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A Channel Selection Approach in Cognetive Radio Network using Fuzzy and ANN

A Dissertation

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By

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بِسۡمِ ٱللَّهِ ٱلرَّحۡمَٰنِ ٱلرَّحِيمِ

اقْرَأْ بِاسْمِ رَبِّكَ الَّذِي خَلَقَ ﴿١﴾ خَلَقَ الْإِنْسَانَ مِنْ
عَلَقٍ ﴿٢﴾ اقْرَأْ وَرَبُّكَ الْأَكْرَمُ ﴿٣﴾ الَّذِي عَلَّمَ بِالْقَلَمِ
﴿٤﴾ عَلَّمَ الْإِنْسَانَ مَا لَمْ يَعْلَمْ ﴿٥﴾

صدق الله العظيم

الآيات (1-5) سورة العلق

Declaration

To the best of my knowledge, this dissertation "**A Channel Selection Approach in Cognetive Radio Network using Fuzzy and ANN**" , this dissertation contains no material which has been accepted for the award of any other degree in any other university.

Signature:

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Supervisor's Certification

I certify that the dissertation entitled "**A Channel Selection Approach in Cognetive Radio Network using Fuzzy and ANN**" was prepared under my supervision at the Department of Software\ College of Information Technology \ University of Babylon as partial fulfillment of the requirements of the degree of Doctor of Philosophy in Information Technology - Software.

Signature:

Supervisor Name: Prof. Dr. Sattar B. Sadkhan

Date: / /2022

The Head of the Department Certification

In view of the available recommendations, I forward the dissertation entitled "**A Channel Selection Approach in Cognetive Radio Network using Fuzzy and ANN**" for debate by the examination committee.

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Certification of the Examination Committee

We, the undersigned, certify that (Akeel Ibrahem BDRANY) candidate for the degree of Doctor of Philosophy in computer sciences, has presented his dissertation on titled (**A Channel Selection Approach in Cognetive Radio Network using Fuzzy and ANN**) as it appears on the title page and front cover of the dissertation that the said dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on: Nov 27, 2022.

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Dedication

To the name graved in my heart 'IRAQ'

, TO MY LOVELY FAMILY

specially my Mother

With All Respect,

TO

My Sweetheart Wife

Who has always offered

her Patience and prayers, To

my sons Mustafa and my daughter

Rafal.

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First of all, Thanks to Allah for providing me the great willingness and strength to finish this work.

I would like to express my sincere gratitude and give my deepest thanks to my supervisor ***Prof. Dr. Sattar B. Sadkhan*** *for suggesting the research project and for his continuous guidance and support. This work wasn't possible without his guidance and his solid knowledge that made me greatly esteemed.*

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Abstract

Cognitive radio makes it possible to sense and detect the status of radio channels, allowing radio transceivers to determine which channels are in use and which are not. Navigation to empty channels while avoiding crowded channels is the primary goal of cognitive radios. As a result, spectrum utilization is optimized while reducing interference with other users by allowing signals to be broadcast to multiple users on a single channel.

There were two phases in the development of this study. In the first phase, we developed a straightforward approach to modeling cognitive radio networks to encourage better spectrum management through its opportunistic use. In the second phase, we propose to use three algorithms from the fuzzy logic system (Mamdani, Tsukamoto, and TSK) and two neural networks (ANN, ANFIS) to improve the decision-making process in selecting the best available channels in the radio network. In order to achieve this, two types of systems were tested: the non-cooperative system and the cooperative system for secondary users.

Using the modeling method proposed in the first phase as a basis. After all simulations were implemented, three metrics were used for evaluation, including network throughput of data, handoffs (transitions between channels), and delay time (includes search, selection, and transition time to the new available channel). Where a comparison and analysis of the simulation results, where the Adaptive Neural Fuzzy Inference System (ANFIS) algorithm showed an advantage over the rest of the algorithms and also over the standard algorithms.

The results proved that the ANFIS and TSK algorithms gave the best results when increasing the number of channels compared to other methods (ANNs and standard algorithms). The results also showed that the (MCCA) algorithm achieved the best results in the number of conversion operations compared to the rest of the algorithms. It was found that the ANFIS algorithm provided better results than the rest of the algorithms in terms of throughput (the amount of data exchanged) with acceptable values for the rest of the measurements when compared to other methods and algorithms.

Declaration Associated with this Dissertation

Some of the works presented in this dissertation have been published or accepted as listed below:

Published papers

1. Decision-Making Approaches in Cognitive Radio-Status, Challenges and Future Trends.

- Authors: Akeel Bdrany, Sattar B Sadkhan
- Publication date: 2020/12/23
- Conference: 2020 International Conference on Advanced Science and Engineering (ICOASE)

2. Decision-making approach in Cognitive Radio using Tsukamoto and Mamdani FIS.

- Authors: Akeel Borany, Sattar B Sadkhan
- Publication date: 2021/4/28
- Conference: 2021 1st Babylon International Conference on Information Technology and Science (BICITS).

Other Published papers:

1. Enhance Channel Selection in Cognitive Radio Networks by using Fuzzy Approach.

- Authors: Akeel I.Bdrany, Sattar B Sadkhan
- Publication date: the manuscript is being reviewed.
- **Conference**: IEEE conference

2. Decision-Making Approach to Enhance Channel Selection in Cognitive Radio Network by using Neural Network Algorithms.

- Authors: Akeel Bdrany, Sattar B Sadkhan
- Publication date: the manuscript is being reviewed.
- **Journal**: the Intelligent Networks and Systems Society.

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Table of Abbreviations

Abbreviations	Definition
A	Additive White Gaussian Noise
ANFIS	Adaptive Neural Fuzzy Inference System
ANN	Artificial Neural Network
Bs	Bandwidth Symbol
BS	Base Station
BW	Bandwidth
CP	Cognitive Processes
CR	Cognitive Radio
CRNs	Cognitive Radio Networks
CRS	Cognitive Radio System
CSI	Channel State Information
dB	Decibels
DSA	Dynamic Spectrum Access
DSM	Dynamic Spectrum Management
DSM	Dynamic Spectrum Management
DTH	direct-to-home (DTH)
ECS	Evolving Connectionist Systems
FCC	Federal Communications Commission
FIS	Fuzzy Inference System
GHz	Giga Hertz
Hz	Hertz
IEEE	Institute of Electrical And Electronics Engineers
IoT	Internet of Thing
IoV	Internet of Vehicles
LabVIEW	Graphical Programming Environment
LAN	Local Area Network
LSA	Licensed Shared Access
LTE	Long Term Evolution
MAC	Medium Access Control
MAB	Multi-Armed Bandit
MCCA	Minimum collision channel allocation
NANS	Network Assisted Networks' Resource Selection
OSA	Opportunistic Spectrum Access
PUs	The Primary Users
QOS	The Quality of Service

SAS	**Spectrum Access System**
SDR	**Software-defined radio**
SNR	**Signal-To-Noise Ratio**
SUs	**Secondary Users**
GaussMF	**Triangle Membership Function**
Ts	**Symbol Transmission**
TSK	**Takagi-Sugeno Fuzzy Model**
USA	**United State of America**
VANS	**Vehicular CR Node-Assisted Networks**
WCNs	**Wireless Cognitive Networks**
Wi-Fi	**Wireless Fidelity**
WiMAX	**Worldwide Interoperability For Microwave Access**
WLAN	**Wireless Local Area Network**
WMAN	**Wireless Metropolitan Area Network**
WWAN	**Wireless Wide Area Network**

Table of Symbols

Symbol	Description
sel	Selection process
D	Time delay spread
∑	Summation
par1	First Parameter
BW	Bandwidth
par2	Second Parameter
C	Channel capacity
Value*set*	selection value
par3	Third Parameter
par4	Four Parameter
W	Weight
par_RSSI	The Parameter of RSSI
par_value	The value of a parameter
val	Value
Para*w*	The weight of a parameter
Maxpar_val	The maximum value of the parameter
par_CQI	The Parameter of CQI
par_Band	The Parameter of bandwidth
par_Dist	The Parameter of distance
par_dem	The parameter of spectrum demand
par_idle	The parameter of idle time

Chapter One

Introduction

1.1 Introduction

The tremendous expansion of the use of wireless networks over the past few years has led to an increase in demand for the use of spectral frequencies. Significant growth in connected devices is expected soon with the overall adoption of the Internet of Things (IoT). A huge amount of spectral frequencies is required to support this growing number of wireless devices[1].

Nowadays fixed spectrum policy is the policy of the wireless network system. The spectral frequencies are assigned to licensees for long periods. This policy has led to the emergence of the so-called spectrum scarcity due to the increasing demand for spectral frequencies. One of the solutions proposed to address this problem (spectrum scarcity) is so-called Dynamic Spectrum Management (DSM). This approach allows Secondary Users (SUs) who are not authorized to use the frequency spectrum, in a case where it is in an idle state or not used by the authorized persons who are the Primary Users (PUs) or to share the spectrum with others where this spectrum is protected [2].

Thus, secondary users can gain the opportunity to transmit without the need for a dedicated spectrum, this concept is known in the literature, as (DSA), and it is divided into two types: the first is called the concurrent spectrum access (CSA), and Dynamic Spectrum Access the second is called the Opportunistic Spectrum Access (OSA) [2].

In the Opportunistic Spectrum Access (OSA) model for detecting spectrum holes by SUs, there are two methods Geolocation Database and Spectrum Sensing.

The Geolocation Database is used with PUs if it was predictable and regular also, but if we do have no Geolocation Database, we can use spectrum sensing by SU periodically or consistently to detect the holes in the primary spectrum [2].

The principle objective of the methods of sensing is finding the holes in spectral frequencies, which are employed for addressing the issue through spectrum scarcity. Sensing technologies are divided into three types: Cooperative detection, Transmitter detection, and Inference base detection [3].

Cognitive radio represents a wireless communication system; it is one of the systems that use Opportunistic Spectrum Access (OSA). Cognitive radio can sense and reorganize its working settings.

1.2 Cognitive Radio Networks

A cognitive radio system uses the dynamic access technology of spectral frequencies, to adapt to the unused spectral frequencies dynamically even when conditions change. In the following two sections, a brief explanation of cognitive radio technology:

The cognitive radio cycle consists of the processes: {observation, guidance, planning, decision-making, and action}, as described in Figure (1.1)[4].

Step 1, the observation step, involves the process of sensing the spectral frequencies in the surrounding environment by sensing different measurements (signal strength, frequency capacity, noise, so on).

Step 2, includes the guidance and planning process where this information is processed, arranged, and prioritized, and the tables are planned according to regulatory constraints [5].

Step 3, decision-making step, where the best frequency is chosen from among the available spectral frequencies, and allocated to the secondary user until the arrival of the primary user or the completion of the secondary user of the broadcast and evacuation of the frequency.

Step 4 and final, The learning step improves the ability of cognitive radio to learn from previous experiences and modify its standards to choose the best spectral frequencies from its surrounding environment [5].

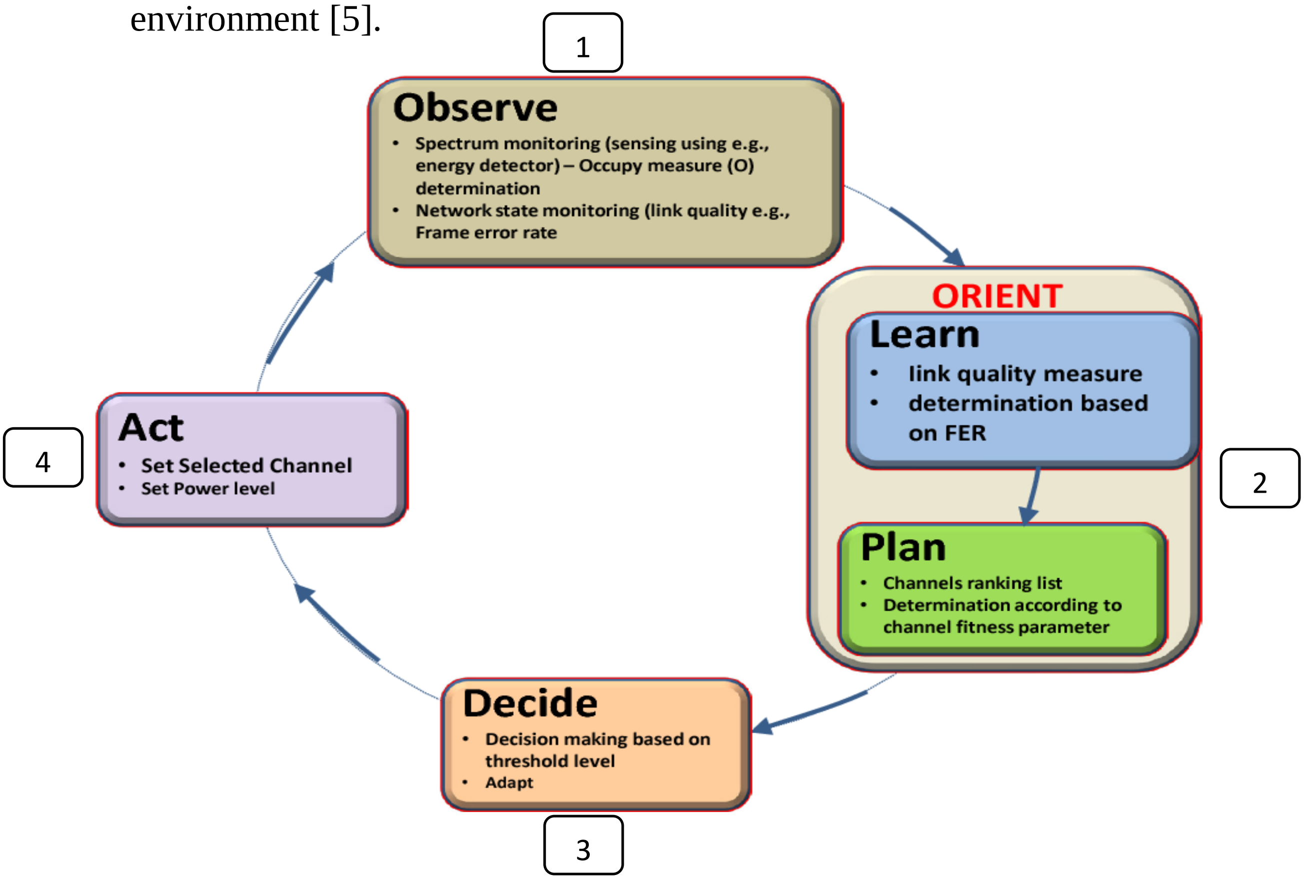


Figure 1.1: cognitive radio cycle [4].

Today many research trends in the decision-making process take into account the existence of prior knowledge about the relationships between internal and external standards and standards that have been sensed and collected in the knowledge cycle [6], additionally, the Quality of Service (QoS) offered by the users, making the decision-making process, an improvement problem.

There are many algorithms used in the decision-making engine that analyze and compare the metrics and parameters of the available spectral frequencies and choose the best among them.

In the cognitive radio concept, it is not necessary to find the best solutions, but instead to find acceptable solutions during the best time [6].

The problem of decision-making in the concept of cognitive radio is considered fundamental, so in the field of analysis the focus is on the principle of learning and decision-making.

1.2.1 The need for cognitive radio

Spectrum access is a problem in many spectral bands due to spectrum scarcity. Spectrum users have limited access to the spectrum due to the old control policy and driving regulations [7].

The radio spectrum can be divided into three types depending on its occupancy rate:

1. **Spectral frequencies are largely unoccupied most of the time.**
2. **Partially occupied spectral frequencies.**
3. **Spectral frequencies are widely used.**

Spectrum bands, which contain spectral holes, are assigned certain frequencies to specific users for some time and in a specific geographic area. This domain will be reserved at this time for one user and cannot be used by others.

Cognitive radio technology allows the exploitation of unused spectral frequencies, where secondary users can use these free bands, which are called spectrum holes, this technology improves the use of the spectrum and makes effective use of the spectrum.

1.3 Literature Review

This section analyses the existing and related literature associated with the scope of the dissertation besides the challenges and existing work presented in the previous section.

In the paper [8], the author propose a real-time scenario that considers additive Laplacian noise to dynamic primary user (PU).

In the paper [9], the researchers enhance the spectrum sensing process, by proposing the concept of multiple attributes to improve adaptive energy detection technique.

In the paper [10], the researchers proposed two protocols. The first proposal is for cognitive radio networks with fixed data packets. The second is suitable for dynamic networks with variable sizing packets. The second protocol uses the scheduling system to take advantage of the available capabilities of the spectral frequencies.

The authors in the article [11], examine SU decision-making processes for three different types of oligopolistic market markets as well as spectrum pricing practices used by spectrum owners, or main operators (POs). The single-band exclusive use market takes into account two POs, each of which offers a single band specifically for SUs.

In the paper [12], the three contributions made by this paper are the utilization of real data, the adoption of a cooperative decision-making approach, and the measurement of information volume through the frequency of unsuccessful handoffs. The decision-making approach employs the Feedback Fuzzy Analytical Hierarchical Process (FFAHP) and Simple Additive Weighting, two multi-criteria techniques (SAW).

The paper [13], contributes in two ways. In this study, two resource selection algorithms for vehicular CR networks—GRA-based Vehicular CR node Assisted Networks (VANS) and Network Assisted Networks' resource Selection (NANS)—are proposed. First, the focus is given to the group mobility component of vehicular communication. Second, a testbed using the LabVIEW communications system design suite software and a programmed scripting tool is considered to research the practical realization difficulties in vehicle CR networks.

The authors in [14], proposed a hybrid optimization algorithm, in which the optimal clustering and relay selection technique is taken into account. The goal of the model is a unified assessment of network isolation and some minor differences. Also, to calculate the continuity of decision-making by implementing the relay selection technique.

In [15] S. Jang *et al*., propose a system for the optimal band and also select a channel by using Q- learning dynamic, this system takes into consideration the wireless environment to increase transmission time and capacity in time.

In [16], J.Ma *et al*., Propose an algorithm of machine learning that uses Tug of War dynamic for IOT communication by using cognitive select the channels.

In [17], R. Saifan *et al*., propose Protocol for CRNs called (PDPS) the probabilistic and deterministic path detection Protocol. This protocol increases the probability to find the best path between the destination and the source.

In [18], V. Zuniga *et al*., propose a system to predict the future occupation bands and permit to adapt dynamically the best channel by changing the specifications of radio frequency and the analog. For doing this, the system uses Long Short-Term Memory networks.

In [19], A. Ali *et al*., propose a fuzzy logic-based decision support system (FLB-DSS) that jointly deals with channel selection and channel switching to enhance the overall throughput of CRNs. The proposed scheme reduces the SU channel switching rate and makes channel selection more adaptable. The simulation results are promising in terms of the throughput and the number of handoffs and make the proposed FLB-DSS a good candidate mechanism for SUs while making judicious decisions in the CR environment.

Table (1.1), shows some of the related works has been proposed in different directions on CRNs.

Table (1.1): summary of related works

Authors	Techniques	Directions	Datasets	Evaluation
D. Dasic, et al.,2021. [20]	A multi-agent reinforcement learning.	spectrum sensing and	Experimental Data.	the effects of denoising, the possibility of

		channel selection		organizing coordinated actions, and the convergence rate
S. Nandakumar, et al., 2019. [9]	the simple additive weights method, the technique for order preference by similarity to an ideal solution	Spectrum sharing	Experimental Data	the delay, data rate, Packet Loss Ratio and price
A. Musa, et al., 2019.[10]	propose a power-controlled MAC protocol for CRNs based on the interference-channel occupancy model	Spectrum sharing	Experimental Data	
J. zou et al.,2019. [11]	A pre-emptive resume priority (PRP) M/M/1 queueing model.	Spectrum sharing	Simulation Datasets	generalized scenario with multiple POs and multiple priority queues.
D. Giral and C. Hern, 2020. [12]	Feedback Fuzzy Analytical Hierarchical Process (FFAHP) and Simple Additive Weighting (SAW).	Spectral decision making	the implementati on of real data	the number of failed handoffs, the level of collaboration for the number of failed handoffs
M. Gupta, K. Kumar.	(GRA-based Vehicular CR	decision making	Experimental	Testbed using coded scripting program,

2020. [13]	node Assisted Networks' resource Selection (VANS) and Network Assisted Networks' resource Selection (NANS))		Data (testbed)	and LabVIEW communications system.
Y. Teekaraman, et al., 2020. [14]	integrating a hybrid optimization algorithm with an effective decision-making mechanism.	decision making	Experimental data	considering capacity, spectrum sharing, data rate, and interference for each subordinate user in the entire network.
S. Jang *et al.*,2019. [15]	Q- learning dynamic	Channel selection	Experimental data	Data Rate
J.Ma *et al., 2019.* [16]	Tug of War dynamic (TOW)	Channel selection	Real data	Channel access ratio, the frame reception
R. Saifan *et al.*, 2019. [17]	the probabilistic and deterministic path detection Protocol (PDPS)	Channel selection (path selection)	Experimental data (simulation data)	Throughput, Stability and end-to-end delay.
A. Ali *et al.*,2019.[19]	fuzzy logic-based decision support system (FLB-DSS)	Channel selection	Experimental data	Enhance the overall throughput of CRNs. Reduces the SU channel switching rate.
V. Zuniga *et al., 2020.* [18]	Long Short-Term Memory networks (LSTM) NN.	Channel selection	Experimental data	A band-pass filter, bands occupied

F. Javaid, et al., 2022. [21]	scheme based on dual-channel and the multi-node mobility system	Channel selection	Experimental data	The estimation of received signal power, delay spread, and signal-to-noise power ratio (SNR).

