IMPROVING SPECTRUM EFFICIENCY ON COGNITIVE RADIO SPECTRUM SENSING WITH ENHANCED DIVERSITY CONCEPT

MOHSEN AKBARI

THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF ENGINEERING
UNIVERSITY OF MALAYA
KUALA LUMPUR

2016

UNIVERSITY MALAYA

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: Mohsen Akbari

Matric No.: KHA120153

Name of Degree: PhD of Engineering

Title of Dissertation: Improving Spectrum Efficiency on Cognitive Radio Spectrum Sensing With Enhanced Diversity Concept

Field of Study: Wireless

I do solemnly and sincerely declare that:

(1) I am the sole author/writer of this work.
(2) This work is original.
(3) Any use of any work in which copyright exists was done by way of fair dealing and for permitted purposes and any excerpt or extract form, or reference to or reproduction of any copyright work has been disclosed expressly and sufficiently and the title of the work and its authorship have been acknowledged in this work.
(4) I do not have any actual knowledge nor ought I reasonably to know that the making of this work constitutes an infringement of any copyright work.
(5) I hereby assign all and every rights in the copyright to this work to the University of Malaya (UM), who henceforth shall be owner of the copyright in this and that any reproduction or use in any form or by any means whatsoever is prohibited without the written consent of UM having been first had and obtained.
(6) I am fully aware that if in the course of making this work I have infringed any copyright whether intentionally or otherwise, I may be subject to legal action or any other action as may be determined by UM.

Candidate's Signature Date

Subscribed and solemnly declared before,

Witness's Signature Date

Name:

Designation:

ABSTRACT

The frequency spectrum is a scarce resource for wireless communication. Due to the rapid advances in a wireless communication system, there has been an increasing demand for the new wireless services in both the used and unused Electromagnetic spectrum. However, this increasing demand faces a great barrier which is the limitation of radio resources. FCC researches proved that the main reason for the scarcity of spectrum is the underutilization of frequency spectrum by the licensed users either temporally or spatially. To overcome this problem scientists have used new model known as cognitive radio (CR) that is envisioned as a promising paradigm of exploiting intelligence for enhancing efficiency of underutilized spectrum bands. Frequently monitoring spectrum bands is the main feature of CR networks and the other characteristic is detection of occupancy and then opportunistically usage of spectrum holes with least possible interference with primary user (PU) caused of secondary users (SUs). Users in the CR network must determine which portions of the spectrum are available, Select the best available channel, coordinate access to this channel with other users and vacate the channel when a licensed user is detected. These capabilities can be realized through spectrum management functions that address four main challenges: spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. To the benefit of readers a brief overview of cognitive radio and the current research challenges of spectrum management is presented and new algorithm is proposed to improve QoS in CR system especially in sensing and decision part. At the first step, this research proposes an analytical study on the optimality of common soft decision fusion (SDF) cooperative spectrum sensing (CSS) and decision based on the modified imperialistic competitive algorithm (ICA) at which low total probability of error (P_e) and high probability of detection (P_d) are achieved. Also the

sensing performance of best existing methods based on previous researches, namely, genetic algorithm (GA), particle swarm optimization (PSO), maximal ratio combining (MRC), modified deflection coefficient (MDC) and normal deflection coefficient (NDC) are investigated (under both Neyman-Pearson and Minimax criteria). In Minimax criteria for fix P_e of 0.5×10^{-4}, the mean modified ICA-based requires about 23 iterations while the same error rate can be obtained after 38 and 124 iterations for mean PSO- and GA-based consequently (about 40% improvement in terms of required numbers of iterations which leads to less complexity and real time application). Also, SNR in space diversity combining is improved by new proposed modified ICA algorithm in compare with MRC (for instance, for a two-branch diversity, the MRC approximately requires almost 3 dB higher SNR than that of ICA-based to achieve a BER = 10^{-4}). To improve the overall outcome of CRCSS, ICA-based diversity combining proposed at each SU's receiver (ICA-based diversity CRCSS) to improve the received signal quality by SUs and reduce the number of required SUs in CRCSS (less complexity and laboratory set up cast of CR network). To support our proposed technique, the NON-diversity based ICA (which proposed earlier) compared with diversity based to demonstrate the reliability and efficiency of new proposed diversity based method (12% less P_e compare to NON-diversity based ICA.

ABSTRAK

Spektrum frekuensi adalah sumber yang terhad untuk komunikasi wayarles. Kerana kemajuan pesat dalam sistem komunikasi tanpa wayar, terdapat permintaan yang kian meningkat untuk perkhidmatan tanpa wayar yang baru di kedua-dua spektrum elektromagnet yang digunakan dan yang tidak digunakan. Walau bagaimanapun, permintaan yang semakin meningkat ini menghadapi halangan besar yang merupakan had sumber radio. Kajian FCC membuktikan bahawa sebab utama kekurangan spektrum adalah digunakan sepenuhnya spektrum frekuensi oleh pengguna yang dilesenkan memuat temporal atau ruang. Untuk mengatasi masalah ini ahli sains telah menggunakan model baru yang dikenali sebagai radio kognitif (CR) yang dibayangkan sebagai paradigma menjanjikan mengeksploitasi perisikan untuk meningkatkan kecekapan jalur spektrum kurang digunakan. Kerap memantau jalur spektrum adalah ciri utama rangkaian CR dan ciri-ciri yang lain adalah pengesanan penghunian dan kemudian peluang yang penggunaan lubang spektrum dengan gangguan-kurangnya mungkin dengan pengguna utama (PU) yang disebabkan dari pengguna sekunder (SUS). Pengguna dalam rangkaian CR mesti menentukan bahagian-bahagian spektrum yang ada, Pilih saluran yang terbaik, menyelaras akses kepada saluran ini dengan pengguna lain dan mengosongkan saluran apabila pengguna berlesen dikesan. Keupayaan ini boleh dicapai melalui fungsi-fungsi pengurusan spektrum yang menangani empat cabaran utama: sensing spektrum, keputusan spektrum, perkongsian spektrum, dan mobiliti spektrum. Untuk manfaat pembaca gambaran ringkas mengenai radio kognitif dan cabaran penyelidikan semasa pengurusan spektrum dibentangkan dan algoritma baru adalah dicadangkan untuk meningkatkan QoS dalam sistem CR terutama dalam penderiaan dan bahagian keputusan. Pada langkah pertama, kajian ini mencadangkan satu kajian analisis mengenai optimaliti common gabungan

keputusan lembut (SDF) sensing spektrum koperasi (CSS) dan keputusan berdasarkan algoritma yang kompetitif imperialis yang diubah suai (ICA) di mana jumlah kebarangkalian yang rendah kesilapan (P_e)) dan kebarangkalian tinggi pengesanan (P_d) tercapai. Juga prestasi penderiaan kaedah terbaik yang sedia ada berdasarkan kajian terdahulu, iaitu algoritma genetik (GA), zarah sekumpulan pengoptimuman (PSO), nisbah maksimum menggabungkan (MRC), diubah suai pekali pesongan (MDC) dan pekali pesongan normal (NDC) disiasat (di bawah kedua-dua Neyman-Pearson dan Minimax kriteria). Dalam kriteria Minimax untuk menetapkan P_d 0.5 × 10-4, min diubahsuai berasaskan ICA memerlukan kira-kira 23 lelaran manakala kadar ralat yang sama boleh diperolehi selepas 38 dan 124 lelaran bagi min PSO- dan berdasarkan GA-akibatnya (kira-kira 40% peningkatan dari segi bilangan yang diperlukan lelaran yang membawa kepada kerumitan kurang dan aplikasi masa sebenar). Juga, SNR dalam kepelbagaian ruang menggabungkan bertambah baik dengan mencadangkan algoritma ICA baru diubahsuai di bandingkan dengan BSMM. Kepelbagaian untuk meningkatkan hasil keseluruhan CRCSS, ICA berasaskan menggabungkan dicadangkan pada penerima setiap SU ini (berasaskan ICA kepelbagaian CRCSS) untuk meningkatkan kualiti isyarat yang diterima oleh SUS dan mengurangkan bilangan SUS diperlukan dalam CRCSS (kerumitan kurang dan makmal ditubuhkan cast rangkaian CR). Bagi menyokong teknik kami dicadangkan, ICA berdasarkan BUKAN kepelbagaian (yang dicadangkan sebelum ini) berbanding dengan kepelbagaian berasaskan untuk menunjukkan kebolehpercayaan dan kecekapan kaedah kepelbagaian baru yang dicadangkan berdasarkan (12% kurang P_e berbanding BUKAN kepelbagaian berdasarkan ICA.

ACKNOWLEDGEMENT

First of all I am very much grateful to almighty Allah for giving me strength, knowledge, and power of thinking and making me proficient for the successful ending of the research.

With the deepest gratitude and indebtedness, I would like to thank to my supervisors, Professor Madya Dr. Kamarul Ariffin Bin Noordin and Dr. Ahmed Wasif Reza for providing me a definite guidelines and intellectual support. Their kind attitude, patience, sincere sympathy, encouragement and invaluable suggestions always inspired me to complete this research work steadfastly. It was completely impossible to finish this project work without their kind help. I am so much grateful to my supervisors for their great support.

I am also thankful and grateful to my wife and parents for their never-ending support, love and continuous encouragement in the bad phase of my life that helped me a lot for finishing this work. Finally, I want to appreciate everyone who has come into my life and given me inspiration through their presence.

LIST OF CONTENT

LIST OF FIGURES

LIST OF TABLES

LIST OF SYMBOLS AND ABBREVIATIONS

SD	Sustainable Development
DSA	Dynamic Spectrum Access
FCC	Communications Commission
SDR	Software Defined Radio
CR	Cognitive Radio
QoS	Quality of Service
CAPEX	Capital Expenditures
SM	Spectrum Management
CRSM	Cognitive Radio Spectrum Management
CRCSS	Cognitive Radio Cooperative Spectrum Sensing
RF	Radio Frequency
PU	Primary User
SU	Secondary User
WRAN	Wireless Regional Area Network
SNR	Signal to Noise Ratio
MRC	Maximal Ratio Combining
EGC	Equal Gain Combining
SC	Selection Combining
NDC	Normal Deflection Coefficient

MDC	Modified Deflection Coefficient
MICA	Modified Competitive Algorithm
PSO	Particle Swarm Optimization
GA	Genetic Algorithm
BS	Base Station
FC	Fusion Center
SDF	Soft Decision Fusion
HDF	Hard Fusion
CSS	Cooperative Spectrum Sensing
BER	Bit Error Rate
OSA	Opportunistic Spectrum Access
i.i.d	Independent and Identically Distributed
i.n.d	Independent but Not Identically Distributed
H_0	Hypothesis of PU Absence
H_1	Hypothesis of PU Present
$X_i[n]$	Received Signal by SUs
T_s	Sensing Time
g_i	Channel Gain
$S[n]$	PU Signal
$\sigma_{W_i}^2$	Variance

δ_i^2	Variance
$N_i[n]$	Noise
$W_i[n]$	SU Signal
B	Bandwidth
$P_{R,i}$	Transmitted power by SU
h_i	Channel Gain
Z_C	Test Statistic
Z_i	Total Collected Energy by FC
Φ_{H_1}	Covariance Matrices
β	Energy Global Threshold
P_f	Probability of Flus Detection
P_d	Probability of Detection
P_e	Probability of Error Detection

CHAPTER 1 : INTRODUCTION

1.1. Background

The telecommunications industry is growing rapidly over the past decade and in the meantime, wireless standards are also growing rapidly that are making a very difficult situation in case of radio spectrum in wireless communication. The electromagnetic radio spectrum is a precious natural resource, used by transmitters and receivers and licensed by governments (Aatique, 1997) & (Kolodzy, & Avoidance, 2002). To prevent significant interference between different systems, usually, the spectrum bands are statically allocated to specific services. Consequently, only portions of the spectrum are heavily utilized. The standards of wireless communication are also growing very fast which makes a difficult situation in terms of allocating radio spectrum in wireless communication. Wireless communication networks, nowadays, are categorized by static frequency assignment rules by which authorized parties, for a long period of time, allocate wireless spectrum to licensed subscribers in big geographical places. Lately, these rules of spectrum allocation sometimes fail and encounter scarcity in some particular frequency bands. On the other hand, a large number of allocated frequency bands are utilized infrequently resulting in underutilization of a large portion of the spectrum (Palicot & Roland, 2005) & Palicot, Moy & Hachemani 2009).

In reality, radio spectrum is poorly utilized by the licensed users, which are allocated for television broadcasting, amateur radio, and paging (Palicot, 2009). The FCC reported that, utilization of the spectrum varies from 15% to 85%. On the other hand, the research on the Deface Advance Research Projects Agency (DARPA) points out, that just 2% of the spectrum is underutilized at the same time (Han et al., 2011). Currently, 3% of the world-wide energy is consumed by the ICT infrastructure which causes about 2% of the world-wide CO2 emissions (which is comparable to the worldwide CO2 emissions by airplanes or one quarter of the world-wide CO2 emissions by cars) (Grace et al., 2009), (Han et al., 2011) & (Gur & Alagoz 2011) These values of carbon footprint are very impressive. It has been confirmed by a lot of reports and studies (Grace et al., 2009) which searchers claim that CR, thanks to its sensors, is an enabling technology for Green Communications (Hasan, Boostanimehr & Bhargava, 2011) & (Treeumnuk & Popescu, 2013).

Since modern communications networks must deliver ever increasing data rates at an ever decreasing cost per bit, the spectral efficiency has to be further improved. Hence, a new communication paradigm, i.e., dynamic spectrum access (DSA) (DSA technology suffers from low scalability and convergence) whose key enabling technology is referred to as Cognitive Radio (CR), was lately suggested to take care of spectrum scarcity issue (Haykin, 2005). CR networks are imagined as a future possibility to supply mobile subscribers with large bandwidth by means of heterogeneous wireless architectures and DSA (this objective can be merely fulfilled via CR spectrum management (CRSM)). In other words, the situation of poorly-used spectrum can be improved by using CR technique and making it possible for secondary user (SU) to utilize and access the spectrum hole vacant by the licensed user (PU) at the right time and space (Xing, Chandramouli, & Mangold, 2006), (Cao & Zheng, 2012). However, due to fixed allocation and inefficient usage of the frequency spectrum, spectral utilization is very much lower than what is expected. To deal with this issue and increase spectrum utilization, CR has emerged as a promising technology to enable the access of vacant frequency bands which defined as spectrum holes or white spaces (Zhou et al., 2014).

Furthermore, some challenges, such as the increasing complexity with configuration and management of large scale networks, the upgrading capital expenditures (CAPEX) and Operating Expenditures (OPEX) (Grondalen, Lahteenoja, & Gronsund, 2011) & (Zhang et al., 2010) and the intensifying difficulties of centralized control, etc., will further arise in the future heterogeneous networks (Hämäläinen, Sanneck, & Sartori. 2012). In order for dealing with these challenges, every cognitive radio in the CR network should:

Specify vacant parts of the frequency channel (Nekovee, Irnich, & Karlsson, 2012) & (Tragos et al., 2013).

Choose the best frequency channel (Lee & Cho, 2013) & (Lee, & Akyildiz, 2012).

Collaborate with other SUs to access the spectrum (Lu et al., 2013) & (Bian, Park, & Gao, 2014).

Leave the band as a licensed user shows up. (Wang et al., 2014) & (Sun et al., 2013).

These abilities can be obtained by means of CRSM functions that cope with four principal issues: spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility. CRSM, nevertheless, is quite challenging as significant fluctuations happen at frequency bands. In addition, different applications require different quality of service (QoS) (Palicot & Roland, 2005). This part introduces definition, functions and challenges of CRSM and review of cognitive radio technique has been given, and the CR network architecture is provided. The idea of CRSM and its capabilities is examined. Subsequently, represent spectrum sensing, spectrum decision, spectrum sharing, and spectrum mobility concepts.

1.1.1. Fundamentals of Cognitive Radio and Diversity

a) Fundamentals of Cognitive Radio

Xing, Chandramouli, & Mangold, (2006), introduced concept of software-defined radio (SDR) which also was named as Software Radio (SR) and directed to the CR concept.

Software-Defined Radio (SDR)

Comparison between traditional and software radio is presented as follows:

i) Traditional Radio equipment

The procedure is done in the analog domain

Hardware oriented

Interference vulnerability in higher RF

Limited flexibility

For extra characterize, redesigning system is required

ii) Software-Defined Radio

The procedure is done in the digital domain

Less vulnerability to RF interference

Limitless flexibility

Software oriented

Inflexibility in Recent Radio Equipment

Current wireless devices have very limited flexibility due to the fact that they are mostly implemented in hardware. All the processing tasks are performed by its internal hardware component in order that the device to be functional. Hence, the production of devices is done for a specific mission and nothing more. For instance, Bluetooth devices which are used in laptops do not have the ability to communicate with WIMAX base stations.

Scenario 1:

Duplex communication among teams of police forces, fire departments and savior committees was very crucial during the tsunami of Japan. Thousands of people were trapped under ruined buildings and they needed medical help and food. However, the teams did not have the same radio frequency to communicate; also distributing hundreds of devices which work under the same radio frequency was not a practical solution at that time.

Solution: with the help of SDR, police officers could speak with a fire department officer to increase the quality of rescue mission. Since the system is now software-based, it can be promptly configured to any frequency or standard desired.

Scenario 2:

Consider Telco service provider in Malaysia (CEO) which has been spent huge amount of money to develop infrastructure to 2G then after a while had to upgrade it to 3G because of being in the market, also not to be far from its competitor companies. Nowadays CEO has too much nucleated debt and people are interested to use 3.5G instead of 3G and use a higher bit rate and better quality. It means CEO should pay again huge money to be still in the market.

Solution: With the technology of the SDR, the CEO could build an infrastructure which can be upgraded as required. The hardware platform can be built first and whenever a new development in the technology happened, changes can be made on the software side while retaining the same hardware.

Fundamental execution of Software-Defined Radio

As indicated before, SDR devices are adaptable equipment or will be adapted to the surrounding environment by doing some changes in the software of them which means it should be implemented in digital domain. For instance, a digital-to-analog converter (DAC) and an analog-to-digital converter (ADC) are generally used at intermediate frequency (IF) part in order that the received RF digital signal can convert to analog signal one step before digital signal processing (DSP). It is shown in Fig.1.1 also a comparable block diagram is in Fig. 1.2.

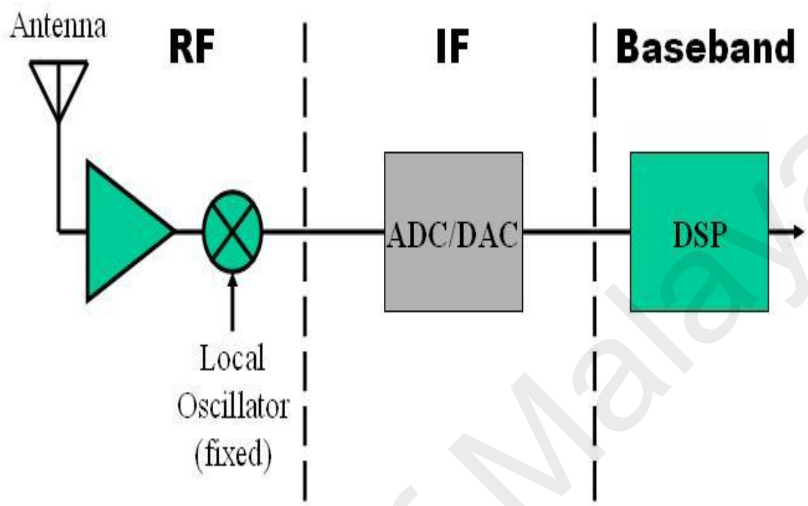


Figure 1.1: Block Diagram of a Basic Software-Defined Radio

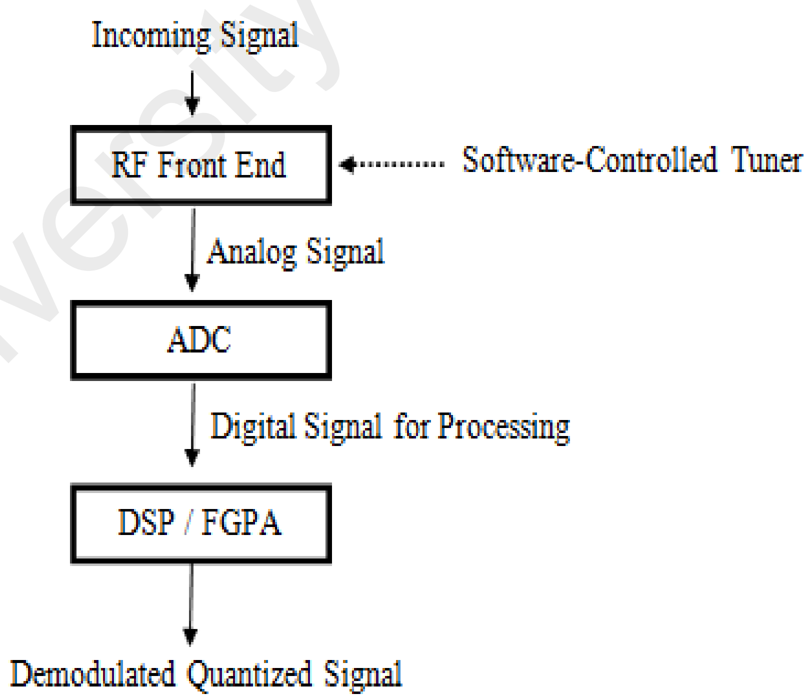


Figure 1.2: Simplified Software-Defined Radio Block Diagram

Advantages and Disadvantages of Software-Defined Radio

In the sense of engineering, every method has a tradeoff and the same ideology applies to SDR as well. This section just looks into the pros and cons of SDR compared to conventional radio.

i) Advantages of SDR

Changes can be made swiftly and adapt to the environment to operate in the desired manner using the same hardware set.

Reduced the expanses in analog hardware by replacing with FGPAS and DSPs.

Correction of imperfections in RF area in DSP.

Reduction of co- channel interference.

Create the chance for new experimentation.

Wide range oriented architecture motivates more researchers.

ii) Disadvantages of SDR

Difficulty of software implementation.

Comparatively narrow dynamic range.

Security problem, since SDR is now more susceptible to intimidation of different models.

Very high consumption of power.

Producing of SDR is very costly.

Software-Defined Radio (SDR) and Software-Controlled Radio

Despite the fact that SDR is software-controlled, it must be noticed that Software-Controlled Radio (SCR) is different from SDR. Table 1.1 briefly differentiates between SDR and SCR schemes.

Table 1.1: distinguish between Software-Controlled Radio and Software-Defined Radio

Software-Defined Radio	**Software-Controlled Radio**
Use software to instruct the radio what to do.	Uses software to control various functions that are fixed in the radio.

b) Cognitive Radio Concept

The CR is defined in this part as previously SDR investigated. CR is a developed version of the conventional software radio theory in which the radio has sense about its environment. Also, it is capable to change strategies independently in the physical layer and able to adopt statically with the environment (Mitola, 2000) & (Mitola & Maguire, 1999). In simpler term, CR is a subset of SDR with artificial intelligence and ability to perform sensing which is adapting to the environment.

The similarity in concept of SDR and CR might make readers confused where these schemes are often alternately used. Fig. 1.3 illustrates the dissimilarity between conventional radio methods, CR and SDR. Furthermore, it is obvious that CR intelligence has the ability to sense, optimize and learn about the neighboring environment or clutter levels.

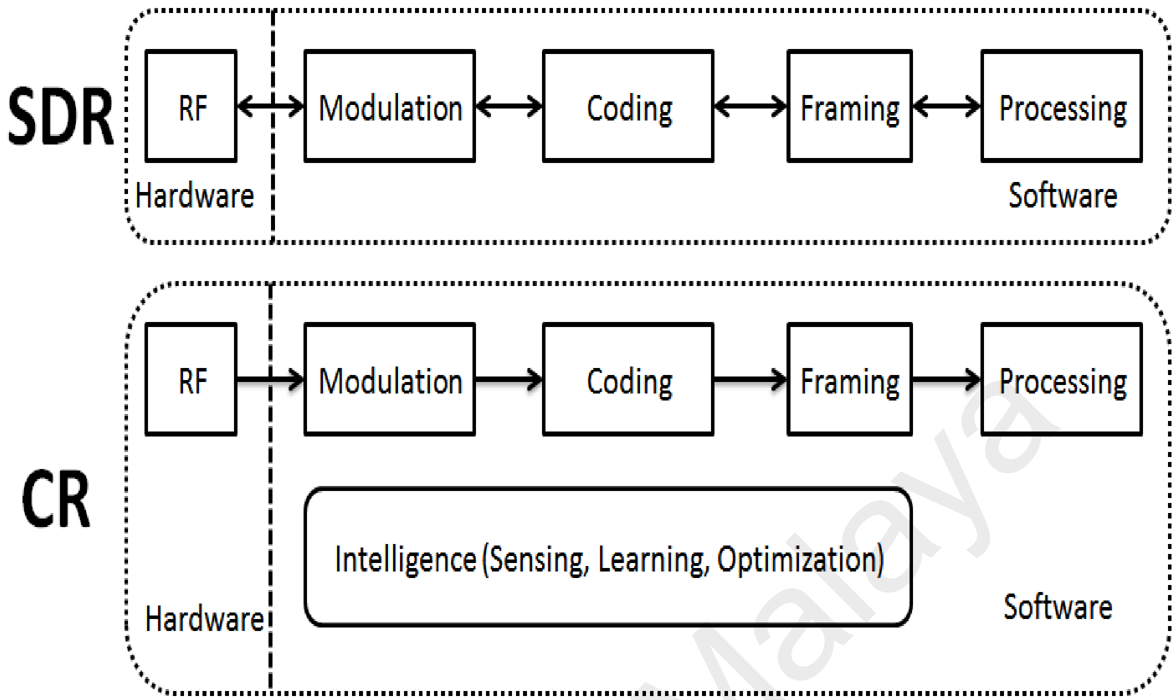


Figure 1.3: Comparison of Different Radios methods design

Generally, CR is proposed as a system when based on interaction with its environment transmitter parameters of CR can be changed (Ge et al., 2013). So, the main characteristics of CR can mark as below (Bougard et al., 2007). & (Fang, Yang, & Xue, 2013).

i) Cognitive Capability

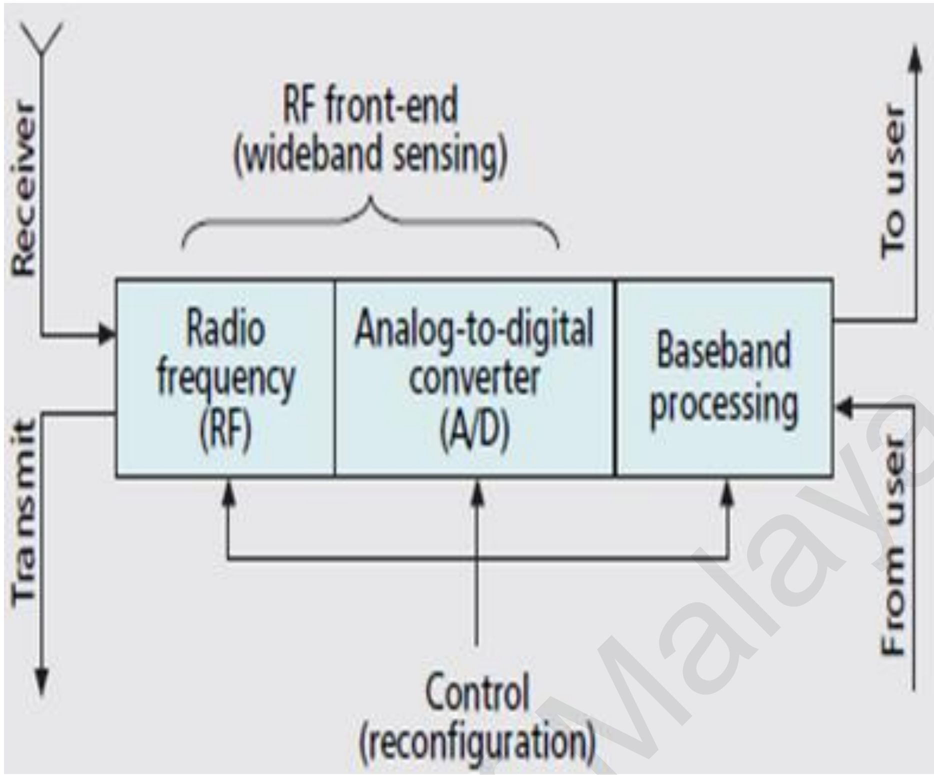
The portions of the spectrum, which is unoccupied at a specific period of time or location can be identified at real-time application. As shown in Fig. 1.4, CR users enable to temporally use unused frequency bands (like spectrum hole or white space). Consequently, unutilized band can be selected, shared among SUs without harmful interference with the PUs.

ii) Re-configurability

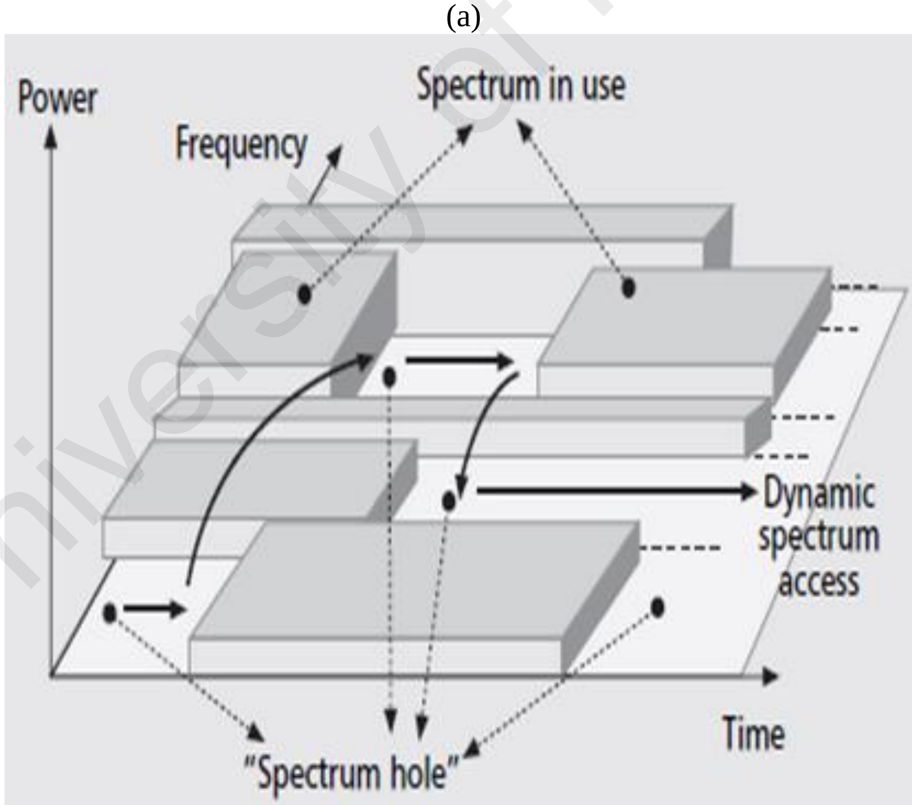
A CR defined as programmable radio transceivers on a variety of frequencies, and compatible with different access technologies supported by its hardware.

The best goal of CR is usually to uncover the ideal available spectrum band through re-configurability or cognitive capability seeing that described above (Ghosh, Roy & Rao, 2012). Because the majority of the spectrum is already allocated, the most crucial concern is to identify and share the licensed spectrum with very little interference with other licensed users as demonstrated in Fig. 1.4. If the transceivers activity of licensed user confirmed by the system, the SUs must immediately move to another available spectrum band or adjusting the transmission power level at the same band to avoid any conflict as shown in Fig. 1.4 a.

