PERFORMANCE OPTIMIZATION OF ENERGY EFFICIENT, FULL DUPLEX ENERGY HARVESTING COGNITIVE RADIO NETWORK

Thesis Submitted for the Award of the Degree of

DOCTOR OF PHILOSOPHY

in

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DECLARATION

I, hereby declared that the presented work in the thesis entitled "PERFORMANCE OPTIMIZATION OF ENERGY EFFICIENT, FULL DUPLEX ENERGY HARVESTING COGNITIVE RADIO NETWORK" in fulfilment of degree of **Doctor of Philosophy (Ph. D.)** is outcome of research work carried out by me under the supervision Dr. Parulpreet Singh, working as Assistant Professor, in the School of Electrical and Electronics of Lovely Professional University, Punjab, India. In keeping with general practice of reporting scientific observations, due acknowledgements have been made whenever work described here has been based on findings of other investigator. This work has not been submitted in part or full to any other University or Institute for the award of any degree.

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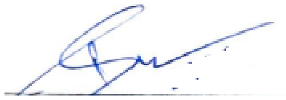
CERTIFICATE

This is to certify that the work reported in the Ph. D. thesis entitled "PERFORMANCE OPTIMIZATION OF ENERGY EFFICIENT, FULL DUPLEX ENERGY HARVESTING COGNITIVE RADIO NETWORK" submitted in fulfillment of the requirement for the reward of degree of **Doctor of Philosophy (Ph.D.)** in the Department of Electronics and Communication, School of Electronics and Electrical Engineering, is a research work carried out by Vikas Srivastava, Registration No.-41800911, is bonafide record of his/her original work carried out under my supervision and that no part of thesis has been submitted for any other degree, diploma or equivalent course.



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ABSTRACT

Wireless communication is one of the fastest-growing technologies. Increasing radio spectrum demand has resulted from the emergence of feature-rich wireless technology. Due to exponential increase in the number of wireless connected devices (such as internet-of-things, machine-to-machine communication, wireless sensor networks etc.), these are predicted to be 75.44 billion in 2025 which is almost five times more as compared to that of the 15.41 in the year 2015. In this thesis, we have initialized with the state-of-art of Cognitive Radio (CR) and its significance in the next generation communication systems to fulfil the huge spectrum demand. The significance of spectrum sharing/accessing techniques in CR and encouragement as well as motivation to pursue research in this field is presented. One key challenge is scarcity of available radio spectrum that make it ineffective. With the current spectrum allocation, particular bands are allocated to specific facilities, and only Primary users (PUs) can access licensed bands. CR technology is required enabling method that can opportunistically share the channel related to wireless with Secondary Users (SU). Each CR network user must be capable of doing sensing of spectrum, decision of spectrum, sharing of spectrum, and mobility of spectrum. To fulfil these functions, a CR must be cognitive, reconfigurable, and self-organized.

The main functions of CRs are spectrum sensing. Energy-Efficient design is essential in practical Cognitive Radio Networks (CRN) powered by batteries. The transmission power affects the Energy Efficiency (EE) of a CRN. The larger the transmission power, the more throughput can be obtained. However, it consumes more energy. This research work focuses on power allocation for maximizing the EE of CRN.

This thesis investigates the RF (Radio Frequency) energy harvesting (EH) technique in the CRN with energy detection spectrum sensing and examines different optimisation studies. First, EH is considered with the machine learning-based metaheuristic algorithm to measure residual energy of SU that can be utilized to increase SU's transmission efficiency and obtain throughput and lifetime. Therefore, in spectrum sensing, energy consumption can decrease and increase harvested energy, compare with previously proposed schemes, where sensing and EH are performed sequentially. In EH, use fraction of incoming RF power. So it, allows more energy to be available for

transmission, increasing SU's throughput and lifetime. Transmission power, harvested energy, lifetime and throughput are analysed with full-duplex and half-duplex modes.

This thesis proposes enhancements to spectrum sensing algorithms that improve detection performance while reducing computational complexity. The set objectives of the current work are as follows:

1. To propose a machine learning-based algorithm to optimize multi-band spectrum sensing in energy-harvesting Cognitive Radio Networks.
2. To propose a clustering-based spectrum sensing technique to improve system performance.
3. To develop a machine learning-based algorithm to reduce spectrum handoff events to minimize energy consumption.
4. To propose a machine learning-based predictive resource allocation strategy to enhance the performance of energy-harvesting CRNs.

Details of Four objectives are given below:

The first objective identifies Spectrum gaps through probability of detection, transmitting power, and sensing bandwidth with the help of metaheuristic algorithm based on machine learning (learnheuristic algorithm). So, EE increases by “Hybrid Support Vector Machine- Red Deer Algorithm” (“SVM-RDA”) concerning above parameter and compared with algorithms like Hybrid “Particle Swarm Optimization - Gravitational Search algorithm” (PSO-GSA), “PSO”, and “Artificial Bee Colony” (ABC).

Objective 2 proposes a clustering-based spectrum sensing technique for CRN. SUs makes a cluster. So, these clusters transfer local sensing data to a Fusion Centre (FC), and FC decides the status of the SU channel. The proposed SVM-RDA is evaluated on probability of error and probability of detection. Cluster-based spectrum sensing proposed in different literature has high complexity. The help of proposed cluster-based spectrum sensing increases the probability of detection. It decreases probability of error at various parameters like SUs' number, occupied band, and “signal-to-noise ratio (SNR)”. So, SVM-RDA’s performance is improved than other algorithms.

Objective 3 describes Spectrum handoff (SH) management, an important issue handled in CRN to ensure indefinite connection for SUs. The disadvantages of SH are consumption of power and communication delay . To reduce it, handoff should be minimized. During handoff, Dynamic spectrum access (DSA) check channel availability for SU , this thesis suggests using learnheuristic algorithm to tackle issue. Simulation results demonstrate that suggested “SVM-RDA” is less complex. The proposed algorithm's setup offers different parameters like total spectrum bandwidth, SU bandwidth, SNR, throughput, handoff delay time, unsuccessful handoffs number and total handoffs number. Thesis improves system handoff performance. Proposed algorithm's simulation results are compared with different PSO and genetic algorithm. Results demonstrate that proposed technique is better than other algorithms.

In objective 4, we address the problems of delayed convergence and the need for substantial state spaces in current deep Q-learning (DQL) based resource allocation (RA) techniques. RA in EH-CRN is enhanced by suggested “machine learning-based metaheuristic algorithm” (SVM-RDA), which considers capacity, average latency, and transmission power restrictions. Simulation results suggest the proposed algorithm provides resource utilization and greater convergence than previous methods in the literature.

ACKNOWLEDGMENTS

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Vikas Srivastava

VIKAS SRIVASTAVA

Date: 28 November 2023

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LIST OF ABBREVIATION

1.	Defence Advanced Research Projects Agency	DARPA
2.	Next-Generation	XG
3.	Dynamic Spectrum Access	DSA
4.	Secondary User	SU
5.	Primary User	PU
6.	Cognitive Radio	CR
7.	Cognitive Radio Networks	CRN
8.	Energy Efficiency	EE
9.	Spectrum Efficiency	SE
10.	Radio Frequency	RF
11.	Support Vector Machine- Red Deer Algorithm	SVM-RDA
12.	Particle Swarm Optimization -Gravitational Search algorithm	PSO-GSA
13.	Artificial Bee Colony	ABC
14.	Fusion Centre	FC
15.	Signal-to-Noise Ratio	SNR
16.	Deep Q-learning	DQL
17.	Resource Allocation	RA
18.	Quality of Service	QoS
19.	Non-Cooperative Spectrum Sensing	NCSS
20.	Cooperative Spectrum Sensing	CSS
21.	Cluster Head	CH
22.	Half-Duplex	HD
23.	Full-Duplex	FD
24.	Wireless Network after Next	WNaN
25.	Maximum Power Point Tracker	MPTT
26.	Energy Harvesting	EH
27.	Wireless Sensor Network	WSN
28.	Machine Learning	ML
29.	Social Cognitive Handover	SCH
30.	Genetic Algorithm	GA

31.	Improved Particle Swarm Optimization	iPSO
32.	Iterative Water Filling	IWF
33.	Energy Detection	ED
34.	Shuffled Frog-Leaping Algorithm	SFLA
35.	Artificial Intelligence	AI
36.	Artificial Neural Networks	ANN
37.	Fuzzy Logic	FL
38.	Spectrum Handoff	SH
39.	Received Signal Strength	RSS
40.	Cognitive Radio Ad Hoc Network	CRAHN
41.	Deep reinforcement learning	DRL
42.	Q Learning Resource Allocation	QLRA
43.	Stochastic Adaptive Random Sampling Algorithm	SARSA
44.	Finite Markov Decision Process	FMDP
45.	Energy Harvesting Resource allocation	EHRA
46.	Waterfall-based Power Allocation	WFPA
47.	Deep Q Learning reinforcement algorithm	DQLRA

LIST OF SYMBOLS

1.	Bandwidth of SU	B
2.	Sensing Spectrum Bandwidth	B_s
3.	Transmitting Data Bandwidth	$B-B_s$
4.	Energy Used by the SU	E_s
5.	Power Spectral Density of SU Signal	G_t
6.	SU's maximal transmitting power	$Q_{t,max}$
7.	AWGN noise	$W(n)$
8.	PU signal	$s(n)$
9.	AWGN channel gain	h
10.	Probability of Detection	P_d
11.	Probability of Missed Detection	P_m
12.	Probability of False Alarm	P_f
13.	PU Occupy the channel	p_{on}
14.	PU not occupy the channel	p_{off}
15.	Probability of detection by energy detector	q_d
16.	Probability of false alarm by energy detector	q_f
17.	Period of frame	T_p
18.	SNR of PU measured at SU	SNR_{pr}
19.	Throughput	c_1, c_2, c_3, c_4
20.	Energy consumption	e_1, e_2, e_3, e_4
21.	Total energy consumption	E_T
22.	Channel gain from PU to i^{th} SU	h_i
23.	PU signal	$S(j)$
24.	Noise	$n(j)$
25.	Hypothesis for PU existence	H1
26.	Hypothesis for PU absence	H0
27.	Cooperative probability of detection	C_d
28.	Cooperating SU numbers	L

CHAPTER 1

INTRODUCTION

Wireless communication is one of the few technologies drastically altering human life. The new age of communication began in 1901 when Marconi successfully demonstrated wireless transmission for the first time. Since that time, communication has seen significant changes. These wireless applications have changed over the past 100 years and are essential to modern life. Therefore, the twenty-first century has observed exponential growth of wireless devices in markets ranging from highly commercialized cellular and satellite communication systems to privately used amateur radio, from Wi-Fi networks to rarely seen deep space communication systems, from infrastructure-based radio and television broadcast systems to ad hoc-oriented wireless microphones and Bluetooth devices. The need for extra radio spectrum has expanded tenfold due to the fast adoption of smartphones and tablets and the recent developments in broadband technologies that offer internet access over large areas. It has been extremely challenging to meet this demand, partly due to differences in frequency assignments between different International Telecommunication Union regions. Most of the spectrum has already been allocated for various applications other than communications. Much of this spectrum was designated long ago based on policies that ensure access exclusivity [1].

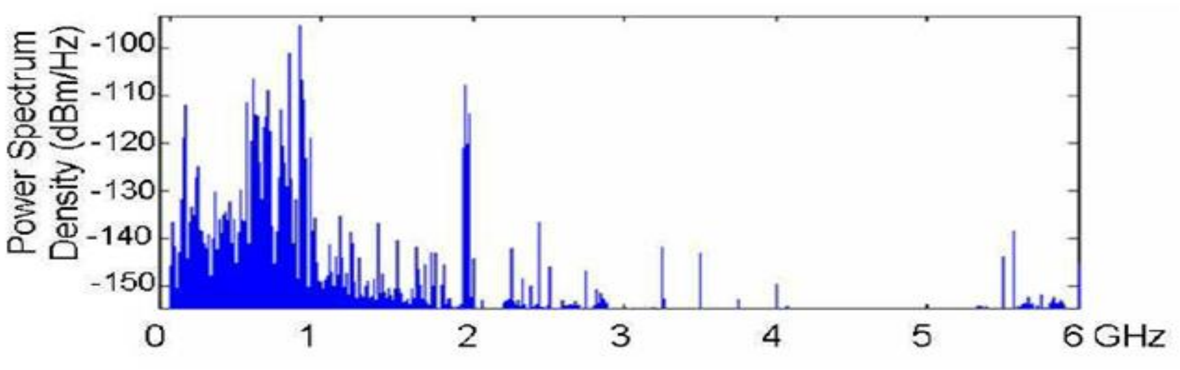

Figure 1.1: Spectrum utilization measurements up to 6GHz band [1]

3

The traditional approach to allocating spectrum is highly rigid in that frequency bands are granted exclusive licenses to their respective users for an extended time. In addition, there are limitations on transmitter power, which are intended to prevent systems from interfering with one another at all times. Since the majority of spectrum has already been allocated, locating unoccupied frequency bands for deploying new wireless applications or improving current ones has become challenging. In contrast to the spectrum scarcity issue, a study released by the Federal Communication Commission is a wake-up call for the whole communication sector all over the globe. Due to the strict spectrum allocation procedures in place, it has been discovered that a significant portion of bandwidth is often underutilized and that the given spectra are only sometimes used[1].

Figure 1.1 illustrates the spectrum utilization up to 6 GHz band. It can be observed that the spectrum is heavily used over a specific range of frequencies while some portion of spectrum is not utilized. Between 15% and 85% of the spectrum is used at different times and places. Because of this tight spectrum distribution strategy, there is a spectrum shortage and essentially no room for the effective deployment of future communication technologies[1].

1.1 HISTORICAL BACKGROUND

J. Mitola first presented CR in 2000. In 2002, the Federal Communications Commission (FCC) revealed very low spectral utilization and identified CR as important technology to remove this virtual spectrum shortage through spectrum awareness. As a consequence of this report, the FCC opened up the TV bands for opportunistic spectrum use (followed by the complete Digital Television transmission in February 2009) [2].

In the meantime, Defence Advanced Research Projects Agency (DARPA) embarked on the next-generation (XG) project that allows radios to go beyond regulatory borders with simple policy changes. The next-generation radios allocate new frequency bands among a group of radios that together form an XG-domain (opportunistic allocation) and identify the mechanisms for using those channels (opportunistic sharing). Finally, on November 4th, 2009, FCC issued a notice to allow opportunistic spectrum usage in the TV bands [2].

Since then, cognitive radio technology has developed into one of the most promising spectrum access technologies, offering great promise for resolving the issue of spectrum shortage. Contrary to the fixed spectrum allocation strategy, it allocates spectrum using the DSA method [3].

1.2 COGNITIVE RADIO

Radio frequency (RF) is essential in wireless communication because of securely regulated resources. Due to the growth in wireless services, RF spectrum demand increases, causing scarce spectrum resources. In contrast, it is reported that geographic spectrum and localized temporal consumption are shallow. When PU is absent, the FCC develops new spectrum policies, which permit SUs to access a licensed band opportunistically. Next-generation cellular networks are having trouble finding enough spectrum, but CR provides a possible solution using possibilities in the time, frequency, and space domains. Due to CR's capacity for learning about and interacting with its surroundings, conflicts may be avoided by recognizing the spectrum in the area. CR has been described in many different ways by different scholars and groups. One of the famous definitions is as follows: CR can change the parameters of the transmitter dynamically based on the operating environment, and it can also change itself based on the transfer parameters and the environment.CR senses external world and acquires information via signal processing assisted by artificial intelligence. Adjusting the wireless signal's statistical features in real-time is one of CR's capabilities, depending on the operational conditions. CR is intelligent and can pick up on changes in its surroundings in real-time[4].

In his PhD thesis, J. Mitola III first proposed the fundamental concept of enhancing spectrum usage using cognitive radio technology[5]. It's a radio that can detect the RF environment across a broad frequency range and change its transmission parameters to match the user's Quality of Service (QoS) needs. These radios include a distinctive feature that sets them apart from other current radio architectures: a broad sensing capability implemented in hardware for real-time assessment of the spectrum's utilization. It makes it possible for cognitive radio to identify the spectrum section that is not utilized or to determine the PU's location while operating in a licensed band. When licensed bands are available, it chooses the optimum channel to fit the end user's QoS needs. Some of the famous CR definitions are:

J. Mitola defined CR as [6]

"Cognitive radio is a goal-driven framework in which it autonomously observes the radio environment, infers context, accesses alternatives, generates plans, supervises multimedia services, and learns from its mistakes. This observes – think – act cycle is radically different from today's handsets that either blast out on the frequency set by the user or blindly take instructions from the network."

According to Simon Haykin, cognitive radio is [7]

"An intelligent wireless communication system that is aware of its surrounding environment and uses the methodology of understanding by building to learn from the environment (e.g., transmit power, carrier frequency, and modulation strategy) in real-time, with two primary objectives in mind.

(i) Highly reliable communication whenever and wherever needed

(ii) Efficient utilization of radio spectrum."

A definition of software-defined radio is[8]

"Radio in which communication systems are aware of their environment and internal state and can make decisions about their radio operating behaviour based on the information and predefined objectives. The environmental information may or may not include location information related to the communication system."

Two main characteristics of CR are:

(i) ***Cognitive capability:*** Radio can gather information about temporal and spatial fluctuations from its environment without the PU knowing its existence. This ability refers to the radio's capacity to collect data from its surroundings. Consequently, the optimal operating parameters and spectrum that are now accessible may be chosen.

(ii) ***Reconfigurability***: With the help of this feature, cognitive radio may be dynamically programmed to the radio environment. More particularly, the hardware configuration of the cognitive radio terminals allows for the programming of some frequencies and transmission protocols.

1.3 COGNITIVE RADIO MODULES

Figure 1.2 discuss cognitive radio module. Spectrum sensing allows SUs to find unutilised parts of radio spectrum by keeping an eye on the PU. Based on result of sensing, SU can access the channel.

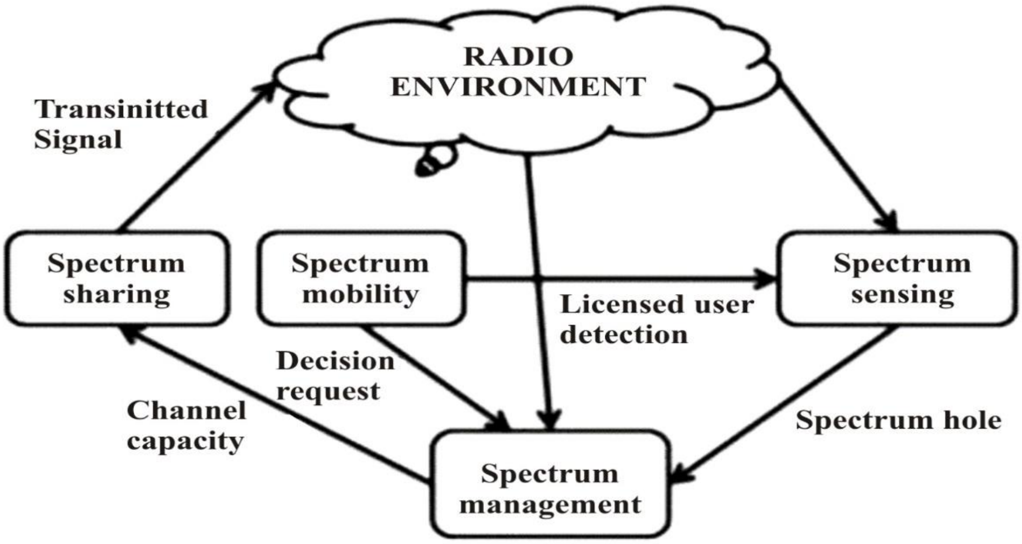

Figure 1.2: Modules of cognitive radio[12]

1.4 ARCHITECTURE OF COGNITIVE RADIO

Figure 1.3 represents a cognitive radio system architecture with 2 fundamental networks, i.e., primary and secondary networks, jointly utilizing spectrum in the same environments. The joint spectra are separated into sub-groups to accommodate various types of users. Spectrum bands are generally classified into 2 types: licensed (authorized) bands and unlicenced(unauthorized) bands. Licensed bands are held for particular applications, e.g., TV channels, radio, or radio communications, while anybody can utilize unauthorized bands without authorization. In contrast, unlicenced users are considered secondary BSs through unauthorized or authorized channels when licensed users are not involved. This design aims to improve wireless users' spectrum efficiency (SE) [9].

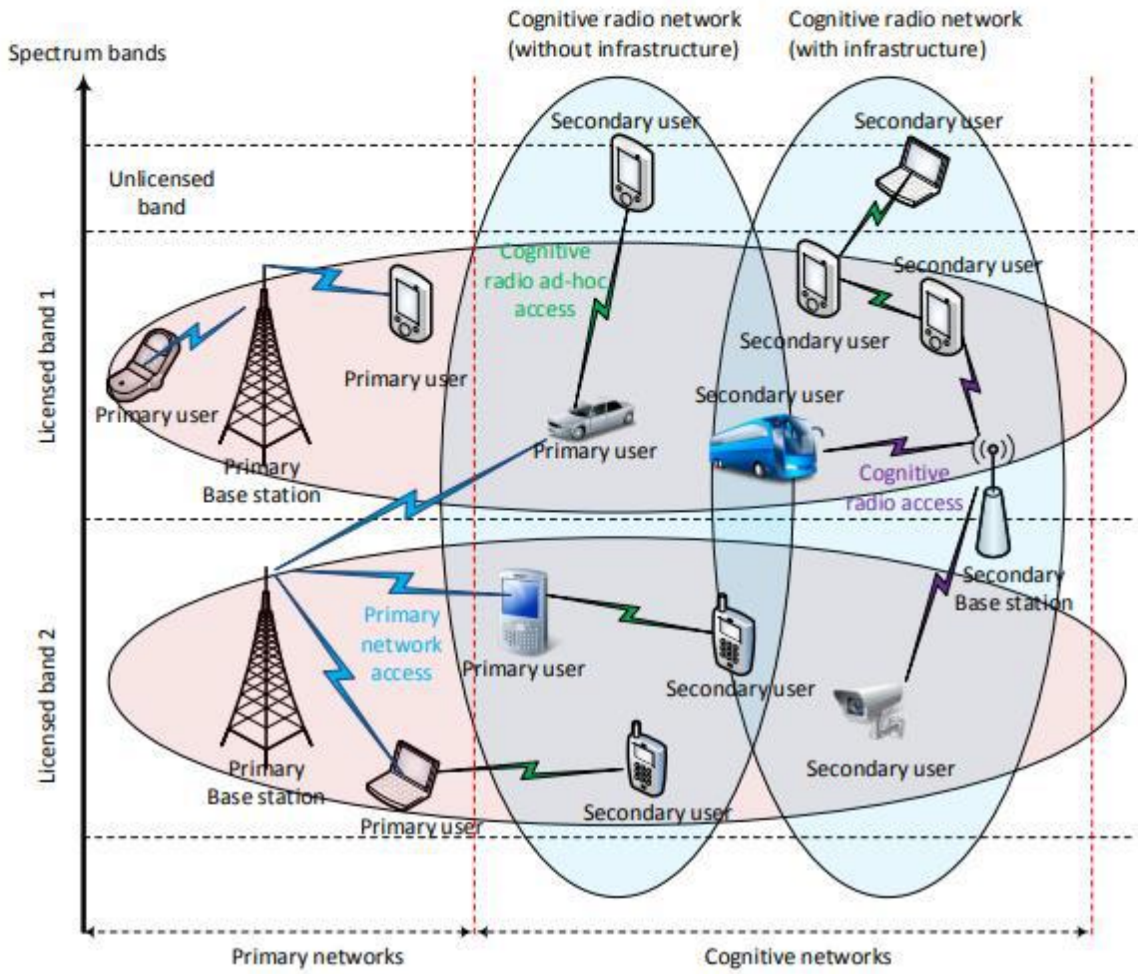

Figure 1.3: A basic architecture of CRN[9]

1.5 COGNITIVE CYCLE

The technique enables a cognitive user, also known as a SU, to be continually aware of its surroundings and to change its communication parameters so that it may live with PUs on the same channel without exceeding the PU's interference limit. The three significant steps of cognitive cycle are as follows:

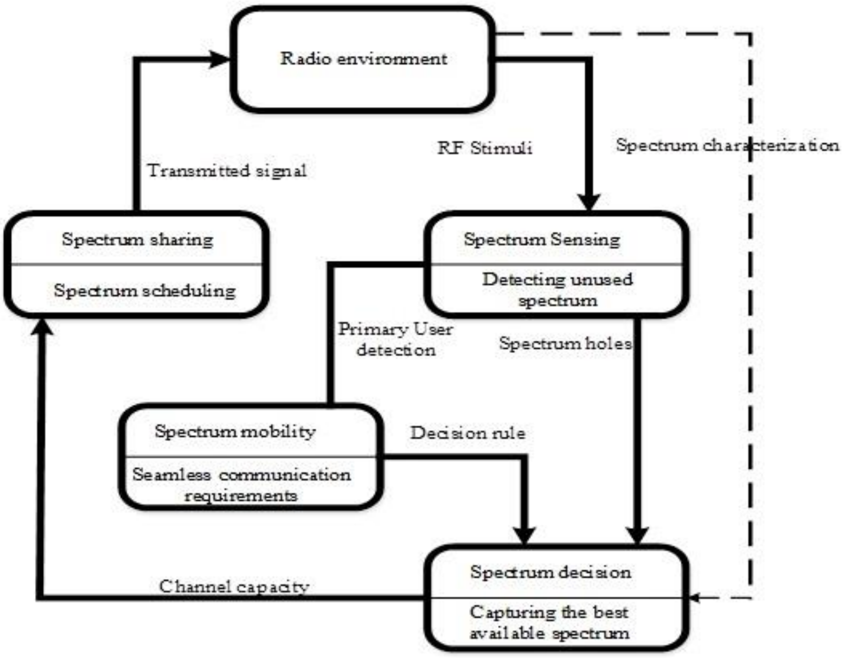

Figure 1.4: Cognitive Cycle[9]

(i) ***Spectrum Sensing***: It allows cognitive radio to monitor spectrum, capture information, and detect the spectrum.

(ii) ***Spectrum Analysis***: It estimates characteristics of the available spectrum opportunities.

(iii) ***Spectrum Decision***: Once the transmission opportunities are detected and their channel characteristics are estimated, the most appropriate spectrum band is selected to meet end-user requirements through its decision-making capabilities.

It may efficiently employ spectrum resources by adjusting the adaptive change and decision-making parameters. The categorization of network users may be divided into PUs (authorized users) and SUs (also known as unauthorized users). SUs may sense idle spectrum based on spectrum openness. Without user communication collision, PUs access frequency band [10].

CR can adjust the communication parameters. The radio should detect nature continually because of the outcome; it desires to modify the parameters bringing forth a cognitive cycle. For proficient spectrum usage, the CR can change transmission parameters like carrier frequency, power, bandwidth, symbol rate, modulation method, index, etc. Four fundamental elements of CR for empowering DSA are the following:

- ***Spectrum sensing:*** Without interfering with the PU, detecting unused spectrum in CR.
- ***Spectrum management:*** CR must find best spectrum to optimise the communication requirements.
- ***Spectrum mobility:*** When needed to leave the currently used spectrum, CR transmits the spectrum used for communication.
- ***Spectrum sharing:*** It is necessary to communicate the existing spectrum between the coexisting SUs in CR [11].

The reconfigurable capability adopts the sensed environment, and the self-organized capability analyses the discovered data in the spectrum environment. To recognize or detect spectrum holes, CR can sense the spectrum. Also, it includes service discoveries and network details to find nearby networks like GSM, WiFi, and so on[12].

1.6 COGNITIVE RADIO COMMUNICATION PARADIGMS

Four communication paradigms are feasible based on network information and regulatory limitations. They are listed as follows:

1) Underlay communication paradigm
2) Overlay communication paradigm
3) Interweave communication paradigm
4) Hybrid communication paradigm

Different spectrum-sharing approaches for CRN are shown in figure 1.5. PU and SU can broadcast concurrently over the same channel using the underlay technique [13].

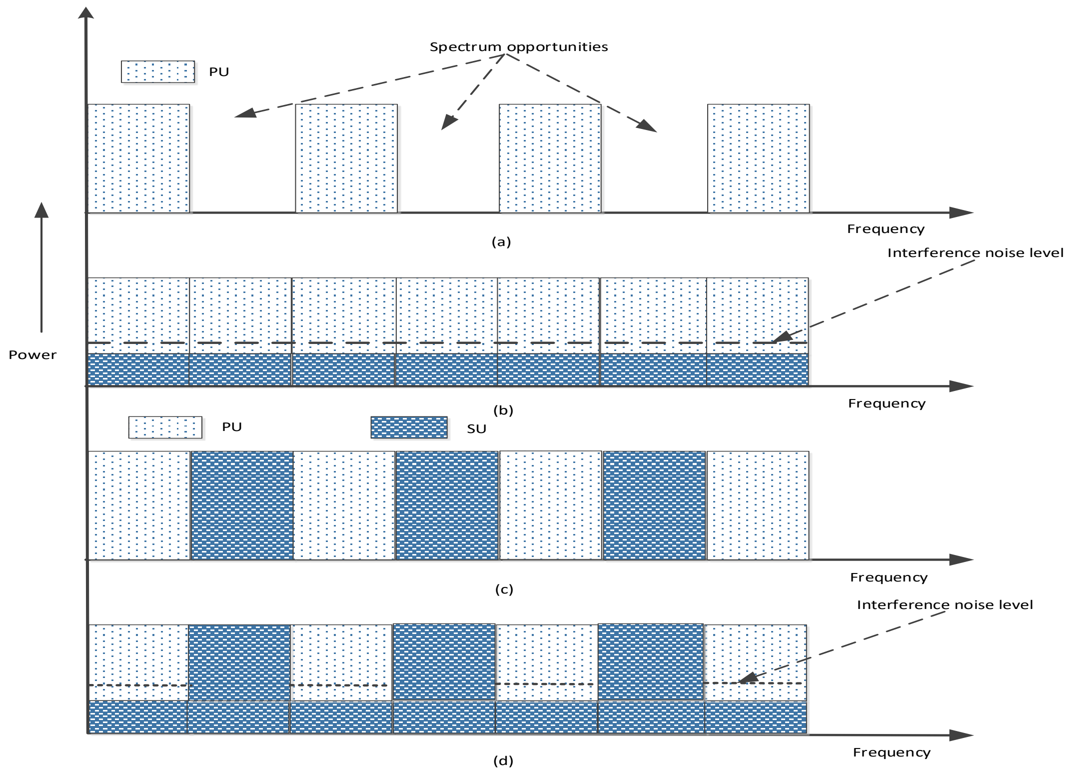

Figure 1.5: Spectrum sharing paradigms (a) spectrum opportunities/holes (b) Underlay paradigm (c) Interweave paradigm (c) Hybrid paradigm[13]

Like underlay method, overlay scheme permits SUs to broadcast with PU in the licensed band without affecting PU performance. In this paradigm, the two primary coding are network and channel coding. In channel coding, PU broadcasts SU-known packets. The SU will transmit its packet with the PU packet so that SNR at PU receiver will not be significantly impacted. So, SU doesn't need access to the spectrum to send packets, and PU's transmission isn't affected.

In contrast to previously stated techniques, interweave method prohibits SU from transmitting in the licensed frequency range while PU operates on it. This method, which also goes by opportunistic spectrum access, requires spectrum sensing for SU to take advantage of spectrum possibilities in the space, time, and/or frequency domain. In contrast to underlay approach, this technique permits high transmission power levels to accommodate high data speeds. When PU enters the channel, however, communication is suddenly cut off. However, these limitations may be avoided by using a hybrid spectrum access system [14].

1.7 SPECTRUM SENSING

Spectrum sensing is the most fundamental procedure among others for the foundation of CR. A few works have been distributed on spectrum sensing so far, where spectrum sensing is characterized, and the different parts of spectrum sensing assignments are talked about in detail. A few difficulties discovered in spectrum sensing are likewise managed in[15].

Sensing of spectrum is capacity to detect frequency spectrum to free portions of channel and to adjust the radio parameters. The "FCC" estimated that most of the assignment frequency range, between 15% and 85%, was unutilized in the band under 3 GHz. Current estimations indicate that frequency utilization is highly concentrated on specific spectrum segments. These spectrum holes or white spaces can be categized into

• Black Spaces recorded by high-powered interferences.

• Grey Spaces partially populated by low-powered interference

• White Spaces, which are entirely unoccupied.

Spectrum Sensing mostly depends on the modulation type, frequency, and modulating power. Spectrum Sensing is often regarded as a spectrum detection method.

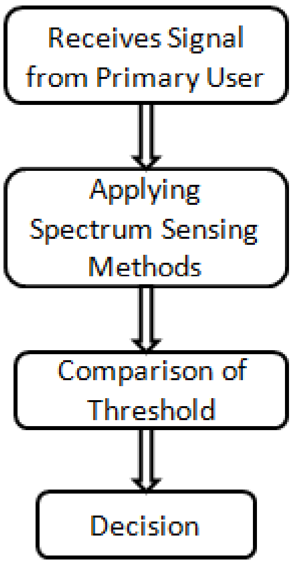

Figure 1.6: Flow of spectrum sensing[16]

Various approaches to spectrum sensing are illustrated in figure 1.7.

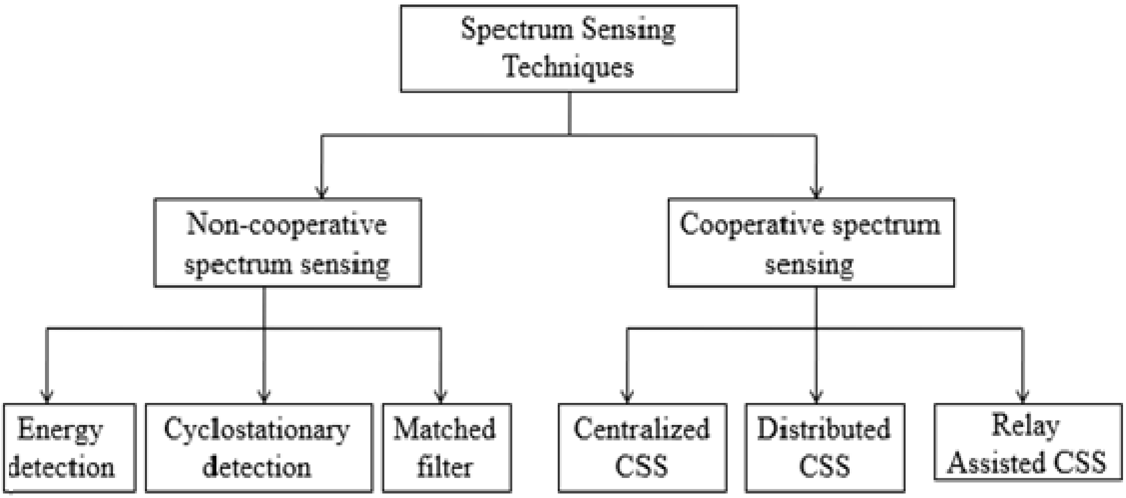

Figure 1.7: Spectrum Sensing Techniques[16]

1.7.1 Non-Cooperative Spectrum Sensing (NCSS)

In NCSS, a single SU detects PU availability. Spectrum sensing may be non-cooperative or cooperative [17]. Frame structure of conventional cognitive radio SU is comprised of 2 slots, i. e. a sensing and transmission slot. Figure 1.8 gives the frame structure of SUs for the time T. In a sensing slot, SU detects the presence of PU for the time τ. If the spectrum is not under the usage of PUs, then SUs can transmit for time (T-τ).

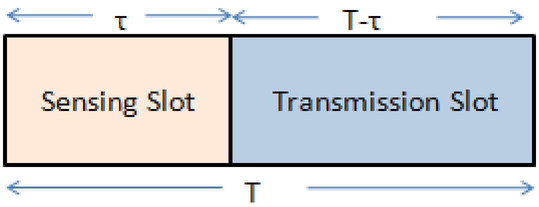

Figure 1.8: Frame structure SU[23]

1.7.2. Cooperative Spectrum Sensing (CSS)

CSS solves main issues of NCSS, which are receiver uncertainty, shadowing, multipath fading, and hidden terminal power. This hidden terminal problem will be answered with a "cooperative spectrum sensing technique." Here, every SU gets neighbourhood sensing data of a PU and shares it with the others in binary form. If a SU fails to detect a PU, other SUs can make sense of it. The final decision is made by taking average of all SUs energy detections, and spatial diversity improves ability of SUs to work together to sense the spectrum[18]. Figure 1.9 shows how cooperative spectrum sensing works.

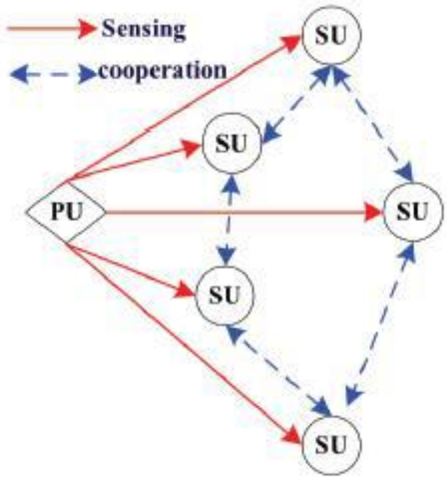

Figure 1.9: Process of CSS[18]

Figure 1.10 depicts the frame creation of CSS, comprised of a local sensing, cooperative, and data transmission slot.

Local sensing slot	Cooperative slot	Transmission slot
Energy statistic	Exchange of information	Data transmission

← Frame structure →

Figure 1.10: Frame structure of CSS[18]

CSS is mainly classified into 3 types:

(a) ***Centralized CSS Technique***

In Centralized cooperative spectrum sensing, each of the SUs independently carries out the sensing operation through the sensing channels and then sends its findings to FC through reporting channels. FC decides on PU availability based on information given by the SUs. This decision is sent back to all SUs, as illustrated in figure 1.11.