1.4 Problem Statement

The concept of CRNs is always related to the decision-making process, so the research problem is The decision-making process of selecting the best radio channel (most appropriate for the secondary user) in cognitive radio is an open problem, since the sensing information for radio channels is not only imprecise and inaccurate but also involves a major uncertainty factor.

Therefore, choosing one of the different decision-making algorithms, which can be used to improve the process of selecting the best channel among a group of radio channels, represents an open challenge in the field of cognitive radio.

In addition, how to implement the cognitive process, as there are the central model and the distribution model. This aspect is very important, as how decision-making can be affected by the cooperation between the secondary users ?.

1.5 The motivation for this Dissertation

A finite natural resource that enables wireless communication between transmitters and receivers is the radio frequency spectrum. Different services, including mobile, fixed, broadcast, fixed satellite, and fixed satellite services, are designated to specific frequency bands that make up the radio spectrum. Forecasts of the future mobile telecommunications market specifically foresee considerable increases in per user and aggregate data rates for mobile services. Therefore, where to find adequate carrier frequencies and bandwidths to match the anticipated demand of future services is a crucial question facing wireless communication systems. and How can spectrum allocation and planning to support licensed and non-licensed services operate with guaranteed levels of quality?

The motivation of this dissertation is the study of the different techniques of decision making and their use to select the best channel, this selection will improve the performance of the cognitive network, when there are many channels available.

1.6 The Challenges of this Dissertation

There are some challenges that we faced in this dissertation, including:

1. There is no existing benchmark dataset available to the public that includes the information of base stations and users (primary users and secondary users) in the same dataset.
2. Databases for cognitive radio research and studies are often generated using simulations and have specific goals for the research topic.
3. There are no standard deployment scenarios to use to evaluate proposed algorithms and techniques, but general concepts and directions exist.

It was, therefore, necessary to propose deployment scenarios, and also to create our databases for testing and evaluating the proposed decision-making techniques.

1.7 Main Objectives of this Dissertation

The general goal, enhancing cognitive radio management by Model, simulating, suggesting, and evaluating different techniques (Fuzzy inference system, neural network models ANN and ANFIS).

The objectives of this dissertation, they can be summarized in the following points:

- The first objective is to enhance the performance of cognitive network, by using a FIS algorithm to achieve the decision-making process in the wireless communication environment. A comparison scheme has been proposed over the proposed algorithms.
- The second objective is to suggest an improved decision-making technique for cognitive radio systems. Depending on neural network models to enhance selecting the best channel.
- The third objective is to evaluate the proposed methods by using Benchmark methods.

1.8 Main Contributions of this Dissertation

Contribution 1: Proposing a concurrent (synchronous) framework for improving the cognitive radio network.

Contribution 2: Employ three methods of fuzzy inference systems in the decision-making step to enhance the cognitive radio network, where Mamdani, Tsukamoto, and TSK FIS have proposed to improve the process of selecting the best channel from many available channels and deal with uncertainty. Algorithms have been formulated and a comparison of proposed algorithms with existing algorithms has been presented.

Contribution 3: Employ two neural network models ANN and ANFIS for improving the decision-making step.

Recent research initiatives in the general field of cognitive radio networks served as inspiration for the new methodologies based on the concept of decision engines and channel parameters to enhance the selection of the best free channel.

Contribution 4: Creating two sets of fuzzy rules, one for each set of parameters, which are used by fuzzy logic methods to select the best channel.

1.9 Dissertation Organization

There are five chapters in the dissertation. Each chapter begins with a brief introduction of the subject, the overall structure of this dissertation is shown in figure (1.2). The remaining parts of each chapter are as follows:

The second chapter includes a detailed overview of cognitive radio systems such as the characters of the system and functions of CRs. Then, decision-making techniques, channel selection, and application of CRs for the cognitive system are introduced.

In the third chapter, the practical side of the dissertation is reviewed, where various work algorithms are reviewed, such as the simulation environment configuration algorithm, various decision-making algorithms as well, such as fuzzy logic system techniques, neural network algorithms and also, and benchmark algorithms, and finally, evaluation metrics are explained, which includes (throughput data, handoffs, delay time).

The fourth chapter, shows the simulation and discussions the results using the different proposed techniques of fuzzy inference system (Mamdani, Tsukamoto, TSK), and also, two neural network techniques for enhancing channel selection in CRNs. The performance of various techniques is evaluated with benchmark algorithms and proposed methods and then compared in different metrics. The best channel selection technique for two different datasets is implemented and compared to select the best technique for decision-making in CRNs.

Lastly. Chapter Five provides a summary of the conclusions, and provides recommendations for future work.

Chapter Two

Theoretical Background

2.1 Introduction

This chapter includes a overview of some the concepts of cognitive radio networks and some of the different techniques that are used in applying this concepts in modern communications, in addition to review the use of the concept of cognitive radio in many different wireless and satellite applications.

2.2 The Principles of Cognitive Radio Networks

The ability of networks to adapt to a variety and changing conditions is generally constrained by present network technology, which may lead to suboptimal performance [22]. In addition, there is another problem, due to the current inefficient allocation of the spectrum, which has led to a waste of resources and access to a limited number of business models. There are several exceptional cases, but in general, the elements of the existing network are limited (e.g., state, scope, and response facilities). This makes them unable to make smart decisions. Mostly, the coping mechanisms that are available after the occurrence of problems become effective, but before that, they are present and inactive, so effective and smart solutions are available in a limited way, in addition to green networks as well as business models that are described as useful [23].

Cognitive Radio Networks (CRNs) is considered one of the solutions to the problems of inefficient use of the unused or not properly used spectrum. The cognitive radio technology allows unauthorized persons to access the licensed spectral frequencies, taking into account that the interference is minimal [24].

Therefore, there is a need for new networks and efficient communication technologies to use spectral frequencies, as well as an increase in advanced technologies that use spectral frequencies. All this shows several technical challenges and for these technologies to be accepted, efficient solutions are needed.

Cognitive radio devices (CRDs) represent the basis of cognitive radio networks, which can configure different parameters during the operation period (such as waveform, frequency band, and also transmission power), depending on the surrounding environment. These activities aim to exploit the unused spectral frequencies and avoid bottlenecks. Cognitive Processes (CP) are used for many purposes for collecting information, as well as for machine learning. Depending on this, analysis and decision-making [25].

To implement cognitive process decisions, software defined radio (SDR) platforms are used for this purpose. In an ideal conditions, this system could also perform predictive actions [25].

The technology of cognitive radio can be considered as part of the fifth generation networks in terms of the concept.

The fifth generation technologies, which are being employed by transportation corporations and international standardization bodies, are viewed as a generation that addresses the issues that arose in the fourth generation, which has achieved widespread adoption. Further, these technologies can be considered not only as a faster generation than 4G, but also in the development of engineering and networking aspects.

The researcher Joseph Mitola, first introduced the term "radio cognitive", while studying in Stockholm, at the Royal Institute of

Technology. The term cognitive radio is different from the term SDR [26].

The concept of cognitive radio (CR) revolves around the principle of control that helps the SDR how to operate and determine the most appropriate parameters that can be used in the case of specific networks.

SDR is a radio array, where most of the RF and MF functions are digitally implemented when compared to classic radio technology. SDR technology gives cognitive radio flexibility in operation.

The decision-making process must take into account the range of available policies, as well as profile inputs, which can be followed in certain contexts.

2.3 Basic characteristics of cognitive radio devices

The cognitive radio, according to the basic characteristics of the operating frequency, changes the parameters of the transmitter and the operating frequency. Cognitive radio equipment has two main characteristics, which are cognitive Capability and reconfiguration [7].

2.3.1 Cognitive Capability

Cognitive Capability is the radio's cognitive ability to sense the channels that can use for transmission by secondary users and the surrounding environment and also to derive the channels' information status, see Figure (2.1)[27].

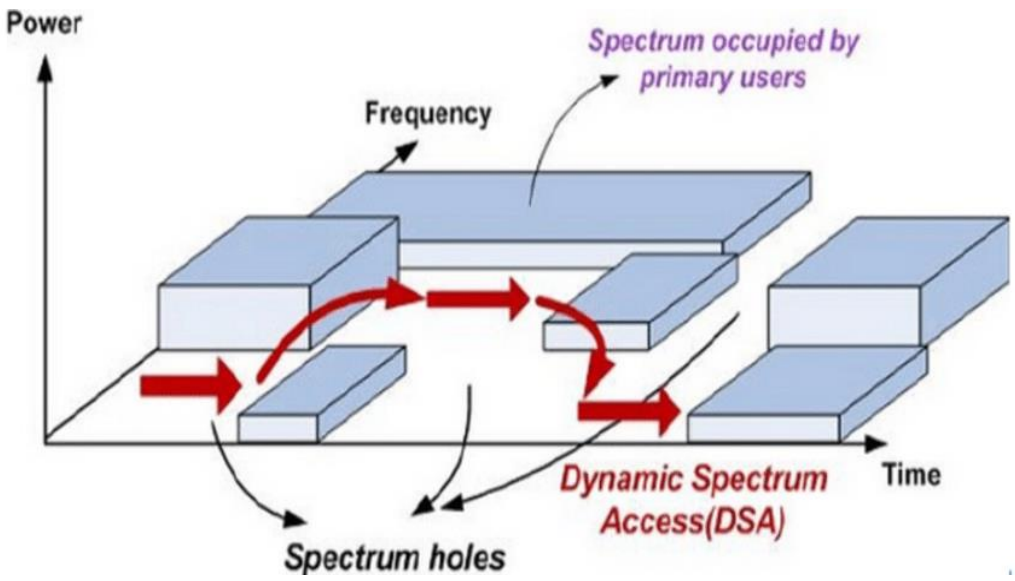
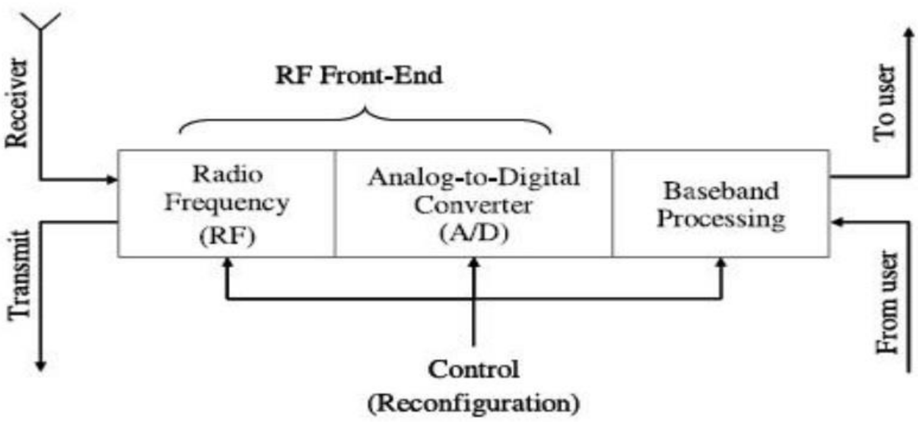


Figure 2.1: Spectrum Hole Concept [27].

2.3.2 Re-configurability

Re-configurability represents a dynamic programming process of cognitive radio without changing the hardware components of the devices. Cognitive Radio is a software-based radio, with the ability to switch between different wireless protocols.

Cognitive radio uses software-based radio technology, as it can support many applications, in addition to switching between



wireless protocols, and uses the available spectral frequencies [28], [29], see Figure (2.2).

Figure 2.2: Re-configurability process [31].

The radio spectrum bands can be divided into three categories:

1. White Spaces: These bands are free from sources of interference, but can contain artificial or natural noise sources.
2. Gray areas: Partially occupied by sources of interference and noise
3. Black spaces: Because of the common presence of communications, as well as interference and noise signals, these frequencies are almost full [30].

2.4 Cognitive Radio Cycle and Their Functions

The cognitive radio can encrypt and decode signals, fine and approve its user, detect its geographic position, and modify output power and modulation parameters, the cognitive radio has many functions, see Figure 2.3 [31].

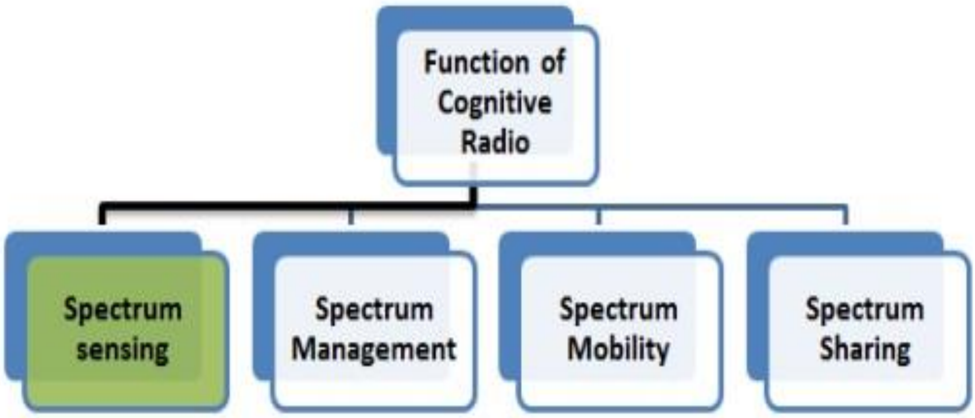


Figure 2.3: the principle function of CRNs [31].

Cognitive radio is a type of radio that can alter its transmitter properties in response to interactions with the surrounding environment. Making network protocols adaptable to the available spectrum is the next task for cognitive radio after choosing the optimum channel. In which an xG network needs additional features to enable its adaptability [32][33][34].

2.4.1 The functions of cognitive radios in networks

2.4.1.1 Spectrum sensing

Spectrum sensing, in which cognitive radios scan the whole frequency band in search of key users, represents important criteria for cognitive radio networks. A group of cognitive users or a single user can execute the sensing function. Spectrum sensing methods are critical in the networks of cognitive radio because they allow cognitive users to comprehend their surroundings [34][35].

Cognitive users use spectrum sensing to monitor the actions of primary and secondary users to take advantage of unoccupied frequency bands. It utilizes a range of sensing techniques, such as energy detection, and matching filter detection, to find the presence of primary users[35], [36].

Several characteristics can be used to determine the appropriateness of the available frequency bands for communication, such as delays, waiting time, signal strength, signal-to-noise ratio (SNR), etc., to find the best channel in the frequency band.

The cognitive user moves to the new bandwidth after choosing it. The user must leave the frequency band if it detects the existence of transmission for the primary user, and it starts searches for an available frequency, this process is known as spectrum handoffs.

One of the problems with delaying spectrum delivery is making cognitive networks vulnerable to various attacks. The spectrum sensing can be central or distributed [37]:

First, in central spectrum sensing, in this type, the sensor control unit searches for available frequency bands, and the information obtained is shared with the rest of the other devices in the system. The central sensing functions are done in the sensor control unit, and this can reduce the complexity of the cognitive radio network [38].

In a distributed system the sensing function is done separately by unauthorized users. Results of the spectrum sensing can be used either individually (uncooperative) or collectively where the sensing information is shared with other users (cooperative) [39].

The cooperative sensing system (CSS) ("*in this system all SUs report their sensing information through reporting channel to the central base station called fusion center (FC)"*) in spectrum sharing techniques is more accurate than non-cooperative spectrum sensing, although cooperative sensing includes communication and processing costs as well [40].

2.4.1.2 Spectrum management

The ability to choose a spectrum hole that satisfies the quality standards of SUs is known as a spectrum management. The process goes as follows: when spectrum holes are found, it is required to choose the best one based on quality.

The SUs require parameters without interfering with the PU. After that, new transmission parameters must be set for accessing the new spectrum hole [41]. Spectrum management includes the decision-making process, where there are many tasks, and these tasks are related to the rest of the cognitive radio functions, see figure 2.6 [42].

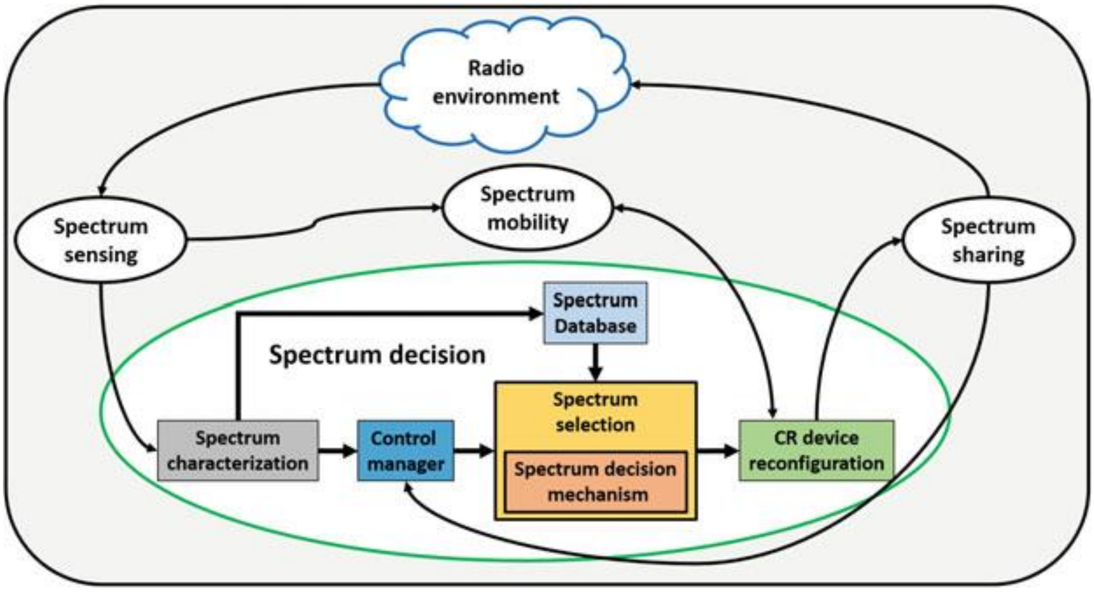


Figure 2.6: Process of decision making in cognitive radio cycle [42].

2.4.1.3 Spectrum mobility

Spectrum mobility is the capacity of a cognitive radio user to change operational frequency bands. An unlicensed user may switch to an open spectrum band when a primary user first uses a radio channel that is in use by that user. The protocol parameters at the various tiers of the protocol stack must be changed to match the new operating frequency range during the spectrum handoff [35] [43].

It is important to take the unlicensed user's ability to continue delivering data in the new frequency band into account when sharing the spectrum. Spectrum mobility enables cognitive radio users to transfer to unoccupied frequency bands in the case that the principal user interrupts a cognitive radio communication. However, the design of the cognitive radio network's spectrum is made more difficult by primary and secondary user mobility [35].

The presence or absence of a licensed channel for a cognitive user who is walking or standing still will be unclear if a licensed user moves quickly in a particular area. Additionally, detecting a specific channel in a scenario may not be accurate for a cognitive user moving quickly since the channel availability status at the cognitive user's present location may vary. Rapid cognitive users should often scan the spectrum to reduce false alarms and improve their chances of finding a licensed channel [44].

It is important to create efficient spectrum handoff methods so that cognitive users can predict the channel when the main user transmission on that channel starts. To predict the behavior of main users based on prior behavior, a Markov process has been utilized [18], the example of spectrum mobility explain in Figure 2.4 [45].

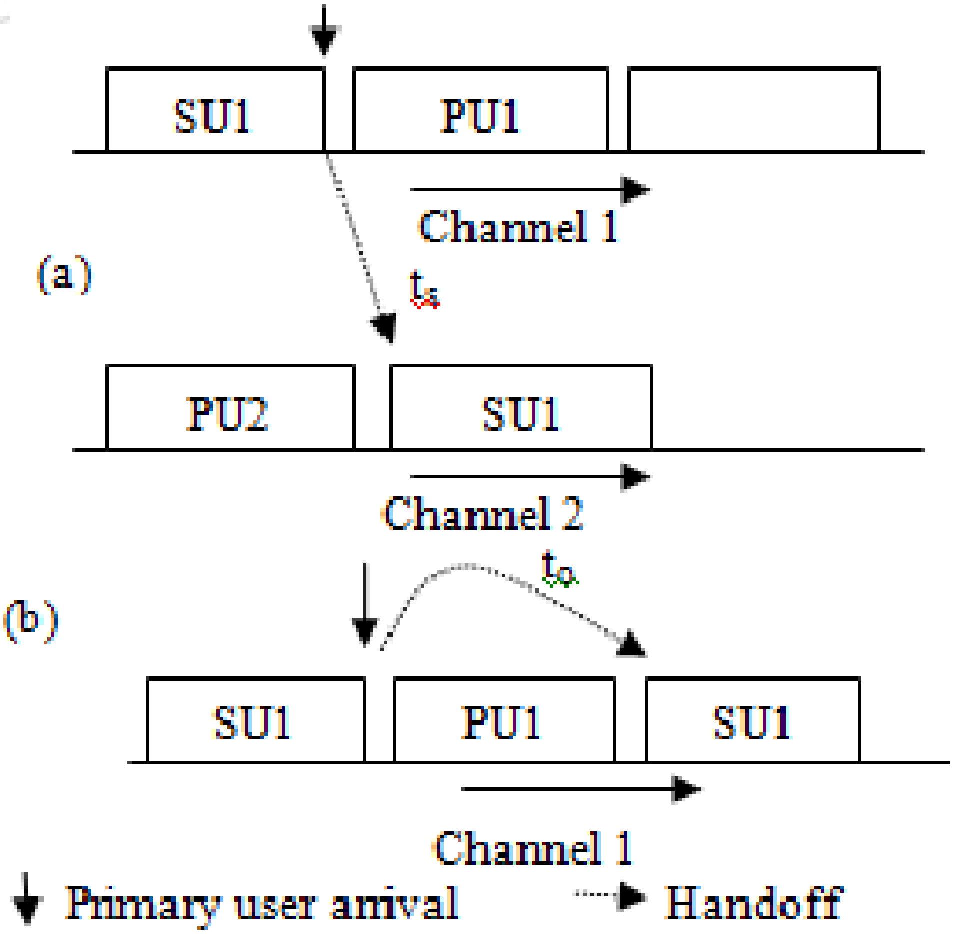


Figure 2.4: the example of spectrum mobility [45].