The front-end radio frequency (RF) transceivers design which proposed for SDR can be used for CR to provide these capabilities as shown in Fig. 1.4 b. (Cabric, Mishra, & Brodersen, 2004) & (Lee, & Akyildiz, 2012). The novel characteristic of the CR transceiver is the front-end with a wideband radio frequency which is able to sense the channel simultaneously over an extended frequency range. Nevertheless, since the CR receiver deals with signals from different transmitters and functions at various signal strength, CR transceiver must be able to sense a poor signal in a large dynamic range, which is a main challenge in CR transceiver design (which is not the focus of this research).



(a)



(b)

Figure 1.4: Overview of cognitive radio: a) cognitive radio transceiver architecture; b) the spectrum whole concept (Akyildiz et al., 2006).

i) Cognitive Radio Spectrum Heterogeneity

SUs are able to have an access to both the unlicensed and licensed spectrum band that used by PUs. Consequently, the CR network operation can defined as unlicensed and licensed band operation.

Licensed Band Operation: Licensed band CR is authorized to use frequency bands owed to PU as well as SU. For instance, standard group of the IEEE 802.11 implement for wireless regional area network (WRAN) in the range of 2.4, 3.6 and 5 GHz and which is operated in unused television channels (Akyildiz et al., 2006) & (Jondral, 2005). Therefore, detection of PUs is the main concern of the CR networks in this case.

The channel capacity relies on the interference at adjacent PUs. In addition, if the PU is detected in the frequency band of interest that is employed by SUs, CR user must leave that band and move to available spectrum instantly.

Unlicensed Band Operation: Unlicensed band operation: In the unlicensed bands, CR users have the equal privilege to get into the spectrum. Hence, complicated spectrum sharing techniques are necessary for SUs to contest to get access to the unlicensed band (unless with very low transmitting power to avoid interfere with each other) (Cabric, Mishra, & Brodersen, 2004) & (Yücek, & Arslan, 2009).

ii) Cognitive Radio Network Components

The CR architecture components shown in Fig. 1.5 can be categorized as CR network and primary network). The primary network is the existing network, where the PUs have priority to operate in a certain band (Zhao, Biao & Jiandong, 2013). In infrastructure based primary networks, operations control by primary BS, PU (Zhao, Biao & Jiandong, 2013) & (Hamdi et al., 2013). The CR network does not have a license to have an activity in any licensed band and SUs must have special functionality to operate in licensed band. Lastly, CR networks may consist of brokers that play a role to distribute available frequency band among different CR networks (Salameh, Krunz & Manzi, 2014), (Wang, Shin & Wang, 2012) & (Chen & Liao, 2012).

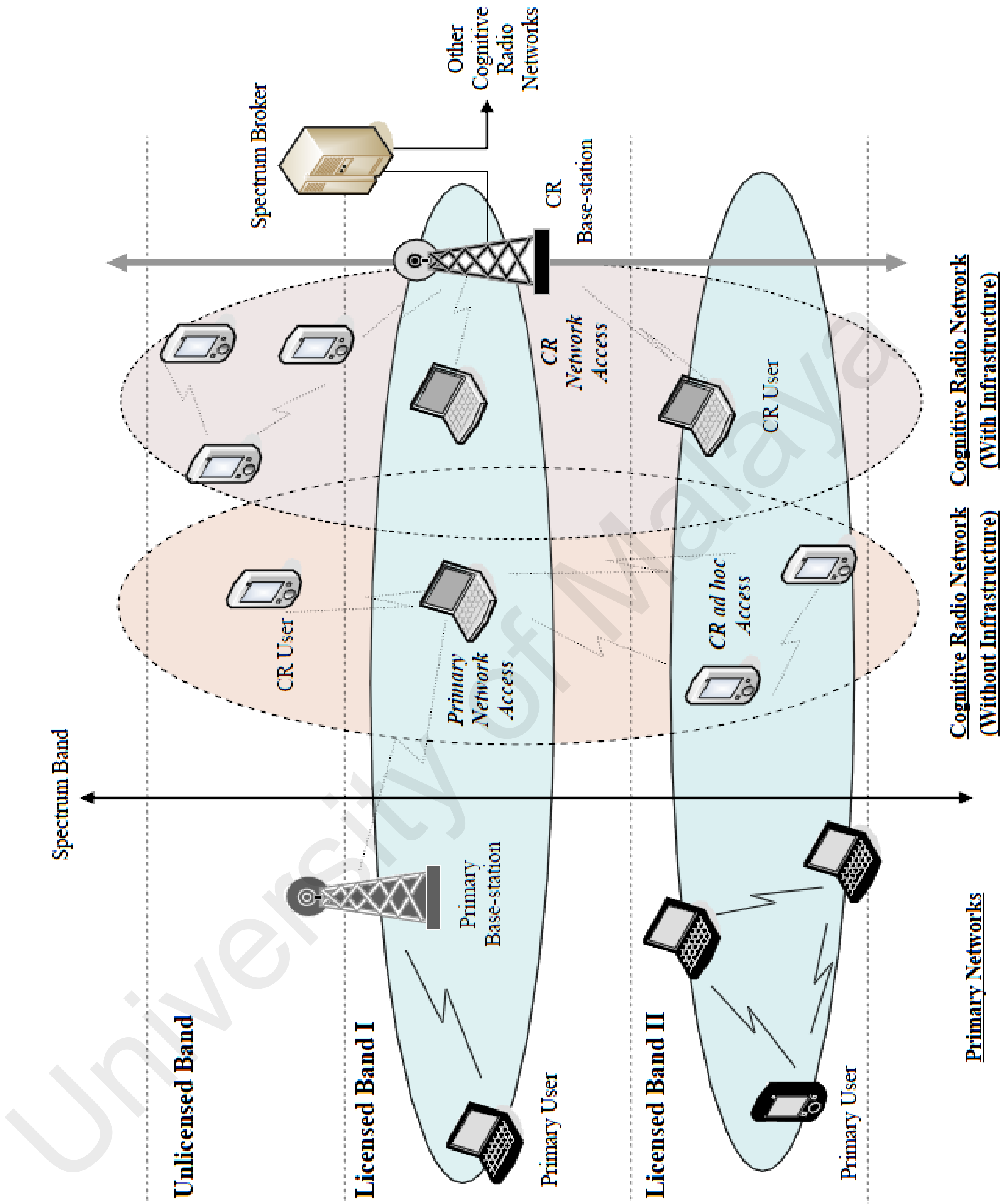


Figure 1.5: Cognitive radio network architecture (Akyildiz et al., 2006) .

1.1.2. Fundamentals of Diversity Combining

THE TERM “diversity” refers to the availability at the receiver of multiple copies of the desired signal, each of which being affected by different channel characteristics. This allows the implementation at the receiver of a combiner, which generally consists of a weight-and-sum structure where the weights are chosen to obtain the best possible estimate of the desired signal. While diversity is mostly useful to combat fading due to multipath, it also provides a gain against white noise and interference.

1.1.2.1. Different Type of Receive Diversity Combining

a) Time Diversity Combining

The same data are transmitted repeatedly several times; a buffer at the receiver can be used to store and combine the multiple copies (Gomez-Cuba, Asorey-Cacheda, & Gonzalez-Castano, 2012) & (Jetz et al., 2012).

b) Frequency Diversity Combining

The data is transmitted simultaneously in multiple frequency bands which may have completely or partially uncorrelated fading characteristics (Al-Dhahir, Uysal & Mheidat, 2008) & (Kildal et al., 2011).

c) Space Diversity Combining

The receiver is equipped with an antenna array made up of antenna elements. In a multipath fading environment, sufficient spacing can be introduced between the elements to decorrelate the fading envelopes (Lee, & Williams, 2000) & (Tsiftsis, Sandalidis & Karagiannidis, 2009).

d) Impulse Diversity Combining

In code division multiple access (CDMA) or other systems where the band is sufficiently large to resolve the individual impulses in the impulse response, each individual impulse constitutes a diversity channel with its own fading characteristics. They can be weighted and summed by a RAKE combiner to achieve the same benefits as in time, frequency or space diversity (Lozano, & Jindal, 2010) & (Hussain, Alouini & Hasna, 2012).

Space diversity combining is most well-known and applicable among different mentioned types of receive diversity combining. This research modified and proposed an algorithm to enhance SNR at each receiver in space diversity combining. Space diversity combining is one of the prominent ways to improve the reliability of wireless communication systems (Manesh et al.,m 2012) & (Skraparlis, Sakarellos, Panagopoulos, & Kanellopoulos 2009). The main idea of diversity is to extract information from the received signal components transmitted over multiple fading channels to improve the received signal-to-noise ratio (SNR) (Tsiftsis, Sandalidis, Karagiannidis, & Uysal, 2009) & (Karagiannidis et al., 2005). The large-enough spacing is essential in order to assure that the received signals are independent, which is a vital requisite to acquire the full benefit of the diversity receiver (Annavajjala & Milstein, 2005). It is obvious that there would be a small probability that all the received versions of signal are in a deep fade. Therefore, these techniques assume independent fading effects over the different signal paths. Out of the three mechanisms, path loss, large scale and small scale fading, the first two mechanisms are somehow similar and can be mitigated by the power control over a long period of time. Diversity techniques are particularly intended to overcome the small scale fading.

In the past decades, different kinds of diversity receivers functioning over a variety of fading channels have been comprehensively reviewed in the literature (Simon & Alouini 2005). The widely used diversity techniques are maximal ratio combining (MRC), equal gain combining (EGC), and selection combining (SC) (Sakarellos et al. 2011) & (Kong, 2009). The aim of these techniques is to find a set of weights $\overrightarrow{\omega} = [\omega_1, \omega_2, \dots, \omega_M]$, as shown in Fig. 1.6, which optimizes a specific objective function. Here, the weights are selected to minimize the effect of fading on the received multiple signal components for each individual user.

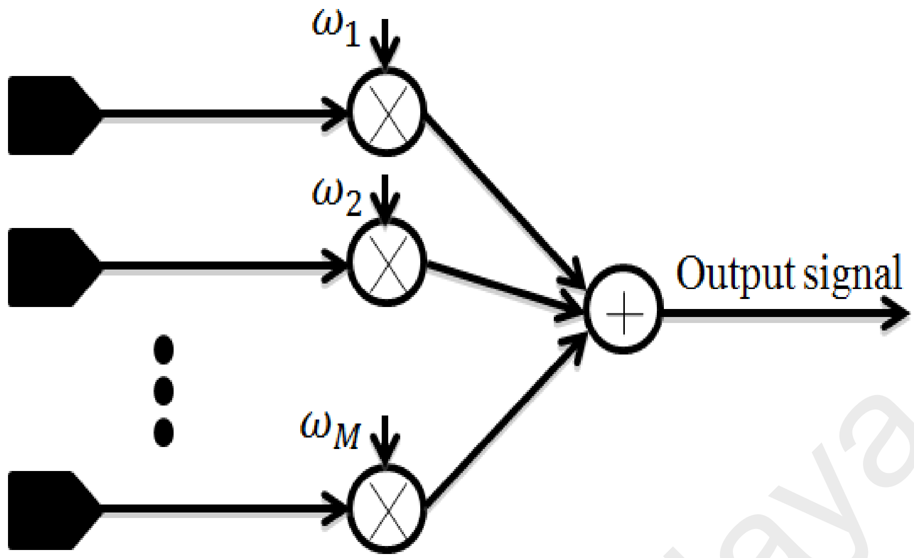


Figure 1.6: Diversity combining block diagram

1.2. Problem Statement

A fixed spectrum assignment policy results in underutilization of the available spectrum. New technologies and demand for high data rates require efficient utilization of underutilized spectrum (Palicot, 2009). Existing Medium Access Control (MAC) protocols of other technologies like Bluetooth cannot be implemented in Cognitive Radio networks since they do not have a primary user (PU) and secondary user (SU) mechanism (Unnikrishnan, Veeravalli, 2008). The Cognitive Radio technology gives an efficient design for utilizing the available spectrum, but it also introduces new challenging problems which are not present in conventional wireless networks, specifically the changing availability over time of channels in CR networks. One of the important design problems of CR is how SUs should take decisions about which channel they will use and at which time in order to enable SU communication while avoiding damage to PUs by analyzing spectrum sensing information provided by the physical layer. Current problems of wireless communication and cognitive radio system are listed as below and considered in this research:

1. Currently, inefficient use of spectrum increases approximately by a factor of 10 every 5 years, which corresponds to an increase of the associated energy consumption (Grace et al., 2009), (Han et al., 2011) & (Gur & Alagoz 2011).

2. Spectrum is getting more and more crowded as the number of wireless devices increases drastically which causes scarcity. There is also too much loss of data in communication system. Loss of data in CR network caused by miss detection of PU by SUs (FCC, 2002).

3. At the system level, cognitive radio networks, formed by cognitive radio devices, are required to make better usage of available spectrum to achieve higher end-to-end quality of service, e.g., in throughput and/or delay performance (Akbari et al., 2012) & (Shen, & Kwak, 2009).

4. Developing an algorithm and scheme of fully-functioning cognitive radio network can be challenging especially for green communication (El-Saleh et al., 2011).

5. The existing methods of cognitive radio system mute be improved in oriented wireless network to meet a certain level of Quality of Service (QoS) (Akbari et al. 2012), (Mukherjee, A., & Swindlehurst, 2013).

6. Laboratory and industrial system design of cooperative cognitive radio systems are too expensive and must be considered as an issue.

1.3. Objectives

The aim of this research is to develop the spectrum management framework that exploits the dynamic spectrum environment and the cross-layer design advantages in CR networks to address the unique challenges posed by the dynamic spectrum access paradigm. The unique characteristics of the spectrum management framework and the proposed solutions for defined problem statements are addressed in this research by using the concept of diversity. The main objectives of this research are summarized as below:

7. To investigate the traditional and current techniques of spectrum management and diversity received signaling and identify the main problems associated that result is inefficient use of spectrum.

8. To design iterative techniques' concept and mechanism and apply an advanced iterative technique for higher efficiency of dynamic resource management in cognitive radio network.

9. To develop efficient use of frequency in cognitive radio oriented wireless network by means of cutting-edge iterative methods and importing the concept of diversity to cognitive radio spectrum management.

10. To mathematically model the cognitive radio system and perform extensive simulations which will confirm the proposed schemes.

1.4. Thesis Contributions

In this research, first CR cooperative spectrum sensing (CRCSS) is well investigated by itself and then new proposed modified CRCSS ICA-base algorithm is proposed on both Neyman-Pearson and Minimax criterion to improve detection performance and decrease error and miss detection in the network. In the second part, diversity antenna concept is reviewed and new ICA-based method is proposed on space diversity to maximize SNR and the receivers. In general, the weights are selected to minimize the effect of fading on the received multiple signal components for each individual SU and reduction in probability of miss detection and probability of error on FC center. At the end, the proposed space diversity combining is implemented in new CRCSS modified ICA-based method (which is own proposed in the first part) to improve and guarantee efficient usage of spectrum. Also mathematically modeled to have a better comparison with non-diversity based method.

1. Current techniques of spectrum management and diversity received signaling are well investigated and main problems of the methods are well mentioned. Modified CRCSS ICA-base algorithm is completely defined and proposed on both Neyman-Pearson and Minimax criterion to improve detection performance and decrease error and miss detection in network. Also received SNR in space diversity combining maximized by proposing ICA-based method.

2. The proposed space diversity is applied to new CRCSS method to improve the spectrum utilization, increase the number of users and guarantee frequently usage of spectrum in cognitive radio oriented wireless network.

3. At last, CRCSS diversity based mathematically modeled and perform extensive simulations and compared with all other existing techniques (non-diversity based method) to confirm the efficiency of the proposed methods.

1.5. Organization of the Thesis

For convenience of the reader, this thesis is organized into five chapters. This research addresses the two weight optimization methods which are Neyman-Pearson Criterion and Minimax Criterion in CRCSS and proposed modified imperialistic competitive algorithm (ICA) to find efficient weighting vector and enhance spectrum efficiency in CRN. Also, space diversity combining is investigated, improved and proposed on CRCSS to improve QoS and overall sensing performance of CRN. As a result, the proposed methods can be considered as a real time application in a new generation of wireless communication.

Chapter 1 gives a preface to the communication's history and explains the limitation of spectrum and how spectrum is allocated currently to different users. The problem statement is defined and limitation of the spectrum and motivation of this research in CR network (CRN) is also defined in this chapter. At the same time, concept of receive diversity combining is presented as a brief introduction to propose diversity based method in the next chapters.

Chapter 2 introduces the four main designs of CRSM (spectrum sensing, sharing, decision and mobility in terms of interaction between SUs and PUs is considered). Also shows how clustering and CSS can reduce the interference between PUs and SUs. In addition, introducing diversity combining concept in CRCSS will be continued and will well investigate on coming chapters.

Chapter 3 will present two hypotheses of the CR meanwhile the mathematical modeling of it under both Neyman-Pearson and Minimax criterion reviewed. Also, all the necessary parameters that impact on the performance of the network are presented such as channel condition or additional noise and the power of the transmitter. Weighting coefficient and threshold value will also be discussed as really important parameters which effect on the performance of the network. Also, these all channel parameters will use on diversity combining scheme when the proposed diversity model will apply on CRCSS.

Chapter 4 proposes modified ICA and some of the advantages of this algorithm over current algorithms such as PSO, GA and other conventional techniques same as equal gain combining (EGC), maximal ratio combining (MRC), normal deflection coefficient (NDC) and modified deflection coefficient (MDC) explained. Also the performance of the modified ICA investigated on the CR. On the other hand, modified ICA will also apply to diversity method as a new proposed technique in this area. The result will confirm the advantages of the proposed method over existing techniques. At the end, we used the proposed diversity method on each individual SU in CRCSS to improve the total efficiency of the system and reduce the number of SUs which consequently reduce the complexity of the system and make the designed system as real time application.

Finally, **Chapter 5** states the conclusions drained from this study. It presents a summary of the generated results found from the previous chapter to prove the superiority of the proposed algorithms. The applications and future improvements are also suggested in this chapter.

CHAPTER 2 : LITERATURE REVIEW

2.1. Spectrum Management Framework

CR networks impose unique challenges due to their coexistence with primary networks as well as diverse QoS requirements. Thus, required functions for CRSM are Interference avoidance with PU, QoS awareness for all users and Seamless communication for SUs regardless of the appearance of primary users.

Since CR network coexists with PU network and different QoS requirements are involved, some challenges are associated with it. Therefore, required functions for CRSM are Interference avoidance with PU, QoS awareness for all users and Seamless communication for SUs irrespective of the arrival of PU to the network. To cope with these challenges, a directory for various functions needed for CRSM networks is provided. The CRSM procedure contains four key steps:

Spectrum Sensing

- SUs detect a particular unoccupied spectrum bands (white holes) (Akbari et al., 2012).
- On the absence of PUs, SUs can occupy the spectrum bands, but must be vacant once PUs are back to the bands or reduce transmission power as much as no interfere happens to PUs (Yao, Erman & Popescu 2011).

Spectrum decision

- Interference to PU must be kept to the minimum. To meet the requirements and QoS, CR needs to locate the best spectrum band over the entire available frequency range (Lee & Akyldiz 2011) & (Christian, Chung, & Lee, 2012).

Spectrum Sharing

- Offers fair spectrum scheduling alternative (Lee & Cho 2013).
- As discussed in earlier chapter, this is still a problem in open spectrum usage (Stotas & Nallanathan 2011).

Spectrum Mobility

- Ability of CR to exchange its operating frequency with a smooth transition even internally or externally (Ma, Li & Juang, 2009) & (Sboui, Rezki, & Alouini, 2014).

2.1.1 Spectrum Sensing

As already described, CR has emerged as a promising technology to enable access of vacant frequency bands which defined as spectrum holes or white spaces (Krasniqi, Wrulich, & Mecklenbräuker, 2009). The elementary assignment of each user in CR network, in a mainly primeval sense, is to distinguish the users with license (i.e., PUs) in the certain band. This is generally obtained with sensing the radio frequency (RF) in the environment, this method called spectrum sensing CR. The spectrum sensing objectives are divided into two fields (Visotsky, Kuffner, & Peterson, 2005) first, the harmful interference from CR users must not cause for PUs. This harmful interference can be solved with shifting to an available band or making limit its interference to PUs at a satisfactory level. In fact, Spectrum sensing enables CR users to adapt to the environment by detecting spectrum holes without causing interference to the primary network. Second, CR users must professionally exploit and recognize the spectrum holes for requisite QoS and throughput. Therefore, the level of detection in spectrum sensing is crucial to the performance of CR networks. Due to shadowing effect and hidden terminal problem, the SU may not detect the activity of the PU within the short interval of sensing period. Therefore, the detection performance might be hugely degraded (Akbari et al., 2012). In (Qi, Wang & 2009) & (Sherman et al., 2008) the authors proposed CR cooperative spectrum sensing (CRCSS) to overcome this problem and minimize the interference.

2.1.1.1 Cognitive Radio Cooperative Spectrum Sensing

Most researchers believe that Spectrum sensing is one of the significant functions in the CR and it would be the basic technique of the future wireless communication. But spectrum sensing in CR suffers from hidden terminal and multipath Fading problems, thus, cooperative Spectrum sensing introduced as an effective approach to reduce the impact of hidden terminal and multipath fading in CR to enhance QoS.

In November 2008, rules of the FCC had changed and unlicensed fixed or even portable wireless equipment are officially permitted to use the TV white spaces. However, they should apply spectrum sensing technique to detect wireless microphone signals and TV broadcasting which are defined as PUs to avoid any interference (Ghasemi, & Sousa, 2005,). TV frequencies are chosen because they possess very good propagation characteristics for long range wireless networks. To summarize only the important procedures in spectrum sensing, a flowchart is shown below in Fig. 2.1.

Now the problems of destructive channel effects have been drastically decreased by engaging more SUs over the whole network to perform spectrum sensing to detect the existence of PU. However, things may get a bit complicated if the quantity of SUs in the network is very high. The Base Station (BS) which is responsible for the final decision will be overwhelmed by measurements from all the cooperating SUs. Thus, to tackle this issue SUs are divided into a few groups, each covering a smaller geographical area, which is refereeing to the concept of cluster-based cooperative spectrum sensing. This is better explained in Fig. 2.2.

To facilitate the analysis of cooperative sensing, we classify cooperative spectrum sensing into three categories based on how cooperating CR users share the sensing data in the network: centralized (Zhang, Zhang & Wu, 2010), (Li, & Jayaweera, 2013) & (Bae, & Kim, 2014) distributed (Ganesan & Li 2007) and relay-assisted (Kim, Dall'Anese, & Giannakis, 2011) & (Sakarellos, Skraparlis, Panagopoulos, & Kanellopoulos, 2011). These three types of cooperative sensing are illustrated in Fig. 2.3.

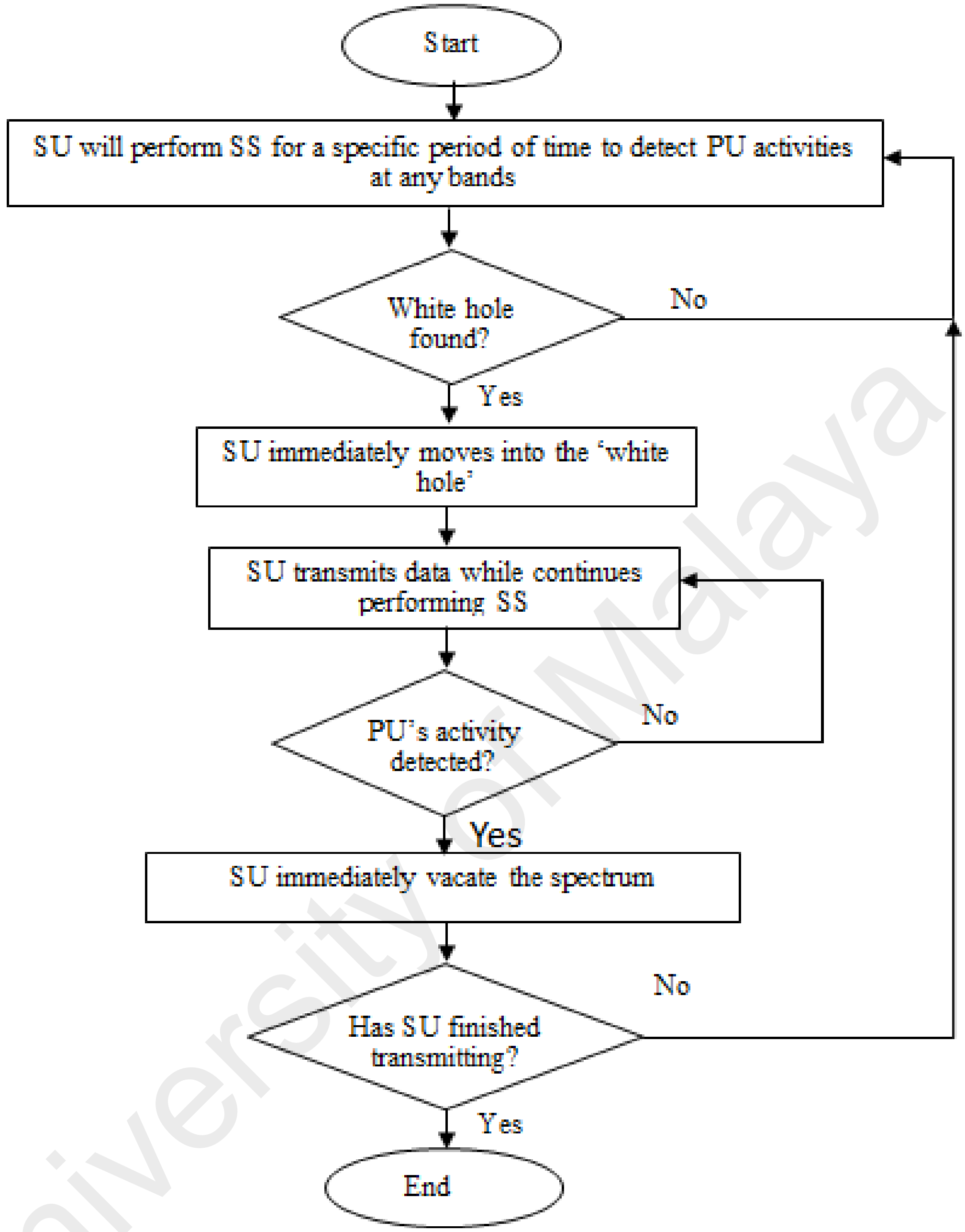


Figure 2.1: Flow Chart of Spectrum Sensing

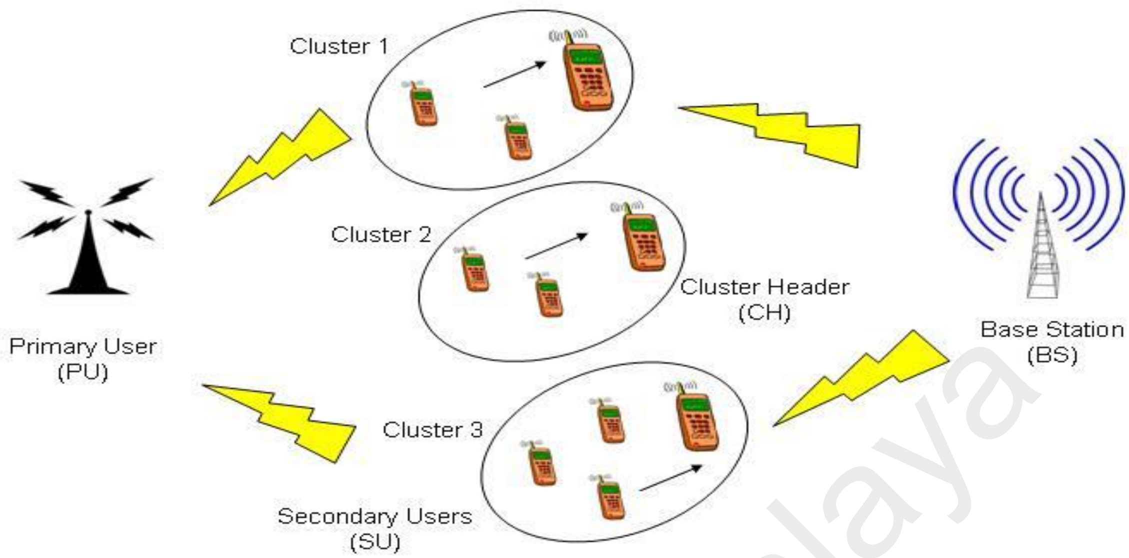


Figure 2.2: Cluster-Based Cooperative Spectrum Sensing

a) Centralized Cooperative Spectrum Sensing

Centralized method, the core identity known as Fusion Center (FC) regulates procedure's steps of cooperative sensing. FC (Jayaweera, Bkassiny, & Avery, 2011) & (Guimaraes & de Souza, 2012) is usually often known as BS, common receiver, incorporating node, designated controller and master node (Zhang, Zhang & Wu, 2010) & (Li, & Jayaweera, 2013) Initially, FC chooses an interest intended frequency band or channel for sensing as well as instructs just about all SUs to individually and independently execute local sensing. Secondly, all SUs report their sensing outcomes through predefined and reliable band to FC. Next the FC brings together all obtained sensing data from all SUs and decides about PUs activity in band, as well as sending back decision for all cooperating SUs. While proven within Fig. 2.3 (a), CR0 could be the FC and CR1–CR5 tend to be cooperating SUs executing local sensing and sending the results to CR0. With regard to local sensing, almost all SUs tend to be tuned to the chosen licensed frequency band where a physical point-to-point link between PU and every single SUs to observe PU's signal which named sensing channel. With regard to information exposure, all SUs tend to be tuned to a control channel certainly where a physical point-to-point link between every SU end along with the FC with regard to transmitting the actual sensing results is known as any reporting channel.

In centralized cooperative sensing, a central identity called fusion center (FC) controls the three-step process of cooperative sensing. The fusion center (Jayaweera, Bkassiny & Avery, 2011) is also known as base station (BS), common receiver, combining node, master node, designated controller (Zhang, Zhang & Wu, 2010) & (Li, & Jayaweera, 2013).

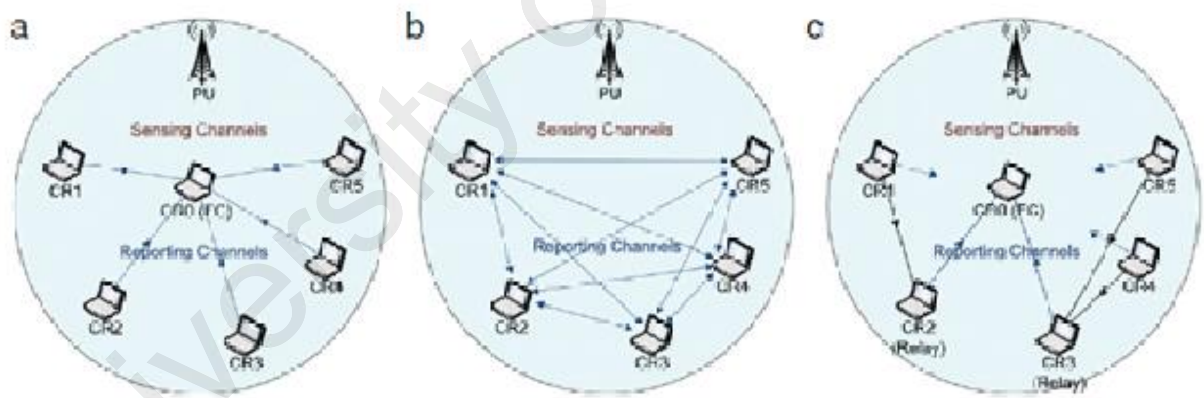


Figure 2.3: Classification of Cooperative Sensing: (a) centralized, (b) distributed, and (c) relay-assisted

b) Distributed Cooperative Spectrum Sensing

Distributed cooperative sensing would not rely on a FC to make the cooperative determination like centralized cooperative sensing. In cases like this, SUs communicate by each other and converge to a specific conclusion and decision about the absence or presence of PUs by iterations. Fig. 2.3 (b) shows the cooperation in the different approach. After local sensing, SUs (CR1–CR5) send their local sensing to other SUs in the system within their predefined band. Based on distributed steps, each SU shares its own observed data to all SUs, merges its data with the received sensing data, and by using a local criterion decides if the PU is present or not. If the criterion is not satisfied, SUs send their merged output results to other SUs and repeat this loop till the algorithm is converged and a decision is made. In this scheme, this distributed manner may take some iterations to end with the common cooperative decision.

c) Relay-Assisted Cooperative Spectrum Sensing

Relay-assisted cooperative sensing is the third scheme. Since report channel and sensing channel may not be perfect, a SU may have a strong report channel and a weak sensing channel or weak report channel and strong sensing channel, as an example, should cooperate and complement with other SUs to enhance the performance of cooperative sensing. In Fig. 2.3 (c), SU1, SU4, and SU5, which have strong sensing signals, may suffer from a weak report channel. SU2 and SU3 which have a trustable report channel can act as relays to assist in transmitting the sensed results from SU1, SU4, and SU 5 to the FC. In cases like this, the report channels from SU2 and SU3 to the FC is named relay channels. It is notable that Fig. 2.3 (c) shows a relay-assisted cooperative and centralized structure exists in a distributed manner. Also, the relay for cooperative sensing here serves a different purpose from the relays in cooperative communications (Bae, & Kim, 2014) where reporting about PU activity send by CR relays.