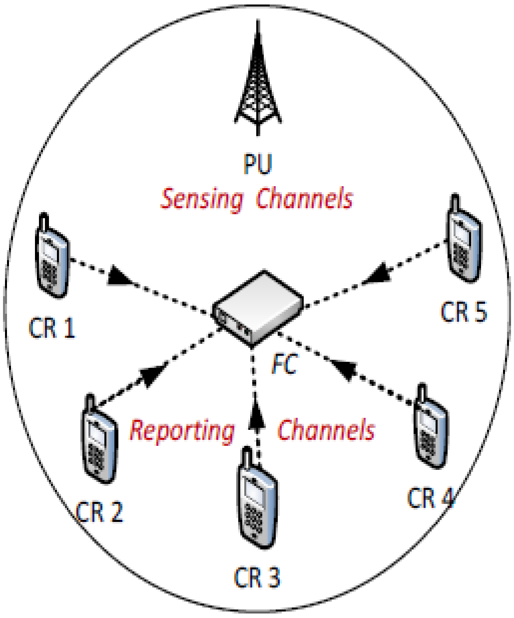

Figure 1.11: Centralized CSS Model[18]

(b) ***Distributed CSS Technique***

None of SU serves as the FC in this CSS approach. With the help of distributed algorithm, every SU communicates its particular sensing data to other users through reporting channels. That data is integrated with data received from the other SUs to make a combined judgment on PU's appearance [19]. The distributed CSS model is shown in figure 1.12. If the criterion is not met, SUs resends their result of sensing to each other and continue this process until to reach a convergent decision. This mechanism's major drawback is that it needs more iterations to make a decision, which can require more network issues and increase sensing time.

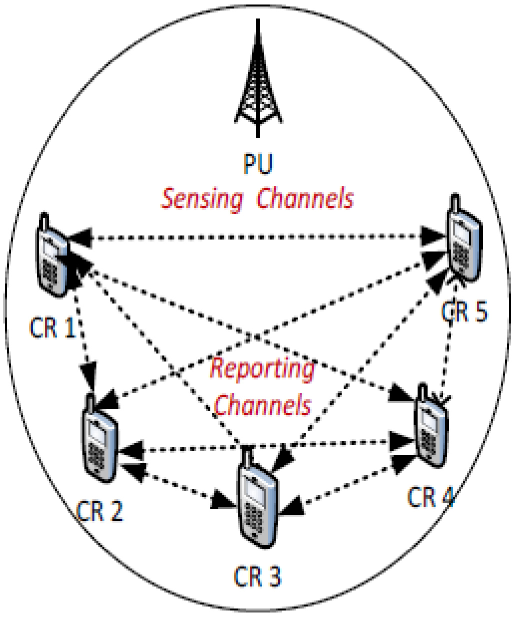

Figure 1.12: Distributed CSS Model[19]

(c) ***Relay Assist CSS Technique***

In Relay Assist CSS, certain SUs operates as relays, collecting data from other SUs through sensing channels and sending it to the FC via reporting channels. The FC will reach final judgment regarding PU and report to all SUs in network, as seen in figure 1.13. The structure of Relay assisted CSS is a combination of centralized and distributed CSS, where sensing and reporting operations are performed based on the requirement at a particular time [19].

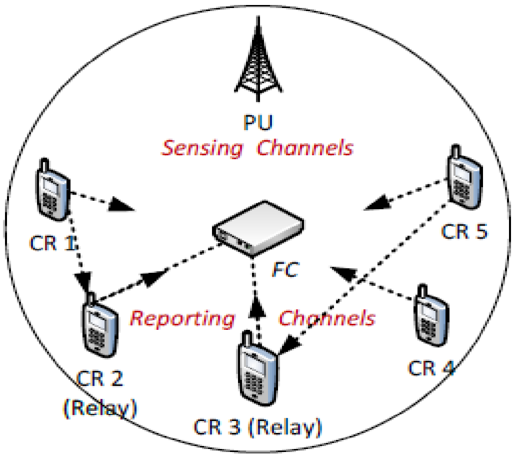

Figure 1.13: Model of Relay Assist CSS[19]

Out of three techniques mentioned above, centralized CSS is an optimization technique that has relatively easy implementation, needs less cost, and requires less sensing duration compared to distributed and relay-assisted CSS techniques; thus, will be considered the preferred choice for this research. When many SUs are involved in sensing, centralized technique does not show the problems of control channel bandwidth, EE, and reporting delay[16].

1.7.3 Challenges in the Spectrum Sensing

Spectrum sensing for CR has several challenges. Solving these challenges is crucial.

(a) ***Uncertainty in Channel***

Variations in the received signal intensity due to shadowing and fading in channel lead to inaccurate predictions about the PU. Because the PU experiences significant amounts of fading and shadowing, for this reason, the receiver sensitivity needs to be as high as possible.

(b) ***Uncertainty in Noise***

The receiver can't predict random noise behaviour. Sensitivity is the minimum SNR to identify the PU with a 0.99 probability at the CR node. Due to calibration errors and thermal noise, the detector's sensitivity must be high.

(c) ***Sensing Interference Limit***

It's important to note that CR users might cause interference for PU. PU's receiver's location is unknown to the CR user. For this reason, interference is ignored in the receiver's calculations. The CR transmitter would be unaware of the PU if it were a passive device. Therefore, it is necessary to consider both of these conditions while assessing the interference limit.

(d) ***Sensing Time***

Two crucial factors are the transmission and sensing time, which are complementary. So, if sensing time is long and transmission time is short, information about the spectrum is not broadcast to each CR node within the required time frame and becomes outdated. If the sensing time is short, the transmission time will also be long, making it impossible to get accurate data on the unused spectrum. CR technology is opportunistic; thus, designing the sensing slot is vital. If T_f is the total frame duration consisting of sensing time Ts and transmission time or channel access time T_a then

$T_f = T_s + T_a$

$T_a = T_f - T_s$…………………………………………………………..…………….(1.1)

The CR has to vacate channel immediately once the PU becomes active to avoid interference with PU. Thus, sensing time Ts is too short may result in poor detection and harmful interference. However, if T_s is large, it may provide very little time for CR to access the data transmission channel, resulting in poor throughput.

(e) Hidden PU Problem

This problem arises whenever the line of sight between the SU receiver and PU transmitter is blocked or hindered. When unable to detect the PU signal, the SU receiver considers that PU is inactive and may start transmitting, which may cause interference. To circumvent this problem of spatial diversity is employed, which is implemented using collaboration amongst various SUs.

(f) Spread Spectrum PU

The power of the PU signal employing spread spectrum technique is distributed over a broad bandwidth, making signal detection extremely difficult. Further, PU, which utilizes frequency hopping, makes the process of detection even more challenging

(g) ***Other Challenges***

Additional difficulties in spectrum sensing include the existence of multiple CR Nodes, power consumption, computational complexity, hidden node issue, etc.

1.8 SPECTRUM SHARING MANAGEMENT

Spectrum sharing is the most critical part of DSA. DSA dramatically increases spectrum usage and boosts communication system performance. It ensures that PUs and SUs can use the spectrum reasonably and efficiently. However, SUs may access the radio spectrum when PUs entirely or partly occupies it. This model of spectrum sharing is an effective solution to reduce spectrum wastage by allowing the coexistence of SU with PU without disrupting their QoS constraints[20]. Based on CRN parameters, spectrum-sharing models can be classified as follows:

1.8.1 Architecture-Based Spectrum Sharing

Based on the architecture, cognitive radio systems may be typed as:

(a) Centralized CRN

A central controller manages spectrum detection and allocation in centralized CRNs [18]. Also, all communications between SUs go through a central controller, which decides how long SUs can use a specific frequency band and how much power they can send. The central controller gathers information on PUs' spectrum use, and all SUs' spectrum needs to perform this. Based on this information, the central controller proposes an optimal solution to maximize the secondary network throughput without degrading QoS requirements of PUs. However, main disadvantage of centralized CR system is that the information exchange between central controller and the SUs increases system overheads[20].

(b) Distributed CRN

SUs communicates peer-to-peer in a distributed CRN without a central coordinator. Each SU makes spectrum access decisions independently. Since each SU independently collects information about RF radio environment, secondary equipment requires more excellent power backup and computational capabilities than the centralized cognitive network[20].

1.8.2 Spectrum Allocation Behaviour

Based on spectrum access behaviour, CR system may be classified as follows:

- Cooperative Spectrum Sharing
- Non-Cooperative Spectrum Sharing

(a) Cooperative Spectrum Sharing

Cognitive users cooperate to share the spectrum to maximize their spectral efficiency. Sensing data is shared among themselves to decrease sensing error, sense time, and increase the degree of fairness. In this context, significant work has been reported on cooperative spectrum sharing to reduce communication overheads, power consumption, and system complexity by processing sensing results locally through clustering. In clustering, a cluster head (CH) reports the sensing results to a central controller for final decision regarding channel access [21]

(b) Non-Cooperative Spectrum Sharing

The cognitive users don't share their sensory data in this spectrum-sharing method. Small networks benefit from selfish spectrum sharing because it reduces transmission overhead. But it seriously reduces the spectral efficiency of large networks. The probability of false alarms is relatively high in this manner of spectrum sharing. It may severely impair the performance of the PU or SU when it is utilized to make spectrum-sharing decisions[13].

After spectrum sensing and analysis, next step is spectrum sharing. This step allocates the spectrum to the SU, which is classified and detailed in [13]. The entire CU uses Industrial Scientific Medical's spectrum in the unchecked model. This model does not require CU power control. To accomplish best performance, the spectrum owner imposes some conditions. So, the CU optimizes its parameters, such as frequency and power. Dynamic and long-term exclusive models are two kinds of models in CRN. A small portion of spectrums is allocated to CU at a specified time in the dynamic model, while the licensed user gives a spectrum to CU for a particular time in the long-term model. The central entity controls the centralized approach, a fusion centre that controls all spectrum allocation and access mechanisms.

Additionally, to allot spectrum in CR, the central nodes have all of the necessary information on the other nodes in the network. At the same time, the individual node in distributed method takes the spectrum allocation decision. To evade the collision between the different SUs, the data about the spectrum is exchanged among the nodes. The detection of interference at various SUs is followed by the cooperative sharing of interference information amongst all SUs and, lastly, the spectrum allocation. Measured interference on a specific SU is delivered as a message to all SUs in the non-cooperative spectrum sharing[13].

1.9 SPECTRUM MANAGEMENT AND DECISION

Spectrum management involves selecting the best possible spectrum available among multiple spectrum holes. The selection is based on parameters like transmit power, bandwidth, coding schemes, etc. QoS influences packet success ratio, end-to-end delay, and throughput[8]. The spectrum slots must be characterized depending on the following parameters before making a spectrum decision.

1.9.1 Interference on the primary network

Interference is attributed to multiple adjacent PUs within a specified geographical area. Sometimes transmission events with PU activity in the presence of hidden terminal problems can also result in interference. The lowest interference probability signal must be selected to solve this problem among multiple spectrum holes.

1.9.2 Mutual CR interference

When two or more users compete for the same slot, it results in mutual CR interference. This mutual interference is also an essential factor in selecting spectrum slots. Preference should always be given to low potential interference levels, allowing transmitting at higher powers.

1.9.3 Holding time

Holding time is the period a CR node occupies a spectrum hole before releasing it due to the reentering PUs. When a CR user occupies a spectrum slot before releasing the PUs, the maximum holding time is kept for uninterrupted services in CR transmission.

1.9.4 Frequency band

The spectrum selection also depends on available frequency spectrum slots. Path loss is increased due to higher frequencies.

1.9.5 Channel capacity

A well-known Shannon's formula gives the channel capacity. Spectrum access depends on three factors: centralized, distributed, and cluster-based. Multiple SU's send their spectrum sensing results to the FC. FC combines these results and analyses them to decide the status of the PU as present or absent. The centralized process considers the following factors.

i Network throughput optimization

ii Inter and intra-network interference reduction

iii Fairness between SU devices

iv Prioritize critical devices with additional spectrum resources.

The main disadvantage of centralized decision-making is higher communication overhead. This overhead is due to SU sending information like sensing results, power level, and spectrum access to the fusion center. The diversity of the network increases linearly when the overhead increases. A dedicated control channel must be reserved for this communication. Due to spectral and EE being reduced. This extra energy consumption makes CR impossible for small portable battery-powered devices.

Each SU decides PU status individually in distributed spectrum sensing, avoiding needing a centralized controller. The complete control over the decision rests on each SU. Decision delay is less in distributed sensing as there is no need to wait for FC. However, the problem with this approach is that local decisions made at each SU may not be optimal for the network as a whole. Also, the results can be inaccurate due to interference of PU and SU[22].

In cluster-based decision-making, CR nodes form a cluster and select a CH node among them. Individual CR nodes transfer their decision of spectrum to CH, and final decision is made at CH. The communication overhead of centralized is reduced by selecting a small cluster size. Smaller cluster size also reduces the transmission power requirements[23].

1.10. SPECTRUM MOBILITY

To hop among the different CR users in the spectrum slot is called spectrum mobility. The hoping can be due to the following conditions.

i PU needs the spectrum hole.

ii Channel condition is getting bad

iii Demand for higher bandwidth

iv Higher data rate

The shift from one spectrum hole to another is called SH or spectrum mobility. It is more like cellular handoff. However, a seamless handoff is necessary to avoid CR outages or latency. If the spectrum slot is empty, it is assigned to an unlicensed SU. So, seamless handoff becomes a challenge[24].

1.11. HALF DUPLEX AND FULL DUPLEX IN CRN

The word "duplex" describes the sending and receiving of information. Two types of simultaneous transmission and reception exist: half-duplex (HD) and full-duplex (FD). As HD is simple to implement, it is widespread in wireless networks. This system cannot transmit and receive simultaneously; hence, spectrum sensing and transmission cannot be done simultaneously. Due to this, the entire time will not be used for communication, reducing the throughput. Orthogonal spectral resources will be assigned separately for transmission and reception. Mobile networks' uplink and downlink transmissions hence use two sets of frequencies.

HD CR devices have two serious drawbacks. First drawback is that spectrum sensing and communication are not simultaneous. The first step is spectrum sensing, and the second is information transmission. This long time in spectrum sensing and less time for data communication. One more limitation of HD CR is that it requires sending and receiving data across two orthogonal channels. This leads to a requirement for precious spectral resources. It also increases latencies in spectrum sensing. The usage of FD will mitigate these issues. FD's benefits are high network capacity and effective spectrum detection; disadvantages are higher energy costs and more complicated hardware.

"FD" refers to a transceiver system that allows simultaneous transmission and reception on the same frequency band. In contrast, "CR" is a technique that improves the criteria for joining a network and dividing the available frequency spectrum. Bringing together these two infrastructures can increase the network's overall capacity. When dealing with many people nearby, full-duplex and cognitive communication systems have proven problematic and don't seem to have a solution. Investigate full-duplex/spectrum-sharing networking security, multi-transceiver resource allocation, single-interface simplification, efficient design, full-duplex/cognitive media access control, and higher-layer protocol safety [25].

A new CR user in HD-CR should recognize the available spectrum by colliding with licensed recipients and with present CR users in a distributed system. But, FD-CR users need not collide with other users because of the separate bidirectional antennas. In centralized networks, FD-CR can use a single antenna for accomplishing communication. Two potential technologies have recently been developed to enhance spectrum, network effectiveness, and system performance. Combining cognitive and full-duplex radios is a method for developing the results of wireless networks going back to the fifth generation [25].

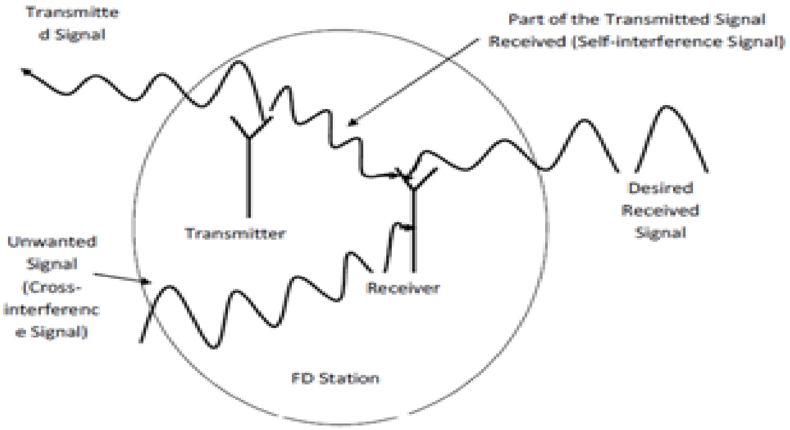

Figure 1.14: interference in full duplex system[25]

FD achieves two-fold capacities. FD allows for simultaneous transmission and reception of data inside a single network using the same radio frequency. Compared to HD networks, FD networks only use half of the available spectrum resources[25]. SUs of HD-CRNs cannot sense the PU when it transmits data; hence, it may sometimes collide with PU's activity. This will lead to interference with PU. This is not happening in FD-CRN since the PU will do both sensing and transmission simultaneously. This will reduce the interference for PUs [25].

Sensing the available spectrum in FD-CRNs will be done continuously when the data is transmitted. This will provide better spectral efficiency. The SUs will get more available spectrum, and their sensing performance will be improved further in FD compare to HD-CRNs. In FD-CRNs, sensing operation and data transmission are simultaneous, so the sensing operation will not get interrupted. But in HD-CRNs, sensing operation will not get interrupted during data transmission. The uninterrupted data transmissions will lead to enhanced data rates for SUs.

In HD-CRNs, SU collisions often occur during transmission. This reduces the system performance as it will take more time to detect. In FD-CRNs, collision probability can be minimized without interruptions during data transmission. PUs will become eavesdroppers and weaken the network's security by disturbing the privacy of SUs. As the anti-jamming signals are available from a specific antenna in FD-CRNs, this can be overcome, and the security concern is managed well in CRN. As spectrum sensing and data transmission in FD-CRNs remain uninterrupted, energy from external sources may

be effectively captured. A significant consideration for wireless communication is EE. Sensing and transmission should happen at the same time. But in HD-CRNs, this is impossible because the sensing and transmission should be halted for EH [26].
In the HD CRN, when it senses the spectrum, the data is not shared even though it is available. Similarly, the sensing is stopped when it sends the data, leading to interference. These shortfalls are not available in FD [26].

1.12. ADVANTAGES OF CR

Some of the advantages of CR are briefly discussed below:

- When white spaces exist in the radio frequency environment, CR detects them.
- It considerably improves spectrum usage efficiency.
- The unused spectrum can offer high-speed internet and high data rate network applications in rural areas and video conferencing[5].

1.13. APPLICATION OF CR

Spectrum sharing is already employed in many applications, including WiFi and Bluetooth networks. However, because of technological advancements, additional particular bands are now employed for service. Numerous practical applications and situations may also use CRNs' methods. The following are the major applications of CRNs:

1.13.1 Cellular Networks

Increased use of smartphones has enormously contributed to current traffic burden on the internet's networks. Cellular service providers face difficulties in the form of restricted resources due to an expansion of geographic coverage area. The traffic needs of the cellular network may be met by allocating network [27].

1.13.2 Mesh Networking

Wireless mesh networking is a practical and growing method of delivering broadband connectivity. The main problem with typical mesh networks is that as networking density rises, more bandwidth is needed to meet application needs. The cognitive mesh networks offer broadband connectivity in very dense geographic locations, much as cognitive radio technology is used to address spectrum constraints[28].

1.13.3 Smart Grid Applications

Traditional electricity grids have been transformed into more advanced "smart grids" due to the continuous development and enhancement of communication technology. Multiple communication channels are required to distribute and transmit these grids to monitor and control the power-producing process effectively. This is necessary for the creation of energy.

1.13.4 Sensor Nodes

Akan et al. developed cognitive radio sensing networks as a replacement networking device paradigm. Due to event-based detection, WSNs create traffic bursts. Dense node deployment increases contention latency. The opportunistic strategy decreases conflicts and rivalry [29]

1.13.5 Cognitive Radio-based Body Area Network

Body Area Network offers medical services. Wireless medical technology adoption causes QoS and interference issues. CRN in medical industry is a suggested and potential solution since it can watch, detect and make decisions based on radio environment[30].

1.13.6 CRNs in Military Applications

It ensures that military communication networks are reliable and safe. Also, army operations require a large amount of bandwidth, which limits the capabilities of this type of network. The Wireless Network after Next (WNaN) program was started by the DARPA so that the military could have a wireless network that was both flexible and reliable. The WNaN is made to help support low-cost CR devices that can choose their frequency to help with different military communication applications[31].

1.14 ENERGY HARVESTING

The abundance of fossil fuel by-products because of the increasing demand for energy causes critical issues. Renewable energy has been developed and examined as a substitute energy source to mark rising energy costs and reduce carbon. EH is collecting energy from the surrounding, transforming and saves for future purposes. Like a traditional power supply, an EH system can also provide a continuous power supply. In particular, wireless communication systems with energy-harvesting circuits have significantly increased observation.

There are various sources for EH comprising natural and other atmosphere sources of energy. Natural resources, such as solar and wind, can supply limitless energy from the atmosphere. In addition to the natural resources, other techniques exist to harvest energy from the ambient energy sources: vibrational, electromagnetic, thermal, and biological systems. EH from solar can supply a limitless amount of energy without creating any impression of carbon. Solar energy can be converted into electrical energy by using photovoltaic cells. Solar EH can supply a massive amount of energy and is purely dependent on sunlight and geographical location. For example, this technique will work better in countries in Asia and Africa where sunlight will be available whole day. Wind is another EH technique suitable for cloudy atmospheric conditions. Although traditional energy sources such as sun, wind, and water flow can supply a limitless amount of energy, these sources depend on time. EH from RF has introduced radio communication to solve these issues. The EH systems have initially increased a major of attention in remote applications where providing traditional energy is impossible. Without a battery lifetime, EH can increase wireless nodes [32].

1.14.1. EH Techniques

In EH, we produce electrical energy from wasted ambient energy. This electrical energy is called harvested energy. For electricity generation, environmental energy sources are utilized. So, there are following types of EH techniques:

a) ***Photovoltaic EH***

Photovoltaics convert solar energy into electricity. Structure includes a voltage converter, maximum power point tracker (MPTT), and solar cell. MPPT ensures that most of the power is drawn out from the sun-based cell with the help of voltage converter[33].

b) Wind EH

Wind is a generally accessible surrounding energy asset with help of wind turbine generators used as energy-gathering devices. This combination allows the turbine to convert wind kinetic energy into mechanical energy and the generator into electrical energy [34].

c) ***Piezoelectric EH***

The mechanical energy, stress, or vibration applied to piezoelectric devices is converted into electrical energy. Output power is increased by amplifying low-power variations. Indeed, higher output power is conceivable when the framework resonates with the external input vibration[35].

d) ***RF EH***

RF- EH framework gives energy-reliant WSNs the ability to extract energy from radio waves. It combines rectifier, impedance matching circuit, and direct current to a direct current converter. It was developed to effectively gather radio signals and convert them to their respective electrical equivalents 36].

e) Thermal EH

The use of a thermoelectric generator is an essential component in the process of extracting thermal energy. Thermal energy comprises a pair of n-type and p-type semiconductors connected electrically but in parallel thermally. These semiconductors are sandwiched between two layers of artistic work. An improved power manager introduces a WSN based on thermal power. The power manager adjusts the framework's presentation by changing the hub's duty cycle[37].

1.14.2. Comparison of EH Techniques

EH comparison is presented qualitatively in Table.1.1. The significant benefit of sunlight-based energy lies in its efficient power energy with unlimited accessibility. However, the highlight is that a sun-powered-based framework is practical when focusing on daylight. The wind is not controlled, and unusual necessities, exceptional caring, and strategies to receive the best in return. Generally, a wind-based EH framework comprises mechanical parts which may deliver more disturbance. The climate calls for the most effective sort of EH technology, which is called piezoelectric EH. It depends mainly on the weather or the mechanical component configured to excite or create vibration.

Table 1.1: Comparison of different EH techniques for Wireless Sensor Network (WSN)

Harvesting Technique	Energy Source	Energy Type	Harvesting Device	Merit	Demerit
Solar Energy	sun	Radiant Energy	Solar cell	Infinite availability	Need exposure to light, poor indoor efficiency
Wind Energy	Wind	Kinetic Energy	Wind Turbine	High Power density	Noisy unpredictable
Piezoelectric energy	Stress or vibration	Mechanical energy	Piezoelectric film	Equally efficient indoor and outdoor	Piezoelectric devices are fragile
Thermal energy	Heat	Heat energy	Thermo electric generator	simple	leakage of current
RF energy	Radio signal	Electromagnetic energy	Rectenna	No mechanical parts	Fading with distance

In radio communication, EH methods will provide a favorable solution to supply required energy to complete the communication between two end users. Advances in Communication systems will consume more energy—for example, 5G networks in cellular communication. Different techniques were implemented in radio communication depending on the incoming energy and storage mechanism [38].

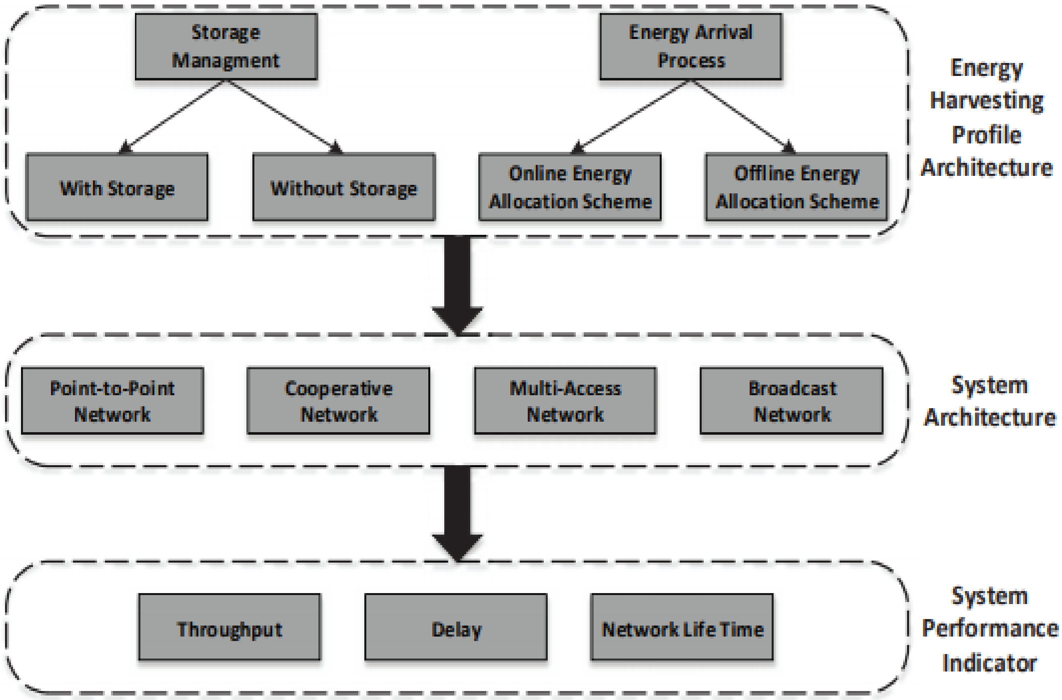

Figure 1.15 : EH systems classification[38]

Figure 1.15. gives the basic technology implementation of EH. Designing the energy arrival process is divided into two types: online and offline. In offline techniques, incoming energy and channel quality information are known before signal transmission. In online techniques, present and past information on incoming signal energy and channel gain are available. Because of unpredictable behavior of environment, offline methods are not practical. EH systems can be classified into storage and without storage. Without storage, no storage devices are available to store the harvested energy. In EH with storage, with support of batteries, harvested energy can be stored and used for further operation. Designing EH with storage can be further divided regarding battery storage capacity as ideal and non-ideal. EH techniques can be applied to system architectures like point-to-point, corporative, multiaccess, and broadcast networks. System performance indicators are throughput, delay, and network life time [38].

1.14.3 RF-Enabled EH

The ambient wireless signals can supply continuous energy sources for wireless EH. RF EH can permit wireless appliances to support the RF environment to perform operations on their data and make a transmission. Coupling inductors, magnetic resonant coupling, and radiation of EM waves perform various wireless EH techniques. Because of radio networks, RF signals are accessible in the form of electromagnetic radiation, and thus RF EH method has a lot of importance [38].

Radiofrequency-enabled appliances will have an extensive range of usage for radio networks, wireless body systems, and Radio Frequency Identification device systems. Because of signal propagation and path loss, a receiver can perform simultaneous operations of harvesting and decoding information from an incoming signal. Signal power can explain accompanying wireless information and power transfer systems by considering multiple users with formation of an energy beam. It is important to note that receivers' decoding information and harvesting energy work at different power levels. A few more techniques have been proposed to overcome this drawback of the simultaneous wireless information and power transfer method to decrease receiver implementation difficulties [38].

1.15 ENERGY-EFFICIENT IN CRN

This thesis studies CRNs from an EE perspective. Existing research work has been analysed to study challenges for EE and their trade-offs. After a proper study of the background of the problem in cognitive radio systems, the solutions are proposed for energy-efficient optimal power allocation in different scenarios of CRN. The remaining part of this section discusses the overall structure of the EE problem with motivation, EE matrices, and research efforts.

Information and communication technologies, the backbone of 5G networks, are among the biggest energy consumers. The Information communication technology sector is responsible for 10% of world's total power consumption due to the exponential demand for wireless services. In mobile telephony services, 10% of energy is used by end-user equipment, while network core components use 90% of energy. The base station subsystem of the network itself consumes two-thirds of the total energy consumption of system[39]. Due to increasing energy consumption, policymakers also endorse green and renewable usage. The European Council is targeting at least 27% renewable energy and 27 % or more improvement in EE by the year 2030. Also, battery technology is increasing, for example, by 10% every two years, compared to an exponential rise in demand for energy by devices[40].

Energy generation and consumption have environmental and financial concerns for end consumers of wireless services. For a wireless system, energy consumption is critical regarding availability, feasibility, cost, QoS, usability, and network robustness. These parameters are multi-objective, and usually, they contradict. Several factors related to the design and size of wireless nodes contribute to the demand for energy-efficient wireless networks. We consider all these factors while designing future wireless networks. Factors related to design and size affect the device's form factor and power requirement. A small form factor means a handheld device but with more restrictions on battery. A typical modern wireless device has a small form factor. Due to this, they have limited battery storage capacity. These devices have extra mobility and additional ad-hoc settings. Because of extra mobility and instantaneous networking requirements, these devices need advanced signal processing algorithms, which need EE as their main component.

The design of these devices is more complex and has diverse capabilities. Complexity is due to extra signal processing capabilities needed to sustain additional capabilities. More focus on green communication systems is also the driving force for energy-efficient network design[40]. Another motive of green communication is to address environmental issues. The energy cost of networks is a significant part of its overall cost, and an energy-efficient approach can reduce it. Also, as discussed above, there is a huge gap in energy storage capacity and advancement in circuit design. Battery storage capabilities legs far behind advanced circuit design. Therefore, the energy-efficient approach is essential for sustainable operations of wireless networks. Several areas can be designed with a green perspective in the green wireless network paradigm. A renewable energy source as power is future wireless networks. The network nodes such as mobile devices, access networks, core, and transport networks can be designed with energy-aware algorithms[41].

All these elements in greenfield design toolbox would contribute to EE at the hardware or software level. Defining and understanding EE matrices is essential for proper design and evaluation of energy-efficient networks. EE is the number of bits that can be successfully communicated per unit of energy utilization. We can use Shannon's capacity formula to determine EE as bits per joule capacity.

A broader perspective is needed for more accurate and holistic EE analysis, e.g., from component to system-level manufacturing process to maintenance systems. There are several other matrices for EE, such as QoS or spatial matrices (bits per joule per unit area). This thesis will use bits per joule as EE metrics. Many research projects involve designing, analysing, and optimizing energy-efficient communication systems. Research in energy-efficient wireless communication has several dimensions.

Researchers and academicians are focusing on a systematic solution for EE. There are also efforts in the research community to provide a domain-specific or driven solution where energy-efficient solutions are based on the needs of domain-specific applications. Empirical findings are also given for select areas in wireless networks. The cognitive radio paradigm helps to overcome spectrum shortage problems in wireless networks. Energy-efficient cognitive radio systems have the potential for energy and spectrum challenges of wireless networks[42].

Cognitive radios are radio systems that are aware of their environment. They sense their surrounding environment, and based on sensing data, they learn about system states and status of system parameters. The cognitive radio then plans according to its goals, priorities, and constraints. The cognitive radios then make decision rules and then act on these decision rules to allocate resources. This process repeats itself to work according to the current operational environment. Cognitive radios are agile, adaptive, and learning; hence, they utilize resources like spectrum more efficiently. To make CRNs energy efficient or to design an energy-efficient solution for cognitive wireless networks, the vital point is to understand power consumption; energy consumption can be given as a power function $f(P_x)$, where P_x is the power component.

Transmission power (P_t) is a significant component of total power consumption. It is generally proportional to transmission power. The frequency switching of power (P_f) is usually proportional to frequency separation. Sensing energy consumption (P_s) is generally proportional to sensing duration. The processing component (P_p) is proportional to the processed data quantity. Control and signalling overhead (P_c) depends on the network protocol and configuration. Idling overhead (P_i) depends on hardware attributes and is proportional to idling duration. The energy consumption's deep sleep component (P_d) depends on the hardware attributes and is proportional to idling duration. Each of these mechanisms has a different outcome on EE of cognitive networks that needs to be considered for EE calculations[40].

For EE calculations, we need to consider several trade-offs [43]. EE (EE) vs. QoS, EE vs. Fairness, EE vs. PU interference, EE vs. Network Architecture, and EE vs. Security are the primary trade-offs for CRN. Each trade-off affects others and must be balanced according to the operating environment. QoS trade-offs are hard to satisfy with stringent EE requirements[44]. Interference, power budget, and wireless channel limitations affect CRNs' QoS. We can perform better sensing with more processing, but it adversely affects QoS. A balance is needed to achieve the desired target. Cognitive radio can exploit diversity techniques to enhance EE. All cognitive radios need to share SE fairly [44].

EE objective generally favors unfairness, e.g., cognitive radio that requires minimum transmit energy always gets a chance to transmit. EE vs. PU interference trade-offs aim to balance EE and interference to the non-cognitive user[45]. Miss-detection and reappearance of PU are the leading cause of PUs' interference. Miss-detection of PU can be avoided by increasing probability of detection. Detection probability can be increased by increasing energy expenditure, sampling rate and sensing time [45].

PU reappearance happens when the PU starts using a channel between two sensing periods. It causes collision between PU and SU communication and severely degrades PU and SU link quality. The main reason is periodic sensing, which can be avoided by increasing sensing frequency. However, high sensing frequency has extra overhead, and the SU would get less data transmission time. Cognitive radio should increase sensing accuracy and reduce transmission power to decrease interference. Relaying and channel aggregation, or transmission via numerous channels, are different methods. But these methods require sophisticated hardware to get desired results[43].

Relaying could not be energy-efficient with low traffic volume, proper channel conditions of channel, and close distances between receiver and transmitter. The best strategy is to use different network architectures on a requirement basis. Security is also a big problem in the cognitive environment. The principal target of the attack is the sensing part of the cognitive process, where attackers can use spectrum sensing data falsification and PU emulations to gain access inside the network [46].

In cooperative spectrum sensing, a hostile CR that regularly reports is "busy." Cognitive radio can utilize authentication and reward-punishment methods to prevent security risks. However, more security means more energy requirements as security checks like authentication create extra security overhead. This thesis will focus on EE vs. PU interference trade-off with spectrum sensing by the SU [47].

1.15.1 EE in CRN

The market for wireless services has been increasing exponentially, so energy consumption is a concern for service providers and users of these services. The cost of energy and environmental concerns associated with energy generation are significant challenges for service providers. For wireless service users, the primary concern is the battery constraint in wireless devices. Consequently, EE for wireless networks is main focus area of the research and industry community. In recent years, reliability and QoS have been the focus area of wireless system design. Spectral efficiency and data transmission efficiency over an allotted bandwidth has been the key performance metric of system design. However, this metric does not include energy consumption. Energy-efficient communication has become the focal point of academic and industry efforts to reduce energy usage in wireless networks. In this section, we emphasize energy-efficient cognitive radio systems where we maximize the SU EE with interference and power constraints[36].

1.15.2 Energy-Efficient Machine Learning

In recent years, CRN has been attracted by machine learning (ML) algorithms and artificial intelligence (AI) applications. Moreover, bandwidth allocation, interference and power management, spectrum availability estimation, resource allocation, and cognitive engine design are done by using Fuzzy logic, neural network, game theory, and other technologies. The ML algorithm significantly enhances the spectrum sensing process of CRN. Compared to traditional sensing methods, this ML-based sensing provides high sensing accuracy and self-adaptation to environments[49].

1.16. PROBLEM IDENTIFICATION AND MOTIVATION

There is a large power difference between locally transmitted and received signals from different nodes, which makes some difficulty to extract the locally transmitted signals from the received signals. So, we can't use full-duplex transmission in wireless communication. The FD can be used by combining the RF Interference Cancellation, Antenna Cancellation, and Digital Interference Cancellation techniques in wireless communication, as shown by previous research. Without causing any severe interference at a primary network, SU can access spectrum allocated to PU in a conventional CRN. The PU does not wait for the SU to use the channel nor notify SU when they begin or stop the transmission. So, a back-off mechanism is required for SU to recognize the spectrum holes or gaps. Every SU sense the spectrum with a sensing strategy and tests the following two assumptions; one is spectrum idle, and another one is the spectrum occupied by a PU at the beginning of each time slot. To minimize the probability of collision among SUs, the SUs transmits the remaining time of the slot based on the scheduling scheme once the spectrum is idle. At the same time, combining EH technologies with CRNs is an exciting solution due to the spectrum scarcity and increasing energy consumption, so it offers a spectrum and energy-efficient wireless communication system. Cognitive radio techniques offer efficient spectrum and energy resources to enhance the energy management of future wireless networks. Thus, we suggest and estimate the wireless FD scheme for CRNs, which should optimize EH and minimize energy consumption and data loss through an optimized spectrum selection method. We will use artificial intelligence-based prediction methods or meta-heuristic optimization algorithms for spectrum sensing.