This technique (Markov process) enables the cognitive user to terminate the channel before the primary user starts transmitting and avoids forced termination of the cognitive user's transmission. Proactive handoff is the phrase for this method of closing the authorized channel.

In contrast, the spectrum is abruptly released during a reactive spectrum handoff without the cognitive user's understanding [46].

2.4.1.4 Spectrum sharing

Spectrum Management and Sharing Unlicensed users have access to the spectrum holes when a decision regarding spectrum access is made based on spectrum analysis. To avoid conflicts with both licensed and unlicensed users, spectrum access is carried out via a cognitive medium access control (MAC) protocol [14] [21]. The cognitive radio transmitter and receiver must coordinate to synchronize the transmission to ensure that the transmitted data is received. based on random access or fixed allocation MAC [47] [21].

The Dynamic Spectrum Access (DSA) technique significantly enhances frequency band utilization and communication system efficacy. Spectrum sharing is a critical component of DSA in cognitive radio technology because it provides effective and equitable spectrum allocation or scheduling solutions among licensed and cognitive users. In the spectrum-sharing idea, a main and cognitive user network can share the radio spectrum at the same time. Furthermore, if the radio spectrum is free or underutilized by large users, unlicensed or cognitive users may gain access to it opportunistically. Unauthorized users can continue to use the available radio channels if the level of interference is low, and under the permissible threshold [47]. There are three different types of spectrum-sharing techniques, see Figure 2.5 [48].

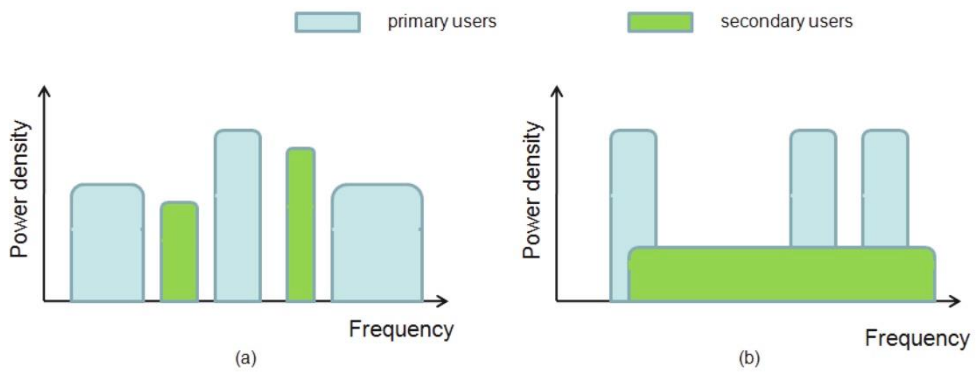


Figure 2.5: Different types of spectrum sharing [48].

2.4.1.5 Spectrum Access Techniques

A. Interweave paradigm : The idea of opportunistic access is the basis of the principle of the **i**nterweave model. Spectrum holes exist, which are transitory space-time-frequency voids that are not in use by licensed or unlicensed users. These holes shift throughout time and space. The interweave approach requires spectrum users' activity information. This system checks the spectrum regularly, identifies occupancy in various sections of the system intelligently, and then transmits opportunistically via the spectrum holes with little interference.

B. The Underlay paradigm is aware of the disturbance that all users produce. It requires that simultaneous transmission of the primary and secondary systems only take place if the interference caused by the SU at the PU is below a certain acceptable level.

C. The SU in overlay systems is aware of the PU's codebooks and communications [3]. The PUs broadcast at any power, thus relaying the PUs message can reduce interference to the PUs.

The characteristics of these techniques are given in table (2.1)[49] [50].

Table2.1: Characteristics of underlay, overlay, and interweave techniques [50].

Underlay	Overlay	Interweave
SU knows the channel strengths of PU	SU knows the channel gains, codebooks and messages of the PU.	When the PU is not using the spectrum, SU knows the spectral holes in space, time, or frequency.
As long as the interference is below an acceptable limit, SU can simultaneously transmit with PU.	SU can simultaneously transmit with PU; the interference to PU can be offset by using part of the SUs power to relay the PUs message.	SU can simultaneously transmit with a PU only in the case of false spectral hole detection.
SUs transmit power is limited by the interference constraint.	SU can transmit at any power; the interference to the PU can be offset by relaying the PU's message.	SUs power is limited by the range of its spectral hole sensing

2.5 The Challenges in The Filed of Cognitive Radio

The challenges of research in this field are divided into:

2.5.1 Spectrum decision

By enabling secondary users to dynamically exploit the available spectral frequencies without annoying the primary users, cognitive radio devices offer a significant potential to increase the usage of spectral frequencies [51] [52].

The main challenge in operating these wireless devices as a network includes: what is an effective mechanism for controlling the process of media access? and how it can effectively allocate the transmission and spectrum powers between the cognitive radios while taking into consideration the surrounding environment?.

Most of the works that address this challenge are central solutions and suboptimal heuristics [53].

2.5.2 Unlicensed Spectrum

There is a discrepancy between the actual use of the frequency spectrum and the specializations of the Federal Communications Commission (FCC). Therefore, there was a need to develop a new method for managing spectrum licensing. The new approach should provide efficiency as well as incentives to use the spectral bands of unlicensed devices, and enable future systems to access the spectrum more flexibly while giving higher priority to primary users [51] [54].

2.5.3 Spectrum sharing

The concept of spectrum sharing represents the distribution through the spectrum frequencies for shared and unlicensed services in unprecedented quantities. Avoiding interference in opportunistic communication faces many challenges for detect sharing in radio systems that include many users. Many design challenges cannot be solved in traditional wireless systems, such as the priority of primary and secondary users. The concept of participation is a major challenge in a multi-user secondary environment, so this was a topic of research that aroused a lot of interest in the recent period [51] [53].

2.5.4 Hardware and Software Architecture

The hardware components of Radio Cognitive are a very good methodology, and it is an extension of the programmatically defined radio where these different components are used to send and receive information through wireless communication devices. Cognitive Radio selects the best available options based on the performance of each application. The measurement parameters of the performance can be power, antenna, frequency, bandwidth, and so on. Because of the different types of baseband and also the different types of radio frequencies. All of this requires more power and efficiency, as the software and hardware are reconfigurable[35] [55].

2.6 Channel Selection Techniques

The concept of channel selection in the cognitive radio system represents the mechanism for selecting the appropriate channel to use in the transmission process by users.

The smart channel selection mechanism regulates the interaction between different transmitters, when we have wireless networks operating in an unlicensed spectrum, where this mechanism is useful in the case of poor coordination between these transmitters, Wi-Fi or LTE networks are typical of these unlicensed networks [56].

Improving the overall efficiency of the wireless system can be done by designing the appropriate channel selection function when using the unlicensed spectrum, as it will affect the reduction of the total interference between the receivers and thus increase the performance efficiency of the cognitive network [56].

2.7 Decision-Making Techniques

During the past few years, many techniques for the decision-making process have emerged. Therefore, to review these techniques, it is necessary to classify these techniques.

One of these classifications is based on prior knowledge of the environment. In figure (2.7) it is proposed to classify these technologies based on prior knowledge that is provided to the engine of cognitive radio to decision-making [6].

Therefore, some approaches to decision-making are better suited than others in the decision-making process, based on prior knowledge of the environment [57].

There is also the possibility of having many cognitive engines in one cognitive system, so it is necessary to coordinate between them.

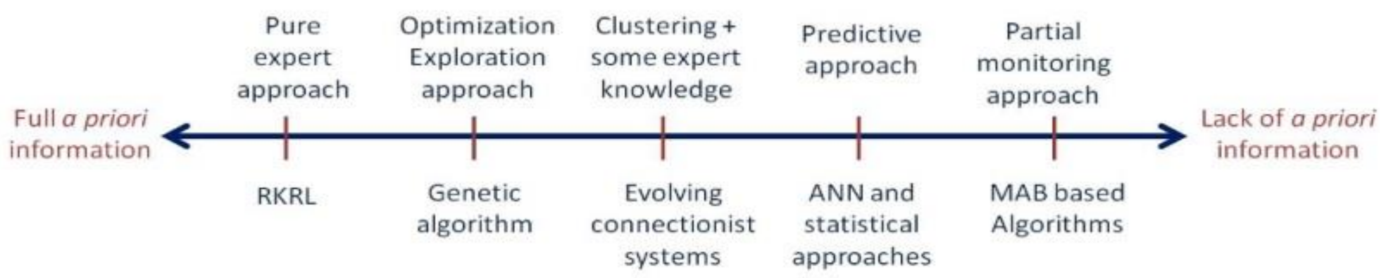


Figure 2.7: Decision-making techniques classification based on priori knowledge [6].

2.7.1 Techniques based on Expert Approaches

This type of system is based on the accumulated experience and a large amount of knowledge by researchers and experts in the field of communication, this knowledge is related to the surrounding environment and radiocommunication parameters [6].

There are sets of inference rules, that are provided to experts system through simulations.

The equipment can adapt to the dynamic environment around it, and more knowledge is available. The knowledge radio system, based on the expertise of experts, gives the possibility of making a simple decision if it is well equipped with knowledge in the form of a set of rules[58].

This approach is designed for all users and not for a specific user, and also for a range of possible environments. Also, the models are the basis for expert knowledge and the designer's need for a great effort [59], thus this approach may behave poorly when faced with an unexpectedly dynamic environment [59].

2.7.1.1 The Fuzzy Logic

Fuzzy logic is a concept that uses in machine control, the fuzzy logic can deal with problems that are partially true and cannot express as “true” or “false” simply.

Many alternative approaches can deal with different cases as well as fuzzy logic, but fuzzy logic has the solution for cases of problems in terms of operations that can understand by a human. Fuzzy logic is often used in to design of the controller. Therefore, problems previously solved by a human can be easily modeled using fuzzy logic [60].

The fuzzy inference system represents the principle component of the fuzzy logic system, and decision-making is its primary purpose. The "OR" or "AND" operators as well as the "IF... THEN" rules are used by the fuzzy inference system to build basic decision rules [61].

A. Characteristics of FIS

The fuzzy inference system has many characteristics, including:

- Always, the outputs of the inference system are a fuzzy set, and its inputs can be fuzzy or crisp.

- If a fuzzy logic system is used as a control, the output should be a fuzzy set.
- A fuzzy inference system often contains a defuzzification unit for converting fuzzy values into crisp values.

B. The Functions of Fuzzy Inference System

In the fuzzy logic system five basic functions explain its structure:

- **Rule Base**: The rules IF..THEN would be represented here.
- **Database**: The membership functions that are used in the rules of fuzzy are defined in the database.
- **The Unit of Decision making**: The rules are implemented from the operations performed in this unit.
- **Fuzzification Interface Unit**: This unit is responsible for converting crisp values into fuzzy values.
- **Defuzzification Interface Unit**: This unit is responsible for converting fuzzy values into crisp values [62].

  In the Figure (2.7): represent the fuzzy interference system block diagram.

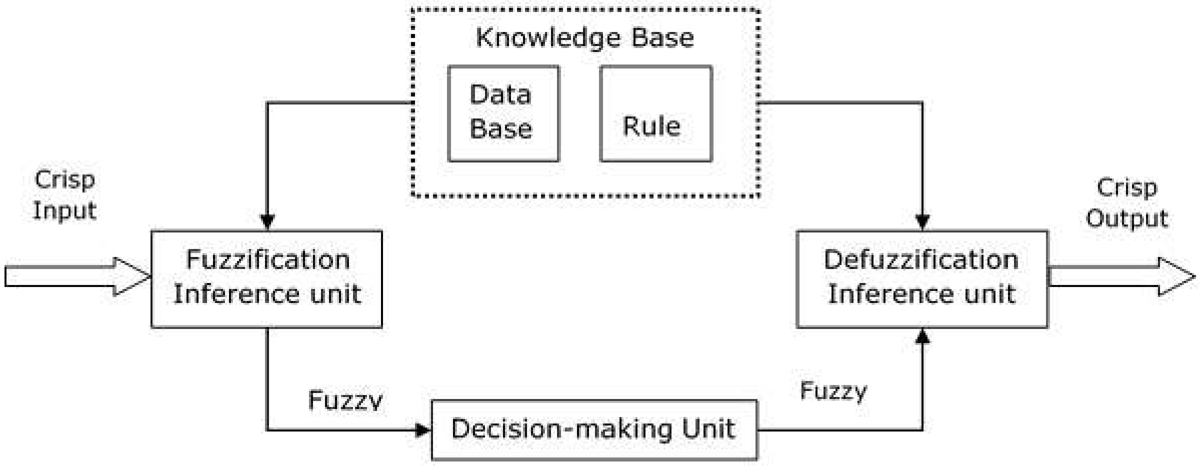


Figure 2.7: The fuzzy interference system block diagram [63].

C. The Fuzzy Inference System

The fuzzy inference system includes several working steps:

- A fuzzification unit : use and deal with many methods of fuzzification, and also transfer the inputs value from crisp into fuzzy.
- A knowledge base: In this step, the crisp inputs are converted to the fuzzy inputs, through collection of database and rules base.
- The defuzzification unit: finally, this unit convert input from fuzzy situation into crisp situation in output.

D. Methods of FIS

The fuzzy inference system includes many methods, and these methods have different consequences for fuzzy rules:

- Mamdani Fuzzy Inference System
- TSK method (Takagi-Sugeno Fuzzy Model).
- Tsukamoto Fuzzy Inference System

1. Mamdani Fuzzy Inference System

For the purpose of controlling the steam engine system in addition to the boilers, a Mamdani system was developed by Ebhasim Mamdani in the year 1975, where he proposed a set of fuzzy rules, where the rules were set through the experience of people working in this field [64].

- **The Output of FIS Computing:**

The following procedures must be followed for calculate this FIS's output:

- Step 1: In this step, a set of fuzzy rules must be specified.
- Step 2: involves making the input fuzzy by employing an input membership function.
- Step 3: Now combine the fuzzified inputs in accordance with fuzzy rules to get the rule strength.
- Step 4: In this step, you'll combine the rule strength and the output membership function to determine the rule's outcome.
- Step 5: Combine all the results to obtain the output distribution.
- Step 6: A defuzzified output distribution is then discovered in step six.

Following figure (2.9) is a block diagram of the Mamdani Fuzzy Interface System.

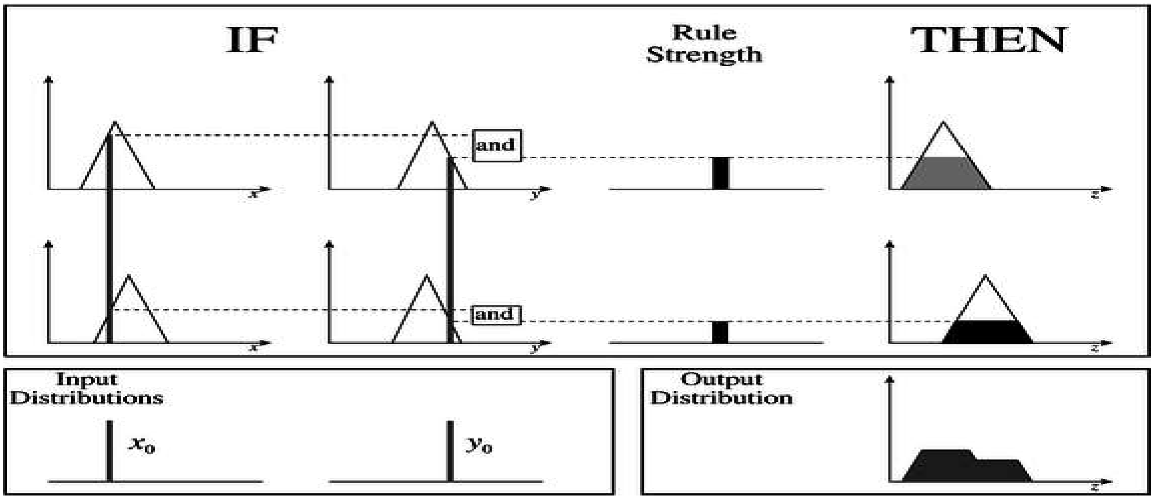


Figure 2.9: The Mamdani Fuzzy Interface model[64].

2. Tsukamoto Fuzzy Inference System

The tsukamoto fuzzy models have a consequence that is represented by a fuzzy set with a monotonically membership function. Because of this, each rule's inferred output is expressed as a sharp value brought on by the firing strength of the rule. The weighted average of each rule's findings is used to produce the final output [65].

Figure (2.10) demonstrates the two-input, two-rule system's reasoning process [64].

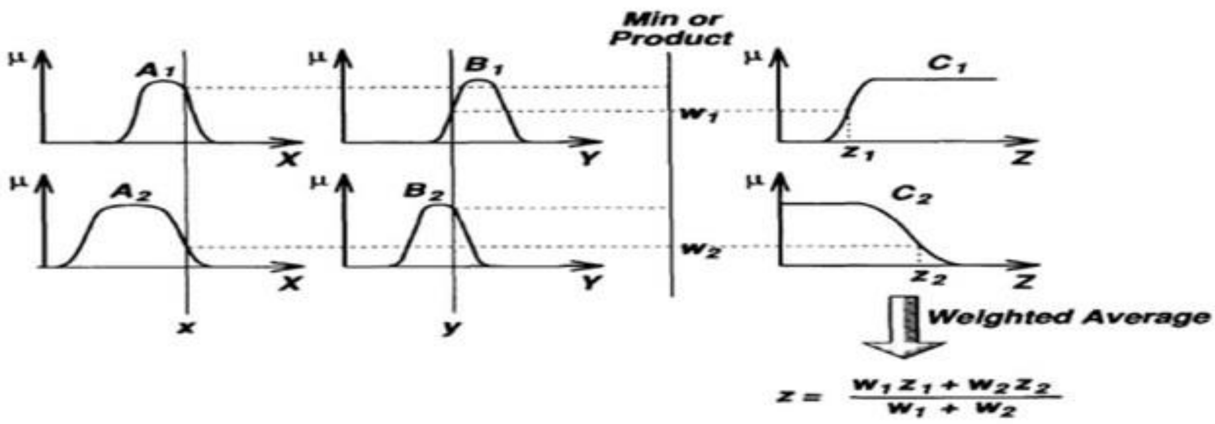


Figure 2.10: The Tsukamoto fuzzy model [64]

The Tsukamoto fuzzy model aggregates each rule's output using the weighted average approach since each rule indicates a crisp output, avoiding the time-consuming step of defuzzification. The Mamdani and Sugeno fuzzy models are more transparent than the Tsukamoto fuzzy model, which is why it is less frequently utilized.

3. Takagi-Sugeno Fuzzy Model (TSK Method)

This model was proposed by Takagi, Sugeno and Kang in 1985.

This rule is formatted as:

$$IF\ w\ is\ T\ and\ v\ is\ S\ THEN\ Z = f(w,v)$$

Where, *T and S* represent fuzzy sets as antecedents, but for $Z = f(w,v)$, that represent the consequent is function of crisp.

- The Process of fuzzy Inference

According to TSK FIS, the fuzzy inference procedure functions as follows:

Step 1: Fuzzifying: in this step, the inputs in the system convert to fuzzy formal.

Step 2: The fuzzy process – In this step, to get the output in fuzzy formal will be applied fuzzy operator.

- The form of Sugeno rule:

This format of rule is given by:

if s=3 and f = 8 then output is t = as+bf+c.

The Mamdani System's differentiation from the Sugeno Model.

1. **Membership Function for Output** – the important different between Mamdani and Sugeno FIS is the output membership functions are linear form or constant form.
2. **The Procedure of aggregation and Defuzzification:** Their aggregation and defuzzification processes also vary as a result of the outcome of fuzzy rules, which is another factor explaining why they are different.
3. **The Rules of Mathematical:** The Sugeno rule has more mathematical rules than the Mamdani rule.

4. **Adjustable Parameters**: The Sugeno controller has more parameters for adjustment than the Mamdani controller.

2.7.2 Techniques based on Exploration

In some situations, it is possible to assume that there is a priori information about the intricate connections between the metrics observed, the parameters to adjust, and the requirements to meet.

In this scenario, the issue seems to be one of multi-criteria optimization. By resolving a series of equations, the CR decision-making engine works within this framework to determine the optimum settings to match the users' expectations [66].

Several factors make this problem recognized to be complex:

A. There is no one notion of optimality in this situation. In light of a specific function, typically referred to as fitness, that assesses how well the requirements were achieved, the solution to this problem is thus satisfactory (or not).

B. As a result, a sizable range of potential "good" arrangements is typically conceivable.

An examination of the universe of potential configurations is required if we suppose that the aforementioned off-line expert rule extraction step has not (or only partially) been completed. To investigate a vast pool of probable candidates, there are numerous viable algorithms. The most obvious one is undoubtedly an "exhaustive search," in which every potential candidate is calculated and assessed to identify the best answer. Such methods, however, can become computationally taxing as the number of applicants increases and cause them to miss the deadlines for making decisions. In situations like this, heuristics are typically preferable. Finding the ideal answer may not be necessary for the context of CR. The cognitive engine would rather discover a good answer within the constrained time constraint [67].

As a result, if the following conditions are true:

1. Accessible prior knowledge of the intricate connections between the metrics observed, the settings to modify, and the standards to meet.