2.1.1.2 Cognitive Radio Centralized Cooperative Spectrum Sensing Methods

This research is mainly focus on centralized CSS which is very closed in concept to spectrum decision in CRN or almost sticks together in performance so I prefer to explain their formula in the next step.

CR based on cooperative spectrum sensing is one of the best candidates in the short range for the future generations of wireless communication. In other words, CRCSS can detect the spectral holes intelligently and dedicate the under-utilized frequency bands to the CR users without any harmful interference to the PUs. Different results in CR come from using different methods at FC at networks. The three different methods which are used to make decision in FC are listed as follows, soft-fusion detection (SDF), hard-fusion detection (HDF) and soft-hard fusion detection (SDF-HDF). The results in (Senthuran, Anpalagan, & Das, (2012) & (Akbari et al., 2012) confirm that SDF is much more accurate than HDF and less complicated than SDF- HDF so at the following we investigate CRN based on SDF method.

The reliability of detected weak signals from unknown types of users with low SNR is very necessary for the spectrum sensing to monitor the activity of PUs. The trustworthiness of detection of PU transmission is the main issue` when the cooperation between SUs and PUs is very poor. Recently some researchers have been done on CR cooperative spectrum sensing SDF-based scheme (detection of PU transmission) and widely usage of this in modern wireless communication system. Some techniques that have been proposed in this area are listed as follows: equal gain combining (EGC), maximal ratio combining (MRC), normal deflection coefficient (NDC), modified deflection coefficient (MDC), Genetic algorithm (GA), Particle swarm optimization (PSO) (Akbari et al. 2012), (Mukherjee, A., & Swindlehurst, 2013) & (El-Saleh et al., 2011). Fig. 2.4 demonstrates the centralized CSS SDF-based scenario where M SUs (as relays) send their measurements on activity of PU to FC to make decision on the presence of PU. Also, Fig. 2.4, is modeled as channels starting from PUs to FC are assumed to be Rayleigh fading (different gains) and noise is AWGN with different variance in each path which will completely investigated in below sections.

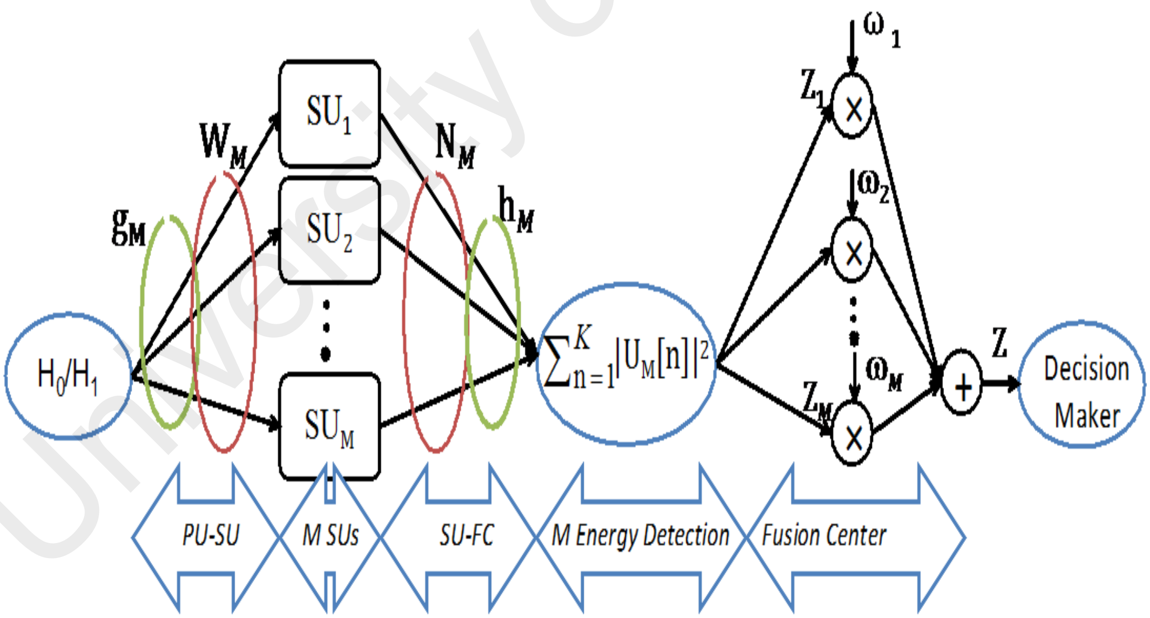


Figure 2.4: Block diagram of the cooperative spectrum sensing

a) Equal Gain Combining Based Weighting Scheme

The EGC scheme is one of the simplest weighting schemes based on SDF and is same as the one used in systems with multiple receive antennas. It does not require any channel estimator, but still performs much more accurate than conventional HDF techniques. Weights of each path are individually assigned at fusion center and are reversely related to the number of SUs (El-Saleh et al., 2010). All the branches are equally weighted as follows:

$$\omega_i = \sqrt{1/M} \tag{2.1}$$

This EGC weighting scheme is applied in (3.12) and (3.16) for Neyman-Pearson (Neyman & Pearson, 1933) and MINIMAX (Shen, & Kwak, 2009) and compared with other methods in Chapter 5. The detection performance is appraised using receiver operating characteristics (ROC) curve.

b) Maximal-Ratio Combining Based Weighting Scheme

Weighting coefficient is allocated for each SU signal at the fusion center which contributes to the final decision. Thus, if higher SNR is received at FC that may cause for a better detection, it will calculate a larger amount of weighting coefficient. On the other hand, weighting coefficient decreased to reduce the negative contribution to the final decision when SU faced by shadowing or deep fading. By considering $||\omega|| = 1$, weighting coefficient for the i^{th} SU is measured as follows (El-Saleh et al., 2011):

$$\sum_{i=1}^{M} SNR_i = SNR_T \Longrightarrow \sum_{i=1}^{M} \frac{SNR_i}{SNR_T} = 1 = \sum_{i=1}^{M} \omega_i^2 \Longrightarrow \omega_i^2 = \frac{SNR_i}{SNR_T}$$

$$\omega_i = \sqrt{\frac{SNR_i}{SNR_T}} \tag{2.2}$$

Where SNR is the estimated SNR at the FC for the i^{th} SU. To see the performance of the MRC under MINIMAX and Neyman-Pearson criterions, weighting coefficient obtained in (2.2) should apply to (3.16) for MIMAX and (3.12) for Neyman-Pearson.

c) Deflection Coefficient Based Weighting Scheme

Deflection coefficient (DC) measures detection performance and it is formulated based on two hypothesizes: H_0 and H_1. The DC based weight scheme is categorized in two groups, first normal DC and second modified DC as formulated below.

i) Normal Deflection Coefficient

As previously mentioned normal deflection coefficient (NDC) is used to fined optimal weighting vector. The NDC weighting schemes formula is based on hypothesis H_0 which means the PU is absent. In simple world, the derivation of objective function Equation (3.12) or (3.16) and calculation of the roots and used to fine the optimal weighting vector is named NDC methods when PU is absent. The below formula is derived in (El-Saleh et al., 2011) for Neyman-Pearson criterion.

$$\vec{\omega}_{opt.NDC} = \frac{\vec{\omega}^T \Sigma_{H_0} \vec{\omega}}{\vec{\omega}^T \vec{\theta}} \Sigma_{H0}^{-1} \vec{\theta} \tag{2.3}$$

$$\alpha_{NDC} = \frac{\vec{\omega}^{T}\Sigma_{H_0}\vec{\omega}}{\vec{\omega}^{T}\vec{\theta}} \tag{2.4}$$

Let us assume that α_{NDC} that is scalar and equal to 1 and also making normalized each weighting vector as below:

$$\vec{\omega}^{*}_{opt,NDC} = \vec{\omega}_{opt,NDC}/\left\|\vec{\omega}_{opt,NDC}\right\| = \Sigma_{H0}^{-1}\vec{\theta} \tag{2.5}$$

And by applying the optimal weighting vector to (3.12) and (3.16), $P_{d,NDC}$ and $P_{e,NDC}$ will be calculated.

ii) Modified Deflection Coefficient

Also this technique is used to fined weighting coefficient vector same as NDC. The only difference is, MDC uses hypothesis H_1 which means when PU is present and NDC uses the hypothesis H_0. Optimal weighting vector is defined by El-Saleh et al., 2010 for Neyman-Pearson criterion:

$$\vec{\omega}_{opt.MDC} = \frac{\vec{\omega}^{T}\Sigma_{H_1}\vec{\omega}}{\vec{\omega}^{T}\vec{\theta}}\Sigma_{H1}^{-1}\vec{\theta} \tag{2.6}$$

$$\alpha_{MDC} = \frac{\vec{\omega}^{T}\Sigma_{H_1}\vec{\omega}}{\vec{\omega}^{T}\vec{\theta}} \tag{2.7}$$

Let's suppose α_{MDC}that is scalar and equal to one and also making normalized each weighting vector as below:

$$\vec{\omega}^{*}_{\mathrm{opt,MDC}} = \vec{\omega}_{\mathrm{opt,MDC}} / \left\| \vec{\omega}_{\mathrm{opt,MDC}} \right\| = \Sigma_{\mathrm{H1}}^{-1} \vec{\theta} \tag{2.8}$$

After that by applying optimal weighting vectors in this technique to (3.12) the maximum probability of detection will be calculated.

d) GA Based Cooperative Spectrum Sensing

GA is classified as a stochastic evolutionary search algorithm that mimics natural evolution (Haupt & Haupt, 2004). It has been used to solve difficult non-deterministic problems and machine learning as well as for many other engineering applications. GA is a population-based method in which each individual in the population evolves to create new individuals that form new populations. This evolutionary process continues until no improvement on the fitness score and then the optimal individual is obtained from the last obtained population.

In this paper GA-based method has been proposed, an initial population of pops possible solutions is generated randomly and each individual is normalized to satisfy the constraints. The goal is to find the optimal set of weighting vector values to maximize detection performance. When it reaches the predefined maximum number of generations, GA is terminated and the weighted vector values that minimize the probability of error is considered as the best solution. Let us assume that, there are M SUs and Z1, Z2…ZM are the soft decisions of SU1, SU2….SUM on the presence of PUs, and $\vec{\boldsymbol{\omega}}_j$ is the weighting vector of the j^{th}individual that consists of $\omega_1, \omega_2, \omega_3, \dots \omega_M$, the fitness value for the jth individual is defined as follow:

$$f_j = p_e(\overrightarrow{\boldsymbol{\omega}_j}) \text{ where } \|\overrightarrow{\boldsymbol{\omega}_j}\|=1 \tag{2.9}$$

p_e stands for probability of error. The main operations of the proposed GA are selection, crossover, and mutation. For selection, the idea is to choose the best chromosomes for reproduction through crossover and mutation. The smaller the fitness (probability of error) value the better the solution obtained. In this paper "Roulette Wheel selection" method has been used. The probability of selecting the $\boldsymbol{j}$ th individual or chromosome p_j can be written as:

$$p_j = \frac{f_j}{\sum_{j=1}^{pops} f_j} \tag{2.10}$$

The chromosomes with minimum probability of error value will be directly transferred to the next generation through elitism operation. After the selection process is done, the next step is crossover. The crossover starts with pairing to produce new offspring. A uniform random number generator has been used to select the row numbers of chromosomes as mother (ma) or father (pa). Here a random population of choromosomes is shown in matrix A, where pops is total number of chromosomes, M is number of secondary users.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1M} \\ a_{21} & a_{22} & \dots & a_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ a_{pops\,1} & a_{pops\,2} & \cdots & a_{pops\,M} \end{bmatrix} \tag{2.11}$$

It begins by randomly choosing a variable in the first pair of parents to be the crossover point. In the illustration crossover point is α and β is a random value on the interval [0, 1]. As for the GA crossover operation, two parents are chosen and the new off springs are formed from combinations of these parents. For crossover scheme used in our proposed algorithm is a hybridization of an extrapolation method with a crossover method to enhance the quality of obtainable solutions (Rieser, 2004). The GA crossover operation is graphically explained in Fig. 2.5.

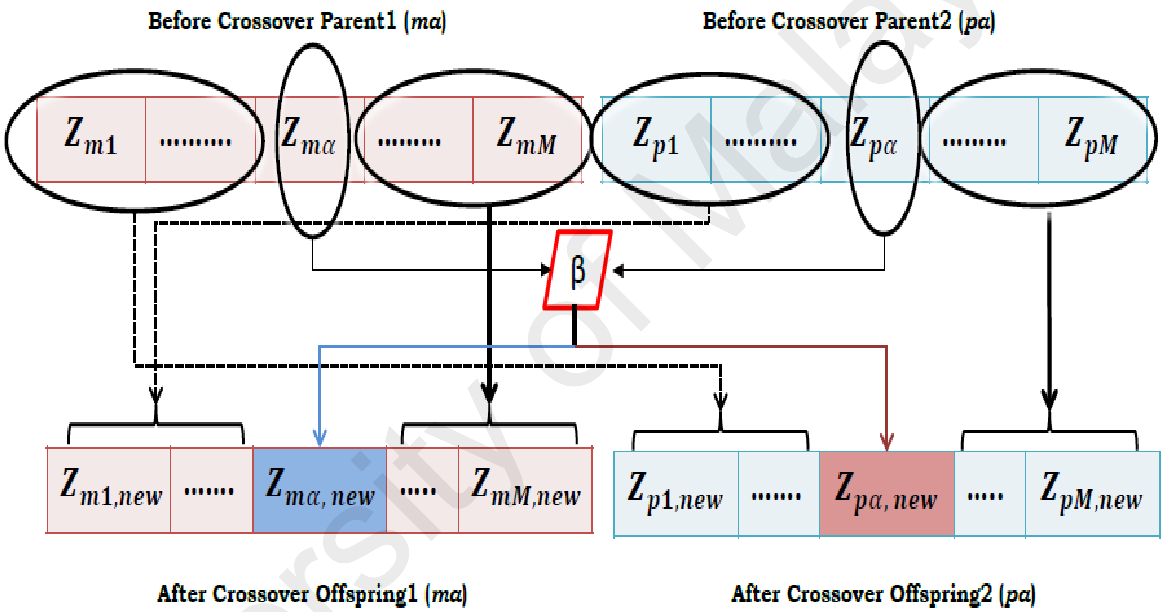


Figure 2.5: GA crossover operation

For Parent1 (ma) → offspring1 (ma):

$$\begin{gathered}\{Z_{p1}, \dots, Z_{p(\alpha-1)}\} \rightarrow \{Z_{m1,new}, \dots, Z_{m(\alpha-1),new}\} \\ \{Z_{m(\alpha+1)}, \dots, Z_{mM}\} \rightarrow \{Z_{m(\alpha+1),new}, \dots, Z_{mM,new}\} \\ Z_{m\alpha,new} = Z_{m\alpha} - \beta[Z_{m\alpha} - Z_{p\alpha}]\end{gathered} \tag{2.12}$$

For Parent2 (pa) → offspring2 (pa):

$$\begin{gathered}\{Z_{m1}, \dots, Z_{m(\alpha-1)}\} \rightarrow \{Z_{p1,new}, \dots, Z_{p(\alpha-1),new}\} \\ \{Z_{p(\alpha+1)}, \dots, Z_{pM}\} \rightarrow \{Z_{p(\alpha+1),new}, \dots, Z_{pM,new}\} \\ Z_{p\alpha,new} = Z_{p\alpha} + \beta[Z_{m\alpha} - Z_{p\alpha}]\end{gathered} \tag{2.13}$$

The next step after crossover is the mutation operation. The total number of variables that can be mutated equals to the mutation rate times the population size. The row and column numbers of variables are nominated randomly and then these nominated variables are replaced by new random ones. For instance, if the mutation rate is 60% and the population size equal to 5 chromosomes as it shown in matrix A, then the total number of variables that have to be mutated is 0.6 * 5 = 3 variables. Assume that the following pairs have been selected randomly from A:mrow = [4 3 5] and mcol = [2 5 1], where mrow is the row index and mcol is the column index of the population. Then, the variables to be mutated can be highlighted as shown in matrix A below.

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} \end{bmatrix} \tag{2.14}$$

Assume that the 4th chromosome in A is defined as [a_{41} a_{42} a_{43} a_{44} a_{45}] = [0.0551 0.8465 0.9891 0.2478 0.0541]. Then, the mutation process of, for example, the variable A (4, 2) → a_{42} is illustrated in Fig. 2.6. During the mutation operation, the previous value of $a_{42} = 0.8465$ is replaced by another random value and the new coefficient becomes $a_{42} = 0.3041$.

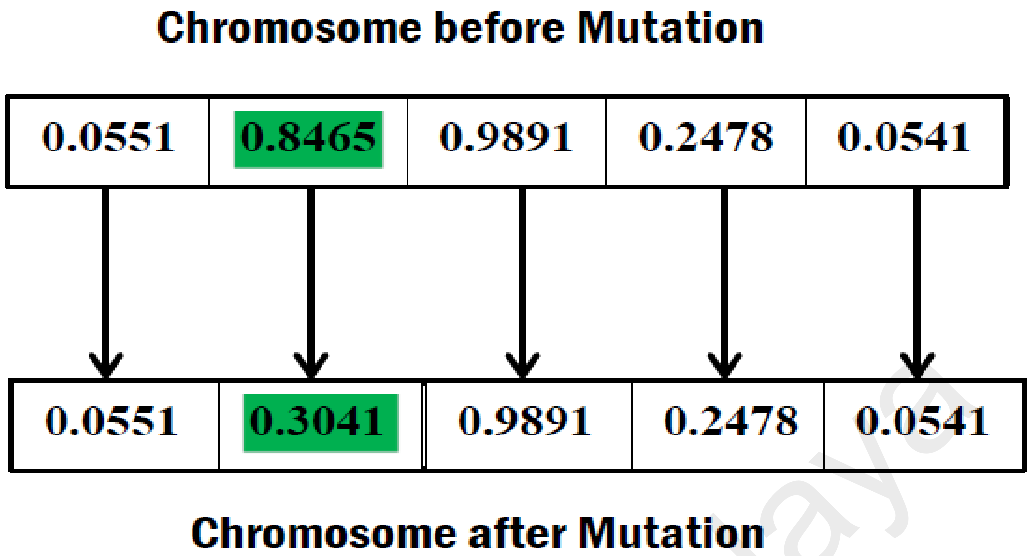


Figure 2.6: GA mutation representation.

i) Mini-Max Criteria for Genetic Algorithm

The GA based optimization algorithm for SDF-based CSS can be outlined as follows:

Step 1: Set t = 0 and randomly generate a population of pops chromosomes each of which is M digits long, where M is the number of secondary users in the network.

Step 2: Decode each chromosome in the random population into its corresponding weighting coefficients vector where the weighting coefficient vector $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]^T$; $\omega_1 \geq 0$ satisfying the condition; which is used to minimize the detection error.

Step 3: Normalize the weighting coefficient vector dividing $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]^T$ by its 2-norm such that $\vec{\boldsymbol{\omega}_i} = \vec{\boldsymbol{\omega}_i} \Big/ \left[\sum_{i=1}^{M}(\omega_i)^2\right]^{1/2}$ so that the constraint $\|\vec{\boldsymbol{\omega}_i}\| = 1$ is satisfied.

Step 4: Compute the fitness value of every normalized decoded weighting vector, $\vec{\boldsymbol{\omega}_i}$ rank their corresponding chromosomes according to their fitness value and identify the best chromosomes$\lfloor pops * elite \rfloor$, where $elite \in [0,1)$ and $\lfloor . \rfloor$ denotes floor operation.

Step 5: Update $t = t + 1$ and reproduce $\lceil pops * (1 - elite) \rceil$ new chromosomes (candidate solutions) using GA operations: selection, crossover and mutation where $\lceil . \rceil$ denotes ceiling operation.

Step 6: Construct a new set of population pops by concatenating the newly $\lceil pops * (1 - elite) \rceil$ reproduced chromosomes with the best $\lfloor pops * elite \rfloor$ found in $P(t-1)$.

Step 7: Decode and normalize the chromosomes of the new population pops as in Step 2 and Step 3 respectively.

Step 8: Evaluate the fitness value of each chromosome as in Step 4.

Step 9: If it is equal to predefined number of generation (iterations) ngener, stop. Otherwise go to Step 5.

ii) Neyman-Pearson Criteria For Genetic Algorithm

Step 1: Remains the same as Mini-Max criteria step.

Step 2: Remains the same as Mini-Max criteria step but the condition must satisfy the condition: which is used to maximize the detection probability.

Step 3: Remains the same as Mini-Max criteria step.

Step 4: Remains the same as Mini-Max criteria step.

Step 5: Remains the same as Mini-Max criteria step.

Step 6: Remains the same as Mini-Max criteria step but this time reproduced chromosomes with the best $\lfloor pops*elite \rfloor$ found in P(t-1) (higher value).

Step 7: Remains the same as Mini-Max criteria.

Step 8: Remains the same as Mini-Max criteria.

Step 9: Remains the same as Mini-Max criteria.

e) PSO Based Cooperative Spectrum Sensing

PSO algorithm, introduced by Eberhart & Kennedy (1995), is abstracted from social behavior of swarm of fishes and birds. The behavior of these social organizations is emulated by PSO algorithm .Each particle in PSO algorithm functions based on its own knowledge as well as group knowledge and has two main features: position and velocity. The particles follow an important and simple rule: to take after the success of individuals and their own successes. In this algorithm, each particle in the design space iteratively tries to find the best position, such as objective function optimum value. The information about the best position is exchanged among the particles during many iterations. This information enables individual particles to update their positions and velocities to obtain the best position. As such, after adequate number of iterations, the algorithm converges to the optimal solution of the objective function.

i) Mini-Max Criteria For Particle Swarm Optimization Algorithm

In this part, the problem is to minimize the objective function $P_e(\vec{\boldsymbol{\omega}})$ where $\vec{\boldsymbol{\omega}} = [\omega_1, \omega_2, \dots, \omega_M]$ and M is the number of variables of $P_e(\vec{\boldsymbol{\omega}})$ with $\boldsymbol{\omega}^l \leq \boldsymbol{\omega} \leq \boldsymbol{\omega}^u$ where $\boldsymbol{\omega}^l = 0$ and $\boldsymbol{\omega}^u = 1$ are lower and upper limits on $\boldsymbol{\omega}$. The steps involved in the PSO algorithm are as follows:

Step 1: The first step is initialization of the algorithm and consists of randomly generating N numbers of particle position as $\vec{\boldsymbol{\omega}}_s = [\omega_1, \omega_2, \dots, \omega_M]^T$ in the range of $\boldsymbol{\omega}^l$ and $\boldsymbol{\omega}^u$ and N numbers of length-M particle velocity vector which are initially set to zero as $\vec{\boldsymbol{v}}_s^{(j)} = [0, 0, \dots, 0]^T \;:\; (s = 1, \dots, N)$. To simplify the notation, particle position and velocity at iteration j are demonstrated by $\vec{\boldsymbol{\omega}}_s^{(j)}$ and $\vec{\boldsymbol{v}}_s^{(j)}$, respectively.

Step 2: In this step, the value of the objective function for each of the particle positions generated in step 1 is calculated as $P_e\left(\vec{\boldsymbol{\omega}}_1^{(0)}\right), P_e\left(\vec{\boldsymbol{\omega}}_2^{(0)}\right), \dots, P_e\left(\vec{\boldsymbol{\omega}}_N^{(0)}\right)$.

Step 3: The values of the objective functions obtained in step 2 are compared in this step and their smallest value is selected. Next, the particle position corresponding to minimum function value is defined as $\boldsymbol{P}_{best,0}$ and iteration number is set to $j = 1$.

Step 4: The velocity of the s^{th} particle at the j^{th} iteration is updated based on the following equation:

$$\vec{\boldsymbol{v}}_s^{(j)} = \vec{\boldsymbol{v}}_s^{(j-1)} + c_1 r_1 \left[\boldsymbol{P}_{best,j} - \vec{\boldsymbol{\omega}}_s^{(j-1)}\right] + c_2 r_2 \left[\boldsymbol{G}_{best} - \vec{\boldsymbol{\omega}}_s^{(j-1)}\right] \tag{2.15}$$

Where individual and social learning acceleration coefficients are, respectively, denoted by c_1 and c_2, r_1 and $r_2 \sim U(0\,,1)$ are random numbers with uniform distributions in the range of 0 to 1 which introduce stochastic components to the algorithm. At the j^{th} iteration, the best experienced particle position which minimizes the objective function is denoted by $\boldsymbol{P}_{best,j}$. The best experienced particle position among all iteration is called global best position and is expressed by $\boldsymbol{G}_{best}$.

Step 5: At the j^{th} iteration, the new position of the s^{th} particle is updated as follows:

$$\vec{\boldsymbol{\omega}}_s^{(j)} = \vec{\boldsymbol{\omega}}_s^{(j-1)} + \vec{\boldsymbol{v}}_s^{(j)} \tag{2.16}$$

Again, the value of the objective function for each of the particle positions generated in this step is calculated as:

$$P_e\left(\vec{\boldsymbol{\omega}}_1^{(j)}\right), P_e\left(\vec{\boldsymbol{\omega}}_2^{(j)}\right), \ldots, P_e\left(\vec{\boldsymbol{\omega}}_N^{(j)}\right) \tag{2.17}$$

Step 6: The values of the objective functions obtained in step 5 are compared and the particle position corresponding to minimum value of the objective function is defined as $\boldsymbol{P}_{best,j}$. The value of the $\boldsymbol{G}_{best}$ will be replaced by the value of the $\boldsymbol{P}_{best,j}$ if the following condition is satisfied as follow:

$$P_e\left(\boldsymbol{P}_{best,j}\right) \leq P_e(\boldsymbol{G}_{best}) \tag{2.18}$$

Step 7: The convergence of the algorithm is checked in this step and if the algorithm is converged to a stable value, the procedure is terminated. Otherwise, the iteration number is set to $j = j + 1$ and the process in repeated from step 4.

ii) Neyman-Pearson Criteria For Particle Swarm Optimization Algorithm

Step 1: Remains the same as Mini-Max criteria step.

Step 2: Evaluate the values of objective function corresponding to initial particle positions as $P_d\left(\vec{\boldsymbol{\omega}}_1^{(0)}\right), P_d\left(\vec{\boldsymbol{\omega}}_2^{(0)}\right), \ldots, P_d\left(\vec{\boldsymbol{\omega}}_N^{(0)}\right)$.

Step 3: Find the maximum value of the objective function in the step 2 and set its corresponding particle position as the $P_{best,0}$. Set the iteration number $j = 1$.

Step 4: Like step 3 in Mini-Max criteria.

Step 5: Update the i^{th} particle position at the j^{th} iteration using:

$$w_i^{(j)} = w_i^{(j-1)} + v_i^{(j)} ; \quad (i = 1, \dots, N) \tag{2.19}$$

Evaluate the values of objective function corresponding to new particle positions as $P_d\left(w_1^{(j)}\right), P_d\left(w_2^{(j)}\right), \dots, P_d\left(w_N^{(j)}\right)$.

Step 6: Find the maximum value of the objective function in the step 5 and set its corresponding particle position as the $P_{best,j}$. If $P_{best,j} \geq G_{best}$, replace G_{best} with $P_{best,j}$.

Step 7: If the algorithm is converged to a stable value, stop the process. Otherwise, set the iteration number as $j = j + 1$ and repeat from step 4.

2.1.2 Spectrum Decision

CR networks must have the ability to distinguish the best frequency band from the accessible bands based on the QoS requirement of the system/application. This concept is named spectrum decision and establishes a rather critical yet unidentified subject in CR technology. The most important thing to enhance the ability of deciding about the activity of PU in real time CRN is how to choose an accurate and suitable spectrum decision method. In other word, spectrum decision method effects on the performance of whole system in CR. As far as I know energy detection is the most efficient with less complexity in CRN:

2.1.2.1 Spectrum Decision Schemes

Spectrum decision scheme is divided into three important types which are cyclostationary detection, energy detection and matched filter detection (Zhang, Zhang & Wu, 2010), (Li, & Jayaweera, 2013) & (Bae, & Kim, 2014) which are defined as below.

a) Cyclostationary Feature Detection

- Distinguish PU signal energy from local noise energy by estimating the autocorrelation function of one or a few known cyclic frequencies.

- In general, signal is periodic or cyclostationary (symbol frequency).

- Can only detect signals with known cyclostationary properties.

b) Matched Filter Detection

It is suitable when PU is known by SU.

Signal phase and amplitude are extracted**.**

Detection probability is high

c) Energy Detection

It is suitable when SU is not completely known by PU or has less knowledge about PU signal**.**

Comparison of the energy of the received signal and threshold level illustrate the presence of the PU**.**

Having information about the surrounding noise in environment is required.

2.1.2.2 Decision Procedure

After the available spectrum bands are characterized, the most appropriate spectrum band should be selected, considering the QoS requirements and spectrum characteristics. Accordingly, the transmission mode and bandwidth for the transmission can be reconfigured. To describe the dynamic nature of CR networks, a new metric — PU activity is proposed (Peng, Zheng & Zhao, 2006) & (Zheng, & Cao, 2005), which is defined as the probability of a PU appearance during CR user transmission. Because there is no guarantee that a spectrum band will be available during the entire communication of a CR user, it is important to consider how often the PU appears on the spectrum band.

However, because of the operation of primary networks, CR users cannot obtain a reliable communication channel for a long time period. Moreover, CR users may not detect any single spectrum band to meet the user's requirements. Therefore, multiple noncontiguous spectrum bands can be simultaneously used for transmission in CR networks, as shown in Fig.1.4. This method can create a signal that is not only capable of high data throughput, but is also immune to interference and PU activity. Even if spectrum handoff occurs in one of the current spectrum bands, the rest of the spectrum bands will maintain current transmissions.

2.1.2.3 Spectrum Decision Challenges

In the progress of the spectrum decision, numerous challenges still stay unanswered:

- **Decision Model:**

The approximation of the capacity of the spectrum by means of signal-to-noise ratio (SNR) is not satisfactory to differentiate the spectrum bands in CR networks. Besides, different QoSs are required for different applications. As a result, constitution of application-adaptive and spectrum-adaptive models of spectrum decision is still an unsolved problem.

- **Cooperation with Reconfiguration:**

In order to function optimally, CR methods should be able to adjust the transmission parameters in a specific spectrum band. For instance, assuming that SNR is altered, bit rate and bit error rate (BER) can be kept by utilizing adaptive modulation rather than spectrum decision. Therefore, a collaborative framework with adjustment capabilities is necessary in spectrum decision.

- **Spectrum Decision over Heterogeneous Spectrum Bands:**

Typically, specific frequency bands are allocated to applications, so that some bands stay unlicensed. Hence, a CR network must be capable of providing spectrum decision functions on both the licensed and unlicensed bands.