This thesis aims to propose a novel optimization algorithm to improve life and throughput of cognitive radio under EH. Energy-harvesting CR network's performance is affected by problem of collision constraint and energy causality . Energy causality constraint contracts with total consumed energy of SU. The collision constraint states that PU should not suffer from any harmful interference from the SU whenever it requires to utilize spectrum.

Traditional secondary user performs data transmission and spectrum sensing. Frame structure of CR consists of two slots, a sensing and transmission slot. SU can sense existence of PU during sensing slot. But SU loses a certain amount of energy for sensing, and even if the channel is available, it cannot transmit its data because of insufficient energy. To avoid this, SU can harvest the energy from the PU signal to transmit data whenever the channel is free. This can be achieved with an energy-harvesting CRN. Here frame structure of SU can have three slots; sensing slot, harvesting slot, and transmission slot. SU can harvest the energy during the harvesting slot, reducing the transmission time. So, to avoid this problem, harvesting and sensing can be performed independently and parallelly, providing sufficient time for data transmission for SU.

1.17. CLASSIFICATIONS OF THE OPTIMIZATION ALGORITHM

Optimizations Algorithms are guidelines or procedures used to identify the ideal response to engineering issues within a workable search space. Engineering issues may be adequately goal-oriented and developed within restrictions. Design parameters are design variables in engineering design issues, design approval is goal function, search techniques are optimization techniques, and search spaces are workable solutions. The goal function of cognitive radio may include sensing time, throughput and sensing error, etc.

According to mirajili et al., optimization techniques are classified as either deterministic or stochastic. This proposal defines deterministic optimization techniques without certainty of obtaining an optimum solution. These methods may be broken down into the subspaces from the search space. These methods will provide the optimal value for each subregion. However, these methods deliver the optimal answer with less computational complexity and in less time [50]. The categorization of deterministic optimization based on the concept presented above is shown in figure 1.16. According to Vivek Gupta et al., traditional optimization techniques depend on restrictions, variable nature, and integers [51].

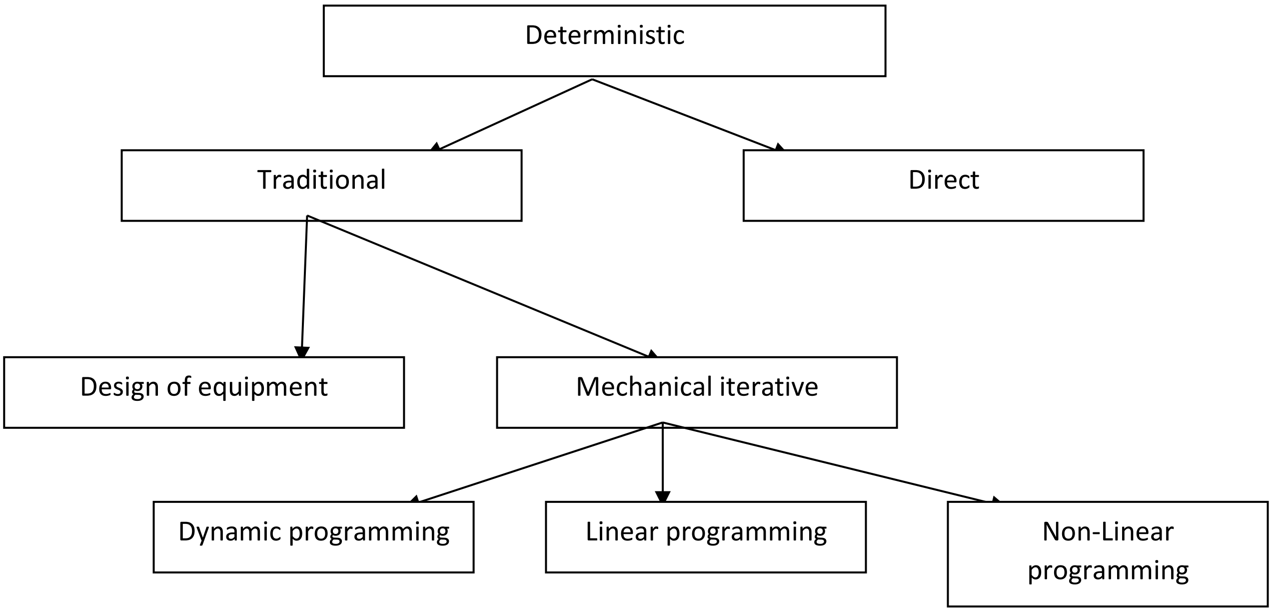

Figure 1.16: Deterministic optimization technique[67]

Xin-She Yang's stochastic optimization method may be divided into heuristic and metaheuristic classes. Heuristic algorithms search using expert knowledge and experience. These algorithms employ trial and error to obtain the objective function's optimal value in a reasonable time, but they may not yield the optimum global value [52].

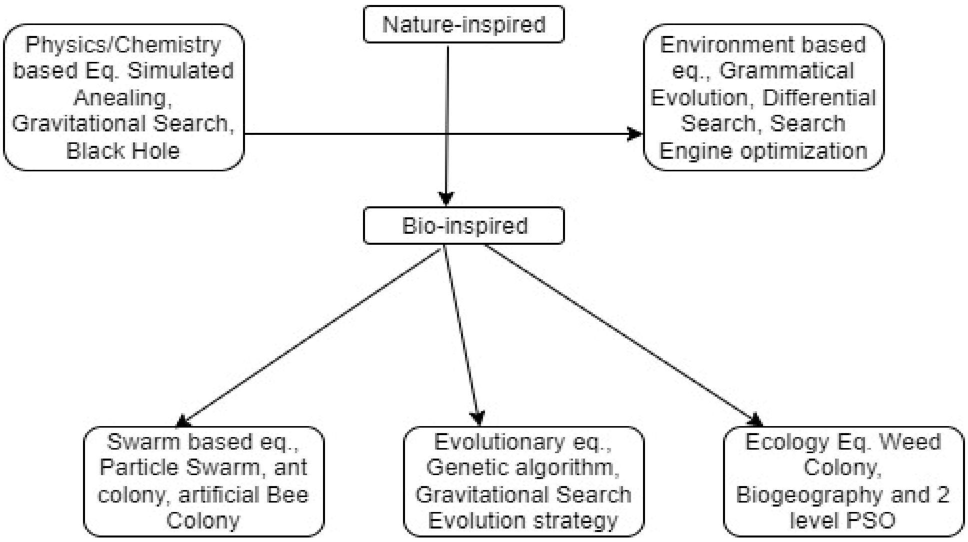

Figure 1.17: Classification of nature-inspired optimization technique[52]

The “metaheuristic algorithm” has several advantages that can alter itself to generate optimized versions, possibility of hybridization within these algorithms, and the fact that these algorithms are adaptable against environmental and dynamic changes. Ahmad et al. define nature-inspired algorithms as techniques to solve any real-time issue, similar to how nature solves problems[53]. Bio-inspired algorithms solve optimization problems by mimicking the actions of plants and animals in their natural environments. Evolutionary algorithm, a bio-inspired algorithm guided by the Darwinian method, is another (survival of the fittest). The genetic algorithm is one example of this method. Particle swarm optimization is an example of the second subclass of bio-inspired optimization. This approach models animals' cooperative and competitive behaviour to discover the best solution to the decision issue. Ecology algorithm is the last category of biologically inspired algorithms. These algorithms' techniques imitate the goal function and arrive at the optimal value by using the behaviour of natural ecosystems.

Abobakar et al. suggest nature-inspired algorithms as population-based and trajectory-based. Population-based optimization uses numerous search agents to locate a solution. Population-based algorithm is also known as exploration-based optimization since diversification will be conducted well in this optimization search area. There is just one search agent in trajectory-based optimization techniques, which travels in a zigzag route until it reaches the optimal value after convergence. The starting solution in trajectory-based optimization is chosen at random[54]

The optimization algorithm performs in a specific way to find an optimum or satisfactory solution. Also, compare its current value with previous value to obtain optimal weight and continues this process until it reaches best solution. The design objective of an optimization algorithm is to maximize production efficiency or minimize production costs[55].

1.17.1 Evolutionary algorithm

An evolutionary algorithm is a division of evolutionary computation or a generic population-based-meta-heuristic optimization technique in artificial intelligence. This evolutionary algorithm method is motivated by biological evolutions like reproduction, mutation, and recombination. In this kind of algorithm, the fitness or objective function calculates the quality of the solutions[56].

1.17.2 Bio-inspired algorithm

This bio-inspired algorithm is inspired by the biological evolution of nature to develop new and robust computing methods. It has a big scope in computation techniques because of its principles. Also, it is motivated by the behaviour of birds or animals to find an optimal or better solution to a given problem[57].

1.17.3 Clustering based methods

Various fields like image analysis, information retrieval, machine learning, and pattern recognition use the clustering technique, a common technique for statistical data analysis. This technique allows us to group similar data objects in a single cluster[58].

1.17.4 Heuristic Techniques

The Latin word 'heuristic,' which means to discover or find, refers to solving a problem using a specific procedure. It is a technique for obtaining the best and most satisfactory answer quickly. Hence, optimality, perfectness, and precision are traded for the pace using heuristics. A guess, thumb rule, and common sense are all small heuristics. Heuristics have earned a respectable space in a busy and fast world where many complex real-life problems must be solved.

Metaheuristics are a level above heuristics, where they are more like a black box capable of solving a problem more efficiently, similar to heuristics. Both these words are very often used interchangeably in literature. Numerous problem-solving optimization algorithms exist, each with its unique attribute [59].

1.18. MACHINE LEARNING (ML) ALGORITHM

ML algorithms are based on math and logic programs. Also, adjust the parameters inside the algorithms to achieve better classification with numerous data. A change in humans for data processing through learning, the programs also changing for data processing over time. This is termed the "learning" part of machine learning techniques. Also, his algorithm adjusts its parameters in a particular way to make predictions about data and give feedback on its previous forecasts. ML is a data analytics technique resembling the human behaviour of classifying based on training [60].

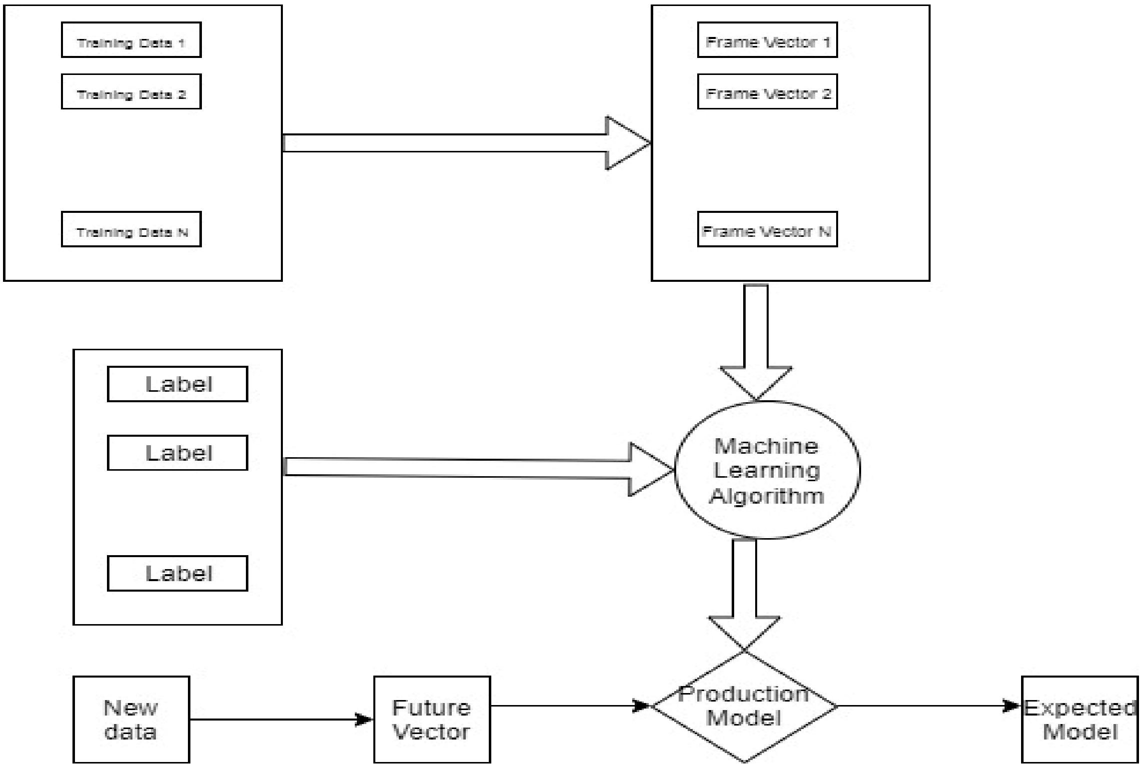

Figure 1.18: Machine learning algorithm[60]

ML overlaps a large field of study and is used in many fields for different applications, like artificial intelligence. ML is used in CR for learning and acquiring knowledge from the available data. Various techniques are used from ML to analyze the data for sensing and decision-making[61]. These methods are computation-based, and they learn information without applying pre-determined equations. Machine learning is classified into supervised, unsupervised, and reinforcement learning techniques and is used to solve problems. Machine learning algorithms can learn from experience without explicitly programming the situation. It comes under artificial intelligence, where the program learns from the available data and can decide on unknown data by matching the learned patterns. Learning begins from data observation and learning patterns. These learned patterns are then used to make better decisions. This learning can be done without human intervention. Machine learning is mainly used in Computer vision-based applications, face recognition, object detection and recognition, Credit score, market trading, Cancer detection, Discovery of drugs, DNA Sequencing, and Voice interaction-based applications[62].

1.18.1 Supervised Learning

Supervised learning needs a labelled dataset to guide the learning process. The labelled dataset has a matching output for each input data. The dataset is split into a ratio (usually 80/20), with 80% used for training and 20% for testing**.** The model is learned from the training dataset. Supervised learning can be classified into two categories. These are classification and regression. In the case of classification, the output is a well-defined, discrete label. In the case of regression, the output is a constant value. The following are some of the supervised learning methods.

i Linear Regression

ii Nearest Neighbor

iii Naive Bayes

iv Decision tree

v Support Vector Machine (SVM)

vi Random Forest

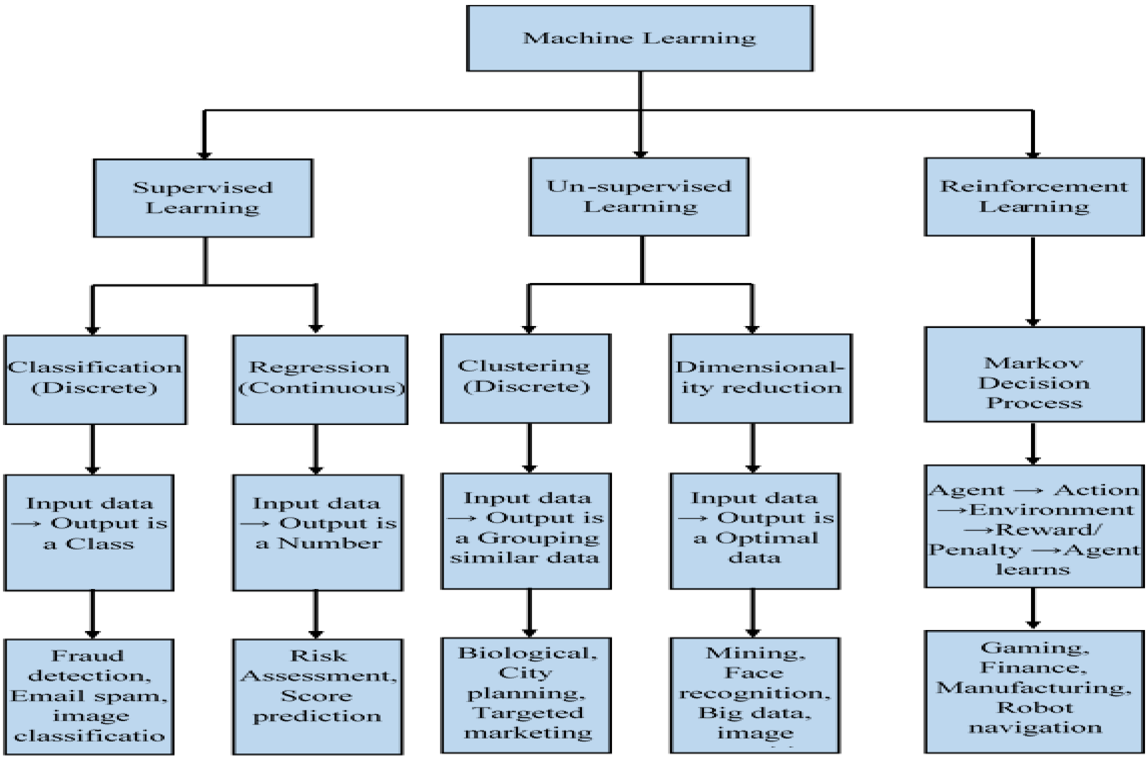

Figure 1.19: Machine Learning Techniques & its applications[60]

1.18.2 Un-Supervised Learning

The algorithms act on input data alone without any guidance. The learning is based on information like similarities, patterns, and differences in the data. The objective of an SVM is for newly presented input data to predict the correct label.

There are two categories of unsupervised algorithms.

i **Clustering:** These algorithms group the data based on inherent similarities and use this data as a guide for further classification.

ii **Dimensionality reduction:** The inherent relation in data ordering guides further classification[63].

1.18.3 Reinforcement Learning

In this learning scheme, the best actions are learned by continuously comparing the actions taken with actual output and scoring them in rewards and punishments. Essential characteristics of reinforcement learning search using trial and error and delayed reward. The best actions are learned using a simple reward feedback mechanism called reinforcement signal. Reinforcements can be either positive or negative. The event positively affects the behaviour in the case of positive reinforcement[64].

The advantages of positive reinforcement learning are:

i Performance is maximized

ii Changes sustained for a longer duration.

iii Disadvantages of positive reinforcement learning:

iv Overloading of states due to too much reinforcement.

In Negative Reinforcement, the negative behaviour affecting the learning strength is stopped.

The advantages of negative reinforcement learning are:

i Increase in behavior

ii A minimum performance guarantee.

The Disadvantages of negative reinforcement learning:

i It can meet only minimal behavior.

ii Its desired output is not reached.

1.19. RESEARCH OBJECTIVES

1. To propose a machine learning-based algorithm to optimize multi-band spectrum sensing in energy-harvesting CRNs.
2. To propose clustering-based spectrum sensing technique to improve system performance.
3. To develop a machine learning-based algorithm to reduce spectrum handoff events to minimize energy consumption.
4. To propose a machine learning-based predictive resource allocation strategy to enhance the performance of energy-harvesting CRNs.

1.20. WORK IMPLICATIONS

The first objective is to implement machine learning in CRNs so they can detect the spectrum. In this method, every user generates a sensing report under various conditions based on a global decision. At the FC, the SUs' local decisions are combined based on a majority vote, and every SUs in the training stage is given a global decision. All SUs compares their current sensing classes and distance vectors in the classification stage. After that, quantitative class computes the sensing report to classify the presence or absence of PU. The machine learning concept achieves this. The spectrum sensing method is adopted for spectrum sensing and optimal spectral estimation to concentrate on energy detection. This also recognizes the spectrum holes and allows unlicensed users to interrelate with one another throughout the licensed bands. So, this objective mainly utilizes the optimization-based spectrum sensing technique to diminish energy consumption. This technique quickly senses spectrum in CRN to consume energy and improve throughput of spectrum.

The second objective mainly concentrates spectrum sensing depend on a clustering algorithm to obtain better sensing accuracy in CRN. Status of the PU is detected based on the performance. In this method, two different kinds of levels are performed. At initial level, the spectrum selection sharing method is selected based on the cluster, which is presented with SUs. Next level is status of PU based, so a spectrum is determined. Finally, presence of PUs was detected based on the cluster-based cooperative spectrum sensing method. So, a clustering-based spectrum selection technique is proposed to increase performance of CRN. A cluster-based CSS has a massive effect on sensing accuracy rather than CSS. Thus, the performance of CRN is enhanced by the best scheme selection and relay selection techniques.

The third objective discusses handoff reduction, measured as exhilarating challenges in CRN. SH occurs when a PU wants to access a channel engaged by a SU. After that, the SU must move to an inactive channel when the entry of authorized user has been detected. This process continues until the unlicensed user finishes his transmission. So, this motivates us to propose the recently developed “SVM-RDA” algorithm to achieve handoff reduction in CRN. Also, it tackles spectrum mobility issue in a known radio-electric environment to guide SUs over routes produced with an optimization algorithm.

The fourth objective discusses resource allocation strategy in a CRN. Resource allocation among PUs and SUs in CRN in a cognitive environment is considered the most important key feature. It is essential to have cognitive radio theory to raise the usage of licensed spectrum bands inside a similar network of PUs or SUs. Moreover, resource allocation is utilized to use the whole frequency spectrum. SUs' traffic demands, interference threshold of Pus and transmission power are some issues that decrease the system's EE. This fourth objective provides a resource allocation approach based on an evolutionary algorithm to reduce highest energy consumption and the slightest EE problem. Spectrum prediction is also considered one of the challenging issues in cognitive CRNs to avoid crashes with licensed users, which conserve more energy and lead to delays. Spectrum prediction technologies are mainly utilized to minimize energy consumption, delay consumption, and predict future channels based on historical information. So, the machine learning-based spectrum prediction technique is presented with a metaheuristic algorithm.

1.21 ORGANIZATION OF THESIS

Chapter 2 discusses about literature review. Chapter 3 gives information about proposed methodology and algorithm (SVM-RDA). Chapter 4 gives solution of first objective i.e. “To propose a machine learning-based algorithm to optimize multi-band spectrum sensing in energy-harvesting Cognitive Radio Networks.” Chapter 5 gives solution of second objective i.e., “To propose a clustering-based spectrum sensing technique to improve system performance.” Chapter 6 gives solution of third objective i.e.," To develop a learnheuristic algorithm to reduce SH to minimize energy consumption." Chapter 7 gives solution of fourth objective i.e.," To propose a machine learning-based predictive resource allocation strategy to enhance the performance of energy-harvesting CRNs." Chapter 8 discusses conclusion and future scope.

CHAPTER 2

LITERATURE REVIEW

A. de Baynast al. developed cross-layer optimization based on ARQ for CRN wireless multi-carrier transmission. The cognitive radio's primary feature for wireless communication systems is optimizing the related communication parameters and providing a complex wireless channel environment. Genetic algorithms were introduced to find the optimum parameters iteratively based on the recognition signal. Neither information about the network state nor estimation of the channels is needed. The objective functions we derive from implementing genetic algorithms guide the system-level optimization against any QoS[65].

W. Cheng et al. developed a FD wireless CRN communications network. Dynamic spectrum exposure as a key in CRNs must be planned to reduce interference and delay to PUs. To solve this issue, they propose a FD wireless communication scheme for CRNs. In particular, Digital Interference Cancelation, RF Interference Cancelation, and Antennas Cancelation were used by SUs to check for active PUs when transmitting. If PUs are detected, SU must immediately release spectrum to stop PU's intrusion and delay. We examine PUs 'packet loss rates in wireless full-duplex CRNs and compare them to PUs' packet loss rates in wireless half-duplex CRNs[66].

S. Lee et al. developed opportunistic wireless harvesting in CRN. They made significant progress in designing efficient circuits and devices for low-power wireless applications. So, this paper proposed a technique for wireless networks. Also, this method considers a stochastic-geometric model for both primary and secondary transistors to access the spectrum licensed to the primary network. Moreover, optimal transmission power and secondary transistor density increase the secondary network's throughput[67].

H. Sun et al. presented various wideband spectrum sensing algorithms are presented, together and discussed pros and cons of each algorithm and the challenging issues. Wideband spectrum sensing is essential for next-generation cellular networks to find spectral opportunities and access opportunistic spectrum[68].

S. Park et al. identified the best spectrum sensing strategy for optimizing the total throughput under energy causality and collision constraints. Energy causality constraint is based on principle that harvested energy must be more than or equal to the total energy spent. In contrast, the collision constraint must be satisfied to ensure the safety of the PU. Under limitless battery capacity, authors calculated the best detection threshold. In addition, they demonstrate that a drop in the probability of accessing the occupied spectrum does not necessarily reduce probability of accessing the unoccupied spectrum in an energy-limited environment[69].

X. Huang et al. examined energy-efficient CR approaches and wireless network optimization for green energy sources. They investigated existing energy-conscious spectrum sensing, management, and sharing. The current energy-efficient CR-based wireless access network is reviewed in various contexts, like small cells, relays, and cooperative radio. Because renewable energy is expected to become a significant energy source shortly. Green energy's arrival rate, which relies on the surroundings of energy harvesters, is unpredictable and sporadic. The author discusses research issues in constructing CRNs powered by energy harvesters to maximize and adjust green energy consumption to opportunistic spectrum availability[70].

Yun Liao et al. are planning CRNs with FDs. A 2-stage "listen-before-talk" in standard CRNs was utilized by the SUs who usually access the spectrum of PUs. To this end, a "listen-and-talk” protocol was introduced with help of FD technique enabling SUs to access and sense available spectrum simultaneously. Proposed LAT protocol analyses the sensing performance and SU throughput[71].

J. Zhang et al. designed a full-duplex, wireless-powered supplementary system for CRNs. In this study, we provide a cognitive radio underlay approach in which a source in a secondary network broadcasts information with full-duplex to a wireless destination node via power-splitter architecture. The receiving antenna at the destination node will receive notification from source. Collected energy is then used to send jamming signals in the transmitting antenna to reduce the decoding capability of the eavesdropper. Probability from the lower and upper bounds was derived for strictly positive secrecy capacity [72].

H. B. samalleh et al. perform an age of information for an EH CR. This age of information performance metric estimated the freshness of information. So, this paper discovers the minimization of age of information in CR EH communications. Moreover, this paper studies the spectrum access rights of Pus and SUs. In this method, SUs act as EH sensors to harvest the ambient energy and update the sensing data to its destination. After that, the age of information was minimized by SUs to check whether the spectrum was perfect or imperfect. Moreover, Markov decision process was initiated to solve the problems[73].

A.M. Koushik et al. developed a machine-learning technique in CRN for spectrum decisions. This paper proposed a cognitive spectrum decision model merged with Raptor Code and SH in CRN [74].M. M. Abdel-Sayed et al. proposed a sparse signal reconstruction algorithm based on threshold, Fast Matching Pursuit (FMP). They have discussed that FMP can accurately and fast sparse signal reconstruction[75].

H. Ananda Kumar et al. discussed a new way to share a spectrum based on social language inspired by natural communities. This was done to solve the problem of spectrum being underused and scarce. Together, social data and mobile communication networks form the Social CRN, which offers various data delivery services related to the social connections of mobile users. A bio-intelligent supervised learning system called SpecPSO is developed for conducting social cognitive handover (SCH) to a) Evaluate effective spectrum usage and b) Increase data rate for apps such as Facebook, LinkedIn, and Twitter. By optimizing different handover issues, the proposed SCH-SpecPSO performs 75% better than the other mobile social networks that are currently available[76].

H. Anandakumar et al. discussed the idea for the Spectrum PSO algorithm (Spec-PSO) algorithm, which can learn from its dynamic surroundings. The effectiveness of the Spectrum PSO algorithm is comprised of a more significant secondary link number. Compared to conventional CSS approaches, the proposed methodologies would describe more optimal call regions on the feature area, resulting in better detection performance. As a result, the developed technique is far more reliable than the traditional CSS approach, which calls for prior knowledge of an element's potential for optimization. Cognitive radio research focused on communication networks, not data applications. Cognitive radio needs wireless channel data and network load[77].

A. Masadeh et al. developed a CRN with CSS and EH. The transmit power of secondary source was examined by derivation of closed-form expressions; also, relay in source maximizes network throughput. After that, the secondary network was allocated by power with projected sub-gradient technique. The performance of proposed method was obtained from the numerical simulations. This proposed technique was compared with existing methods and outperformed by increasing the high SNR. As a result, both the proposed and conventional-based scheme performs similar results[78].

H. Xing et al. developed optimization-based direct and forward -CRNs through which full-duplex access points were allowed for electricity. They use successive convex approximation techniques to investigate a weighted problem of maximization of sum-rate subject to transmitting power constraints and a total cost limit [79].

R. Zhang et al. developed a full duplex, wireless EH cooperative CRNs. The secondary receiver is equipped with an FD radio. It is an FD hybrid access point to gather information from its connected secondary EH transmitter and relays the signals. The ST is believed to have an EH generator and a rechargeable battery so that the primary transmitter and the hybrid access point can collect and store energy from the radio frequency signals. Authors construct analytical formulas for the possible throughput of primary and secondary connections by defining the ST battery's complicated charging and discharging behaviours. This allows the authors to understand the battery's capabilities [80].

K. Lee et al. studied Secondary Network EH using Primary Network RF signals to increase CRN energy efficiency. Specifically, the authors presented an optimum sensing time and power allocation method to optimize energy efficiency. This technique considers the practical limits produced by EH in CRNs and aims to maximize energy efficiency. Optimization techniques, like nonlinear fractional programming, were used to solve the problem, and an iterative method was used to find the best way to use power and time for sense. Lastly, authors used simulations to show that their approach was the best, even though it might not be possible to get enough energy from RF signals to keep wireless networks running smoothly[81].

S. Kochar et al. discussed spectrum sensing based on popular optimization techniques: Genetic algorithm (GA) and PSO, inspired by nature for solving various problems. PSO gives low complex optimal solutions as compared to GA. In contrast, GA seems to arrive at a final value in fewer generations than the PSO and is better in implementation [82].

H. Zhu et al. proposed the SVM scheme for detecting MSU (Malicious SUs). "The concepts of misclassification probability and recognition probability are introduced.

Besides, they analyze the trade-off relationship between misclassification probability and the threshold of classification accuracy. Moreover, the asymptotic optimal property is derived. They verify the algorithm's efficiency in several performance indexes in a simulation. Simulations show that the proposed scheme can excellently deal with Spectrum Sensing data Falsification attacks to improve the system's robustness and achieve a significant gain in the PU estimate[83].”

H. Sah et al. proposed reliable machine learning-based spectrum sensing in CRN. They propose a k-nearest neighbour for spectrum sensing. Each user provides a sensing report that communicates or remains silent throughout training. In training, every user makes a global choice. The classification stage says the absence or presence of PUs[84].

M. Tuberquia-David et al. performed a handoff reduction in CRN using evolutionary algorithms. In CRN, handoff reduction was considered one of the exciting challenges. When a PU wants to access the channel, but it was already accessed by a SU, in that time, spectrum handoff occurs between the two channels. This paper proposed a bio-inspired algorithm to solve the problems of spectrum mobility in an electric radio environment [85].

M. Kalpana Devi et al. developed a strategy for successfully enriching channel use for SU. To overcome this challenge, this model employs the swarm-based intelligence algorithm, “improved Particle Swarm Optimization” (iPSO). The proposed algorithm iPSO improved performance based on the throughput, SNR, fitness function, SU bandwidth, and total bandwidth. iPSO outperforms GA and specPSO. Allocating SU's channel to CRN focuses on improved network connectivity[86].

V. Agarwal et al. proposed an Artificial Neural Network-based handoff algorithm and its implementation. A data set is created in Network Simulator NS-2 tool for training a neural network. The trained neural network helps determine the vacancy of channels in future time slots. Furthermore, all primary channels are ranked in the order of least occupancy by PU. The target channel selection for handoff is based on the channels' ranking. This facilitates SU to select a channel for handoff having a negligible probability of occupancy by PU. The selection of a best channel for handoff decreases required handoffs. Reduction of handoff leads to improvement in throughput and delay[87].

X. Liu et al. proposed an intelligent clustering CSS based on Bayesian learning with intra-cluster CSS and inter-cluster CSS that can improve sensing performance in perfect and imperfect sensing reports. The intra-cluster CSS sensing threshold is optimized by reducing the overall Bayesian cost, which is determined by the rate loss. In contrast, Bayesian fusion determines the inter-cluster CSS's detection probability and overall false alarm probability. A clustering approach is suggested to ensure the accuracy of the reported sensing information and judgments based on K-means learning[88].

S. Mondal et al. proposed a new adaptive time-based EH scheme and discussed working of secondary networks in terms of secondary receiver data. The effects of the efficiency of EH on outages. The suggested technique adaptively adjusts harvesting time based on the harvesting link's channel state, interfering links, and harvesting circuit efficiency. Energy efficiency affects time-out probability. It has been found that adaptive time-based harvesting always has better outage performance than fixed time-based harvesting[89].

Y.Li et al. used EH technology to execute a bandwidth allocation for cognitive relay networks related to a smart grid. This paper examines the cognitive relay protocol for a smart grid in which the primary transmitters search for energy from natural sources. Also, to forward the primary signal, it utilizes the harvested energy. A SU acts as a relay node dependent on the strength of the natural energy collection. Moreover, “amplify-and-forward” and “decode-and-forward” protocols were investigated. This study calculates primary and secondary smart grid transmission rates. Optimal bandwidth allocation maximized the suggested method's sum rate[90].

A. Banerjee et al. developed residual energy for EH CRN. With a cooperative spectrum sensing technique, this paper simultaneously performed a power-splitting mode of operation. After that, a SU harvests RF energy from the PU through transmission and sensing techniques[91].

Fan F. Zhang et al. jointly optimise transmit power and spectrum sensing in EH CRN. In this paper, resource allocation problem was formulated as Markov Decision Process, which maximizes the long-term expected throughput. This research utilizes an optimal sensing transmission policy for spectrum sensing and power transmission. With this method, the throughput was increased with available energy of battery. Furthermore, a high SNR power ratio of primary signal was computed by this method. Also, an efficient sensing transmission technique was developed [92].

X. Dong et al. planned a multi-objective optimization technique for spectrum allocation. A multi-objective optimization approach for network selection and idle spectrum distribution was suggested to maximize total bandwidth while minimizing cost. The complex network selection and spectrum allocation problem were solved using two technical paths. First was the simplification method to analyse the relationship between objectives and constraints. An Intelligent optimization algorithm was a second algorithm. An improved NSGA-II algorithm was discussed to enhance the traditional multi-objective optimization algorithm. In this algorithm, service quality requirements and interference constraints were combined with the help of PUs[93].

Z. Ali et al. developed a joint optimization framework for EH-based CRNs. Sum rate maximization was the primary goal of this work to limit the power budget and interference of primary network. A non-convex optimization was performed under various constraints. This paper obtains the solution for non-convex optimization from the simplex and duality theory. Two resolutions were obtained: uniform time with optimized power and homogeneous power distribution with optimized time[94].

P. Bharathi et al. developed a hybrid water-filling method to allocate resources in CRNs. To overcome the minimum energy efficiency and maximum energy consumption, a Hybrid Water Filling algorithm was proposed. The Hybrid Water Filling method combines the Iterative Water Filling (IWF) and Multi-Objective "PSO" algorithms. Multi-Objective "PSO" algorithms optimized the sub-channels and energy distribution to maximize capacity while adhering to the overall energy restriction. IWF and MOPSO collaborated on resource allocation to improve energy transmission[95].

J. Arun et al. utilized artificial bee colonies and genetic algorithms to optimize CRN. A lowest ID clustering algorithm was proposed to choose a particular node as CH with the lowest ID. In addition, a meta-heuristic algorithm was integrated with the ABC method to improve spectrum allocation for increased efficiency and fairness[96][97].

G. Eappen et al. presented a proposal for a CRN that used PSO-GSA to optimize energy efficiency in spectrum sensing. The opportunistic throughput, sensing time, sensing bandwidth, sensing energy consumption, and power consumption are considered while estimating the energy efficiency function. The performance of PSO has been improved by combining it with Gravitational Search Algorithm (GSA). Compared to existing ABC and PSO algorithms, simulation results of proposed PSO-GSA method show that it is more energy-efficient for spectrum sensing. When the transmission power or sensing time of environment changes, PSO-GSA saves large energy than the ABC or PSO algorithms. For variable Power Spectral Density, the suggested PSO-GSA outperformed PSO and ABC, while for varied sensing bandwidth, the proposed method was more energy efficient than PSO and ABC [98].

P. Supraja et al. mentioned Cognitive radio, which would access available spectrum dynamically. This approach will cause a revolution in wireless communication, reducing the spectrum consumption issue**.** The use of machine learning in every technology field is becoming more critical. In this case, it teaches the model how to predict available spectra in CR. Cognitive users use range detection algorithms to identify groups before sending any data through them to neglect interference with PUs, which may cause delays in transmission and waste energy. Range expectation procedures are used to reduce waiting time and energy use and predict how channels will be used. Spectrum prediction predicts a channel's future state based on information collected over time. To solve this problem, a backpropagation training model has been proposed for neural system-based spectrum prediction. It is suggested to use a hybrid GA and shuffled frog-leaping algorithm (SFLA) to improve the neural system's structure. In this case, GA has been used to avoid snatching up on locally optimal solutions. The selection, crossover, and mutation functions were performed to build the haphazardness, which stretches out the populace to unite to the set that contains the ideal global solution. The suggested approach shows great prediction accuracy, and simulation results demonstrate that GA-SFLA hybrid algorithm improves outcomes of finding the optimal weights[99][100].

A. M. Fathollahi-Fard et al. investigated the unusual behaviour of Scottish red deer (RD) to construct a novel nature-inspired meta-heuristic algorithm called the red deer algorithm (RDA). This behaviour was seen in Scottish red deer. Primary motivation for developing this suggested algorithm is mating behaviour of RD in breeding sessions. The algorithm's starting population consisted of RD. This group was separated into male RDs and hinds. The superior solutions were evaluated as male Rds. The primary phases of this algorithm cantered on male RD's competition to obtain a harem with more hinds by shouting and fighting[101].

K. Xia et al. developed an optimization technique for spectrum sensing delay in CRNs using decoding forward relays. The SE was increased by using decode and delaying technique in CRN. This paper presents an optimization algorithm for spectrum sensing calculation for cognitive relay networks. There were two kinds of consequences brought up by sensing time. The first view calculated the channel parameters accurately to diminish interference and enhance cognitive users' throughput. Secondly, the system throughput was decreased by shortening the transmission time. So, the throughput of the proposed method was maximized by an optimal sensing time. The stochastic programming method was proposed to optimize the sensing time for cognitive relay networks[102].

