, Philip Knirsch,Klaus-robert Müller,Gunnar Rätsch and Alexander J.Smola,“Input Space Versus Feature Space in kernel-Based methods,” IEEE Transactions on Neural Networks,Vol.10,No.5September 1999,pp. 1000-1017

[23] Bernhard Schölkopf, Alexander J.Smola “Learning with Kernels: Support Vector Machines, Regularization, Optimization and Beyond” MIT press Cambridge, MA, USA 2001, ISBN:0262194759

[24] Li Zhang, Weida Zhou and Lichen Jiao, “Wavelet Support Vector Machine“, IEEE Transactions on Systems, Man and Cybernetics- part B :Cybernetics,Vol.34,No.1,Feburary2004.

[25] Yong Zhong Xing, Xiaobei Wu, Zhiliang Xu, “Multiclass Least Square Wavelet Support Vector Machines,” IEEE International Conference on Networking, Sensing and Control, ICNSC 2008,6-8 April 2008,pp.498-502

[26] G.Y.Chen, G.Dudek, “Auto-correlation Wavelet Support Vector Machine,” Journal of Image and Vision Comuting ,Vol.27, Issue 8,July, 2009 pp.1040-1046

[27] Jose George, K. Rajeev, “Hybird Wavelet Support Vector Regression,” 7th International conference on Cybernetic Intelligence Systems, ICS 2008,9-10 Sept.2008,pp.1-6

[28] William A. Gardner, “Signal Interception: A Unifying Theoretical Framework for Feature Detection,” IEEE Transactions on Communications, Vol.36, NO.8, August 1988, pp.897-905

[29] Sophocles J.Orfanidis, “Introduction to Signal Processing”, Prentice Hall International, Inc, 1999

[30] Bernard Sklar,”Digital Communications Fundamentals and Applications,” Second Edition, Prentice Hall PTR, Upper Saddle River, New Jersey 07458,ISBN 0-13-084788-7

[31] Rakesh Rajbanshi,ITTC-FY2008-Tr-31620-05,“Technical Report: OFDM Based Cognitive Radio for DSA Networks,” The University of Kansas,2335 Irving Hill Road, Lawrence, Ks 66045-7612, September 2007

[32] Marina Petrova, Petri Mähönen and Alfredo Osuna,"Multi-Class Classification of Analog and Digital Signals in Cognitive Radios using Support Vector Machines,"7th International Symposium on Wireless Communication Systems (ISWS) 2010,19-22 Sept.2010,pp.986-990

33 Kwang-Cheng Chen, Peng-Yu Chen, Neeli Prasad, Ying-Chang Liang, Sumei Sun, "Trusted Cognitive Radio Networking,"Wireless Communications and Networking, Vol. 10,Issue 4, April 2010,pp.467-485.

34 Younlong Zou, Yu-Dong yao, Baoyu Zheng, "Outage Probability Analysis of Cognitive Transmissions: Impact of Spectrum Sensing Overhead," IEEE Transactions on Wireless Communications, August 2010, Vol.9, Issue 8, pp.2676-2688

35 El-Naqa ,I; Yongyi yang, wernick, M.N;galatsanos,N.P; Nishikawa,R.M; "A Support Vector Machine Approach for Detection of Microcalcifications,"IEEE transactions on Medical Imaging, Volume 21,Issue:12,pp.1552-1563

5 Fuzzy Logic Based Spectrum Sensing

5.1 FUZZY INFERENCE SYSTEM

A fuzzy inference system (FIS) deals with a nonlinear mapping of the input data vector and defines scalar output by using fuzzy rules. This mapping process uses input/output membership functions, FL operators, fuzzy if–then rules, aggregation of output sets and defuzzification. A general model of a fuzzy inference system (FIS) is shown in Figure 5.1 [1].

The FLS maps crisp inputs into crisp outputs. It can be seen from the Fig 5.1, that the FIS contains four components: the fuzzifier, inference engine, rule base, and defuzzifier.

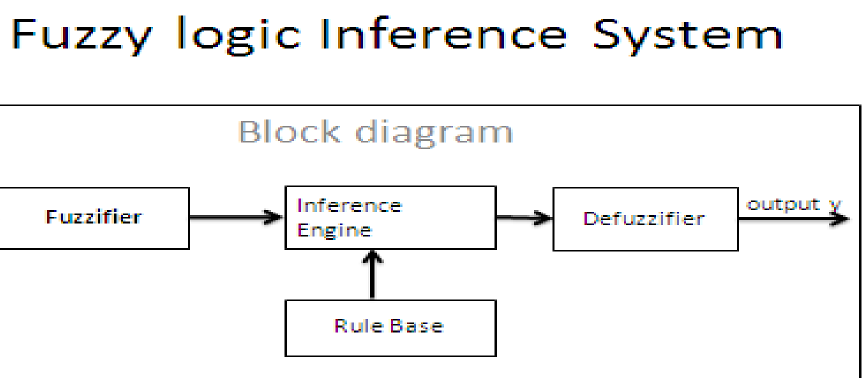


Figure 5.1 Block Diagram of a Fuzzy Inference System

5.1.1 Fuzzifier

Fuzzification is a process through which we can convert the input value to a fuzzy set. This process takes place in the Fuzzifier. The fuzzy set consists of two values which describes the degree of belongingness with a certain membership function. The crisp values of input variables from sensors are fuzzified into linguistics values using predefined membership functions (MSFs). The outputs of fuzzifiers are a set of fuzzy numbers, two fuzzy numbers for each input variables.

5.1.2 Inference Engine

Inference Engine is 2nd component of fuzzy logic control system. IF-THEN fuzzy logic rule can be assembled as IF antecedent THEN consequent. When an input is given to the control system then against this input, the inference engine fires an appropriate rule. The inference engine defines mapping from input fuzzy sets into output fuzzy sets and determines the degree to which the antecedent is satisfied for each rule. It is possible that one or more rules may fire at the same time.

5.1.3 Rule Base

The rule base contains linguistic rules that are provided by experts. It is also possible to extract rules from numeric data. Once the rules have been established, the FIS can be viewed as a system that maps an input vector to an output vector. Outputs for all rules are then aggregated. During aggregation, fuzzy sets that represent the output of each rule are combined into a single fuzzy set. Fuzzy rules are fired in parallel, which is one of the important aspects of FIS. In FIS, the order in which rules are fired does not affect the output [1].

5.1.4 Defuzzifier

The defuzzifier maps output fuzzy sets into a crisp number. Given a fuzzy set that encompasses a range of output values, the defuzzifier returns one number, thereby moving from a fuzzy set to a crisp number. Defuzzification is a process through which we can convert linguistic values to crisp values. This process takes place in the defuzzifier. Against each output one defuzzifier exist. The main objective of the defuzzifier is to determine single numeric crisp (singleton) value of each output variable [2]. .

In order to process the input to get the output reasoning there are six steps involved in the creation of a rule based fuzzy system [3].

1. Identification, names and ranges to inputs.

2. Identification, names and ranges to outputs.

3. For each input and output, creation of the degree of fuzzy membership functions.

4. Construct the rule base for the system to operate.

5. Decide how the action will be executed by assigning strengths to the rules

6. Defuzzify the output by combining the rules.

The fuzzy inference process can be described completely in the five steps as shown in Fig.5.2

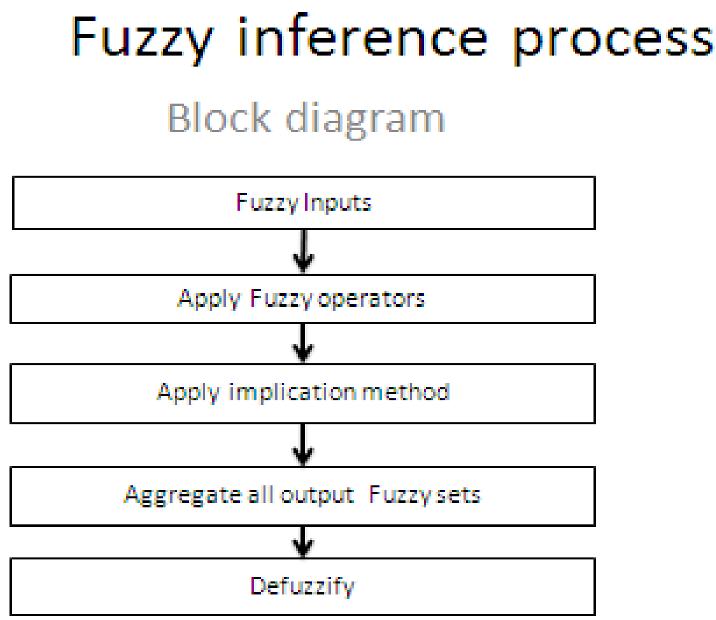


Figure 5.2 Fuzzy Inference Process

Step 1: Fuzzy Inputs

The first step is to take inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions.

Step 2: Apply Fuzzy Operators

Once the inputs have been fuzzified, we know the degree to which each part of the antecedent has been satisfied for each rule. If a given rule has more than one part, the fuzzy logical operators are applied to evaluate the composite firing strength of the rule.

Step 3: Apply the Implication Method

The implication method is defined as the shaping of the output membership functions on the basis of the firing strength of the rule. The input for the implication process is a single number given by the antecedent, and the output is a fuzzy set. Two commonly used methods of implication are the minimum and the product.

Step 4: Aggregate all Outputs

Aggregation is a process whereby the outputs of each rule are unified. Aggregation occurs only once for each output variable. The input to the aggregation process is the truncated output fuzzy sets returned by the implication process for each rule. The output of the aggregation process is the combined output fuzzy set.

Step 5: Defuzzify

The input for the defuzzification process is a fuzzy set (the aggregated output fuzzy set), and the output of the defuzzification process is a crisp value obtained by using some defuzzification method. The most commonly used method is the centroid. Other methods include the maximum, the means of maxima, height, and modified height method.

5.2 Cognitive Radio Using Fuzzy Logic

A cognitive radio is a two way radio capable to change its parameters of transmission or reception automatically considering several factors; radio frequency spectrum, user behavior and network states.

The main problem in the cognitive radio is the spectrum sensing, and if the spectrum holes are available then select the best spectrum hole on the basis of communication parameters is an important task. The classical signal processing technique can detect the spectrum hole but cannot do the decision, which hole will be best. The hole which is idle most of the time will be more secure from interference produced due to communication of licensed primary user. The signal will be detected at Physical layer and the decision will be done at MAC Layer [4].

IEEE 802.22 standard is designed for Wireless regional area networks. The white spaces available from licensed TV spectrum are used for CR communication [5, 6, 7 and 8].

The components of the dynamic channel selection scheme for a wireless node are instantaneous collision probability and signal strength. Estimated collision probability Pc (f) is often very imprecise and cannot be computed very accurately. Information processing based fuzzy logic control has been deployed successively in many real world automatic systems including autonomous robot navigation, autofocus cameras, image analysis, diagnosis systems, washing machines, automobile transmissions, air conditioners and aerospace.

The key efforts in the area of fuzzy logic based algorithms and new software and hardware architecture are needed to address new challenges in the evolution of CR networks.

Fuzzy logic is useful for multidimensional decision making problems in dynamic and distributed uncertain environment by saving computational complexity. Fuzzy logic control and decision making have proven useful when time-invariance and linearity of the controlled process cannot be assumed by lacking a well posed mathematical model. Fuzzification process is needed to change the imprecise collision probability in each channel into a fuzzy set which can be used by inference rules to determine the traffic load in each channel. The decision on dynamic channel selection at node is based on a utility factor. The signal strength r_f is the function of distance between the access point AP and the wireless node and the channel condition. Both collision probability & received signal strength impact the channel utility function [9].

Recently an approach to use fuzzy logic in networks and telecommunication system has been organized into three efforts: modeling and control, forecasting and management and performance estimation.

5.3 A Proposed Cascaded Fuzzy Logic Control System for Decision Making in Cognitive Radio System

The proposed cascaded Fuzzy logic control system shown in Fig.5.3 consists of three fuzzy logic controllers: FLC-1, FLC-2 and FLC-3, and a ROM [10].

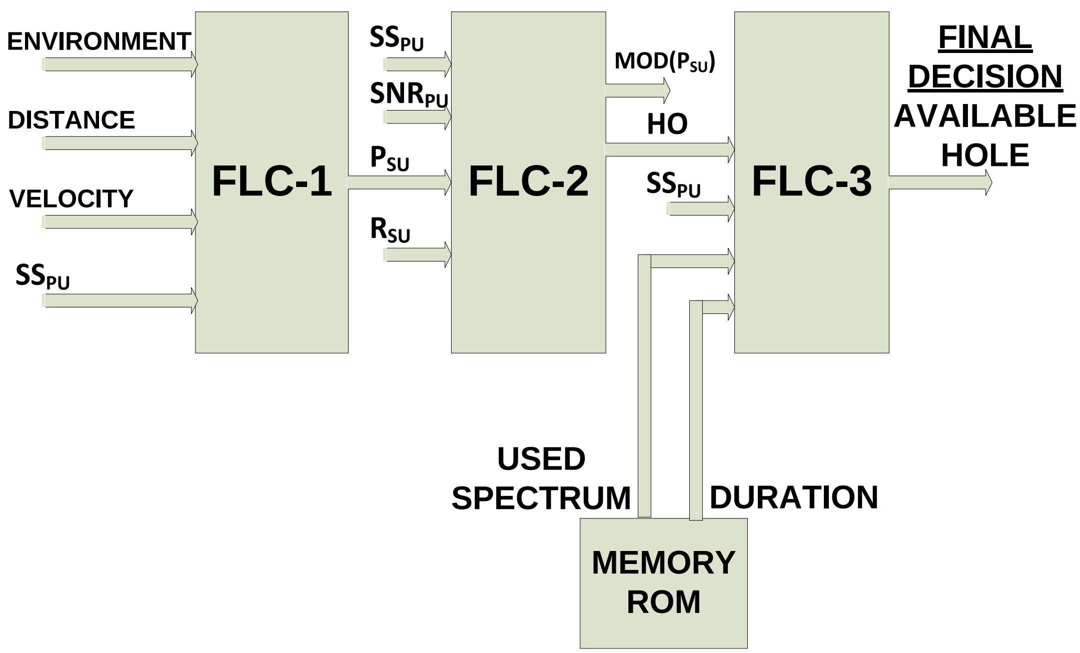


Figure 5.3 Block Diagram of Cascaded Fuzzy Logic Control System for CRs.

5.3.1 FLC-1

This fuzzy controller deals with four input variables: Environment condition, distance of SU from PU, speed of SU and the signal strength received at secondary user SU from the primary user PU (SS_{PU}). For distance, velocity and SS_{PU}, each linguistic variable is characterized by a term set of three fuzzy sets: Small, Medium and High.