2.1.3 Spectrum Sharing

In cognitive radio network PUs coexisted with SUs in the same frequency band to achieve better spectrum utilization. The current researches on spectrum sharing intend to deal with these issues and can be categorized by four features: the architecture, spectrum allocation behavior, spectrum access technique, and scope.

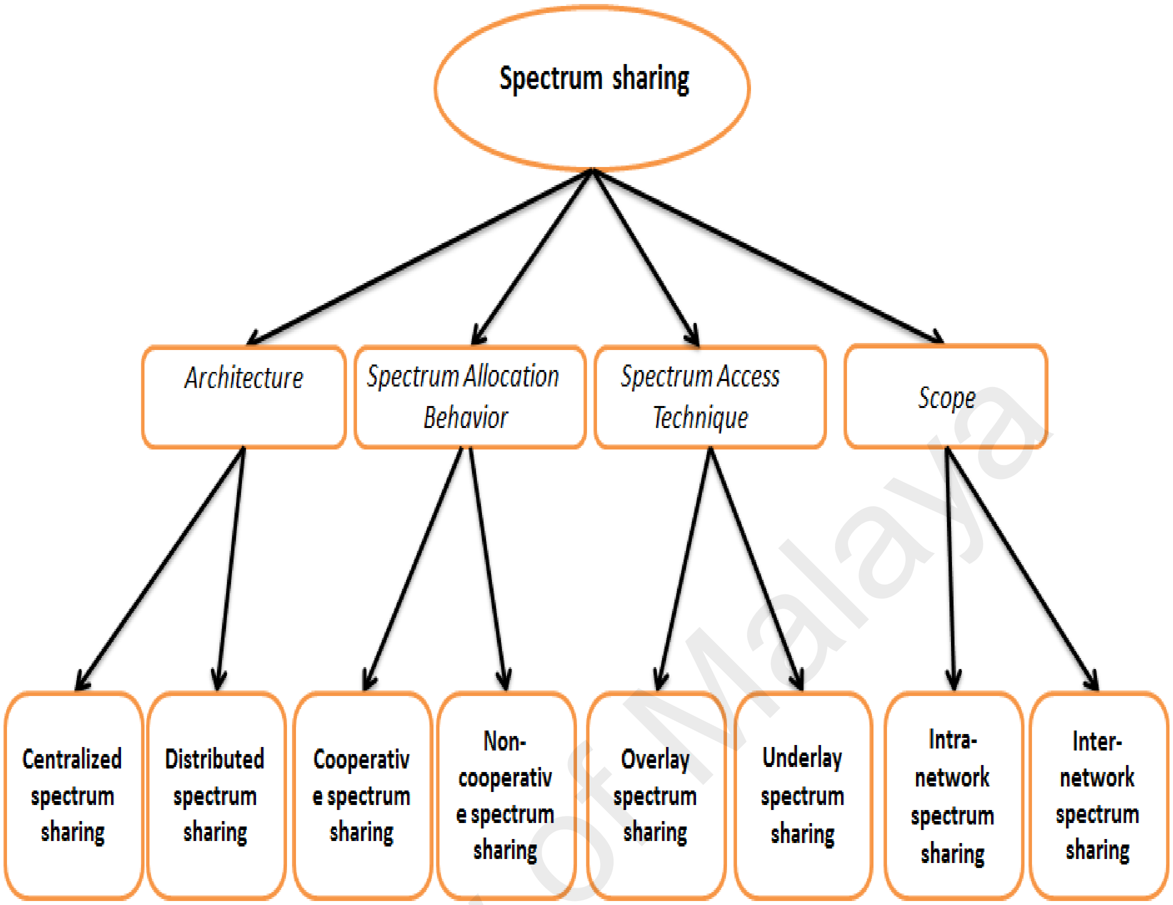


Figure 2.7: inter-network spectrum and intra-network sharing in CRN.

Generally, in cognitive radio networks three models have been considered in the literature for spectrum sharing: **interweave**, **underlay** and **overlay model** Fig.7 **(**Menon, Buehrer, & Reed, 2005), (Senthuran, Anpalagan, & Das, 2012) & (Mukherjee & Swindlehurst, 2013). In the opportunistic spectrum access (OSA) or interweave model, CRs (SUs) opportunistically access the unused licensed band, commonly referred to as “spectrum hole” only when it is detected idle. However, the main problems of the interweave models are high sensitivity to the detection error and PU traffic pattern. In underlay model, SUs are allowed to transmit simultaneously with the PUs as long as the interference generated by SU’s to PUs below some accepted threshold. Because of the strict power constraints imposed on SUs and the interference from PUs, the SUs may have bad transmission performance which is a major problem in underlay approaches. In the overlay model, the SUs simultaneously transmit with the PUs over the same spectrum provided that the SUs may help the PUs such that PUs can transmit by cooperative communication technique, such as advanced coding or cooperating relaying techniques. However, due to the mutual interference between PUs and SUs, the overlay approach may still experience secondary transmission performance degradation. The interweave and overlay models are jointly considered in to facilitate the spectrum sharing protocols, dirty paper coding and perfect spectrum sensing are used in (Han & Pandharipande, 2012). Hybrid spectrum sharing model jointly considering overlay and underlay model is proposed in **(**Menon, Buehrer, & Reed, 2005) & (Senthuran, Anpalagan, & Das, 2012). In (Wang, Krunz & Cui, 2008) under hybrid spectrum sharing protocol, an optimal transmission allocation scheme to achieve maximum energy-efficiency is investigated.

2.1.3.1 Architecture Spectrum Sharing

a) Centralized Spectrum Sharing

A central unit is responsible for controlling spectrum assignment and access process. Furthermore, we can use a sensing process spread over the area of interest such that measured data of the spectrum sensing are redirected to the central unit, and a spectrum assignment chart is formed. In addition, subscribers in a given geographical area can get the spectrum from central unit for a particular amount of time. Besides contest for the frequency band, competition for subscribers can also be taken into account via a central spectrum policy server (Niyato & Hossain, 2008) & (Akyildiz, Lee, Vuran, & Mohanty, 2006).

b) Distributed Spectrum Sharing

Local or probably global procedures separately conducted by each node perform spectrum assignment and access (Suris, J. E., DaSilva, L., Han, Z., & MacKenzie, A. B. (2007). Different networks also employ distributed architecture so that a BS contend with its interfering BSs based on the QoS need of its subscribers to assign a part of the band. The latest researches comparing distributed and centralized spectrum sharing discover that distributed architecture typically imitate the centralized one closely taking into account the message exchanges cost among nodes (Suris et al., 2009).

2.1.3.2 Spectrum Allocation

a) Cooperative Spectrum Sharing

Cooperative approaches use the measured interference data of each node such that the impact of the communication of one node on other nodes is taken into account. A typical method used in these schemes is establishing clusters to share interference data between members. This localized process offers an efficient equilibrium between a fully centralized and a distributed method.

b) Non-Cooperative Spectrum Sharing

Merely an individual node is assumed in non-cooperative or so called non-collaborative or selfish method (Chouhan & Trivedi, 2013). Since interference in other cognitive radio nodes is not taken into account, non-cooperative method may lead to decreased spectrum usage. But, these schemes do not need numerous message interactions among nodes in contrast to cooperative methods. Cooperative schemes normally perform better than non-cooperative methods. Besides, these methods can closely estimate the global optimum (Chen et al., 2008). Furthermore, cooperative approaches lead to 42 a specific level of fairness, as well as enhanced throughput. On the other hand, the performance deterioration of non-cooperative methods are typically offset by the considerably low information exchange and hence, energy consumption.

2.1.3.3 Spectrum Access Technique

a) Overlay Spectrum Sharing

In the overlay model, the SUs simultaneously transmit with the PUs over the same spectrum provided that the SUs may help the PUs such that PUs can transmit by cooperative communication technique, such as advanced coding or cooperating relaying techniques **(**Menon, Buehrer, & Reed, 2005). However, due to the mutual interference between PUs and SUs, the overlay approach may still experience secondary transmission performance degradation. The interweave and overlay models are jointly considered in Goldsmith, Jafar, Marić, & Srinivasa, 2009).

b) Underlay spectrum sharing:

In underlay model, SUs are allowed to transmit simultaneously with the PUs as long as the interference generated by SU's to PUs below some accepted threshold **(**Menon, Buehrer, & Reed, 2005). Because of the strict power constraints imposed on SUs and the interference from PUs, the SUs may have bad transmission performance which is a major problem in underlay approaches.

2.1.3.4 Scopes of Spectrum Sharing

a) Interanetwork Spectrum Sharing

These solutions focus on spectrum allocation between the entities of a CR network, as shown in Figure 1.5. Accordingly, the users of a CR network try to access the available spectrum without causing interference to the primary users. Intranetwork spectrum sharing poses unique challenges that have not been considered previously in wireless communication systems.

b) Internetwork spectrum sharing

In the opportunistic spectrum access (OSA) or interweave model, CRs (SUs) opportunistically access the unused licensed band, commonly referred to as "spectrum hole" only when it is detected idle. However, the main problems of the interweave models are high sensitivity to the detection error and PU traffic pattern.

2.1.4 Spectrum Mobility

CR users are generally regarded as `visitors' to the spectrum. Hence, if the special portion of the spectrum in use is required by a PU, the communication needs to be continued in another vacant portion of the spectrum. This notion is called spectrum mobility. Spectrum mobility gives rise to a new type of handoff in CR networks, the so-called spectrum handoff, in which, the users transfer their connections to an unused spectrum band. In CR ad hoc networks, spectrum handoff occurs 1) when PU is detected, 2) the CR user loses its connection resulting from the mobility of users involved in an on-going communication, or 3) with a current spectrum band cannot provide the QoS requirements. Among all SM functions, spectrum mobility imposes unique characteristics in mobility management for CR cellular networks. Mobility management, especially a handoff scheme, is one of the most important functions in classical cellular networks. Thus, much research on cellular networks has explored the handoff issues, mainly focusing on cell selection and resource management in the last couple of decades. Although diverse cell selection methods have been proposed to support seamless handoff schemes while maximizing the network capacity (Lee, & Cho, 2013) & (Lee, & Akyildiz, 2012) they are based on the classical multi-cell based networks and do not consider the fluctuating nature of spectrum resources in CR networks. Especially, no special attention is given to either time and location-varying spectrum availability or switching delay in traversing the spectrum distributed over a wide frequency range. The main deference between classical wireless networks and CR networks lies in the PU activities. Because of the PU activity, CR networks necessitate a new type of handoff, the so-called spectrum handoff, which also must be considered in designing mobility management schemes. Thus, mobility management constitutes an important but unexplored topic in CR networks to date.

In the following, the main functionalities required for spectrum mobility in the CRN are described:

2.1.4.1 Spectrum Handoff

The CR user switches the spectrum band physically and reconfigures the communication parameters for an RF front-end (e.g. operating frequency, modulation type).

2.1.4.2 Connection Management

The CR user sustains the QoS or minimizes quality degradation during the spectrum switching by interacting with each layering protocols. In spectrum handoff, temporary communication break is inevitable because of the process for discovering a new available spectrum band. Since available spectrums are discontinuous and distributed over a wide frequency range, CR users may require the reconfiguration of operation frequency in its RF front-end, which leads to a significantly longer switching time. The purpose of the spectrum mobility management in CR ad hoc networks is to ensure smooth and fast transition leading to minimum performance degradation during a spectrum handoff. Furthermore, in spectrum mobility, the protocols for deferent layers of the network stack should be transparent to the spectrum handoff and the associated latency, and adapt to the channel parameters of the operating frequency.

2.2 Different Diversity Technics Overview

Diversity, as an effective solution, is employed to overcome the detrimental effects of channel fading and to improve the reliability of wireless communication systems (Godara,

2001) & (Thompson, 2004). In other words, having received multiple signals from multiple fading channels, diversity techniques are used to derive the information from received signals and consequently, enhance the received signal-to noise ratio (SNR).In MRC, the received signals are weighted accordingly so that the SNR at the output of the combiner is the sum of the average SNR of each branch. In EGC, on the other hand, the received signals are weighed equally, and then added. In SC, branch with the highest SNR is selected. In all cases, we consider that the receiver has the necessary information of channel fading.

The performance of these methods has been extensively examined in the literature for Rayleigh fading. If the channel is perfectly estimated at the receiver, MRC can be applied to maximize the output SNR and minimize the bit error rate (BER). However, since the channel estimation is often imperfect in practice, the estimated (Peña-Martin al., 2009) & (Radaydeh, 2009) on error will decay the system performance. While this problem has long been investigated the recent evolutions in mobile communication systems have renewed the attention in comprehending and mitigating the effect of imperfect channel estimation on diversity techniques (Mallik & Win, 2002). The error performance of MRC in Rayleigh fading environment with independent and identically distributed (i.i.d.) diversity branches are investigated in (Roy, & Fortier, 2004). In (Verdu, 1998), the SNR distribution is given for similar scenarios. In (Godara, 2001), the error performance of MRC with independent, but not identically distributed (i.n.d.) branches are studied. In (Thompson, 2004) & (You, Li & Bar-Ness, 2005), a comparison of hybrid SC/MRC scheme with SC and MRC schemes over Rayleigh fading channels in two scenarios of flat and exponentially decaying multipath intensity profile (MIP) has been done. In 9 (Kong & Milstein, 1995) the hybrid diversity scheme is studied as such selection combining and

MRC are at the first and second stages, respectively. In (Eng, Kong & Milstein, 1996), *L* out of *N* diversity branches was selected and combined using MRC over Rayleigh fading channel. The performance study of conventional MRC receiver in the presence of co-channel interference has also been a substantial interest of researchers (Win & Winters, 1999), (Cui & Sheikh, 1999), (Aalo, V., & Zhang, J. (1999) & (Dinamani et al.m 2013). Particularly in (Peña-Martin et al., 2009), the effect of the number of interferers on the diversity gain has been investigated in the context of frequency-selective Rayleigh fading. The study, however, has been done with the assumption of the prefect channel estimation of a desired user, which may not be the case in practice. The impact of imperfect channel estimation on the performance of diversity receivers in noise-limited circumstances has been presented in (Zhang & Beaulieu, 2007), (Radaydeh, R. M. (2009) (Pamula et al., 2013), (Annavajjala & Milstein, 2005) & (Ma, Schober & Zhang, D. 2007). However, considering frequency-nonselective fading, the investigation has been widened to circumstances with multiple co-channel interferers (Annavajjala, R., Cosman, P. C., & Milstein, L. B. (2007), (Roy, & Fortier, 2004) & (Gifford, W. M., Win, M. Z., & Chiani, M. (2008).

2.2.1 Selection Combining Diversity Based

In selection combining (SC), the branch with the greatest SNR is chosen as output SNR to be used in the next step.

$$\boldsymbol{\omega}_i = \begin{cases} 1 & \gamma_i = Max \\ 0 & otherwise \end{cases} \tag{2.20}$$

The average output SNR for SC is defined as (Godara, 2001):

$$\gamma_T = \Gamma \sum_{i=1}^{M} \frac{1}{i} \ \cong \Gamma \left(\mathrm{C} - \ln M + \frac{1}{2M} \right) \tag{2.21}$$

in which C is the Euler's constant. The final approximation is valid for $M \geq 3$. The overall BER is obtained by bringing together the conditional BER at a certain SNR. In BPSK modulation, the conditional BER is $erfc\sqrt{2\gamma_T}$ and the total BER is:

$$\mathrm{BER}_T = \int_0^{\infty} erfc(\sqrt{2\gamma_T}) \frac{M}{\Gamma} e^{\gamma_T/\Gamma} \left[1 - e^{\gamma_T/\Gamma} \right]^{M-1} d\gamma_T \tag{2.22}$$

2.2.2 Equal Gain Combining Diversity Based

Equal gain combiner (EGC) sets unit gain at each branch to increase the average SNR in the system. In the equal gain combiner,

$$\omega_i = e^{j\angle g_i} \ \Longrightarrow \omega_i * g_i = |g_i| \ \Longrightarrow \vec{\boldsymbol{\omega}}\vec{G}^T = \sum_{i=0}^{M-1} |g_i| \ , \vec{G} = [g_1, g_2, \dots, g_M \tag{2.23}$$

$$\gamma_i = \frac{\left[\sum_{i=0}^{M-1} |g_i|\right]^2}{M\sigma_n^2} \tag{2.24}$$

$$\gamma_T = \frac{\mathrm{E}\{[\sum_{i=0}^{M-1} |g_i|]\}^2}{M\sigma_n^2} \ = \ [\,1 + (M-1)\,\frac{\pi}{4}]\Gamma \tag{2.25}$$

There is no closed form solution for the BER for general *M*, but several researchers have investigated the BER performance in several kinds of fading channels (You, Li, & Bar-Ness, 2005) & (Thompson, 2004).

2.2.3 Maximal Ratio Combining Diversity Based

In MRC, receiver linearly combines the received signal $r_i(t)$ with ω_i, which is the weighting coefficient of the i^{th} branch. The output signal $r(t)$ of the linear diversity combiner is then given by:

$$r(t) = \sum_{i=1}^{M} \omega_i r_i(t) = S(t) \sum_{i=1}^{M} \omega_i g_i + \sum_{i=1}^{M} \omega_i n_i \tag{2.26}$$

Since $S(t)$ is assumed to have unit power, SNR at the output of combiners is

$$\gamma_T(\vec{\omega}) = \frac{1}{\sigma_n^2} \frac{\left|\sum_{i=1}^{M} \omega_i g_i\right|^2}{\sum_{i=1}^{M} |\omega_i|^2} = \frac{\left|\vec{\omega}\vec{G}^T\right|^2}{\mathrm{E}\left\{\left|\vec{\omega}\vec{N}^T\right|^2\right\}} \tag{2.27}$$

$$\mathrm{E}\left\{\left|\vec{\omega}\vec{\mathrm{N}}^{\mathrm{T}}\right|^2\right\} = \mathrm{E}\left\{\left|\vec{\omega}\vec{\mathrm{N}}^{\mathrm{T}}\vec{\omega}^{\mathrm{T}}\vec{\mathrm{N}}\right|\right\} = \sigma_n^2\vec{\omega}^2 \tag{2.28}$$

According to the Cauchy-Schwarz inequality, MRC with perfect channel estimation has maximum output SNR among all methods if $\vec{\omega}$ is linearly proportional to $\vec{G}$. If $\vec{\omega} = \vec{G} \Longrightarrow \gamma_T = \frac{|\vec{G}\vec{G}^T|^2}{\sigma_n^2 \vec{G}^T\vec{G}} = \frac{\vec{G}\vec{G}^T}{\sigma_n^2} \Longrightarrow \gamma_T = \sum_{i=1}^{M} |\gamma_i|$. The output SNR is, therefore, the sum of the SNR at each element. By using the above assumption, the expected value of the output SNR is therefore *M* times the SNR at each branch.

For the case of imperfect channel estimation, which is the main issue in practice, it is observable that the SNR is highly dependent on ω_i. Therefore, the optimal solution is the weighting vector, which maximizes the objective function γ_T in Eq. (2.27). We assume

p_i is the estimate of the complex gain g_i on the i^{th} diversity branch and e_i is the estimation error with zero mean and variance of $\sigma_e^2 = \sigma_g^2(1-\rho^2)$ where $\rho \in [0, 1]$ is the normalized estimation error correlation coefficient. Under Gaussian-error model, g_i and p_i are related as $g_i = p_i + e_i$ (You, Li & Bar-Ness, 2005). According to the diversity combining rule, the combiner weights take on the $\omega_i = p_i^*$ for MRC diversity, which is based on the Cauchy–Schwartz inequality, maximizes Eq. (2.27) if the channel is perfectly estimated (i.e., $\rho = 1$). However, since channel estimation is often imperfect in practice, the MRC is a suboptimal solution (Cui & Sheikh, 1999), (Aalo, V., & Zhang, J. (1999) & (Dinamani et al.m 2013).

2.2.4 Genetic Algorithm Diversity Based

In the genetic algorithm (GA), a group of chromosomes will be arbitrarily generated. Eq. (2.27) is used as the fitness function to evaluate the SNR of randomly-generated chromosomes of the initial population. Then, a new population from the former population will be reproduced based on the fitness scores (output SNR values) of its chromosomes and the process is repeated until a predefined termination criterion is met. Better populations can be continually formed due to the concept of surviving the fit/best chromosomes. In GA terminology, the evolutionary process of forming an offspring population from a parent population is called generation (El-saleh et al. 2010). The number of produced generations is pre-determined by the designer or self-set based on the quality of obtainable solutions. The algorithm is configured to maximize the SNR and it is outlined as follows:

Step 1: Randomly generates a population of pops chromosomes.

Step 2: Decode each chromosome into its corresponding weighting vector $\vec{\omega}_j = [\omega_{j1}, \omega_{j2}, ..., \omega_{jM}]^T$, where $\omega_{ji} \in$ [0,1] , i = 1, 2, ..., M and j = 1, 2, ..., pops.

Step 3: Compute the SNR value of every decoded weighting vector $\vec{\omega}_j$ using Eq. (2.27) and rank and identify the best $\lfloor pops * elite \rfloor$ chromosomes that have maximized SNR. elite is a parameter that determines a fraction of pops, i.e., elite $\in$ [0,1), and $\lfloor . \rfloor$ denotes the floor operation.

Step 4: If the stopping criteria are satisfied, the procedure is terminated. Otherwise, increase the generation number by one.

Step 5: Reproduce $\lceil pops * (1 - elite) \rceil$ new chromosomes where $\lceil . \rceil$ denotes ceiling operation and construct new population by concatenating the newly $\lceil pops * (1 - elite) \rceil$ reproduced chromosomes with the best $\lfloor pops * elite \rfloor$ found in Step 3. Jump to Step 2.

After large-enough generations (runs of algorithm), if the output SNR of the system converges to a stable value, the algorithm stops. Therefore, the optimal weighting vector (decoded chromosomes) that leads to highest stable value of output SNR can be indicated and used.

2.2.5 Particle Swarm Optimization Diversity Based

PSO algorithm is abstracted from the social behavior of swarm of fishes and birds. The behavior of these social organizations is emulated by the PSO algorithm. Each particle in PSO algorithm functions based on its own knowledge as well as the group knowledge and has two main features: position and velocity. In each iteration, information about the best position is cooperatively exchanged among the particles. The steps involved in the PSO algorithm are as follows:

Step 1: Randomly generate N numbers of particle positions (weighting vectors) as $\vec{\omega}_s = [\omega_1, \omega_2, \ldots, \omega_M]^T, (s = 1, \ldots, N)$ and N numbers of length-M velocity vectors $\vec{v}_s^{(j)}$, which are initially set to zero. Here, particle position and velocity at iteration j are demonstrated by $\vec{\omega}_s^{(j)}$ and $\vec{v}_s^{(j)}$, respectively.

Step 2: Calculate the objective function (SNR in Eq. (2.27)) for particle positions as $\gamma_T\left(\vec{\omega}_1^{(j)}\right), \gamma_T\left(\vec{\omega}_2^{(j)}\right) \ldots \gamma_T\left(\vec{\omega}_N^{(j)}\right)$. Find the maximum SNR and name its corresponding position as $P_{best,j}$. The best-experienced particle position among all iterations is called global best position and is expressed by Gl_{best}.

Step 3: Update the velocity of the particles by:

$$\vec{v}_s^{(j)} = \vec{v}_s^{(j-1)} + c_1 r_1 \left[P_{best,j} - \vec{\omega}_s^{(j-1)}\right] + c_2 r_2 \left[Gl_{best} - \vec{\omega}_s^{(j-1)}\right] \qquad (2.29)$$

Where individual and social learning acceleration coefficients are, respectively, denoted by c_1 and c_2, and r_1 and r_2 are the random numbers between 0 and 1.

Step 4: Update the position of particles:

$$\vec{\omega}_s^{(j)} = \vec{\omega}_s^{(j-1)} + \vec{v}_s^{(j)} \tag{2.30}$$

Step 5: Check the convergence. The output SNR in Eq. (2.27) is regularly checked at each iteration. After a large enough number of iterations, if the algorithm results in a same output SNR at each iteration, the procedure is terminated. Otherwise, set $j = j + 1$ and the process in repeated from the Step 2.

Therefore, the value of the $\mathrm{Gl_{best}}$ is the optimal weighting vector that maximizes the SNR at the output of the combiner.

In this research, to overcome the effect of imperfect estimation of channel state information on each SU, a diversity combining technique based on the ICA is proposed in which the signals received by the SUs are iteratively weighted based on ICA operation. The ICA method shows faster convergence speed when compared with PSO- and genetic algorithm GA- based methods. This makes ICA a promising solution for the real-time applications and accurate received signal on SUs.

2.3 Summary

Electromagnetic spectrum is often a scarce resource for wireless communication. While using advancement of technological innovation, demands for new spectrum bands have more than doubled and have consequently generated spectrum scarcity. Data loss is the main problem associated with wireless communication and available frequency resource in real time communication is very important to avoid communication disconnection and loss of date. This chapter focused on the overview of the defined radio software and background of CR which make usage of spectrum more efficient for real time applications with very less interference with licensed users. Therefore, recently numerous of researchers focus on improving QoS, complexity and interference of SUs and PUs in CRN to make spectrum as utilize as possible (which all major methods defined and investigated in this chapter). In fact the existing methods in CRN cannot be assumed as "fast acting with less complexity and interference methods" to maintain the communication between SUs in real time applications. As a result, this research tried to improve the sensing and detection performance in CRN and increase the number of users as many as possible in network with minimum interference and loss of data. Also, diversity combining concept defined in details to use in next chapter to propose real time application.

CHAPTER 3 : RESEARCH METHODOLOGY

3.1 Cognitive Radio Cooperative Spectrum Sensing and Decision System Model

SDF-based cooperative spectrum sensing is used to improve detection reliability when the local spectrum sensing method is applied, thus, local spectrum sensing can be realized by means of energy detection without any prior knowledge of the PU signal. Fig. 3.1 demonstrates the centralized cooperative spectrum sensing SDF-based scenario where M SUs (as relays) send their decision or sensing measurements to a common base station for fusion. The final decision on the presence of PU is made by the FC as it conducts SDF-based linear weighted calculations on the received SUs signals. In this research, the system is modeled such that the channels between PUs to SUs and SUs to FC are assumed to be Rayleigh fading channels and are defined with different gains. In addition the noise is AWGN with different variance at different paths. It should be noted that Rayleigh model is the simplest and the most controllable model, but it is not effective in all circumstances. However, since this research basically aims at studying the use of evolutionary algorithms on receiver diversity, the authors believe that Rayleigh model is enough. During the entire frame duration, it is assumed that the PU can be either present or absent, thus, the spectrum sensing process is then a binary hypothesis testing problem and can be given as:

$$Presence \rightarrow: X_i[n] = g_i S[n] + W_i[n], H_1$$

$$Presence \rightarrow: X_i[n] = W_i[n], H_0 \tag{3.1}$$

The received sampled signal is symbolized by $X_i[n]$ at each i^{th} SU receiver and $i = 1,2,\dots,M$, $n = 1,2,\dots,K$, where K is the number of received signal's samples explained by $K = 2BT_s$ in which B is the signal bandwidth and T_s is the sensing time. Sensing channel gain between the PU and the i^{th} SU is defined by g_i and PU signal is denoted by $S[n]$ which is assumed to be independent and identically $(i.i.d)$ Gaussian random process with zero mean and variance σ_S^2, i.e., $S[n] = (0, \sigma_S^2)$, and $W_i[n]$ is additive white Gaussian noise (AWGN) of i^{th} sensing channel (PU-SU) with zero mean and variance $\sigma_{W_i}^2$ i.e., $W_i[n] = (0, \sigma_{W_i}^2)$. It is assumed that noise $N_i[n]$ $(SU - FC)$ is AWGN and variance δ_i^2 i.e., $N_i[n] = (0, \delta_i^2)$ and finally, weighting vectors of the i^{th} path are shown by ω_i. $U_i[n] = \sqrt{P_{R,i}} h_i X_i[n] + N_i[n]$ is the corresponding received signal at FC in which $P_{R,i}$ is the transmit power of i^{th} SU and h_i is gain of i^{th} channel $(SU - FC)$. Now, by considering the two hypotheses in (1), the received signal at FC can be expressed as:

$$U_i[n|H_0] = \sqrt{P_{R,i}} h_i W_i[n] + N_i[n] \tag{3.2}$$

$$U_i[n|H_1] = \sqrt{P_{R,i}} h_i W_i[n] + N_i[n] \sqrt{P_{R,i}}\, g_i h_i S[n] = \sqrt{P_{R,i}}\, g_i h_i S[n] + U_i[n|H_0] \tag{3.3}$$

This statistically shows e.g., $U_i[n|H_0] \sim \mathcal{N}\left(0, \sigma_{0_i}^2\right) \sim \mathcal{N}\left(0, P_{R,i}|h_i|^2 \sigma_{W_i}^2 \delta_i^2\right)$ and $U_i[n|H_1] \sim \mathcal{N}\left(0, \sigma_{1_i}^2\right) \sim \mathcal{N}\left(0, P_{R,i}|g_i|^2|h_i|^2\sigma_S^2 + \sigma_0^2\right)$.