A. Nasser et al. proposed FD CRNs mode. This mode aims to monitor the activities of PUs on operating channels while making an in-band full-duplex communication among SUs. This means that SUs can broadcast and obtain same frequency band. For the communication between two SUs, spectrum sensing performs some sub-carrier analysis. To achieve spectrum sensing accurately, the SUs utilizes SCs with residual self-interference of secondary transmission. A SU vacated the channel to activate by PUs[103].

M. K. Giri et al. proposed an intelligent RA method based on DQL for an energy-harvested CRN. Adopting DQL enables algorithm to achieve faster convergence and in large state space systems [104].

CHAPTER 3

PROPOSED METHODOLOGY

3.1 SUPPORT VECTOR MACHINE

Nowadays, professional systems constructed on AI are gaining attractiveness among researchers and industry professionals. Artificial Neural Networks (ANN) and fuzzy logic (FL) are most conventionally used. The ANN is undergoing small traps, difficulty forming layers, and learning rate. Indeed, despite these limitations, the ANN is still deliberately used for diagnosis problems. In contradiction with ANN and other machine learning methods, the SVM established structural risk minimization. An SVM is a regulated statistical learning-based machine learning technology. Classification and regression analysis using SVM can be used in fault identification and diagnosis [105].
The SVM learning method is the expert system built on statistical learning principles [106]. Many issues in real-world are about binary classifications or decisions. An SVM classifier, a non-probabilistic binary linear classifier, is one of the finest approaches to solving such binary issues. With the help of a training data set, the SVM attempts to estimate accuracy on new datasets due to the type of abstract learning machine. Training data includes input vectors xi, each with several elements known as features. There are $\boldsymbol{p}$ such pairings **(i = 1, 2… p)** of input vectors associated with a label represented by $\boldsymbol{y_i}$. There are two groups of data in a binary classification, which can be referred to as positive class or negative class, $\boldsymbol{y_i}=+\mathbf{1}$ or $\boldsymbol{y_i}=-\mathbf{1}$, which are the respective data labels[107].
Figure 3.1 shows training data sets as labelled data points in input space. Hyperplane separate both classes of data. Figure 3.1 (a) shows that the hyperplane can be oriented to separate the two classes' data in many ways. On the other hand, the hyperplane is the furthest away from 2 classes of labelled points on either side. Both side hyperplanes near data points are most affected by orientation and position and called support vectors. Figure 3.1 (b) shows that dark markings identify them. In the space, the classifying hyperplane is given by (dot product) H. Symbol $\boldsymbol{w^T}\ \boldsymbol{x}+\boldsymbol{b}=\mathbf{0}$ in a space H. Symbol b denotes the hyperplane's bias or offset from source in space; weights w determines the

orientation of the hyperplane, which is defined by the points x that are normal to the hyperplane[107].

In Figure 3.1, a 2-D space linear hyperplane , which can nicely classify two data clusters. Unfortunately, the clusters are not always linearly separable as figure 3.2.

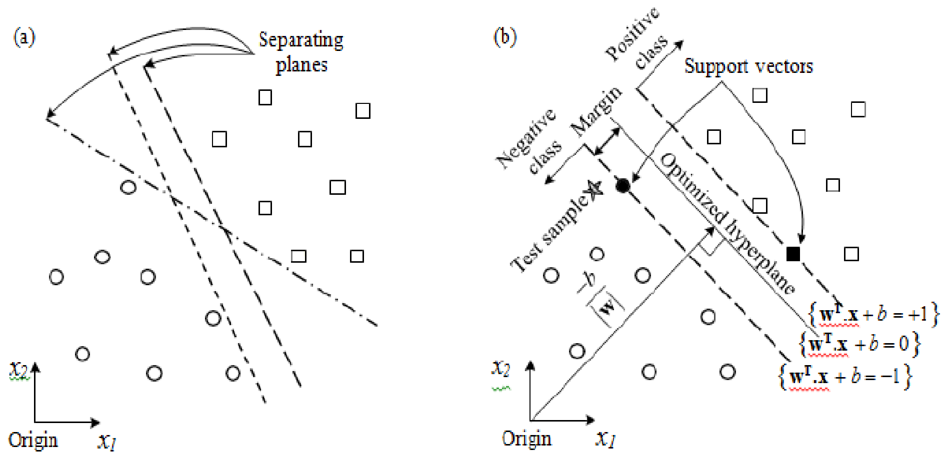

Figure 3.1: (a) Data separated into planes in various orientations; (b) the hyperplane's optimal orientation[108].

Classifiers based on SVMs are attractive because of their ability to predict previously unknown data points (training samples) with analytical higher limit bound on the rationalization inaccuracy. There are two critical characteristic features of this generalization error.

a) By margin maximization, the bound is minimized. Margin is Euclidean distance between sorting hyperplane and each class's support vector.

b) Bound is independent of input space's dimensionality[109].

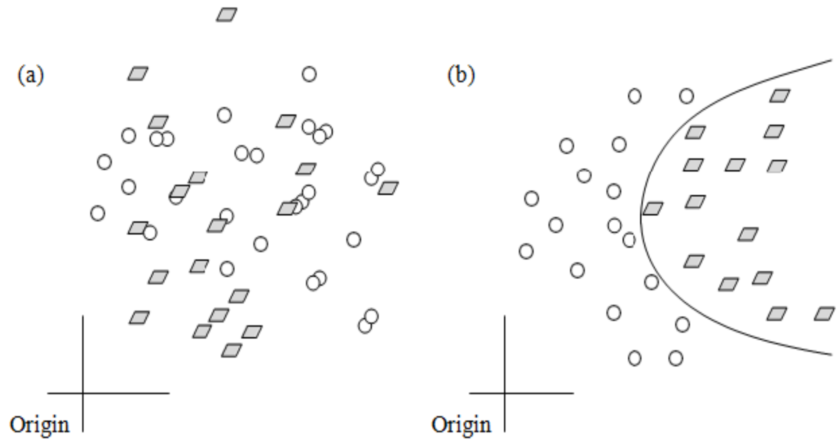

Figure 3.2 : (a) Intermeshed non-linearly separable data (b) data is separable by using a non-linear boundary in feature space with a Gaussian kernel[108].

Consider the case of classifying P sets of training data using binary classification $(\boldsymbol{x_1},\boldsymbol{y_1}),(\boldsymbol{x_2},\boldsymbol{y_2}),\ldots,(\boldsymbol{x_p},\boldsymbol{y_p})$ into 2 classes, where $x_i \in R^n$, i=1,2……. p and $y_i \in\{-1,+1\}$ specifies its class label. Now let decision function be

$$f(x)=\text{sign}\ (w^T.x+b) \tag{3.1}$$

"From given "decision function", it is clear that data is correctly classified if it satisfies $(\boldsymbol{w^T.x_i+b})$ is positive for $\boldsymbol{y_i=+1}$ and $(\boldsymbol{w^T.x_i+b})$ is negative for $\boldsymbol{y_i=-1}$. **"**Decision function" is invariant with positive rescaling of $(\mathbf{w^T.x_i+b})$. Hence, an unspoken scale for $(\boldsymbol{w^T}$, b) is defined by setting $(\boldsymbol{w^T.x+b=+1})$ for closest data points on one side and $(\boldsymbol{w^T.x+b=-1})$ for closest data points on the other side. Canonical hyperplanes pass through $(\boldsymbol{w^T.x+b=+1})$ and $(\boldsymbol{w^T.x+b=-1})$, and the region between them is called the "margin band". Let $\boldsymbol{x_1}$ and $\boldsymbol{x_2}$ be two points on opposite sides of canonical hyperplanes. That is, if $(\boldsymbol{w^T.x_1+b=+1})$ and $(\boldsymbol{w^T.x_2+b=-1})$, it can be deduced that $(\boldsymbol{x_1-x_2})\boldsymbol{=2}$. For the separating hyperplane $\boldsymbol{w}^{\mathrm{T}}.\boldsymbol{x_i+b=0}$, the orientation of the hyperplane can be given as $\boldsymbol{w^T}/\|\boldsymbol{w^T}\|$. The projection of $(\boldsymbol{x_1-x_2})$ onto $\boldsymbol{w^T}/\|\boldsymbol{w^T}\|^2$ is equal to the distance between two canonical hyperplanes, that is, $\boldsymbol{w^T}x+b/\|\boldsymbol{w}\|$. Margin can be written as $\boldsymbol{\gamma}=2/\|\boldsymbol{w}\|$ since it is half the length of canonical hyperplanes. So maximum margin is M=Max $(2/\|\boldsymbol{w}\|)$. Therefore, maximizing margin implies minimizing the function given by Equation (3.2), subject to constraints given in Equation (3.3)[108]."

Minimize $\frac{1}{2}\|w\|^2$ (3.2)

Subject to constraints, $y_i[w^T.x_i+b]\geq 1 \quad \forall i$ (3.3)

Equations (3.2) and (3.3) represent a "constrained optimization problem". A Lagrange function reduces this to a minimization problem by multiplying the p constraints, and objective functions are multiplied with the corresponding Lagrange multiplier. Prime function is given as,

$$L(w,\beta,b) = \frac{1}{2}w^T.w - \sum_{i=1}^{P}\beta_i\,[y_i.(w^Tx_i + b) - 1] \tag{3.4}$$

Where $\boldsymbol{\beta_i}$ are the "Lagrange multipliers" and $\boldsymbol{\beta_1 \geq 0}$, to minimize Equation (3.4), partial derivatives for ***w*** and ***b is*** equal to zero. That gives,

$$\frac{\partial L}{\partial w} = w - \sum_{i=1}^{P}\beta_i\,y_i.x_i = 0 \tag{3.5}$$

$$w = \sum_{i=1}^{P}\beta_i\,y_i.x_i \tag{3.6}$$

$$\frac{\partial L}{\partial b} = -\sum_{i=1}^{P}\beta_i\,y_i = 0 \tag{3.7}$$

"And from Eq. (3.7), we have $\sum_{i=1}^{P}\beta_i\,y_i = 0$. Substituting these two deductions into $\boldsymbol{L}$, we get a Wolfe dual formulation [110]." That gives,

So $\mathrm{w}\,(\beta,b) = \frac{1}{2}w^T.\sum_{i=1}^{P}\beta_i\,y_i.x_i - \sum_{i=1}^{P}\beta_i\,[y_i.(w^Tx_i + b) - 1]$ (3.8)

$$\mathrm{w}(\beta,b) = \frac{1}{2}w^T.\sum_{i=1}^{P}\beta_i\,y_i.x_i - w^T\sum_{i=1}^{P}\beta_i\,y_i.x_i - b\sum_{i=1}^{P}\beta_i\,y_i + \sum_{i=1}^{P}\beta_i] \tag{3.9}$$

in a 2-D space (due to equation 3.6)

$$\mathrm{w}(\beta,b) = \sum_{i=1}^{P}\beta_i - b\sum_{i=1}^{P}\beta_i\,y_i - \frac{1}{2}.\sum_{i=1}^{P}\sum_{j=1}^{p}\beta_i\,\beta_j y_i.y_j x_i^T x_j \tag{3.10}$$

But $\sum_{i=1}^{P}\beta_i\,y_i = 0$

So $\mathrm{w}(\beta) = \sum_{i=1}^{P}\beta_i - \frac{1}{2}.\sum_{i=1}^{P}\sum_{j=1}^{p}\beta_i\,\beta_j y_i.y_j x_i^T x_j$ (3.11)

And this is followed optimum problem in duality function, so we have to get

Maximum ($\sum_{i=1}^{P}\beta_i - \frac{1}{2}.\sum_{i=1}^{P}\sum_{j=1}^{p}\beta_i\,\beta_j y_i.y_j x_i^T x_j$)

For $\beta_i \geq 0$ for all i=1,2,…..p and $\sum_{i=1}^{P} \beta_i \, y_i = 0$.

This dual objective function is quadratic concerning Lagrange multipliers β_i and has constraints in Equation (3.10). Hence this issue is termed a constrained quadratic programming issue.

Nevertheless, generalisation theorem demonstrates that: bound is dimensionality independent of input space, which has not yet been considered in formulation's development. From dual objective function in Equation (3.9), it can be seen that input vectors $\boldsymbol{x_i}$ only appear in scalar product. These data vectors can be "mapped" to another space with different dimensions, called a "feature space," to get a different representation by,

$$x_i . x_j \to \varphi x_i . \varphi x_j \tag{3.12}$$

Where $\emptyset$ is the mapping function. Figure 3.1 (a) reveals that the two data sets are superimposed. This is beauty of altering input space's dimensions. In addition, this transformation is valid because bound is independent of the space's dimension. This "mapping transformation" is called "kernel transformation", which is given as,

$$K x_i . x_j \to \varphi x_i . \varphi x_j \tag{3.13}$$

"Kernel choice" is limited by many factors, including that the feature space must be a Hilbert space, where inner product is defined consistently. Thus, choosing a kernel function that minimises training error is crucial. Kernel substitution introduces the "kernel" with its implied mapping to feature space. Some of common "kernel choices" are,

$$K\{a, b\} = a.b \qquad linear$$

$$K\ \{a, \mathrm{b}\} = va.b + c^d \qquad \text{Polynomial}$$

$$K\ \{a, \mathrm{b}\} = e^{-\gamma|a-b|2} \qquad \text{Gaussian RBF}$$

$$K\ \{a, \mathrm{b}\} = tanh\ va.b + c \qquad \text{Sigmoid}$$

In which case, $K\{a, b\} = \emptyset_a \emptyset_b$ for vectors $\boldsymbol{a}$, RBF is a radial basis function. Assuming given kernel is used in a binary classification, dual objective function in Equation (3.8) becomes,

$$w(\beta) = \sum_{i=}^{P} \beta_1 - \frac{1}{2} \sum_{i,j=1}^{P} \beta_i \, \beta_j y_i y_j K x_i x_j \tag{3.14}$$

Subject to constraints given in Equation (3.9). For data point,y_i=+$\mathbf{1}$, and i=1, we note that,

$$\min_{i y_i=+1} w^t \, x + b = \min_{i y_i=+1} \left| \sum_{j=1}^{P} \beta_j y_j K x_i x_j \right| + b = 1 \tag{3.15}$$

Similarly, an expression can be written for data points with $\boldsymbol{y_i}$=$-\mathbf{1}$.

$$\max_{i y_i=-1} w^t \, x + b = -\max_{i y_i=-1} \left| \sum_{j=1}^{P} \beta_j y_j K x_i x_j \right| - b = 1 \tag{3.16}$$

$$\min_{i y_i=+1} \left| \sum_{j=1}^{P} \beta_j y_j K x_i x_j \right| + b = -\max_{i y_i=-1} \left| \sum_{j=1}^{P} \beta_j y_j K x_i x_j \right| - b \tag{3.17}$$

On combining both the equation, we get,

$$b = -\frac{1}{2} \{ \min_{i y_i=+1} \left| \sum_{j=1}^{P} \beta_j y_j K x_i x_j \right| + \max_{i y_i=+1} \left| \sum_{j=1}^{P} \beta_j y_j K x_i x_j \right| \} \tag{3.18}$$

“Therefore, to construct an SVM binary classifier, data $\boldsymbol{x_i y_i}$ need to be substituted in Equation (3.13), subject to constraints given in Equation (3.9). After finding optimal value of Lagrange multiplier (β_i^***),** bias can be calculated from Equation (3.13)”. As a result, the predicted class for a new input vector n depends on the sign of

$$fn = \sum_{i=1}^{P} \beta_i^* y_j K x_i, n + b^* \tag{3.19}$$

Where $\boldsymbol{b}^*$ signifies the bias's optimal value. Only points that are closest to the hyperplane of maximal margin have β_i^*>$\mathbf{0}$, value, these points are called support vectors. As a result, the decision function is independent of the other points with β_i^*=$\mathbf{0}$.

3.2 RED DEER OPTIMIZATION

The Red Deer Algorithm (RDA) begins by randomly deploying a preliminary population of search agents across the entire population [111]. Initially, the SUs are chosen as male RDs, and leftover users are referred to as hinds. SUs are selected for their great potential in terms of residual energy, CH distance, and cluster-to-base station distance. The SUs are initially likely to be chosen as CH are male RD. Male RD nodes entirely govern the hinds, the SUs, and cluster members. According to their capacity to serve as CHs by fulfilling the objective function, male RD (CH nodes) are two types:

commander and stag CH nodes. Commander and stags' nodes fight against each other throughout selecting the CH, and the node with the highest energy efficiency serves as the cluster's (harem) CH for that round.

The capacity and controlling capability of the commander nodes play a crucial role in determining how many hinds (cluster members) make up a cluster throughout clustering procedure. Quantity of hinds in the cluster is always shown on commander sensor node (Primary CH) (harem). Also, during each round of implementation, the secondary stag users (secondary CH) compete with nearby hind nodes of clusters. The RDA procedures are also designed to complete exploration and exploitation. In addition, local search is used to decide on competitive commander phase and stag sensor nodes, even if it only accepts the best solutions discovered throughout procedure. Exploration phase is employed when clusters are formed, and commander's PU is allotted to them depending on their strength.

Furthermore, neighbourhood hind nodes near the stag SUs (secondary CH) compete with them. This competition phase between hind nodes and SUs of stag contributes to the simultaneous exploration and exploitation stages. This Red Deer Optimization algorithm comprises the mating procedure that produces possible offspring (candidate solutions) capable of advancing the development of new and improved solutions in solution space. It also provides a higher possibility for worst solutions to prevent the weakest nodes from being selected as CH.

3.2.1 Initial generation of red deer population

Main goal of optimization is to find a global solution, or as close to it as possible, given variables used in the problem. A variables array is considered for optimization in this CH selection optimization issue. The red deer in this RDOA indicates the collection of viable solutions (F_s) inside solution space. The dimension of the solution in this context is determined by element number (d) examined throughout CH selection process. If the RDA CH selection procedure is considered d-dimensional optimization problem, red deer indicates d-dimensional arrays number ranging from 1 to d. Equation (3.20) is used to define this red deer array.

$$(R_{D(array)}) = [F_{S(1)}, F_{S(2)}, F_{S(3)} \dots \dots \dots \dots \dots \dots F_{S(d)}] \tag{3.20}$$

Where $R_{D(array)}$ denotes the various dimensions that provide an investigation into the viable solution F_S When CH is chosen, The fitness function, which was developed based on distance between base station and CH, distance between CH and cluster member, and residual energy, may be assessed for each red deer using the equation (3.21).

$$Fit_{value}(R_{D(array)}) = Fit_{Fn}[F_{S(1)}, F_{S(2)}, F_{S(3)} \dots \dots \dots \dots \dots \dots F_{S(d)}] \tag{3.21}$$

To begin the implementation of the method, the initial population size (P_{size}) is produced. Remaining search solutions are then classified as hind deer ($RD_{hind} = P_{size} - RD_{male}$), and the best male RDs are selected from the best red deer (RD_{male}). So, number of "male deer solutions" represents algorithm's essentialist criteria and that the numbers of RD_{male} and RD_{hind} support the algorithm's intensification and diversification.

3.2.2 Roaring phase of male RD

"Male red deer solutions" are best in "algorithmic search space". Objective function of "male RD solutions" and their recognized nearby solutions are compared at this roaring phase to discover which solution is the best among them, which will aid in improved CH selection. If fitness function of "red deer solutions" in surrounding area is higher than that of "male red deer solutions," earlier ones will be replaced with the newer ones. Particularly, solutions for the male RD constantly change their location, and their updation is performed using Equation (3.22).

$$RD_{male} = \begin{cases} RD_{male-old} + UDUD_{R(2)}\, X\, (\left(\left(U_{TH} - L_{TH} * UD_{R(2)}\right) + L_{TH}\right) & if\ UD_{R(3)} \geq 0.5 \\ RD_{male-old} - UD_{R(1)}\, X\, (\left(\left(U_{TH} - L_{TH} * UD_{R(2)}\right) + L_{TH}\right) & if\ UD_{R(3)} < 0.5 \end{cases} \tag{3.22}$$

Whereas $RD_{male-old}$ indicates present location of the "male red deer solution," and U_{TH} and L_{TH} Indicate "upper and lower search space limiting thresholds", respectively, to create possible neighbouring solutions of male red deer, $RD_{male-old}$ is present location of "male red deer". In addition, random variables such as $UD_{R(1)}$, $UD_{R(2)}$, and $UD_{R(3)}$) are produced in uniform distribution. Its range is 0 and 1.

3.2.3 Male commanders' selection from 'β' percent of male red deer solutions

At this point, "male red deer solutions" are two types: stage and commander "red deer solutions." In same manner, stage and commander "red deer solutions" are selected based on their capacity to operate like CH in terms of relevance in regulating its cluster members, intra-cluster distance, inter-cluster distance, and residual energy. It is done in same way as described before. Depending on Equation (3.23), the number of male commander solutions has been established.

$$RD_{Comd-count} = Round\ (\beta, RD_{male}) \tag{3.23}$$

Number of commanders "male red deer solutions" in clusters indicates term."$RD_{Comd-count}$" (harems). Initial value associated with percentage of solutions considered for exploitation is indicated by the symbol " β." The range of β is 0 to 1. At this point, an Equation is used to determine the stag red deer solutions $RD_{stag-count}$. Represented in equation (3.24).

$$RD_{stag-count} = RD_{male} - RD_{Comd-count} \tag{3.24}$$

3.2.4 Fighting phase of male commander and stag

During this fighting phase, every commander's RD and stag strategies are randomly compared as they get closer. Therefore, two new, better solutions replace the commander RD solutions. In this situation, one solution stands out as being superior to the others, including two new solutions, the stag, and the commander, that were discovered along the approach ($New_{Sol(1)}, New_{Sol(2)}$). Equations (3.25) and (3.26) numerically depict this fighting process.

This fighting process is mathematically based on Equations (3.25) and (3.26).

$$New_{Sol(1)} = \frac{(Sol_{comd}+Sol_{Stag})}{2} + UR_{D(1)}\ X\ ((U_{TH} - L_{TH}) * UR_{D(2)}) + L_{TH}) \tag{3.25}$$

$$New_{Sol(2)} = \frac{(Sol_{comd}+Sol_{Stag})}{2} - UR_{D(1)}\ X\ ((U_{TH} - L_{TH}) * UR_{D(2)}) + L_{TH}) \tag{3.26}$$

U_{TH} is upper search space limiting threshold and L_{TH} is lower search space limiting threshold that produces new solutions in fighting phase. "However, $UR_{D(1)}$ and $UR_{D(2)}$ are random variables with uniform distribution". $UR_{D(1)}$ and $UR_{D(2)}$ range is 0 and 1. The best solution is chosen in this battle phase from identified commander, stag, and two new solutions ($New_{Sol(1)}$ and $New_{Sol(2)}$). The first solution ($New_{Sol(1)}$) in this fighting phase provides the result of the winning solution, while the second solution ($New_{Sol(2)}$) identifies the losing solution.

3.2.5 Formation of Clusters (Harems)

When the clusters are being constructed, the male commander solution takes on the role of CH, and CH has authority over the group of hinds that make up the cluster. To build clusters, the commander solutions numbers (CH) are given a proportionate fraction of hind solutions number using the equation (3.27)

$$N_{Val} = Cmd_{power(n)} - Max\ (Cmd_{power(i)}) \tag{3.27}$$

N_{Val} is the commander's normalized value, and $Cmd_{power(n)}$ is commander's power with each round of implementation. Normalized power of the commanders is thus based on Equation (3.28)

$$RD_{Comd\ (power)} = \left| \frac{Cmd_{power(n)}}{\sum_{i=1}^{RD_{Comd-count}} Cmd_{power(i)}} \right| \tag{3.28}$$

Where "$RD_{Comd\ (power)}$" is power generated by each commander red deer throughout CH selection and clustering process. Equation (3.29) calculates hinds' number that might conceivably occur in a cluster (harem).

$$RD_{Hind-Harem} = Round\ (RD_{Comd\ (power)} \,.\, RD_{Hind}) \tag{3.29}$$

Where throughout the process of choosing CH, "$RD_{Hind-Harem}$is number of hinds in a cluster. RD_{Hind} is number of total hinds. Commander, red deer solution, outperforms the hind solutions regarding fitness function. Therefore, in the clustering process in the CRN, the commander is the CH, and the hinds are cluster members.

3.2.6 "Commander red deer" mating with γ % of hinds of a cluster (harem)

A "commander red deer" solves the mating process with portion of hinds in group (harem) where it resides. This mating procedure refers to integrating commander and certain specified "hind solutions" of "search space" to create offspring solutions according to Equation (3.30).

$$Hind_{Count\ (Mate)} = (\gamma\ , Harem_{nth}) \tag{3.30}$$

Number of hind solutions selected from n_{th} cluster to mate with related commander red deer solutions in solution space is $Hind_{Count\ (Mate)}$. The γ percentage of hind solutions is based on the total number of formated clusters. Its ranges are 0 and 1. Mating procedure gives potential offspring solutions generation. That is based on Equation (3.31).

$$Offspring_{Sol} = \frac{(Sol_{comd} + Sol_{Hind})}{2} + (U_{TH} - L_{TH}) X\ U_{RV} \tag{3.31}$$

Where U_{RV} is a uniformly distributed random function; its range is 0 and 1.

3.2.7 "Commander red deer" mating with ∂ percent of hinds of another cluster (harems)

New offspring solution for this mating procedure is evaluated by merging the male commander solution with a certain percentage of hinds in other clusters. These hinds come from different populations (say k). This selection of the k^{th} cluster for mating is entirely random.

$$Hind_{Count\ (Mate-k)} = (\partial\ , Harem_{kth}) \tag{3.32}$$

In this scenario, the ∂ percentage of "hind solutions" is chosen randomly from the k^{th}-formed cluster. The production of offspring solution in this mating technique is based on Equation (3.33)

$$Offspring_{Sol(comd-hind(kth))} = \frac{(Sol_{comd} + Sol_{Hind(k)})}{2} + (U_{TH} - L_{TH}) X\ U_{RV} \tag{3.33}$$

3.2.8 Stag mating with neighbouring hinds

Each stag solution is made to mate with the local hind to produce better offspring solutions. In this case, stag solutions determine the closest hind solution based on distance between each stag solution and all hinds in the d-dimensional space indicated in Equation (3.34).

$$Dist_{Stag-hind} = \sqrt{\sum_{d \in D}^{ND} (Sol_{stag}} - Sol_{hind(j)}^{i}) \tag{3.34}$$

Where $Dist_{Stag-hind}$ is the distance between hind and stag solutions. Therefore, the mathematical method stated in Equation (3.34) fully handles the mating procedure.

3.2.9 Next-generation selection process

Two distinct techniques are used to choose the next generations in RDA-based CH selection system. The commander, all stags, and male red deer participated in the initial strategy. The second method, the exploration process, considers the surviving population in the next generation. To choose best hind solutions from whole set of hind and offspring solutions obtained via various mating processes.

3.2.10 Termination Criterion

The procedure is stopped when the quality of the best solution remains constant over time or after the maximum number of iterations.

3.3. PROPOSED METHODOLOGY: "SUPPORT VECTOR MACHINE-RED DEER ALGORITHM (SVM-RDA)"

Pseudo code for "SVM-RDA" Algorithm and flowchart is below:

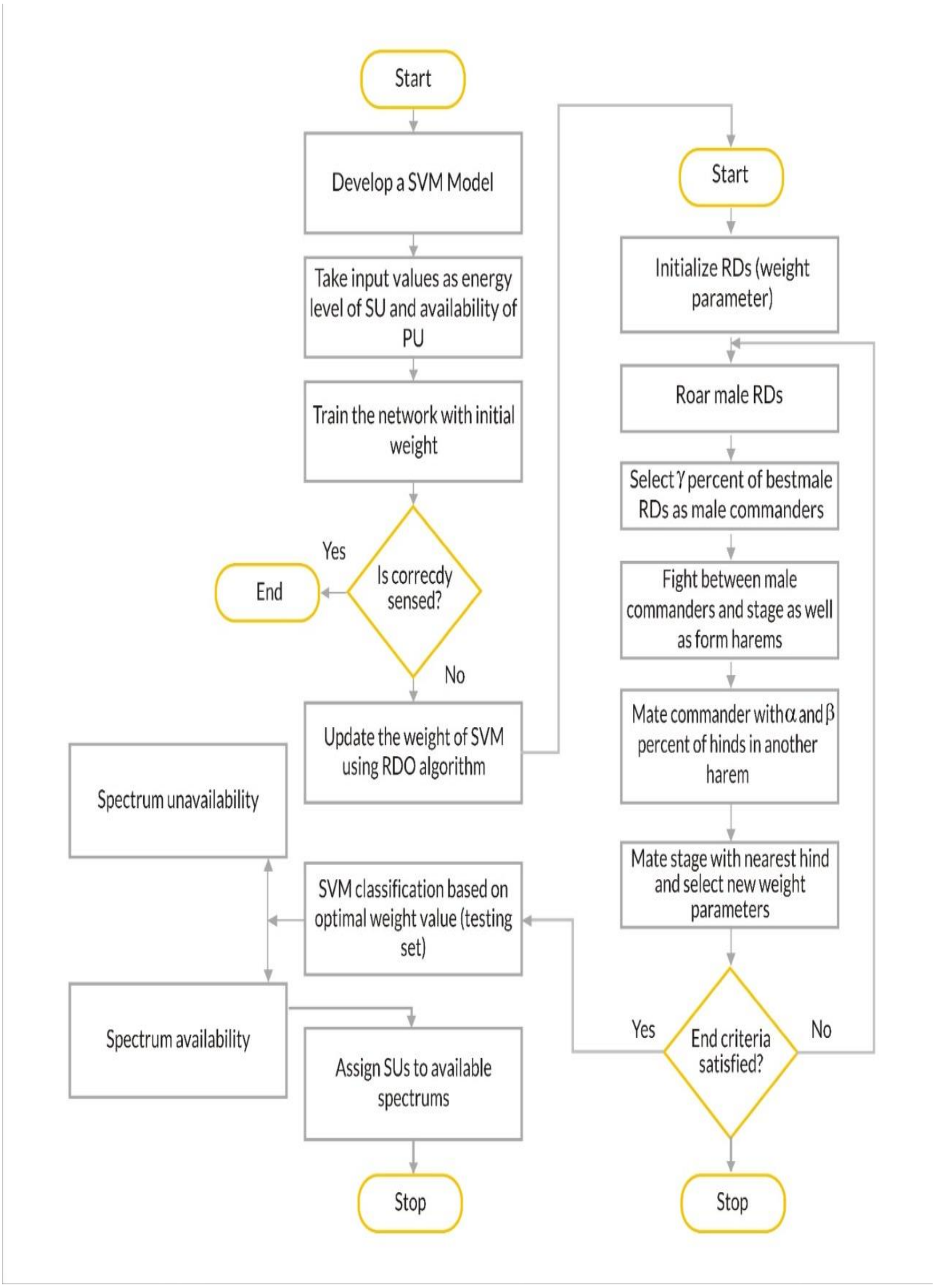

Figure 3.3 : Algorithm of SVM-RDA

Pseudocode for spectrum sensing using Support Vector Machine (SVM) based Red Deer Optimization (RDO) Algorithm

Create system model using Primary Users (PUs), Secondary Users (SUs), and Fusion centre (FC).
Generate full duplex multi-band signal.
Separate multi-band into several subbands.
Initialize energy for SUs, PUs and subband.
Placement PUs in a subband.
Check the availability of PUs in spectrums and collects FC the energy value submitted by SUs in each round.
Sense the availability of spectrum using SVM algorithm.
Begin
Initialize **the parameters of SVM, such as bias and weight vector (training).**
for **each SU_i**
Take input as energy level and availability of PU (k).
Calculate weight and bias vector by

$$w_i.Z_i(k)+b_i>1, \quad if\, PU(k)=1$$

$$w_i Z_i(k)+b_i\leq 1 \quad if\, PU(k)=0$$

Here, w_i is weight vector, b_i is a bias vector, and $Z_i(k)$ is an energy value submitted by SU_i in each k^{th} round.
end for
Weight vector is randomly updated and cannot sense the spectrum availability accurately.

Optimize $\min \Phi(w_i,\zeta)=\frac{1}{2}\|w_i\|^2+C\sum_{i=1}^{N}\xi_i$, N is number of samples, ξ_i is slack variable and C is set by user to limit the misclassification rate.
Initialize **Red Deer population (weight vectors)**
Calculate fitness, sort them according to fitness, and form hinds and male Red Deer.
X^* is the best solution (weight vector)
While $(t<\max\_iter)$
for **each male RD**
Roar male
Update the position if better than previous one.
end for
Sort the males and form the commanders and stags
for **every male commander**
Fight among stags and male commanders
Update the male commanders' position and stage position
end for
for **each male commander**
Mate a male commander with selected hinds of his harems randomly
Select a harem randomly and name it
Mate a male commander with some selected hinds of harem
end for
for **each stag**
Calculate distance between stag and all hinds and select nearest hind

Mate stag with selected hind

end for

Select next generation

Update X^*, if there is a better solution.

end while

***Return* X^* (optimal weight value)**

With trained energy vector, test energy vector in classification module

Classify the CRN with two classes like spectrum availability and spectrum unavailability class.

SUs access available spectrums.

End whole process.

CHAPTER 4

TO PROPOSE A MACHINE LEARNING-BASED ALGORITHM TO OPTIMIZE MULTI-BAND SPECTRUM SENSING IN ENERGY-HARVESTING CRNS

4.1 ABSTRACT

This first objective identifies Spectrum gaps through probability of detection, transmitting power, and sensing bandwidth with the help of learnheuristic algorithm. So, EE increases by SVM-RDA concerning above parameter and compared with algorithms like PSO-GSA, PSO, and ABC.

4.2 INTRODUCTION

As per the literature observation, cooperative sensing can improve cognitive radio's sensing efficiency. To maximize spectrum utilization in cognitive radio, SU may use the least energy for spectrum sensing while achieving maximum throughput. Most current works assume fixed frame structure for data transmission, spectrum sensing, and EH. Due to simultaneous implementation of spectrum sensing and EH, EE is relatively poor and cannot provide enough energy efficiency for appropriate CSS. So, throughput of SU will decrease. Innovative and creative EH technologies are offered to boost the output and lifespan of SU.

4.3 EH COGNITIVE RADIO NETWORK (EH-CRN)

Cognitive radio is an efficient technique in radio communication to share the spectrum among licensed and unlicensed systems without any effect on network performance. Introducing EH method in cognitive radio will improve wireless transmission. For energy-harvesting CRNs, an access technique of SUs with EH had discussed in [112].
The SUs is used with energy harvesters and storage devices. The unlicenced users observe the operations of random spectrum sensing and access using the primary automatic repeat request feedback. This will work on increasing throughput of SU under the consideration that both the PUs and SUs are fixed. While the PUs are only

provided with information queues, the unlicenced users have energy and information queues. By studying the status of channel and energy source, the throughput optimization of the unlicenced user over a finite time view. An optimum policy for SU is implemented to choose a spectrum for sensing to improve SE. In reference [113], unlicenced users' achievable throughput with energy was discussed by considering the opportunistic spectrum access to the licensed user.

A self-supportable technique with RF EH in CRN is discussed in [114]. Transmission power of the SU is obtained from the given outage-probability constraints. Considering the random similarity of the primary information leads to the proper usage of harvested energy. CRN provided with RF EH is discussed in [114]. It can lead to determining the operating modes of sensors.

4.4 IMPORTANT METRICS IN CRN

Important metrics are considered for better performance evaluation in CR networks: throughput, SE, EE, etc.

4.4.1 Throughput

Hou *et al.* [115] stated that throughput is ratio of number of data transmitted to the total transmission time. When SNR of received PU signal is higher, better detection can be achieved with lesser sensing duration. This is also way for increased transmission time and improved throughput. While in the case of low SNR conditions, detection performance can still be improved by increasing the sensing time. Since more time is utilized for sensing, the data transmission time is reduced. As a result, throughput can be affected. Still, due to more sensing time, collisions can be avoided, and hence throughput can be maximized as described by Althunibat *et al.* [116].

The transmit power can be fixed concerning the distance between PU and SU transmitters. This enables interference-free transmission with improved throughput, as described by Peh *et al.* [117]. EHCRN throughput is examined using several factors such as sensing time, harvesting time, and PU SNR. As sensing time rises, data transmission time reduces, resulting in a drop in SU throughput. Throughput of SU increases with an increase in PU SNR. The SU performs harvesting in the presence of

PU and data transmission during the absence of PU. Therefore, increase in harvesting energy will increase the transmission power and further increase the throughput of SU.

4.4.2 Spectrum efficiency (SE)

SE is the throughput achieved over a given bandwidth. Since spectrum is a scarce resource, it must be utilized efficiently. Better spectrum utilization can be achieved when larger quantity of successful data is transmitted, or larger throughput is achieved. Also, this efficiency or data rate has to be achieved without creating interference for both users.

4.4.3 Energy Efficiency (EE)

Energy is a significant resource for any user in a network. It has to be consumed so that system performance is enhanced. EE is the ratio of average throughput achieved or bits transmitted during a time period to the average amount of energy consumed in joules. Sensing is the essential functionality that must be efficiently done to avoid user interference and correctly detect spectrum availability. This sensing consumes energy. Also, as the PU may reappear in its respective frequency band at any time, the sensing process must be performed continuously, which yields more energy. But still, this process can detect spectrum opportunity properly so that SE can be achieved; also, as PUs are detected more effectively.

Even though sensing is improved and spectrum is utilized efficiently by employing sensing cooperatively, CSS has certain notable drawbacks, which are listed below:

1. Energy consumption increases due to multi-user sensing.
2. Due to increased reporting users, control channel communication and traffic overhead increases, which increased network complexity.
3. When many users are employed in cooperation, communication cost increases.

4.4.4 Sensing time

The amount of time needed for a SU to detect a free channel used by a PU and announce its availability. If the sensing period is prolonged, small time is available for data transmission, lowering SUs' throughput.

4.4.5 Detecting modulation type PU signal

In specific applications, it's required to identify the signal's modulation type so that the receiver settings may be modified.