T(Distance)=T(Velocity)=T(SS_{PU})={ Small, Medium , Large}={ S, M , La}

One input variable, environment is labeled as:

T(Environment)={ Worst, Bad, Normal}={ W, B, N}

The one output variable, transmission power of SU (P_{SU}) is also characterized by a term set of three fuzzy sets: Small, Medium and High

$T(P_{SU})$={ Small, Medium , High}={ S, M , H}

Total numbers of active rules for FLC-1 are 81.

Total number of active rules= $m^n=3^4=81$

Where, m=Maximum number of overlapped fuzzy sets=3, n=Number of inputs=4

".

5.3.1.1 Fuzzy Rules Base for FLC-1

The input variables and output variables are labeled with the term of three fuzzy sets. In Table 5.1, T(environment)=T{W,B,N}={Worst, Bad, normal} are the terms of three Fuzzy sets for the environment. Similarly T(distance)= T{S,M, La}={small, medium, large}, T(speed)= T{L,M, H}={low, medium, high},and T(SSpu)= T{L,M, H}={low, medium, high} are the terms of three fuzzy sets for distance, speed and signal strength received at SU from the PU. T(Psu)={Small, Medium, High}={S,M,H} are used for the speed of secondary user. IF -Then rule base arrangement for FLC-1 is shown in Table 5.1.

IF					THEN
Rule No.	**Environment**	**Distance of SU from PU**	**Speed of SU**	**SS_{PU} Signal strength received at SU from the PU**	**P_{SU} Transmission power of SU**
1,2,3	W	S	L	L,M,H	L,M,M
4,5,6	W	S	M	L,M,H	L,M,M
7,8,9	W	S	H	L,M,H	L,M,M
10,11,12	W	M	L	L,M,H	L,M,H
13,14,15	W	M	M	L,M,H	L,M,H
16,17,18	W	M	H	L,M,H	L,M,H
19,20,21	W	La	L	L,M,H	L,M,H
22,23,24	W	La	M	L,M,H	L,M,H
25,26,27	W	La	H	L,M,H	L,M,H
28,29,30	B	S	L	L,M,H	L,M,M
31,32,33	B	S	M	L,M,H	L,M,M
34,35,36	B	S	H	L,M,H	L,M,M
37,38,39	B	M	L	L,M,H	L,M,M
40,41,42	B	M	M	L,M,H	L,M,M
43,44,45	B	M	H	L,M,H	L,M,M
46,47,48	B	La	L	L,M,H	L,M,M

49,50,51	B	La	M	L,M,H	L,M,M
52,53,54	B	La	H	L,M,H	L,M,M
55,56,57	N	S	L	L,M,H	L,L,L
58,59,60	N	S	M	L,M,H	L,L,L
61,62,63	N	S	H	L,M,H	L,L,L
64,65,66	N	M	L	L,M,H	L,L,L
67,68,69	N	M	M	L,M,H	L,L,L
70,71,72	N	M	H	L,M,H	L,L,L
73,74,75	N	La	L	L,M,H	L,M,M
76,77,78	N	La	M	L,M,H	L,M,M
79,80,81	N	La	H	L,M,H	L,M,M

Table 5.1 Fuzzy Rules Base for FLC-1

5.3.1.2 MATLAB Surface Viewer for FLC-1

Fig. 5.4 shows MATLAB Surface Viewer for FLC-1 considering SSpu, environment and Psu. This shows that with the increase of SSpu, Psu is also increasing and change in environment also effects in the value of Psu.

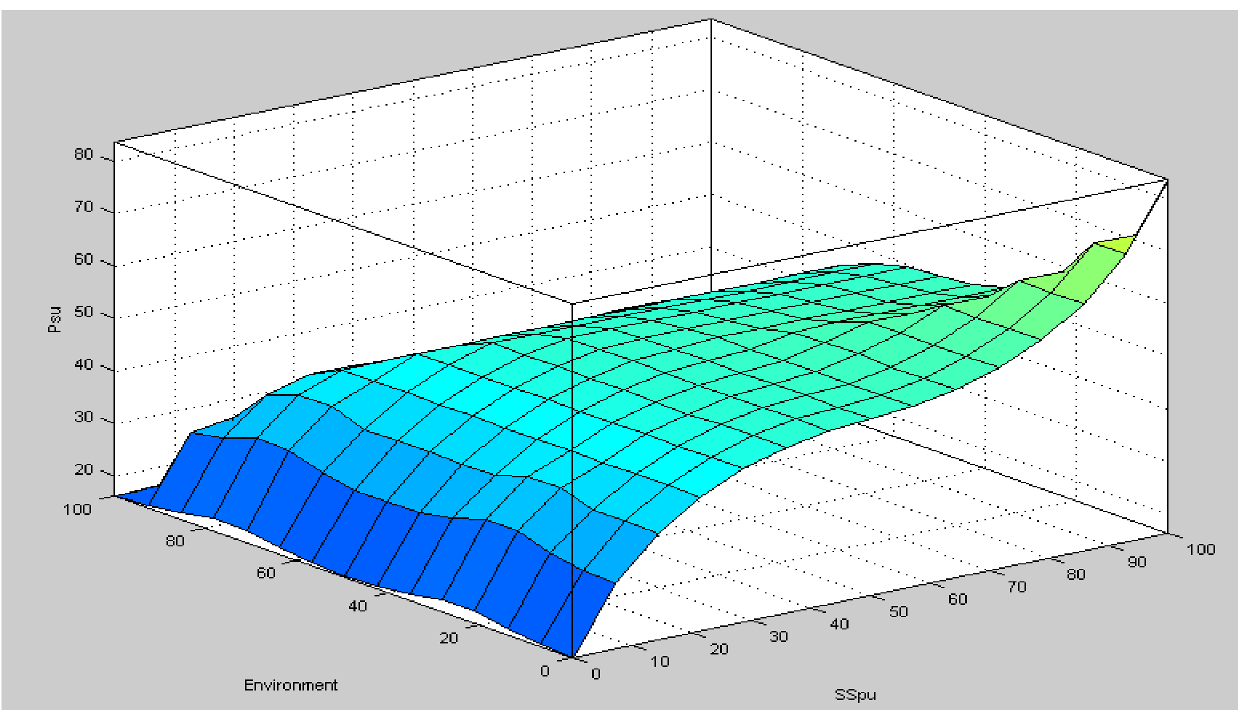


Figure 5.4 MATLAB Surface Viewer for FLC-1, Showing Relation between Velocity, Environment and Psu.

Fig.5.5 shows MATLAB Surface Viewer for FLC-1, showing relation between SSpu, distance and Psu. It shows that when SSpu increases Psu also increases. The change in distance also causes the change in SSpu for certain range of values according to selected rule base.

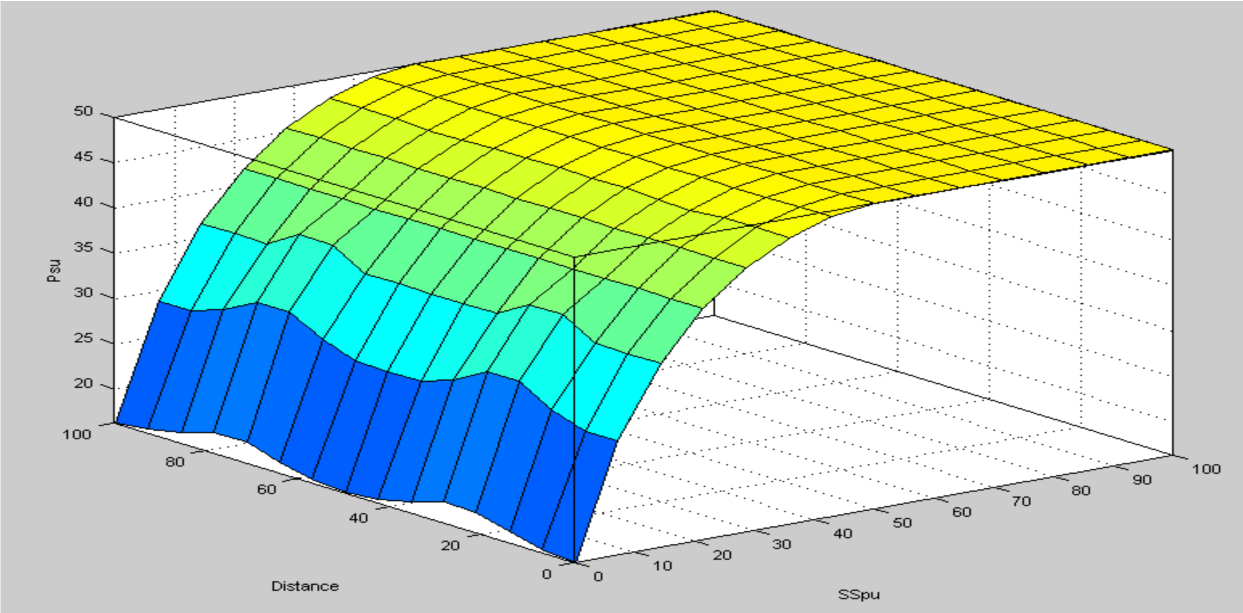


Figure 5.5 MATLAB Surface Viewer for FLC-1, Showing Relation between Velocity, Environment and Psu.

Fig. 5.6 shows that after certain condition of environment, the value of Psu also changes.

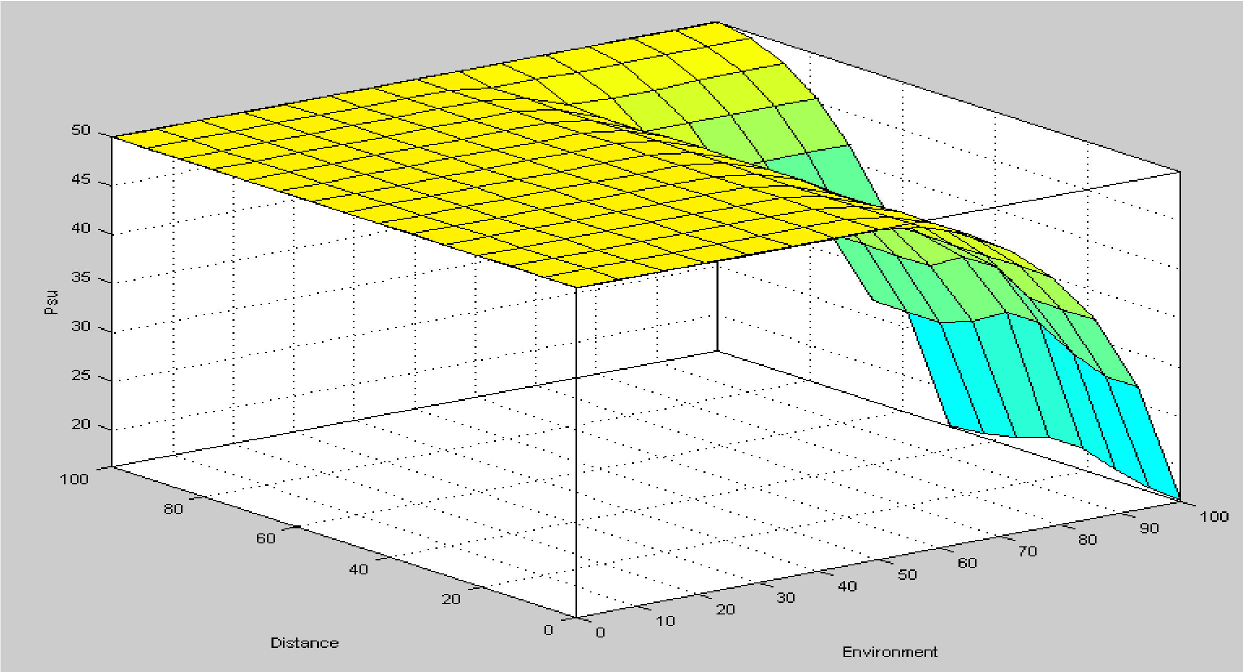


Figure 5.6 MATLAB Surface Viewer for FLC-1, Showing Relation between Velocity, Environment and Psu.

Fig.5.7 shows the environmental effects on Psu and also change in Psu due to change in velocity at certain range of selected rule base values.

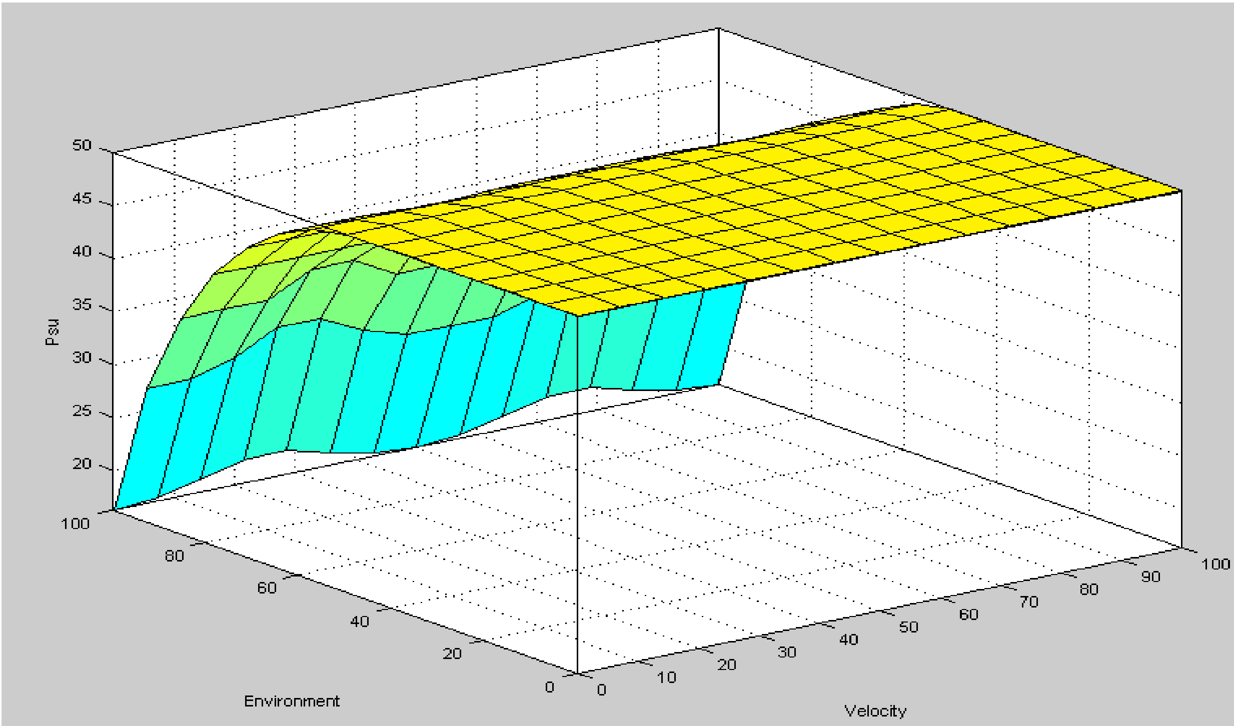


Figure 5.7 MATLAB Surface Viewer for FLC-1, Showing Relation between Velocity, Environment and Psu.