2. Potentially intensive parallel processing.

Then, a broad range of decision-making techniques is feasible, including, for example, simulated annealing [68], GAs, and swarm algorithms[69]. It's important to note that such methods did not wait for CR to be used in radio technologies. Simulated annealing was first mentioned as a potential technique to handle channel assignment for cellular networks in an article from 1993.

Techniques that are inspired by biological systems or evolution, such as genetic algorithms, swarm algorithms, and insect colony-inspired algorithms, are frequently referred to as such. Rieser and Rondeau were the first to examine this established CR decision-making paradigm. To address this framework, they recommended using GAs. GAs are renowned for their ability to adapt to changing environments and were initially created to imitate Darwin's evolutionary theory. Without employing our formalism, their research demonstrated that the GAs give cognitive radios an effective and adaptable decision-making engine within what we characterize as design space and with the a priori information described [67] [6].

However, we are unable to apply their model as a generalization for all CR use scenarios, necessitating the integration of alternative solutions.

2.7.3 Techniques based on Approaches of Learning.

Numerous methods based on learning techniques were proposed, including Artificial Neural Networks (ANN), Evolving Connectionist Systems (ECS), statistical learning, regression models, and others, to get over these restrictions and deal with more realistic scenarios. While each of these strategies has merits and cons, they all share the fact that they primarily rely on studies done in actual environments to extrapolate from them the decision-making guidelines for CR equipment. These learning tools require direct interaction with the environment to develop a posteriori knowledge about their surroundings since they strive to reflect the functional link between the environment (through sensed metrics), the system parameters, and the criteria to satisfy [6] .

According to how these algorithms learn and use their principles, and these algorithms subclassify to:

On the one hand, there are a set of methods that distinguish the periods of exploration and exploitation.

On the other hand , there are more adaptable approaches that combine the two processes. In the first example, can see that several technologies, including ANNs and statistical learning, have already been employed and exploited in other domains that call for specific cognitive abilities (robotics, video games, etc.). These techniques consist of two phases: a pure "exploration" phase when the CR decision-making engine learns and infers to find (explicitly or implicitly) decision-making rules, and a second phase where the decision-making engine employs this a posteriori knowledge.

To extract trustworthy knowledge from modern learning techniques, which rely on a first learning phase, a significant amount of data and processing capacity are required. For instance, this issue is already recognized with ANN. Statistical learning is still valid. that the offered techniques are still computationally expensive and not yet ready for usage in actual equipment. The second phase, however, is typically quite easy and doesn't require much time or effort provided the first phase is completed [68].

In the second scenario, can discover interesting methods for configuration adaption that have only recently been made public and still require additional research [5].

These methods aim to give the CR a flexible and gradual decision-learning engine. Colson recommended the application of a developing neural network in the context of an ECS-based decision-making engine [70]. The ECS-NN can modify its structure, unlike the conventional ANN without "forgetting" previously learned information. As a result, by adding additional neurons to the neural network, new rules can be learned. The proposed architecture in [70] requires expert advice (a priori knowledge) on the various configurations possible to be effective. The additional information rates the various configurations according to specific characteristics (robustness, spectral efficiency, etc.), without necessarily knowing which one is more suitable for a particular situation.

The performance of the equipment can only be evaluated while trying a particular configuration, which also assumes that no a priori knowledge is available. The accompanying tools are built using what is known as the MAB framework [71]. The ability to offer learning solutions while the cognitive engine is running, even in an entirely new environment, is one advantage of this. Undoubtedly, performance improves as learning advances. You should take note that this strategy is demonstrating its accuracy in the OSA context. As we draw to a close, we would like to underline how the proposed classification in this article demonstrates that CR equipment cannot rely on just one main technique for making decisions, but rather on a variety of approaches.

The equipment needs to estimate its reliability and a priori knowledge each time it interacts with a new environment.

2.7.3.1 Neural Network Algorithms

1. Artificial Neural Networks (ANNs)

The biological neural network is used to model the artificial neural network. The ANN, like the biological network, is an interconnection of nodes that are comparable to neurons. Each neural network is comprised of three important components: node characteristics, network structure, and learning rules. Every number of inputs and outputs related with the node, the weight associated with each input and output, and the activation function all influence how signals are processed by the node. The topology of a network specifies how nodes are grouped and connected. The weights are established and adjusted according to learning criteria[64]. Each of these components is explained in detail in the sections that follow.

A. Artificial neurons

Artificial neurons that make up ANNs are conceptually developed from biological neurons. Each synthetic neuron contains inputs and only one output that can be distributed to many additional neurons. The inputs may be the outputs of other neurons or they may be the feature values of a sample of external data, such as photos or documents. The goal, such as identifying an object in an image, is accomplished by the outputs of the neural network's final output neurons. The weighted sum of all the inputs, adjusted for the weights of the connections from the inputs to the neuron, is what we use to determine the neuron's output. To this total, we add a bias term. The activation is another name for this weighted total.

The output is then created by running this weighted sum through an activation function, which is often nonlinear. External data, such pictures and papers, are used as the initial inputs. The final results, such as identifying an object in an image, successfully complete the objective, see Figure 2.11.

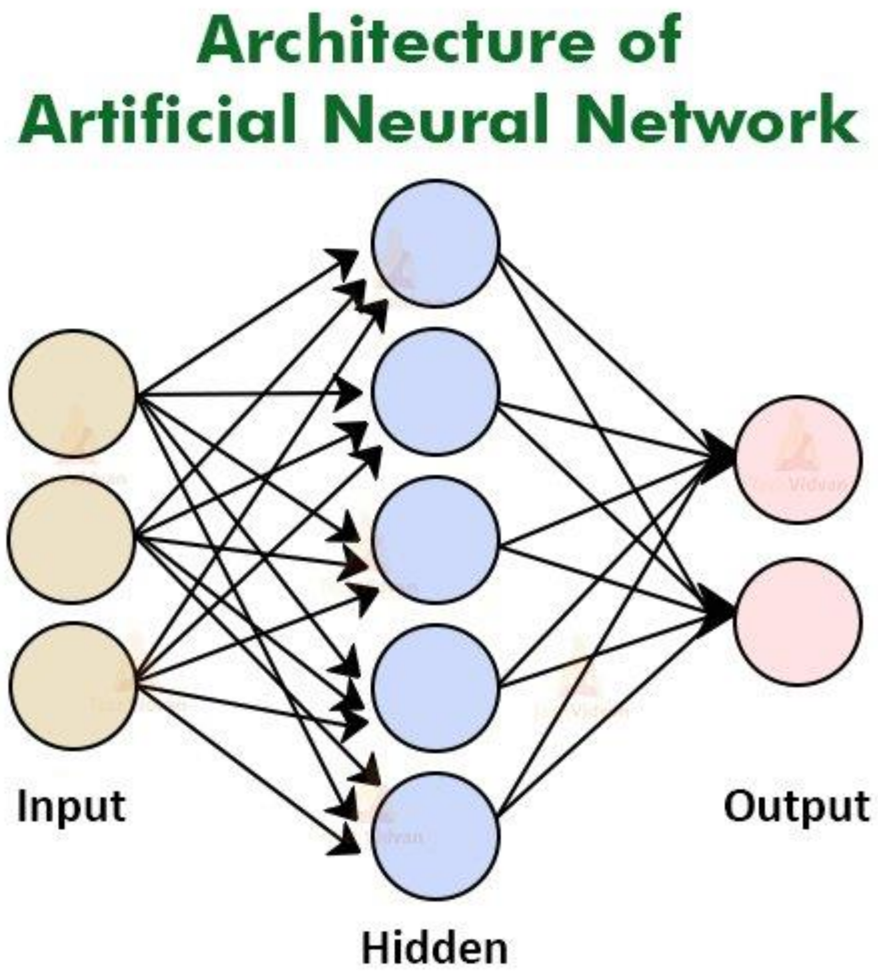


Figure 2.11: Architecture of ANNs [72].

2. An adaptive neuro-fuzzy inference system (ANFIS)

The Takagi-Sugeno fuzzy inference system serves as the foundation for an artificial neural network called an adaptive neuro-fuzzy inference system (ANFIS), also referred to as an adaptive network-based fuzzy inference system. In the early 1990s, the technique was developed. Because it incorporates both into a single framework, it can benefit from both fuzzy logic and neural network concepts. A set of fuzzy IF-THEN rules with the ability to learn and approximation nonlinear functions serve as its representation of an inference system. ANFIS is therefore viewed as a global estimator. The ANFIS can be employed in a more effective and optimal way by using the best parameters discovered by a genetic algorithm. It can be used in energy management systems that are intelligent and situationally aware.

A. **ANFIS architecture**

The premise and consequence components of the network structure can be separated. There are five layers in all to the architecture. When the input values are received, the first layer computes the membership functions related to them. The layer of fuzzification is another name for it. The membership degrees of each function are calculated using the set of parameters used for the premise, namely a, b, and c. The firing strengths of the rules are created by the second layer. Due to its purpose, the second layer is also referred to as the "rule layer." The third layer's job is to divide each value by the total firing strength for normalize the computed firing strengths. The fourth layer takes as input the normalized data together with the output parameter set p,q,r [73]. See Figure (2.12).

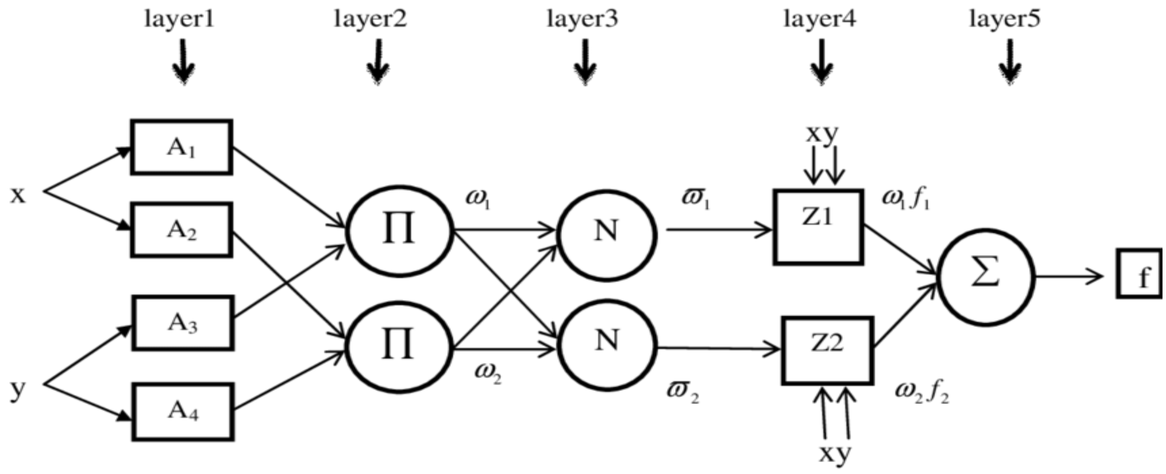


Figure 2.12: Adaptive neuro-fuzzy inference system structure[74].

2.8 Applications of Cognitive Radio

The most popular use of CR is dynamic spectrum access (DSA) [75], but it is not the only one. For solve issues caused by outdated static spectrum allocation methods between increasing spectrum demand and underutilization, DSA/CR was primarily developed. The coexistence of numerous wireless communication systems in the same wavelength region is made possible by this spectrum access paradigm, allowing for a more effective use of the spectrum resources [34] [76].

Over the past few years, research, business, and regulatory organizations have been exploring for fresh approaches to integrate the cognitive radio and dynamic spectrum access tenets to current WCNs. The advantages that cognitive radio technology might have for various wireless communication systems are known to these organizations [76].

There are two main areas of application of cognitive radio techniques:

2.8.1 Mobile Communication Networks

Since their debut, mobile communication networks have required more and more capacity [77]. Mobile carriers are under pressure to develop cutting-edge plans to expand the capacity of their networks as a result of the persistent rise in traffic demand. By improving spectrum efficiency, deploying denser networks, and acquiring new spectrum resources, wireless communication system capacity may be raised.

The two main projects for the spectrum coexistence of mobile communication systems in licensed bands are the licensed shared access (LSA), that is concentrate on the sharing of the 2.3 Ghz range in Europe, and the spectrum access system (SAS), that is concentrate on the sharing of the 3.5 Ghz range in the USA [78].

Mobile networks can expand their capacity by buying extra spectrum in bands that were previously licensed to other systems thanks to these operations, which allow multiple parties to share licensed airwaves. Using carrier aggregation techniques, mobile network providers can combine their already licensed spectrum with the extra spectrum gained from these bands [79] .

The two most well-liked efforts that enable mobile radio communications to coexist in unlicensed bands are LTE Unlicensed and Licensed Assisted Access [80] [81][82][83]. These efforts propose to use the unlicensed 5 GHz range, also known as the unlicensed national information infrastructure range, and the “3GPP LTE bands 46 and 47”, which are often used by radar systems and wireless LAN based on “IEEE 802.11a/g/n/ac”.

Utilizing unused spectrum in other (licensed and unlicensed) bands to increase the capacity of the mobile network is one way that CR techniques are employed in the context of mobile communications. The application of CR concepts can be advantageous in many events and circumstances.

In addition to offering straightforward answers to some of the problems mobile communication networks confront, CR has the ability to increase the effectiveness and efficiency of currently implemented solutions [14].

Numerous wireless cell types, such as "Macro, Micro, Pico, and/or Femtocells," sharing often, same area and use always same spectrum due to the trend toward network densification.

2.8.2 Satellite Communication Networks

To accomplish the challenging goal of supplying everyone with rapid internet access in the future, satellite communication networks are now crucial. The option of using satellite networks for communication is an ideal option when dealing with large areas normally, and because not economically the construction of different types of networks such as wired and wireless [84].

Ground, aircraft, maritime, transit, the military, rescue, and disaster relief are just a few of the many uses for satellite communications beyond interactive direct-to-home (DTH) television streaming [85].

Access to spectrum possibilities in frequency bands other than licensed and allotted spectrum may be advantageous for future satellite communication systems. By adopting CR approaches to skillfully manage interference, satellite communications can benefit from spectrum sharing and its advantages.

Spectrum sensing, one of the most essential methods for spectrum awareness in CR-based systems, may also apply to satellite communications with a few additional factors taken into account. By scanning a small number of chosen frequency bands and analyzing the acquired samples using state-of-the-art signal processing techniques, spectrum sensing seeks to identify the presence of current user signals. The range through the spectrum sensing techniques available as well as their effectiveness depends on whether the signal to be detected is completely known, only partially known, or unknown [2].

The cognitive system can use this knowledge to acquire opportunities of spectrum through using appropriate spectrum techniques that can ensure interference-free operation once it has gathered sufficient spectrum awareness data about the existing system. Recognizing a cognitive zone, or the area around a receiver that might be interfered with is a straightforward technique for interference protection. A variety of spectrum usage strategies can be used in the cognitive zone. Overlay and interweave spectrum access techniques are the most often used CR approaches for satellite communications, but overlay-based techniques are less widely used because of their inherent complexity and practical difficulties [76].

2.8.3 Additional Wireless Communication Systems Using CR.

In addition to the aforementioned applications of cognitive radio, there are other and different applications of cognitive radio in the field of wireless networks. By giving WCNs intelligence and allowing to the different users the ability to access for many air interfaces with diverse communication demands and some conditions, the CR paradigm's ideas help to enhance multiple filed of wireless communications. These enhancements go beyond merely increasing network capacity and spectrum usage efficiency [14].

Military communications represent one of the important and first applications of the cognitive radio concept, where it was able to identify spectrum opportunities automatically in areas with different frequency allocations or in circumstances where an adversary was jamming communications. Adopting CR can help in networks of emergency and also public safety, where it can provide dependable and adaptive communications in disaster situations in case of the infrastructure of the network is destroyed completely or partially [14] [62].

Ad hoc communication networks between surviving nodes can be configured by devices with CR capabilities. Ad hoc networks' decentralized, self-configuring multi-hop capabilities are ideal for putting CRs concepts into practice.

Both general ad hoc networks and specific subsets of them, such as vehicular ad hoc networks [62], have received considerable study attention due to the difficult practical problems that cognitive ad hoc networks provide. It has also been thought about [86], and how CR techniques might be used in the field of communication in aeronautical systems [87].

The depletion of aeronautical radio channels has been exacerbated by the expansion of the aviation sector and the ongoing increase in air traffic[86] [88].

The increased usage of unmanned aerial systems in recent years, which necessitate a sizable amount through the operation of spectrum in remote real-time, has made this issue worse.

Aeronautical communications include a variety of systems and technologies, such as “air-ground” systems, “air-air” systems, communications by satellite, “in-flight” information and entertainment systems, and “LTE air-ground” links. The aviation spectrum can be utilized more effectively by using CR approaches, which can also reduce interference in these systems and technologies [87] [86].

2.9 Benchmark Algorithms

In this section, we will present three types of benchmark algorithms. These algorithms make the decision and choose the radio channels either randomly, which is the simplest method, or depending on one of the properties (parameters) of the radio channel to make the decision and choose the channel and then assignment to the Secondary user.

2.9.1 Random channel allocation (RCA)

This is the most basic strategy for channel selection. At the beginning of every time slot, a channel is selected randomly for transmission. Any algorithm for DSA should perform better than RCA. Also, this allows us to measure how well any algorithm performs[89].

The algorithm (3.9) represents an algorithm of channel selection by Random channel allocation (**RCA**).

Algorithm 2.1: An algorithm of channel selection by Random channel allocation (**RCA**)
1: ***Input***: a set of available channel
2: ***Output***: selected channel number.
3: **begin**
4: No_channel ← Random_select (set of the available channels).
5: selected channel ← No_channel;
6: Return (selected channel);
7: **END**

2.9.2 Minimum collision channel allocation (MCCA)

This channel selection scheme tries to avoid costly channel switching by choosing the channel at every timeout with the least usage estimation or the greatest idle probability.

The algorithm (3.10) represents the algorithm of channel selection by Minimum collision channel allocation (MCCA)[90].

Algorithm 2.2: An algorithm of channel selection by Minimum collision channel allocation (MCCA)
1: ***Input***: a set of the available channels.
2: ***Output***: Best channel
3: **begin**
4: Idle ← 0; // initial value.
5: **For i:** 1 to No. of Set of available channel
6: **if** (ch_{i_idle} > Idle)

7: Idle ← ch_{i_idle}.

8: No_channel ← i.

9: **else**

10: Do nothing.

11: **End for**

12: Best channel ← No_channel;

12: Return (Best channel);

13: **END**

2.9.3 Signal to noise ratio algorithm (SNRA)

This algorithm depends on the parameter SNR, where the channel with the highest value SNR is selected from a set of available channels.

The algorithm (3.11) represents an algorithm of channel selection by Signal to noise ratio algorithm (SNRA).

Algorithm 2.3: An algorithm of channel selection by Signal to noise ratio algorithm (SNRA)

1: *Input*: a set of the available channel, an initial value.// set=-value.

2: *Output*: select channel.

3: **begin**

4: Max ← initial value.

5: **For i: 1 to No. of Set of available channels**

6: if (ch_{i_SNAR} > Max)

7: Max ← ch_{i_SNAR}.

8: No_channel ← i.
9: else
10: Do nothing
11: **End for**
12: select channel ← No_channel;
12: Return (select channel);
13: **END**

2.10 The Evaluation Metrics used in the Proposed Approach.

Evaluation metrics are used to evaluate how well a statistical or machine learning model is performing. Every project has to evaluate machine learning models or algorithms. To test a model, a wide variety of evaluation measures are available. These consist of confusion matrix, logarithmic loss, classification accuracy, and other metrics. To test a model or algorithm, evaluation metrics combine each of these unique assessment metrics. In this dissertation, there are four metrics used to evaluate the algorithms used to enhance decision-making in cognitive radio.

2.10.1 Throughput of SU's

Network throughput in data transmission is the amount of data successfully transferred from one location to another in a predetermined amount of time. It is commonly measured in bits per second (bps), such as megabits per second (Mbps) or gigabits per second (Gbps).

To calculate the throughput of the secondary user while navigating (switching) between radio channels, while working within the cognitive network, we perform the following steps:

4. Determine the channel bandwidth. It can be 1.4, 3, 5, 10, 15, or 20 MHz, then map it to several Resource Blocks (RB) using the table (3.7).

Table (3.7): table to map bandwidth on the number of available RB

	Channel bandwidth, MHz					
	1.4	3	5	10	15	20
Number of Resource Blocks	6	15	25	50	75	100

5. Choose/define radio link quality; The efficiency of the link is determined by the value of (SNR) or (CQI) parameters.
6. Take a look at the Transport Block Size table (*7.1.7.2.1-1*), to determine how many bits can be transmitted per 1 TTI and multiply it by 1000 to get bps.
7. To simplify the process of calculating throughput we will assume that, multiplexing technology is (TDD), modulation and code schema will be (16 QAM, MCS index= 12, and TBS=11) for all networks, and transmission mode will be (SISO).
8. The transmission Time Interval (TTI) size in a bit (each frame has 10 TTI) will be found in the table (3.8) which was extracted based on the previous assumptions from table (3.7), and step 4, from the technical reference [91], table(7.1.7.2.1-1).
9. Now, to calculate the throughput of the secondary user based on the above steps, we will use the following equation [92]:

$$\text{Throughput}_{SU} = \sum_{ch}^{n\_ch} \mathrm{F_N}(t)_{ch} * (\text{frame size} * \mathrm{Ch}_{efficiency}) \quad \textbf{(2.1)}$$

where **frame size** *(bit)* is TTI size in bit multiplied by 10, **Ch** ***efficiency*** represents the channel efficiency, which is a percentage, obtained from the parameter (CQI) or (SNR), which is one of the dataset parameters (*If the value of the CQI or SNR is higher, then the percentage is better and vice versa*). ***ch*** is no. of the actual channel, ***n_ch*** sum of channels in the cognitive radio network, **FN(t)*ch*** represents a number of the frame for channel *ch* in *t* time (transmission time for an actual channel * the number of frames per second, note: *the number of frames is fixed, 100 frames per second to all channels and in all case of quality, (frame=10 ms)*).