4.4.6 Complexity and implementation issues

The sensing algorithms must be straightforward, easily implementable, and economical in energy. As a result, it is essential to have an accurate assessment of both the cost of the hardware, its energy efficiency, and the level of computing complexity.

4.4.7 Harvested Energy

Harvesting energy rises as SU harvesting time grows, resulting in increased throughput. The proposed technique will harvest more energy and increase transmission power than existing EH techniques.

4.4.8 Lifetime

EH technique will increase the lifetime of SU. The proposed method can achieve longer life as compared to non-EH technique.

4.4.9 Probability of Detection (P_d)

P_d is possibility that PU will be identified within the specified frequency range. The throughput of cognitive radio framework relies on P_d. If the sensing time is large, the PU will be able to use its spectrum at that moment, and the condition will be met where the SU cannot disrupt the PU's transmission. If the PU detection capability is more than interference provided by the SU on the PU is small. The weakening of the SU signal caused by multipath fading, building penetration, and shadowing might lead to an inaccurate assessment of the radio environment, which, in turn, can cause interference at the approved PU caused by the SU broadcast.

4.4.10 Probability of missed detection (P_m)

Probability of the sensing method that finds the existence of PU in the spectrum accidentally while the PU is missing or absent at that specific moment. P_m ought to be limited to give more possibilities for the SUs to utilize the detected spectrum. The lesser the probability of miss detection, the more possibilities the spectrum can be reused by the SU when it is free; this increases throughput of SU. Because of SUs, probability of miss detection will increase the possibilities for SUs to interrupt PUs signals that can be kept away in CR organizations. For a better sensing method, P_m should be more to reduce the interference in the accessible frequency range.

4.4.11 Probability of False Alarm (P_f)

Probability of detecting method that detects existence of PU in the frequency range accidentally while the PU is absent at that specific moment. The more options for reusing the spectrum while it is free, the better the throughput for the network of unlicensed users and the smaller the probability of false alarms. From SU's perspective, the lower the false alarm probability, the more spectrum they may use while it's free.

4.5 SPECTRUM SENSING

It is critical part of cognitive radio that can't be done without it. It is process of finding spectrum that isn't being used enough so that it can be used more. In a broader sense, spectrum sensing is learning how the spectrum is used and its characteristics in time, space, frequency, and code. [118] divide spectrum sensing into a narrow band and wideband.

4.6 NARROW BAND AND WIDE BAND

It is mentioned that EH and decoding information are isolated at the receiver. If the transmission power tends to be high, an optimal trade-off can occur between transmission and harvested energy. A trade-off between transmission information and outage probability occurred with single beam at finite transmit power and high harvested energy. Thus, the time-switching technique provides optimum performance and switching operation using harvested energy.

The standard sensing algorithm repeats the sensing process at regular intervals and only performs the sensing task during the quiet phase, resulting in a large transmission time loss. This is because the old method is inefficient. Techniques for narrowband sensing may be organized into various classes and subclasses, all shown in figure 4.1. Narrowband sensing may be broken down into two categories: monitoring and sensing. Using either dynamic frequency hopping, in which SU may switch its band of operation, this sensing monitoring procedure can be carried out. Routine sensing will be carried out regularly when there is no CR transmission.

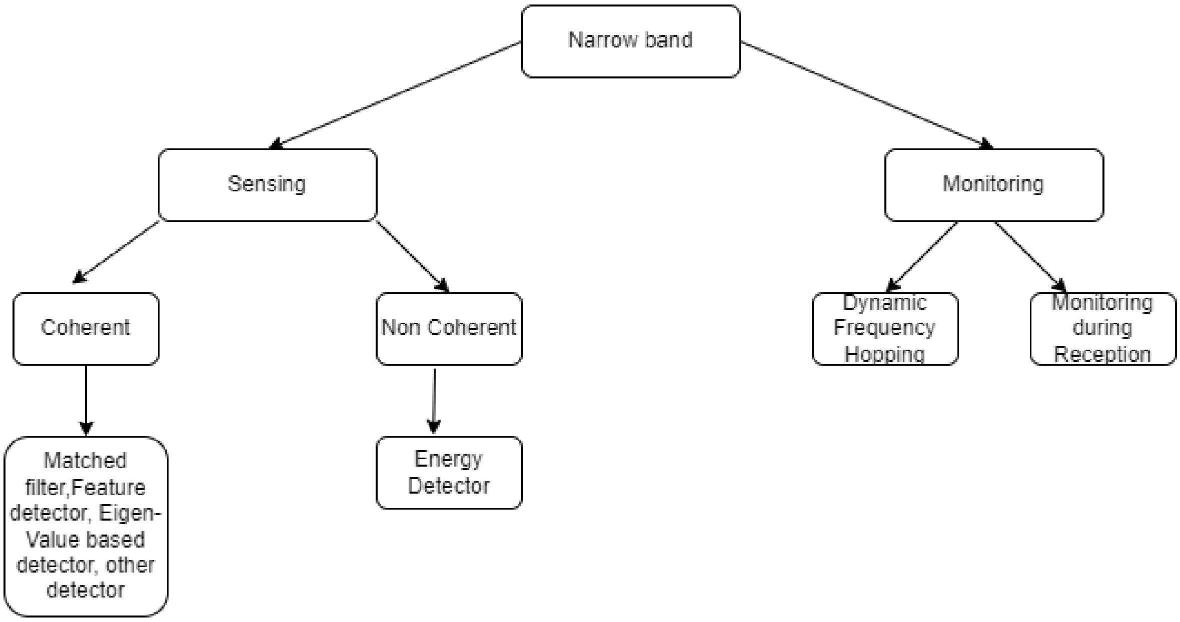

Figure 4.1: Classification of Narrowband Spectrum Sensing[119]

David L. Donoho [119] presents a different suggestion for wideband sensing. This approach would lower the complexity of the hardware, as well as its cost and the required sensing time. Compressive spectrum sensing is the most prevalent application for this type of sensing.

Z Quan et al. investigated the possibility that wideband sensing may be divided into two categories, depending on the Nyquist rate, and figure 4.2 depicts the various classifications of wideband sensing. The initial proposal also investigated the possibility of doing Sub-Nyquist wideband sensing. In context of this approach, collecting the spectral opportunity and eliminating the aliasing mistake both suffice with partial information. Compressive sensing is the most typical illustration of the Sub-Nyquist sampling technique [120].

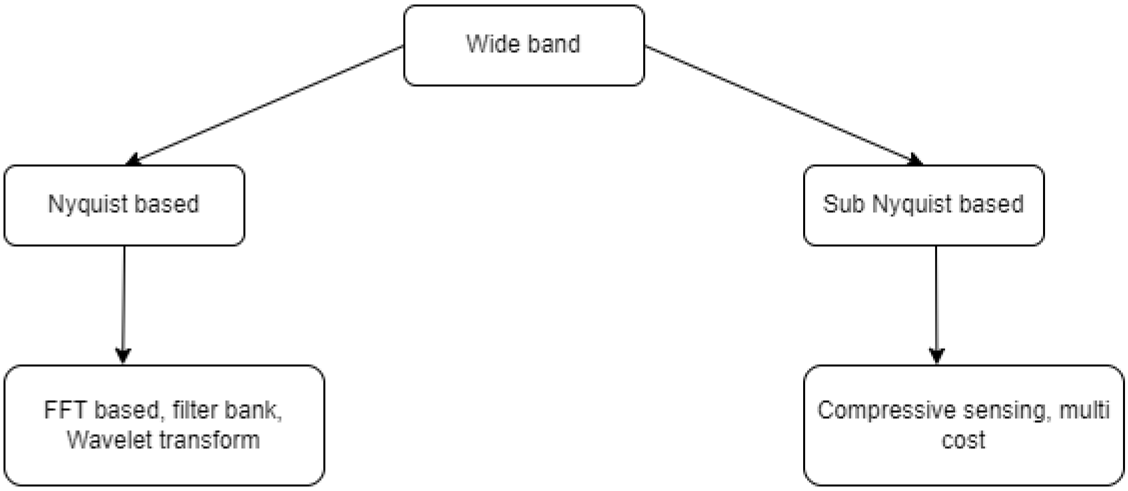

Figure 4.2: Classification of Wideband Spectrum Sensing[120]

4.7 RELATED ALGORITHM

4.7.1 PSO-GSA

G. Eappen et al. trained “feedforward neural networks” using hybrid PSO-GSA by adding GSA acceleration to PSO. GSA and PSO are hybridised in “high-level teamwork” hybrid methods to prevent premature convergence to local optima, have acceptable trade-offs between exploitation and exploration, and implement for heterogeneous computing systems. GSA excels in local search, but PSO may rapidly approach the optimal value. PSO-GSA divides the population into two subgroups. The PSO system governs one population sector, whereas the GSA scheme governs the other. The populations of both regions are generated at random [98].

For every position, i.e., Mutated position, best position (GSA and PSO), and Crossover position, evaluation of fitness function and saved in Memory pool. After comparing mutated solutions with best PSO, GSA, and Crossover solutions, memory pool selects the optimal solution. The optimum solution produced after each iteration in PSO and GSA would lead the remaining search agents. These search agents replace those in GSA with the lowest fitness rating. Like PSO, the GSA search agents are chosen based on their fitness and have the same migration probability.

4.7.2 ABC

“ABC algorithm is a swarm-based meta-heuristic algorithm Karaboga introduced in 2005 for optimizing numerical problems. The intelligent foraging behaviour of honey bees inspired it. The model comprises three essential components: employed, unemployed foraging bees and food sources. The employed and unemployed foraging bees in the first two components look for rich food sources, while the nearby bees in the third component are close to their hive. The model also identifies two dominant behavioural patterns essential for self-organization and collective intelligence: foragers' recruitment to abundant food sources and their rejection of scarce food sources. In ABC, a colony of artificial forager bees (agents) searches for rich artificial food sources[121].”

In summary, ABC algorithm:

1) It is motivated by honeybees' foraging behavior.
2) The method is a global optimization one.
3) It was first suggested for numerical optimization.
4) It is also applicable to combinatorial optimization issues.
5) It applies to both unconstrained and constrained optimization issues.
6) Just three control parameters (population size, maximum cycle number, and limit) are user-definable (population size, maximum cycle number, and limit).
7) It is quite robust, simple, and flexible.

4.7.3 PSO

“In computational science, PSO is a method that optimizes a problem by iteratively trying to improve a candidate solution about a given quality measure. It solves a problem by having a population of candidate solutions, here dubbed particles, moving around in the search space according to a simple mathematical formula over the particle's position and velocity. Each particle's movement is influenced by its local best-known position. Still, it is also guided toward the most prominent positions in the search space, updated as other particles find better positions. This is expected to move the swarm toward the best solutions. The algorithm was simplified, and it was observed to be performing optimization.

Also, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods.

A basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around the search space using a few simple formulae. The movements of the particles are guided by their best-known position in the search space and the entire swarm's most prominent position. When improved positions are discovered, these will recommend the swarm's movements."

4.7.4 Energy Detector

"Energy detection (ED) is an appealing signal detection technique for spectrum sensing due to its low computational complexity and generic implementation, i.e., it does not require knowing structure of primary signal to make decisions regarding its presence. In traditional approach for ED, energy is compared and estimated against a threshold detection. A fundamental issue with this approach stems from the fact that the noise in communications systems is aggregation by random sources of power, including thermal noise. Suppose ED's detection threshold is not adjusted to the noise power fluctuations. In that case, its performance is likely reduced dramatically, giving place to limit on SNR, known as SNR-wall, below which signal detection becomes unreliable or even impossible, regardless of the time the signal is observed[122]."

4.8 ENERGY-EFFICIENT OPTIMIZATION FACTOR

This objective is directed to improve EE when addressing different theories of spectrum sensing. In addition, to improve EE, we use hybrid SVM-RDA. Periodic sensing is required for smooth communication.

Within spectrum sensing, data transfer is finished if a free channel is found, and the SU repeats the process at next sensing time. For this reason, bandwidth of SU "B" is split in 2 parts: "B_s" for sensing the spectrum and "$B-B_s$" for sending data with small amounts of energy beyond the spectrum. If the PU is not followed, the SU sends the data. The data transfer stops entirely if the new spectrum sensing finds PU. In this scheme, data transfer through SUs can be turned on and off for bandwidth $B-B_s$ based on whether or not PU is present. But spectrum sensing done this way over the bandwidth "B" is always the same. So, the method of consistent spectrum sensing is called an effective spectrum sensing scheme [44].

4.8.1 The EE through data transfer and spectrum sensing in terms of energy utilization and overall opportunistic throughput

During spectrum sensing, sampling of signal contributes significantly to energy consumption. Considering how much energy is utilized per sample period is essential since the sampling procedure uses a significant amount of energy during spectrum sensing. “During sensing phase, E_s is the energy used by the SU per sampling time, and G_t is power spectral density of SU signal used during data transfer throughout channel. SU's maximal transmitting power is $Q_{t,max}$, which is spread uniformly around the range of B-B_s.”

Here 2 hypotheses are proposed for energy detection-based on spectrum sensing :

$$\begin{cases} H0: x(n) = w(n) \\ H1: x(n) = hs(n) + w(n) \end{cases} \tag{4.1}$$

“Where n =1, 2...M; M is number of samples. w (n) denotes Additive white gaussian noise (AWGN) noise with zero mean and variance $E[|w(n)|]^2 = \sigma_w^2$., s (n) denotes the PU signal with zero mean and variance σ_s^2**,** h denotes AWGN channel gain.”

The p^{on} and p^{off} denotes PU currently occupies channel or not. p^{on} + p^{off} = 1, P_f and P_d can be expressed as equation (4.2) and (4.3).

$$P_f = q_f p^{off} \tag{4. 2}$$

$$P_d = q_d p^{on} \tag{4.3}$$

Where q_d = probability of detection by energy detector and q_f= false alarm probability by energy detector.

For sensing spectrum, normalized energy detection is written as equation (4.4)

$$T_H = \frac{1}{\sigma_w^2} \sum_{n=1}^{2T_pB_s} |x_n|^2 \tag{4. 4}$$

T_p = period of frame and $2T_pB_s$ = samples number. Due to the huge value of $2T_pB_s$

$$T_H \sim \begin{cases} H_0 : N(2T_pB_s, 2T_pB_s) \\ H_1 : N(2(1 + SNR_{pr})T_pB_s, 2(1 + SNR_{pr})T_pB_s \end{cases} \tag{4.5}$$

SNR_{pr} denotes the SNR of PU measured at SU, Probability of detection q_d =

probability $\{T_H > \gamma' | H_1\} = Q\left(\frac{\gamma}{(1+SNR_{pr})\sqrt{2T_pB_s}} - \sqrt{2T_pB_s}\right)$ (4 6)

Probability of false alarm q_f=

probability $\{T_H > \gamma' | H_0\} = Q\left(\frac{\gamma}{\sqrt{2T_pB_s}} - \sqrt{2T_pB_s}\right)$ (4.7)

Q function is $Q(x) = \frac{1}{\sqrt{2\pi}} \int_x^{\infty} e^{-t^2/2}\, dt$ (4. 8)

q_d *and* q_f are inversally proportional to each other. Threshold probability of detection $q_d^{th} < q_d$

So the probability of false alarm

$q_f = Q(Q^{-1}(q_d^{th})(1 + SNR_{pr}) + SNR_{pr}\sqrt{2T_pB_s}$ (4.9)

Considering that spectrum sensing energy efficiency is dependent on spectrum sensing variables, the following hypotheses may be applicable in various spectrum sensing contexts:

Table 4.1 Value of probability, throughput and energy consumption

Contexts	Probability	Throughput	Energy consumption	Remarks
Spectrum is occupied	$q_d p^{on}$	c_1=0	$e_1 = 2T_pB_sE_sp^{on}q_d^{th}$	The PU uses spectrum, and the SU has correctly recognized this utilization.
Missed Detection	$p_{on}(1 - q_d^{th})$	c_2=0	$e_2 = p^{on}(1 - q_d^{th})(2T_pB_sE_s + G_t(B - B_s)T_p)$	The channel will be occupied simultaneously by SU and PU for data transmission.

False Alarm	$q_f p^{off}$	c_3=0	$e_3 = 2T_p B_s E_s p^{off} q_f$	The SU does not send transmissions when no PU exists on the channel.
Useful Detection	$p_{off}(1 - q_f)$	$c_4 = T_p p_{off}\left(1-q_f\right)(B - B_s)log_2(1 + \|H\|^2 \left[\frac{G_t(B-B_s)}{G_0(B-B_s)}\right])$	$e_4 = p^{off}(1 - q_f)(2T_p B_s E_s + G_t(B-B_s)T_p)$	SU appropriately locates the empty channel.

Total energy consumption

$$E_T = \sum_{k=1}^{4} e_k = 2T_p B_s E_s + G_t(B-B_s)T_p(1 - p^{on} q_d^{th} - p^{off} q_f) \quad (4.10)$$

Throughput

$$C_T = \sum_{r=1}^{4} c_r = T_p p_{off}\left(1-q_f\right)(B-B_s)log_2(1+|H|^2\left[\frac{G_t(B-B_s)}{G_0(B-B_s)}\right]) \quad (4.11)$$

$$\text{Energy Efficiency} = \frac{C_T}{E_T} = \varepsilon = \frac{p^{off}(1-q_f)(B-B_s)\times log_2(1+|h|^2\frac{G_t(B-B_s)}{G_0(B-B_s)})}{2B_s E_s + G_t(B-B_s)(1-p_{on}q_d^{th} - p_{off}q_f)} \quad (4.12)$$

4.8.2 Spectrum Sensing Spectrum Model

Wireless network (IEEE 802.22), where CRN has N SUs, one FC, and one PU. Every SUs compute energy and transmit it to FC, determining PU state. For time duration τ_0, every SU compute energy. The sampling rate is f_s, so energy value of SU_i is given by-

$$y_i = \begin{cases} \frac{2}{\sigma_i^2}\sum_{j=1}^{f_s\tau_0}[n_i(j)]^2 & H_0 \\ \frac{2}{\sigma_i^2}\sum_{j=1}^{f_s\tau_0}[h_i S(j) + n_i(j)]^2 & H_1 \end{cases} \quad (4.13)$$

h_i = channel gain from PU to i^{th} SU, n(j)=noise signal, $S(j)$=PU signal . Noise power $\sigma_i^2 = E[|n_i(j)|^2]$.

4.9 SIMULATION RESULTS

The EE of CRN is based on probability of detection, transmitted power, and sensing bandwidth using simulation data of MATLAB. The EE parameters (bits/joule) obtained from ABC, PSO, PSO-GSA, and SVM-RDA, PSO-GSA algorithms were simulated for 50 runs, with 200 iterations/ run for every algorithm. With help of optimization process, collection of "transmission power Q_t and its B_s can be achieved "

Simulation Parameters:

When computing the numerical results, following criteria are taken into account:

T_p = 0.01s, B = 1 × 10^6 Hz, q_{on} = 0.3, E_s = 1 × 10^{-6}J, number of PU=10, number of SU=90.

4.9.1 Transmission power vs. Energy efficiency

EE curve for different Q_t for different SNR values is seen in figures 4.3 and 4.4. The EE vs. Q_t graph shows that the EE increases as Q_t increases but gradually drops as "Q_t increases after reaching a high value". Opportunistic throughput increases as transmission power increases. The EE function rises until increase in throughput outperforms power level, at which time it peaks. The increase in power level dominates the throughput, causing the EE function to drop steadily. The EE function has a better probability of identifying spectrum gaps since the Pf_a decreases to zero at high SNR. As a consequence, the opportunistic throughput increases, increasing the EE function.

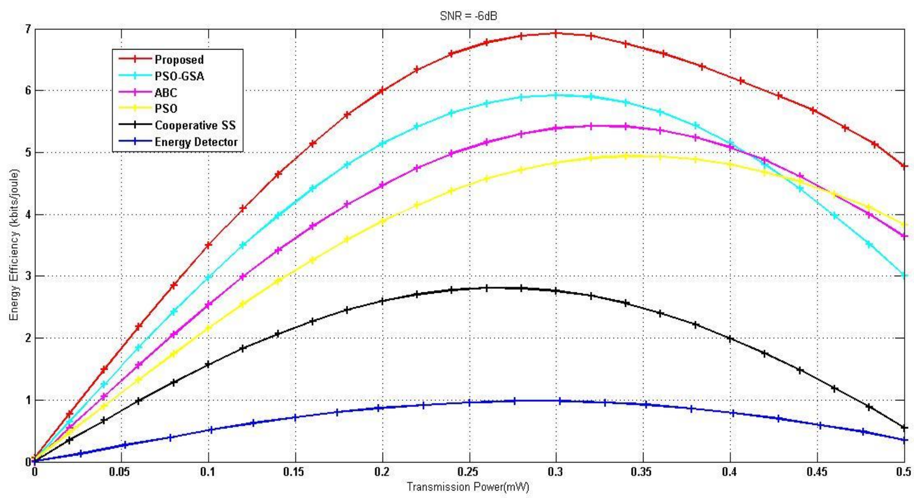

Figure 4.3: Analysis for transmission power at Signal to noise ratio=-6dB

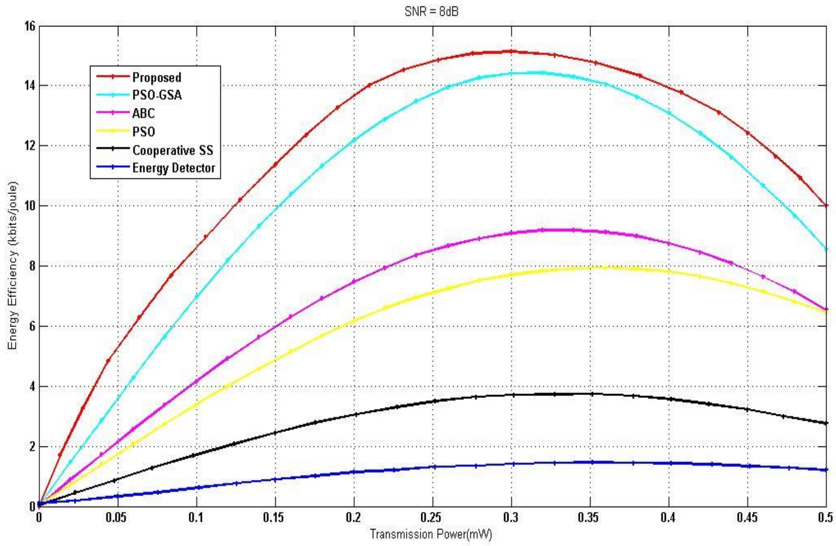

Figure 4.4 :Analysis for transmission power at Signal to Noise Ratio = 8dB

4.9.2 Sensing bandwidth vs. Energy efficiency

Because high sensing bandwidth B_s leads to a lower transmitting bandwidth, throughput, and EE. EE decreases as sensing bandwidth increases.

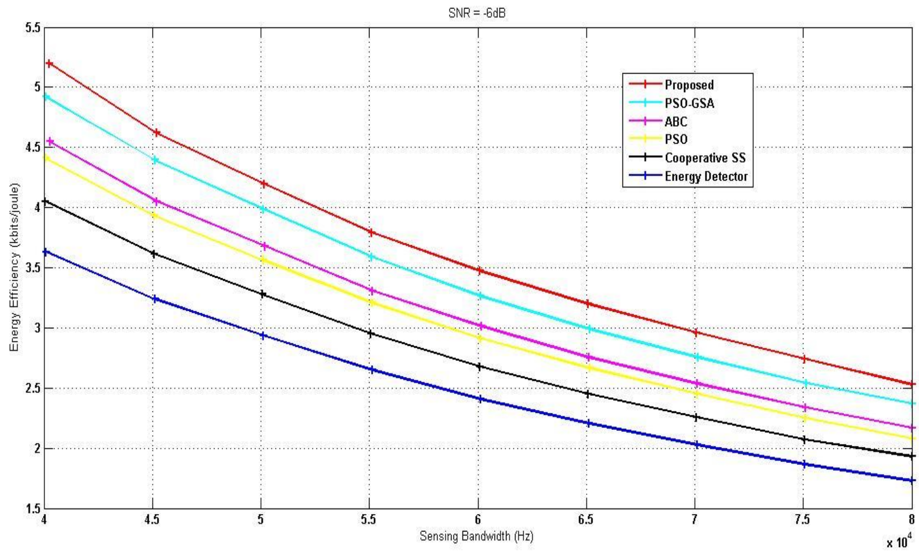

Figure 4.5 : Analysis for sensing bandwidth at Signal to Noise Ratio = -6dB

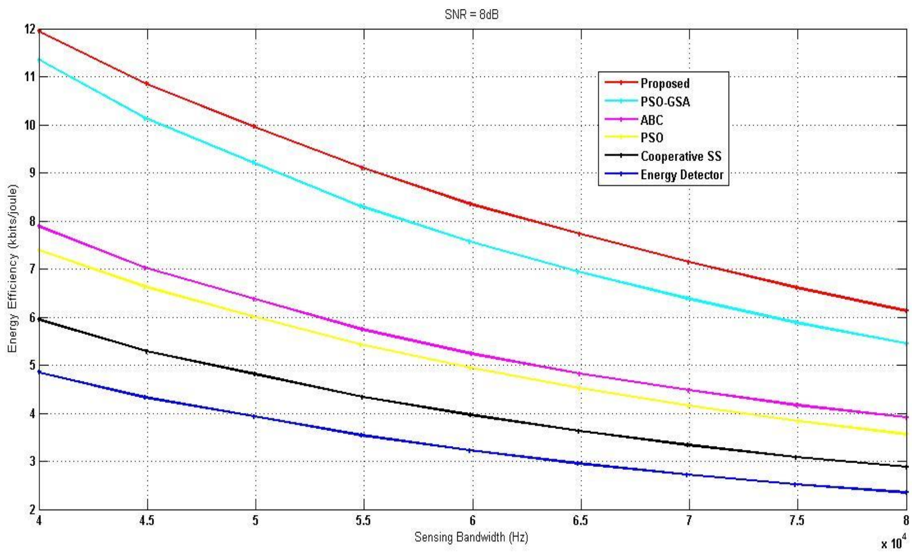

Figure 4.6 : Analysis for sensing bandwidth at Signal to Noise Ratio =8 dB

4.9.3 Probability of detection vs. Energy efficiency

Figures 4.7 and 4.8 show that as detection probability increases, concerning energy efficiency. A greater detection probability ensures better opportunistic throughput, suggesting an increased EE function value. Because of its greater exploitation potential, SVM-RDA technique outperforms ABC, PSO, and PSO-GSA in obtaining a higher energy efficiency peak.

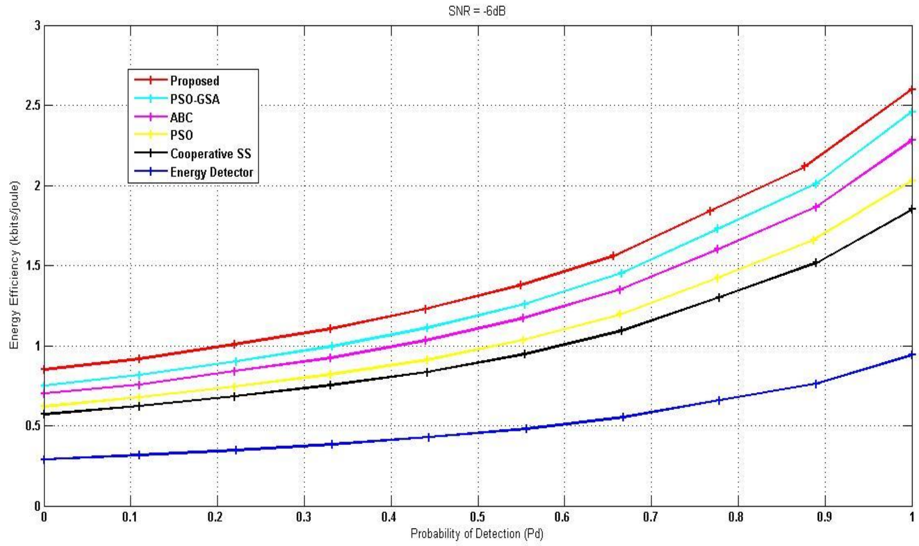

Figure 4.7: Analysis for probability of detection at Signal to Noise Ratio = -6dB

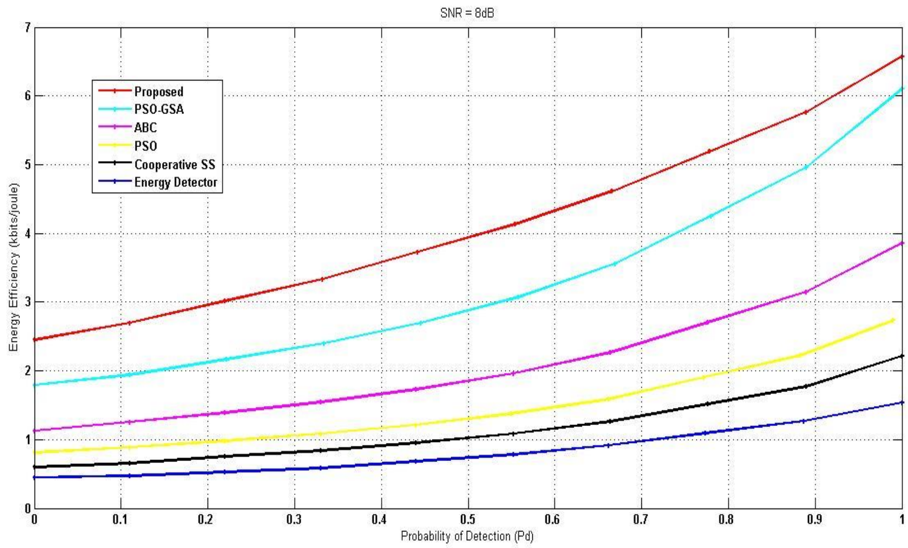

Figure 4.8 : Analysis for probability of detection at Signal to Noise Ratio = 8 dB

4.10 TABLE-BASED COMPARATIVE ANALYSIS

Optimization algorithms (ABC, PSO-GSA, PSO, and SVM-RDA) are demonstrated in table 4.2 concerning peak value energy efficiency on SNR= 6dB and SNR= 8 dB and different parameter values like detection probability, sensing bandwidth and transmission power.

Table 4.2 Optimum EE using SVM-RDA, PSO-GSA, PSO, and ABC for different Signal to noise ratio values

Energy efficiency function	Optimization methodology	Peak values Energy efficiency	
		SNR=−6 dB	SNR=8 dB
In terms of transmission power (mW)	SVM-RDA	7	15
	PSO-GCA	6	14.3
	ABC	5.5	9.7
	PSO	4.8	8
In terms of Sensing Bandwidth (Hz)	SVM-RDA	5.2	12
	PSO-GCA	4.9	11.2
	ABC	4.6	8
	PSO	4.4	7.2
In terms of Detection Probability	SVM-RDA	2.6	6.5
	PSO-GCA	2.5	6.1
	ABC	2.3	3.9
	PSO	2	2.8

4.11 CONCLUSION

This chapter discusses SVM-RDA algorithm proposed for increasing EE in spectrum sensing for CRN. EE function is determined by probability of detection, sensing bandwidth, and transmission power. The SVM-RDA has considerably enhanced performance of RDA. Result of SVM-RDA is better than PSO-GSA in terms of EE.

CHAPTER 5

TO PROPOSE CLUSTERING-BASED SPECTRUM SENSING TECHNIQUE TO IMPROVE SYSTEM PERFORMANCE

5.1 ABSTRACT

This objective proposes a clustering-based spectrum sensing technique for CRN. SUs makes a cluster. So, these clusters transfer local sensing data to a FC, and FC decides the status of the SU channel. The proposed SVM-RDA is evaluated on probability of error and probability of detection. Cluster-based spectrum sensing proposed in different literature has high complexity. The help of proposed cluster-based spectrum sensing increases the probability of detection. It decreases probability of error at various parameters like SUs' number, occupied band, and SNR. So, SVM-RDA's performance is improved than other algorithms.

5.2 INTRODUCTION

In the clustering method, the CR users in the network are grouped into clusters of same size or different sizes. Each cluster has a CH, its central entity, and the remaining users become the Cluster members (CMs). Fusion of the sensing results occurs more than once, both at the cluster and FC levels. The selection of CH and cluster formation is the critical stage in clustering in CSS. Various methods and algorithms are adopted.

The CH selection depends on some of the following parameters such as reporting channel gain, residual energy of CRs, sensing channel or reporting channel SNR values, distance between SUs, distance of SU from FC, spatial correlation, geographical position, available common channels, speed of the SUs, etc., as listed by Nguyen-Thanh et al. [123] Kumar et al. [124]. The cluster size and structure can be decided on aspects of sensing channels and number of SUs in networks stated by Hussain et al. [125]. The CH depends on the sensing performance of users. The clustering can be done as either a single level of grouping or with multiple levels.

Awin et al. performed that each cluster can be further grouped multiple times, where each group has a separate central control for forwarding their group decisions to CH.

By modifying the structure of clusters, reporting distances are reduced, thereby conserving reporting energy. Like centralized methods, clustering is also performed in distributed CR networks, where each CH forwards the cluster decision regarding PU status among themselves without needing an FC. Increasing the number of members in a cluster can improve energy conservation without affecting sensing accuracy. In the clustering method, as the reporting duration is shorter, the users can report with less transmit power, thereby conserving energy. But still, this approach has the drawback of increased computational complexity when more SUs are involved in the process [127]. A common illustration explaining a simple clustering approach for CSS is given in figure 5.1.

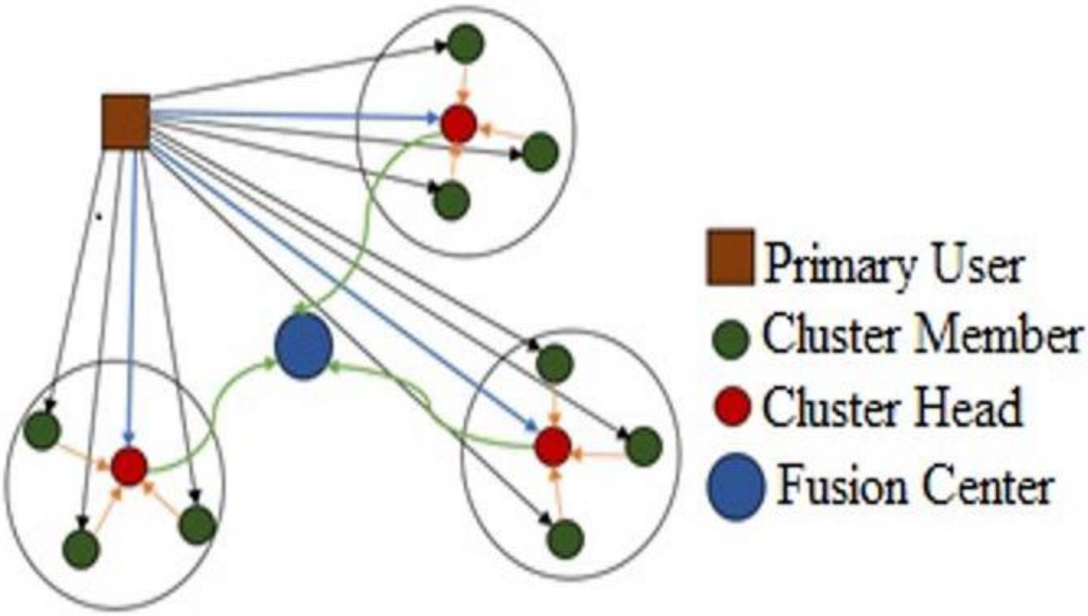

Figure 5.1: Clustering in CR Networks[127]

Clustering is considered a superior technique for bringing SE and conserving energy in CR networks. Various cluster methods have been followed previously, which differ in CH identification and cluster setup. To overcome the Rayleigh fading scenario in the channel between the reporting SU and FC, Sun *et al.* performed a clustering method for CSS. Here, the SUs were grouped into clusters using a distributed algorithm. Each cluster's user with the most significant reporting gain was chosen as CH. The method was analyzed for hard and soft fusion schemes within the cluster. An OR rule was employed at the FC. Sensing was improved along with the reduction in reporting errors[128]. Guo *et al.* developed a clustering methodology for optimizing the number of clusters. As a result, the control channel overhead and sensing performance accuracy were balanced, thereby increasing the sensing results [129].

If we increase the number of SU and report distance, energy consumption will increase, which is disadvantage. To address this disadvantage, a multi-hop method was proposed by Kozal *et al.,* where the cluster distribution had multiple levels. Hence, the reporting distance was shortened. As a result, power consumption was minimized with a little increase in reporting duration and delay [130].

Wang et al. analyzed a soft fusion-based cluster method. Initially, the SUs reported their sensed energies to their respective CHs. Each CH combined these data with weight and said them to FC. False alarm and detection probability were estimated based on these weights and thresholds. For a required value of detection probability, false alarm was minimized for both AWGN and Rayleigh conditions[131]. Jiao *et al.* performed a three-stage clustering. Here, the low SNR users with unreliable sensing results were avoided. Among the selected users, the SUs with higher trust values were chosen as CHs. Later, the remaining users were grouped to form cluster using correlation method. Sensing and reporting were not performed periodically. Once a change point was observed at the PU status, sensing was performed, and the change point results were reported. As a result, reporting overhead was minimized [132].

Salah *et al.* proposed a GA method for centralized clustering with LEACH algorithm. CHs were chosen based on their energy values and distance concerning FC. This method resulted in minimized energy consumption [133].

Salout et al. further proposed a hierarchical method where levels numbers and SUs for every level were optimized. Soft fusion was performed at lower levels, while hard fusion was at higher levels[134]. The fuzzy c-means scheme was followed by Bhatti *et al.* for cluster formation [135]. Using spatial correlation reduced the number of reported SUs, thereby conserving energy.

The users were grouped into small number of large-sized clusters. By this method, throughput was improved while maintaining network stability. As a result, requirement for re-clustering was reduced. Mashreghi et al. proposed a clustering strategy for imperfect channels. Initially, sensing was performed by all SUs. Following this, each SU combined its own decision with decisions of other users, and an improved result was obtained [136]. Among these results, most accurate one was chosen by each cluster and forwarded to FC. In this scheme, a weighted incremental fusion was followed to improve sensing accuracy of local results. Also, an orthogonally distributed space-time block code was developed to address the fading errors.