5.3.2 FLC-2

The Fuzzy Logic Controller FLC-2 deals with four input variables: Single Strength received by SU as transmitted by PU (SS_{PU}), Signal to noise ratio at the PU (SNR_{PU}), transmission power of SU without interfering the PU (P_{SU}), and bit rate of the PU (R_{SU}) [10].

Each input variable is characterized by a term set of three fuzzy sets: Small, Medium and High.

$T(SS_{PU})=T(SNR_{PU})=T(P_{SU})=T(R_{SU})=$ {Low, Medium, High}={L,M,H}

The two output variables: Modification in the transmission power of SU – MOD(P_{SU}) and spectrum hand off (HO).

The output MOD (P_{SU}) linguistic variable is characterized by a term set of the three fuzzy sets: Low, Medium and High.

T (MOD $_{Psu}$) = {Low, Medium, High} = {L, M, H}

Another output HO is characterized by a term set of the three fuzzy sets: Yes, Probable Yes and No.

T(HO)={Yes, Probable Yes, No}={Y, PY, N}.

Total numbers of active rules for FLC-2 are 81.

Total number of active rules= $m^n=3^4=81$

Where, m=Maximum number of overlapped fuzzy sets=3, n=Number of inputs=4

5.3.3 Fuzzy Rules Base for FLC-2

FLC-2 deals with four inputs and two output variables. The three fuzzy sets for each variable are shown as:

T(SSPU)= {Low, Medium, High}={L,M,H}

T(SNRPU)= {Low, Medium, High}={L,M,H}

T(PSU)= {Low, Medium, High}={L,M,H}

T(RSU)= {Low, Medium, High}={L,M,H}

T (MOD Psu) = {Low, Medium, High} = {L, M, H}

T(HO)={Yes, Probable Yes, No}={Y, PY, N}.

IF					THEN	
Rule No	**SSPU** **Signal strength received at SU from the PU**	**SNR_{PU}** Signal to noise ratio at PU	**P_{SU}** **Power of SU**	**R_{SU}** **Bit rate of PU**	**MOD(P_{SU})**	**HO**
1,2,3	L	L	L	L,M,H	M,L,L	Y,PY,N
4,5,6	L	L	M	L,M,H	M,L,L	Y,PY,N
7,8,9	L	L	H	L,M,H	L,L,L	Y,PY,N
10,11,12	L	M	L	L,M,H	M,L,L	PY,PY,N
13,14,15	L	M	M	L,M,H	M,L,L	PY,N,N
16,17,18	L	M	H	L,M,H	L,L,L	PY,N,N
19,20,21	L	H	L	L,M,H	M,L,L	PY,N,N
22,23,24	L	H	M	L,M,H	M,L,L	N,N,N
25,26,27	L	H	H	L,M,H	L,L,L	N,N,N
28,29,30	M	L	L	L,M,H	M,L,L	Y,PY,N
31,32,33	M	L	M	L,M,H	L,L,L	Y,PY,N
34,35,36	M	L	H	L,M,H	L,L,L	Y,PY,N
37,38,39	M	M	L	L,M,H	M,M,M	PY,N,N

40,41,42	M	M	M	L,M,H	L,L,L	PY,N,N
43,44,45	M	M	H	L,M,H	L,L,L	PY,N,N
46,47,48	M	H	L	L,M,H	M,M,M	N,N,N
49,50,51	M	H	M	L,M,H	L,L,L	N,N,N
52,53,54	M	H	H	L,M,H	L,L,L	N,N,N
55,56,57	H	L	L	L,M,H	M,L,L	Y,PY,N
58,59,60	H	L	M	L,M,H	L,L,L	Y,PY,N
61,62,63	H	L	H	L,M,H	M,M,M	Y,PY,N
64,65,66	H	M	L	L,M,H	L,L,L	PY,N,N
67,68,69	H	M	M	L,M,H	L,L,L	PY,N,N
70,71,72	H	M	H	L,M,H	L,L,L	PY,N,N
73,74,75	H	H	L	L,M,H	M,L,L	N,N,N
76,77,78	H	H	M	L,M,H	L,L,L	N,N,N
79,80,81	H	H	H	L,M,H	L,L,L	N,N,N

Table 5.2 Fuzzy Rules Base for FLC-2

5.3.4 MATLAB Surface Viewer for FLC-2

MATLAB surface viewer gives the various relations between inputs and outputs variables using different selection modes. Fig. 5.8 represents the relation of SSpu, SNRpu and MOD(Psu) according to the selected rule base. MOD(Psu) changes with the change in SNRpu. While change in SSpu also effects in MOD(Psu).

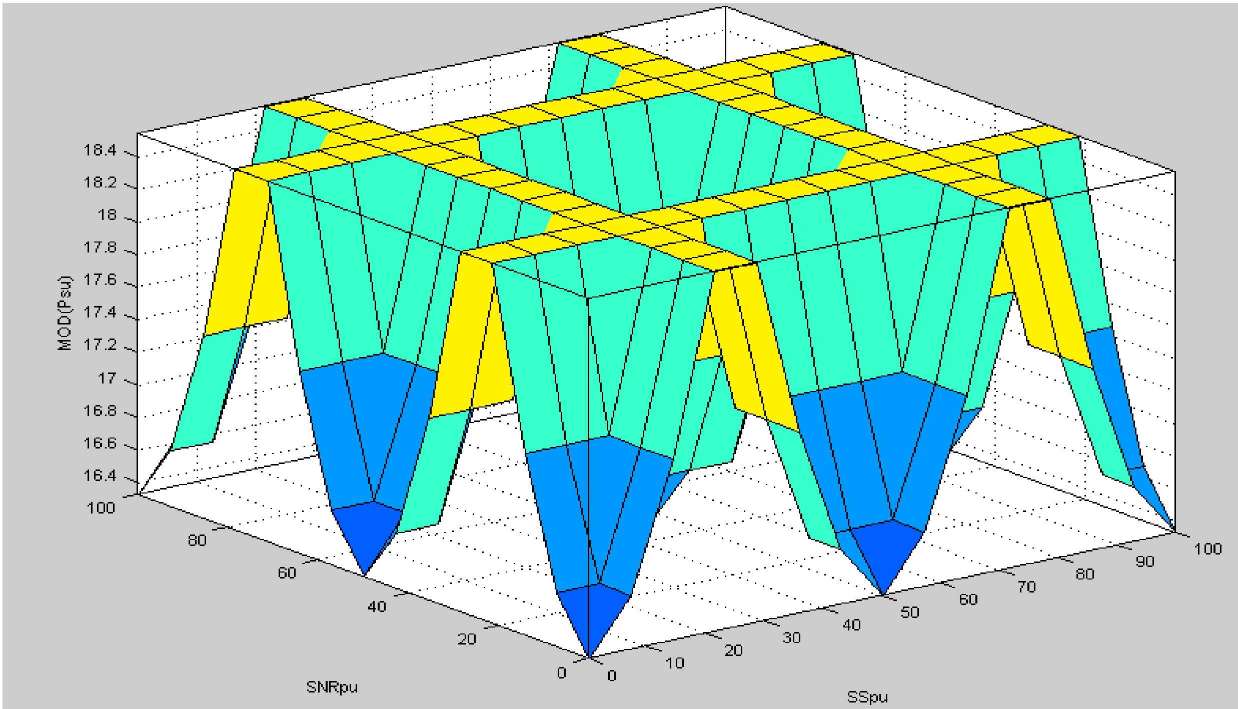


Figure 5.8 MATLAB Surface Viewer for FLC-2, Showing Relation Between SSpu, SNRpu and MOD(Psu).

Fig. 5.9 shows the relation of Psu, SSpu and MOD(Psu) according to the selected rule base applied. MOD(Psu) changes with the change in SSpu. While change in Psu also effects SSpu for some range of values according to the selected rule base for some range of values.

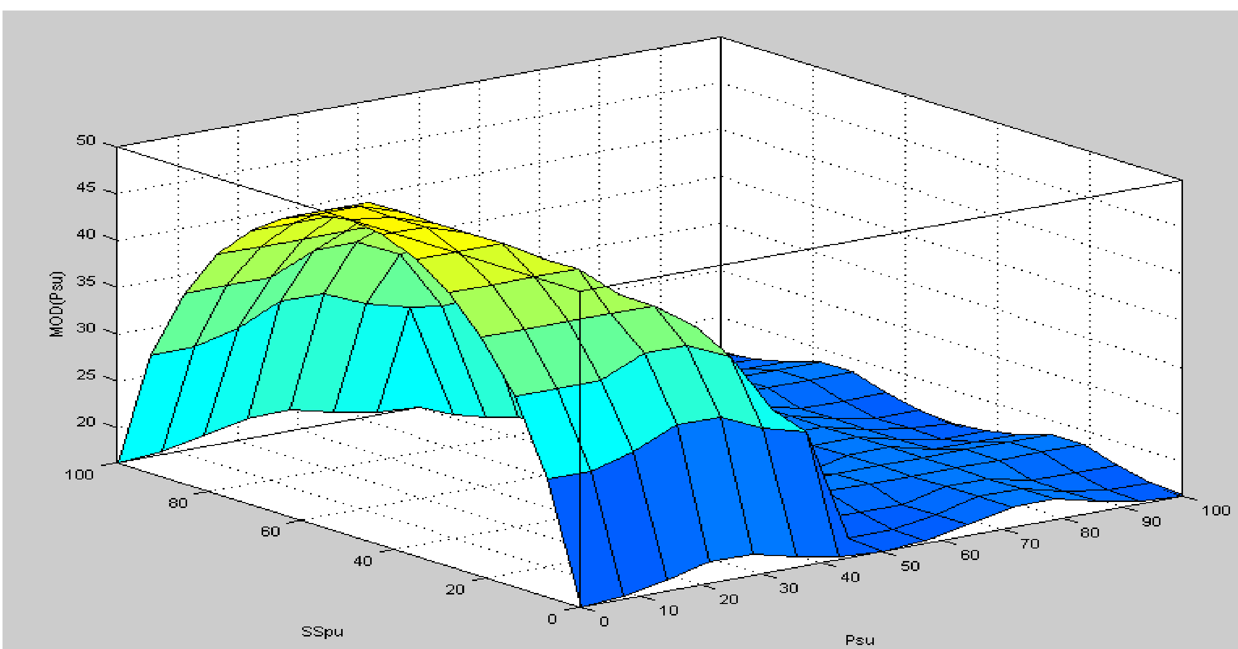


Figure 5.9 MATLAB Surface Viewer for FLC-2 Showing relation Between Psu, SSpu and MOD(Psu).

Fig. 5.10 shows the relation of Rsu, SSpu and MOD(Psu)according to the selected rule base applied. Keeping SSpu constant for some range of values, Rsu causes influence in MOD(Psu).

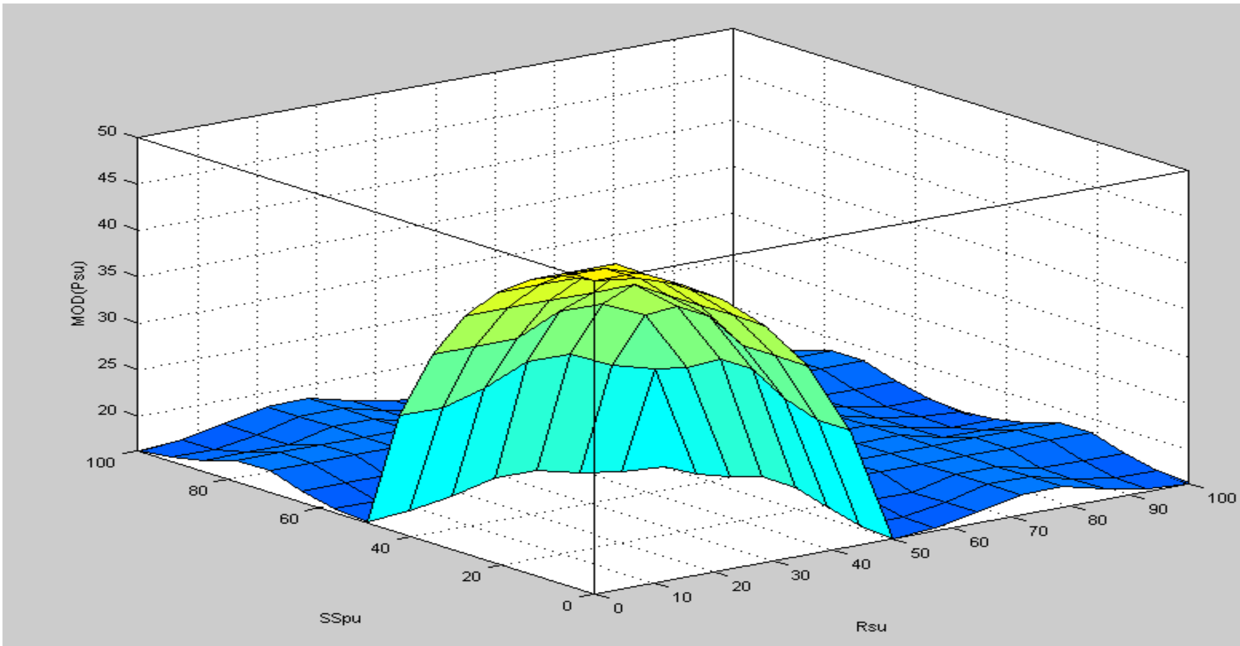


Figure 5.10 MATLAB Surface Viewer for FLC-2, Showing Relation Between Rsu, SSpu and MOD(Psu).

Fig. 5.11 MATLAB Surface Viewer for FLC-2 shows the relation between SNRpu, Rsu and HO. The value of SNRpu causes change in the HO.