To measure the throughput of the secondary user during the simulation time, the following table has been assumed which represents the channel bandwidth with transmission time interval (TTI) for each channel depending on their bandwidth and TBS index from step 4.

Table 3.8: Calculate the transmission time interval (TTI) depending on the channel bandwidth and its TBS index.

Transmission mode (LTE TDD)	MCS index= 12 , TBS index=11	In (1ms)
Bandwidth (MHz)	**Number of Resource Block**	**TTI (** ***bit*** **)**
1.4	**6**	1192
3	**15**	2984
5	**25**	4968
10	**50**	9912
15	**75**	15264
20	**100**	19848

2.10.2 Handoffs

The process that an active call or data session is transferred from one cell in a cellular network to another, or from one channel in a cell to another, which is called a handoff. For a caller or user of a data session to have uninterrupted service, a handoff must be properly executed.

The handoff process in the cognitive radio network will be calculated as **The number of times the secondary user switches from one radio channel to another during the transmission period**.

2.10.3 Delay time

The delay time represents the time needed by the secondary user in the process of searching and selecting one of the available channels, as well as the waiting time. The formula for this is:

$$\mathbf{Delay}_{\boldsymbol{time}} = \mathbf{D}_{\mathbf{search}} + \mathbf{D}_{\boldsymbol{selection}} + \mathbf{D}_{\boldsymbol{wait}} \qquad \mathbf{(2.2)}$$

Where D_{search} is the delay in discovering an available channel, $D_{selection}$ is the time spent to select one channel from the available channel, and D_{wait} is the time spent waiting. n is the total number of SU in a network and is used to calculate the average delay.

Chapter Three

The Proposed Methodology

3.1 Introduction

This chapter describes the completely developed techniques used to enhance the decision-making for channel selection in cognitive radio networks. To achieve this, a combination of the methods mentioned in the previous chapter would be a great way to use in the proposed model.

The proposed model to enhance the channel selection in cognitive radio networks is generally illustrated in section **3.2** to show the architecture of the proposed approach, the strategy of decision-making environment initialization, and the simulation algorithm. The dataset simulation is defined in section **3.3.**

The fuzzy inference system procedure is described in section **3.4**, and in section **3.5**, the neural network procedures are described. Section 3.6, represent the proposed method to calculate the selection value.

Three benchmark algorithms were described in section 3.7. In section 3.8, the evaluation metrics are described. Finally, the chapter summary is stated in section 3.9.

3.2 The Proposed Approach

The proposed cognitive radio approach was designed and developed to enhance channel selection by using four parameters rather than depending on one or two parameters only.

The approach consists of several stages; each stage works to improve the approach for providing the best approach to cognitive radio.

3.2.1 The Framework of the Proposed Approach

Figure (3.1) shows the framework of the proposed approach in steps as follows:

In the first step the cognitive radio environment is initializing, where the setting of the base stations, primary users, and secondary users are in the simulation area.

In the second step, the parameters (attributes) are selected (extraction) from Channel State Information (CSI), this will be done manually and it can be developed into the dynamic in future work.

These parameters represent the characteristics of the input data, and its (parameters) are used to select the best channels through the use of fuzzy logic algorithms and neural network algorithms.

In the third step, decision-making algorithms are applied based on the inputs, and the output is an evaluation of each available channel, and then choose the best of these channels based on the best output value (highest value).

In the four step, simulated the cognitive user in a wireless network until the simulation time runs out.

Within the simulation process, the secondary user will continuously sense the surrounding radio channels, exploit the spectral holes if needed, and leave (evacuate the channel) upon sensing the presence of the primary user.

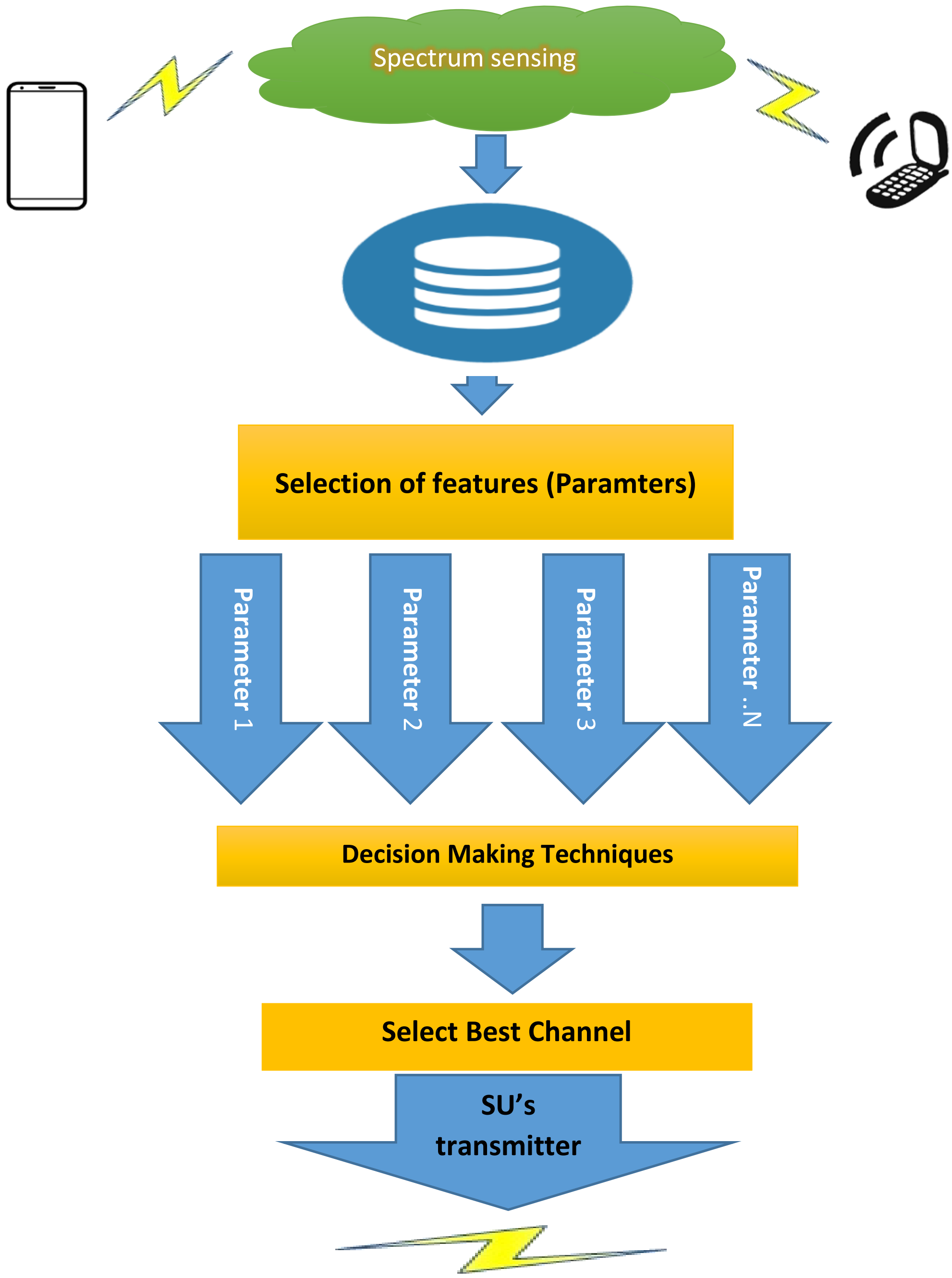


Figure 3.1: The framework of the cognitive radio network**.**

The figure (3.1) represents the general framework of cognitive radio technology, which includes the above basic steps.

3.2.2 Strategy of Decision Making for Proposed Approach

Cognitive radio technology depends on many steps, which start from sensing the surrounding environment, analyzing the sensor data, and then applying the techniques of choosing the appropriate frequency available (free channel) to use in transmission operations.Figure 3.2, shows the detailed steps of the proposed strategy for cognitive radio. The strategy shown in figure (3.2) can be illustrated by the following steps:

1. Initialization step: In this step, the work environment is created where base stations, primary users, and secondary users are created.
2. The extraction features step: In this step, the characteristics that will be used to make the decision are selected (normally, four characteristics are chosen).
3. Dataset step: In this step, simulation data or training data for neural network algorithms are generated.
4. Data Check Step: In this step, when the secondary user needs to find an available radio channel.
5. Research step: This step includes searching the spectral band for all available channels, and choosing the best one by using one of the decision-making techniques.
6. Transmission step: This step involves the secondary user modifying their settings to perform the transmission and reception process on the selected radio channel.
7. Verification step: This step involves the secondary user verifying the presence of the primary user or the secondary user. Complete the data transmission process. In the first case, the secondary user will stop broadcasting and vacate the channel and return to the search

step to choose a new channel. In the second case, the user will secondary evacuates the channel and returns to the waiting state.

8. Waiting step: In this step, the secondary user is in the waiting state in two states: the first case, when all channels are occupied, and the second case, when the secondary user has no data to transfer.

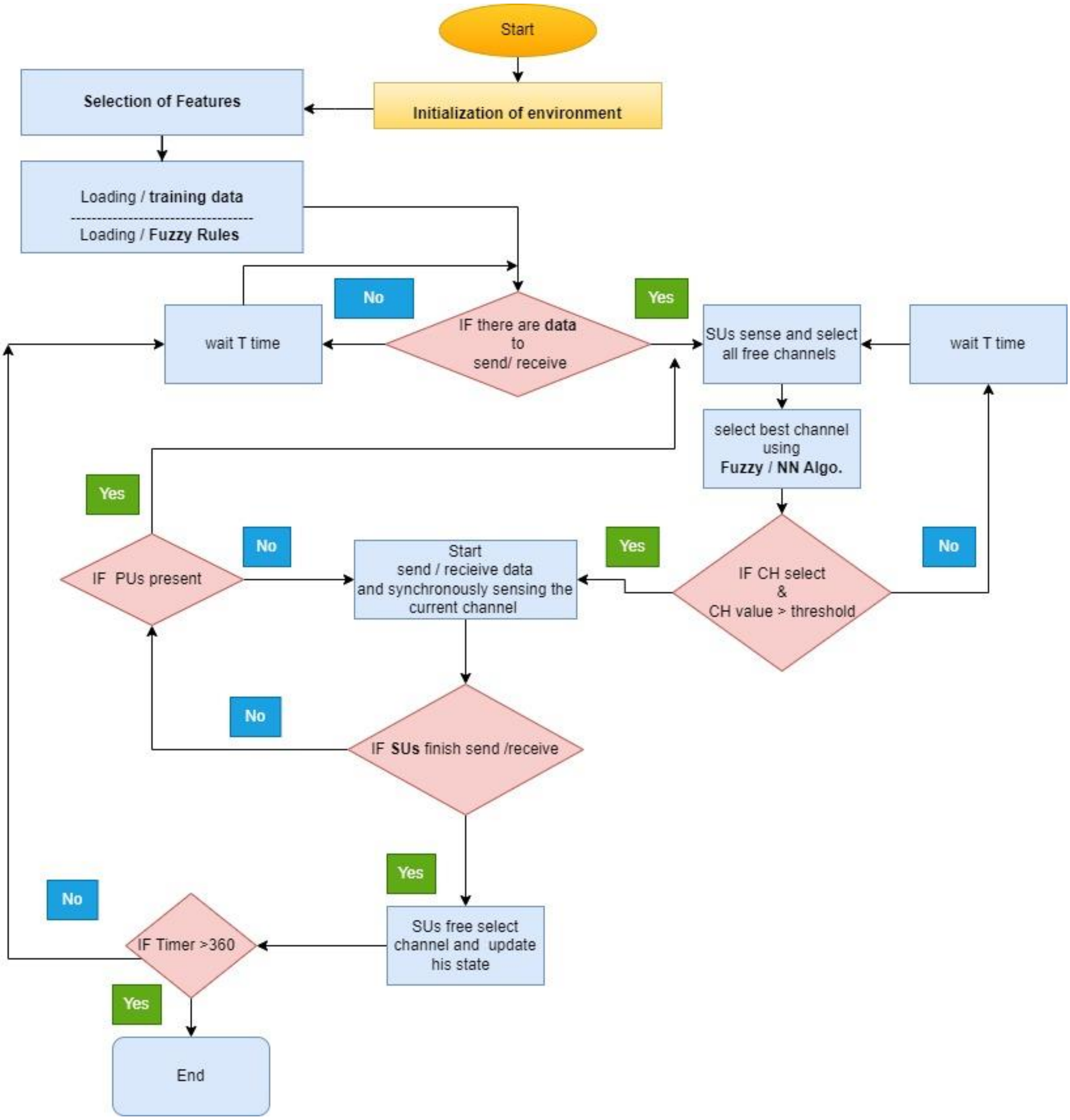


Figure 3.2: the flowchart of cognative radio strategy.

3.2.3 Environment Initialization

The initialization of the environment step is an essential part of our cognitive radio approach since the base stations, PUs users, and SUs users are identified at this step. All these elements are the fundamental units passed to all further processing steps for the analysis and detection of information.

The algorithm (3.1) represents the initialization algorithm of the cognitive radio environment for the proposed approach.

Algorithm 3. 1: Environment Initialization
Input: width, length, Number_SUs, Number_PUs, Number_Basestation. ***Output***: Matrix_Area Begin 1: X_location ← random(width); 2: Y_location ← random(length); 3: For i to Number_Basestation 4: BaseStation(i, X_location, Y_location). 5: X_location = Random(width). 6: Y_location = Random(length) 7: END for 8: For j to Number_SUs 9: X_location = Random(width). 10: Y_location = Random(length). 11: Plan_SUs (j, X_location, Y_location) 12: END for 13: For j to Number_PUs 14: X_location = Random(width).

```
        Y_location = Random(length).
        Plan_PUs (j, X_location, Y_location)
END for
Matrix_Area ← Add(BaseStation)
Matrix_Area ← Add( Plan_SUs)
Matrix_Area ← Add(Plan_PUs)
End
```

In algorithm (3.1), the simulation environment is created and configured, and the algorithm work can be detailed in the following steps:

First step: In this step, base stations are created by distributing them randomly within the simulation area.

Second step: In this step, the primary users are randomly distributed within the simulation space, taking into consideration (making sure) that the same place is not taken for the base stations or the rest of the users.

In third step, the secondary users are also randomly distributed within the simulation space, taking into consideration (making sure) that the same place is not taken for the base stations or the rest of the users.

3.2.4 Selection of Parameters

Datasets were generated by MATLAB simulator and stored in excel format. Table (3.1) shows a sample excel file. On spectral frequencies, a radio channel has a set of parameters (attributes) of more than 15 attributes. Some attributes were selected from **channel state**

information (CSI) for this radio channel to use in this work such as RSSI, CQI, Bandwidth, and Distance see table (3.1), and also, RSSI, SNR, or by **cooperating with other users**, such as **Spectrum demand** and **Idle time** see table (3.2), an excel spreadsheet with the prior data along with columns was built. For datasets collected from the simulator, attributes are extracted and stored in Excel files.

Table 3.1: Example of First Dataset

Sensing Time	CH. No	CH. State	RSSI	CQI	Bandwidth	Distance
03:02:03	1	0	-60	4	5	530
03:02:03	2	1	-73	7	10	287
03:02:04	3	1	-65	13	15	632
03:02:04	4	0	-89	6	3	725
03:02:05	5	0	-92	12	20	340

Table 3.2: Example of Second Dataset

Sensing Time	CH. No	CH. State	RSSI	SNR	Spectrum Demand	Idle Time
04:11:45	1	1	-74	13	7	3
04:11:46	2	0	-55	9	5	9
04:11:46	3	0	-85	16	10	12
04:11:48	4	1	-71	5	3	2
04:11:52	5	0	-67	7	2	10

3.2.5 Generation of Dataset

The algorithm (3.2), briefly describes the process of generating data that will be used in the simulation process, where each parameter is generated separately, taking into account the correlated parameters, where they are calculated interdependently.

The algorithm (3.2) contains many functions, each of which has a special work, these functions generate the parameters of the dataset.

Algorithm 3.2: Algorithm of generation of the dataset

Input: Time_Max, No_channels, No_BaseStation, timer,time_free.

Output: File_DataSet. // A file containing radio channels data.

Begin

i=1.// start of index of table in dataset file.

Do

    File_DataSet [i, 1] ← time;

    For j : 1 to No_channels Do

        File_DataSet [i, 2] ← j;// No. of channel.

        IF idel_time_ch_j < time_free do

        File_DataSet [i, 3] ← state is 0;// state 0 or 1.

        File_DataSet [i, 4] ← Generate.1(j, Par1);// par1

        File_DataSet [i, 5] ← Generate.2(j, Par2);// par2

        File_DataSet [i, 6] ← Generate.3(j, Par3););// par3

        File_DataSet [i, 7] ← Generate.4(j, Par4);

      Else File_DataSet [i, 3] ← state is 1.

    End for

  wait (random(time))

  SUs_location ← random (change_location)

  i=i+1

Until (timer >Time_Max)

Return (File_DataSet)

End

The dataset that is generated simulates the kinematics of cognitive devices within the simulation environment, so the changes in the parameter values are gradual, taking into account the generation of data that simulates real networks.

The algorithm (3.2) creates a dataset that is used to simulate the cognitive network, and its work can be summarized in the following steps:

The first step: The state of the channel, whether it is occupied or not (through the state variable), is determined partially randomly, by making sure that the idle time has finishing.

The second step: If the channel is free, simulation data is generated for all parameters, taking into account the previous values, with a partial and random change to the mutable values.

The third step: the secondary user's location in the cognitive network is changed, as this change causes an update and a change in the parameter values. This process continues until the simulation time finishing.

3.2.6 Cognitive radio network Simulation

The algorithm (3.3) represents a simulation of the cognitive radio network in figure (3.2), where the cognitive radio cycle is represented in this simulation, which includes (spectrum sensing, spectrum management, spectrum mobility, and spectrum sharing).

Algorithm 3.3: Cognitive Radio Simulation

1. **Start**
2. **Call** Environment Initialization. // **Algorithm 3. 1.**
3. **Call** Generation Data Set. // **Algorithm 3.2.**
4. **IF FIS** as technique of selection **then**
5. **Load** Dataset; fuzzy rules;
6. **Else IF** Neural Network **THEN**
7. **Load** training dataset & **training** the neural network algorithm.
8. END IF.
9. **Start** Simulation process;
10. **IF** (the SU's has **Data** to Send/Receive) **then**
11. **Start** *delay_timer*.
12. SU's device start sensing and search all free channels
13. **SUs Select Best channel** // use **channel selection Algorithms (3.4..3.11)**

    A. IF CH (**select channel)** & CH value > threshold **then**

    i. **Stop** *delay_timer*.

    ii. **Start** to send / receive Data **&** SU's device **synchronously** sensing the current channel selected **& Start** *th_timer*.

    1. **While (**SU's not finishing **AND** PU's not present**)**

       SU's continues send/ receive data.

       End while.

    a. **Stop** *th_timer* **& SU's** free channel.

    b. **Calculation (***SU's_throughput***)**. // see equation no.

    c. **Increase(***Handoff_counter***).**

    d. **IF** PU's present **then**

       i. Go to step **12** & **Start** *delay_timer*.

    e. Else

i. wait **T** time
ii. Go to step 10.

f. End if

B. Else

i. wait **T** time
ii. Go to step 8.

End if.

14. Else

A. wait **T** time.
B. Go to step 7.

15. End if

16. Return (*SU's_throughput***);**

17. Return (*Handoff_counter*)**;**

18. Return (*delay_timer*)**;**

19.End

The algorithm (3.3) above can be detailed in the following steps:

1. The first step: is a call to the simulation environment initialization algorithm, which is explained in section (3.2.3).
2. The second step: In this step (**feature selection**) the parameters that will be selected from CSI to assist in decision-making are defined, this is explained in section (3.2.4).
3. The third step: In this step, the technique that will be used in the decision-making process is determined, if it is one of the fuzzy inference methods; the fuzzy logic rules will be loaded, but if one of

the methods of neural networks: the training dataset will be generated, and then training the neural network.

4. The fourth step: the simulation process will be started by generating a simulation dataset through a call to the dataset generation algorithm, which is explained in section (3.2.5).
5. The fifth step: includes checking the secondary user's need to use the network, and if so, the search for available radio channels will start.
6. The sixth step: includes calling one of the decision-making methods which will be explained later in this chapter, to choose one of the available channels and move to use it.
7. Step Seven: The secondary user will continue to use the radio channel until the secondary user empties the transmission of data or the presence of the primary user, where the secondary user will vacate the channel.
8. Last Step: The simulation process will continue until the simulation time is finished and the process stops.

3.3 Fuzzy Inference systems

An important part of fuzzy logic is represented by fuzzy inference systems and is used in many different applications. The fuzzy inference systems create a clear non-linear map. Where logical knowledge or fuzzy rules encoding experts are identified about the problem.

3.3.1 Fuzzy Inference Rules

Fuzzy inference systems use a set of rules that are prepared by experts or prior knowledge.

The tables (3.3, 3.4, 3.5, 3.6, 3.7, 3.8) represent ranges of inputs parameters in the dataset for fuzzy rules.

Table 3.3: Represents the ranges of Fuzzy Logic for RSSI.