When the cluster size was larger, scalability of the network was enhanced, and reporting overhead was reduced. But at the same time, lower number of common channels would affect the stability of the network. Also, it would increase overhead and re-clustering. Hence, Javed et al. proposed a clustering scheme with reinforcement learning algorithm to address this issue. This method concentrated on determining the size of the cluster based on the availability of free spectrum. As a result, network stability and scalability were enhanced with reduced overhead and re-clustering [137]. In the clustering strategy developed by Kumar et al., a weight value was calculated for each SU using the user's speed, channel availability, and PU interference level. This weight value was forwarded to neighbouring users to enable cluster formation. Also, the required number of users with higher weight values was chosen as CHs. A deputy CH was also selected to act as head in the absence of CH. This clustering strategy obtained more significant results for networks with mobile users and varying channel conditions [124]. A clustering method was performed with different AND, OR combined fusion methods by Sharma et al. Clustering with AND rule was employed at the cluster level, and OR fusion at the FC level. A larger EE was achieved. Also, a scheme for obtaining clusters number and CMs was developed to enhance EE [138].

Olawole *et al.* modified the K-out-of-N rule, where local CH result was combined with the results of the necessary K users. This scheme achieved lower error rate during fading conditions. Different CH-selecting methods were analysed for varying detection thresholds. A CH selecting method was proposed for heterogeneous networks. The user that minimized penalty based on false alarms and missed detections was chosen as CH for varying threshold values [139]. Cluster construction was performed by using machine learning algorithm by Bhatti *et al.* Similarity information was shared among the neighbouring users for determining the CHs. SUs with an SNR value larger than the SNR threshold was chosen for cluster formation alone. After selecting CHs, the users nearer to the CHs were grouped to form clusters. Energy consumption was reduced due to reduction in reporting users [140]. To overcome the poor reporting conditions, Bayesian fusion-based clustering was proposed by Liu *et al.* The local single-bit results from all CHs were combined at the FC using Bayesian rule. Bayesian values were obtained using the P_f, and P_d were allotted to the local result. Wrong decisions were given larger values than the right ones. Algorithm based on K-means method was proposed for selecting CHs. The users nearer to FC were set as CHs, to address the poor reporting channel conditions [88].

The network performance enhancement has been provided using clustering, the technique employed for sensing nodes arranged in logical groups—several factors influence cluster formation, including geographical location, channel availability, and SNR. Three types of nodes are present in every cluster. They are the CH, the member node, and the gateway node. Among all the member nodes, only one is chosen to be the CH based on features like high reliability, higher energy, lower hops, and a higher level of node degree. The rest of the secondary nodes will be member nodes. Every member node will sense the channel availability independently using energy detection, and their data was reported as a decision to the CH. The CH has several other roles, such as routing, making some final decisions for the clusters, scheduling the users of the CR to access available channels, and coordinating the spectrum of the cluster member and its sensing process. There was also an interaction between the CH and the member nodes where the intra-cluster communication had been provided.

5.3 ENERGY-EFFICIENT CLUSTER-BASED COOPERATIVE SPECTRUM SENSING METHOD

Clustering is classifying and grouping users or members in any wireless network with multiple users. These users are arranged into specific groups and subgroups as categorized by Alqawasmeh *et al.,* thereby improving the reliability and efficiency of the network. Similarly, in CR networks, the SUs can be grouped into favourable clusters to achieve system efficiency and satisfy QoS conditions. Different clustering algorithms are available for this purpose. Based on the algorithm employed, the organization and functions of the SUs are varied. This chapter analyses the cluster-based sensing process and proposes different clustering approaches to improve detection with better EE in CR networks[141].

5.3.1 Need for Clustering

To address the issues of fading, shadowing and other uncertainty conditions occurring while detecting the PU status, cooperative sensing is employed to sense the PU channel simultaneously with multiple SUs. In CSS, sensing period is common for all users. Increased reporting users boost FC's local decisions. Also, these decisions are reported in individual time slots. Hence, larger reporting period is required. Therefore, the time left for data transmission is reduced, affecting the network throughput. Also, the reduction in throughput and high energy consumption will affect the EE. Certain sensing and reporting parameters are optimized to conserve network energy and improve system throughput. Optimizing sensing users' numbers and varying samples sensed can enhance efficiency. Also, better efficiency can be achieved by optimizing duration in the time frame slots.

To balance both, optimize the amount of sensing users. In addition to these optimization methods, other techniques are employed to bring better EE. These techniques include censoring, clustering, relaying, etc. Applying these techniques in CR networks can balance SE and EE trade-offs. Some parameters that impact cooperative sensing process in CR are sensing accuracy, fusion methods, sensing, reporting channel conditions, reporting overhead, etc. It also minimizes the control channel overhead when the number of cooperative users is larger, as performed by Kozal *et al.* [142].

5.3.2 Types of Clustering Techniques

Some of the popular clustering approaches available for cluster formation and CH selection, as listed by Singh *et al.* [143] are

i. K-Means Clustering
ii. Fuzzy C-Means Clustering
iii. Hierarchical Clustering
iv. LEACH
v. Centralized LEACH
vi. Power-Efficient Gathering in Sensor Information System
vii. Hybrid Energy Efficient Distributed Clustering

5.3.3 Basic Clustering Method in CR Network

A CRN is considered with *N* SUs. Here, single PU is located at a fixed position. The network has a centralized FC. The SUs are categorized into Kc clusters with N=Kc users following the clustering algorithm. Among these *N*=*Kc* users, a single SU is selected as the CH for each K_c cluster, and the remaining users of each cluster act as CMs, as analyzed by Sun *et al.* Cluster construction and CH selection are the two main phases in this process. The cluster formation includes grouping SUs into clusters, and CH selection involves selecting a relevant head for each cluster. Then, sensing results reporting, and decision-making is carried out [128].

After that, the local decisions of the CMs are combined at the CHs, and each CH's decision is forwarded to FC, where the reported results are combined to obtain the global status regarding PU availability. Soft or hard fusion methods are employed at CH and FC to determine PU status, as obtained by Salout *et al.*. Concerning the number of CMs in each cluster and the clusters formed in the network, the detection performance and system reliability can vary. Figure 5.2 illustrates the basic system model of a simple clustering structure in CR network[134].

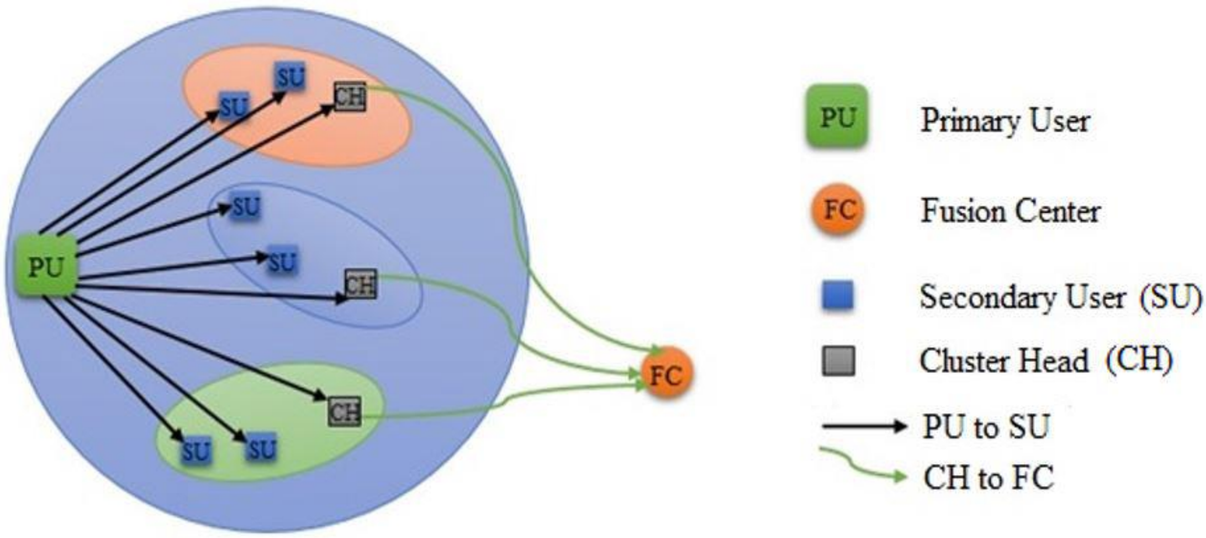

Figure 5.2: A System Model of Simple Clustering Structure in CR Network[134]

Selecting appropriate number of clusters and CMs also improves the system's performance. While dividing the network into more clusters, each cluster may have little number of CMs. Hence, individual users' reporting energy (concerning SUs) can be reduced. Reduced number of CMs at each cluster can minimise delay. At the same time, with more CMs at each cluster, complexity in the reporting process between CH and FC is minimized. Hence, optimizing cluster size and the number of clusters is necessary for balancing network stability and performance.

5.3.4 Cluster Scheme

This grouping process will be in a collection called clustering. This is very effective channel coordination for switching the operation in which a single CR node in a cluster will detect PUs. A CH can make CR devices within a cluster that stop making a payload transmission on the channel of operation and vacate the channel, aside from the clusters reducing interference among the cognitive clusters. This has resulted in the clustering of CRNs.

Even though a larger cluster size makes reporting easier for the FC, any clustering in the CRN will be subject to many challenges, which will be the deficit of many common channels among clustering nodes resulting in connectivity of the CHs and their member nodes. This may also result in the requirement of a process to re-cluster the maintenance. Even though the cluster structure changes when the network's topology changes. Clustering scheme clusters are of two types: with the CH and without the CH. Several tasks within the network consider assigning resources to members by bringing down the packet collision. Clustering algorithms have been used in the literature to solve this problem smartly. For example, the common channels between cluster nodes are growing because of how their clustering algorithms work. This means that gateway nodes often don't re-cluster because they don't have a common channel. In the other multi-hop clustering schemes, there was a maximum distance between a CH and its cluster member. This is done so the member can exit out of the communication range. This way, the members will make an intermediate transmission of messages among the CHs for their members [134].

Figure 5.3 depicts cluster-based CSS. Assume L clusters with M SUs each. So, M x L users have CR. All CR users are presumed to be clustered. CH is SUs.

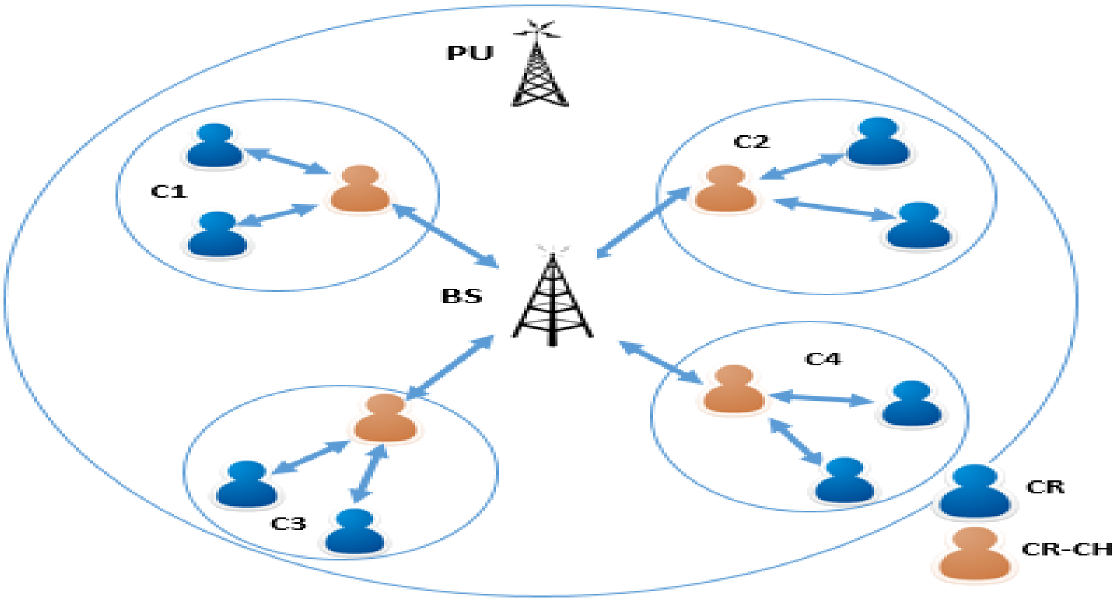

Figure 5.3: Cluster-based CSS[144]

In cluster-based CSS, each SU does local spectrum sensing and then shares this data with the CH within the same cluster, using some fusion rule, to determine the existence of the PU. Therefore, the presence of PU is determined individually inside each cluster. There are now several nodes in the network, each of which sends data to the base station, which then applies a fusion rule to determine whether or not any PUs are present. CH gathers data, circulates information, and administers networks. Non-cluster heads sense and collects environmental data. This cluster-based CSS may fuse OR-OR, OR-AND, AND-OR, and AND-AND [144].

PU has a higher priority in using the spectrum, while SU only can use the spectrum if PU does not use the spectrum. SU senses the spectrum or presence of vacant bands through spectrum sensing with different methods. In single-user spectrum sensing scenarios, sense performance is altered by different environments like obstacles, fading, path loss, and noise. So single-user sensing is not reliable; to mitigate this issue, CSS has been proposed. In CSS, all SUs senses the PU activity and send the information to the common base station or FC. FC makes a final decision using different fusion techniques. All SUs senses the presence of PU independently. There are three steps in CSS summarized:

- All SUs forward sensing information to FC.

- FC makes a final decision through different fusion rules and sends it back to the global.
- Decision to every SU.

When SUs number is large, then overloading issue occurs on the control channel. To remove this, cluster-based CSS is suggested. In Cluster-based CSS technique, SUs are divided into two categories, as figure 5.4. The non-CH member or other SUs transmit their information to the CH, and the FC or base station only collects them from CH. “In clustering technique, all SUs individually detects the PU signal and send their result to CH. The CH decides whether the PU signal exists or not. The decision of the CH is the decision of the particular cluster in the SUs group; in the same way, all CHs decide the PU's existence.”

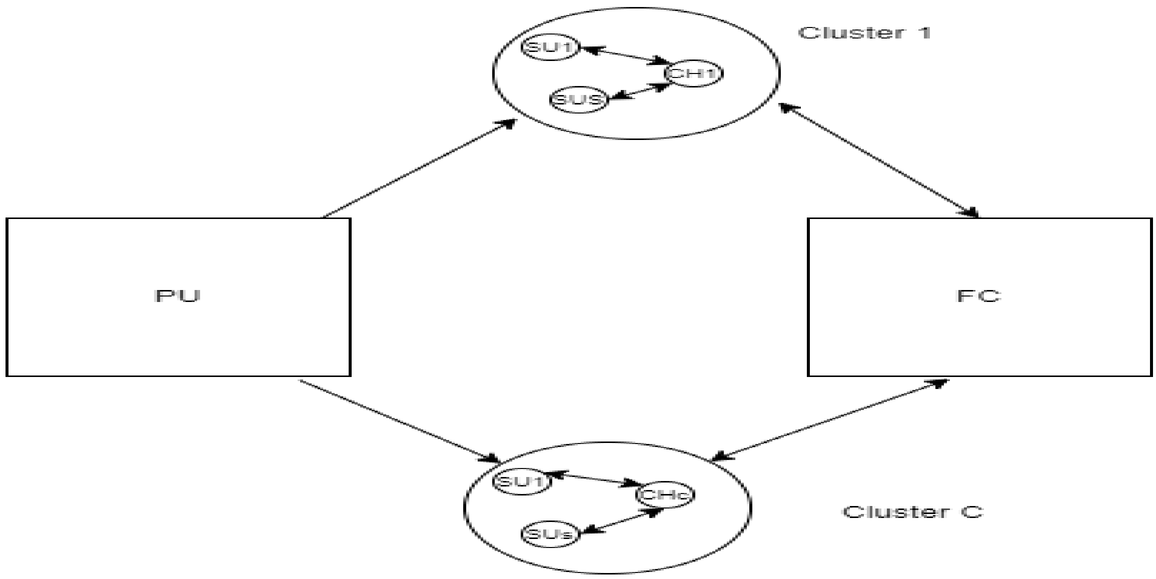

Figure 5.4: Schematic diagram of Clustering scheme[144]

Then CHs transfer their data to FC. After receiving this data, FC uses a fusion rule, decides whether a PU exists, and sends its final decision to the SUs or non-CH members via CH.

5.4 IMPORTANT MATRICS

5.4.1 Probability of Detection (P_d)

Possibility that PU will be identified within the specified frequency range is referred to as P_d.

5.4.2 Probability of false alarm (P_f)

The probability of false alarm is the percentage of free bands mistakenly classified as occupied bands.

5.5 THEORETICAL BACKGROUND

The SUs in network work together, but every SU does "local spectrum sensing" on its own. The j^{th} SU signal received is:

$$x_j = h_j * s + n_i H_1 \quad (5.1)$$

$$x_j = n_j H_0 \quad (5.2)$$

x_j does j^{th} SU receive signal, h_j is gain of channel between PU and j^{th} SU, s is the PU signal and noise (n_i). H_1 is PU existence, and H_0 is PU absence. For large clusters of SU, FC conducts ultimate spectrum sensing and coordination among participating SUs. There are two ways to do it. In the first method, SUs that work together do local spectrum sensing independently to get sensor results.

As a result, they convey their local results to FC, which makes final decisions through sensing channels. FC combines incoming data and decides if the detected channel contains a PU signal. FC gives full judgement to every SU. According to the second strategy, cooperative SUs transfers their acquired data to FC, which performs spectrum sensing.

It calculates CSS performance with the help of individual spectrum sensing performance. Here measure, P_d, P_{fa}, and P_{md}. "P_d is the probability of detection, which means an SU announces a PU signal existence while spectrum is busy".

$$P_d = Prob(\frac{H_1}{H_1}) \quad (5.3)$$

H_1 is a hypothesis means PU exist. P_{fa} is the probability that SU announces PU existence with a clear spectrum.

$$P_{fa} = Prob(\frac{H_1}{H_0}) \quad (5.4)$$

H_0 is a hypothesis means PU not exist. P_{md} is probability that SU reports PU absence while spectrum occupy by PU. Missed detection probability is

$$P_{md} = Prob(\frac{H_0}{H_1}) \quad (5.5)$$

C_d is "cooperative probability of detection".

$$C_d = 1 - (1 - P_d)^L \quad (5.6)$$

L is cooperative SU numbers. “Probability of error” (P_e) is:

$$P_e = P_{md} + P_{fa} \tag{5,7}$$

CSS techniques provide acceptable detection rates. In addition, CSS works well with a low density of SUs. With a high concentration of cooperative SUs, these procedures are complex and time-consuming. As a result, [145] – [147] proposed a clustering technique directed to CSS. Clustering of SUs concerning particular parameter, (i) geographic region, and (ii) SU – PU distance. Each cluster has a SU that acts as the CH, managing connections between its users and the FC. Each cluster's SUs conducts their SS independently, using a network of communication connections to send their results to CH. The results are sent to FC, where CH makes final decisions. CSS additionally uses individual spectrum sensing clustering performance indicators [146].

5.6 RELATED ALGORITHM

5.6.1 Dynamic Dual Threshold

“In traditional methods of energy detection technology, SUs usually makes decisions by comparing the received signals with a prior threshold. The decision of H_0 or H_1 depends on whether the received signal power of PU is higher or lower than the threshold. According to the above decision rule and given threshold value , the accuracy of final decision results is closely related to the fusion method, and probability of false alarm (P_f) and probability of detection (P_d) can be obtained. For a single SU, the error probability includes false alarm probability when PU does not exist and the probability of missed detection when the PU exists.”

As shown in figure 5.5, the dual threshold is applied to decide whether PUs are present.

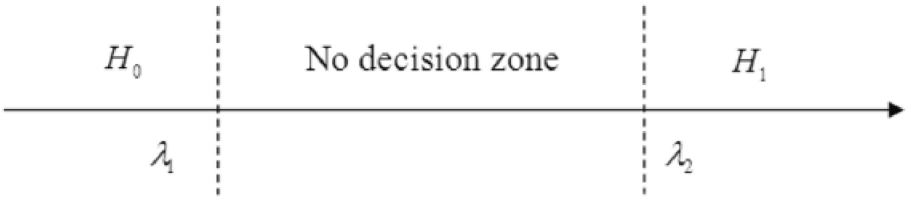

Figure 5.5: Dual threshold energy detector[148]

“If the detected values are more significant than the upper threshold 2 or less than lower threshold 1, signal absent or present will be declared respectively. In addition, the energy statistic between two thresholds is treated as the “no decision” zone. With the increase of noise uncertainty, ψ tends to be infinite, and most of the test statistics will be in a confusing area. In such scenario, all the decision results depend on the previous channel observation state, while the current channel information does not contribute to the decision results[148].”

5.6.2 Discover

“The algorithm is based on electing a leader, and then the leader node performs neighbour discovery and informs other nodes about their neighbours. When a new node (say Node A) is ready to join the network, it first checks if a leader already exists or whether some nodes are already trying to become the leader. This is done by listening on all channels for a sufficiently larger time. If a leader is detected, node A lets leader node discover itself. Suppose node A hears from a node trying to become the leader; node A backs off and waits for the leader to be elected. If node A does not hear from existing nodes, it tries to become the leader. If the attempt is successful, it elects itself as the leader. Otherwise, it waits until a leader is elected. Once a node is selected as the leader, it executes neighbour discovery procedures. Then the leader starts normal network operations. During normal operations, the leader periodically performs neighbour discovery to discover newly arrived nodes. After each neighbour discovery period, the leader node informs all discovered nodes about their neighbour and the neighbour’s available channel sets[149].”

5.6.3 Fuzzy Energy Detection

“Between the two hypotheses H0, the null hypothesis versus the alternative hypothesis, H1. In some situations, we face many practical problems in which the observed data are associated with some uncertainty. Over the past years, some efforts have been made to analyze this uncertainty using the fuzzy set theory. Pausing account in the hypothesis test introduces an exciting problem called Fuzzy Hypothesis Test. Energy detector is standard for spectrum sensing because of their low computational and implementation complexities. Figure 5.6 shows block diagram of the energy detector. The frequency band of the interest is chosen by applying a Band Pass Filter to the received signal [150].”

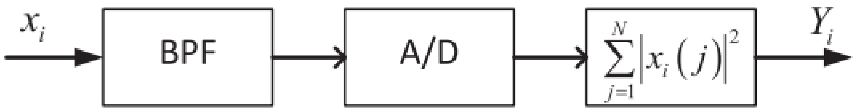

Figure 5.6: Block diagram of energy detection[150]

5.7 PROPOSED METHODOLOGY

N SUs and one FC are considered in CSS, and FC controls all cooperative secondary user channel monitoring and allocation. The proposed system obtains received signal of SU via an "SVM-RDA". Each SU delivers a signal to the CH, which decodes the data from the SUs to recover and perceive the spectrum signal. The CH then sends its local selections to an FC, who decides on spectrum occupancy. For spectrum sensing, all cooperating SUs send signals to CH. Each SU of CH detect its spectrum in shortest time, and then each SU transmits its result to FC. So, proposed method has low P_e and a high P_d at various SNRs.

5.8 SYSTEM MODEL

Assume CRN with M PU, N SU, and central FC related to Rayleigh fading effect. Same SU set, make a group in cluster. Every SU determine SNR, which is compared with threshold of SNR. If predefined threshold of SNR is greater than evaluated SNR, cooperative sensing is not permitted for SU. When SU's SNR is larger than threshold of SNR, cooperative sensing for SU is performed.

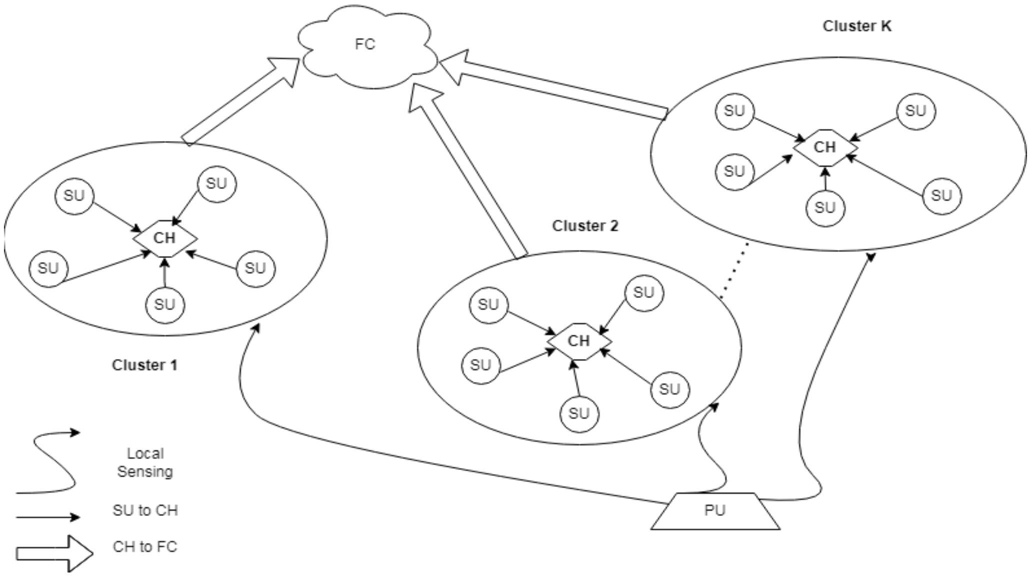

Figure 5.7: System model of clustering CSS[128]

Let N SUs are selected for specific sensing phase. So, in single cluster, SU's number is D=N/K. Here K is number of clusters. From figure 5.7, A cluster has one SU that is CH. There are 2 types of clustering CSS: "intra-cluster CSS" and "inter-cluster CSS". In "intra-cluster CSS", SU senses existence of PU data and sends this data to related CH. Cluster's final decision makes by CH and forwards data to FC. In "inter-cluster CSS", all CH send their data to FC, and FC makes final decision corresponding to CH's data. It occurs between two clusters. Due to weak received signal of PU, cluster decisions may sometimes be inaccurate. So single cluster decision has uncertainty. So, overcome this problem in which different clusters make collective decisions , use "inter-cluster CSS". The CH of every cluster is chosen with the help of "SVM-RDA" among selected SU set.

5.9 **RESULT**

The proposed performance is assessed with the help of "MATLAB R2014a with a 64-bit, core i5 processor and 4 GB RAM system. Range of SNR is -20 dB to 20 dB. p(H0) = p(H1) = 0.5 are the probabilities of the PU being idle or busy". The listening channels are assumed to be additive white Gaussian noise, and binary phase shift keying is applied for transmitting the hard decision result to FC. "The signal bandwidth is 7.56 MHz and broadcasts on 720 MHz central radio frequency". The number of samples is equal to 400. The occupied band numbers vary from 10 to 60 at ten steps, corresponding to spectrum occupancy from 10 to 60%. Band amplitude is uniformly distributed from 0 to 100. The measurements taken are 400, with compression ratio of 40%. Suppose 50 SU, 1 PU, and 4 CH are randomly distributed in a square field with a length of 70m. We assign each cluster to satisfy minimum similarity =0.85.

The simulation results have shown "dependency of P_d and P_e of CRN" on SNR. P_e is summation of "P_{fa} and the P_{md}". P_d and P_e analysis is based on SNR using MATLAB. "The detection rate improvement of CSS systems has shown acceptable results. Due to the additional complexity and processing time needed for several cooperative SUs, this technique is less efficient. So, FC solution based on CSS was proposed. SU is synchronized with FC. So, SUs independently sense spectrum and provide their findings to FC for decision-making. Figure 5.8 represents FC-based CSS. Suppose 90 SUs and 1 PU are randomly distributed in a square area with a length of 70 meters. Here, PU uses free-space path loss model. Figure 5.8 shows FC, CH, SU and PU are distributed over 70 x 70 meters".

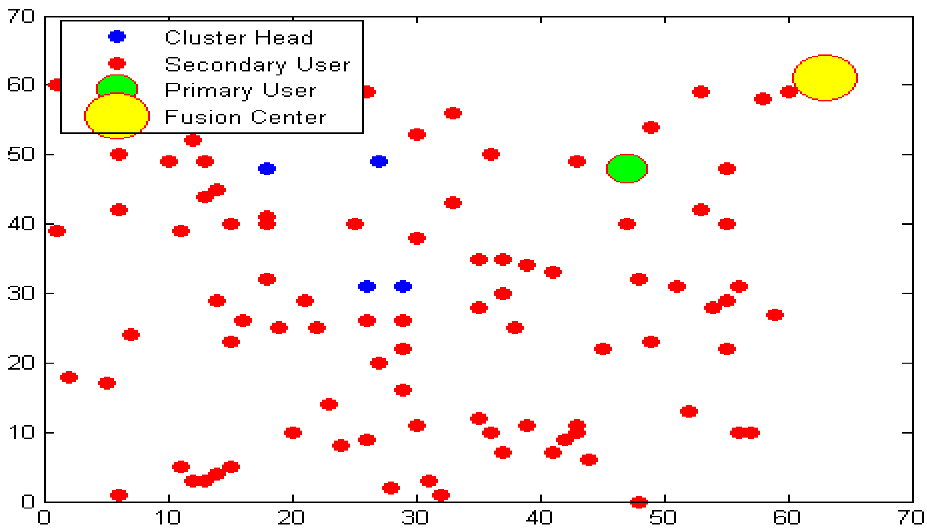

Figure 5.8: shows the positions of the PU, SU, FC and CH

"SVM-RDA algorithm's" performance is compared with dynamic dual-threshold, "Traditional-ED", Fuzzy-ED and DIsCOVER. Figure 5.9 shows the P_d vs. P_{fa} with noise uncertainty under -12 dB SNR. Because SUs have a low P_{fa}, they can easily access new authorized bands. P_d is decreasing means SU disturbed PU. Figures 5.10 show the detection probability of proposed methods with different SNR. It can be observed that the spectrum-sensing performance is significantly improved by using the proposed SVM-RDA approach compared with the traditional energy detection methods, particularly under very low SNR circumstances.

In comparison, the suggested algorithm can demonstrate strong detection performance in worst case. So, it can accomplish a large P_d than another algorithm with same P_e. In "SVM-RDA", P_d is large, and P_e is small.

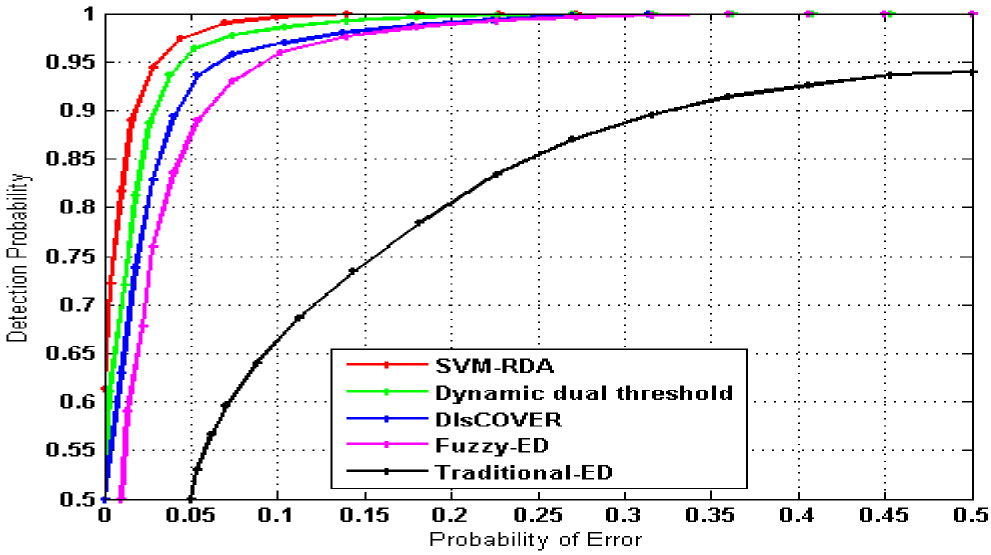

Figure 5.9: Probability of detection vs Probability of error

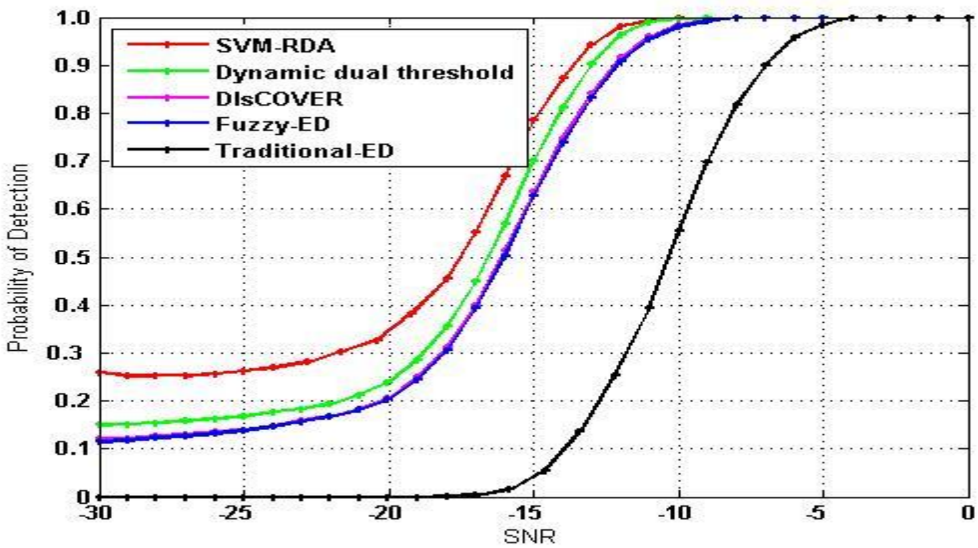

Figure 5.10: Probability of detection vs SNR

Figure 5.11 shows P_d, vs. cooperating SUs numbers. P_d is directly proportional to cooperative SUs number. “Hence, the detection rate rises when the number of SUs grows and detection efficiency improves.”

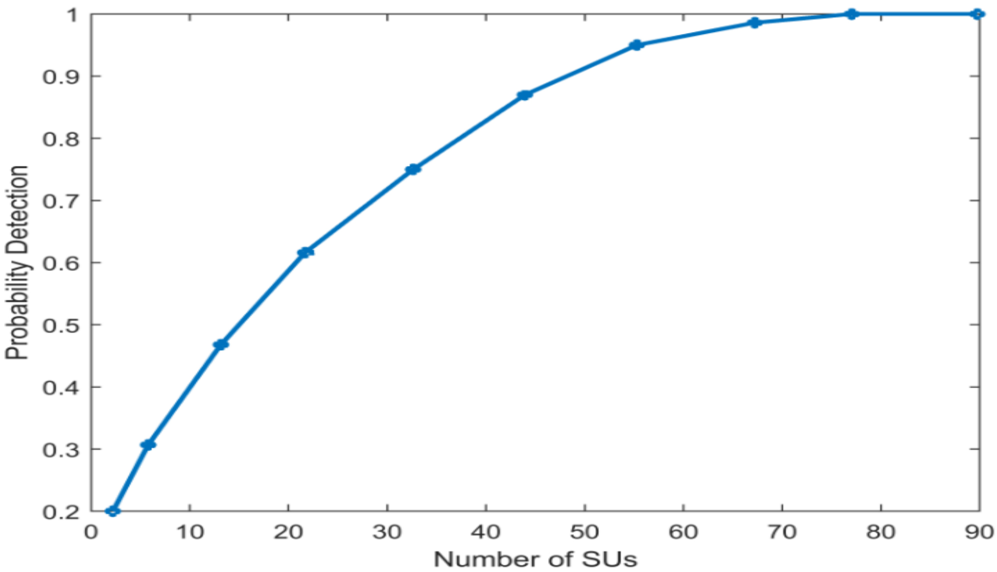

Figure 5.11: Probability of detection versus no. of cooperative SU

For different number of SUs, figure 5.12 shows P_d related to “SVM-RDA” and “dynamic dual-threshold model” as an “SNR function”. Range of SNR is -20 db and 20 db. As predicted, P_d increases with SNR. “At SNR=5 dB, the P_d is 100% for suggested algorithm with 10 SU”.

Nevertheless, in both circumstances, P_d (5 SUs) is less than P_d (10 SUs). “P_d of “dynamic dual-threshold” with 10 SU and 5 SU is close to 20dB SNR; for suggested model, it is SNR=13 dB”. So, cooperating SUs number increases and improves detection performance.

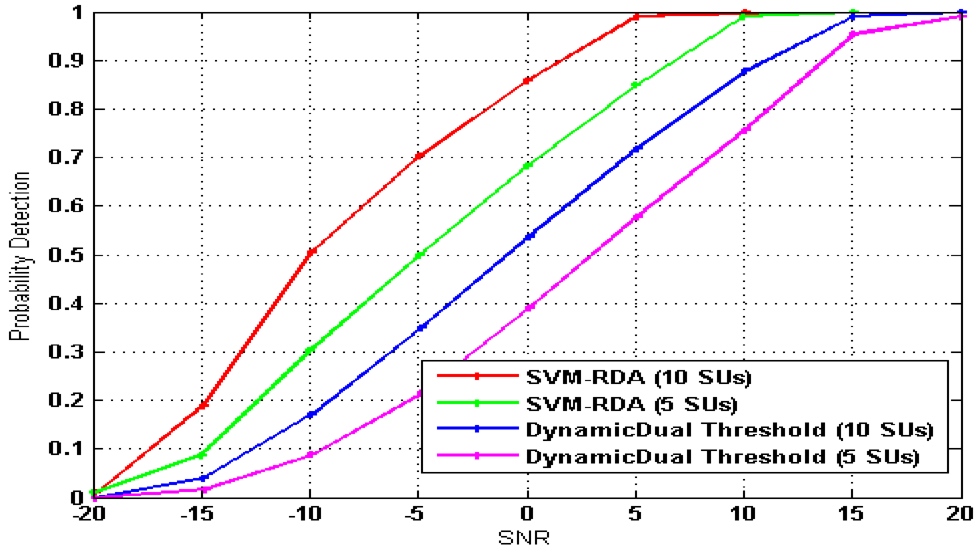

Figure 5.12: Probability of detection versus SNR at different cluster sizes

Figure 5.13 shows P_e of "SVM-RDA" and "dynamic dual-threshold model" as SNR for various SUs numbers. P_e decreases as SNR increases. However, P_e decreases as cooperating SUs number within cluster increases. P_e is low for 10 SUs and large for 5 SUs at high SNR, more cooperating SU can explain that can describe for spectrum sensing, resulting in lower P_e. Thus, "CSS-based clustering scheme" decreases P_e by sensing unused spectrum with many users.