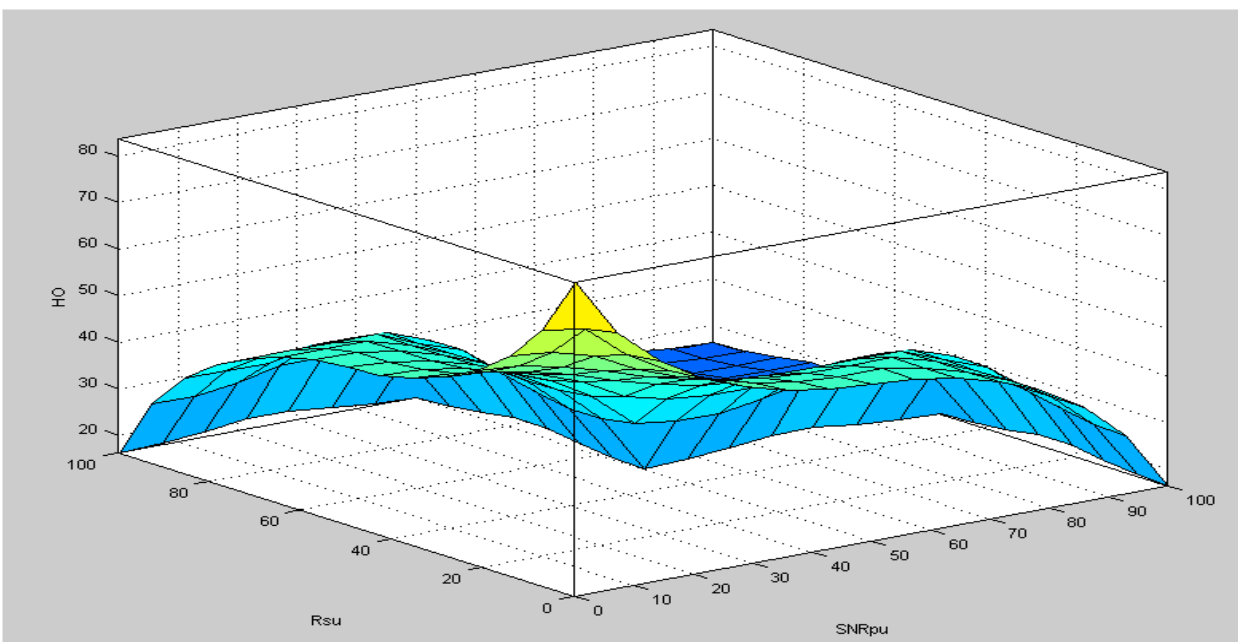


Figure 5.11 MATLAB Surface Viewer for FLC-2 , Showing Relation Between SNRpu, Rsu and HO.

Fig.5.12 shows the relation between SSpu, Rsu and HO. Keepin SSpu constant, change in Rsu results the change in the value of HO.

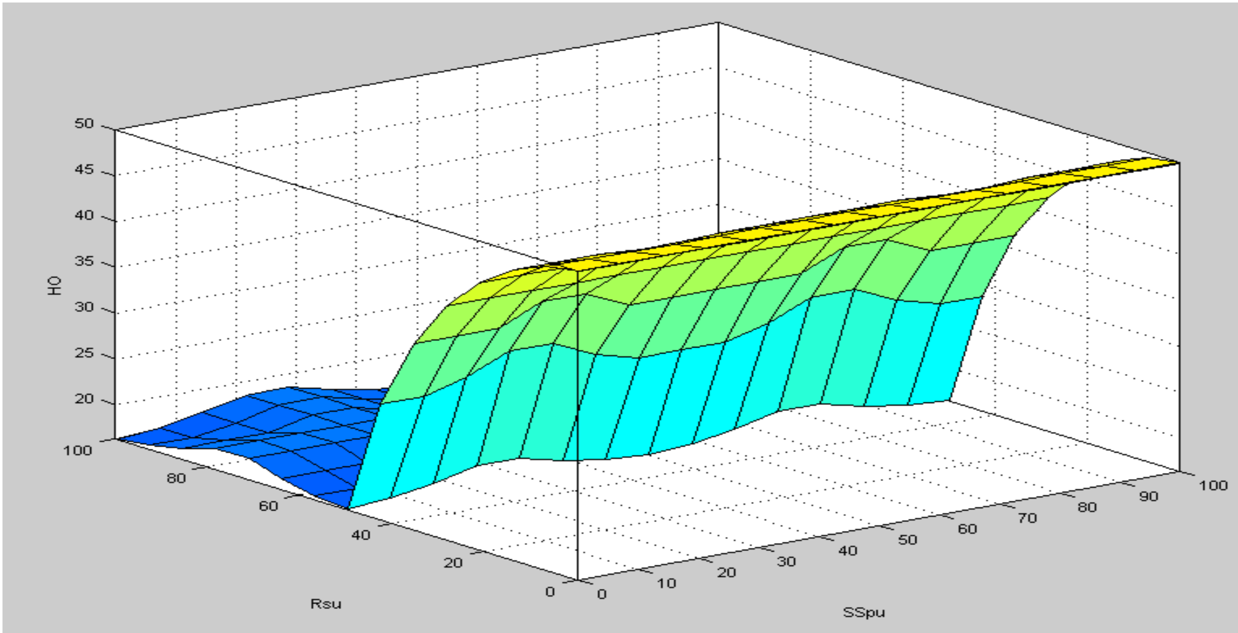


Figure 5.12 MATLAB Surface Viewer for FLC-2, Showing Relation Between SSpu, Rsu and HO.

Fig.5.13 shows that keeping Psu constant, change in Rsu needs the change in HO.

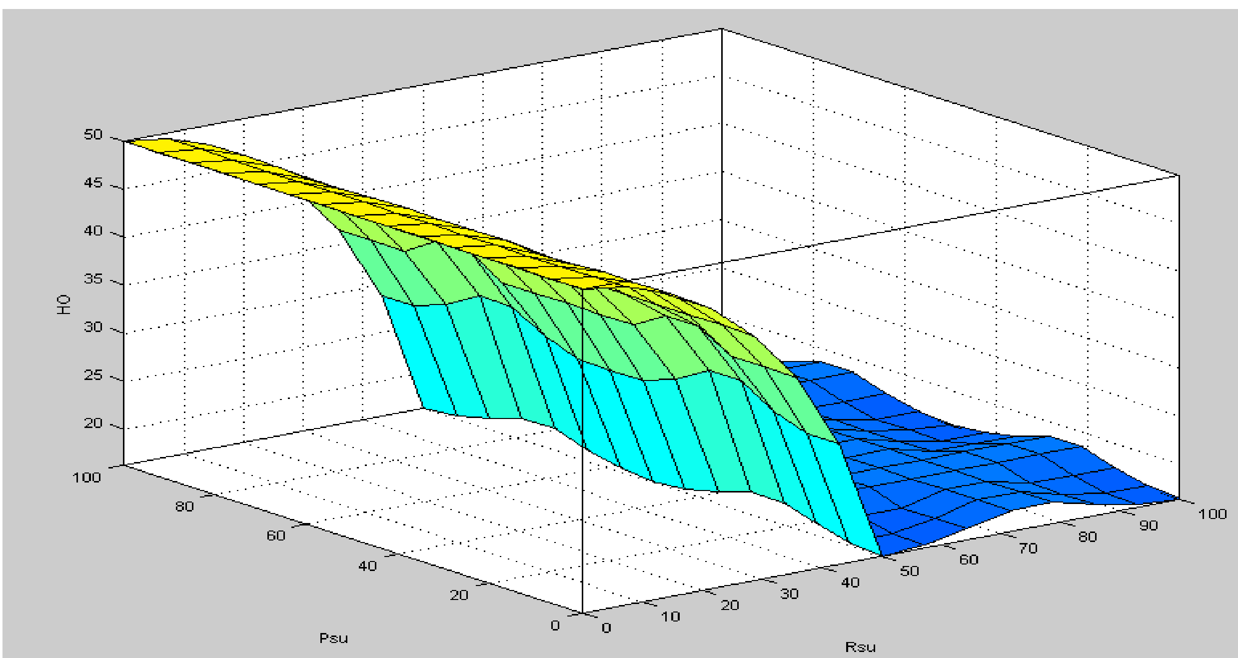


Figure 5.13 MATLAB Surface Viewer for FLC-2, Showing Relation Between Rsu, Psu and HO.

Fig.5.14 shows MATLAB Surface Viewer for FLC-2, showing relation between SSpu, Rsu and HO for certain range of selected rules. Decrease in Rsu causes increase in HO keeping SSpu constant according to certain rules applies.

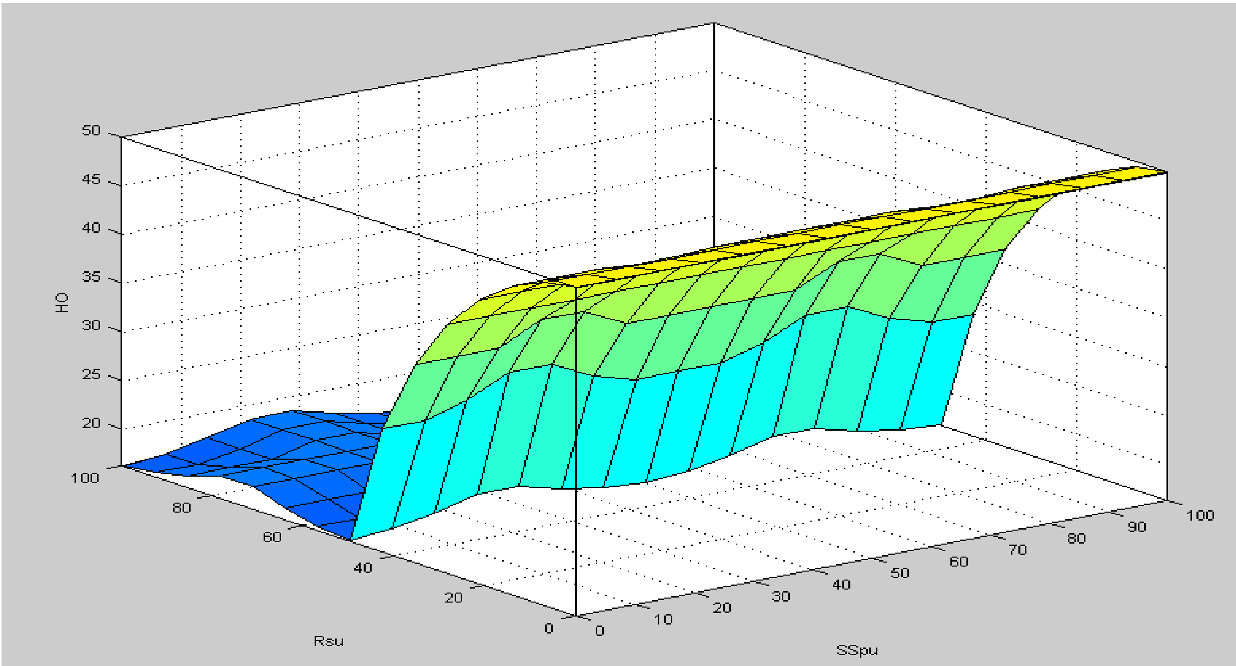


Figure 5.14 MATLAB Surface Viewer for FLC-2 Showing Relation Between SSpu, Rsu and HO.

5.3.5 FLC-3

The Fuzzy Logic Controller FLC-3 deals with four input variables: SS_{PU} -Signal strength received at SU from the PU, Spectrum Hand off (HO), available used frequency spectrum and Spectrum availability duration (Information stored in ROM).

SS_{PU} input variable is characterized by a term set of three fuzzy sets: Small, Medium and High.

$T(SS_{PU})$= {Low, Medium, High}={L,M,H}

The input HO is characterized by a term set of the three fuzzy sets: Yes, Probable Yes and No.

T(HO)={Yes, Probable Yes, No}={Y, PY, N}.

Available used frequency spectrum input variable is characterized by a term set of three fuzzy sets: Low Bandwidth, Medium Bandwidth and High Bandwidth.

T(Available frequency Band)={ Low Bandwidth, Medium Bandwidth , High Bandwidth}={LB,MB,HB}

T (Frequency Band) = {Low Band, Medium Band, High Band} = {LB, MB, HB}

Spectrum time duration input variable is characterized by a term set of three fuzzy sets: Limited Average and Unlimited.

T(Available frequency time duration)={ Limited, Average , Unlimited}={L,A,UL}

The output available Spectrum Hole is characterized by a term set of the three fuzzy sets: Low Range, Medium Range and High Range.

T (Spectrum Hole) = {Low Range, Medium Range, High Range}={LR, MR, HR}

Total numbers of active rules for FLC-3 are 81.

Total number of active rules= $m^n=3^4=81$

Where, m=Maximum number of overlapped fuzzy sets=3, n=Number of inputs=4

5.3.5.1 Fuzzy Rules Base for FLC-3

The fuzzy rule base for FLC-3 is shown in Table 5.3. The following three fuzzy sets for four input variables: SSpu, HO, available frequency Band and available frequency time duration. While one output with three fuzzy sets is taken.

T(SSPU)= {Low, Medium, High}={L,M,H}

T(HO)={Yes, Probable Yes, No}={Y, PY, N}.

T(Available frequency Band)={ Low Bandwidth, Medium Bandwidth , High Bandwidth}={LB,MB,HB}

T(Available frequency time duration)={ Limited, Average , Unlimited}={L,A,UL}

T (Spectrum Hole) = {Low Range, Medium Range, High Range}={LR, MR, HR}

IF					THEN
Rule No.	**SS_{PU} Signal strength received at SU from the PU**	**HO Hand Off**	**Available Spectrum**	**Time Duration Of Available spectrum**	**Spectrum Hole**
1,2,3	L	N	LB	L, A, UL	LR
4,5,6	L	N	MB	L, A, UL	LR
7,8,9	L	N	HB	L, A, UL	LR
10,11,12	L	PY	LB	L, A, UL	MR
13,14,15	L	PY	MB	L, A, UL	MR
16,17,18	L	PY	HB	L, A, UL	MR
19,20,21	L	Y	LB	L, A, UL	LR
22,23,24	L	Y	MB	L, A, UL	MR
25,26,27	L	Y	HB	L, A, UL	HR
28,29,30	M	N	LB	L, A, UL	MR

31,32,33	M	N	MB	L, A, UL	MR
34,35,36	M	N	HB	L, A, UL	MR
37,38,39	M	PY	LB	L, A, UL	MR
40,41,42	M	PY	MB	L, A, UL	MR
43,44,45	M	PY	HB	L, A, UL	MR
46,47,48	M	Y	LB	L, A, UL	LR
49,50,51	M	Y	MB	L, A, UL	MR
52,53,54	M	Y	HB	L, A, UL	HR
55,56,57	H	N	LB	L, A, UL	HR
58,59,60	H	N	MB	L, A, UL	HR
61,62,63	H	N	HB	L, A, UL	HR
64,65,66	H	PY	LB	L, A, UL	HR
67,68,69	H	PY	MB	L, A, UL	HR
70,71,72	H	PY	HB	L, A, UL	HR
73,74,75	H	Y	LB	L, A, UL	LR
76,77,78	H	Y	MB	L, A, UL	MR
79,80,81	H	Y	HB	L, A, UL	HR

Table 5.3 Fuzzy Rules Base for FLC-3

5.3.5.2 MATLAB Surface Viewer for FLC-3

The various MATLAB rule viewer graphs are shown for different relations according to the selected rule base.