Fuzzy Logic	Range
Low	-100..-90
Moderate	-89..-81
High	-80..-75

Table 3.4: Represents the ranges of Fuzzy Logic for CQI.

Fuzzy Logic	Range
Low	0-5
Moderate	6-10
High	11-15

Table 3.5: Represents the ranges of Fuzzy Logic for Bandwidth (MHz).

Fuzzy Logic	Range
Low	3 - 5
Moderate	10 - 15
High	18 - 20

Table 3.6: Represents the ranges of Fuzzy Logic for Distance.

Fuzzy Logic	Range
Low	700-1000
Moderate	400-699
High	0-399

Table 3.7: Represents the ranges of Fuzzy Logic for Spectrum Demand.

Fuzzy Logic	Range
Low	1-3
Moderate	4-6
High	7-10

Table 3.8: Represents the ranges of Fuzzy Logic for Idle time.

Fuzzy Logic	Range
Low	1-3
Moderate	4-7
High	8-10

In the proposed system, there are two models of parameters, the non-cooperative model and the other model is the cooperative model. So two sets of rules will be developed, one for each model.

Table (3.9) represent the rules of the fuzzy inference system for four parameters in the first model (non-cooperative model), where there are eighty-one fuzzy rules.

Table (3.9): The rules of the fuzzy inference system used for the first model.

Seq.	RSSI	CQI	Bandwidth	Distance	selection value
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Moderate	Low
3	Low	Low	Low	High	Low
4	Low	Low	Moderate	Low	Low
5	Low	Low	Moderate	Moderate	Low
6	Low	Low	Moderate	High	Low
7	Low	Low	High	Low	Moderate
8	Low	Low	High	Moderate	Moderate
9	Low	Low	High	High	Low
10	Low	Moderate	Low	Low	Low
11	Low	Moderate	Low	Moderate	Low
12	Low	Moderate	Low	High	Low
13	Low	Moderate	Moderate	Low	Moderate
14	Low	Moderate	Moderate	Moderate	Moderate
15	Low	Moderate	Moderate	High	Low
16	Low	Moderate	High	Low	Moderate
17	Low	Moderate	High	Moderate	Moderate

18	Low	Moderate	High	High	Moderate
19	Low	High	Low	Low	Moderate
20	Low	High	Low	Moderate	Moderate
21	Low	High	Low	High	Low
22	Low	High	Moderate	Low	High
23	Low	High	Moderate	Moderate	High
24	Low	High	Moderate	High	Moderate
25	Low	High	High	Low	High
26	Low	High	High	Moderate	Moderate
27	Low	High	High	High	Moderate
28	Moderate	Low	Low	Low	Moderate
29	Moderate	Low	Low	Moderate	Low
30	Moderate	Low	Low	High	Low
31	Moderate	Low	Moderate	Low	Moderate
32	Moderate	Low	Moderate	Moderate	Low
33	Moderate	Low	Moderate	High	Low
34	Moderate	Low	High	Low	Moderate
35	Moderate	Low	High	Moderate	Moderate
36	Moderate	Low	High	High	Low
37	Moderate	Moderate	Low	Low	Moderate
38	Moderate	Moderate	Low	Moderate	Moderate
39	Moderate	Moderate	Low	High	Low
40	Moderate	Moderate	Moderate	Low	Moderate
41	Moderate	Moderate	Moderate	Moderate	Moderate
42	Moderate	Moderate	Moderate	High	Moderate
43	Moderate	Moderate	High	Low	High
44	Moderate	Moderate	High	Moderate	High
45	Moderate	Moderate	High	High	High

46	Moderate	High	Low	Low	High
47	Moderate	High	Low	Moderate	Moderate
48	Moderate	High	Low	High	Moderate
49	Moderate	High	Moderate	Low	High
50	Moderate	High	Moderate	Moderate	High
51	Moderate	High	Moderate	High	High
52	Moderate	High	High	Low	High
53	Moderate	High	High	Moderate	High
54	Moderate	High	High	High	High
55	High	Low	Low	Low	Low
56	High	Low	Low	Moderate	Low
57	High	Low	Low	High	Low
58	High	Low	Moderate	Low	Moderate
59	High	Low	Moderate	Moderate	Moderate
60	High	Low	Moderate	High	Low
61	High	Low	High	Low	Moderate
62	High	Low	High	Moderate	Moderate
63	High	Low	High	High	Moderate
64	High	Moderate	Low	Low	Moderate
65	High	Moderate	Low	Moderate	Moderate
66	High	Moderate	Low	High	Moderate
67	High	Moderate	Moderate	Low	High
68	High	Moderate	Moderate	Moderate	High
69	High	Moderate	Moderate	High	High
70	High	Moderate	High	Low	High
71	High	Moderate	High	Moderate	High
72	High	Moderate	High	High	High
73	High	High	Low	Low	High
74	High	High	Low	Moderate	High
75	High	High	Low	High	High

76	High	High	Moderate	Low	High
77	High	High	Moderate	Moderate	High
78	High	High	Moderate	High	High
79	High	High	High	Low	High
80	High	High	High	Moderate	High
81	High	High	High	High	High

Table (3.10) represent the rules of the fuzzy inference system for four parameters to the second model (cooperative model), Where there are eighty-one fuzzy rules.

Table (3.10): The rules of fuzzy inference system used for the second model.

Seq.	RSSI	SNR	Bandwidth	Idle Time	Selection value
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Moderate	Low
3	Low	Low	Low	High	Low
4	Low	Low	Moderate	Low	Low
5	Low	Low	Moderate	Moderate	Low
6	Low	Low	Moderate	High	Low
7	Low	Low	High	Low	Low
8	Low	Low	High	Moderate	Low
9	Low	Low	High	High	Low
10	Low	Moderate	Low	Low	Low
11	Low	Moderate	Low	Moderate	Low
12	Low	Moderate	Low	High	Low
13	Low	Moderate	Moderate	Low	Moderate
14	Low	Moderate	Moderate	Moderate	Moderate
15	Low	Moderate	Moderate	High	Low
16	Low	Moderate	High	Low	Moderate

17	Low	Moderate	High	Moderate	Moderate
18	Low	Moderate	High	High	Moderate
19	Low	High	Low	Low	Moderate
20	Low	High	Low	Moderate	Moderate
21	Low	High	Low	High	Low
22	Low	High	Moderate	Low	High
23	Low	High	Moderate	Moderate	High
24	Low	High	Moderate	High	Moderate
25	Low	High	High	Low	High
26	Low	High	High	Moderate	Moderate
27	Low	High	High	High	Moderate
28	Moderate	Low	Low	Low	Moderate
29	Moderate	Low	Low	Moderate	Low
30	Moderate	Low	Low	High	Low
31	Moderate	Low	Moderate	Low	Moderate
32	Moderate	Low	Moderate	Moderate	Low
33	Moderate	Low	Moderate	High	Low
34	Moderate	Low	High	Low	Moderate
35	Moderate	Low	High	Moderate	Moderate
36	Moderate	Low	High	High	Low
37	Moderate	Moderate	Low	Low	Moderate
38	Moderate	Moderate	Low	Moderate	Moderate
39	Moderate	Moderate	Low	High	Low
40	Moderate	Moderate	Moderate	Low	Moderate
41	Moderate	Moderate	Moderate	Moderate	Moderate
42	Moderate	Moderate	Moderate	High	Moderate
43	Moderate	Moderate	High	Low	High
44	Moderate	Moderate	High	Moderate	High
45	Moderate	Moderate	High	High	High
46	Moderate	High	Low	Low	High

47	Moderate	High	Low	Moderate	Moderate
48	Moderate	High	Low	High	Moderate
49	Moderate	High	Moderate	Low	High
50	Moderate	High	Moderate	Moderate	High
51	Moderate	High	Moderate	High	High
52	Moderate	High	High	Low	High
53	Moderate	High	High	Moderate	High
54	Moderate	High	High	High	High
55	High	Low	Low	Low	Low
56	High	Low	Low	Moderate	Low
57	High	Low	Low	High	Low
58	High	Low	Moderate	Low	Moderate
59	High	Low	Moderate	Moderate	Moderate
60	High	Low	Moderate	High	Low
61	High	Low	High	Low	Moderate
62	High	Low	High	Moderate	Moderate
63	High	Low	High	High	Moderate
64	High	Moderate	Low	Low	Moderate
65	High	Moderate	Low	Moderate	Moderate
66	High	Moderate	Low	High	Moderate
67	High	Moderate	Moderate	Low	High
68	High	Moderate	Moderate	Moderate	High
69	High	Moderate	Moderate	High	High
70	High	Moderate	High	Low	High
71	High	Moderate	High	Moderate	High
72	High	Moderate	High	High	High
73	High	High	Low	Low	High
74	High	High	Low	Moderate	High
75	High	High	Low	High	High
76	High	High	Moderate	Low	High

77	High	High	Moderate	Moderate	High
78	High	High	Moderate	High	High
79	High	High	High	Low	High
80	High	High	High	Moderate	High
81	High	High	High	High	High

3.3.2 Simulation Dataset

The dataset is generated through the simulation process during the implementation process.

The proposed cognitive radio environment simulates the activity of secondary and primary users who work in an area of the city measuring (1 km in width and 1 km in length). Secondary users are navigating the simulation environment by pedestrian or by car.

3.4 Fuzzy Inference System Algorithms

The fuzzy nesting system includes many different algorithms, and each algorithm has its characteristics.

In this dissertation, we will use three algorithms: Mamdani, which computes a centroid of a two-dimensional area, Tsukamoto's algorithm which uses a membership function monotonous, and algorithm TSK which uses a weighted average to calculate the outputs.

3.4.1 Mamdani FIS

Mamdani's fuzzy inference system is suitable for expert system applications because they have rules that are easy to understand and are more intuitive, so rules are created by human experts based on their cumulative knowledge.

The algorithm (3.4) represents the Mamdani algorithm, which is used in the decision-making process by processing the input parameters that represent the characteristics of radio channels.

Algorithm 3.4: An algorithm of channel selection by Mamdani FIS

Input: inputs_file, No_free_ channels.

Output: Best_value.

Begin

```
A ← Create (NewFis);
A ← Addvar(parameter1);
A ← Addvar(parameter2);
A ← Addvar(parameter N);
A ← addvar(output1);
Create (rule1; rule2; ....rule N);
ruleList ← [rule1; rule2; ....rule N];
sys ← addrule(A, ruleList);
  read (inputs_file)
    for j : 1 to No_free_ channels do
        Tip ← Eval_Mamd (sys , [input1, input2, input3, input4]);
        Matrix ← Tip;
    end for
  Best. Value ←  Max(Matrix);
  Return ← Best. Value.
```

END

The algorithm (3.4) represents the pseudocode of the Mamdani fuzzy interference method, which is used to decide to choose the radio channel, and the method can be summarized in the following steps:

1. The first step: includes creating a field entity and adding the values of the variables (parameters) and dividing the extent of this variable into three sections (low, medium, and high).
2. The second step: includes adding the outputs and dividing this output into three sections (low, medium, and high).
3. The third step: involves adding the rules of fuzzy logic to the entity of the Mamdani method. These rules usually take all the potentials of the inputs as well as the outputs.
4. The fourth step: involves starting the simulation process, evaluating the parameters of all available channels, and selecting the best radio channel.

The fourth step called by the simulation algorithm continuously to evaluate the quality of channels and select the best channel.

3.4.2 Tsukamoto FIS

Tsukamoto's fuzzy inference system algorithm uses a monotonical membership function, they have rules that are easy to understand and are more intuitive, so rules are created by human experts in the inputs and the outputs calculate dynamically.

The algorithm (3.5) represents the Tsukamoto algorithm, which is used in the decision-making process by processing the input parameters that represent the characteristics of radio channels.

Algorithm 3.5: An algorithm of channel selection by Tsukamoto FIS

Input: inputs_file, No_free_ channels.

Output: Best_value.

Begin

1: A ← Create (Tsukamoto_Fis);
2: A ← Addvar(parameter1);
3: A ← Addvar(parameter2);
4: A ← Addvar(parameter N);
5: A ← addvar(output1);
6: Create (rule1; rule2; ....rule N);
7: ruleList ← [rule1; rule2; ....rule N];
8: sys ← addrule(A, ruleList);
9: read (**inputs_file**)
10: for j : 1 to **No_free_ channels** do
11: Tip ← Eval_Tsuk (sys , [input1, input2, input3, input4]);
12: Matrix ← Tip;
13: end for
14: Best. Value ← Max(Matrix);
15: Return ← Best. Value.

END

The algorithm (3.5) works similarly to the previous algorithm (3.4) with the difference in the type of output.

3.4.3 Takagi-Sugeno-Kang FIS

Sugeno's method has many similarities with Mamdani's method, in which the operations of obfuscation of the input and application of the fuzzy operator are the same in both methods.

As for the two methods, they are different like the outputs, where the outputs of the Mamdani method are a fuzzy set, while the Sugeno method has linear or constant outputs.

The algorithm (3.6), represents the Sugeno algorithm, which is used in the decision-making process by processing the input parameters that represent the characteristics of radio channels.

Algorithm 3.6: An algorithm of channel selection by TSK fuzzy FIS
Input: inputs_file, No_free_ channels. ***Output***: Best_value. **Begin** 1: A ← Create (NewFis); 2: A ← Addvar(parameter1); 3: A ← Addvar(parameter2); 4: A ← Addvar(parameter N); 5: A ← addvar(output1, Linear equation1); 6: A ← addvar(output N, Linear equation N); 7: Create (rule1; rule2; ....rule N); 8: ruleList ← [rule1; rule2; ....rule N]; 9: sys ← addrule(A, ruleList); 10: read (**inputs_file**) 11: for j : 1 to **No_free_ channels** do 12: Tip ← Eval_TSK (sys , [input1, input2, input3, input4]); 13: Matrix ← Tip; 14: end for 15: Best. Value ← Max(Matrix); 16: Return ← Best. Value. END

This algorithm (3.6) has a system of processing the inputs similar to the previous algorithms, but it produces the output differently as it uses the weighted average to evaluate the inputs and produce a constant output or linear output.

3.5 Neural Networks

Machine learning algorithms include a wide range of algorithms, including neural networks, which have been highly successful. Thanks to the development of neural networks, computers have learned to think and understand similarly to humans.

In this dissertation, there are two algorithms of neural networks were used. The first is an artificial neural network (ANN) and the second is an adaptive neural fuzzy inference system (ANFIS).

3.5.1 Training Dataset

The neural network algorithms need a dataset for the training process, this dataset will allow the neural networks to find the best patterns that can be extracted from the dataset under training.

The training dataset was generated through the MATLAB code, where two types of the dataset were randomly generated, the first type is the training dataset with four parameters: **RSSI, Distance, Bandwidth, and CQI**, and the second type is the training dataset, which consists of four parameters: **SNR, RSSI, Idle time, and Spectrum demand**.

The training dataset was generated in a simulation of 4G LTE networks. 4G LTE Networks was chosen, because it supports cognitive radio networks, and it is also characterized by high speed and the ability to transfer large amounts of data due to its large bandwidth.

The size of the training dataset that is generated consists of 1000 records, and each record represents individual channel state information (CSI) with four parameters that we mentioned above.

The neural network algorithms we use are supervised algorithms. So we need to preprocess the training dataset by finding the target dataset.

The target datasets (estimation of selection value) are generated by a proposed method, see the description of this method in section (3.6). The training dataset was divided into 70% for training, 15% for testing, and 15% for validation, as shown in table (3.5) and table (3.6) represent examples of dataset training.

Table 3.5: Example of the first set of training dataset.

RSSI	CQI	Bandwidth (Mbit)	Distance from BS (Meter)	Selection value
-79	15	10	531	66
-97	2	3	162	31
-71	2	18	491	46
-73	8	5	518	51
-98	14	15	613	47
-75	4	5	274	43
-74	12	3	879	50
-103	10	15	378	52
-75	15	18	202	85
-82	9	5	733	41
-93	15	3	587	58
-101	6	10	493	32

-87	10	20	361	63
-90	1	10	822	21
-107	2	3	770	10
-87	6	5	341	46
-76	8	10	371	59
-73	2	15	567	50
-108	2	10	572	21
-72	13	5	616	57

Table 3.6: Example of the second set of training dataset.

RSSI	SNR	Spectrum demand	Idle time (sec)	Selection value
-75	22	3	15	98
-82	10	5	3	50
-76	22	10	1	54
-83	6	5	6	49
-77	4	3	15	66
-78	18	15	15	74
-89	22	3	9	66
-98	4	5	11	35
-100	22	10	14	56
-78	9	10	7	35
-100	6	3	4	17
-83	3	5	8	41
-73	21	20	15	83
-92	22	5	13	68
-83	22	10	14	63
-75	8	10	4	28
-80	5	20	15	76
-99	22	3	3	50
-78	4	5	2	32
-84	-1	10	7	17

3.5.2 Generate Simulation Dataset

After training the neural network algorithms ANN and ANFIS with the training dataset, that has previously been generated.

The dataset that is used for evaluation algorithms is generated through the simulation process, the simulation environment is in an area of 1-km-width and 1 km length.

The generated dataset simulates the movement of the secondary user pedestrian or by car within the simulation area.

The data that is generated will change as secondary users' location changes through their navigation. This change in data for each channel will be gradual and random at a certain rate.

3.5.3 Artificial Neural Network Algorithm

Artificial neural networks are one of the most important types of machine learning that simulate processes in the human brain. Artificial Neural networks are used in many fields such as to model nonlinear relationships and are usually used in object classification and control.

Algorithm (3.7) represents the training of an artificial neural network, using the training dataset that we explained in the previous section.

In this algorithm, a supervised learning method was used to train the artificial neural network.

Algorithm 3.7: An algorithm of ANN to channel selection (**initialization, training, and test phase**)
1: ***Inputs*** : epoch, h_layer, training_input, training_target // initialization 2: ***Output***: Trained_network.// **the right weight of parameters.** 3: net = new_ff(training_input, training_target)// Create ANNs 4: net_trainParam_goal=0.01; 5: netconf ← h_layer // use 3, 4, 5,7,10,12,15 hidden layers to train ANN.

```
6: train_Fcn ← trainlm;  // Levenberg–Marquardt algorithm
7: net ← feed_forward_net(netconf, train_Fcn);
8: net_trainParam_epochs ← epoch; //training with different Number of
                                            epochs: 250, 500,1000.
9 : Training_network ← train(net, training_input, training_target );
//Function of training.
10: read (from Training datasets)
11:     for j: 1 to No_free_ channels do
12:          Output ← sim(Training_network, [input1, input2, input3, input4]);
              // output_test  function.
13:          Array_output ← Output;
14:       end for
15:   Return ← Max(Array_output); // Best. Value
 End
```

In the artificial neural network algorithm (3.7) used here, the supervised model was applied. The algorithm settings have been adjusted as follows: different numbers of hidden layers were used (3, 5, 7, 10, 13, 15), and it was proved by experience that the hidden layers with 7 layers gave the best results compared to the rest of the numbers, and the Levenberg-Marquardt optimization method was used as a network training function, it updates the weights and biases. The ANNs were trained with a different number of epochs equal to 250, and 500,1000.

After the trained network is obtained, it will be used to test the four inputs (parameters) that represent the characteristics of the available radio channels and return an evaluation value for each channel.

The channel that has the largest value and is considered the best channel is chosen.

3.5.4 Adaptive Neural Fuzzy Inference System Algorithm

The ANFIS combines two concepts, Fuzzy Logic (FL) and Artificial Neural Networks (ANN). It is characterized by adaptive abilities and fast learning abilities in addition to the awareness of non-linear relationships. The ANFIS algorithm is used to solve common problems to improve time and space complexity.

Algorithm (3.8) represents the training of an adaptive neural fuzzy network, using the training dataset that we explained in section 3.5.1.

Algorithm 3.8: An algorithm of ANFIS to channel selection (**initialization and training step**).

Input: int Nmship, string GeFis, string FuType, int EpNumber.

Output: Fuzzy Rules.

Begin

1. Input_data ← Load(training_input_data);
2. Output_data ← Load(training_output_data);
3. val_data ← Load(validation_data);
4. Gen_option ← Methods_of _Fis ; // FCM_Clustering.
5. Gen_option. Num_Membership_Functions ← Nmship; // 4, 5
6. Gen_option. FunctionType ← FuType ; // gaussian MF.
7. Gen_option. EpochNumber← EpNumber; // use 250, 500, 1000 epoch
8. FIS ← Gen_fis(Input_data, Output_data, Gen_option); // create FIS
9. Opt.anfisOptions ← FIS;

```
10.opt.DisplayErrorValues ← 0;
11.opt.DisplayStepSize ← 0;
12.opt.DisplayFinalResults ← 0;
13.opt.ValidationData ← val_data
14.[fis,trainError,stepSize,chkFIS,chkError]= ANFIS_train([Input_data,
   Output_data],opt); // function of training and finding the fuzzy rules .
15.read (inputs parameters for free channels)
  16. for j: 1 to No_free_ channels do
  17.     Output ← ANFIS (fis, [input1, input2, input3, input4]);
          // output_test function.
  18.     Array_output ← Output
  19. end for
20.Return ←Array_output;
End
```

In the algorithm (3.8), the supervised learning model is used, where the algorithm is provided with inputs (four parameters) and one output (target) from the generated dataset (section 3.5.1) for training and finding fuzzy logic rules, these rules will be used in the simulation process to find (evaluation the inputs) the best available radio channels.

The algorithm (3.8) can be detailed in the following steps:

10. The first part: includes loading training data (input data, output data, validation data).

11. The second part: start to create the Fuzzy Inference System and then configure its settings (the number of the membership function, the type of the membership function, the number of epochs, etc.).