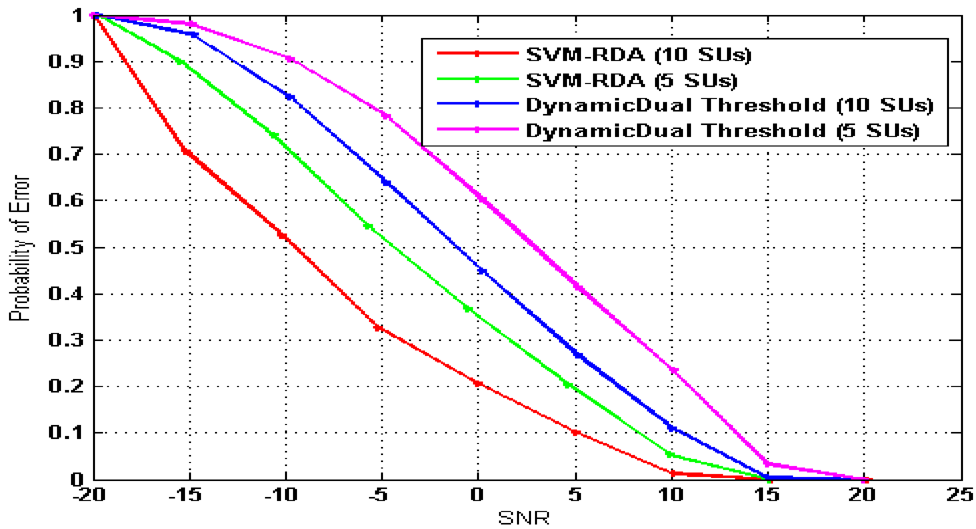

Figure 5.13: Probability of error versus SNR at different cluster sizes

Table 5.1 compares the algorithms against the SNR. SNR is varied from -20db to 20db. Here we use suggested algorithm "SVM-RDA" and "dynamic dual threshold" at cluster size of 5 SU and 10 SU

Table-5.1 P_d and P_e comparison for "SVM-RDA" and "dynamic dual threshold" using Different SNR (in dB) at different cluster size

	Probability of detection				Probability of error			
SNR (db)	SVM-RDA (10 SU)	Dynamic Dual Threshold (10 SU)	SVM-RDA (5 SU)	Dynamic Dual Threshold (5 SU)	SVM-RDA (10 SU)	Dynamic Dual Threshold (10 SU)	SVM-RDA (5 SU)	Dynamic Dual Threshold (5 SU)
-20	0	0	0.01	0	1	1	1	1
-15	0.19	0.04	0.09	0.02	0.7	0.96	0.89	0.99
-10	0.51	0.18	0.3	0.09	0.51	0.81	0.71	0.91
-5	0.7	0.35	0.5	0.23	0.31	0.62	0.51	0.79
0	0.86	0.53	0.69	0.39	0.2	0.45	0.35	0.6
5	0.99	0.71	0.84	0.58	0.1	0.28	0.19	0.41
10	1	0.88	0.99	0.75	0.01	0.11	0.05	0.22
15	1	0.99	1	0.95	0	0	0	0.02
20	1	1	1	0.99	0	0	0	0

It is clear from table 5.1 that at a particular SNR, the SVM-RDA achieves highest P_d and lowest P_e compared to dynamic dual-threshold.

5.10 CONCLUSION

This study implemented a novel cooperative spectrum sensing approach based on SVM-RDA, as explained in this chapter. The proposed system includes several intelligent units that perform various basic tasks. The SVM-RDA algorithm has been used as a local spectrum sensing method because of its simplicity and efficiency. In which each SU periodically and locally senses the PU's signal. The SVM-RDA-based fusion has been used for final decision at FC, in which each SU contextual characteristic is used as data set for training. A trained SVM-based FC was used to fuse all the data of the participating SUs. In addition, all the scenarios used were stored in a knowledge base to achieve the learning and reasoning objectives for future decisions. A variety of simulations in MATLAB determined the performance of the proposed fusion scheme. The probabilities of detection and false alarm were the essential metrics to assess overall performance of a system. Integrating contextual information from SUs into the fusion process has yielded promising results compared to conventional fusion techniques. In this framework, we could improve the probability of detection of the proposed CSS scheme with lower value of false alarm. In addition, the proposed scheme has achieved excellent accuracy compared to other conventional techniques.

CHAPTER-6

TO DEVELOP A MACHINE LEARNING-BASED ALGORITHM TO REDUCE SPECTRUM HANDOFF EVENTS TO MINIMIZE ENERGY CONSUMPTION

6.1 ABSTRACT

This objective describes SH management, an important issue handled in CRN to ensure indefinite connection for SUs. The disadvantages of SH are consumption of power and communication delay . To reduce it, handoff should be minimized. During handoff, DSA check channel availability for SU , this thesis suggests using learnheuristic algorithm to tackle issue. Simulation results demonstrate that suggested “SVM-RDA” is less complex. The proposed algorithm's setup offers different parameters like total spectrum bandwidth, SU bandwidth, SNR, throughput, handoff delay time, unsuccessful handoffs number and total handoffs number. Thesis improves system handoff performance. Proposed algorithm's simulation results are compared with different PSO and genetic algorithm. Results demonstrate that proposed technique is better than other algorithms.

6.2 INTRODUCTION

Spectrum mobility assumes a vital role in SH to occur in CRN. When the SH process is analysed, there are call drops, SH, and interferences with the adjacent channels. To minimize the handoff of the spectrum's probability and call drops.

6.3 SPECTRUM MOBILITY AND SPECTRUM HANDOFF

A CRN assessment of spectrum mobility detailing SH. Based on current research, its categorization, multiple techniques, decision criteria, and assessment metric are presented. The following are the most important spectral mobility issues for CRN:

1. Strategies of SH
2. The SH technique is based on network characteristics.
3. SH's decision/information criterion.
4. The SH control parameter.

5. SH performance assessment criteria.
6. Algorithms that allocate spectrum based on decision criteria and approach.

This chapter covers the most appropriate method from current research, including decision, control, and assessment. A SU changes its operating frequency when a channel's circumstances degrade or a PU arises because the former utilises a licensed band known as a SH. The handoff that occurs in traditional wireless networks differs from the idea of SH used in CR. Since there are two distinct categories of users in a CRN, each with its priority level, PUs (those with the highest priority) are the only ones with authority to stop the transmission of SUs (with low priority). Compared to the traditional handoff, where all users share equal priority[153].

During spectral mobility, communication has to be temporarily stopped to find new frequency bands. So, spectral mobility needs an SH model that allows the SU to switch from its current transmission band to a new one with as little loss of quality as possible by changing its communication parameters. Each time an SH occurs, the CRN's operational settings are modified to minimize the influence on the SU's operation to maintain its QoS [154].

6.3.1 Causes of Spectrum handoff

The following factors may cause the requirement for an SH in CRN:

- ***A PU is occupying the target channel***

The backup channel is selected in proactive strategies, and active status is not reviewed during channel switching. In such circumstances, the SU may learn that another SU or PU already uses channel.

- ***Arrival of a PU on SU's channel***

A PU may arrive on a licensed channel during an SU's data transmission and demand its quick availability.

- ***Degradation of the SU-occupied channel***

Even in the absence of a PU, SU may be compelled to change channels due to a decreased current channel quality.

- ***Interferes of SU with PU***

If SU’s opportunistic usage of licenced channels interferes with PU, an SH must be conducted.

- ***Traffic variations***

If there is a considerable increase in traffic in the frequency band, the SU likely needs to switch channels to provide load balancing and ensure optimal performance.

- ***SU mobility***

An SH must be carried out in a centralized system when the SU relocates outside the node's coverage area.

6.3.2 Requirements while spectrum handoff

- ***Signalling***

Reducing signalling as much as possible is essential since excessive signalling messages might severely affect communication performance.

- ***Consistency***

Minimize effect that handoff has on the QoS. For example, both losing existing calls probability and the probability of the incoming call being blocked in mobile networks must be minimized. Additionally, the traffic must be balanced across adjacent cells.

- ***Multiple handoff criteria***

Selecting the optimum spectral opportunity from many criteria eliminates numerous handoffs.

6.3.3 Phase of spectrum handoff:

Any SH model's primary goal is to transition from 1 frequency to other with the least amount of loss of quality. SH develops in three phases:

- ***Measurement phase***

Wireless network discovery and spectrum opportunity identification are carried out in the networks. Either a distributed or centralised approach may be used to achieve this.

- ***Decision phase***

Based on the many criteria and indicators selected, the choice of "when" and "where" to make the SH is made.

- ***Execution phase***

Considering the mentioned SH criteria, the present spectrum is moved to the new one.

6.3.4 Procedure of SH

The SH procedure consists of the following five steps:

[1] Assume SU1 and SU2 interact on channel Ch1.

[2] When PU comes on Ch1, SU1 performs the SH.

[3] The SU1 stops its communication for a specific time. SU2 is notified before another specified time.

[4] SU1 and SU2 continue contact on the next channel.

[5] Because a frame might be interrupted during transmission, the SH may need to be run many times.

6.4 SH CLASSIFICATION

The SH classify in 4 ways: [1] by timing of target channel selection and change of channel [2] by the network technology used [3] under the method of connecting to the new BS in the centralized system.

6.4.1 Classification A

There are various types of SH models depending on when target channel is selected and when channel is changed: (1) Non-Spectrum Handoff model, (2) purely reactive model, [3] fully proactive model, [4] hybrid model. Each model has advantages and disadvantages:

- ***Non-spectrum handoff model***

The SU remains on original channel and is inactive until channel is restored. After PU left licenced channel, SU continued data transmission. Because delay is as long as the PU is active on the corresponding channel, this architecture produces a significant latency to the SU. This paradigm may be appropriate for delivering short data packets that are not time-sensitive.

- ***Pure reactive model***

The SU may achieve accuracy in target channel, so there is a large delay in spectrum identification and transient interference to PU.

- ***Pure proactive model***

SU identifies and transfers spectrum to the PU before arrival. This technique has many benefits, including (1) less time and energy spent seeking a free channel, (2) a reduced rate of communication failure, and (3) less interference to PUs. However, the proactive SH is based on a stochastic process in which the SUs utilizes previous channel observations to estimate the availability of future spectrum, which might result in numerous needless channel shifts if the prediction model is imperfect.

- ***Hybrid model***

Here, proactive spectral detection and reactive handoff combine the proactive and reactive models[154]

6.4.2 Classification B

Because wireless communication systems use a wide range of technologies, it is important to ensure that spectral mobility between heterogeneous networks is always possible. There are three ways to classify SH, depending on architecture of the network and type of technology: horizontal handoff, vertical handoff, and diagonal handoff.

- ***Horizontal Handoff***

It happens when an SU switches from one BS's coverage to another's while connected to the same access network. This kind of handoff is an intra-cell handoff in cellular networks. To offer "Always best-connected communication," the standard horizontal handoff analyses the received signal strength (RSS) measurement. This handoff occurs when the RSS level falls below a certain threshold.

- ***Vertical Handoff***

This handoff occurs when an SU switches from one BS's coverage to another on a different access network using a different wireless technology. This kind of handoff is called an inter-cell handoff in the context of cellular networks. A SU must switch between several access networks in a heterogeneous wireless environment since each has its characteristics and functionalities. Given that the level of RSS is inadequate for making smart decisions while producing an SH, other criteria and matrices must be considered. Some examples are latency, effective data rate, bandwidth, traffic pattern, and power transfer. However, the complexity of decision-making is increased by using various criteria, which makes the vertical handoff process more difficult.

- ***Diagonal handoff***

It is a mix of vertical and horizontal handoffs. It happens when an SU moves from one base station's coverage area to the coverage area of another base station on a diverse access network.

6.4.3 Classification C

Base Stations number and/or Access Points number to which the SU (or PU) is linked at any moment is another categorization criterion. This is increasingly prevalent in mobile phone networks. This suggests two different handoffs: strong (hard) and soft.

- ***Hard handoff***

Before connecting to the new BS, the SU (or PU) must disconnect from the one it is currently connected to change channels. During this period, there is no connection between it and any BS. Because this handoff only uses a single channel, spectral efficiency is improved, but dependability is decreased. This handoff is used in GSM, FDMA, and TDMA. This is done to maximize data transmission rates.

- ***Soft Handoff***

The SU (or PU), often called "make before break" handoff, occurs when a new BS is connected before the existing channel is disconnected. Even if the execution of the soft handoff has become more complex, communication is conducted across two channels in parallel to prevent the connection from being broken and to increase reliability.

6.5 SPECTRUM HANDOFF APPROACHES

CRN can work in a few basic ways, and each has its pros and cons compared to the others. In this section, we talk about different ways to handle SH. Infrastructure vs. ad-hoc, and centralized vs. distributed.

6.5.1 Infrastructure and ad-hoc

The network architecture may determine whether a CRN is an infrastructure-based or cognitive radio ad hoc network (CRAHN). A central network element that functions similarly to a base station in wireless networks is present in infrastructure-based CRNs. CRAHN does not own any infrastructure. As a result, an SU connects with another SU via an ad-hoc connection in both licensed and unlicensed spectrum bands. In infrastructure networks, each SU transmits the data it has seen to the central entity. As a result, the central entity can maximize communication characteristics, including throughput, bandwidth, SNR, and local balancing, and reduce or remove interference to PUs [155].

6.5.2 Centralized and Decentralized

The CRNs may function as distributed and centralized if they have an infrastructure design. A central body coordinates the function necessary for selecting and allocating the frequency channel during SH in the centralized method. No centralized base station in the distributed or decentralized model coordinates the SH with the SU. As a result, SUs makes decisions alone or with other surrounding SUs by exchanging data and doing actions within a predetermined range. Since only nearby nodes communicate information, the dispersed technique has the additional benefit of requiring less important information.

6.6 IMPORTANT METRICS

6.6.1 Signal to Noise Ratio

The SNR is measured in terms of radiofrequency. It indicates a stronger signal than noise and interference during PU detection.

6.6.2 Throughput

Throughput is calculated with number of the payload by entire time taken for completing transmission.

6.6.3 Delay

SH delay has to be as short as possible to prevent any degradation or interruptions in the communication process.

6.6.4 Handoff rate

The efficiency of the data transmission is adversely impacted when there are an excessive number of unneeded channel changes; as a result, it is essential to reduce the handoff rate as much as possible.

6.6.5 Failed handoff

Number of unsuccessful handoffs is called failed handoffs.

6.7 DIFFERENT ALGORITHM

6.7.1 Genetics Algorithm

Genetic algorithms are a type of optimization algorithm inspired by natural selection. They are used to find the best solution to a problem by simulating the evolution of a population of candidate solutions over a number of generations.

The basic idea of genetic algorithms is to create a set of candidate solutions, called the population, and then use genetic operators, such as crossover and mutation, to create new candidate solutions by combining or modifying existing ones. Each candidate solution is evaluated based on its fitness or how well it solves the problem, and the fittest solutions are selected to produce the next generation of solutions.

The process is repeated for a number of generations, with each generation improving on the previous one until a satisfactory solution is found or a stopping criterion is met.

Genetic algorithms are often used in optimization problems where traditional optimization algorithms may not work well, such as those with non-linear or non-differentiable objective functions or many local optima. They have been used in various fields, including engineering, economics, and biology. [96].

6.7.2 PSO

PSO is a optimization algorithm based on population commonly used to solve optimization problems. It is inspired by the social behaviour of birds flocking or fish schooling.

In PSO, particles (i.e., potential solutions) move around in the search space, seeking the best solution to the optimization problem. Each particle has a position and a velocity, which are updated at each iteration based on its own best-known position and the best-known position of the swarm. The velocity of each particle is also influenced by its own experience and that of its neighbours. In this way, the swarm collectively moves towards better solutions over time.

PSO has several advantages over other optimization algorithms, such as its simplicity, ease of implementation, and ability to handle complex and nonlinear objective functions. It has been successfully applied to various optimization problems, including engineering design, signal processing, and data mining. However, like any optimization algorithm, its performance depends heavily on the specific problem being solved and the settings of its parameters. Particles are PUs and SUs[71].

6.7.3 SpecPSO

SpecPSO (Spectral Particle Swarm Optimization) is an advanced version of PSO incorporating spectral analysis techniques to enhance performance. PSO is a metaheuristic optimization algorithm inspired by the social behaviour of bird flocking or fish schooling, where a group of particles moves in search of the optimal solution to a given problem.

In SpecPSO, the optimization problem is transformed into a frequency domain representation using Fourier analysis. This allows the algorithm to analyze the frequency characteristics of the search space and identify promising regions for exploration. The algorithm then adjusts the particle velocity and position based on these spectral features, which can improve convergence speed and solution quality.

SpecPSO has been applied to various optimization problems, such as function optimization in support vector machines, and feature selection in classification tasks. It has shown promising results regarding convergence speed and solution quality compared to other PSO variants and metaheuristics. SpecPSO is a powerful optimization algorithm that can effectively search for optimal solutions in complex, high-dimensional search spaces. It is used in combination with ML methods to observe channel[86].

6.7.4 iPSO

iPSO stands for “Improved Particle Swarm Optimization”, a metaheuristic optimization algorithm used to solve complex optimization problems. The algorithm is motivated by behaviour of bird flocks and fish schools and simulates their collective intelligence to find the best solution.

The basic idea behind iPSO is that a swarm of particles represents a potential solution to the optimization problem, and each particle's position is adjusted based on its own experience and the experience of the swarm. In iPSO, the positions of the particles are updated using a combination of local and global search strategies, which allows the algorithm to converge quickly to a good solution.

iPSO has been applied to various optimization problems, including feature selection, data clustering, image processing, and financial forecasting. The algorithm is popular because of its simplicity, efficiency, and ability to handle complex problems with high-dimensional search spaces.

SU and PU are related with CRN in this method. It is combined with SS to monitor the availability of free spectrum channels [156].

6.8 METHODOLOGY

The learn heuristic algorithms are collection of machine learning-based metaheuristic algorithms that attempt to replicate resilience of methods and structures employed by biological organisms for evolution and adaptation. This part explains algorithms to the reader and shows how they may be applied to CRNs issues "SVM-RDA" were selected for this goal because they have shown best performance in scenarios analogous to finding opportunity of spectrum in CRNs.

The Combination of "SVM-RDA" and CRN evaluate network parameters like handoffs, number unsuccessful handoffs, throughput and SNR to evaluate decision pattern of handoff ahead for increased data transfer. This method permits SU to forward for empty channel in advance, decreasing failures of connection. The workflow is divided into 2 sections. The first part includes "SVM" data of training and pre-processing, and second part incorporates "RDA" to optimize "SVM" output.

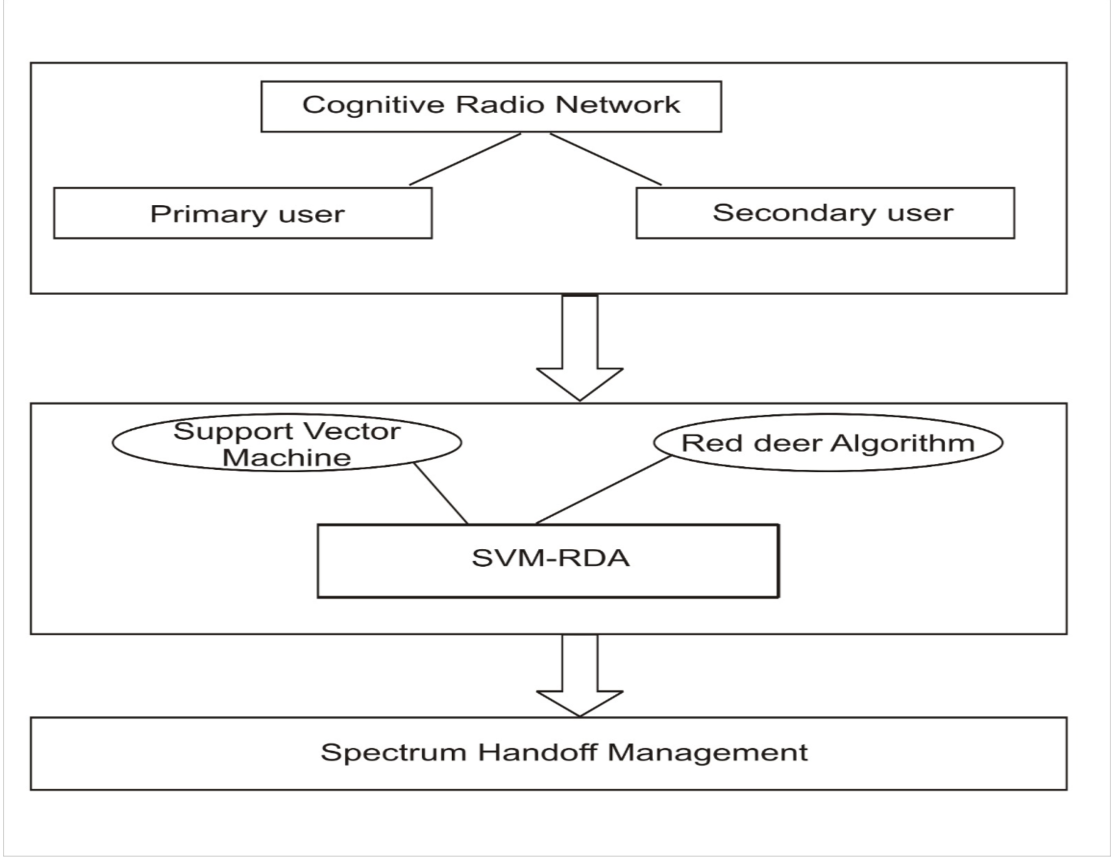

Figure 6.1: Proposed architecture diagram of "SVM-RDA"

6.9 RESULT AND PERFORMANCE ANALYSIS

6.9.1. Configuration of parameter for “SVM-RDA” algorithm

This technique optimize procedure suggestively influences chosen parameters. Table 6.1 demonstrates proposed technique's parameter configuration used in the simulation test. This work incorporates two broad categories of learning heuristic techniques into a handoff scheme that comprises machine learning and metaheuristic. Handoff parameters are analyzed depending on handoff technique, including the Genetic algorithm, iPSO, and SpecPSO.

Table 6.1: **Configuration of Parameter**

Parameter	Value
Type of Channel	Wireless channel
MAC Type	802.11
Radio Propagation model	Two ray ground
Channels number	11
PU users’ number	10
Simulation Time	1000 seconds
Area of simulation	500x500 m^2
Population size	50

6.9.2 Experimental setup

The performance of proposed method is evaluated “using MATLAB R2014a simulation on a 64-bit computer with core i5 processor and 8 GB RAM. The simulation environment consists of 20 nodes” located in 500*500 square meters for 1000 seconds. “Population size is set of 50, and range of iteration is 0 and 100. The estimated user count is 50, and the number of available channels is 200. Bandwidth is 30 kHz, and maximum data transfer rate is 256 Kbps. Table 6.2 summarises simulation results for SU's spectrum and bandwidth during transmission.”

“Unsuccessful handoffs numbers, handoffs numbers, throughput, SNR, and delay “ are parameters used to handoff procedure monitor. SNR indicates a signal is stronger than noise and interference. Throughput is total data quantity transferred from destination node to source node over a specific time, with smallest packet loss. “The delay is time for data to travel from a destination node to a source node. The number of handoffs denotes changes in the state of channels utilised to transmit and receive data in nodes." Unsuccessful handoffs number denotes failed transmissions number in a particular channel state. Failed handoffs lower system efficiency. Here, analysis of handoff failed handoff, delay and throughput depends on transmission time with help of MATLAB simulation.

6.9.3 SU's channel allocation

"CRN is utilised to assign SUs and PUs. When PU arrive, SU transit to channel's next unused frequency bandwidth." Consequently, "SVM-RDA" selects channel with few repeats and hands off to SU to ensure data flow. As shown in figure 6.2, active SUs number in spectrum is provided.

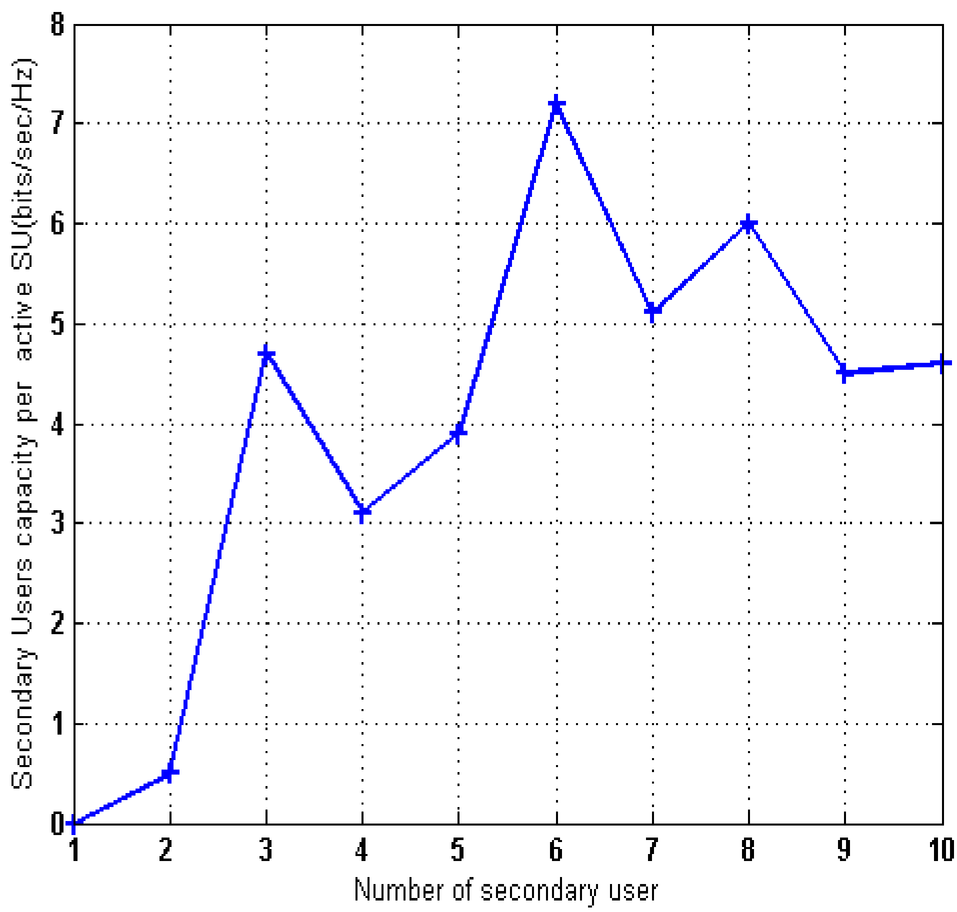

Figure 6.2: Active SU

Table 6.2: Bandwidth allocation for SU

Parameter	Algorithm			
	"Genetic Algorithm"	"Spectrum Particle Swarm optimization"	"Improved Particle swarm Optimization"	"SVM-RDA"
"Total Spectrum Bandwidth"	14.6582	3.9116	3.3202	2.1201
"SU bandwidth"	1.9292	0.1728	0.1544	0.1123

The suggested method's performance is compared to iPSO, Spec PSO, and GA (Genetic Algorithm). The measured total PU bandwidth and the remaining estimated SU frequency yield satisfactory performance with the help of "SVM-RDA". Figure 6.3 describes results of simulations for total spectrum bandwidth and SU bandwidth during transmission.

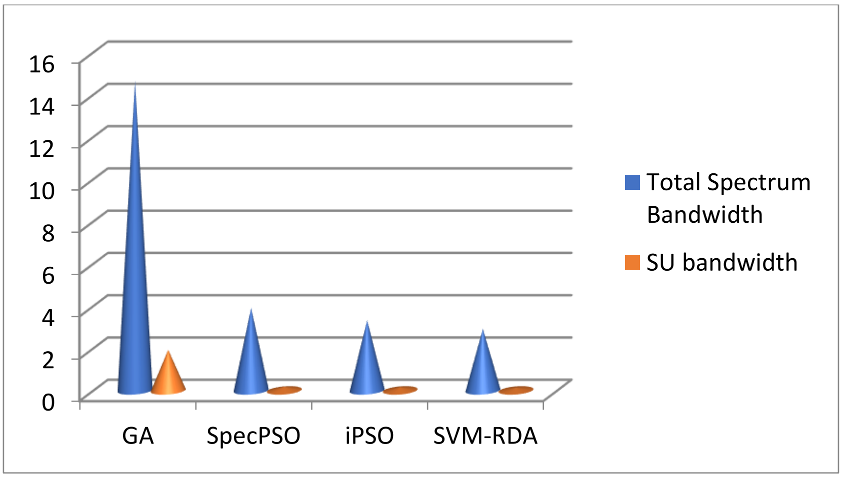

Figure 6.3: Frequency allocation for SU

"Figure 6.4 represents SNR as a function of Average E_b/N_o." The SNR value is calculated using RF frequencies. Comparison plots propose that SVM-RDA has a favourable trade-off among other 3 algorithms, as shown in figure 6.4. Range of E_b/N_0 is 1 to 11 dB.

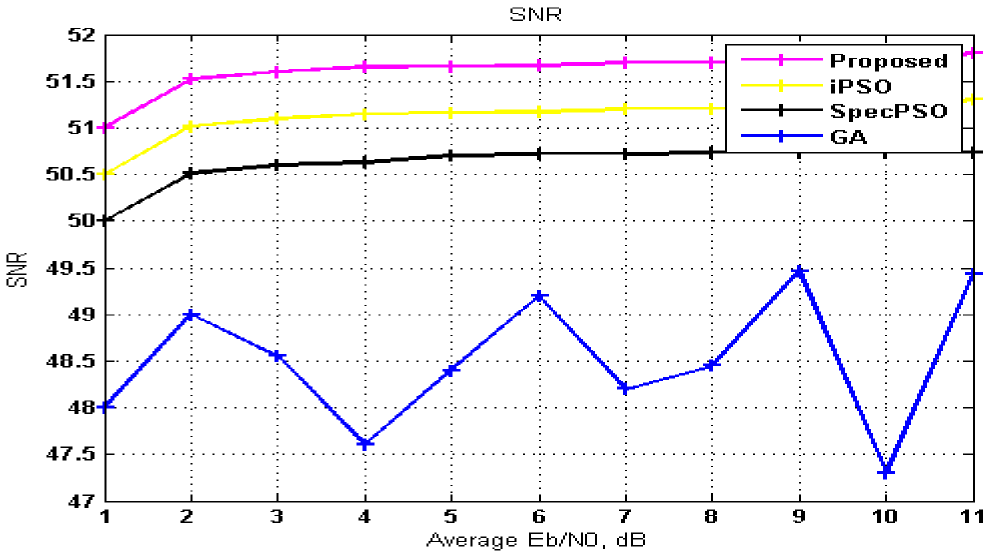

Figure 6.4: SNR vs. average E_b/N_o

Figure 6.5 shows throughput corresponding to “SVM-RDA”, iPSO, SpecPSO, and GA in sensing time. “The simulation results suggest that throughput is high with a shorter transmission time after SU handoff as compared to existing techniques like iPSO, GA, and specPSO, as illustrated in figure 6.5.” The range of transmission time is 1 to 11 seconds.

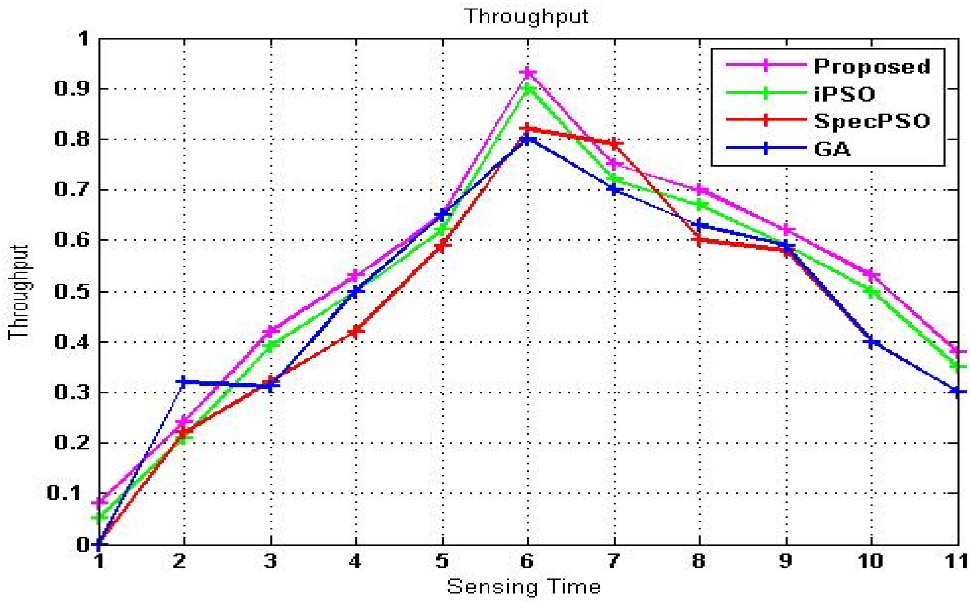

Figure 6.5: SU’s throughput after the handoff

“Figure 6.6 shows delay parameter vs. transmission time. Transmission time is altered, and delay graph shows that suggested SVM-RDA method significantly reduces delay compared to other hybrid handoff strategies.” Afterwards, second-lowest number is shown by iPSO, followed by SpecPSO and GA. The suggested solution has the smallest delay since secondary consumers may access channels immediately.

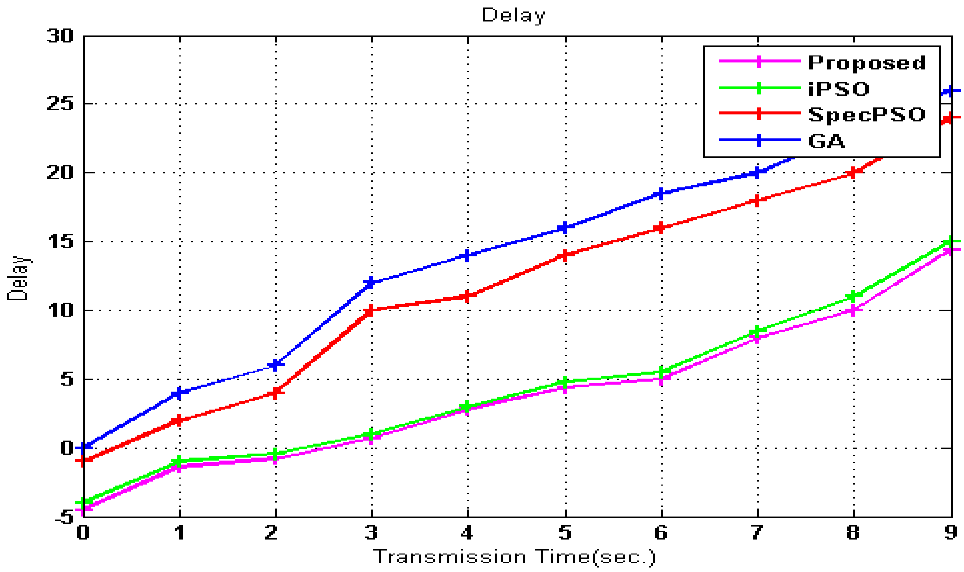

Figure 6.6: Delay vs. transmission time

The unsuccessful handoffs are depicted in figure 6.7, and it is instantly seeming that the proposed “SVM-RDA” has lowest failed handoffs numbers of any algorithm tested. The iPSO algorithm shows minimal states below, followed by GA and SpecPSO algorithms. These algorithms describe increase in failed handoffs due to limited channels and poor prediction available for SU to access. The recommended approach predicts range failure after link failure, which improves network channel availability and handoff prediction, reducing failed handoffs.

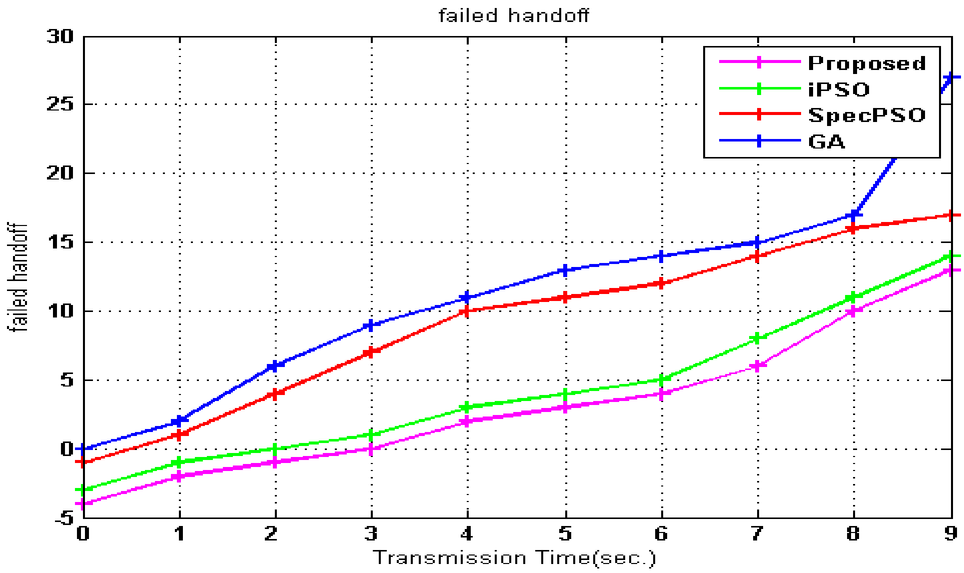

Figure 6.7: Failed handoff versus transmission time

"Compared to other algorithms, the SVM-RDA technique has a much smaller number of handoffs. This lowest value was obtained by SVM-RDA optimization". This minimal value results from the prediction and classification steps taken by these RDAs before making a choice. As demonstrated in figure 6.8, handoffs are reduced by intelligently anticipating their occurrence depend on predicted PU data delivery time.