Fig. 5.15 shows that with increase in HO, the increase in spectrum Hole is also required. Similarly change in SSpu also causes change in Spectrum Hole according to the rule base selected.

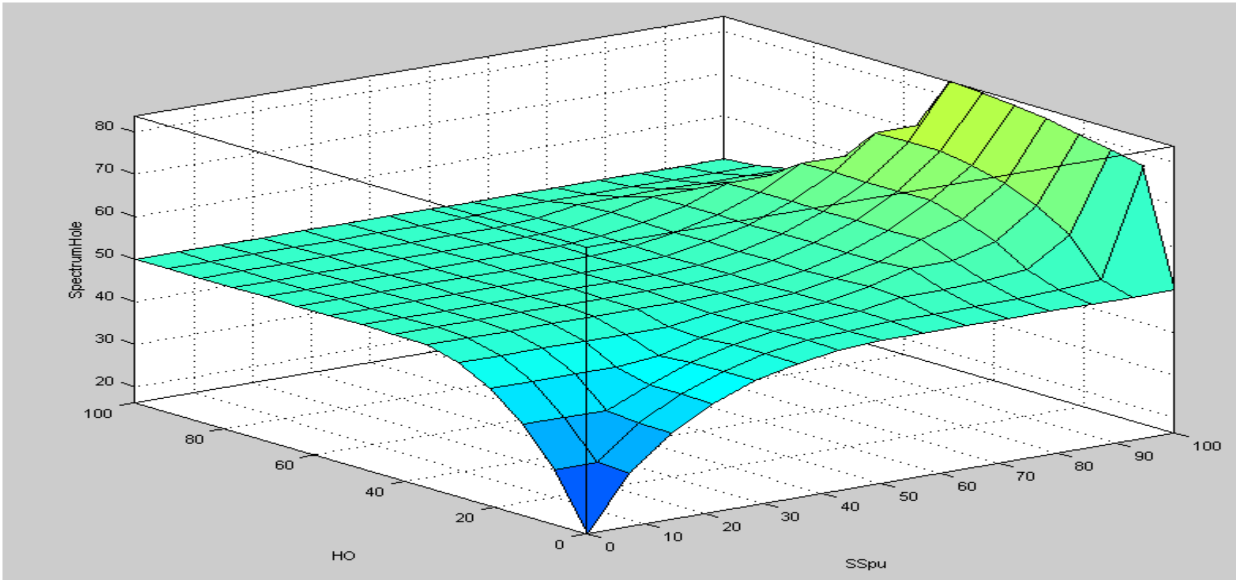


Figure 5.15 MATLAB Surface Viewer for FLC-3, Showing Relation between SSpu, HO and Spectrum Hole.

Fig. 5.16 shows that after certain range of values increase in SSpu also demands the change in spectrum hole according to the selected rule base.

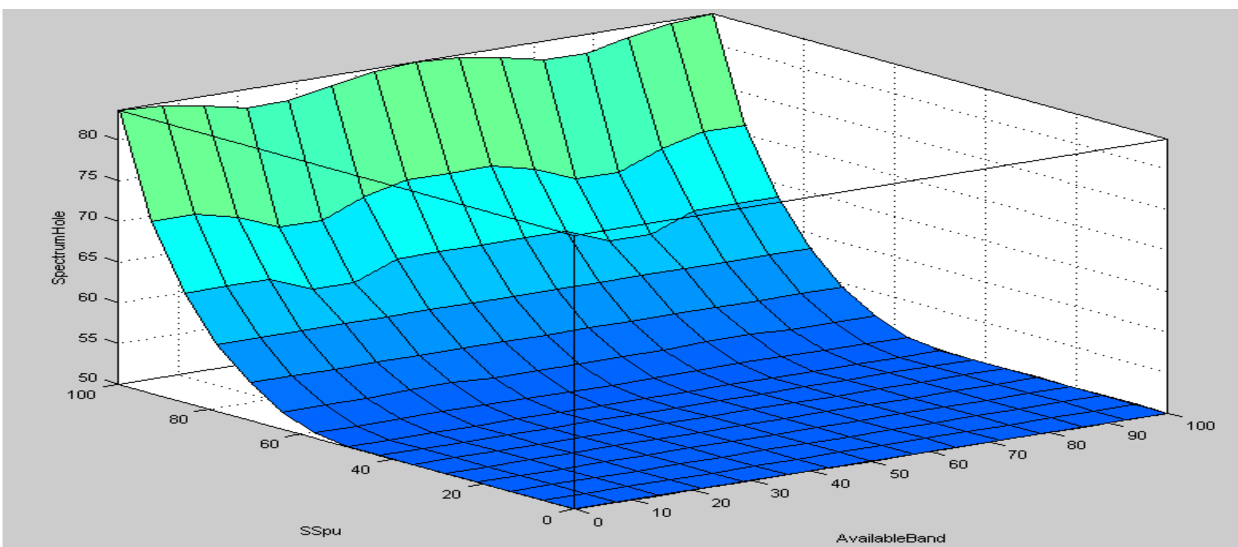


Figure 5.16 Surface Viewer for FLC-3, Showing Relation between Available Band, SSpu and Spectrum Hole.

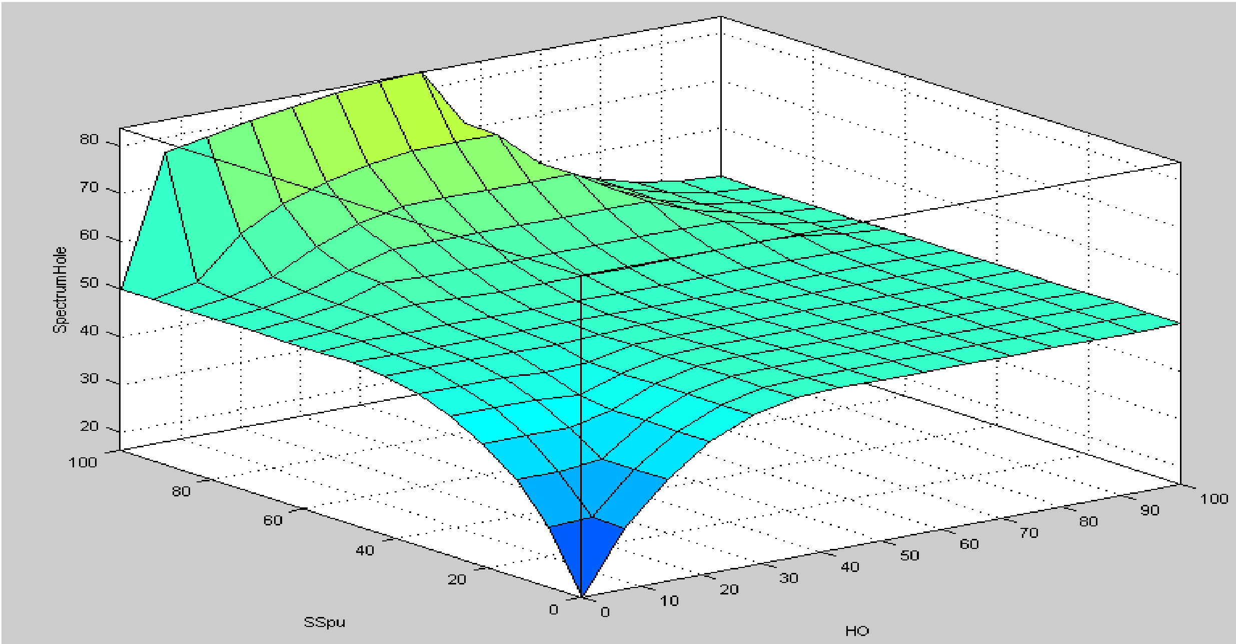


Figure 5.17 Surface Viewer for FLC-3, Showing Relation between HO, SSpu and Spectrum Hole.

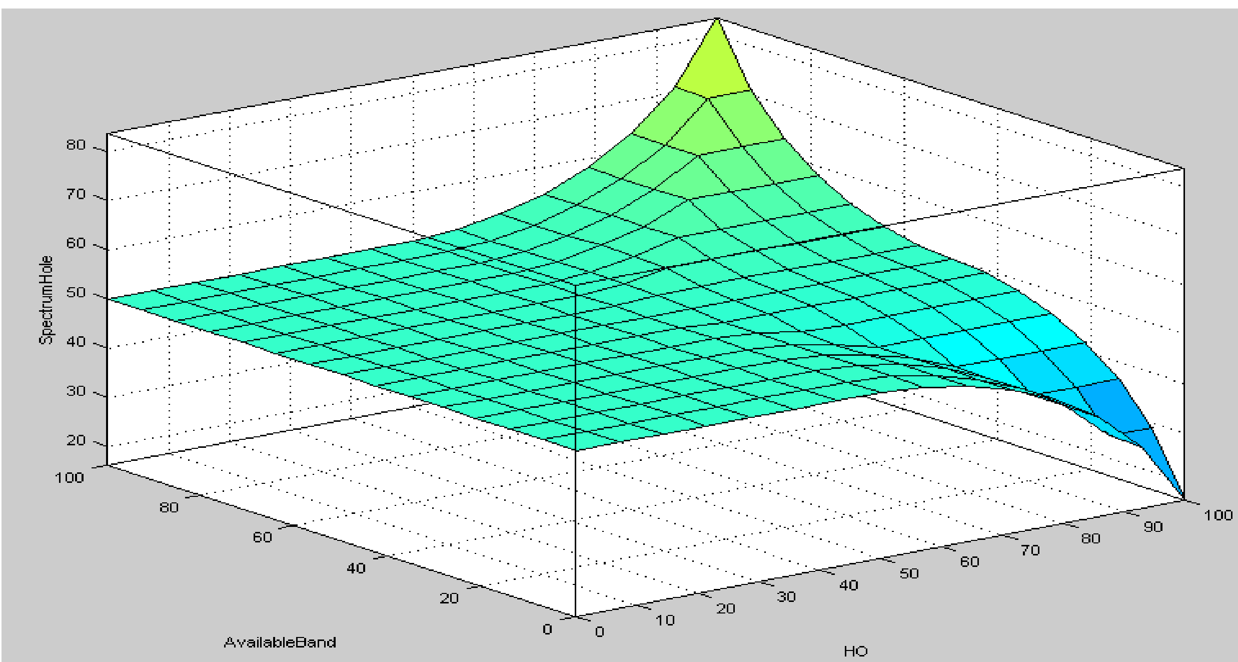


Figure 5.18 MATLAB Surface Viewer for FLC-3, Showing Relation between HO, Available band and spectrum Hole.

5.4 GUI using Microsoft Visual Basic

The graphic user interface GUI for fuzzy logic system for proposed CR system is shown in Fig.5.19.This GUI takes the input values and gives output values for FLC1, FLC2 and FLC2. The back end software uses the inputs values to determine membership functions, find linguistic values, applies fuzzy rule base and determine crisp values for each output using Mamdani model.