12. The third part: Start training the network and find the rules of fuzzy.
13. The fourth part: The Fuzzy rules obtained from the previous part are applied to evaluate the available channels, during the simulation process.

3.6 Calculation of Selection Value

The ANFIS and ANN methods that we use to improve the decision-making process in cognitive radio require a training process on the datasets. Mostly, the training of these methods is supervised, so it needs (one or more) inputs and one output (**target**) at least.

The output in this process call the estimation of selection value, this target (the estimation of selection value) is a percentage consisting of the sum of the different or equal weights of the parameters extracted from the channel state information (CSI), and calculate we will use the following equation:

$$\mathbf{value}_{set} = \mathbf{W_{1\,par1} + W_{2\,par2} + W_{3\,par3} + W_{4\,par4}}. \quad \mathbf{(3.1)}$$

The **W** represents the weight of the parameter, which is suggested by experts in the field. The summation of weights ($\mathbf{value}_{set}$) of the dataset parameters represents the value of the estimation of selection. The greater value of the estimation of selection is the best one, and this value represents an evaluation of the quality of the radio channel in comparison to the other values ($\mathbf{value}_{set}$) of the other channels.

Min_{par_value} It is the smallest value that a parameter can have.

$Para_{value}$ The value of the input parameter.

$Para_{w}$ The Parameter weight in equation (1).

Max_{par_value} The value of the difference between the largest value of a parameter and the smallest value of a parameter.

Calculating the weights for all parameters, as follows:

1. **RSSI** parameter:

$$W_{par\_RSSI} = (|Min_{par\_value}| - |Para_{value}|) * (Para_{w} \;/ Max_{par\_value}) \quad \textbf{(3.2)}$$

W_{par_RSSI} The Parameter weight.

2. **CQI** parameter:

$$W_{par\_CQI} = Para_{value} * (Para_{w} \;/ Max_{par\_value}) \quad \textbf{(3.3)}$$

3. **Bandwidth** parameter:

$$W_{par\_Band} = Para_{value} * (Para_{w} \;/ Max_{par\_value}) \quad \textbf{(3.4)}$$

4. **Distance** parameter:

$$W_{par\_Dist} = (Min_{par\_value} - Para_{value}) * (Para_{w} / Max_{par\_value}) \quad \textbf{(3.5)}$$

5. **SNR** parameter:

$$W_{par\_SNR} = Para_{value} * (Para_{w} / Max_{par\_value}) \quad \textbf{(3.6)}$$

6. **Spectrum demand** parameter:

$$W_{par\_dem} = Para_{value} * (Para_{w} / Max_{par\_value}) \quad \textbf{(3.7)}$$

7. **Idle time** parameter:

$$W_{par\_idle} = Para_{value} * (Para_{w} / Max_{par\_value}) \quad \textbf{(3.8)}$$

Chapter Four

Simulation Result & Analysis

4.1 Introduction

This chapter presents the simulation scenario and the outcomes associated with decision-making and learning in two contexts, the first in a non-cooperative environment, and the second in a cooperative environment between secondary users.

As presented in this chapter, system requirements, datasets properties, simulation settings, and to simulate the cognitive radio network, a scenario will be presented for the use of the cognitive radio network by secondary users. Furthermore, training and simulation dataset generation will be presented. Next, simulation results related to throughput metrics, switching operations (handoffs), and delay time are presented and analyzed. After that, will use some benchmark algorithms, for evaluation and comparison with the proposed techniques (FIS, Neural networks). And, the results will be discussed and analyzed, and finally, a summary of the chapter.

4.2 System Properties

- Hardware, Processor: Intel(R) Core(TM) i7-8565 CPU @ 2GHz.
- Memory: 8 GB RAM.
- Operating System: Windows 10 Pro 64-bit.
- Programming Language: MATLAB LANGUAGE.
- IDE Environment: MATLAB 2018a.

4.3 Datasets properties

The datasets were generated by writing MATLAB code and arranged in tables with the following schema. Considered dataset parameters showed in table 4.1. And also, dataset parameters showed in table 4.2. The simulations necessary to validate the dissertation require a cognitive radio network.

4.4 Simulation Properties

This chapter has several scenarios about enhancing channel selection in cognitive radio networks. This study uses MATLAB code for the simulation process. Table 4.1 shows the parameters that will be used for the simulation. The evaluation will be achieved in the same environment and parameters by comparing the proposed techniques to each other and with the benchmark algorithms. The parameter values are very close to the real value in 4G LTE networks. This study will observe the results in a 4G LTE network with a different number of SUs and PUs. The results of the simulation will determine which proposed algorithms best than others by evaluation metrics.

4.5 Topology of Proposed Scenario

To study the proposed scenario, this study examines simple topology to determine the efficiency of the different methods of decision-making.

The topology consists of many base stations, one primary user for each base station or more, and one or more secondary users. it considers a 4G LTE network scenario where a SU user tries to find the best available radio channel and perform the process of sending and receiving data to some remote users through BS as illustrated in Figure (4.1).

On the other side, The BS which makes the service available to the SUs and PUs is connecting to the remote users via radio channels.

The radio channels that are used by users have distinct characteristics for each and are different from the others, such as bandwidth, channel capacity, signal strength, noise ratio, etc.

The Cognitive Radio Network (CRNs) topology has been built using MATLAB language code randomly with some limitations (relation among parameters).

Table: 4.3**:** Simulation Settings.

Parameters	Value
Simulation Area	1000 M X 1000 M
Simulation time	360 S
Number of PUs	1-10
Number of SUs	1-10
Time required for channel searching, selecting, switching.	0.4 - 6 S
SUs speed (Velocity)	(1 – 3) Meters
Channel bandwidth	3, 5, 10, 15, 20 MHz
Pause time	Random time (S)
Frame size (100 frame in second)	Different size, see table 3.8

Figure 4.1: The Topology of Simulation Environment

Figure (4.1), represents the area of simulation, It represents a residential neighborhood with an area of approximately 1 square kilometer, and contains several communication towers (base station) that are used by users of the cognitive network.

4.5.1 Cognitive Radio Scenarios

The simulation process is carried out through the use of datasets, which are generated using the algorithm (3.2) in chapter three, where two types of a dataset are generated according to the scenarios mentioned below:

4.6 Proposed Scenario

In the proposed scenario, in this scenario, there are five base stations with one radio channel for each BS. Furthermore, there is a primary user (authorized user) for each channel and one secondary user or more.

The secondary user does not have his channel, and he needs to perform data transmission and receiving operations, so he tries to use the spectrum holes (idle channels) that are unused by authorized users. The secondary user usually roams the region (area of simulation) by walking or using a car.

The secondary user in this scenario is almost always on the move, which is one of the reasons why he needs to share the spectrum with others. The secondary user, during his movement, switches between the different radio channels, depending on the change of status. For example, if he senses the presence of the primary user, he will be forced to vacate the channel and go to search for another available radio channel. It will continue in this state until it finishes its work and no longer needs these spectral frequencies.

The proposed techniques help the secondary users to decide to select available channels, these algorithms work to increase of throughput of the cognitive network by enhancing the decision-making for the secondary user in selecting the best radio channel and decreasing the number of switching (Handoffs) and delay time.

To implement this scenario, we will use two sets of features (parameters), the first dataset representing the non-cooperative model (Secondary users do not exchange information between them about radio channels), and the second set representing the cooperative model (Secondary users exchange information between them about radio channels).

The results for each method are calculated by taking the average for each method (the method is applied in the simulation process for three times) and then calculating the average for each evaluation metrics. The experimental datasets generated simulate the datasets from research conducted with the financial support of Science Foundation Ireland (SFI) under Grant Number 13/IA/1892.

4.6.1 First Case Study

Many experiments to assess the proposed work have been executed by applying different decision-making algorithms. The proposed approach was applied in the simulator environment for 360 seconds, in this case; we will use the first dataset that represents the non-cooperative model.

4.6.2 Parameters of simulation

A. **RSSI (Received Signal Strength Indicator):** measures how well your device can pick up a signal from a network or access point. It's a number that can be used to Figure out whether you have an adequate signal to establish a solid wireless connection. It should be noted that an RSSI value is not the same as transmitting power from a router or AP because it is obtained from the Wi-Fi card of the client device (thus, "received" signal strength). The values of RSSI that represent the signal strength indicator in the 4G (LTE) network range between (-75 .. -100).

B. **Distance from BS:** This parameter is used to measure the distance between the secondary user and the communication base station, and this scale plays an important role in measuring the quality of communication. The distance has values ranging from (1..1000 Meters).

C. **Bandwidth:** The capacity at which a network can transfer data is specifically referred to as bandwidth. For instance, if a network's capacity is 40 Mbps, it means that under no circumstances can the network transfer data at a rate greater than 40 Mbps. The values of bandwidth used in this dissertation (3, 5, 10, 15, 20 MHz).

D. **CQI:** A measure of the quality of the network connection, this is for a scale that is composed of 15 codes in a 4G (LTE) network. It has values ranging from (1..15).

E. **The weights parameters:** The weights parameters used in this model were: RSSI (30%) , Distance (20%) **,** Bandwidth (25%), CQI (25%).

4.6.3 Evaluation Metrics

To evaluate the cognitive network scenarios, several measures are used (throughput of SUs, Handoff, Delay time, and complexity).

4.6.3.1 Throughputs of SUs

Table (4.4) offers information on the numerical comparison between the five different techniques in the environment of simulation with (2, 3, 4, 5) channels and during 360 seconds for every simulation process. The comparison process is done according to the effect of the number of channels and decision-making technique on the network throughput.

Table (4.4) and Figure (4.3) Notes network throughput with ANFIS technique in the CR network is the best method among others. By comparing the results from this table, the ANFIS technique is better than other neural network and fuzzy inference systems techniques in throughput network metrics. An ANFIS technique achieved 2556 Mbit during 360 seconds in a 1000 M *1000 M area.

Table 4.4: Comparison of Throughput Among Different Techniques

simulation scenario	Time of Simulation	Decision-making Algorithm	membership function	Number of Channel	Throughput (**Mbps**)
1	360 S	Mamdani	GaussMF	**2**	1679
				3	1752
				4	1825
				5	1898
		Tsukamoto	GaussMF	**2**	1734
	Fuzzy Inference System			**3**	1833
				4	1902
				5	2031
			GaussMF	**2**	1704
				3	1856

		TSK		4	1956
				5	1932
	Neural Networks	ANN		2	1672
				3	1929
				4	2162
				5	2238
		ANFIS		2	1830
				3	2058
				4	2341
				5	2556

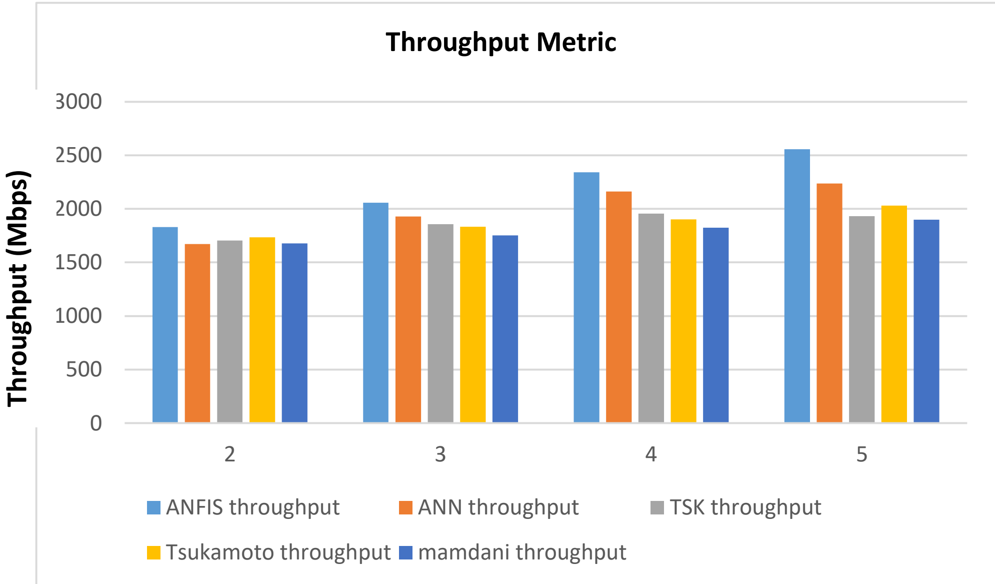


Figure 4.3: Throughput of SUs to Different Techniques

4.6.3.2 Handoffs

Table (4.5) offers information on the numerical comparison between the five different techniques in the environment of simulation with (2, 3, 4, 5) channels and during 360 seconds for every simulation process. The comparison process is done according to the effect of the number of channels and decision-making technique on several switching (Handoffs).

Table (4.5) and figure (4.4) notes handoffs with Neural networks methods ANN and ANFIS in CR network is the best method among others. By comparing the results from this table, the ANFIS technique is marginally better than other neural network and fuzzy inference systems techniques in the handoff metric. An ANFIS technique achieved 25 handoffs during 360 seconds and 5 channels.

Table (4.5) Comparison of Handoffs among different techniques

simulation scenario	Time of Simulation	Decision-making Algorithm	membership function	Number of Channel	Number of Handoffs
1	360 S	Mamdani	GaussMF	2	41
				3	38
				4	37
				5	36
	Fuzzy Inference System	Tsukamoto	GaussMF	2	38
				3	37
				4	33
				5	31
		TSK	GaussMF	2	35
				3	33
				4	32
				5	29
	Neural Networks	ANN		2	36
				3	32
				4	31
				5	27
		ANFIS		2	33

				3	31
				4	28
				5	25

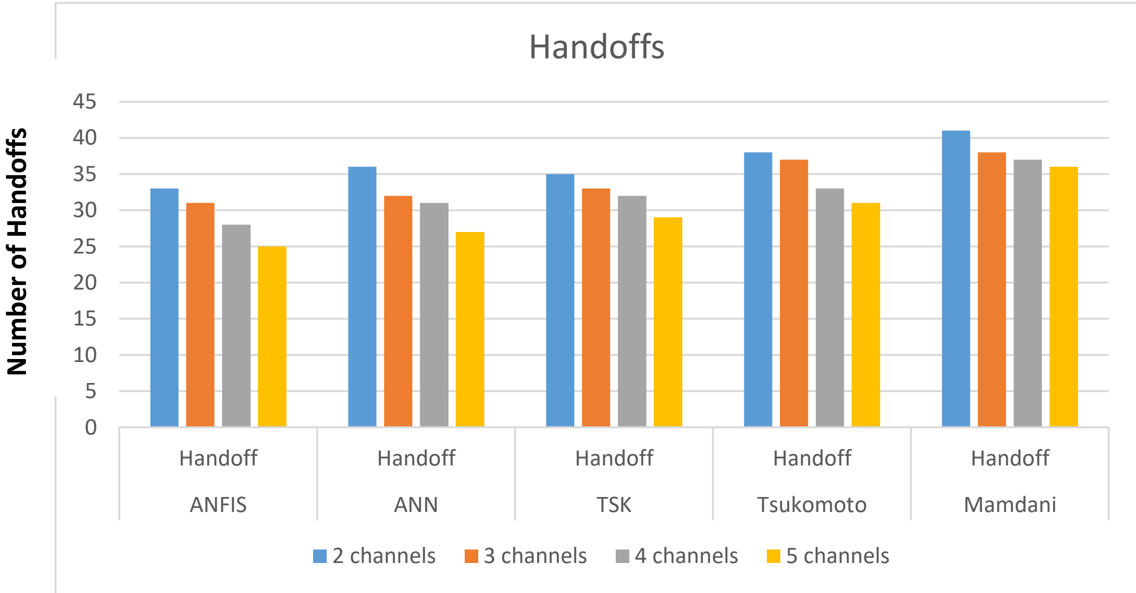


Figure 4.4: Handoff Metric to Different Techniques

4.6.3.3 Delay time

Table (4.6) offers information on the numerical comparison between the five different techniques in the environment of simulation with (2, 3, 4, 5) channels and during 360 seconds for every simulation process. The comparison process is done according to the effect of the number of channels and decision-making technique on the network delay time.

Table (4.6) and Figure (4.5), notes network delay time with ANFIS technique in the CR network is the best method among others. By comparing the results from this table, the ANFIS technique is better than other neural network and fuzzy inference systems techniques in delay time metric for the network. An ANFIS technique achieved the best delay time with (0.63) second with 5 channels.

Table (4.6) Comparison of delay time among different techniques

simulation scenario	Time of Simulation	Decision-making Algorithm	membership function	Number of Channel	Average of Delay time
1	360 S Fuzzy Inference System	Mamdani	GaussMF	**5**	0.79
				4	0.93
				3	1.15
				2	1.36
		Tsukamoto	GaussMF	**5**	0.74
				4	0.89
				3	1.12
				2	1.38
		TSK	GaussMF	**5**	0.69
				4	0.93
				3	1.06
				2	1.29
	Neural Networks	ANN		**5**	0.72
				4	1.08
				3	1.19
				2	1.26
		ANFIS		**5**	0.63
				4	0.91
				3	1.07
				2	1.27

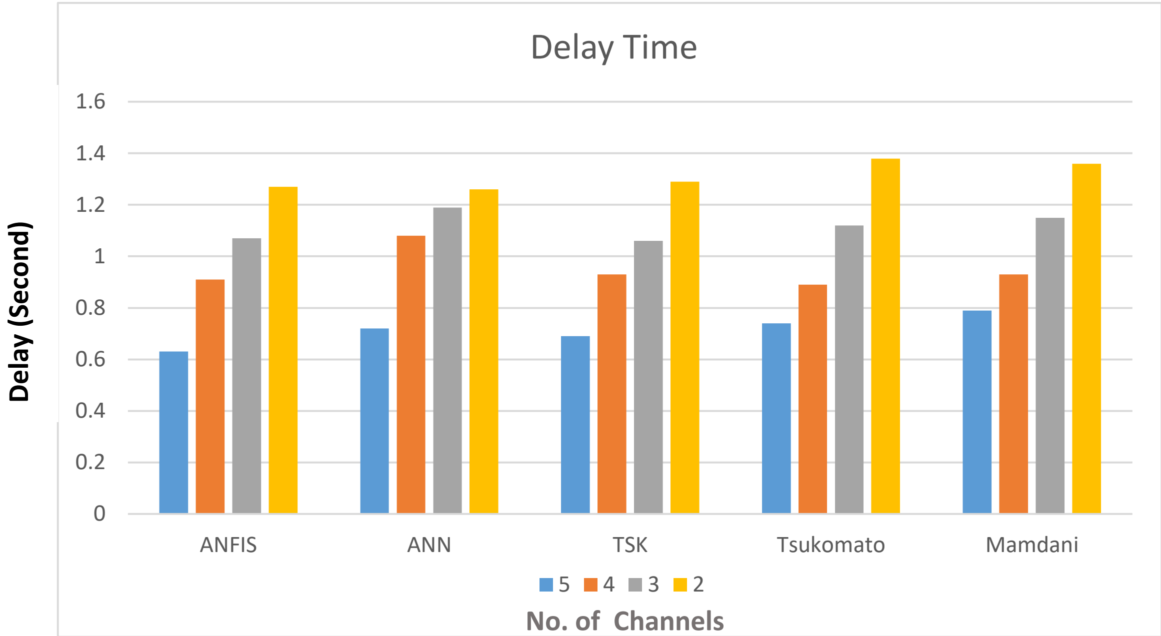


Figure 4.5: Delay Time to Different Techniques

4.6.4 Second Case Study

In the second case study, we will use the same proposed algorithms, and the same metrics of evaluation: throughput, number of handoffs and delay time for searching, selecting and wait time, before starting the data transmission process.

Many experiments to assess the proposed work have been executed by applying different decision-making algorithms. The proposed model was applied in the simulator environment for 360 seconds, in this case; we will use the **second dataset** that represents **the cooperative model**.

4.6.5 Parameters of simulation

A. **SNR:** is a measurement that contrasts the strength of the desired signal with the strength of background noise in science and engineering. SNR is referred to as the signal-to-noise ratio and is frequently stated in dB. More signal than noise is indicated by a ratio greater than 1:1 (more than 0 dB).

B. **Spectrum demand:** It is employed to ascertain the number of secondary users seeking for a specific bandwidth.

C. **RSSI:** measures how well your device can pick up a signal from a network or access point. It's a number that can be used to Figure out whether you have an adequate signal to establish a solid wireless connection. It should be noted that an RSSI value is not the same as transmitting power from a router or AP because it is obtained from the Wi-Fi card of the client device (thus, "received" signal strength).

D. **Idle time:** the amount of time a device is in an operational but unoccupied condition known as idleness.

E. **The weights parameters:** The weights parameters used in this model were: SNR (25%) , Spectrum demand (25%) , RSSI (20%) **,** Idle time (30%).

4.6.6 Evaluation Metrics

To evaluate the proposed algorithms which are used for decision-making, three measures will be used which are throughput, delay time, and handoffs.

4.6.6.1 Throughputs of SUs

Table (4.7) offers information on the numerical comparison between the five different techniques in the environment of simulation with (2, 3, 4, 5) channels and during 360 seconds for every simulation process. The comparison process is done according to the effect of the number of channels and decision-making techniques on the network throughput.

Table (4.7) and Figure 4.6 Notes network throughput for different methods of decision-making. By comparing the results from this table, the ANFIS technique is better than other neural network and fuzzy inference systems techniques in throughput network metrics. An ANFIS technique achieved 2686 Mbit during 360 seconds and use five radio channels in the environment of simulation.