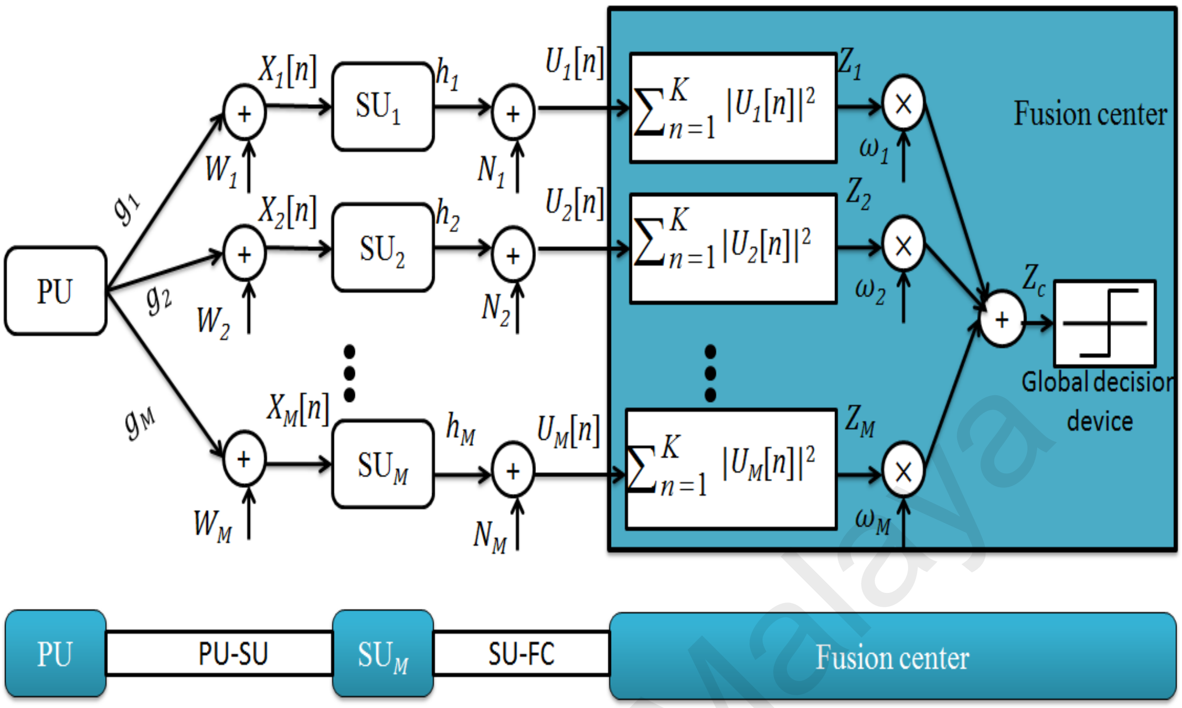


Figure 3.1: Block diagram of the cooperative spectrum sensing

In a Matrix form, the received signals at the FC through the control channel under H_0 and H_1, respectively, can be written as:

$$U_i[n|H_0] = \begin{bmatrix} \sqrt{P_{R,1}}\, h_1 & 0 & \cdots\cdots & 0 \\ 0 & \sqrt{P_{R,2}}\, h_2 & \cdots\cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots\cdots & \sqrt{P_{R,M}}\, h_M \end{bmatrix} \times \begin{bmatrix} W_1[n] \\ \vdots \\ W_M[n] \end{bmatrix} + \begin{bmatrix} N_1[n] \\ \vdots \\ N_M[n] \end{bmatrix} \tag{3.4}$$

$$U_i[n|H_1] = \begin{bmatrix} \sqrt{P_{R,1}}\, g_1\, h_1 & 0 & \cdots\cdots & 0 \\ 0 & \sqrt{P_{R,2}}\, g_2\, h_2 & \cdots\cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots\cdots & \sqrt{P_{R,M}}\, g_M h_M \end{bmatrix} \times \begin{bmatrix} S_1[n] \\ \vdots \\ S_M[n] \end{bmatrix} + \begin{bmatrix} U_1[n|H_0] \\ \vdots \\ U_M[n|H_0] \end{bmatrix} \tag{3.5}$$

The final test statistic Z_C calculated by FC before decision making block can be represented by $Z_C = \sum_{i=1}^{M} \omega_i Z_i$ where $Z_i = \sum_{n=1}^{K} |U_i[n]|^2$ is total collected energy by FC from the i^{th} SU. By denoting $\{Z_{0,i}\} = \{Z_i|H_0\}$ and $\{Z_{1,i}\} = \{Z_i|H_1\}$, the two sets of test statistics can be written as $\overrightarrow{Z_0} = [Z_{0,1}, Z_{0,2}, Z_{0,3} \dots Z_{0,M}]^T$, $\overrightarrow{Z_1} = [Z_{1,1}, Z_{1,2}, Z_{1,3} \dots Z_{1,M}]^T$, each test statistic is approximated by central limit theorem (CLT) for a large number of samples, which is normally distributed with variance and mean:

$$E(Z|H_0) = \sum_{i=1}^{M} \omega_i K\sigma_{0,i}^2 = \sum_{i=1}^{M} \omega_i \mu_{0,i} = \vec{\omega}^T \overrightarrow{\mu_0} \tag{3.6}$$

$$E(Z|H_1) = \sum_{i=1}^{M} \omega_i K\sigma_{1,i}^2 = \sum_{i=1}^{M} \omega_i \mu_{1,i} = \vec{\omega}^T \overrightarrow{\mu_1} \tag{3.7}$$

$$\mathrm{var}(Z|H_0) = \sum_{i=1}^{M} 2{\omega_i}^2 K(\sigma_{0,i}^2 + \delta_i^2)^2 = \vec{\omega}^T \Phi_{H_0} \vec{\omega} \tag{3.8}$$

$$\mathrm{var}(Z|H_1) = \sum_{i=1}^{M} 2{\omega_i}^2 K(\sigma_{1,i}^2 + \sigma_{0,i}^2)^2 = \vec{\omega}^T \Phi_{H_1} \vec{\omega} \tag{3.9}$$

Where $\overrightarrow{\mu_0} = [\mu_{0,1}, \dots . \mu_{0,M}]^T$ and $\overrightarrow{\mu_1} = [\mu_{1,1}, \dots . \mu_{1,M}]^T$. Assuming that $\vec{\theta} = [\theta_1, \theta_2, \dots, \theta_M]^T$ and $\theta_i = KP_{R,i}|g_i|^2|h_i|^2\sigma_s^2$, then: $\mu_{1,i} = \mu_{0,i} + \vec{\theta}$ or $\overrightarrow{\mu_1} = \overrightarrow{\mu_0} + \vec{\theta}$. Also $\vec{\omega} = [\omega_1, \omega_2, \dots, \omega_M]^T$ marks the weighting vectors and the superscript T denotes the transpose of the weighting coefficients vector. The covariance matrices under H_1 and H_0 are $\Phi_{H_1} = \mathrm{diag}\left(2K\left(P_{R,i}|g_i|^2|h_i|^2\sigma_s^2 + \sigma_{0,i}^2\right)^2\right)$ and $\Phi_{H_0} = \mathrm{diag}\left(2K\sigma_{0,i}^4\right)$, where square diagonal matrix is $\mathrm{diag}(.)$ and given vector elements are diagonal elements. β is assumed to be energy global threshold at FC then, $Z \gtrless_{H_0}^{H_1} \beta$ presents the likelihood ratio. CRNs are mathematically modeled under two main criteria: Neyman-Pearson and Mini-Max criterion, which are individually defined as follows:

3.1.1. Neyman-Pearson Criteria

Neyman-Pearson criterion was proposed based on the problem of the most efficient tests of statistical hypotheses (Neyman & Pearson, 1933). This research applied Neyman-Pearson hypotheses as possibility of minimal interference which is caused by SU to PU in active position. The threshold only relies on the statistical noise properties under hypothesis H_0. Since it does not consider the PU signal strength, P_f is referred to a lower bound determined by itself, which cannot be adjusted without considering of how strong the SNR is. Therefore, the final P_d and P_f expressed as ($Q(x) = \int_x^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$):

$$P_f = P(Z > \beta \mid H_0) = Q\left(\frac{\beta - E(Z|H_0)}{\sqrt{var(Z|H_0)}}\right) = Q\left(\frac{\beta - \vec{\omega}^T \vec{\mu_0}}{\sqrt{\vec{\omega}^T \Phi_{H_0} \vec{\omega}}}\right) \quad (3.10)$$

$$P_d = P(Z > \beta \mid H_1) = Q\left(\frac{\beta - E(Z|H_1)}{\sqrt{var(Z|H_1)}}\right) = Q\left(\frac{\beta - \vec{\omega}^T \vec{\mu_1}}{\sqrt{\vec{\omega}^T \Phi_{H_1} \vec{\omega}}}\right) \quad (3.11)$$

Note: The β at the FC is constant based on the fixed known P_f.

Substituting Equations (3.6) to (3.9) into equations (3.10) and (3.11) and computing P_d in terms of P_f, we can conclude:

$$P_d(\vec{\omega}) = Q\left(\frac{Q^{-1}(\overline{P_f})\sqrt{\vec{\omega}^T \Phi_{H_0} \vec{\omega}} - \vec{\omega}^T \vec{\theta}}{\sqrt{\vec{\omega}^T \Phi_{H_1} \vec{\omega}}}\right) \quad (3.12)$$

Equation (3.12) provides a reliable measure of detection performance in SDF-based cooperative sensing for a fixed set of false alarm probabilities.

3.1.2. Mini-Max Criteria

Mini-Max has a trade-off in good ability of spectrum utilization and having high interference in PU (Shen, & Kwak, 2009). In other words, we plan to minimize P_e and P_m which are unwanted in any communication detection task. For simplicity, let us assume that the probability of false alarm P_f in equation (3.10) is the same with the probability of miss-match P_m ($\mathrm{P_f} = \mathrm{P_m}$ or $\mathrm{P_f} = (1 - \mathrm{P_d})$). Hence, by equating the expression in Equations (3.10) and (3.11), we would obtain:

$$Q\left(\frac{\beta - \vec{\omega}^{T}\,\vec{\mu_0}}{\sqrt{\vec{\omega}^{T}\Phi_{H_0}\vec{\omega}}}\right) = 1 - Q\left(\frac{\beta - \vec{\omega}^{T}\,\vec{\mu_1}}{\sqrt{\vec{\omega}^{T}\Phi_{H_1}\vec{\omega}}}\right) \tag{3.13}$$

$$Q\left(\frac{\beta - \vec{\omega}^{T}\,\vec{\mu_0}}{\sqrt{\vec{\omega}^{T}\Phi_{H_0}\vec{\omega}}}\right) = Q\left(\frac{\vec{\omega}^{T}\,\vec{\mu_1} - \beta}{\sqrt{\vec{\omega}^{T}\Phi_{H_1}\vec{\omega}}}\right) \tag{3.14}$$

After some simplifications, we can obtain the optimal threshold β that will minimize the total probability of error, P_e and can be expressed as:

$$\beta = \left(\frac{\sqrt{\omega^{T}\Phi_{H_1}\,\omega}\,\mu_0^{T}\,\vec{\omega} + \sqrt{\omega^{T}\Phi_{H_1}\,\omega}\mu_1^{T}\,\omega}{\sqrt{\omega^{T}\Phi_{H_0}\omega} + \sqrt{\omega^{T}\Phi_{H_1}\omega}}\right) \tag{3.15}$$

Finally, the replaced value of β_j (which should be a scalar value) will then be substituted back into equations (3.10) and (3.14). Summing them up, we would have the total probability of error, P_e and is simply represented by:

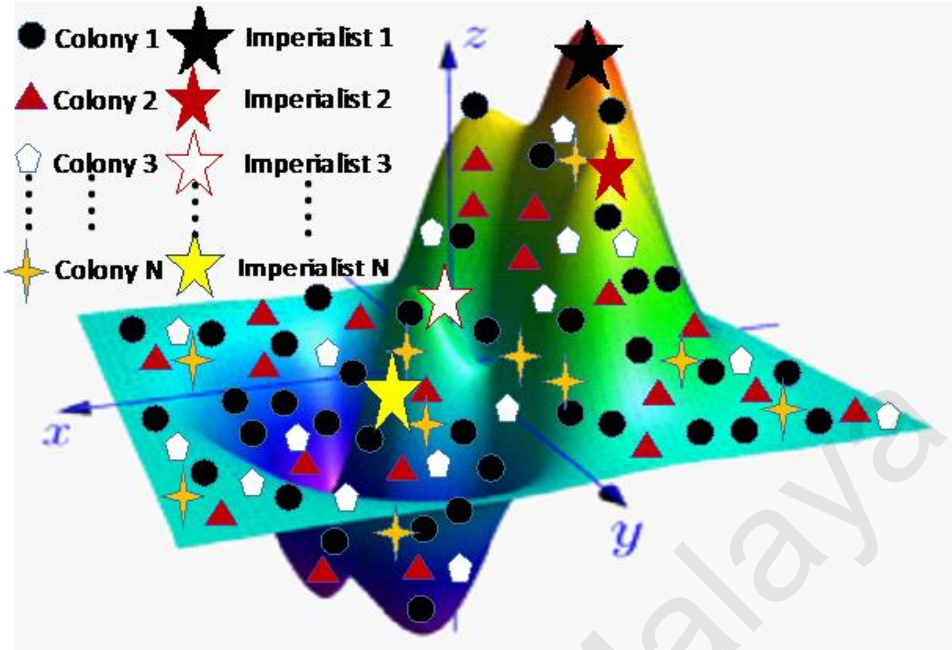
$$P_e(\vec{\omega}) = P_f + P_m = \left(\frac{\beta - \vec{\omega}^T \vec{\mu_0}}{\sqrt{\vec{\omega}^T \Phi_{H_0} \vec{\omega}}}\right) + Q\left(\frac{\vec{\omega}^T \vec{\mu_1} - \beta}{\sqrt{\vec{\omega}^T \Phi_{H_1} \vec{\omega}}}\right) \tag{3-16}$$

It is discernible that $P_d(\vec{\omega})$ and $P_e(\vec{\omega})$ are very dependent on $\vec{\omega}$ when the optimal weighting vector for each probability is the solution which maximizes P_d in (3.12) and minimizes total P_e in (3.16), consequently. However, since any real multiple of optimal weighting vector can also be taken as the optimal solution and to reduce the search space on which iterative algorithms and conventional methods work, the $\vec{\omega}$ applied in this research must satisfies the conditions $0 < \omega_i < 1$ and $\sqrt{\sum_{i=1}^{M} \omega_i^2} = 1$ for both methods.

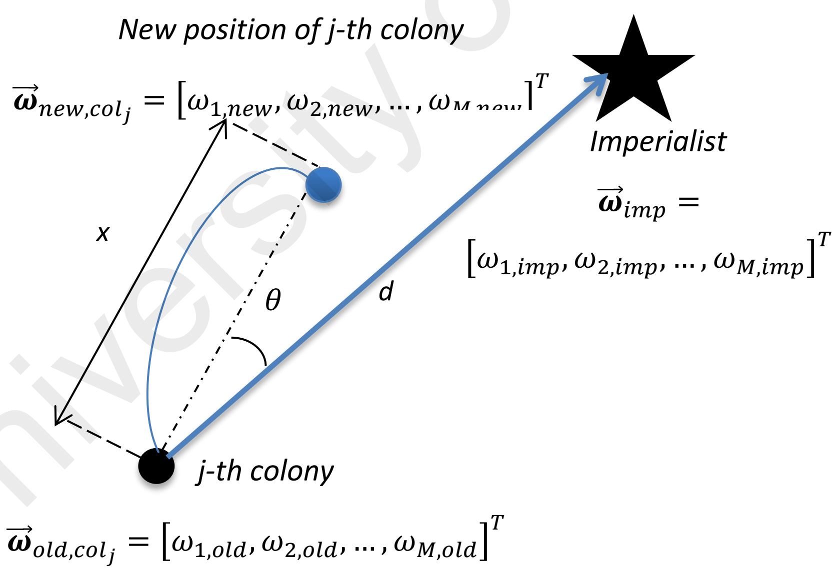
3.2 .Modified Imperialistic Competitive Algorithm

Advantages of iterative algorithms (GA and PSO) in cooperative spectrum sensing over conventional SDF weighting schemes, such as MRC, NDC and MDC are investigated in (El-Saleh et al., 2011), (Akbari et al., 2012) & (Shen, & Kwak, 2009). It is considerably obvious that genetic and physical evolution does not happen as fast as the communal and the academic evolution of human being. Due to this fact, some developing algorithms have applied the cultural side of social life in order to reach well outcomes. Imperialistic competition and human's socio-political evolution inspires ICA and local optima convergence is the main disadvantage of the original ICA method. To overcome this common problem in iterative algorithms, this research introduce a new model of modified ICA and bring Boltzmann distribution concept to select suitable pressure coefficient and apply flow deviation angle in order to able population to do searching all over objective function. The optimization targets in this research are maximizing P_d and minimizing P_e with the lowest possible complexity by applying modified ICA, which will be well defined as below 8 steps. Hence, checking the computational of the algorithms are one of the main disquiet of this research in order to improve the detection performance of the system in the given boundaries. To my best knowledge PSO is still the best method in this issue and any kinds of ICA have not been applied in this topic yet.

Modified ICA begins with a preliminary population containing of countries that are known as individuals in other gradual algorithms. This population is divided in two groups. The group with the finest (in Neyman-Pearson highest and in Mini-Max lowest) objective function values, power, which is chosen to be the imperialists, whereas the remaining group is their colonies. Then the colonies are distributed with the imperialists according to each imperialist power. Fig.3.2 (a) depicts the initial colonies for each empire when superior empires have larger quantity of colonies e.g., imperialist 1. As an imperialist grows stronger, it will own more colonies. Empire is formed from an imperialist with its colonies in modified ICA language when each individual colony will try to discover better position to be named as imperialist of its empire. This method is fulfilled in modified ICA by moving the colonies towards their imperialist, named assimilation. It is possible that a colony turn out to be more powerful than its imperialist during assimilation, so the colony displaces the imperialist and the imperialist become one of its colonies. Moreover, it may be seen that through imperialistic competition the most powerful empires mind to raise their power, while weaker one's mind to break down. Both structures head the algorithm to steadily converge into a single empire, in which the imperialist and all the colonies have the similar culture.



(a)



(b)

Figure 3.2: a) Imperialists and colonies in each empire b) Movement of colony toward imperialist

3.2.1. Neyman-Pearson Criteria for Modified Imperialistic Competitive-Based Diversity Scheme

Step 1: The first step is initialization of the algorithm. At the beginning Number of population (N_{pop}) as $\vec{\omega}_k = [\omega_1, \omega_2, \dots, \omega_M]^T$ in the range of Var_{Min} and Var_{Max} is generated where N_{pop} is numbers of countries($k = 1, \dots, N_{pop}$). Fitness value of each country is calculated and sorted, since Neyman-Pearson criteria needs to use maximization algorithm, the imperialists are usually the countries with the highest objective function values. Amount of the objective function for each of the country generated in this step is calculated as: $P_d(\vec{\omega}_1), P_d(\vec{\omega}_2), P_d(\vec{\omega}_3) \dots \dots \dots P_d\left(\vec{\omega}_{N_{pop}}\right)$.

Step 2: In this step, countries are divided into imperialists (N_{imp})and colonies(N_{col}), we select $N_{imp}$from the most powerful countries. The colonies will be distributed among the imperialists according their power. This research is proposing Boltzmann distribution [20] with suitable selection pressure coefficient (α).

$$p_{imp} \propto \exp(-\alpha P_d(\vec{\omega}_{imp})), \; p_{imp} = \frac{\exp(-\alpha P_d(\vec{\omega}_{imp}))}{\sum_k \exp(-\alpha P_d(\vec{\omega}_k))} \; (k = 1, \dots, N_{pop}) \quad (3.17)$$

Where p_{imp} is probability of imperialist power ($\sum_{N_{imp}} p_{imp} = 1$). From GA we already knew that optimum value for selection pressure (α) is when sum of the half of the pest countries probability must be almost 0.8. The power of imperialists is portion of N_{col} that should be possessed by N_{imp}. Number of colonies for each empire is randomly chosen from N_{col} in terms of power of its empire's imperialistic.

$$\text{Initial number of empire's colonies} = \text{rand}[N_{col}. p_{imp}] \tag{3.18}$$

Step 3: Every imperialist attempt to develop its colonies. Fig.2.2(b) depicts all colonies transfer to their related imperialist that x value is the colony transfers to. The new position of this colony is shown in darker blue. Value of x is uniformly chosen i.e., $x = U(0, \beta \times d)$ where β is assimilation coefficient $(0 < \beta \leq 2)$ and d is distance of colony and imperialist. In Fig. 3.2 (b) assimilation deviation (θ) is uniform random distribution number which can be chosen from $-\frac{\pi}{2} < \theta < \frac{\pi}{2}$. In general there is a trade-off when we choose value of θ, β among number of iterations, Exploitation and exploitation of the system. Section 4 describes the optimum values of assimilation parameters. We replaced the assimilation deviation with a random vector as follow to show the implementation of modified ICA:

$$\text{New position} = \text{Old position} + U(0, \beta \times d) \otimes \text{rand}\ (V) \tag{3.19}$$

Where base vector, V, is beginning the former position of colony and aiming to the imperialistic. Also, random vector and element-by-element multiplications are denoted by rand and $\otimes$ sign respectively.

Inevitably, the colony is departed minus of consuming the classification of θ because these random values are not same essentially. Stating a new vector in order to have suitable exploration (search area) capability satisfies the utilization of θ.

Step 4: If a colony in empire has lower cost than imperialist the position of a colony and the imperialist will exchange. It means while colonies moving toward imperialist, one colony may rich to the better position (get more power) than imperialist.

Step 5: Calculate total cost of all empires. Generally imperialist cost affects the cost of each empire, but to have an accurate view of an empire, average cost of empire's colonies should not be eliminated. Below we have modeled this fact by stating total cost of each empire:

$$(\text{ Total Empire's coast})_{n} = \left(P_{d}(\vec{\omega}_{imp})_{n} + \xi\left(\frac{\sum_{j=1}^{N_{col}} P_{d}\left(\vec{\omega}_{col\ j}\right)_{n}}{N_{col}}\right)\right) j = \{1,2, \ldots . N_{col}\} \quad n = \{1,2, \ldots . N_{imp} \tag{3.20}$$

Where positive number $, \xi,$ is less than one $(0 < \xi \leq 1)$. Slight value of ξ has less effect of empire's colonies on the whole cost of empire.

Step 6: Imperialistic competition. Choice the weakest colony from weakest empire and provide it to one of the best empires.

Step 7: Remove the defenseless empires. When all colonies of an empire move to other powerful empires and just imperialist remains, this imperialist automatically joins to best empires as a simple colony.

Step 8: Stop condition will satisfy, if one empire remains. Otherwise go to step 2. The result of the problem is the final Imperialist.

3.2.2. Mini-Max Criteria for Modified Imperialistic Competitive-Based Diversity Scheme

Steps of modified ICA for Minimax are very close to Neyman-Pearson criteria. Since Minimax is always used for minimization, some steps are different as below while applied parameter remains the same.

Step 1: The imperialists are usually the countries with the lowest objective function values. Amount of the objective function for each of the country generated in this step is calculated as $P_e(\vec{\omega}_1), P_e(\vec{\omega}_2), P_e(\vec{\omega}_3) \dots P_e\left(\vec{\omega}_{N_{pop}}\right)$.

Step 2: The colonies will be distributed among the imperialists according their power:

$$\mathrm{p_{imp}} \;\; \infty \;\; \exp(-\alpha \mathrm{P_e}(\vec{\omega}_{\mathrm{imp}}))\;,\; \mathrm{p_{imp}} = \frac{\exp(-\alpha \mathrm{P_e}(\vec{\omega}_{\mathrm{imp}}))}{\sum_{\mathrm{k}} \exp(-\mathrm{e}(\vec{\omega}_{\mathrm{k}}))} \;\; (\mathrm{k} = 1, \dots, \mathrm{N_{pop}}) \qquad (3.21)$$

Step 3: Colonies move towards imperialist states in different directions (assimilation) and x is transferred colony distance where $x \sim U(0, {}'\Upsilon \times d)$ and $'\Upsilon$ is the assimilation coefficient $(0 < {}'\Upsilon \leq 2)$ and d is the distance of the colony and imperialist. θ is assimilation deviation which can be chosen from $-\frac{\pi}{2} < \theta < \frac{\pi}{2}$. Fig. 3.3(b) depicts how colonies transfer to their related imperialist.

Step 4: If a colony in empire has higher cost than imperialist the position of a colony and the imperialist will exchange.

Step 5: The total cost of each empire:

$$(\text{Total Empire's coast})_n = \left(P_e(\vec{\omega}_{imp})_n + \xi\left(\frac{\sum_{j=1}^{N_{col}} P_e\left(\vec{\omega}_{col\ j}\right)_n}{N_{col}}\right)\right) j = \{1,2,\ldots.N_{col}\} \quad n = \{1,2,\ldots.N_{imp}\} \tag{3. 22}$$

Step 6: Imperialistic competition. Choice the weakest colony from weakest empire and provide it to one of the best empires.

Step 7: Remove the defenseless empires. When all colonies of an empire move to other powerful empires and just imperialist remains, this imperialist automatically joins to best empires as a simple colony.

Step 8: Stop condition will satisfy, if one empire remains. Otherwise go to step 2. The result of the problem is the final Imperialist.

Proposed simulation results and graphs, which are done in MATLAB and compared with other SDF-based methods, will be shown as follows.

3.3. Diversity Receivers Functioning System Model

In this part, it is assumed that the information bits are modulated by binary phase-shift keying (BPSK) modulation. The channel is assumed to be frequency nonselective and slowly fading over the length of the transmitted symbol. We also assume that *M* diversity branches are employed at the receiver of each SU for reception. In addition, this research work assumes that the diversity sufficiently far apart from each other, such that the received signals are statistically independent with negligible correlation. This is a vital requisite to acquire the full advantage of the diversity receiver (Simon & Alouini, 2005). The received signal at the i^{th} branch is given by:

$$\mathrm{r_i(t) = g_i\, S(t) + n_i\,,\ \ i = 1,2, \dots, M} \tag{3.23}$$

where $S(t)$ is the unit-power transmitted signal and g_i denotes the complex channel gain with uncorrelated and Gaussian distributed real and imaginary parts, each with zero mean and variance of $\sigma_{g_i}^2$. The noise random variable n_i is complex additive white Gaussian noise (AWGN) with zero mean and variance $\sigma_n^2 = \frac{N_0}{2}$. The channel gain g_i at two different diversity branches is assumed to be identically distributed. It is also assumed that g_i and n_i are uncorrelated. The signal power over one symbol period T_s, at i^{th} path, is:

$$\mathrm{p} = \frac{1}{\mathrm{T_s}}\int_0^{\mathrm{T_s}} |\mathrm{g_i}|^2 |\mathrm{S(t)}|^2 \mathrm{dt} = |\mathrm{g_i}|^2 \frac{1}{\mathrm{T_s}}\int_0^{\mathrm{T_s}} |\mathrm{S(t)}|^2 \mathrm{dt} = |\mathrm{g_i}|^2 \tag{3.24}$$

Since we are assuming slow fading, the term $|g_i|^2$ remains constant over a symbol period and can be brought out of the integral and $S(t)$ is assumed to have unit power. As a result, the instantaneous SNR at the i^{th} path is:

$$\gamma_\mathrm{i} = \frac{|\mathrm{g_i}|^2}{\sigma_\mathrm{n}^2} \tag{3.25}$$

Since we are considering Rayleigh fading, $g_i = |g_i|e^{j\angle g_i}$ where $\angle g_i$ is uniformly distributed over $[2\pi, 0]$ and g_i has a Rayleigh pdf. Therefore, $|g_i|^2$ and hence γ_i have exponential pdf.

$$|\mathrm{g_i}| \sim \frac{2|\mathrm{g_i}|}{\mathrm{P_0}} \mathrm{e}^{\frac{-|\mathrm{g_i}|^2}{\mathrm{P_0}}}, \ \gamma_\mathrm{i} \sim \frac{1}{\Gamma} \mathrm{e}^{-\gamma_\mathrm{i}/\Gamma}, \ \Gamma = \mathrm{E}\{\gamma_\mathrm{i}\} = \frac{\mathrm{E}\{|\mathrm{g_i}|^2\}}{\sigma_\mathrm{n}^2} = \frac{\mathrm{P_0}}{\sigma_\mathrm{n}^2} \qquad (3.26)$$

P_0 is the statistical average of $|g_i|^2$ and Γ represents the average SNR at each individual branch, which serves as a basic parameter to improve the SNR at the receiver.

The bit error rate (BER) in a BPSK system, given an SNR of γ_i, is identified by $erfc\sqrt{2\gamma_i}$, where $erfc(x) = \frac{2}{\sqrt{\pi}} \int_x^{\infty} e^{-t^2}\, dt$ [12]. Therefore, the BER averaged over the Rayleigh fading in Eq. (3.26) is given by [13]:

$$\mathrm{BER} = \int_0^{\infty} \frac{2|\mathrm{g_i}|}{\mathrm{P_0}} \mathrm{e}^{-|\mathrm{g_i}|^2/\mathrm{P_0}} \ \mathrm{erfc}\left(\sqrt{2\frac{|\mathrm{g_i}|}{\sigma_\mathrm{n}}}\right) \mathrm{d}(|\mathrm{g_i}|) = \frac{1}{2}\left(1 - \sqrt{\frac{\Gamma}{1+\Gamma}}\right) \qquad (3.27)$$

The physical model assumes the fading to be independent from one branch to the next. Each branch, therefore, acts as an independent sample of the random fading process (here, Rayleigh). It means each branch receives an independent copy of the transmitted signal. Our goal here is to combine these independent samples in a way to achieve the desired goal of increasing the SNR and reducing the BER.

In general, SU's receiver linearly combines the received signal $r_i\,(t)$ with ν_i, which is the weighting coefficient of the i^{th} branch. The output signal $r(t)$ of the linear diversity combiner is then given by:

$$r(t) = \sum_{i=1}^{M} \nu_i r_i(t) = S(t) \sum_{i=1}^{M} \nu_i g_i + \sum_{i=1}^{M} \nu_i n_i \quad (3.28)$$

Since $S(t)$ is assumed to have unit power, SNR at the output of combiners is

$$\gamma_T(\vec{\nu}) = \frac{1}{\sigma_n^2} \frac{\left|\sum_{i=1}^{M} \nu_i g_i\right|^2}{\sum_{i=1}^{M} |\nu_i|^2} = \frac{\left|\vec{\nu}\vec{G}^T\right|^2}{E\left\{\left|\vec{\nu}\vec{N}^T\right|^2\right\}} \quad (3.29)$$

3.3.1. Modified Imperialist Competitive Algorithm-Based Diversity Scheme

To my best knowledge any kinds of human's socio-political evolution has not been deep-rooted in refining diversity combining issue yet. Hence, checking the effectiveness of the modified ICA algorithm in comparison to other techniques is the main disquiet of this research. The main steps of modified ICA are explained as follows:

Step 1: Generate N_{pop} numbers of countries (combiner's weighting vector shown in Fig.3.1. Diversity) as $\vec{v}_k = [v_1, v_2, \dots, v_M]^T$ where $k = 1, \dots, N_{pop}$. The SNR value of each country, based on Equation. (3.29), is calculated and sorted.

Step 2: N_{imp} of most powerful (in terms of SNR) countries are chosen as imperialists to form empires and the rest of N_{col} countries are called colonies. Fig.3.3 (a) depicts the initial colonies for each empire. Initial number of colonies for an empire is randomly selected from N_{col} with respect to the empire's imperialist power (p_{imp}) which is its corresponding normalized SNR.

$$\text{Initial number of colonies in an empire} = N_c = \text{round}(N_{col} . p_{imp}) \quad (3.30)$$

Step 3: Colonies in an empire start to move in the search space towards imperialist state in different directions (assimilation). $\vec{\boldsymbol{x}}_j = [x_1, x_2, \dots, x_M]^T \; (j = 1, \dots, N_c)$ is transferred distance of the jth colony which is randomly chosen from interval of $[\vec{\mathbf{0}}, \Upsilon.\vec{\boldsymbol{d}}_j]$ where $\vec{\mathbf{0}}$ is a 1-by-M zero vector, Υ is the assimilation coefficient $(0 < \Upsilon \leq 2)$ and $\vec{\boldsymbol{d}}_j = [d_1, d_2, \dots, d_M]^T$ is the distance between the imperialist and jth colony in an empire which is calculated by

$$\vec{\mathbf{d}}_{\mathrm{j}} = \vec{\mathbf{v}}_{\mathrm{imp}} - \vec{\mathbf{v}}_{\mathrm{col_j}} = \left[\nu_{1,\mathrm{imp}} - \nu_{1,\mathrm{col_j}}, \nu_{2,\mathrm{imp}} - \nu_{2,\mathrm{col_j}}, \dots, \nu_{\mathrm{M,imp}} - \nu_{\mathrm{M,col_j}}\right]^{\mathrm{T}} \tag{3.31}$$

Therefore, the new position of the j th colony is calculated as follows [41]:

$$\vec{\mathbf{v}}_{\mathrm{new,col_j}} = \vec{\mathbf{v}}_{\mathrm{old,col_j}} + \vec{\mathbf{x}}_{\mathrm{j}} + \vec{\mathbf{r}}.\tan(\theta) \tag{3.32}$$

Where $\vec{\boldsymbol{r}}$ is a 1-by-M random vector whose values are uniformly distributed on (-1,+1) and θ is assimilation deviation which can be chosen from $-\frac{\pi}{2} < \theta < \frac{\pi}{2}$. Fig. 3.3 (b) depicts how colonies transfer to their related imperialist.