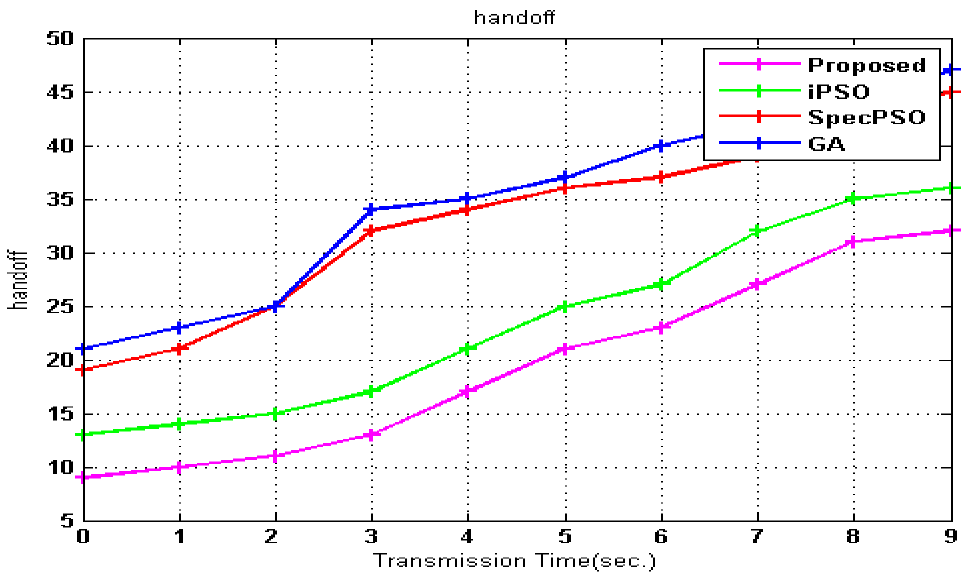

Figure 6.8: handoff versus transmission time

Hence, "SVM-RDA" handoff method is more effective regarding handoff parameters, enhancing spectrum mobility phase in CRN based on comprehensive study of the various hybrid handoff strategies described in this work.

Tables 6.3 and 6.4 show efficiency of individual optimization algorithms (GA, SpecPSO, iPSO and SVM-RDA) regarding handoff, failed handoff, average throughput and average delay in various transmission times.

Table 6.3: Comparison of SNR on different average E_b/N_o for various handoff algorithms

Average E_b/N_0	GA	SpecPSO	iPSO	SVM-RDA
1	48	50	50.5	51
2	49	50.51	51.02	51.52
3	48.55	50.6	51.1	51.6
4	47.66	50.63	51.15	51.65
5	48.40	50.7	51.16	51.66
6	49.2	50.72	51.17	51.67
7	48.4	50.72	51.2	51.7
8	48.45	50.73	51.2	51.7
9	49.47	50.73	51.2	51.7
10	47.3	50.73	51.21	51.71
11	49.44	50.73	51.3	51.8

Table 6.4: Comparison of handoff algorithm

Parameters	Transmission time (second)	GA	SpecPSO	iPSO	SVM-RDA
Average delay in sec	1	5	4	1	0.5
	2	9	7	4	3.6
	3	11	9	4.6	4.2
	4	17	15	6	5.7
	5	19	16	8	7.8
	6	21	19	9.8	9.4
	7	23.5	21	10.5	10

	8	25	23	13.5	13
	9	28	25	16	15
Average throughput	1	0	0	0.05	0.08
	2	0.32	0.22	0.21	0.24
	3	0.31	0.32	0.39	0.42
	4	0.5	0.42	0.5	0.53
	5	0.65	0.59	0.62	0.67
	6	0.8	0.82	0.9	0.93
	7	0.7	0.79	0.72	0.75
	8	0.63	0.60	0.67	0.70
	9	0.59	0.58	0.59	0.62
Number of handoffs	1	16	14	8	4
	2	18	16	9	5
	3	20	20	10	6
	4	29	27	12	8
	5	30	29	16	12
	6	32	31	20	16
	7	35	32	22	18
	8	37	34	27	22
	9	39	37	30	26
Number of failed handoffs	1	5	4	2	1
	2	7	6	4	3
	3	11	9	5	4
	4	14	12	6	5
	5	16	15	8	7
	6	18	16	9	8
	7	19	17	10	9
	8	20	19	13	11
	9	22	21	16	15

Table 6.4 summarises various handoff strategies studied in network parameters such as delay, failed handoffs, throughput, and total handoff occurrences. The lack of an

optimization scheme reveals that GA scheme analysis is an ineffective handoff approach. The SpecPSO approach outperforms GA, but not iPSO, SVM-RDA, or iPSO due to the training of input parameters and optimization with the help of SVM-RDA and time complexity.

"SVM-RDA" algorithm is more effective in SH than other algorithms. "Due to less handoff for spectrum mobility in CRN, results reduce energy consumption. The RDA algorithm provides wide usage of attributes for handoff decisions. SVM is an optimization method to ensure accurate prediction from overall comparison of various hybrid handoff schemes and qualitative analysis of handoff performance indicators."

6.10 CONCLUSION

This chapter suggested that handoff strategy uses an "SVM-RDA" algorithm to solve spectrum mobility phase handoff process. The SVM-RDA algorithm, based on machine learning and inspired by red deer's energy consumption, is a metaheuristic algorithm that uses machine learning. Robustness and flexibility are critical characteristics of CRN.

CHAPTER 7
TO PROPOSE A MACHINE LEARNING-BASED PREDICTIVE RESOURCE ALLOCATION STRATEGY TO ENHANCE THE PERFORMANCE OF ENERGY-HARVESTING CRNS

7.1 ABSTRACT

This objective addresses the problems of delayed convergence and the need for substantial state spaces in current DQL based RA techniques. RA in EH-CRN is enhanced by suggested SVM-RDA, which considers capacity, average latency, and transmission power restrictions. Simulation results suggest the proposed algorithm provides resource utilization and greater convergence than previous methods in the literature.

7.2 INTRODUCTION

In CR, researchers are looking for ways to use that spectrum. CRNs are a new field of study made possible by integrating conventional CR methods. In the CRN, the SU can improve the rate of spectrum use with the help of DSA technology. As previous research has shown, most CRN nodes are batteries powered. So problem is that each node has so much power. Thus, network stability is crucial. Researchers suggest EH for these low-power nodes[158]. EH continues to be one of the most extensively used and adaptable techniques in wireless communication [159].

In [160], the resource allocation (RA) issue was investigated using an offline neural network for dataset training, so output results are produced. But getting enough correct data can take time and be hard to do. Deep reinforcement learning (DRL) is becoming popular for researchers to work around these problems. In DRL, there is less need for data about the system model and the environment. Also, DQL is one of the most popular DRL techniques scientists have used. In DQL, traditional reinforcement learning is used along with deep neural networks [161].

Researchers have paid much attention to ML in the past ten years. ML models are new because of how they are made and how they learn the structures inside them. In the CRN field, traditional methods need complete network information, which is impossible. Several researchers used the Metaheuristic algorithm in machine learning, such as the learn heuristic algorithm, to solve these problems and make them less dependent on information from the network [162].

7.3 RELATED WORK

7.3.1. Conventional optimization-based approaches

Present research on EH-CRN is mostly about choosing relays, figuring out how likely an outage is, allocating resources, and improving security. This method lowers the cost of leasing spectrum for the SUs and maximises the spectrum during transmission. In, wireless power method with non-linear EH model was suggested [163].

7.3.2. Q-learning based approaches

F. Zhang et al. suggested a policy for getting the best access to sensing data. Main objective was to increase expected throughput as much as possible. Authors said that the performance of non-linear EH model could be the same as that linear EH model [164].

To boost functionality of multichannel CRN, authors developed a concurrent CSS and EH approach. Energy efficiency, harvested energy, and throughput are all optimized for SUs across all sub-channels in the created resource allocation issue. For its part, joint sub-channel method uses a greedy approach. Under the cooperative jamming scenario, C. Xu et al. suggested a safe resource allocation mechanism for cognitive WSNs. An iterative optimization strategy was used to find the best solution to the power distribution issue [165]. The proposed solution is a pair of algorithms that function in tandem to handle scheduling and resource allocation, respectively. The main goal was to get the network sum rate as high as possible, use as little energy as possible, and meet the QoS constraints. R. Xie et al. looked at power distribution and transmission time and devised a joint problem. The scenario worked in centralized and decentralized environments in a heterogeneous CRN [166].

7.4. MOTIVATION

Most of our plans are based on Q- learning and traditional optimization. The traditional Q-learning method works well in areas where the curse of dimensionality problem is not a problem. But some problems exist, such as slow learning and trouble generalizing over large state spaces. Researchers in the field of RL have had a lot of trouble with this. On top of that, there is a need for efficient usage of collected energy, and EH technology based on learnheuristic algorithm is still susceptible to significant unpredictability. These works used various EH models to arrive at an ideal solution using traditional optimization methods. However, there is little information on EH systems using DRL for linear or non-linear models. This study proposes a resource allocation strategy based on a heuristic learning algorithm that improves convergence and capacity performance.

The main goal of this work is to look into the proposed resource allocation problem and find the best way to solve it. Given some restrictions, objective is to get most out of EH-CRN system.

1) A problem called RA is made for the EH-CRN environment. Traditional Q-learning algorithms don't work well for systems with many states. Also, mixing EH-SUs with PUs gives the problem a different shape.
2) As far as we could tell from our research, neither the linear nor the nonlinear EH model had been used before in the adopted EH-CRN scenario.
3) Many simulation results show how well the proposed approach works compared to other methods in the literature.

7.5 RELATED MATRICS

7.5.1 Capacity

A digital communication system's link spectral efficiency is measured in bits per second per hertz, or, less commonly but explicitly, in (bits) per hertz. It is the maximum throughput divided by bandwidth, measured in hertz, of communication channel or data connection. The usable information rate is the rate at which information may be sent without regard to error-correcting codes. The spectral efficiency might also be assessed in bits per symbol, the same as bits per channel usage. This would indicate that the net bit rate would be divided by the symbol rate (modulation rate) or line code pulse rate.

7.5.2 Average delay

Average delay means time required to learn from learnheuristic algorithm.

7.5.3 Transmit power

Power is transmitted from EH-SU to PU.

7.6 RELATED ALGORITHM

7.6.1 Deep Q Learning reinforcement algorithm (DQLRA)

“Though Q-learning provides optimal course of action for a given sequence of states, training time becomes increasingly high when the number of states is significant. Furthermore, the state space must be discretized if the variables incorporated are continuous. These limitations of Q-learning can be overcome with DQL. In contrast to conventional Q-learning that generates a finite action-value table, DQN replaces the table with a deep neural network Q(s, a; θ), where θ denotes the weight values of the neural network with state s and action a [104].”

7.6.2 Stochastic Adaptive Random Sampling Algorithm (SARSA)

“SARSA algorithm is a slight variation of the popular Q-Learning algorithm. For a learning agent in any Reinforcement Learning algorithm, its policy can be of two types: -

1. **On Policy:** In this, the learning agent learns the value function according to the current action derived from the currently used policy.

2. Off Policy: In this, the learning agent learns the value function according to the action derived from another policy.

The q-Learning technique is an Off Policy technique and uses the greedy approach to learn the Q-value. On the other hand, SARSA technique is an On Policy and uses the action performed by the current policy to learn Q-value.
Here, SARSA depends on current state, current action, reward obtained, following state, and action. This observation leads to naming the learning technique SARSA stands for State Action Reward State Action, which symbolizes the tuple (s, a, r, s’, a’).

The following steps demonstrate how to implement the SARSA algorithm in cognitive radio environment.

Step 1: Import the required libraries.

Step 2: Building the environment.

Step 3: Initializing different parameters.

Step 4: Defining utility functions to be used in the learning process.

Step 5: Training the learning agent.

Step 6: Evaluating the performance."

State–action–reward–state–action (SARSA) is an algorithm for learning a Markov decision process policy used in the reinforcement learning area of machine learning. Rummery et al. proposed it in a technical note named "Modified Connectionist Q-Learning" . "This name reflects the fact that the primary function for updating the Q-value depends on the current state of the agent "$\mathbf{S}_1$", the action the agent chooses "$\mathbf{A}_1$", the reward "**R**" the agent gets for selecting this action, the state "$\mathbf{S}_2$" that the agent enters after taking that action. Finally, the agent chooses the following action, "A_2," in its new state. The acronym for the quintuple (s_t, a_t, r_t, s_{t+1}, a_{t+1}) is SARSA. They. use a slightly different convention and write the quintuple (s_t, a_t, r_{t+1}, s_{t+1}, a_{t+1}), depending on which time step the reward is formally assigned" [163].

7.6.3 QLRA

Chris Watkins introduced Q-learning in 1989. Watkins and Peter Dayan presented a convergence proof in 1992. Watkins addressed "Learning from delayed rewards," the title of his Ph.D. thesis. Eight years earlier, in 1981, the same problem, under the name of "Delayed reinforcement learning," was solved by Bozinovski's Crossbar Adaptive Array.

"Q-learning is a model-free reinforcement learning algorithm to learn the value of an action in a particular state. It does not require a model of the environment, and it can handle problems with stochastic transitions and rewards without requiring adaptations. For any finite Markov decision process (FMDP), *Q*-learning finds an optimal policy to maximize the expected value of the total reward over any successive steps, starting from the current state. *Q*-learning can identify an optimal action-selection policy for any given FMDP, given infinite exploration time and a partly-random policy. "Q" refers to the function the algorithm computes – the expected rewards for an action taken in a given state."

"It is the most widely used algorithm in reinforcement learning. The basic principle of Q learning is that after an agent takes action, it causes the state of the environment to change, and effect of this change can be quantified as a reward. The return value can reflect the award or punishment to evaluate the agent's movements. The agent selects the following action based on the return value and the current state of the environment. The principle of selection is to increase the probability of being a positive reward value until convergence[167].”

7.6.4 Energy Harvesting Resource Allocation (EHRA)

In RF EH, harvested energy amount depends on transmit power, RF signals wavelength, and distance between harvesting node and an RF energy source. Harvested RF energy can be calculated from Frills equation. “RF EH has the following features:

- RF sources can provide constant energy transfer over distance for RF energy harvesters.
- It is suitable for mobile devices.
- Since harvested RF energy depends on distance from RF source, network nodes in different locations can significantly differ in harvested RF energy amount.

The RF sources are of two types: ambient RF sources and reliable RF sources. Dedicated RF sources can provide energy to network nodes when more predictable energy is needed. Ambient RF sources are RF transmitters not intended for RF energy transfer. EH from dynamic ambient RF sources is used in CRNs. A SU can harvest RF energy from nearby transmitting PUs and transmitting data. RF-EHNs introduce RF EH as a new function for wireless devices[167].”

7.6.5 Waterfall-based Power Allocation (WFPA)

“Water filling algorithm is a general name given to the ideas in communication systems design and practice for communication channel equalisation strategies. As the name suggests, just as water finds its level even when filled in one part of a vessel with multiple openings, as a consequence of Pascal's law, the amplifier systems in communications network repeaters, or receivers, amplify each channel up to the required power level compensating for the channel impairments.”

“Consider abandoning a channel while only doing one user simultaneously to get higher channel capacity and serve more users under the same conditions. Each channel is allocated a certain frequency (resources) when users communicate. Multiple users can be online simultaneously, which significantly reduces the limit of the number of channels to the number of users. So how to allocate resources is a topic worthy of discussion. The resource allocation method based on the water-filling algorithm is more intelligent. The water-filling algorithm, as the name implies, is to inject water. Each channel is treated as a bottle, and a certain amount of water is added. The number of resources or frequency allocated is determined by water level and noise to Carrier Ratio. Because the channel strength and noise power are random, each channel's transmission power is allocated according to water level and noise-to-carrier ratio. More resources can be allocated to the channel with better quality. This can significantly improve the quality of communication. Therefore, the selection of water level; is significant to network performance and communication capacity[167]."

7.7. SYSTEM MODEL

7.7.1. Signal model

In the uplink scenario of a wireless network, different PUs tries to send data to the base station. On the other hand, many pairs of SU transmitters and receivers use the PU spectrum to talk to each other. Here SUs can successfully use the available spectrum of the PUs. Here, only power allocation problem is looked at, which means that we need to find the best power levels for each SU in the network so that a minimum QoS for the PU network is kept. Each SU transmitter has a built-in EH circuit that keeps it working for a long time. This work assumes that SU receiver doesn't need much computing power because decoding uses less power. EH and data transfer occur during transmission. The network has M cognitive linkages due to L PUs and M SU transmitter and receiver pairs. SU communication links interfere with PUs and other SUs. PUs also disrupts other SUs.

7.7.2 EH model

Solar energy is seen as a reliable and low-cost alternative to other energy sources for our daily wireless devices. But the effectiveness and size of this resource vary a lot depending on the environment and where the device is placed. Also, collecting energy is very hard when it's raining. Since these sources aren't always reliable, it's important to develop a better way to use the energy that can be harvested.

7.8 SIMULATION RESULT

This section compares the suggested methods to other well-known approaches. The proposed scenario is tested using MATLAB scripting on a computer with an Intel Xeon W-2133 CPU at 3.6 GHz and 32 GB of RAM. We simulate a 50 m X 50 m network coverage. 2 PUs, 6 SUs, and 1 BS are present. The simulation assumes perfect CSI and Rayleigh-distributed flat fading between PU and SU.

7.8.1 Comparison of suggested technique

The relationship between capacity and EH-SU values is presented in figure 7.1. Other methods, such as DQLRA, Q-learning scheme, EHRA, WFPA, SARSA, and random initialization. As the EH-SUs numbers increase, the network's overall capacity increases, as shown in figure 7.1. The next two rival techniques, DQLRA and SARSA, are table-based reinforcement learning approaches that need action spaces and discrete states and transitions. DQLRA increases the performance of the proposed SVM-RDA since the state space does not have to be discrete, and there are more permutations of states to pick to maximize sum capacity.

More than SARSA and DQLRA, the suggested method converges. Capacity performance is much lower than that of non-reinforcement learning methods. Because the recommended method considers the environment's dynamic nature, it outperforms existing algorithms, which evaluate the immediate capacity value for optimization. The proposed SVM-RDA outperforms the state-of-the-art and all baseline methods. For instance, compared to DQLRA, random initialization schemes, SARSA, WFPA, EHRA, and Q-learning, the proposed technique delivers increases in capacity value of 12.52%, 61.83%, 23.65%, 58.7%, 37.5%, and 25.03%, at number of EH-SU=14.

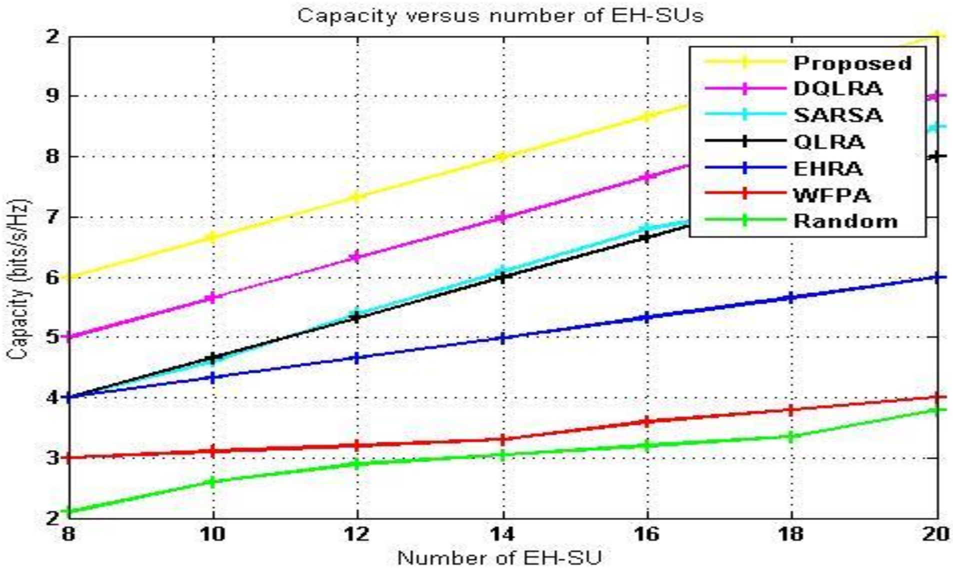

Figure 7.1: Capacity versus number of EH-SUs

Figure 7.2 shows average delay performance for a range of EH-SU numbers. The picture shows that the proposed method keeps minimum average delay. The proposed method gets better results because it gets closer to the truth quicker. A different algorithm might find the best policy faster than the learning process. So, the learning agent (the SU coordinator) may be able to make better use of the available energy to speed up how fast data can be sent over the network. This is especially true for methods that combine random policy with traditional optimization. The suggested SVM-RDA is better than all of the baseline schemes. At number of EH-SU = 14, for example, the proposed method slows down computation by 13.89%, 38.89%, 12.5%, 80.55, 36.11, and 92% less than the DQLRA, random initialization schemes, SARSA, WFPA, EHRA, and Q-learning.

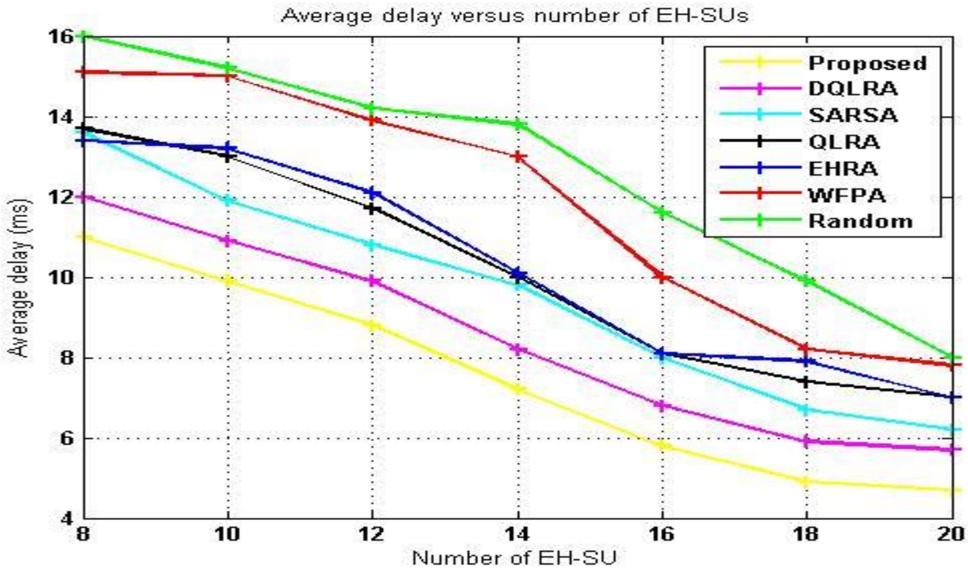

Figure 7.2 :Average delay vs. Number of EH-SU

We looked into capacity under various transmit power parameters, and results are shown in figure 7.3. The outcomes of several algorithms are compared with the proposed algorithm. Range of transmit power is 3 dBm to 0.5 dBm. It can be shown that, for all designs into consideration, capacity of system rises linearly as transmission power value increases. Linear growth is due to proposed work's use of a linear EH model to measure performance. The suggested SVM-RDA outperforms all baseline schemes. Regarding capacity values, next-best performers SARSA and DQLRA, exceed QLRA, EHRA, WFPA, and random initialization methods. For instance, the proposed scheme offers gains in capacity of 5.07%, 25.9%, 41.73%, 28.05%, 20.86, and 50.35% over the DQLRA, Q-learning, WFPA, EHRA, SARSA, and random initialization schemes, respectively, at transmitting power values of 2 dBm.

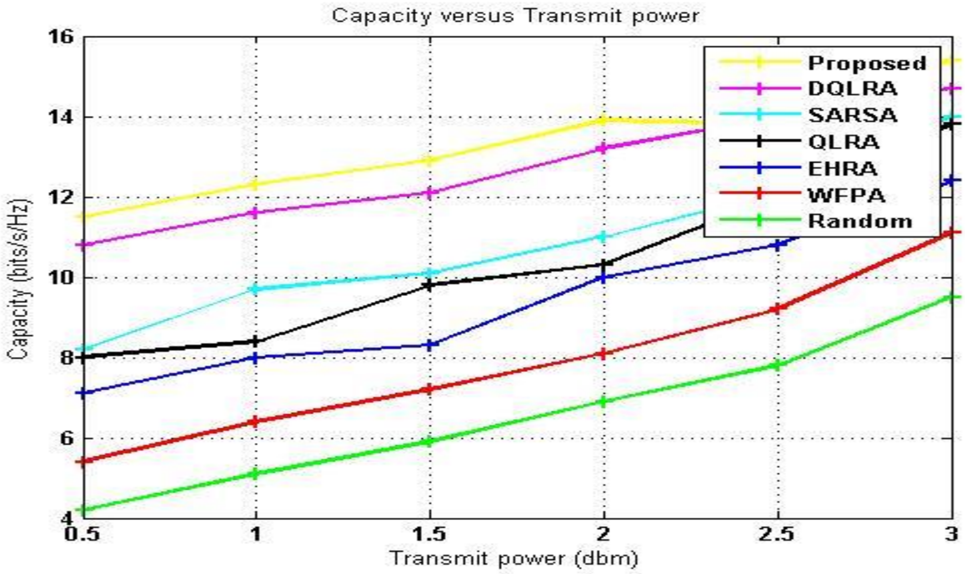

Figure 7.3: Capacity vs transmit power

7.8.2 Discussion

1. Random SU node distribution might cause instability.

2. The linear EH model is more lucrative despite the smaller linear's compensation potential. Energy harvester modeling may not use the linear EH model due to non-linear circuit characteristics. This study compares non-linear and linear EH model findings. Here aim to add non-linear EH models to this study to build on it.

7.9 CONCLUSION

This chapter discusses SVM-RDA for an EH-CRN used as intelligent resource allocation system. SVM-RDA was used to solve this dynamic optimization issue by reformulating the Resource Allocation issue. SVM-RDA provides for faster convergence in large state space systems. Comparing the performance of the proposed algorithm to several current algorithms shows that it is better.

CHAPTER 8

CONCLUSION AND FUTURE SCOPE

8.1 CONCLUSION

The fixed radio frequency allocation guidelines that characterize today's wireless networks cannot meet the current necessities for wireless communication. That is why cognitive radio technology is suggested to mitigate the issue of spectrum management. CR technology's cognitive and learning capabilities dynamically facilitate coexistence between PUs and SUs while preserving the priority of PU. To achieve these goals, a cognitive user must periodically and intelligently sense the available spectrum and make the correct decision. Therefore, spectrum sensing is a significant component of the cognition cycle of CRNs. Cognitive Radio is a critical technology that enables spectrum awareness in spectrum sensing.

The cognitive engine makes the required decisions so that the user's demand supplies the new spectrum allocation. SVM-RDA is fastest optimization approach for generating optimized outcomes. Advantages of SVM-RDA are lesser control parameters, faster convergence, Robustness, and simplicity.

Spectrum sensing is crucial in successfully deploying Energy Efficient CRNs. It is essential to use RF energy intelligently and to maximize the network life by designing energy-efficient CRN. In this thesis, the CRN's EE is maximized to enable green wireless network by exploring various methods. Energy Efficient CR network can be achieved by increasing the energy efficiency in existing and future networks by harvesting energy. The proposed energy-efficient CRN is implemented in real-time in Mobile Network Communication System (5G) based on wireless power transfer technology.

The importance of CR technology in achieving SE has been well established. With the miniaturization of computing devices and advancement in wireless access technologies, spectrum exclusivity will not be possible. Higher data rates and user mobility are putting further constraints on the existing spectrum resources. CR has shown immense potential in emerging as a technology that can offer a solution to this paradigm. This model will revolutionize radio communications.

The quest for an optimal solution has led researchers to explore and use the concepts of Machine learning-based metaheuristic Algorithms. In this work, commonly used SVM-RDA has been referred to for formulating the concept of optimizing various operating parameters of CR. Machine learning-based metaheuristic Algorithm is being used for the first time to implement the cognitive engine design and optimize the cooperative sensing in CRN.

This thesis will focus on energy-harvesting CRNs, maximising energy efficiency by considering energy causality and RF power constraints. Optimization problem is formulated as a ratio of the SE to the total energy consumption under the energy and RF power constraints, which is solved by SVM-RDA algorithm to obtain the optimal solutions. Finally, with the help of detailed results, we show that proposed power allocation scheme immoderately improves the network's average EE and SE performance. All of the work mentioned in this thesis is related to full-duplex modes, where a node can simultaneously transmit data in the same frequency spectrum. However, full-duplex operation consumes more energy. This is a grave concern for the wireless node powered by RF energy. This problem becomes more prominent in CRNs as nodes in these networks need to spend time and RF for spectrum sensing. To tackle this problem, EH and energy transfer with full-duplex communication have become exciting and promising solutions. Several constraints must be addressed while designing future energy-efficient systems, such as delay time, transmitted power, primary QoS, and interference due to full-duplex mode. We focus on energy-efficient solutions for a full cognitive duplex system powered by harvested and transferred energy.

The focus of this thesis was to theoretically analyze and design energy-efficient CRN using spectrum sensing to maximize the achievable throughput, energy efficiency and reduce energy consumption. The dissertation holds few contributions made in the field of CR optimization. Main achievements of the research and conclusions built from the results are summarized below:

Foundation of current research is developed in the first chapter by exploring brass tacks of CR and optimization. Structure of CR is investigated from its features to its applications. Light is being thrown to the need of the work done in this research and clearing the air behind its motivation. The available literature that motivated the proposed research work and objectives are stated. Further, the researcher's contribution and thesis organization are presented.

In second chapter, pages of the literature are turned extensively and read between the lines to decipher limitations in the available work. Discovery of the voids led to the framing of objectives for the research. A detailed literature review is presented here, where the existing literature on PU detection in various methods in the spectrum. The literature survey is mentioned different ways like non-cooperative, cooperative, and cooperative machine learning-based spectrum sensing schemes.

Using MATLAB software, the implementation of CRN with the help of SVM-RDA based on energy detection for PU detection is described in chapter 3.

Chapter 4 discusses SVM-RDA algorithm proposed for increasing EE in spectrum sensing for CRN. EE function is determined by probability of detection, sensing bandwidth, and transmission power. The SVM-RDA has considerably enhanced performance of RDA. Compared to current PSO-GCA , SVM-RDA results show its efficacy in EE for sensing of spectrum. SNR= 6 dB and population size = 20, the proposed SVM-RDA is 22 %, 30 % and 15% high energy efficient than ABC, PSO, PSO-GSA, respectively, for differing transmission power. For the varying P_d, the suggested SVM-RDA outperformed ABC, PSO and PSO-GSA by 16%, 24% and 4%, respectively. In contrast, for varying sensing bandwidth, the proposed algorithm outperforms ABC , PSO and PSO-GSA, , and by16%, 19% and 7% respectively.

This study implemented a novel cooperative spectrum sensing approach based on SVM-RDA, as explained in Chapter 5. The proposed system includes several intelligent units that perform various basic tasks. The SVM-RDA algorithm has been used as a local spectrum sensing method because of its simplicity and efficiency. In which each SU periodically and locally senses the PU's signal. The SVM-RDA-based fusion has been used for final decision at FC, in which each SU contextual characteristic is used as data set for training. A trained SVM-based FC was used to fuse all the data of the participating SUs. In addition, all the scenarios used were stored in a knowledge base to achieve the learning and reasoning objectives for future decisions. A variety of simulations in MATLAB determined the performance of the proposed fusion scheme. The probabilities of detection and false alarm were the essential metrics to assess overall performance of a system. Integrating contextual information from SUs into the fusion process has yielded promising results compared to conventional fusion techniques. In this framework, we could improve the probability of detection of the proposed CSS scheme with lower value of false alarm. In addition, the proposed scheme has achieved excellent accuracy compared to other conventional techniques. At a -5dB SNR value, the proposed SVM-RDA has 46% and 9.8% more probability of detection than a dynamic dual-threshold for 5 SU and 10 SU, respectively. At 10dB SNR, the proposed SVM-RDA has 24.24% and 14% higher detection probability than the dynamic dual-threshold for 5 SU and 10 SU, respectively. At 20 occupied bands, the proposed SVM-RDA outperforms L1 Norm WP, TOMP W, FMP W, and FMP WP by 2.1, 4.02%, 2.1, and 1.5%, respectively. At 30 occupied bands, the proposed SVM-RDA has 1.02%, 0.5%, 1.02%, and 2.04% higher detection probability than L1 Norm WP, TOMP W, FMP W, and FMP WP, respectively.

At the -5dB SNR value, the proposed SVM-RDA has 34.1% and 50% less probability of error than a dynamic dual-threshold for 5 SU and 10 SU, respectively. At a 10dB SNR value, the proposed SVM-RDA has 79.16% and 18% less probability of error than a dynamic dual-threshold for 5 SU and 10 SU, respectively. At 20 occupied bands, the proposed SVM-RDA has 25 %, 22%, 92.85 %, 72 %, and 40% less probability of error than the L1 norm WP. TOMP W, FMP W, and FMP WP, respectively. At 30 occupied bands, the proposed SVM-RDA is 33.33 %, 83.87%, 72%, and 50 % less probability of error than L1 norm WP. TOMP W, FMP W, and FMP WP, respectively.

Chapter 6 suggested that handoff strategy uses an "SVM-RDA" algorithm to solve the spectrum mobility phase handoff process, which plays a critical role and is one of CRN's distinctive properties. Efficiency of "SVM-RDA" is based on prior knowledge of the environment and reduced execution time to complete the task. The SVM-RDA algorithm, based on machine learning and inspired by red deer's energy consumption, is a metaheuristic algorithm that uses machine learning. Robustness and flexibility are critical characteristics of CRN. At a particular transmission time value (5 seconds) average delay is 19 seconds, 16 seconds, 8 seconds and 7.8 seconds for GA Spec PSO, iPSO and SVM-RDA respectively. So proposed SVM-RDA has 58%, 51.25%, and 2.5% less average delay than GA Spec PSO and iPSO respectively. At a particular transmission time value (5 seconds) throughput is 0.65, 0.59, 0.62 and 0.67 GA Spec PSO, iPSO and SVM-RDA respectively. So proposed SVM-RDA has 3.07%, 10.17%

and 8.06% more throughput than GA Spec PSO, iPSO and SVM-RDA respectively. At a particular transmission time value (5 seconds) number of handoffs is 30, 29, 16 and 12 for GA Spec PSO, iPSO and SVM-RDA respectively. So proposed SVM-RDA has 60 %, 58.62% and 25% less handoff than GA Spec PSO, iPSO and SVM-RDA respectively. At a particular transmission time value (5 seconds) number of failed handoffs is 16, 15, 8 and 7 for GA Spec PSO, iPSO and SVM-RDA respectively. So proposed SVM-RDA has 56.25 %, 53.33 % and 12.5% less failed handoff than GA Spec PSO, iPSO and SVM-RDA respectively.

Chapter 7 discussed machine learning-based metaheuristic algorithm (SVM-RDA) for an EH-CRN used as an intelligent resource allocation system. SVM-RDA was used to solve this dynamic optimization issue by reformulating the Resource Allocation issue. SVM-RDA provides for faster convergence in large state space systems. Comparing the performance of the proposed algorithm to several current algorithms shows that it is better. Compared to DQLRA, random initialization schemes, SARSA, WFPA, EHRA, and Q-learning, the proposed technique delivers increases in capacity value of 12.52%, 61.83%, 23.65%, 58.7%, 37.5%, and 25.03%, at number of EH-SU=14. At number of EH-SU = 14, the proposed method slows down computation by 13.89%, 38.89%, 12.5%, 80.55, 36.11, and 92% less than the DQLRA, random initialization schemes, SARSA, WFPA, EHRA, and Q-learning. The proposed scheme offers gains in capacity of 5.07%, 25.9%, 41.73%, 28.05%, 20.86, and 50.35% over the DQLRA, Q-learning, WFPA, EHRA, SARSA, and random initialization schemes, respectively, at transmitting power values of 2 dBm.

8.2 SCOPE OF THE FUTURE WORK

The proposed work can be explored further in the following directions

1. The proposed SVM-RDA can be investigated further using multi-antenna relays and multiple SUs under perfect and imperfect spectrum sensing scenarios.
2. Heterogeneous energy efficient and EH CRN under 2-channel sensing scheme will be develop.
3. The proposed work in the thesis can be further extended by developing a test environment for the EH-HCRN in the smart grid environment.

4. In the case of wideband spectrum sensing, handling noise uncertainty and sparsity level estimation are challenges, so there is a scope for further in these areas.
5. While deploying IoT, more digital devices are to be connected, which requires large amount of spectrum resources. Hence, CR can be combined with IoT to organize these devices efficiently. While implementing IoT technology with CR, the importance of precise sensing and energy consumption minimization of the connected devices has to be analyzed.
6. Millimeter waves and CR aim to address spectrum scarcity. By combining both, spectrum shortage and under-utilization can be managed more appreciably.
7. CR can be analyzed in future 6G technology research to facilitate seamless, affordable, interference-free connectivity among multiple users in heterogeneous wireless networks. To achieve ultra-high data rates, much-reduced latency, and improved reliability, CR-oriented energy conservation analysis can be performed.
8. To improve the connectivity, capacity, and speed of users in a network, CR can be explored with network slicing, virtual networking architecture, and enabling efficient spectrum resource utilization.
9. CR can be integrated with Reconfigurable Intelligent Surfaces (RISs) technology to research a smart, reconfigurable, energy and cost-efficient wireless environment. RIS enables interference mitigation and enhances channel capacity.
10. Visible Light Communication can be integrated with CR technology to achieve interference-free high data rate transmission.
11. Analysis of CR with Unmanned Aerial Vehicle systems can be explored for achieving precise data collection, monitoring, disaster management applications, etc., in a green, secure, and energy-efficient manner.

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