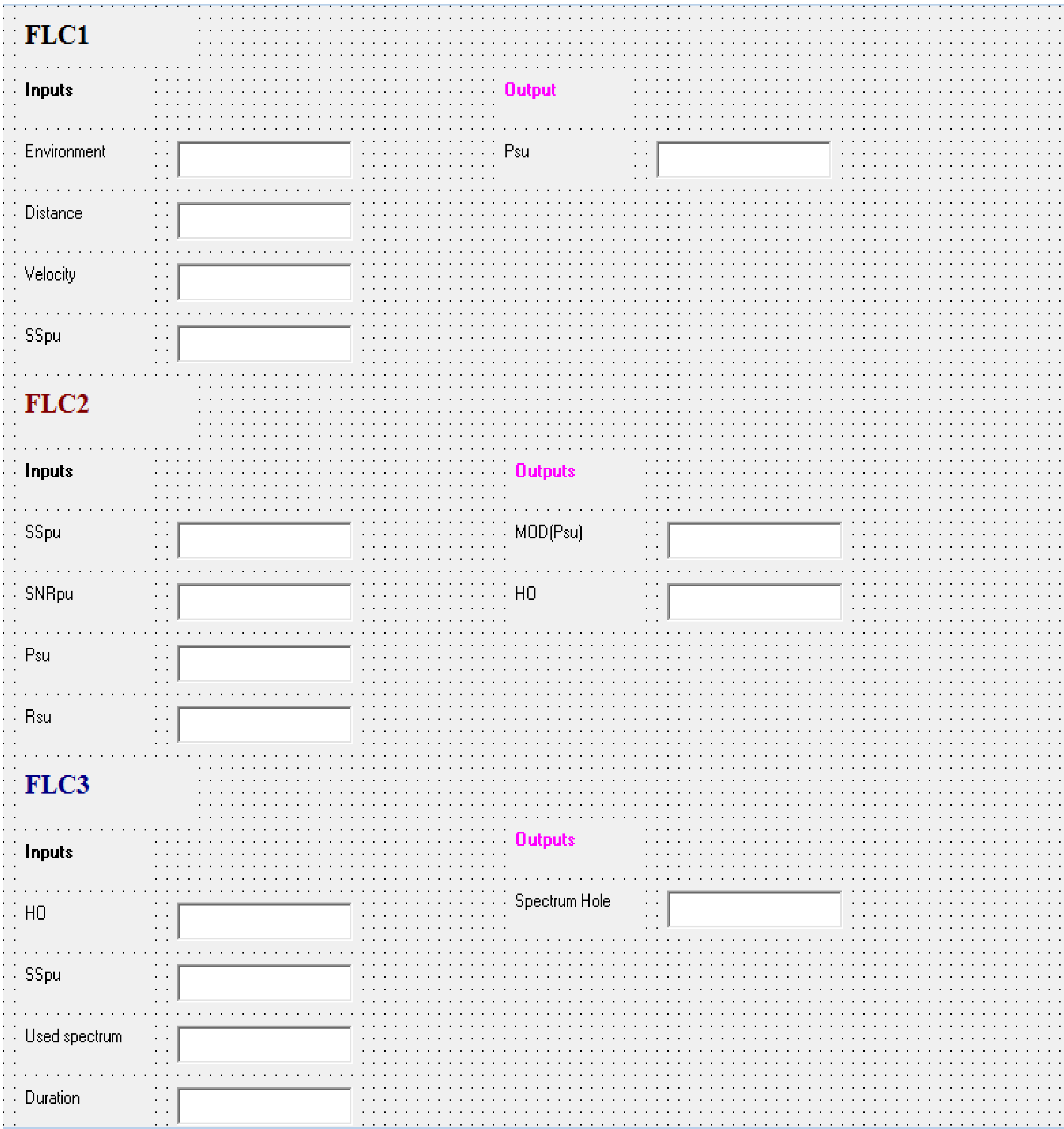


Figure 5.19 Overall representations of the Fuzzy logic controllers

5.5 Design Algorithms

5.5.1 FLC-1

Environment = 31.7

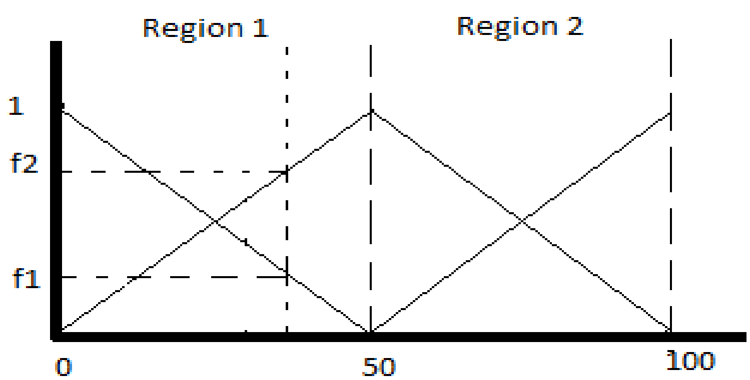
Distance = 28.3

Velocity = 48.3

SSpu = 68.3

Psu = 53.6

5.5.1.1 Environment



f_1 = 50-31.7/50

= 18.3/50

= 0.367

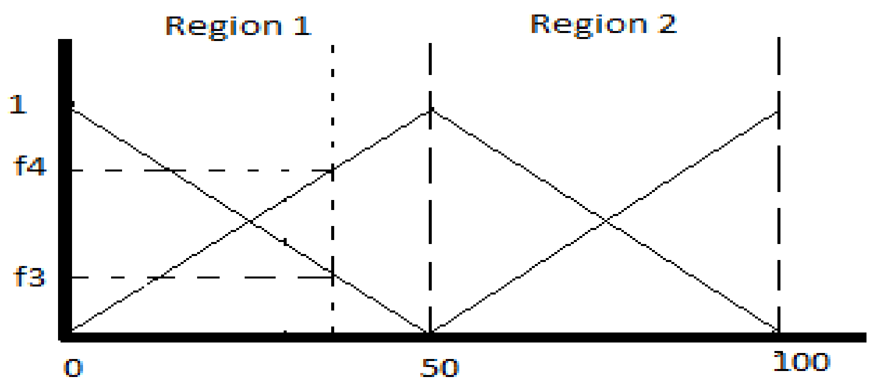
f_2 = 1- f_1

= 0.633

M.SFs involved are : Worst (w) Bad (B)

Environment = 31.7

5.5.1.2 Distance



f_3 = 50-28.3/50

= 0.437

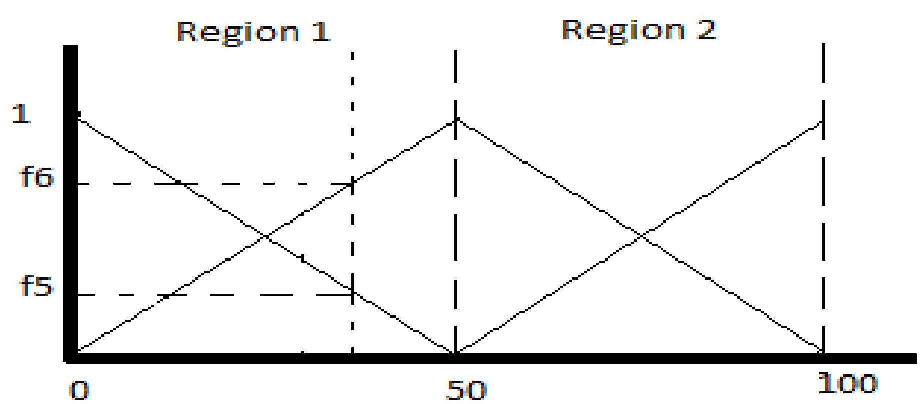
f_4 = 1- f_3

= 0.566

Membership functions involved are: Small (S), Medium (M)

Distance	=	28.3

5.5.1.3 Velocity



f_5 = 50-48.3/50

= 0.034

f_6 = 1- f_5

= 1-0.034

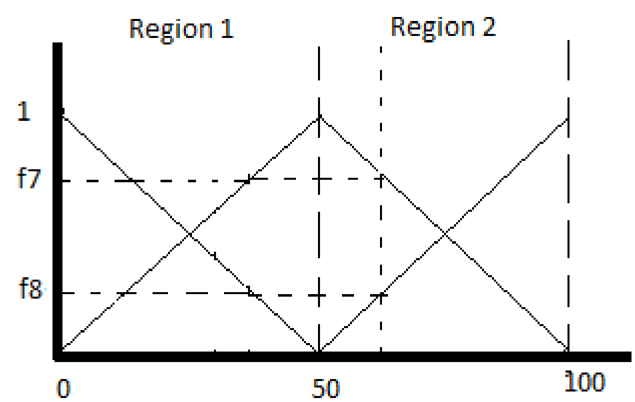
= 0.966

M.Fs involved are: Low (L)

Medium (M)

Velocity	=	48.3

5.5.1.4 *SSPU*



f_7 = 100-68.3/50

= 0.634

f_8 = 1- f_7

= 0.366

M.Fs involved are: M & H

SSpu	=	68.3

Rule No.	Env	Dis	Vel	SSpu	Psu	Singleton Values
R_o	W	S	L	M	M	$S_O = 0.5$
R_1	W	S	L	H	M	$S_1 = 0.5$
R_2	W	S	M	M	M	$S_2 = 0.5$
R_3	W	S	M	H	M	$S_3 = 0.5$
R_4	W	M	L	M	M	$S_4 = 0.5$
R_5	W	M	L	H	H	$S_5 = 1$
R_6	W	M	M	M	M	$S_6 = 0.5$
R_7	W	M	M	H	H	$S_7 = 1$
R_8	B	S	L	M	M	$S_8 = 0.5$
R_9	B	S	L	H	M	$S_9 = 0.5$
R_{10}	B	S	M	M	M	$S_{10} = 0.5$
R_{11}	B	S	M	H	M	$S_{11} = 0.5$
R_{12}	B	M	L	M	M	$S_{12} = 0.5$
R_{13}	B	M	L	H	M	$S_{13} = 0.5$
R_{14}	B	M	M	M	M	$S_{14} = 0.5$
R_{15}	B	M	M	H	M	$S_{15} = 0.5$

R_O	$f_1 \wedge f_3 \wedge f_5 \wedge f_7$	0.367 ^ 0.437 ^ 0.034 ^ 0.634	0.034
R_1	$f_1 \wedge f_3 \wedge f_5 \wedge f_8$	0.367 ^ 0.437 ^ 0.034 ^ 0.366	0.034
R_2	$f_1 \wedge f_3 \wedge f_6 \wedge f_7$	0.367 ^ 0.437 ^ 0.966 ^ 0.634	0.034
R_3	$f_1 \wedge f_3 \wedge f_6 \wedge f_8$	0.367 ^ 0.437 ^ 0.966 ^ 0.366	0.366
R_4	$f_1 \wedge f_4 \wedge f_5 \wedge f_7$	0.367 ^ 0.566 ^ 0.034 ^ 0.634	0.034
R_5	$f_1 \wedge f_4 \wedge f_5 \wedge f_8$	0.367 ^ 0.566 ^ 0.034 ^ 0.634	0.034
R_6	$f_1 \wedge f_4 \wedge f_6 \wedge f_7$	0.367 ^ 0.566 ^ 0.966 ^ 0.634	0.0367
R_7	$f_1 \wedge f_4 \wedge f_6 \wedge f_8$	0.367 ^ 0.566 ^ 0.966 ^ 0.366	0.0366
R_8	$f_1 \wedge f_4 \wedge f_6 \wedge f_8$	0.367 ^ 0.566 ^ 0.966 ^ 0.366	0.0366
R_9	$f_2 \wedge f_3 \wedge f_5 \wedge f_8$	0.633 ^ 0.437 ^ 0.034 ^ 0.366	0.034
R_{10}	$f_2 \wedge f_3 \wedge f_6 \wedge f_7$	0.633 ^ 0.437 ^ 0.966 ^ 0.634	0.437
R_{11}	$f_2 \wedge f_3 \wedge f_6 \wedge f_8$	0.633 ^ 0.437 ^ 0.966 ^ 0.366	0.366

R_{12}	$f_2 \wedge f_4 \wedge f_5 \wedge f_7$	0.633 ^ 0.566 ^ 0.034 ^ 0.634	0.034
R_{13}	$f_2 \wedge f_4 \wedge f_5 \wedge f_8$	0.633 ^ 0.566 ^ 0.034 ^ 0.366	0.034
R_{14}	$f_2 \wedge f_4 \wedge f_6 \wedge f_7$	0.633 ^ 0.566 ^ 0.966 ^ 0.634	0.566
R_{15}	$f_2 \wedge f_4 \wedge f_6 \wedge f_8$	0.633 ^ 0.566 ^ 0.966 ^ 0.366	0.366

$$\sum^{15} R_i \quad = \quad R_O + R_1 + \ldots\ldots\ldots\ldots + R_{15} = 3.473$$

Si x Ri	
0.5*0.034	0.017
0.5*0.034	0.017
0.5*0.367	0.184
0.5*0.366	0.183
0.5*0.034	0.017
1*0.034	0.034
0.5*0.367	0.184
1*0.366	0.366
0.5*0.034	0.017
0.5*0.034	0.017
0.5*0.437	0.219
0.5*0.366	0.183
0.5*0.034	0.017
0.5*0.034	0.017
0.5*0.566	0.283
0.5*0.366	0.183
∑ Si * Ri	1.983

Table 5.4 Rule Based Verification of Algorithm

5.5.1.5 Mamdani's Model

Output variable (crisp value) = $\sum S_i * R_i / \sum R_i * 100$

= 1.938 / 3.473 * 100 = 55.8

MATLAB Simulation Value	53.6
Design Value	55.8

Diff = 2.2

% error = diff / original * 100

= 2.2 / 53.6 * 100

% error = 4.1 %

% error = 4.1%

Similarly design algorithms for FLC-2 and FLC-3 can be explained.

5.6 Hardware Description of Fuzzifiers, Inference Engine and Defuzzifier

For the proposed Cognitive Radio system, the arrangement of three fuzzy logic controllers FLC-1,FLC-2 and FLC-3 are shown in Fig. 5.20.

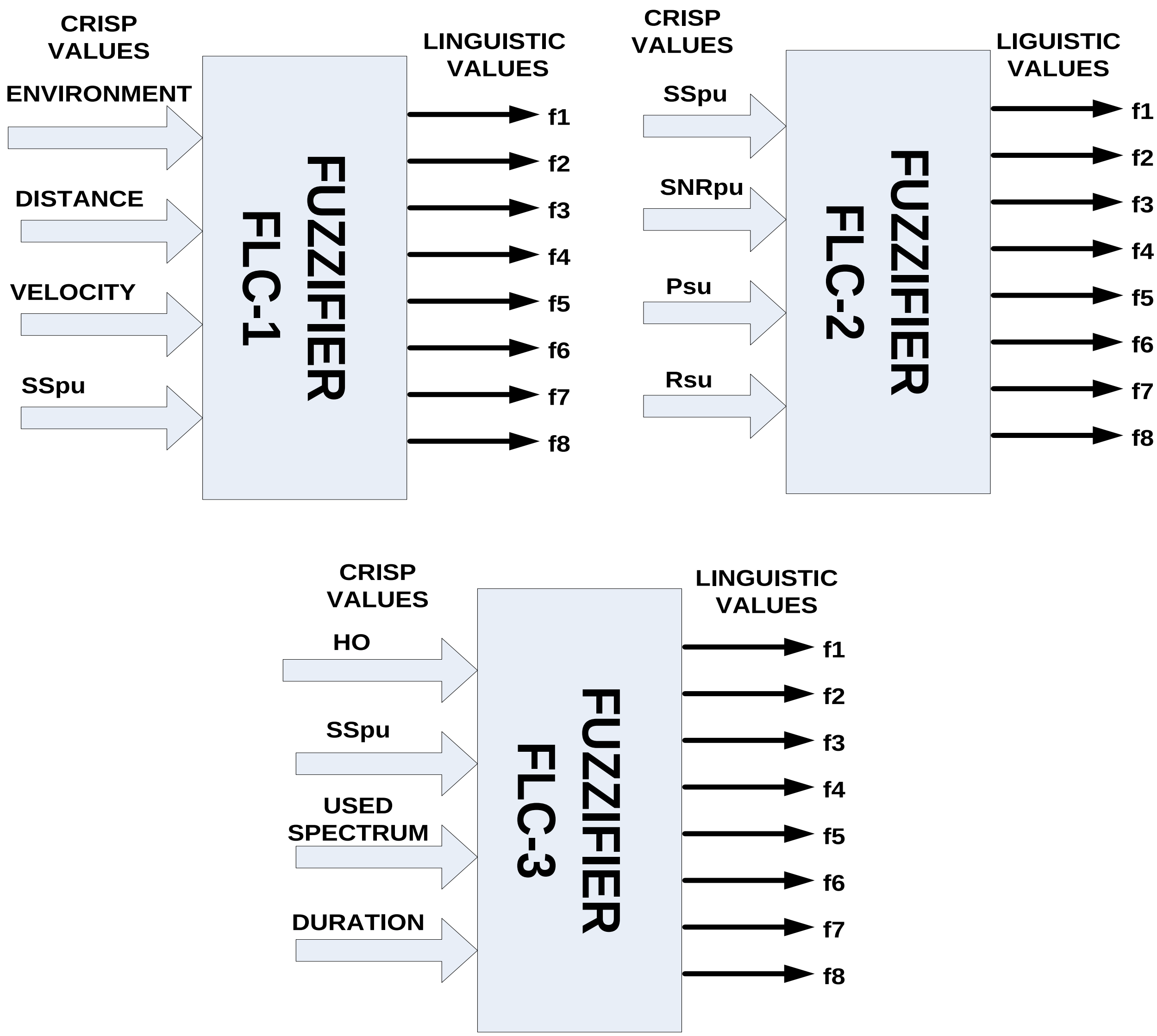


Figure 5.20 Fuzzifiers used for three fuzzy logic controllers-FLC-1, FlC-2 and FLC-3.

Fig. 5.21 shows the construction details of fuzzifier for one FLC . It consists of a multiplier, region selection comparator, multiplexer, subtractors and divider.