Step 4: The cost of each colony in new position is, again, computed based on (3.29). Position exchange between a colony and imperialist can be happened in this step. In other words, if a colony in its new position has a higher SNR than that of the imperialist, it has the chance to take the control of empire by replacing the existing imperialist.

$$\gamma_{\mathrm{T}}\left(\vec{\mathbf{v}}_{\mathrm{new,col_j}}\right) > \gamma_{\mathrm{T}}\left(\vec{\mathbf{v}}_{\mathrm{imp}}\right) \Longrightarrow \text{jth colony will become the impersialist} \tag{3.33}$$

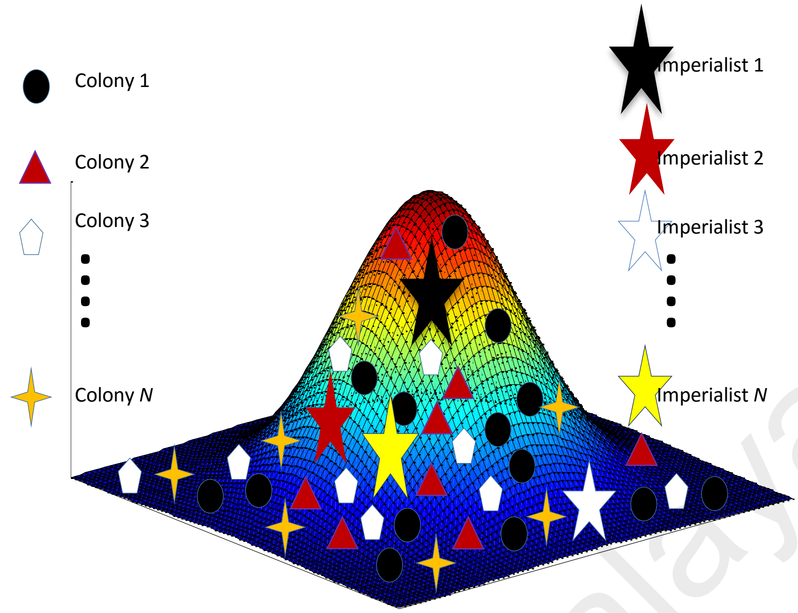
Step 5: Imperialistic competition is being performed in this step. The colony with the lowest SNR value from the empire with the weakest power is chosen and provided to one of the best empires. The total power (in terms of SNR) of an empire is calculated as follows:

$$\text{Total empire's power} = \gamma_{\mathrm{T}}\left(\vec{\mathbf{v}}_{\mathrm{imp}}\right) + \xi\left(\frac{\sum_{\mathrm{j}=1}^{\mathrm{N_c}} \gamma_{\mathrm{T}}\left(\vec{\mathbf{v}}_{\mathrm{col_j}}\right)}{\mathrm{N_c}}\right) \quad (3.34)$$

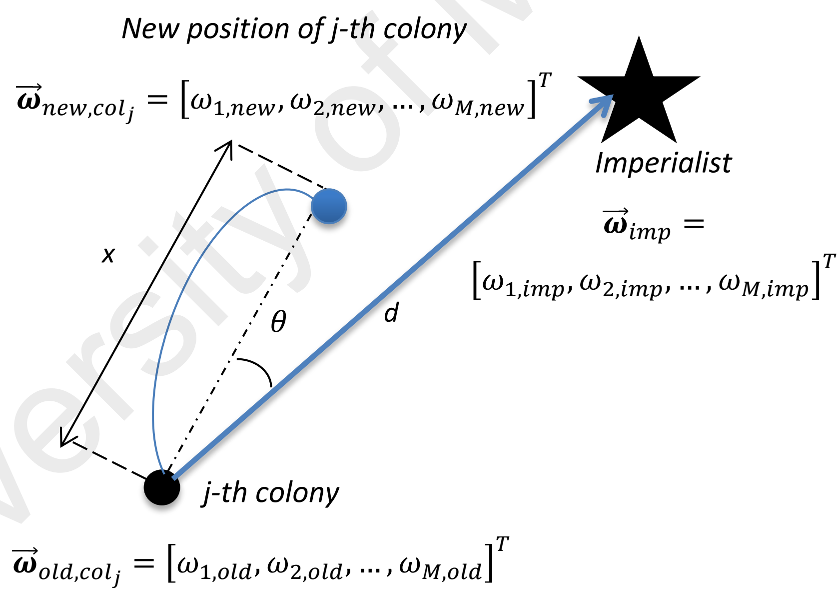
Where positive number, ξ, is equal or less than one ($0 < \xi \leq 1$).

Step 6: When all colonies of an empire move to other powerful empires and just imperialist remains, this imperialist automatically joins best empire as a simple colony. This empire will then be removed.

Step 7: Stop condition will satisfy, if only one empire remains. In other words, after a while only one empire with highest total power (as in Equation.(3.34)) remains which controls all the colonies. In this condition, all of the colonies and the imperialist have the same position (weighting vector) and cost (SNR at Eq. (3.29)). Otherwise, algorithm jumps to Step 3. The equivalent weighting vector of the final imperialist is the best vector that maximizes the output SNR of our diversity problem here.



(a)



(b)

Figure 3.3: Current and future position of imperialists and colonies in imperialistic competitive algorithm. a) Imperialists and colonies in each empire b) Movement of colony toward imperialist

3.4. Proposed Diversity Based Cognitive Radio Cooperative Spectrum Sensing

In previous parts, iterative-based methods employed to get the ideal weight coefficient even in diversity combining method or CRCSS, which in turn ended up implemented while using GA, PSO and modified ICA as well as deterministic linear CRCSS techniques. In this part, diversity combining based is proposed on each SU in CRCSS to increase the received signal quality by each SU and decrease required numbers of SUs in CRCSS with less complexity compare to non-diversity based method accordingly. In general number of SUs, which receive and pass the sensing about received signal from PU to fusion centre (FU) centre, plays important role in CRCSS to minimize probability of error (P_e) about PU's activity. But, less number of SUs causes less complexity, which leads to less number of iteration and generations in iterative-based methods and lower cost of industrial and laboratory set-up.

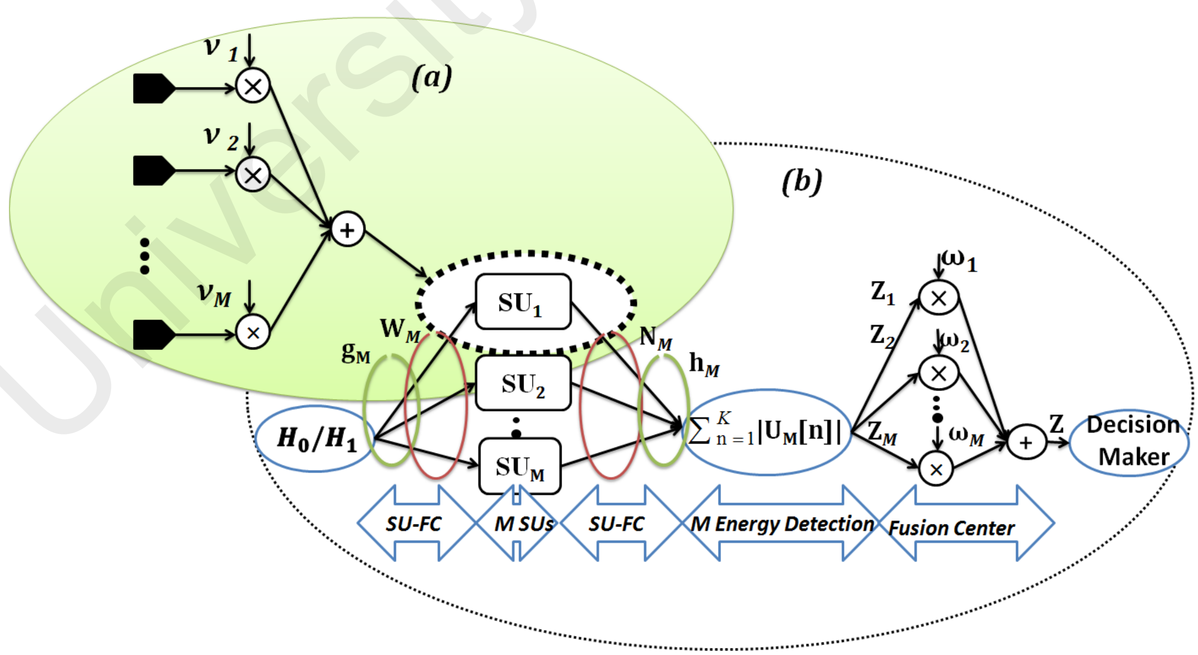


Figure 3.4: Block diagram of the cooperative spectrum sensing applied diversity combining.

Fig.3.4 shows proposed block diagram of diversity based-ICA CRCSS, the aim of these techniques is to find a set of weights $\vec{\omega} = [\omega_1, \omega_2, \dots, \omega_M]$ both in each SU's receiver and in FC center which optimizes a specific objective function showed in next section. This research introduced ICA as best optimization iterative scheme in CRCSS to obtain optimal weighting vectors which enhance SNR at SUs receiver (diversity based method) and minimize P_e at fusion center (FC). Analysis and simulation results confirm that the ICA based scheme is efficient, stable with better detection and convergence performance and outperforms other evolutionary methods, such as particle swarm optimization (PSO) and genetic algorithm (GA) as well as other conventional methods.

3.4.1. Problem Formulation

In problem definition, first we investigate CRCSS by itself, then the space diversity in cognitive radio is proposed mathematically. The weights are selected to minimize the effect of fading on the received multiple signal components for each individual SU (in space diversity part, fig.1.a) and reduce probability of miss detection (P_{md}) and P_e on FC (Fig.3.4. (b)).

3.4.1.1. Problem Formulation Space Diversity Based Cognitive Radio

The particular structure involving CRCSS is actually shown in Fig. 3.4 and to avoid reputation, mathematical formulation of diversity is mentioned in APPENDIX A as well as in Section 3.1.2.

3.4.1.2. Problem Formulation Space Diversity Based Cognitive Radio

Diversity combining is proposed and applied on SUs in network to increase the SNR received by each SU and decrease the number of SUs on CRCSS. In other words, when received signal is improved in terms of SNR, more accurate sensation of SUs can be transmitted to FC and hence, the number of SUs can be decreased to save cost and have better accuracy in making decision as can be seen in Fig. 3.4. APPENDIX B drives space diversity formula for each SUs and the rest of formula is the same as APPENDIX A when the signal send to FC from SU is calculated based on diversity proposed method.

3.4.2. Proposed Imperialistic Competitive Algorithm

Modified ICA is well mentioned in 7 steps to benefit potential in APPENDIX C and all those steps are summarized in pseudo-code as follows as well as Section 3.3.1:

Start

Development of empires (producing weighting vectors randomly)

Create the colonies for each empire (compute and classify the P_e corresponding to weighting vectors)

Select one colony at each empire randomly as imperialist

While there is more than one empire, do

(

Compare colonies with imperialist

If a weighting vector (colony) provides lower P_e than the value provided by the imperialist,

> *Set that colony as the imperialist and the imperialist as a normal colony (make the colony's weighting vector the best vector in its empire)*

Compute total P_e of all empires

Perform imperialistic competition (empires try to catch vectors with lower P_e)

If an empire with no colonies exists,

Eliminate the powerless empire (this empire will be eliminated because there is no weighting vector or colony left inside it)

)

3.5. Summary

The CR hypotheses and its mathematical modeling with respect to both Neyman-Pearson and Minimax criteria are presented. In addition, all the necessary parameters of cognitive network are well designed. At the same time, space diversity combining is defined mathematically and the required system parameters are investigated to have a better comparison with the existing methods. Contributions in this chapter can be summarized in three main groups:

1. Improving performance of cognitive radio cooperative spectrum sensing to make accurate decision about availability of spectrum band (proposed modified ICA based method).
2. Enhancing SNR in space diversity combining to improve the reliability of degraded and faded received signal (proposed iterative based methods to overcome channel estimation problem in space diversity combining)
3. Implementation of the proposed space diversity method to new CRCSS modified ICA-based method for improving the spectrum utilization and decreasing number of required cooperative users which leads to less complexity and real time application.

CHAPTER 4 : RESULTS AND DISCUSSION

4.1. Classification Results and Analytical Parameters

Table 4.1 demonstrates the overall simulation parameters used in this paper. To realize the low SNR conditions (SNR < -10 dB) at SU and FC levels, the values of the g_i and h_i are generated randomly. In addition, since the channel is considered to be a slow fading channel, g_i and h_i values are assumed to be constant over the sensing time, so the delay requirement is short compared to the channel coherence time considered as quasi-static scenario. Since the ICA, PSO and GA parameters are generally problem-dependent, the set-and-test approach is used in this work to obtain the optimal values for them as it is shown in Table 4.2 and Table 4.3. For instance $c_1 r_1$ and $c_2 r_2$ in PSO or θ, β, α in ICA guarantee that the particles or colonies would fly over the target about half the time.

Table 4.1: simulation parameters

CR and channel parameters	
Number of users M	25
Bandwidth B ,Sensing time T_s	$6\ MHz$, $25\ \mu sec$
SU transmit power $P_{R,i}$	12 dBm
The step size of P_f ($0 \leq P_f \leq 1$)	0.01
$P_{R,i}$, $\sigma_s{}^2$	33 dBm,35 dBm
AWGN of i^{th} PU-SU Channel	$20 \leq \sigma_{W_i}^2 \leq 30$ dBm
AWGN of i^{th} SU-FC Channel	$20 \leq \delta_i{}^2 \leq 30$ dBm
channel gains	$10 \leq g_i \leq 20$ dBm
channel gains	$10 \leq h_i \leq 20$ dBm

4.2. Cognitive Radio Cooperative Spectrum Sensing Based

4.2.1. Results & Analysis for Neyman-Pearson Criteria

Fig. 4.1 illustrates the probability of detection of modified ICA-based scheme as well as all other conventional schemes in terms of the different probabilities of false alarm. It is observable that MICA-assisted method outperforms all other schemes with a large difference which validates the robustness of our proposed technique. For instance, for the fixed $P_f = 0.1$, the P_d provided by ICA is 97.8%, which is 0.9 % , 4.81%, 14.63%, 17.12% , 37.86% and 70.26% higher than PSO, GA, NDC, MDC, MRC and OR-Rule, respectively.

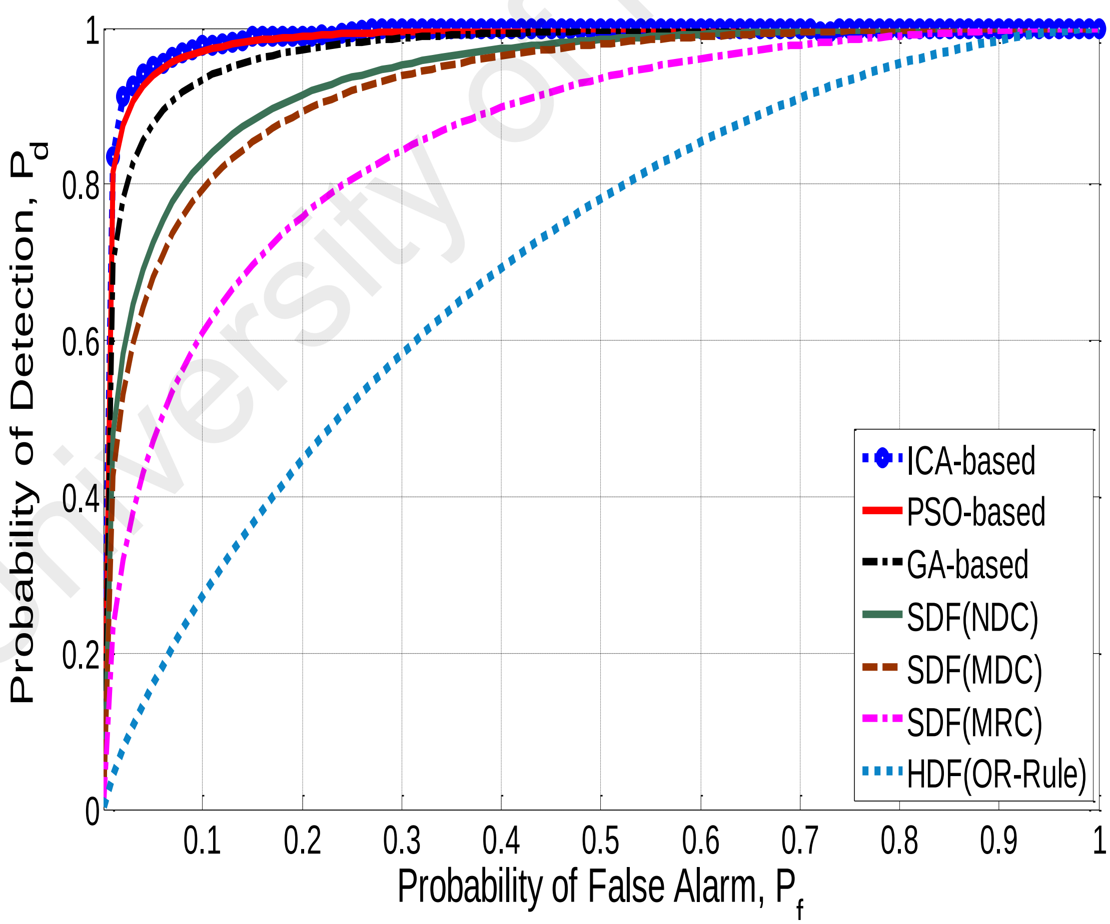


Figure 4.1: Comparison of probability of detection versus probability of false alarm

The convergence comparison of modified ICA-, PSO- and GA- assisted schemes over 200 iterations per simulation for a given $P_f = 0.2$ is shown in Fig.4.2. It is clearly shown that the Max ICA-based method converges roughly after the 29 iterations while the convergence for Max PSO- and GA-based method techniques are attained after 42 and 56 iterations respectively (13 and 27 iterations less that Max MICA iterations convergence) which implies the fast convergence of the ICA algorithm. The approximate improvement of 30.8% and 48.2% of the convergence speed of ICA-based method compare to PSO- and GA-based schemes confirms stability of the algorithm for real time applications. Also, the mean of each algorithm over 100 simulations is shown and compared with its maximum iteration in Table 4.4 which confirms that most of the discovered weighting vectors in each simulation of ICA-based are better than PSO and GA-based. In table 4.2 the different parameters value used for testing in MICA, PSO and GA already shows and the set-and-test approach is used in this work to obtain the optimal values for them (table 4.3).

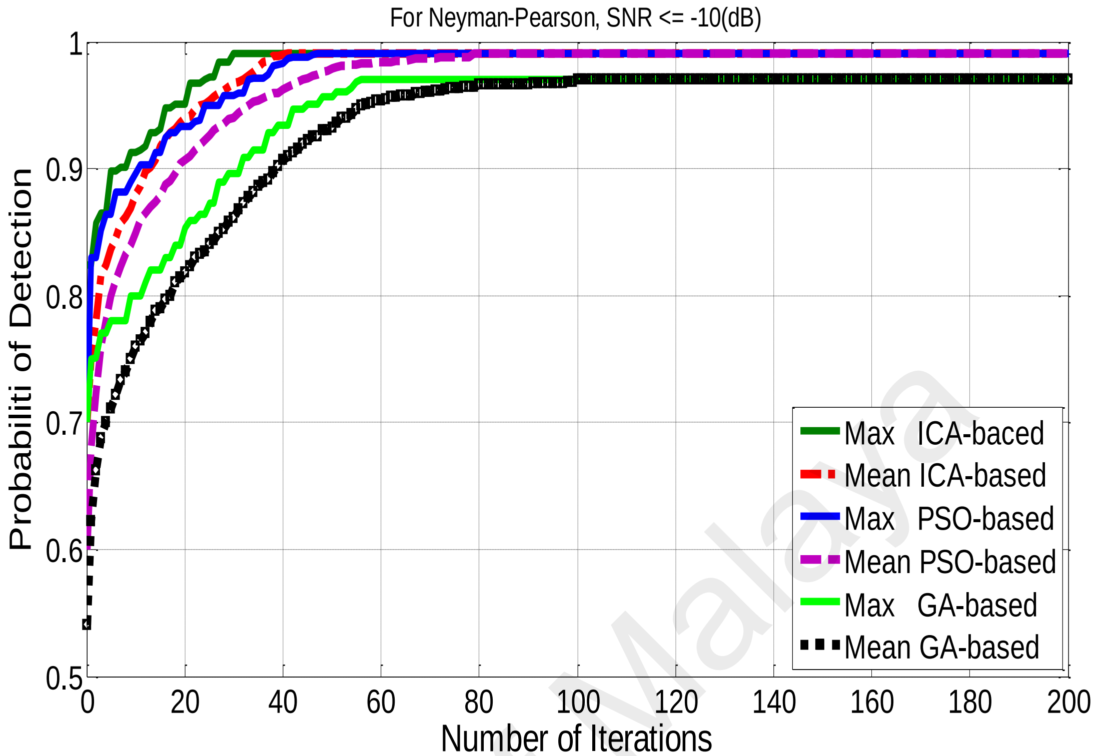


Figure 4.2: Comparison of probability of detection over 200 iterations for fixed $\boldsymbol{P_f}$ of 0.2.

Fig. 4.2 shows a comparison of probability of error versus SNR for MICA- and PSO-assisted scheme. Impact of number of the population is quite visible, as can be seen in Fig. 4.3. In general, with increasing the number of population, performing time and computational complexity of these methods will be increased. On the other hand, choosing the number of countries and particles is problem dependent and depend on different factors like number of iterations, learning coefficient, assimilation coefficient, deviation coefficient and so on, e.g., the performance of the ICA with 25 countries is the best among all, but in comparison with larger numbers of countries, there is still a trade-off between very slight improvements, complexity and performing time, which is well explained in Table 4.3.

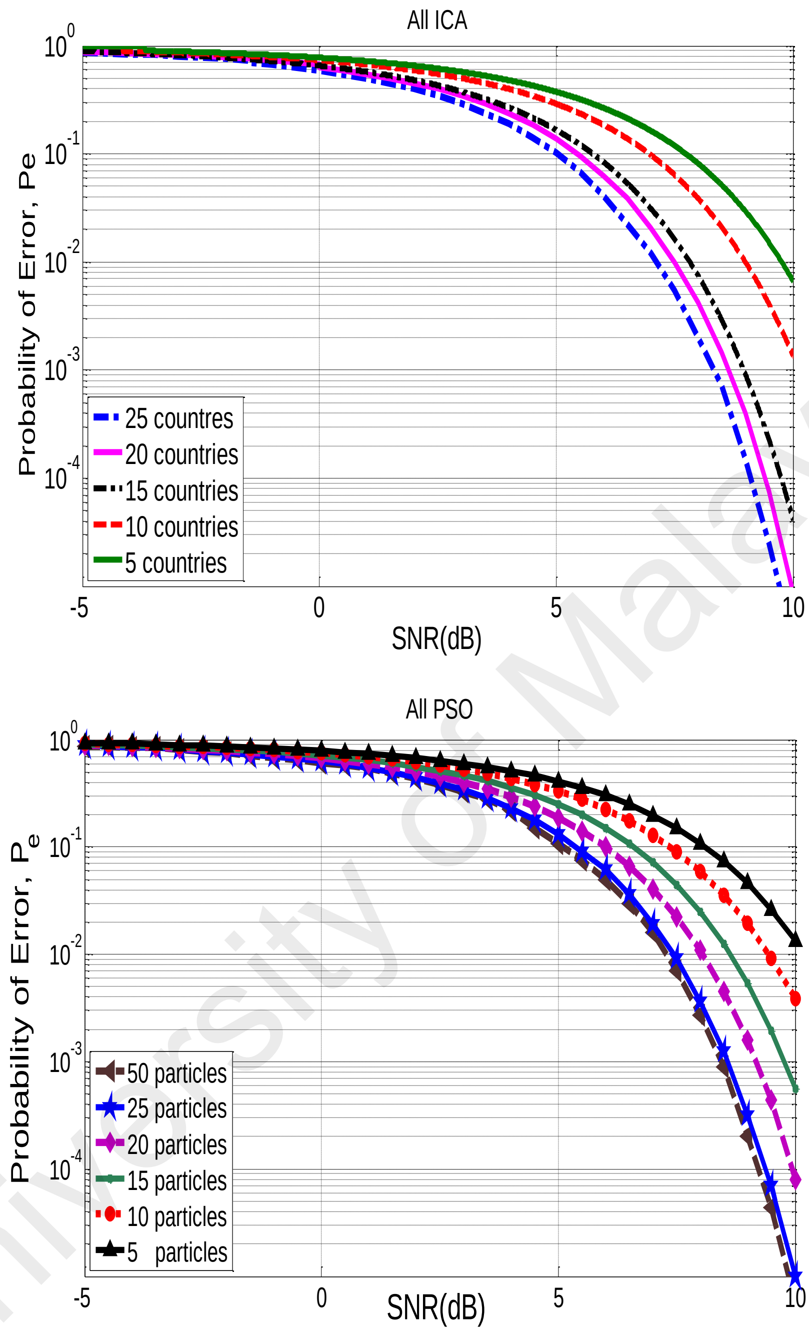


Figure 4.3: Comparison of probability of error versus signal to noise ratio alarm for ICA- and PSO-assisted with different number population

Table 4.2: Different parameters value used for testing

GA		PSO		MICA	
Population size	10,20,30,40,50	Population size	5,10,15,20,25,50	**Population size**	5,10,15,20,25,35
Mutation rate	0.01,0.10.15,0.2,0.3, 0.4,0.5,0.6	learning coefficients	1.8,1,85,1.9,1.95,2, 2.05,2.1	**colonies power coefficient**	$0 < \xi \leq 1$
Crossover rate	0.5, 0.65, 0.75 , 0.85, 0.95	r_1 and r_2	$U(0\ ,1)$	**Assimilation coefficient**	$0 < \beta \leq 2$
reproduction rate	0.5 , 0.6 , 0.7 , 0.8 , 0.9	NON	NON	**selection pressure**	$0 < \alpha \leq 2$

Table 4.3: Optimal parameters value for ICA, PSO and GA algorithms which minimized probability of error

GA		PSO		MICA	
Population size	50	Population size	25	**Population size**	25
Mutation rate	0.3	learning coefficients	2	**Mean colonies power coefficient**	0.15
Crossover rate	0.95	r_1 and r_2	U(0,1)	**Assimilation coefficient**	1.7
Population for reproduction rate	0.9	NON	NON	**selection pressure**	1.2

Table 4.4: Comparison of performance of MICA- and PSO-assisted for different number population

MICA						PSO						
Number of Countries	5	10	15	20	25	**Number of Particles**	5	10	15	20	25	50
Probability of Max Detection $(\boldsymbol{P_f = 0.2})$	0.678	0.928	0.967	0.989	0.991	**Probability of Max Detection** $(\boldsymbol{P_f = 0.2})$	0.760	0.859	0.930	0.964	0.985	0.989
Max Convergence Iterations	195	128	74	48	24	**Max Convergence Iteration**	128	98	79	54	41	29
Mean Convergence iterations	Not	Not	101	56	38	**Mean Convergence Iteration**	168	112	96	71	57	48
Max Iterations(Min)	0.0002	0.009	0.031	0.068	0.093	**Max Iterations(Min)**	0.089	0.136	0.182	0.236	0.275	0.562
Mean Iterations(Min)	Not	Not	1.847	5.758	9.270	**Mean Iterations(Min)**	8.702	13.405	18.282	24.04	26.571	56.538

‘NoN’ in Table 4.3 denotes that MICA-based not convergence within 200 iterations in each simulation, in fact MICA-based needs more iterations to be converged for the number of 5 and 10 populations when the number of imperialist is set to 5. Additionally, convergence time is varied from computer systems to others and it mostly depends on CPU of each computer.

4.2.2. Results and Analysis for Mini-Max Criteria

As it can be clearly observed in Fig. 4.4, the best weighting coefficient vector is generated by MICA- and PSO-based methods, resulting in minimized probability of error of the system with a large difference from other techniques where HDF-based spectrum sensing provides the worst error performance.

Fig. 4.5, compares the convergence rate of modified ICA-assisted based with other schemes. Here, the probability of error over 200 iterations is evaluated for Iterative based methods in both conditions of Mean and Max. The mean and Max of each algorithm are achieved when the algorithms run for 100 times and the average of all results is called mean in our experiment and the best one among these all 100 simulations which results minimum P_e is named as Max algorithm-based. As it is seen, to achieve a probability of error equal to 0.5×10^{-4}, the mean modified ICA-based requires about 23 iterations whereas the same error rate can be obtained after 38 and 124 iterations for mean PSO- and GA-based, respectively.

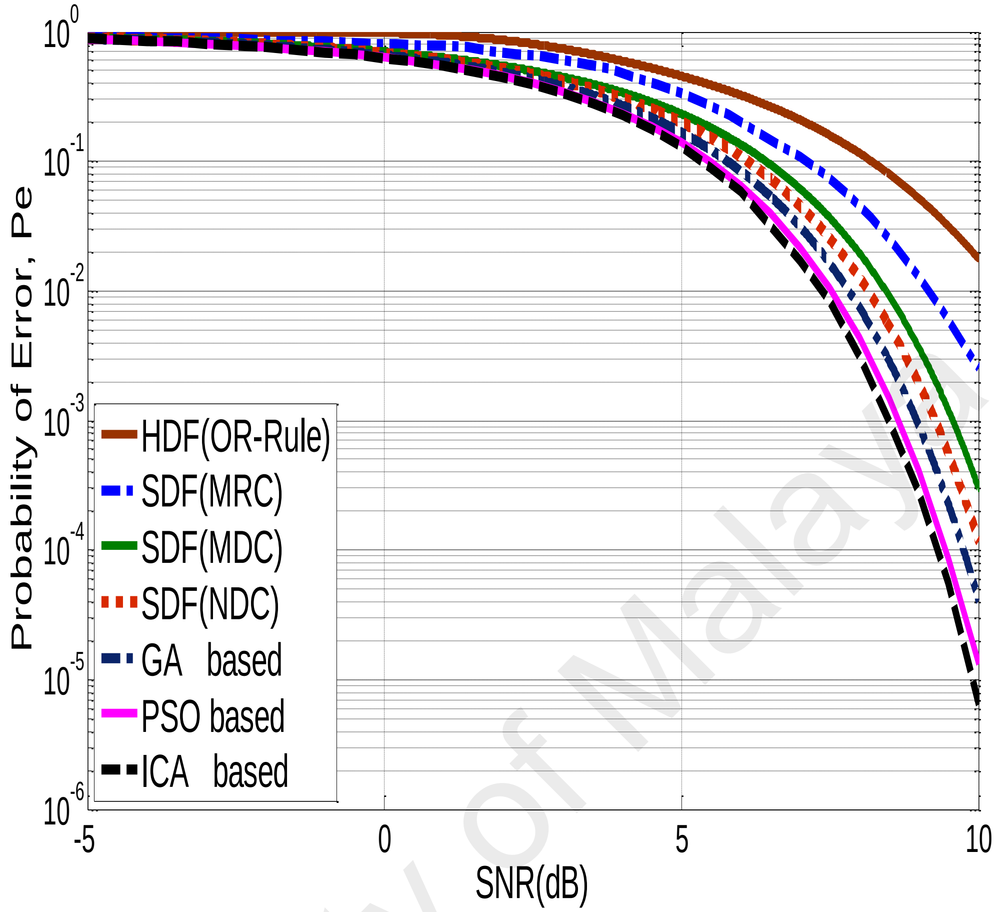


Figure 4.4; Comparison of probability of error versus signal to noise ratio

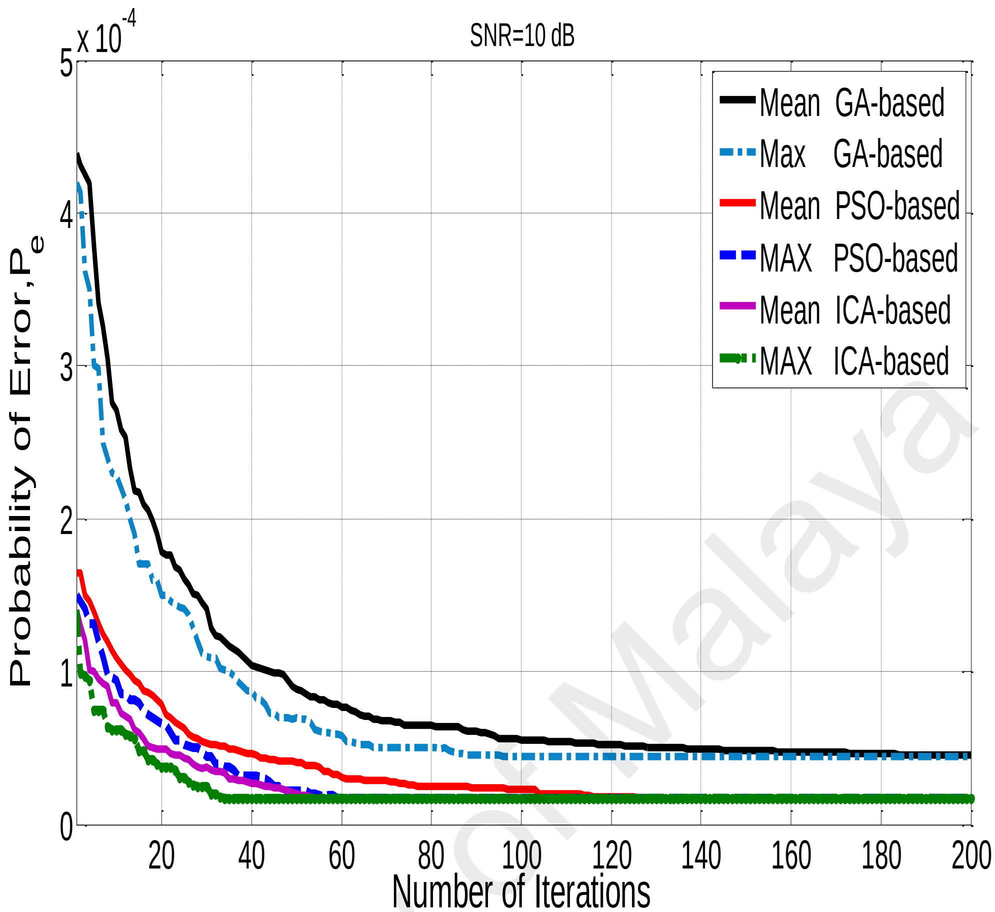
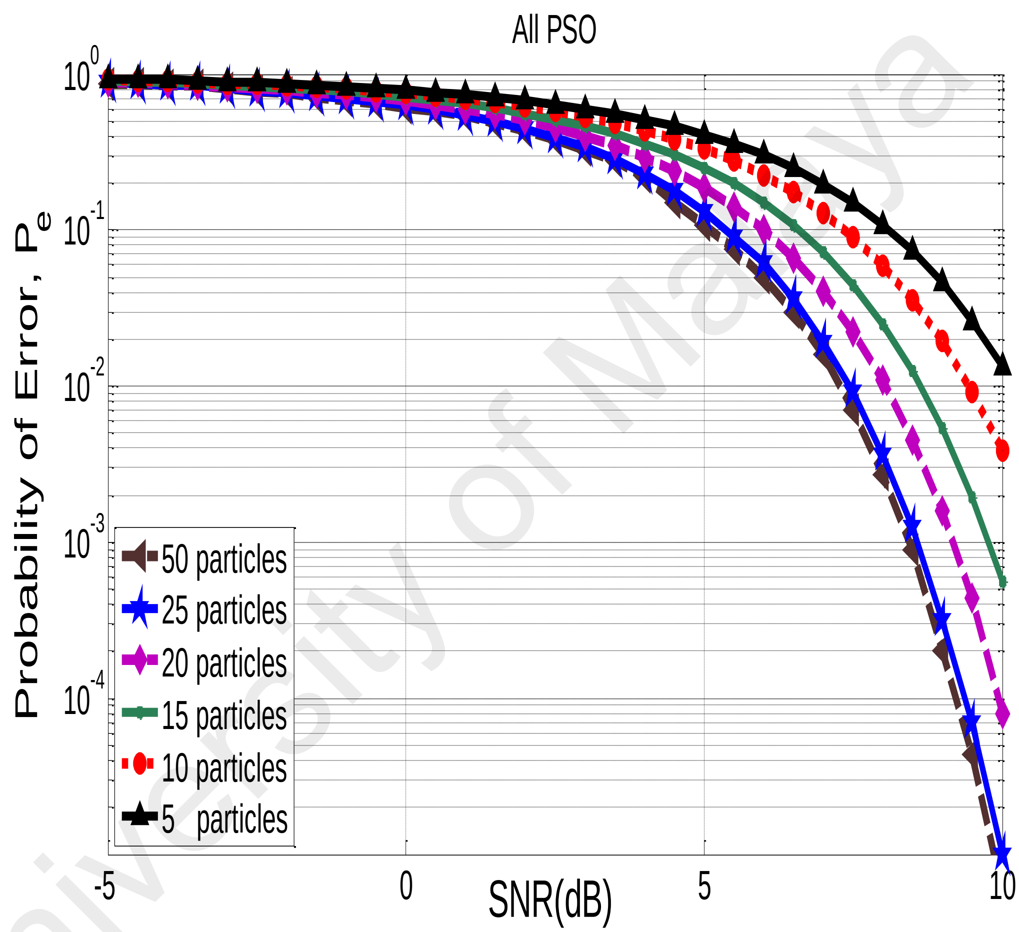


Figure 4.5: Comparison of probability of error over 200 iterations for MICA, PSO and GA

In addition, after the test duration of 200 iterations, the MICA and PSO algorithms are converging to the probability of error of about 0.2×10^{-4} while GA achieves 0.45×10^{-4} with the same number of iterations. The impact of different number of population and countries in CRN simulation is also examined for MICA- and PSO-based methods which are described in Fig. 4.6. It is apparent that improvement in performance is achieved by increasing the number of population in each algorithm. It is notable that there is always a trade-off between performance and complexity in network when number of population increases.

Additionally, when the number of SUs in the system increases the cooperation with the system will be increased. As a result, separation between two hypotheses (H_0 and H_1) increases and the error performance of the system improves accordingly.



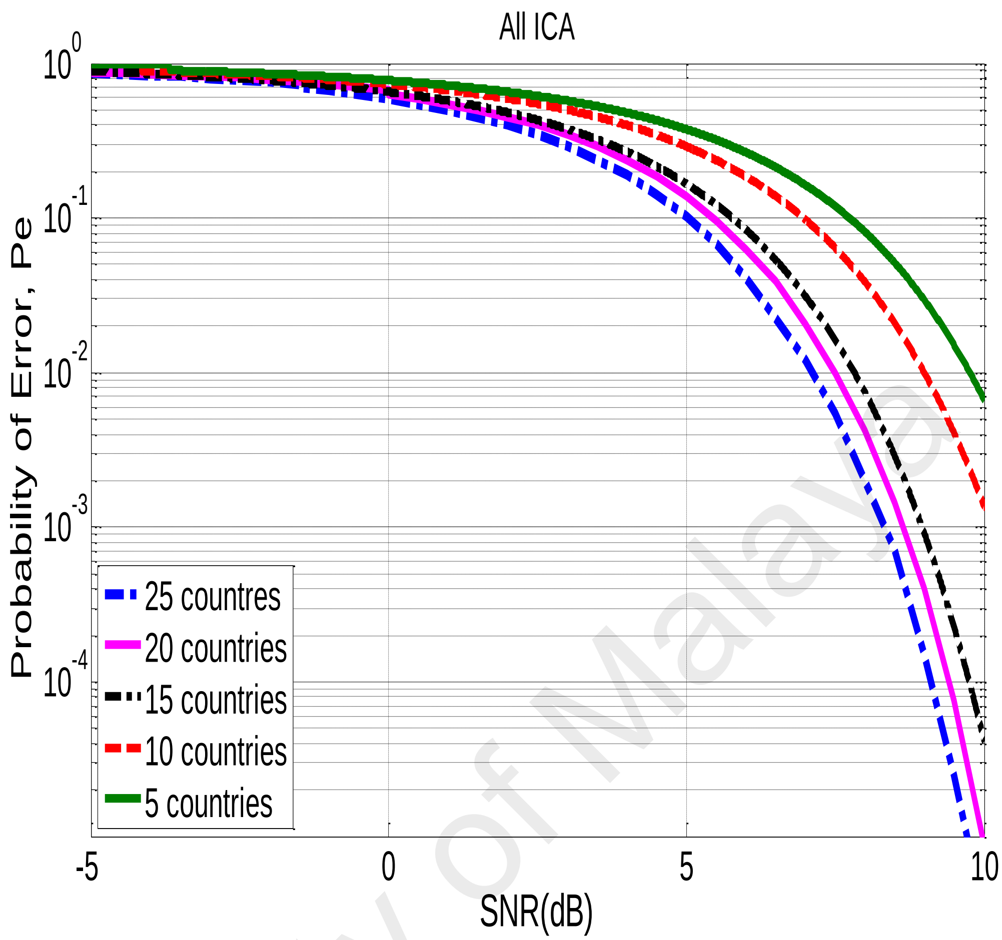


Figure 4.6: Comparison of probability of error versus signal to noise ratio alarm for ICA- and PSO-assisted with different number population

4.3. Results and Analysis for Diversity Techniques

In this section, Monte-Carlo simulation is employed to present the performance of the proposed modified ICA-based diversity combining technique and compare it with PSO, GA, MRC, EGC and SC methods in two different scenarios of the perfect and imperfect channel estimation. It is assumed that the average symbol energy $E_s = 1$ and channel gain and AWGN variances are $\sigma_g^2 = \sigma_n^2 = 0.5$ per dimension. The parameters for the PSO are N = 25 and $c_1 = c_2 = 2$. Fig. 4.7 compares the normalized output SNR of ICA-, PSO-, GA-based combining with MRC, EGC and SC in terms of different number of diversity branches when the channel is perfectly estimated ($\rho = 1$). As expected, we observe that the MRC provides the best performance when channel estimation is perfect. However, the ICA- and PSO-based solutions demonstrate almost the same SNR gain as MRC without the need for channel estimation. Since the parameters in each algorithm are generally problem-dependent, the set-and-test approach is used in this work to obtain the optimal values for them. In other words, $c_1 r_1$ and $c_2 r_2$ in PSO or θ, Υ, α in ICA guarantee that the particles or colonies would fly over the target about half the time. In this respect, the environment has been tested separately for parameters as mentioned in Table 4.5 and the optimal value is found in Table 4.6.

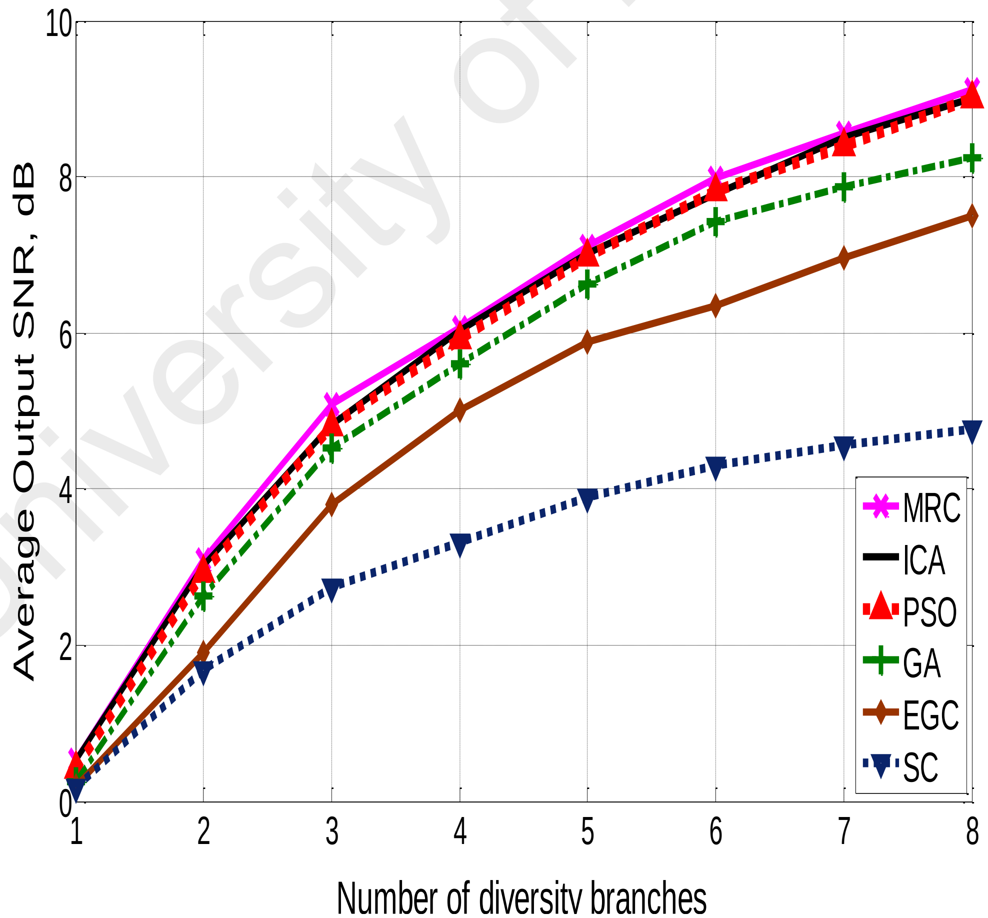


Figure 4.7: Normalized output SNR of MRC-, ICA-, PSO-, GA-, EGC-, SC-based methods when the channel is perfectly estimated.

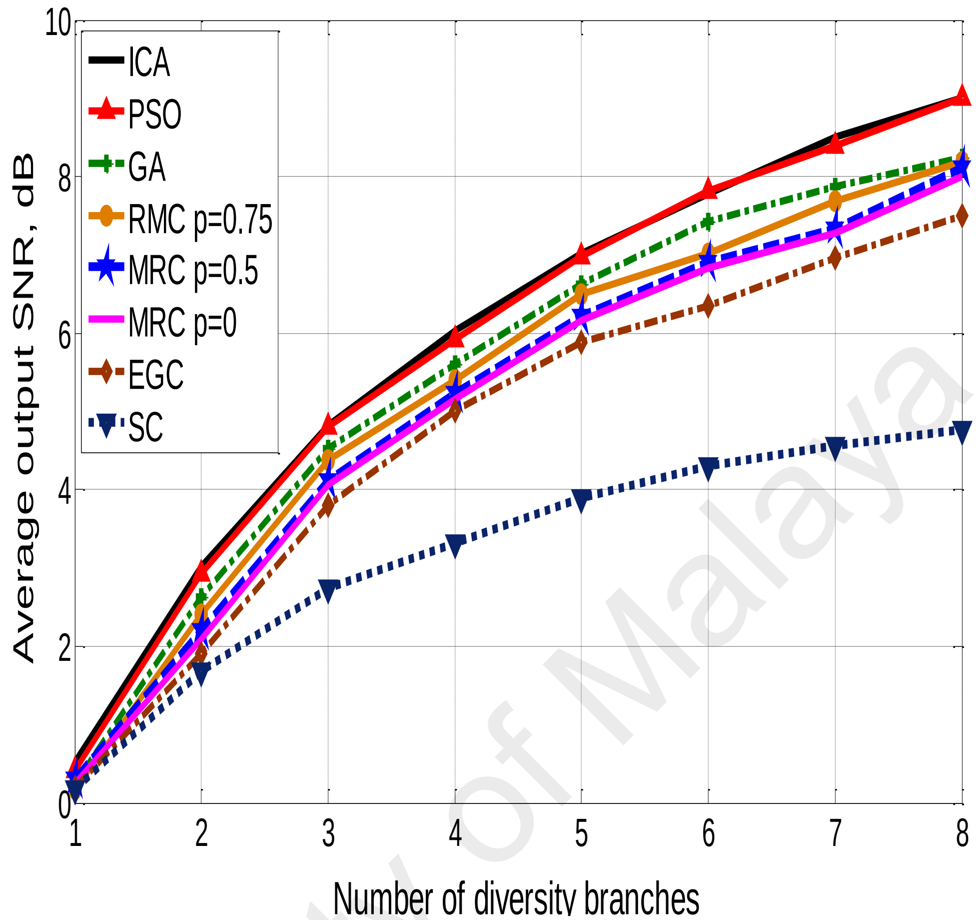


Figure 4.8: Comparison of normalized output SNR of ICA-, PSO-, GA-, MRC-, EGC-, SC-based methods for imperfect channel estimation.

The comparison between the iterative based algorithms and MRC methods in the case of imperfect channel estimation ($\rho = 0,\ 0.5, 0.75$) is illustrated in Fig. 4.8. It can be seen that ICA- and PSO-based methods outperform MRC when channel estimation is imperfect. The improvement achieved can be justified by the ability of the algorithms to thoroughly investigate the search space and evaluate the objective function in (3.29) to maximize the output SNR. As it is shown in Fig. 4.8 and 9, PSO and ICA results are quite close to each other. But on the other hand, Fig. 4.10 and 11 present the superiority of ICA over PSO in terms of achievable BER and SNR, respectively. These two metrics declare that the quality of the diversity performance achieved by ICA is quite better that that of PSO. However, t-test has been carried out to provide an evidence of statistical significance in the difference of means of these two algorithms. With a significance level of 0.10, it has been found that the two-tailed *P* value is 0.0805, which means that the results are considered statistically significant.

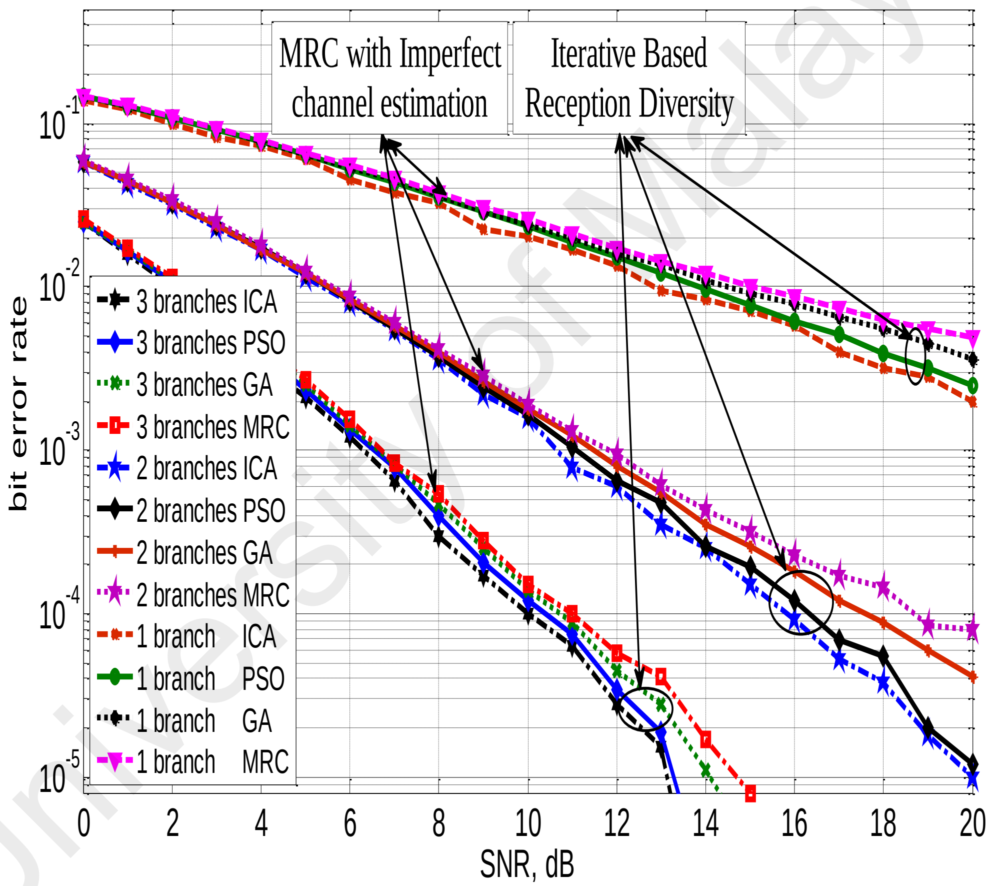


Figure 4.9: Error performance of ICA-, PSO-based and MRC method for different number of diversity branches.

Table 4.5: Comparison of performance of MICA- and PSO-assisted for different number population

MICA						PSO						
Number of Countries	5	10	15	20	25	**Number of Particles**	5	10	15	20	25	50
Probability of Max Error ($SNR = 5$)	0.3971	0.2828	0.1717	0.1398	0.0991	**Probability of Max Error ($SNR = 5$)**	0.4305	0.3532	0.2318	0.1864	0.1482	0.1009
Max Convergence Iterations	128	109	63	34	33	**Max Convergence Iterations**	117	98	79	67	59	38
Mean Convergence iterations	Not	189	131	72	53	**Mean Convergence iterations**	186	167	139	127	117	106
Max Iterations(Min)	0.0002	0.009	0.031	0.068	0.093	**Max Iterations(Min)**	0.089	0.136	0.182	0.236	0.275	0.562
Mean Iterations(Min)	Not	1.821	4.141	4.891	5.201	**Mean Iterations(Min)**	17.028	23.134	26.931	32.739	35.842	62.284

Table 4.6: Different parameters value used for testing

GA		PSO		ICA	
Population Size	10, 20, 30, 40, 50	**Population Size**	5, 10, 15, 20, 25, 50	**Population Size**	5,10,15,20,25,35
Mutation Rate	0.01, 0.1, 0.15, 0.2, 0.3, 0.4, 0.5, 0.6	**Learning Coefficients**	1.8, 1.85, 1.9, 1.95, 2, 2.05, 2.1	**Mean Colonies Power Coefficient**	$0 < \xi \leq 1$
Crossover Rate	0.5, 0.65, 0.75, 0.85, 0.95	**r_1 and r_2**	$U(0\,,1)$	**Assimilation Coefficient**	$0 < \Upsilon \leq 2$
Population For Reproduction Rate	0.5, 0.6 , 0.7, 0.8, 0.9				

Table 4.7: Optimal parameter's value for ICA, PSO and GA

GA		PSO		MICA	
Population size	50	Population size	25	**Population size**	25
Mutation rate	0.3	learning coefficients	2	**Mean colonies power coefficient**	0.15
Crossover rate	0.95	r_1 and r_2	U(0,1)	**Assimilation coefficient**	1.7
Population for reproduction rate	0.9	NON	NON	**selection pressure**	1.2

Considering the BPSK modulation and imperfect channel estimation, the error performance of the MRC, MICA- and PSO-based methods for 1, 2 and 3 diversity branches is illustrated in Figure 4.10. It is observable that the bit error rate of the ICA-based technique is considerably lower than that of the MRC. For instance, for a two-branch diversity, the MRC approximately requires almost 3 dB higher SNR than that of modified ICA-based to achieve a BER = 10^{-4}. In addition, as it is shown, increasing the number of branches results in improved error performance.

Next, Fig. 4.11 compares the convergence of ICA, PSO and GA algorithm used in the diversity method. The number of diversity branches is assumed to be 8. The Mean and Max of each algorithm are achieved when the algorithms run for 100 times. The average of all results is called Mean and the best one among these 100 simulations, which results the maximum output SNR, is named as Max. As it is shown in the figure, Max curve in ICA method converges after 18 iterations whereas about 31 iterations of PSO algorithm are needed for convergence. This indicates the higher convergence speed of the ICA compared to PSO.

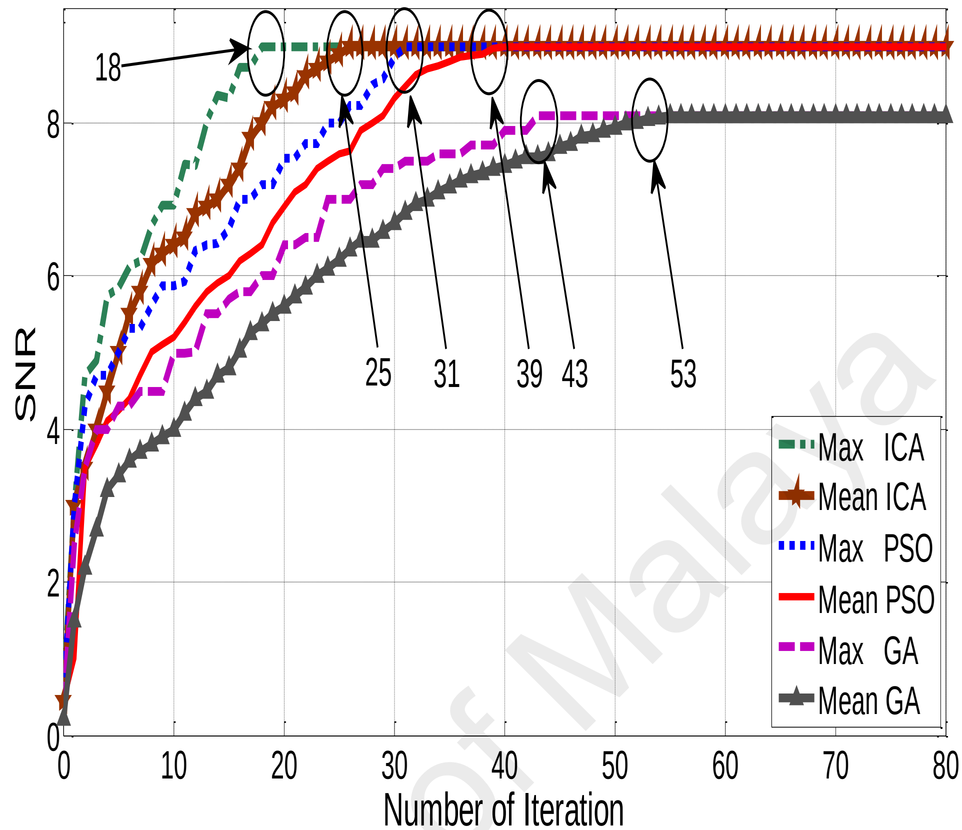


Figure 4.10: Convergence performance of iterative algorithms.

Table 4.8 shows the details of convergence speed for each method. The term NA in Table 4.9 indicates that the iteration number for that specific condition is not available. For instance, ICA-based method with 5 countries cannot converge in 100 iterations. Moreover, the number of fitness evaluation as a parameter to compare the complexity of iterative algorithms has been provided in Table 4.9. The number of fitness evaluation is simply the product of the number of generations by which the maximum SNR fitness is achieved multiplied by the number of fitness evaluations performed in every iteration. The latter equals to the population size of any of these algorithms. For instance, with ICA, the number of iterations required to achieve the maximum SNR is 18 and the number of countries is 25. This means that the number of fitness evaluations to find the optimal setting is 450, which is considerably low with the advancement of signal processing and computing cores.

The SNR variances of ICA, PSO and GA are shown in Table 4.10, and are recorded at every five iterations until the 55th iteration after which the variances are zeroed when all colonies, particles, and chromosomes of ICA, PSO and GA, respectively, converge to the same optima. Considering the values in the table and calculating standard deviations at each iteration, one can conclude that ICA, with all of its fluctuations around its mean, can still outperform the other two algorithms. This validates the superiority of this algorithm in comparison with the other methods.

Table 4.8: Comparison of performance of ICA- and PSO-assisted for different number of population.

ICA						PSO					
Number of Countries	5	10	15	20	25	**Number Of Particles**	5	10	15	20	25
Average Output SNR ($\boldsymbol{N = 8}$)	8.53	8.78	9.09	9.15	9.21	**Average Output SNR** ($\boldsymbol{N = 8}$)	8.46	8.63	8.96	9.06	9.13
Max Convergence Iterations	89	72	53	29	18	**Max Convergence Iterations**	92	4	52	38	31
Mean Convergence Iterations	NA	92	68	43	25	**Mean Convergence Iterations**	NA	96	88	47	39
Number of Fitness Evaluation	445	720	795	580	450	**Number of Fitness Evaluation**	460	740	780	760	775

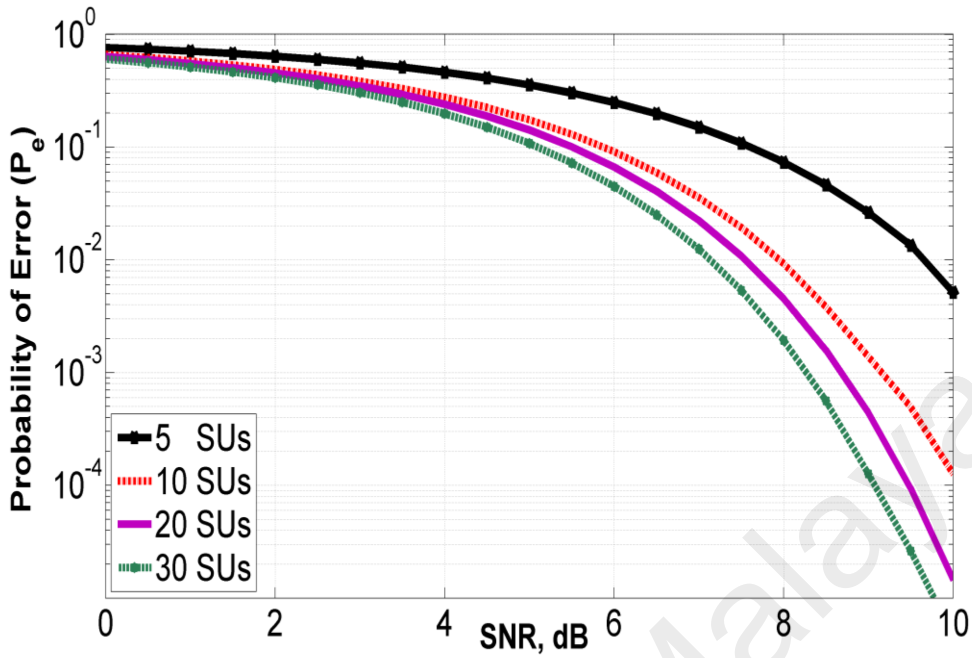
Table 4.9: Variance of SNR of all algorithms when the population size is 25.

Iteration Number	5	10	15	20	25	30	35	40	45	50	55
ICA	0.75	0.21	0.98	0.57	0.0004	0	0	0	0	0	0
PSO	0.65	0.64	0.38	0.24	0.28	0.62	0.04	0	0	0	0
GA	0.98	1	0.79	0.65	0.46	0.28	0.17	0.14	0.05	0.01	0

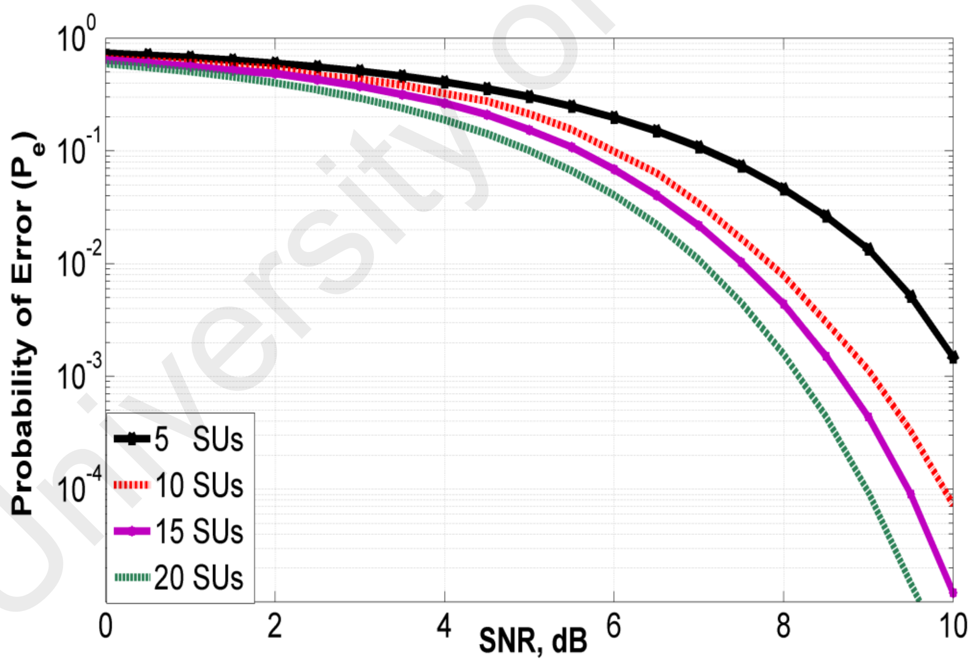
4.4. Results and Analysis for Combination of Diversity and CR Techniques

In the previous section, it is presented that how diversity works out and how it is supposed to be used on CR network. In this part, we go through more details to prove that the diversity concept can be used on system to improve the system efficiency and reduce the complexity of CRCSS. In any specific problem in CRCSS, it is required to find the optimal set of value to get the best performance. Since the parameters in each algorithm are generally problem-dependent, the set-and-test approach is used in this work to obtain the optimal set of parameters. In this respect, the CR environment has been tested separately for parameters as mentioned below in table 1 and the optimal values are found. Also, Table 1 demonstrates the overall simulation parameters used in this research.