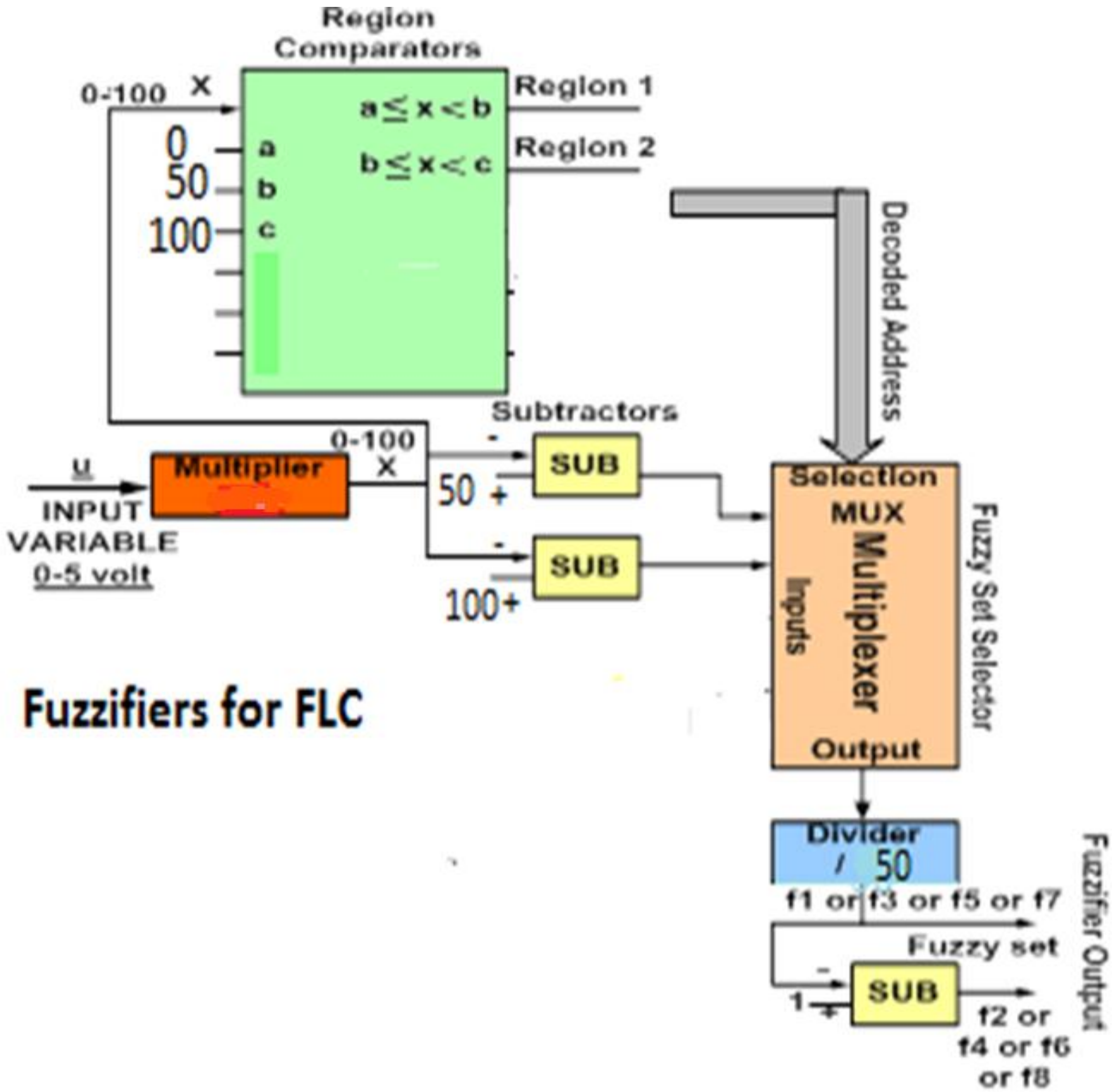


Figure 5.21   Construction details of fuzzifier

Fig. 5.22 shows the hardware arrangement of Inference Engine used in Fuzzy logic controller . For the four input variables the arrangement of sixteen Min-AND Gates is used to find the values of sixteen rules from R1 to R16.

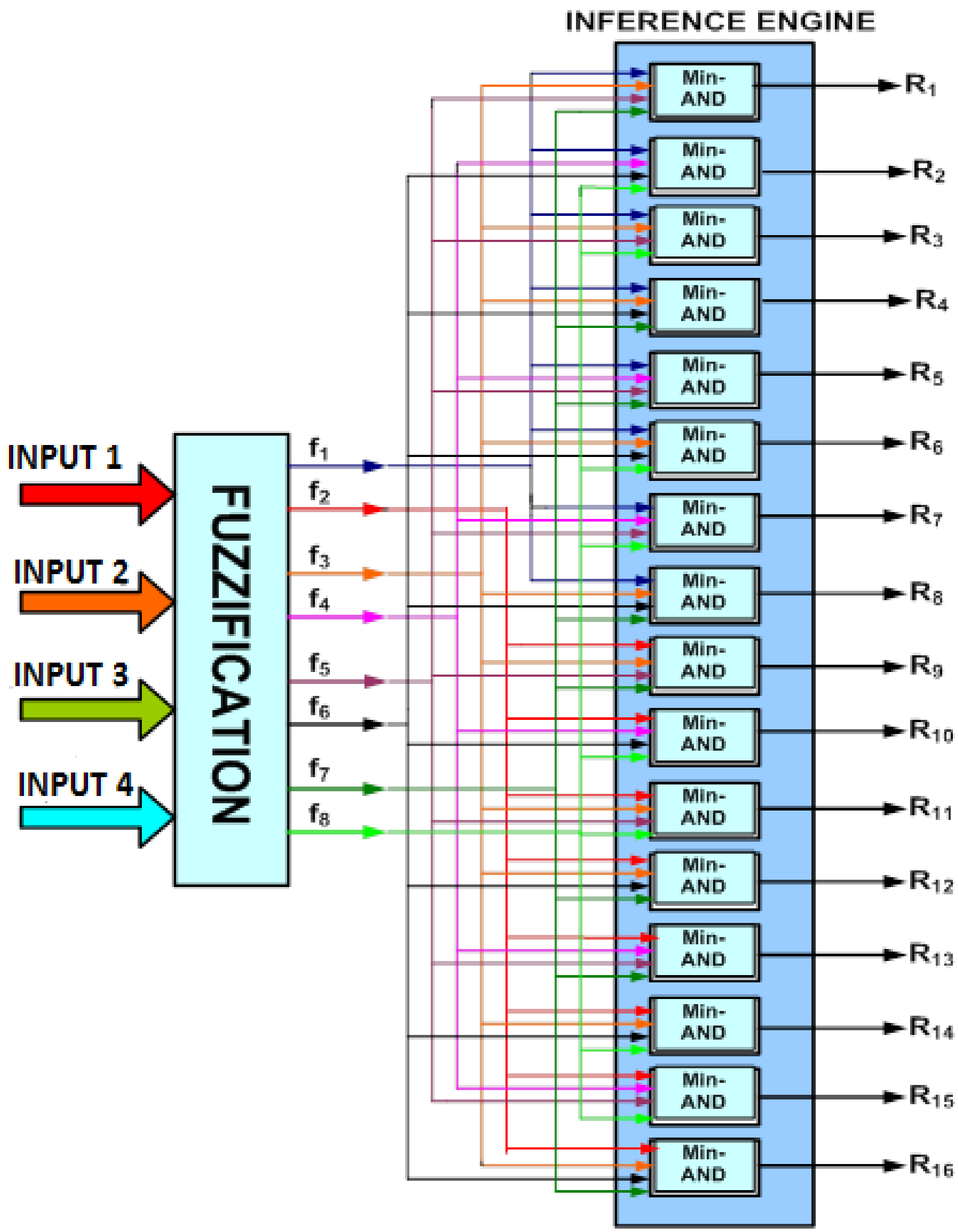


Figure 5.22 Hardware details of inference Engine used in Fuzzy logic controller

The block diagram of Defuzzifier used in FLC is shown in Fig. 5.23.

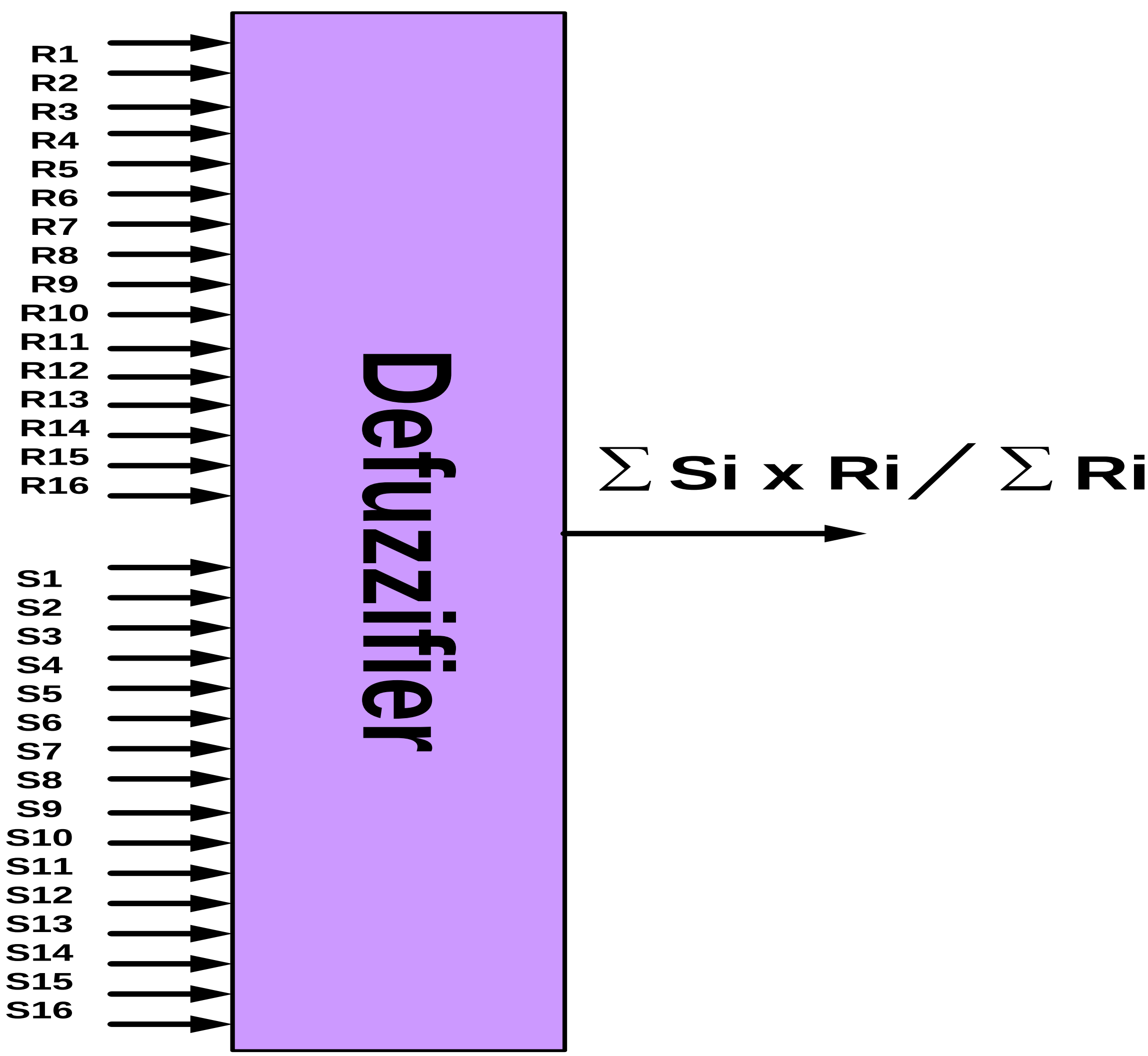


Figure 5.23 Defuzzifier used in FLC

Fig. 5.24 shows the hardware description of defuzzifier used in FLC. It consists of sixteen multipliers, two circuits for summation and one divider circuit to achieve the result of Mamdani model formula.

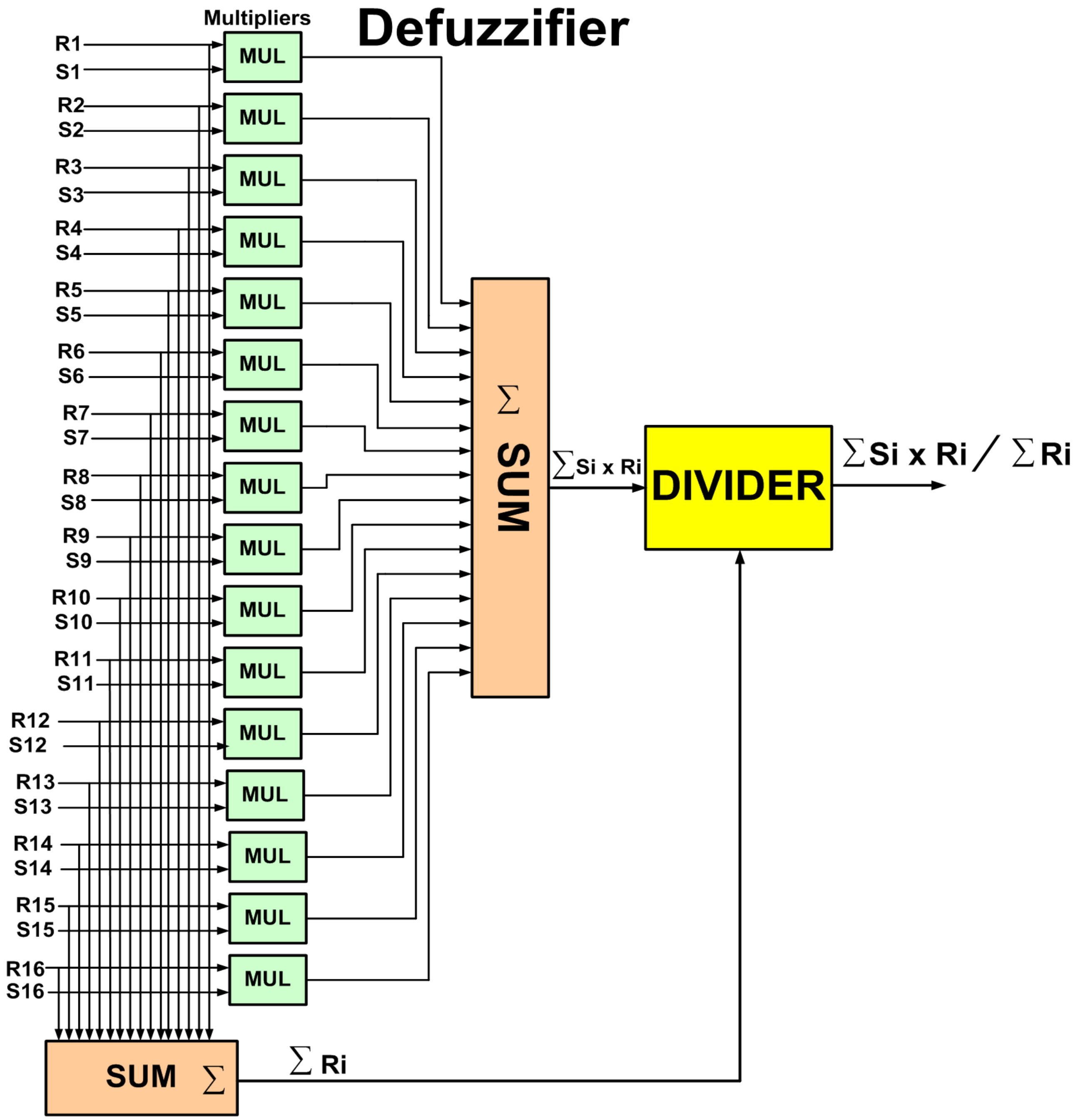


Figure 5.24 Hardware description of defuzzifier used in FLC

References

1. M. Jinturkar, S. S. Deshmukh, S. V. Agarkar and G. R. Chavhan "Determination of water quality index by fuzzy logic approach: a case of ground water in an Indian town", Water Science & Technology—WST Vol 61 No 8 pp 1987–1994 © IWA Publishing 2010

2. *Mohamed Khedr, Hazem Shatila, "CogMAX- A Cognitive Radio* Approach for WiMAX Systems", AICCSA, 550-554, 2009 IEEE**.**

3. *M. Godoy Simões and M. Friedhofer, "An implementation methodology of a fuzzy based decision support algorithm," International Journal of Knowledge-Based Intelligent Engineering Systems, October 1997, vol.1 no. 4, pp. 267-275*

4. Waleed Ejaz, Najam ul Hasan, Saleem Aslam, Hyung Seok Kim, " Fuzzy Logic based Spectrum Sensing for Cognitive Radio Networks", 2011 Fifth International Conference on Next Generation Mobile Applications and Services, IEEE Computer Society**.**

5. Carlos Cordeiro, Kiran Challapali, and Dagnachew Birru , Sai Shankar N "IEEE 802.22: An Introduction to the First Wireless Standard based on Cognitive Radios", JOURNAL OF COMMUNICATIONS, VOL. 1, NO. 1, APRIL 2006

6 Hyunwook Kim*, IEEE*, Jaewoon Kim, Suckchel Yang,Minki Hong*,* and Yoan Shin*, "* An Effective MIMO–OFDM System for IEEE 802.22 WRAN Channels", IEEE TRANSACTIONS ON CIRCUITS AND SYSTEMS—II: EXPRESS BRIEFS, VOL. 55, NO. 8, AUGUST 2008

7 Wendong Hu, STMicroelectronics Inc. and University of California Los Angeles

8 Daniel Willkomm, Murad Abusubaih, and James Gross, Technical University Berlin George Vlantis, STMicroelectronics Inc. Mario Gerla, University of California Los Angeles Adam Wolisz, Technical University Berlin and University of California, Dynamic Frequency Hopping Communities for Efficient IEEE 802.22 Operation,pp.80-87

9 Niyato,D., "Cognitive radio for next-generation wireless networks: an approach to opportunistic channel selection in ieee 802.11-based wireless mesh" Wireless Communications, IEEE Xplore 2009.

10 L. Giupponi, Ana I. Pérez-Neira," Fuzzy-based Spectrum Handoff in Cognitive Radio Networks",Cognitive Radio Oriented Wireless Networks and Communications, CrownCom 2008. 3rd International Conference ,IEEE Xplore 2008

Conclusion

Spectrum is a valuable resource in wireless communication systems. Over many years, spectrum optimization is an attractive focal point for research and development efforts by scientists and engineers. Future wireless communication systems require high performance and will accommodate a large number of users. So, they will need more bandwidth and flexible bandwidth allocation.

In this thesis the Welch periodogram is applied for the detection of 4 narrow and wideband signals at SNR down to ~ -25 dB. The Welch periodogram detector is an efficient, computationally less complex and fast spectrum sensing technique for narrowband signals, but it is slower and a simple energy detector and needs high processing power for very high frequency signals. For example ,the Welch periodogram can detect the QPSK based 1.6, 1.7, 1.8 and 1.9 MHz signals (propagating through an AWGN channel) within few minutes but it needs almost 12 hours to detect the 100,200,300 and 400 MHz signals. This technique failed to detect the signal at SNR<-25dB. It is a non-intelligent and cannot help in the selection of the best spectrum hole.

In this thesis, the autocorrelation kernel function-based spectrum sensing technique along with the Welch periodogram detector has been introduced. This technique may work efficiently at very low SNR values. The results, advantages and disadvantages of this technique are described below.

The results of spectrum sensing in chapter 3 shows that the Welch periodogram-based detector does not perform well at SNR <-30 dB for an AWGN channel. On the other hand, signal detection may be done at SNR<-30dB with the help of the autocorrelation kernel function. There is a problem that SVM can detect the signals at lower SNR values but it is more vulnerable for false alarm or miss detection. More training and research will help to overcome on this problem. Initially this kernel was used for the modulation detection. In this thesis the autocorrelation kernel function was used for the signal detection and frequency recognition for band-limited baseband and pass-band signals. The performance of the detector is better than compared to conventional energy detectors, as the classifier is trained in a supervised way. Therefore, for combination of each new signal combination, it needs the retraining. However, extra time is required for the detection of the signals.

Welch periodogram detector can detect up to -20dB for baseband signals. But when this detector was executed on IGS 64 bit processor based network then it detects the 400 MHz signals up to -30dB.It shows that the performance of the detector depends upon the processing environment.

The main attraction in SVM-based signal detection is its flexibility and its potential ability to operate at very low SNR values. It also helps in the selection of the best spectrum hole out of available holes. SVM also provides a simulation-based training and testing facility. The performance of the autocorrelation detector is improved by the increased number of training examples.

The autocorrelation has the drawback that it is designed on the basis of supervised learning. So, it needs the retraining for new frequency samples, requiring extra time. Also at very low SNR values, it shows the false alarm and miss detection. The performance of the SVM detector depends upon the frequency range of the signals to be detected. By the increase of the frequency range, performance of the detector was reduced. Also an increase in frequency range will increase the time required for the training of the detector.

Performance of the detector depends upon the SNR range. ROC is higher for lower SNR ranges. Also for the higher SNR range, the detector needs more time for training.

Performance of the detector depends upon the number of training sessions. The higher the number of training sessions, the better will be the performance of the detector. The additional time needed for training will lead to better signal detection and less time required for signal detection.

Performance of the detector depends upon the SNR step size. Performance of the detector is improved by the decrease of SNR step size. Reduction of the step size increases the performance of the detector. In case of reduction of the SNR step size the training time will increase, but finally it will increase the accuracy in the signal detection.

The autocorrelation function is an admissible SVM kernel. In this thesis, the autocorrelation function kernel based SVM detector is successfully implemented for the detection of four QPSK based signals propagating through an AWGN channel. As the machine is trained for the four signals, so some times it shows the false alarm or miss detection for less than four signals.

Fuzzy logic is used for the solution of control system problems. In this thesis, as a whole it is worth to mention that the fuzzy logic controller provides the opportunity to solve the interdependence problem in a dynamic environment.

In this system, Fuzzy Logic Controllers (FLCs) may be used in a different way to establish the authenticity of decision for Cognitive Radio System requirements in a future implementation.

Future work will provide the rapid estimation of Cognitive Radio System problems for design and analysis in all sorts of scenarios.

The Mamdani model is a time varying model for the optimal decision and control. The results for the algorithm designed for the implementation of FLC 1 were calculated. The practical results were compared with the values derived from Mamdani's model. The difference between the values was equal to 4.1%. The hardware description of fuzzifiers, inference engine and deffuzifier were shown. The hardware description suggests an idea for the practical implementation. The results of the fuzzy logic will help for the further improvement in the spectrum sensing and spectrum management. A fuzzy logic based algorithm helps for the selection of the best spectrum hole in a time varying environment.

In this thesis a solution of the spectrum scarcity problem is proposed and it gives a ray of hope that improved cognitive radios are possible by the combination of statistical signal processing and machine learning concepts.

Cognitive radio is a generic term which indicates that the problems of wireless communication can be solved by the introduction of cognition in the wireless communication devices.

Future work

The applications of wireless communication and its services are increasing. Spectrum scarcity is the bottleneck for the new wireless applications. Cognitive Radio is a solution of this problem. The worldwide research is done in the various aspects of the Cognitive Radio based systems and networks including spectrum sensing, spectrum management, cross layer design and spectrum decision. The future possibilities for the research the field of spectrum sensing can be:

1. Cross-layer design based cooperative spectrum sensing is required to work for the scheduling and dynamic routing for the cooperative and distributed networks. Improvement in the performance of cognitive radio networks will be done by distributive cooperative spectrum sensing techniques. Also the designing of new dynamic routing protocols is necessary for improvement of the performance of the big cognitive radio based networks

2. Two stage spectrum sensing technique for the solution of the hidden terminal problem at low SNR values: The coarse spectrum sensing technique is computationally less complex and the fine spectrum sensing technique is computationally more complex, but able to detect the signal with low SNR.

3. Spectrum sensing can be done by using machine learning techniques. It can be one by using neural networks, fuzzy logic and Support Vector Machine methods. This is the time to include statistical learning techniques for the solution of the dynamic spectrum sensing and the selection of best spectrum hole. The cognitive radio networks can become intelligent and behave in a really adaptive way with the help of machine learning techniques.

4. In this research the reconsideration, redesigning and new training patterns of the autocorrelation kernel function based SVM based detector is required to solve the problem of false alarm and miss detection of various combinations of the signals, especially at lower SNR values <-20 dB. At higher SNR values >-20dB the combination of welch periodogram and SVM detector are solving this problem. But, still intelligent and more reliable SVM decision is required. This weakness needs the reconsideration about the application and designing of SVM machine detectors. The cross validation will also improve the performance of the detector.

4. The supervised learning based spectrum sensing is good and easy, the hole adaptation by avoiding the interference with the primary user device can be possible by the online unsupervised learning techniques. The new algorithms must be designed by using these techniques, which must be computationally less complex and need less power. Unsupervised spectrum sensing will not need the training time for the detection of new signals.

5. Fuzzy logic controllers will be used to identify the best spectrum holes.

6. The implementation of numerical techniques for the optimized performance of the cognitive radio devices and networks is required.

7. The research, results and algorithm designed and developed for the intelligent networks, WRAN, WPAN can be considered for the improvement of the Cognitive Radio based networks.

8. The performance of the seismic prediction devices can be improved with the help of intelligent spectrum sensing techniques as well. For example, the detection of the signal with the help of wavelet technique and the prediction by using some machine learning techniques with the help of Hidden Markov Model (HMM) or EM algorithm can help to improve the time for seismic prediction.

9. Optical wireless communication is an interesting area in the field of broadband wireless communications. It can provide cheap and high data rate transmission. The main problem for the optical wireless communication is the attenuation problem due to rain and fog. The attenuation can reach very high attenuation levels (several 10 dB). This problem can be solved by the combination of cognitive radio and optical wireless communication concepts. The optical wireless designed on the basis of Cognitive Radio will have the ability to sense the spectrum at very low SNR values .It can be done by using the autocorrelation kernel detector. With the help of fuzzy logic based cognitive decision engine, the radio can adapt various parameters. The adaptation of the various communication parameters e.g.; power levels, coding and modulation scheme may help to overcome the problem of attenuation. Only sensing of the signals and measurement of the attenuation at the receiver end and the adaptation of the parameters at the transmitter end can help in solving the problem. The implementation of different signal recovery and equalization technique will help to communicate in worst attenuation conditions.

10. The main problem in optical wireless communication is non-detection of the transmitter signal at very low SNR. An improvement is possible by the simultaneous transmission of the optical and microwave signals (frequency diversity).

List of my Research Papers

1. Muhammad Tahir Mushtaq, Inayat Khan, Muhammad Saeed Khan, Otto Koudelka.” Autocorrelation kernel function Based SVM Detector for QPSK based Cognitive Radio Systems,” (in progress)

2. Muhammad Tahir Mushtaq, Muhammad Saeed Khan, Inayat Khan, Otto Koudelka.”Cognitive Optical Wireless Communications in Heavy Rain and Fog Attenuation Conditions with the help of autocorrelation kernel based SVM detector” (in progress)

3. M.Tahir Mushtaq, Ghulam Jaffar, Otto Koudelka **, ”**Spectrum Sensing Techniques in Cognitive Radios. A Short Survey,” accepted in International Journal of Scientific and Engineering Research (IJSER) - (ISSN 2229-5518). Paper ID: I018482

4. Muhammad Tahir Mushtaq, Ghulam Jaffar, Otto Koudelka.” Welch periodogram Detector for Base-band and Pass-band Signal Detection Propagating through AWGN Channel for QPSK Based Cognitive Radio Systems.” Submitted in Electronic design and innovation conference 2013(EDI con), Beijing, China, 12-14 March 2013

5. M. Tahir Mushtaq, M. Shoaib Hanif, Otto Koudelka.”SPECTRUM SCHEDULING: THE KEY FACTOR FOR MAXIMUM THROUGHPUT AND OPTIMAL RESOURCE UTILIZATION IN COGNITIVE RADIO NETWORK,” accepted in Science International, Lahore: ISSN 1013-5316; CODEN: SINTE 8

6. Muhammad Tahir Mushtaq, Otto.Koudelka.” Analysis and Implementation of Fuzzy Logic Based Spectrum Sensing Algorithm in Time Varying Cognitive Radio Networks,” (in progress)

7. DR. Muhammad Saeed Khan, R. D. Khan, M.Tahir Mushtaq , S. Anjam , Otto Koudelka.“Modeling of Integrated Particle Surface Area of Fog for Free-Space Optical Links”, (to be submitted)

8. Muhammad Tahir Mushtaq,Muhammad Saeed khan, Otto Koudlea.” Cognitive Radios and Cognitive Networks: A Short Introduction,”submitted in Journal of Electrical Engineering elektrotechnicky capsopis, Ilkovicova3,812 19 Bratislava, Solvakia, ISSSN 1335-3632,http://iris.elf.stuba.sk/JEEEC/

Oral talks

1 Ghulam Jaffer, Cmdr. Ronnie Nader, Prof. Otto Koudelka, M. Tahir Mushtaq, “ An Online and Real-Time Virtual Ground Station for Small Satellites,” UN/ Austria/ ESA Symposium on Small Satellite (Payloads) Programmes for Sustainable Development”, Graz, Austria, 21 - 24 Sep. 2010