The comparison between the diversity based and non-diversity based CRCSS is illustrated in Fig. 4.11(a) demonstrates a comparison of the P_e over different SNR on the FC in non-diversity based CRCSS for different number of SUs while Fig. 4.11(b) compares the effects of different number of SUs on diversity based CRCSS. It can be clearly observed that best weighting coefficients vector is generated by diversity based method with 20 SUs while non-diversity based method with 30 SUs is still slightly worse than that, resulting in maximized P_d. This 10 less number of SUs needed leads to less complexity, huge saving in experimental set up and higher performance.



a) Non-diversity based CRCSS for different number of SUs



b) Diversity based CRCSS

Figure 4.11: Applying diversity scheme on SUs in cognitive radio system

Table 4.10: Channel simulation parameters and different value for ICA in CRCSS

CR and channel parameters		Different parameters on ICA to test	
Number of users M	5,10,15,20,35	**Population size**	5,10,15,20,25,35
Bandwidth B	$6\ MHz$	**Mean colonies power coefficient**	$0 < \xi \leq 1$
Sensing time T_s	$25\ \mu sec$	**Assimilation coefficient**	$0 < \Upsilon \leq 2$
SU transmit power $P_{R,i}$	12 dBm	**selection pressure**	$0 < \alpha \leq 2$
The step size of P_f ($0 \leq P_f \leq 1$)	0.01	**Optimal parameters value for ICA**	
$P_{R,i}$	33 dBm	**Number of countries**	25
${\sigma_s}^2$	35 dBm	**Mean colonies power coefficient**	0.15
AWGN of i^{th} PU-SU Channel	$20 \leq \sigma_{W_i}^2 \leq 30$ dBm	**Assimilation coefficient**	1.7
AWGN of i^{th} SU-FC Channel	$20 \leq {\delta_i}^2 \leq 30$ dBm	**selection pressure**	1.2
channel gains	$10 \leq g_i \leq 20$ dBm		
channel gains	$10 \leq h_i \leq 20$ dBm		

4.5. Summary

In this chapter, all conventional and iterative methods (PSO-, GA-, NDC-, MDC- and MRC-based methods) in CRCSS are discussed and the proposed methods (MICA) compared with the existing techniques to show the robustness of our proposed method. Also, space diversity techniques are rewired and the new iterative algorithms are proposed to overcome imperfect channel estimation and improve received SNR and QoS. Afterwards, the developed diversity method is applied on new CRCSS to improve overall performance of the system and reduce the number of cooperative users (SUs) in system which leads to real time application and less complexity.

Results and comparison of conventional and iterative algorithms confirmed the reliability of the proposed method, i.e., an approximate improvement of 30.8% and 48.2% of the convergence speed of ICA-based method compared to PSO- and GA-based schemes (Neyman Pearson). In Minimax criteria for fix P_e of 0.5×10^{-4}, the mean modified ICA-based requires about 23 iterations while the same error rate can be obtained after 38 and 124 iterations for mean PSO- and GA-based consequently (about 40% improvement in terms of the required numbers of iterations which leads to less complexity and real time application). For a two-branch diversity, the MRC approximately requires 3 dB higher SNR than that of modified ICA-based technique to achieve a BER = 10^{-4}. Also, max curve in ICA method converges after 18 iterations whereas about 31 iterations of PSO algorithm are needed for convergence. This indicates that the convergence speed of the ICA is higher than both PSO and GA methods as well as pother conventional techniques (Space diversity Combining).

CHAPTER 5 : CONCLUSION AND FUTURE WORK

5.1.Conclusion

In this research, intrinsic properties along with current research challenges in CR spectrum management are presented. Especially, we investigate recent spectrum management functionalities for instance spectrum sensing, decision, sharing, and spectrum mobility. Mainly the current thesis contributes in three different subjects in CRN which are improving sensing and detection in CR cooperative spectrum sensing (CRCSS), enhancing SNR in space diversity combining in imperfect channel estimation, and introducing diversity base CRCSS.

Firstly, an evaluation of the detection performance for CRCSS using iterative and conventional methods is proposed. A main challenge facing CRCSS is the proper selection of the weighting coefficient of each SU. Consequently, techniques to optimize these coefficients are vital to the overall detection performance of the system. However, modified ICA SDF-based method has been proposed and extensively compared with all other conventional techniques such as PSO-, GA-, NDC-, MDC- and MRC-based methods. Simulation results indicate that the proposed scheme outperforms all other SDF-based schemes and almost the same performance as PSO-assisted. The sensing capability, detection accuracy, convergence rate and less complexity of modified ICA- assisted method are shown as the advantages of the proposed technique. In Minimax criteria for fix P_e of 0.5×10^{-4}, the mean modified ICA-based requires about 23 iterations while the same error rate can be obtained after 38 and 124 iterations for mean PSO- and GA-based consequently (about 40% improvement in terms of the required numbers of iterations which leads to less complexity and real time application).

Secondly, SNR in space diversity combining is improved by new proposed modified ICA algorithm in comparing with MRC (for instance, for a two-branch diversity, the MRC approximately requires almost 3 dB higher SNR than that of ICA-based to achieve a BER $= 10^{-4}$). Also, to improve the overall outcome of CRCSS, modified ICA-based diversity combining proposed at each SU's receiver (ICA-based diversity CRCSS) to improve the received signal quality by SUs and reduce the number of required SUs in CRCSS (less complexity and laboratory set up cost of CR network).

5.2. Future Works

In the current research, CRCSS are well investigated and new method proposed to enhance sensing and detection performance and guarantee efficient utilization of spectrum. Also, a fair comparison with the existing techniques has been done to show the reliability of our proposed method. On the next part, space diversity techniques are rewired and new iterative algorithms are proposed to overcome the imperfect channel estimation, enhance received SNR and guarantee the robustness of received signal. The proposed space diversity method is implemented to new CRCSS modified ICA-based method for improving the spectrum utilization and decreasing number of required cooperative users (SUs) in CSS which leads to less complexity and real time application. In the future work the security concept in CRCSS communication must be also considered to complete the accuracy of the system.

Since we have no access to the required equipment in the university (and even in Malaysia) to do set up of the whole network, one of the future plan would be doing experiments on diversity based CRCSS methods. On the other hand, spectrum mobility and sharing also are not deeply investigated and still need to do more research on them. It will be a very unique topic for future research to manage all four parts in spectrum management (spectrum sensing, decision, mobility and sharing) in one experiment and set up overall CR network (of course, it would be a very expensive experiment and need to be supported by government or some big serves provider companies, like Maxis, TM, Motorola, Ericsson, and Siemens).

REFERENCES

Aalo, V., & Zhang, J. (1999). On the effect of cochannel interference on average error rates in Nakagami-fading channels. IEEE Communications Letters, 3(5), 136-138.

Aatique, M. (1997). Evaluation of TDOA techniques for position location in CDMA systems (Doctoral dissertation, Virginia Polytechnic Institute and State University).

Ahn, K. S., & Heath, R. W. (2009). Performance analysis of maximum ratio combining with imperfect channel estimation in the presence of cochannel interferences. IEEE Transactions on Wireless Communications , 8(3), 1080-1085

Akbari, M., Hossain, M. K., Manesh, M. R., El-Saleh, A. A., & Kareem, A. M. (2012). Minimizing sensing decision error in cognitive radio networks using evolutionary algorithms. KSII Transactions on Internet and Information Systems (TIIS), 6(9), 2037-2051

Akbari, M., Manesh, M. R., El-Saleh, A. A., & Ismail, M. (2012). Improved soft fusion-based cooperative spectrum sensing using particle swarm optimization. IEICE Electronics Express, 9(6), 436-442.

Akyildiz, I. F., Lee, W. Y., Vuran, M. C., & Mohanty, S. (2006). NeXt generation/dynamic spectrum access/cognitive radio wireless networks: a survey. Computer Networks, 50(13), 2127-2159.

Al-Qahtani, F. S., Zummo, S. A., Gurung, A. K., & Hussain, Z. M. (2010). Spectral efficiency of maximum ratio combining (MRC) over slow fading with estimation errors. Digital Signal Processing, 20(1), 85-96.

Annavajjala, R., & Milstein, L. B. (2005). Performance analysis of linear diversity-combining schemes on Rayleigh fading channels with binary signaling and Gaussian weighting errors. IEEE Transactions, Wireless Communications, 4(5), 2267-2278.

Annavajjala, R., Cosman, P. C., & Milstein, L. B. (2007). Performance analysis of linear modulation schemes with generalized diversity combining on Rayleigh fading channels with noisy channel estimates. IEEE Transactions Information Theory, 53(12), 4701-4727.

Atashpaz-Gargari, E., & Lucas, C. (2007). Designing an optimal PID controller using Colonial Competitive Algorithm. In Proceedings of the First Iranian Joint Congress on Fuzzy and Intelligent Systems, Mashhad, Iran.

Bae, S., & Kim, H. (2014). Unlimited cooperative sensing with energy detection for cognitive radio. Communications and Networks, Journal of, 16(2), 172-182.

Bian, K., Park, J. M., & Gao, B. (2014). Coexistence-Aware Spectrum Sharing for Homogeneous Cognitive Radio Networks. In Cognitive Radio Networks (pp. 61-75). Springer International Publishing.

Bouabdallah, N., & Boutaba, R. (2013). Reliable and energy efficient cooperative detection in wireless sensor networks. Computer Communications, 36(5), 520-532

Bougard, B. ; Pollin, S. ; Craninckx, J. ; Bourdoux, A. ; Ven der Perre, L. ; Catthoor, F. (2007). Green Reconfigurable Radio Systems. IEEE Signal Processing Magazine, 24(3), 90-101.

Cabric, D., Mishra, S. M., & Brodersen, R. W. (2004, November). Implementation issues in spectrum sensing for cognitive radios. In Signals, systems and computers, 2004. IEEE Conference record of the thirty-eighth Asilomar conference on (Vol. 1, pp. 772-776).

Cao, L., & Zheng, H. (2012). Balancing reliability and utilization in dynamic spectrum access. IEEE/ACM Transactions on Networking (TON), 20(3), 651-661.

Chandra, R., Mahajan, R., Moscibroda, T., Raghavendra, R., & Bahl, P. (2008). A case for adapting channel width in wireless networks. ACM SIGCOMM computer communication review, 38(4), 135-146.

Chen, Y. S., & Liao, S. H. (2012). Spectrum-aware routing in discontinuous orthogonal frequency division multiplexing-based cognitive radio ad hoc networks. IET networks, 1(1), 20-33.

Christian, I., Moh, S., Chung, I., & Lee, J. (2012). Spectrum mobility in cognitive radio networks. IEEE Communications Magazine, 50(6), 114-121.

Cole, K. S. (1932). A Theory of Surface Conductance at an Electrolyte-Solid Interface. Journal of Applied Physics, 3(2), 114-118.

Communications and Mobile Computing: Connecting the World Wirelessly (pp. 489-494). ACM.

Cui, J., & Sheikh, A. U. (1999). Outage probability of cellular radio systems using maximal ratio combining in the presence of multiple interferers. IEEE Transactions Communications, 47(8), 1121-1124.

Cui, J., & Sheikh, A. U. (1999). Outage probability of cellular radio systems using maximal ratio combining in the presence of multiple interferers. Communications, IEEE Transactions on, 47(8), 1121-1124.

Dinamani, A., Das, S., Bijendra, L., Shruti, R., Babina, S., & Kiran, B. (2013, December). Performance of a hybrid MRC/SC diversity receiver over Rayleigh fading channel. In Circuits, Controls and Communications (CCUBE), IEEE.2013 International conference on (pp. 1-4).

El-Saleh, A. A., Ismail, M., & Ali, M. A. M. (2011). Genetic algorithm-assisted soft fusion-based linear cooperative spectrum sensing. IEICE Electronics Express, 8(18), 1527-1533

El-Saleh, A. A., Ismail, M., Ali, M. A. M., & Arka, I. H. (2010). Hybrid SDF-HDF cluster-based fusion scheme for cooperative spectrum sensing in cognitive radio networks. KSII Transactions on Internet and Information Systems (TIIS), 4(6), 1023-1041.

Eng, T., Kong, N., & Milstein, L. B. (1996). Comparison of diversity combining techniques for Rayleigh-fading channels. IEEE Transactions on Communications, 44(9), 1117-1129.

Fang, X., Yang, D., & Xue, G. (2013). Taming wheel of fortune in the air: An algorithmic framework for channel selection strategy in cognitive radio networks. IEEE Transactions on Vehicular Technology, 62(2), 783-796.

Ganesan, G., & Li, Y. (2007). Cooperative spectrum sensing in cognitive radio, part I: Two user networks. Wireless Communications, IEEE Transactions on, 6(6), 2204-2213.

Gans, Michael J. "The effect of Gaussian error in maximal ratio combiners." IEEE Transactions on Communication Technology 19.4 (1971): 492-500

Ge, W., Chen, S., Ji, H., Li, X., & Leung, V. C. (2013). Green Access Point Selection for Wireless Local Area Networks Enhanced by Cognitive Radio.Mobile Networks and Applications, 18(4), 553-566.

Ghasemi, A., & Sousa, E. S. (2005, November). Collaborative spectrum sensing for opportunistic access in fading environments. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on (pp. 131-136).

Ghosh, C., Roy, S., & Rao, M. B. (2012). Modeling and validation of channel idleness and spectrum availability for cognitive networks. IEEE Journal Selected Areas in Communications, 30(10), 2029-2039.

Gifford, W. M., Win, M. Z., & Chiani, M. (2008). Antenna subset diversity with non-ideal channel estimation. Wireless Communications, IEEE Transactions on, 7(5), 1527-1539.

Godara, L. C. (Ed.). (2001). Handbook of antennas in wireless communications. CRC press.

Grace, D., Chen, J., Jiang, T., & Mitchell, P. D. (2009, June). Using cognitive radio to deliver ‘green’communications. In Cognitive Radio Oriented Wireless Networks and Communications, 2009. CROWNCOM'09. IEEE.4th International Conference on (pp. 1-6).

Grondalen, O., Lahteenoja, M., & Gronsund, P. (2011, May). Evaluation of business cases for a cognitive radio network based on wireless sensor network. In New Frontiers in Dynamic Spectrum Access Networks (DySPAN), 2011 IEEE Symposium on (pp. 242-253).

Guimaraes, D. A., & de Souza, R. A. A. (2012). Implementation-oriented model for centralized data-fusion cooperative spectrum sensing. IEEE Communications Letters, 16(11), 1804-1807.

Gur, G., & Alagoz, F. (2011). Green wireless communications via cognitive dimension: an overview. IEEE Network, 25(2), 50-56.

Hämäläinen, S., Sanneck, H., & Sartori, C. (2012). LTE self-organising networks (SON): network management automation for operational efficiency. John Wiley & Sons.

Hamdi, K., Hasna, M. O., Ghrayeb, A., & Letaief, K. B. (2013). Opportunistic spectrum sharing in relay-assisted cognitive systems with imperfect

Han, C., Harrold, T., Armour, S., Krikidis, I., Videv, S., Grant, P. M., ... & Hanzo, L. (2011). Green radio: radio techniques to enable energy-efficient wireless networks. IEEE Communications Magazine, 49(6), 46-54.

Hasan, Z., Boostanimehr, H., & Bhargava, V. K. (2011). Green cellular networks: A survey, some research issues and challenges. IEEE Communications Surveys & Tutorials, 13(4), 524-540.

Haykin, S. (2005). Cognitive radio: brain-empowered wireless communications. IEEE Journal on Selected Areas in Communications, 23(2), 201-220.

Jayaweera, S. K., Bkassiny, M., & Avery, K. A. (2011). Asymmetric cooperative communications based spectrum leasing via auctions in cognitive radio networks. IEEE Transactions on Wireless Communications, 10(8), 2716-2724.

Karagiannidis, G. K., Zogas, D. A., Sagias, N. C., Kotsopoulos, S. A., & Tombras, G. S. (2005). Equal-gain and maximal-ratio combining over nonidentical Weibull fading channels. IEEE Transactions on Wireless Communications, 4(3), 841-846

Kaveh, A., & Talatahari, S. (2010). Optimum design of skeletal structures using imperialist competitive algorithm. Computers & Structures, 88(21), 1220-1229.

Khabbazi, A., Atashpaz-Gargari, E., & Lucas, C. (2009). Imperialist competitive algorithm for minimum bit error rate beamforming. International Journal of Bio-Inspired Computation, 1(1-2), 125-133.

Kim, S. J., Dall'Anese, E., & Giannakis, G. B. (2011). Cooperative spectrum sensing for cognitive radios using Kriged Kalman filtering. IEEE Journal of Selected Topics in Signal Processing, 5(1), 24-36.

Kong, N. (2009). Performance comparison among conventional selection combining, optimum selection combining and maximal ratio combining. Paper presented at the Communications, 2009. ICC'09. IEEE International Conference on.

Kong, N., Eng, T., & Milstein, L. B. (1995, November). A selection combining scheme for RAKE receivers. In Universal Personal Communications. 1995. Record., 1995 Fourth IEEE International Conference on (pp. 426-430).

Krasniqi, B., Wrulich, M., & Mecklenbräuker, C. F. (2009, September). Network-load dependent partial frequency reuse for LTE. In Communications and Information Technology, 2009. ISCIT 2009. IEEE. 9th International Symposium on (pp. 672-676).

Lee, E. A., & Messerschmitt, D. G. (2004). Digital communications: Springer.

Lee, W. Y., & Akyildiz, I. F. (2012). Spectrum-aware mobility management in cognitive radio cellular networks. IEEE Transactions on Mobile Computing, 11(4), 529-542.

Lee, W., & Cho, D. H. (2013). Channel selection and spectrum availability check scheme for cognitive radio systems considering user mobility. IEEE Communications Letters, 17(3), 463-466.

Li, Y., & Jayaweera, S. K. (2013). Dynamic spectrum tracking using energy and cyclostationarity-based multi-variate non-parametric quickest detection for cognitive radios. IEEE Transactions on Wireless Communications, 12(7), 3522-3532

Li, Z., Yu, F. R., & Huang, M. (2009, April). A cooperative spectrum sensing consensus scheme in cognitive radios. In INFOCOM 2009, IEEE (pp. 2546-2550).

Lien, S. Y., Cheng, S. M., Shih, S. Y., & Chen, K. C. (2012). Radio resource management for QoS guarantees in cyber-physical systems. IEEE Transactions on Parallel and Distributed Systems, 23(9), 1752-1761.

Lu, K., Rong, B., Kota, S. L., & Wang, X. (2013). Next generation cognitive cellular networks: spectrum sharing and trading [Guest editorial]. IEEE Wireless Communications, 20(2), 10-11.

Ma, J., Li, G. Y., & Juang, B. H. (2009). Signal processing in cognitive radio. Proceedings of the IEEE, 97(5), 805-823.

Ma, Y., Schober, R., & Zhang, D. (2007). Exact BER for M-QAM with MRC and imperfect channel estimation in Rician fading channels. IEEE Transactions on Wireless Communications, 6(3), 926-936.

Mallik, R. K., & Win, M. Z. (2002). Analysis of hybrid selection/maximal-ratio combining in correlated Nakagami fading. IEEE Transactions on Communications, 50(8), 1372-1383.

Mallik, R. K., & Winters, J. H. (2010). Deterministic linear combining receivers for random fading channels. IEEE Transactions on Communications, 58(9), 2630-2638.

Menon, R., Buehrer, R. M., & Reed, J. H. (2005, November). Outage probability based comparison of underlay and overlay spectrum sharing techniques. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on (pp. 101-109).

Mitola III, J., & Maguire Jr, G. Q. (1999). Cognitive radio: making software radios more personal. IEEE Personal Communications, 6(4), 13-18.

Mitola, J. (2000). Cognitive Radio---An Integrated Agent Architecture for Software Defined Radio.

Mukherjee, A., & Swindlehurst, A. L. (2013). Prescient precoding in heterogeneous DSA networks with both underlay and interweave MIMO cognitive radios. IEEE Transactions on Wireless Communications, 12(5), 2252-2260.

Najafizadeh, L., & Tellambura, C. (2006). BER analysis of arbitrary QAM for MRC diversity with imperfect channel estimation in generalized Ricean fading channels. IEEE Transactions on Vehicular Technology, 55(4), 1239-1248.

Nazari-Shirkouhi, S., Eivazy, H., Ghodsi, R., Rezaie, K., & Atashpaz-Gargari, E. (2010). Solving the integrated product mix-outsourcing problem using the imperialist competitive algorithm. Expert Systems with Applications, 37(12), 7615-7626.

Nekovee, M., Irnich, T., & Karlsson, J. (2012). Worldwide trends in regulation of secondary access to white spaces using cognitive radio. Wireless Communications, IEEE, 19(4), 32-40.

Neyman, J., & Pearson, E. S. (1933). On the problem of the most efficient tests of statistical hypotheses. Philosophical Transactions of the Royal Society of London. Series A, Containing Papers of a Mathematical or Physical Character, 231, 289-337.

Niknam, T., Fard, E. T., Pourjafarian, N., & Rousta, A. (2011). An efficient hybrid algorithm based on modified imperialist competitive algorithm and K-means for data clustering. Engineering Applications of Artificial Intelligence, 24(2), 306-317.

O. Ileri, D. Samardzija, and N. B. Mandayam, "Demand Responsive Pricing and Competitive Spectrum Allocation via Spectrum Server," Proc. IEEE DySPAN 2005, Nov. 2005, pp. 194–202.

Palicot, J. (2009, June). Cognitive radio: an enabling technology for the green radio communications concept. In Proceedings of the 2009 International Conference on Wireless

Palicot, J., & Roland, C. (2005, October). On the use of cognitive radio for decreasing the electromagnetic radiations. In URSI (Vol. 5, pp. 23-29).

Palicot, J., Moy, C., & Hachemani, R. (2009). Multilayer sensors for the sensorial radio bubble. Physical Communication, 2(1), 151-165.

Pamula, V. K., Vempati, S. R., Khan, H., & Tipparti, A. K. (2013, October). Performance analysis of linear diversity combining schemes on Nakagami-0.5 fading channels. In Signal and Image Processing Applications (ICSIPA), 2013 IEEE International Conference on (pp. 117-122).

Peña-Martin, J. P., Romero-Jerez, J. M., Aguilera, G., & Goldsmith, A. J. (2009). Performance comparison of MRC and IC under transmit diversity. IEEE Transactions on Wireless Communications, 8(5), 2484-2493.

Peng, C., Zheng, H., & Zhao, B. Y. (2006). Utilization and fairness in spectrum assignment for opportunistic spectrum access. Mobile Networks and Applications, 11(4), 555-576.

Qi, C., Wang, J., & Li, S. (2009, January). Weighted-clustering cooperative spectrum sensing in cognitive radio context. In Communications and Mobile Computing, 2009. CMC'09. WRI International Conference on IEEE. (Vol. 1, pp. 102-106).

Radaydeh, R. M. (2009). MRC in the presence of asynchronous cochannel interference over frequency-selective Rayleigh fading channels. IEEE Transactions on Vehicular Technology, 58(8), 4329-4341.

Reynolds, J. (2003). Going Wi-Fi: a practical guide to planning and building an 802.11 network. CMP Books.

Roy, S., & Fortier, P. (2004). Maximal-ratio combining architectures and performance with channel estimation based on a training sequence. IEEE Transactions on Wireless Communications, 3(4), 1154-1164.

Roy, S., & Fortier, P. (2004). Maximal-ratio combining architectures and performance with channel estimation based on a training sequence. IEEE Transactions on Wireless Communications, 3(4), 1154-1164.

Sakarellos, V., Skraparlis, D., Panagopoulos, A., & Kanellopoulos, J. (2011). Cooperative diversity performance of selection relaying over correlated shadowing. Physical Communication, 4(3), 182-189.

Salameh, H. A. B., Krunz, M., & Manzi, D. (2014). Spectrum bonding and aggregation with guard-band awareness in cognitive radio networks. IEEE Transactions on Mobile Computing, 13(3), 569-581.

Sboui, L., Rezki, Z., & Alouini, M. (2014). Achievable Rate of Spectrum Sharing Cognitive Radio Systems over Fading Channels at Low Power Regime, IEEE Transactions Wireless Communications, 13(11) ,6461 – 6473.

Senthuran, S., Anpalagan, A., & Das, O. (2012). Throughput analysis of opportunistic access strategies in hybrid underlay—overlay cognitive radio networks. IEEE Transactions on Wireless Communications, 11(6), 2024-2035.

Shah, A., & Haimovich, A. M. (2000). Performance analysis of maximal ratio combining and comparison with optimum combining for mobile radio communications with cochannel interference. IEEE Transactions on Vehicular Technology, 49(4), 1454-1463.

Sherman, M., Mody, A. N., Martinez, R., Rodriguez, C., & Reddy, R. (2008). IEEE standards supporting cognitive radio and networks, dynamic spectrum access, and coexistence. IEEE Communications Magazine, 46(7), 72-79.

Simon, M. K., & Alouini, M. S. (2005). Digital communication over fading channels (Vol. 95). John Wiley & Sons.

Skraparlis, D., Sakarellos, V., Panagopoulos, A., & Kanellopoulos, J. (2009). Performance of N-branch receive diversity combining in correlated lognormal channels.

Stotas, S., & Nallanathan, A. (2011). Enhancing the capacity of spectrum sharing cognitive radio networks. IEEE Transactions on Vehicular Technology, 60(8), 3768-3779.

Sun, Y., Phillips, C., Bai, J., Zhang, H., Hou, J., & Wang, S. (2013, December). Cognitive Radio Mobility Based Routing Protocol for CR enabled Mobile Ad Hoc Networks. In Globecom Workshops (GC Wkshps), 2013 IEEE(pp. 603-609).

Tan, K., Liu, H., Zhang, J., Zhang, Y., Fang, J., & Voelker, G. M. (2011). Sora: high-performance software radio using general-purpose multi-core processors. Communications of the ACM, 54(1), 99-107.

Thompson, J. S. (2004, March). Antenna array performance with channel estimation errors. In Smart Antennas, 2004. IEEE.ITG Workshop on (pp. 75-78).

Tragos, E. Z., Zeadally, S., Fragkiadakis, A. G., & Siris, V. A. (2013). Spectrum Assignment in Cognitive Radio Networks: A Comprehensive Survey.IEEE Communications Surveys and Tutorials, 15(3), 1108-1135.

Treeumnuk, D., & Popescu, D. C. (2013). Enhanced spectrum utilisation in dynamic cognitive radios with adaptive sensing. IET Signal Processing, 8(4), 339-346.

United Nations. 1987."Report of the World Commission on Environment and Development." General Assembly Resolution 42/187,11 December 1987. Retrieved: 2007-04-12.

Unnikrishnan, J., & Veeravalli, V. V. (2008). Cooperative sensing for primary detection in cognitive radio. IEEE Journal of Selected Topics in Signal Processing, 2(1), 18-27.

Verdú, S. (1998). Multiuser DetectionCambridge University Press. Cambridge, UK.

Visotsky, E., Kuffner, S., & Peterson, R. (2005, November). On collaborative detection of TV transmissions in support of dynamic spectrum sharing. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on (pp. 338-345).

Wang, W., Shin, K. G., & Wang, W. (2012). Distributed resource allocation based on queue balancing in multihop cognitive radio networks. Networking, IEEE/ACM Transactions on, 20(3), 837-850.

Wang, Y., Zhang, Z., Ma, L., & Chen, J. (2014). SVM-Based Spectrum Mobility Prediction Scheme in Mobile Cognitive Radio Networks. The Scientific World Journal, 2014.

Win, M. Z., & Winters, J. H. (1999). Analysis of hybrid selection/maximal-ratio combining in Rayleigh fading. In Communications, 1999. ICC'99. 1999 IEEE International Conference on (Vol. 1, pp. 6-10).

Xing, Y., Chandramouli, R., & Mangold, S. (2006). Dynamic spectrum access in open spectrum wireless networks. IEEE Journal on Selected Areas in Communications, 24(3), 626-637.

Yao, Y., Erman, D., & Popescu, A. (2011). Spectrum Decision for Cognitive Radio Networks. In Scandinavian Workshop on Wireless Ad-hoc NeLee, W. Y., & Akyldiz, I. F. (2011). A spectrum decision framework for cognitive radio networks. IEEE Transactions on Mobile Computing, 10(2), 161-174.

You, R., Li, H., & Bar-Ness, Y. (2005). Diversity combining with imperfect channel estimation. IEEE Transactions on Communications, 53(10), 1655-1662.

Zhang, H., Gladisch, A., Pickavet, M., Tao, Z., & Mohr, W. (2010). Energy efficiency in communications. IEEE Communications Magazine, 48(11), 48-49.

Zhang, X., & Beaulieu, N. C. (2007). Explicit analytical expressions for outage and error rate of diversity cellular systems in the presence of multiple interferers and correlated Rayleigh fading. IEEE Transactions on Communications, 55(12), 2303-2315.

Zhang, Y., Zhang, Q., & Wu, S. (2010). Entropy-based robust spectrum sensing in cognitive radio. IET Communications, 4(4), 428-436.

Zhao, J., Zheng, H., & Yang, G. H. (2005, November). Distributed coordination in dynamic spectrum allocation networks. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on (pp. 259-268).

Zhao, L., Biao, S., & Jiandong, L. (2013). Interference alignment and cancellation based concurrent transmission and scheduling scheme for multiuser CR-MIMO system. Communications, China, 10(8), 36-43.

Zhao, Q., Tong, L., Swami, A., & Chen, Y. (2007). Decentralized cognitive MAC for opportunistic spectrum access in ad hoc networks: A POMDP framework. IEEE Journal on Selected Areas in Communications, 25(3), 589-600.

Zheng, H., & Cao, L. (2005, November). Device-centric spectrum management. In New Frontiers in Dynamic Spectrum Access Networks, 2005. DySPAN 2005. 2005 First IEEE International Symposium on (pp. 56-65).

Zhou, H., Liu, B., Liu, Y., Zhang, N., Gui, L., Li, Y., ... & Yu, Q. (2014). A Cooperative Matching Approach for Resource Management in Dynamic Spectrum Access Networks.

LIST OF PUBLICATIONS

- Akbari, M., & Ghanbarisabagh, M. (2014). A Novel Evolutionary-Based Cooperative Spectrum Sensing Mechanism for Cognitive Radio Networks. Wireless Personal Communications, 79(2), 1017-1030.

- Akbari, M., Manesh, M. R., El-Saleh, A. A., & Reza, A. W. (2014). Receiver Diversity Combining Using Evolutionary Algorithms in Rayleigh Fading Channel. The Scientific World Journal, 2014.

- Mohsen Akbari, Ahmed Wasif Reza, Kamarul Ariffin Noordin, (2014) Efficient Algorithms on Cognitive Radio Cooperative Spectrum Sensing to Improve Reliability and Performance: A review. The International Journal of Distributed Sensor Networks" (Hindawai). (ISI-indexed).

- Mohsen Akbari, Ahmed Wasif Reza and Kamarul Ariffin Noordin, (2016) Recent Efficient Iterative Algorithms on Cognitive Radio Cooperative Spectrum Sensing to Improve Reliability and Performance. The International Journal of Distributed Sensor Networks".Article ID 3701308, 14 pages (ISI-indexed)

- Akbari, M.; Reza, A.W.; Noordin, K.A.; Manesh, M.R.; Hindia, M.N. (2014) Summary of best efficient algorithms on cognitive radio cooperative spectrum sensing to improve QoS. In: Proceedings of the 3rd International Conference on Computer Engineering & Mathematical Sciences (ICCEMS 2014), 04-05 Dec 2014, Langkawi, Malaysia.