Table (4.7) Comparison of throughput rate among different techniques

simulation scenario	Time of Simulation	Decision-making Algorithm	membership function	Number of Channel	Average Of throughput
1	360 S	Mamdani	GaussMF	2	1679
				3	1836
				4	1983
				5	2183
	Fuzzy Inference System	Tsukamoto	GaussMF	2	1946
				3	2269
				4	2286
				5	2295
		TSK	GaussMF	2	2008
				3	2185
				4	2263
				5	2274
	Neural			2	2145

	Networks	ANN		3	2457
				4	2522
				5	2550
		ANFIS		2	2317
				3	2589
				4	2651
				5	2686

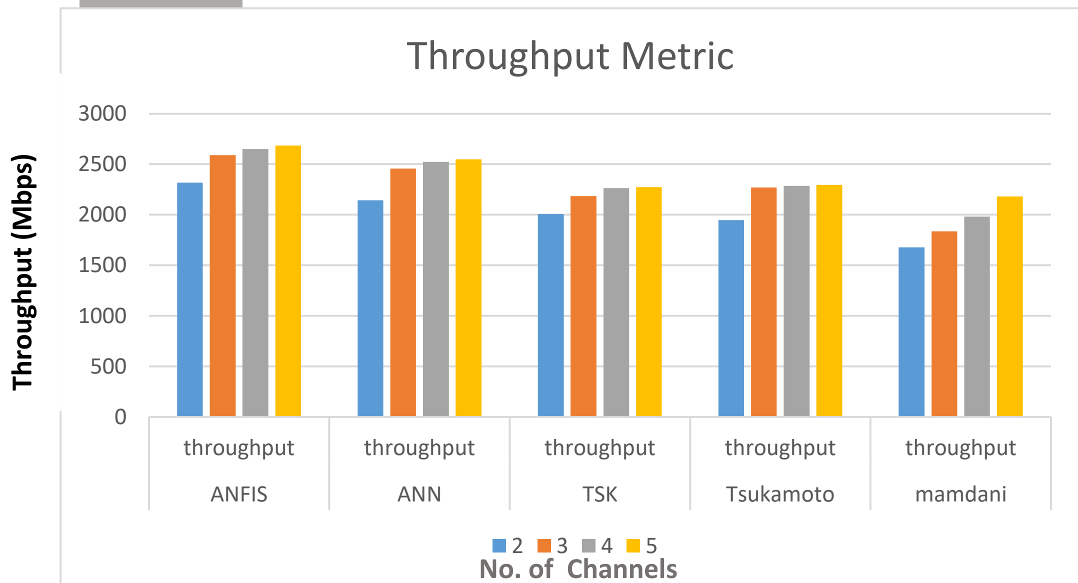


Figure 4.6: throughput to Different Techniques

4.6.6.2 Handoffs

Table (4.8) offers information on the numerical comparison between the five different techniques in the environment of simulation with (2, 3, 4, 5) channels and during 360 seconds for every simulation process. The comparison process is done according to the effect of the number of channels and decision-making technique on the network throughput.

Table (4.8) and Figure 4.3 Notes network handoffs for the different methods of decision-making. By comparing the results from this table, the ANFIS technique is better than other neural network and fuzzy inference systems techniques in the handoffs metric. An ANFIS technique was achieved for 360 seconds in a 1000 M *1000 M area.

Table (4.8): Comparison of Handoff metric to different techniques

simulation scenario	Time of Simulation	Decision-making Algorithm	membership function	Number of Channel	Number Of Handoff
1	360 S	Mamdani	GaussMF	2	34
				3	33
				4	32
				5	31
	Fuzzy Inference System	Tsukamoto	GaussMF	2	31
				3	30
				4	27
				5	26
		TSK	GaussMF	2	28
				3	26
				4	25
				5	22
	Neural Networks	ANN		2	29
				3	26
				4	24
				5	23
		ANFIS		2	26
				3	23
				4	21
				5	20

4.6.6.3 Delay time

Table (4.9) offers information on the numerical comparison

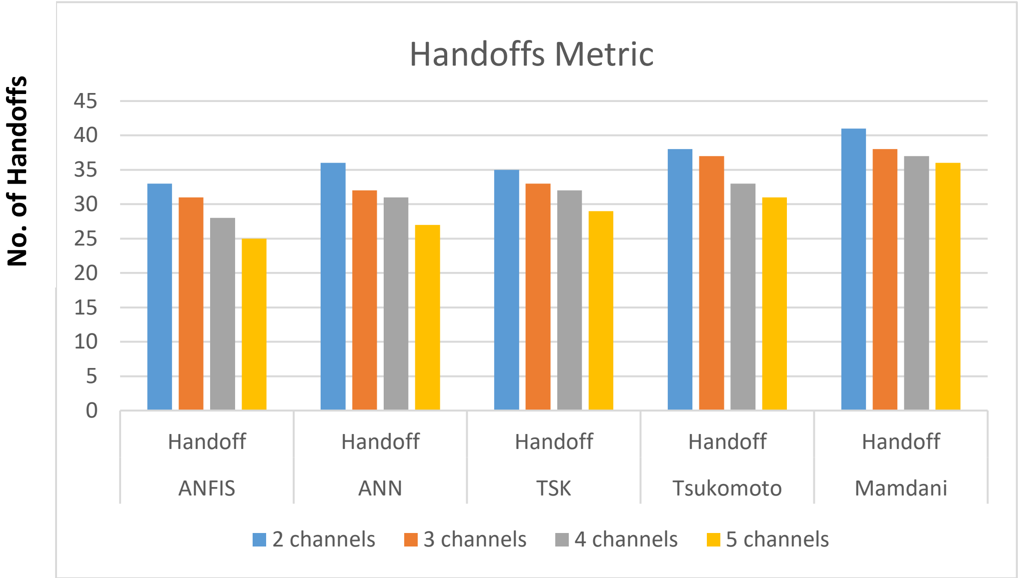


Figure 4.7: Handoff metric to Different Techniques

between the five different techniques in the environment of simulation with (2, 3, 4, 5) channels and during 360 seconds for every simulation process. The comparison process is done according to the effect of the number of channels and decision-making technique for the delay time metric.

Table (4.9) and Figure 4.8 Notes that the delay time for ANFIS technique in the CR network is the best method among others. By comparing the results from this table, the ANFIS technique is better than other neural network and fuzzy inference systems techniques in delay time metric. An ANFIS technique achieved (0.63) seconds with 5 channels for 360 seconds.

Table 4.9: Delay Time Metric for Different Techniques

Simulation scenario	Time of Simulation	Decision-making Algorithm	membership function	Number of Channel	Average of Delay time (Second)
1	360 S	Mamdani	GaussMF	**5**	0.88
				4	1.02
				3	1.06
				2	1.26
	Fuzzy Inference System	Tsukamoto	GaussMF	**5**	0.87
				4	0.95
				3	1.12
				2	1.21
		TSK	GaussMF	**5**	0.69
				4	0.83
				3	1.05
				2	1.19
	Neural Networks	ANN		**5**	0.63
				4	0.88
				3	1.01
				2	1.09
		ANFIS		**5**	0.54
				4	0.76
				3	0.97
				2	1.04

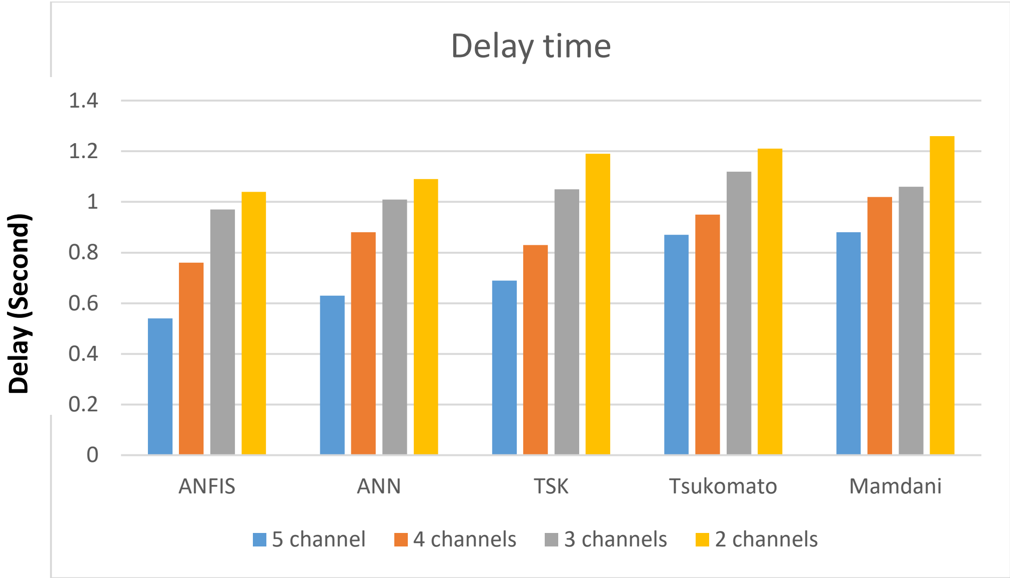


Figure 4.8: Delay Time Metric for Different Techniques

4.7 Performance Analysis

The tables and Figures for displaying the simulation results, which were previously presented for the two sets of parameters, show that the second model (cooperative model) was better for the three measures (throughput of SUs, handoffs, and delay time).

The first metric (throughput of SUs) of the secondary user increases with the increase in the number of available radio channels, due to the increased possibility of having more available channels with the possibility of having a channel with a higher quality of communication, see Figure (4.9).

In Figure (4.9), we notice that the throughput scale increases exponentially with the increase in the number of channels, due to the increased possibility of holes (spectrum unused) in spectral frequencies that can be exploited by secondary users.

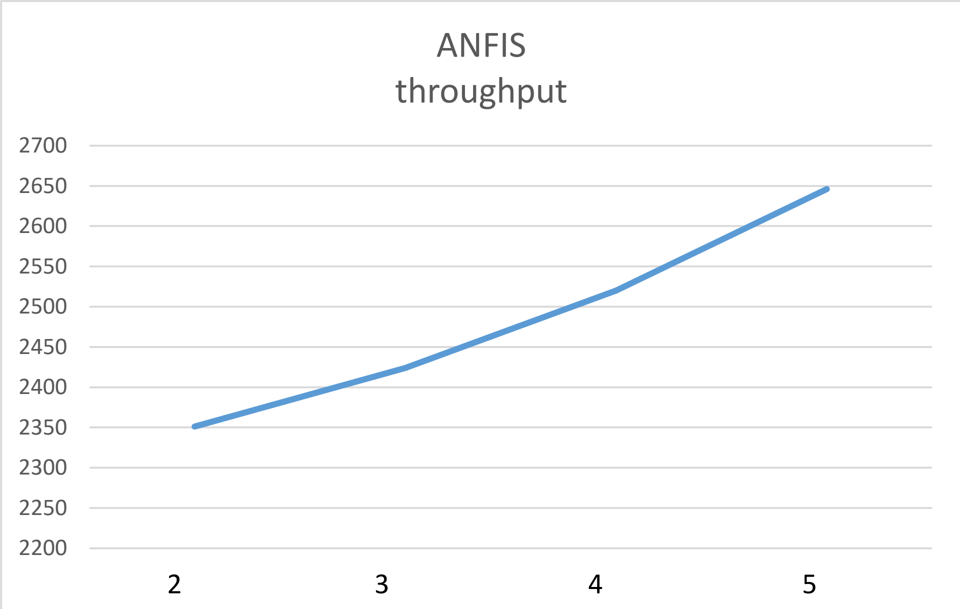


Figure 4.9: throughput curve to ANFIS algorithm

For the handoff metric, it was observed that the number of switching operations (handoff) decreases with the increase in the number of channels that can be sensed, due to the possibility of having channels with long idle periods, see Figure (4.10)

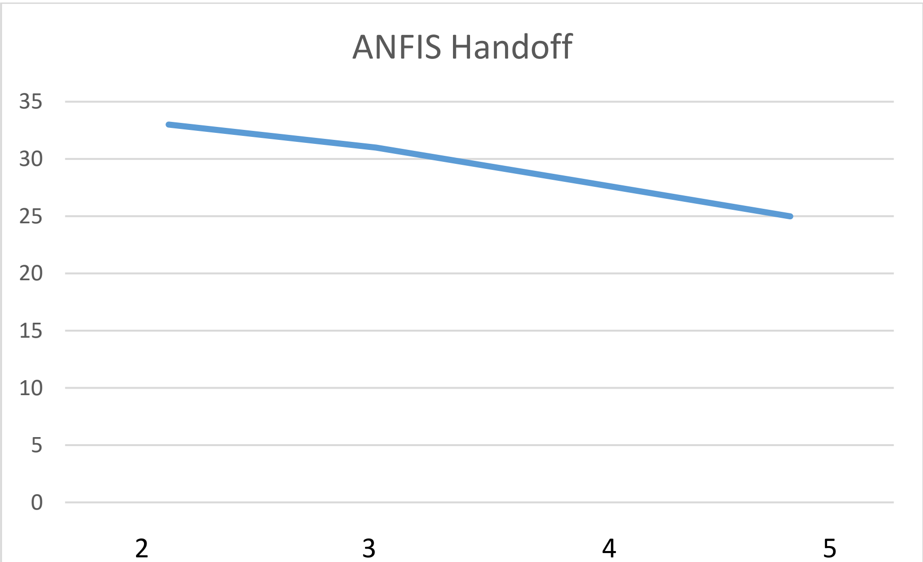


Figure 4.10: Handoff curve to ANFIS algorithm

As for the delay time, which consists of three components (search, selection, and wait time), it was observed that it begins to decrease steadily with the increase in the number of channels in the cognitive network, see Figure (4.11)

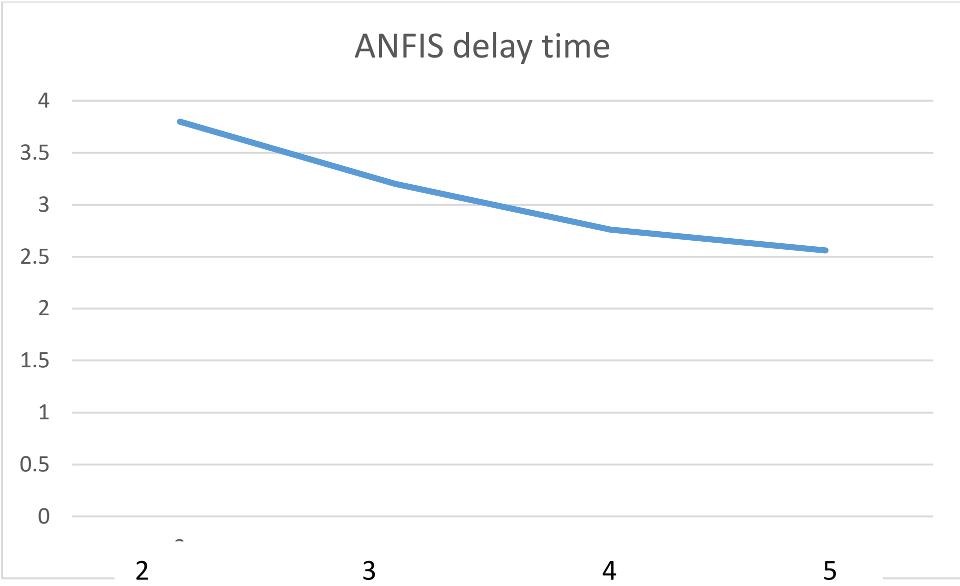


Figure 4.11: Delay time curve to ANFIS algorithm

The reason for this is due to the nature of the cognitive network, where the greater the number of channels in the network, the greater the estimation of having more available channels and a longer transmission period for secondary users, and the number of switches (handoffs) between channels is likely to be less.

4.8 Benchmark Algorithms

The algorithms used in decision-making, which are explained earlier in this chapter, can be compared to a set of benchmark algorithms. Three different types of algorithms were used for comparison (RSN, SNRA, MCCA), Which were explained in Chapter Three, Section (3.6).

4.8.1 Throughput of SUs

Figure (4.12) shows a comparison of the throughput rate results of the cognitive network which consists of several radio channels (2,3,4,5) and uses the decision-making techniques that we explained earlier, in addition to three benchmark algorithms.

The algorithms (MCCA, SNRA) to choose one of the available radio channels are based in the decision-making process on only one parameter (attribute), while the algorithm (RNA) makes the decision randomly.

The simulation results show that the benchmark algorithms performed poorly compared to the algorithms of the fuzzy logic systems and neural network algorithms in the metric of throughput rate.

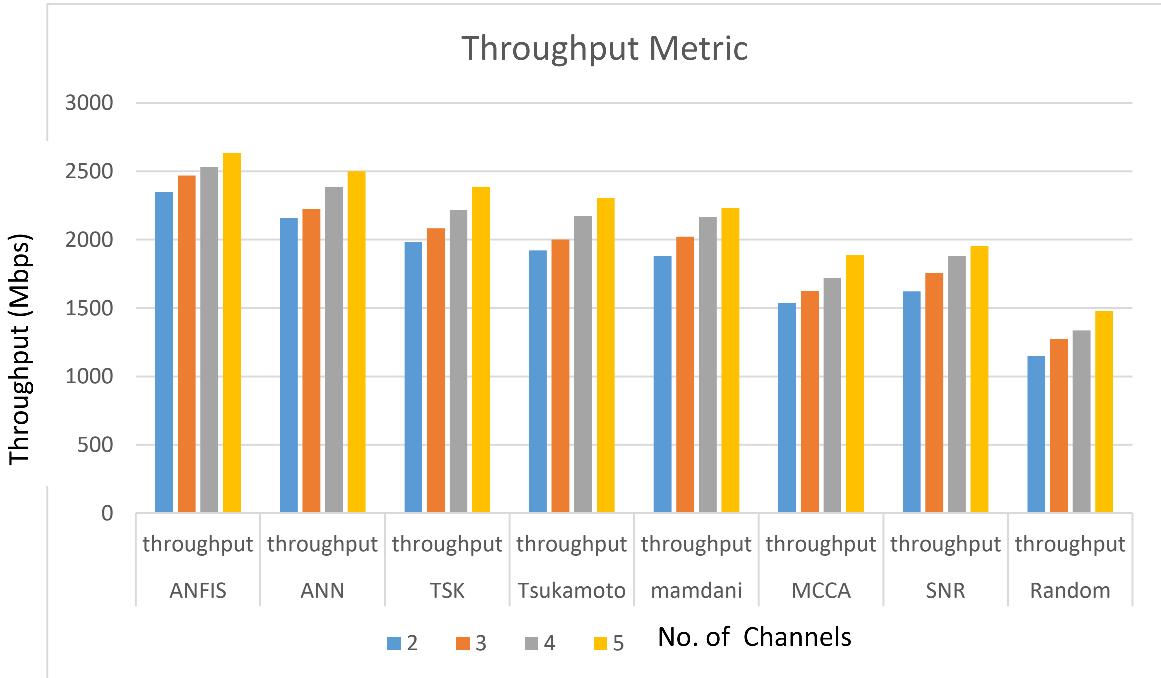


Figure (4.12) Comparison of throughput with benchmark algorithms

4.8.2 Handoffs

The simulation results for the number of switches (handoffs) between radio channels are shown in Figure (4.13).

The results showed that the benchmark algorithm MCCA achieved the least number of switches, followed by ANFIS.

This is because MCCA algorithm selects channels with the longest idle period, so switching operations are low compared to the rest of the algorithms.

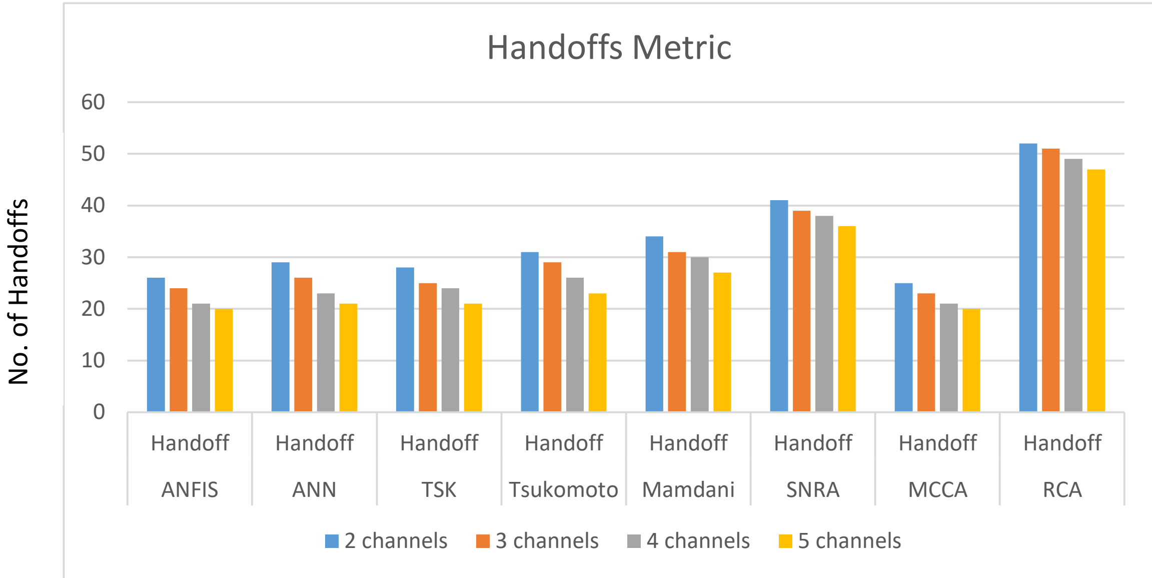


Figure (4.13): Comparison of Handoff among different techniques

4.8.3 Delay time

The simulation results for the delay time for searching and selecting between radio channels are shown in Figure (4.14).

The results showed that the benchmark algorithm MCCA achieved the least delay time, followed by algorithm RCA

This is because MCCA algorithm performs fewer switching operations and less selection time compared to other algorithms.

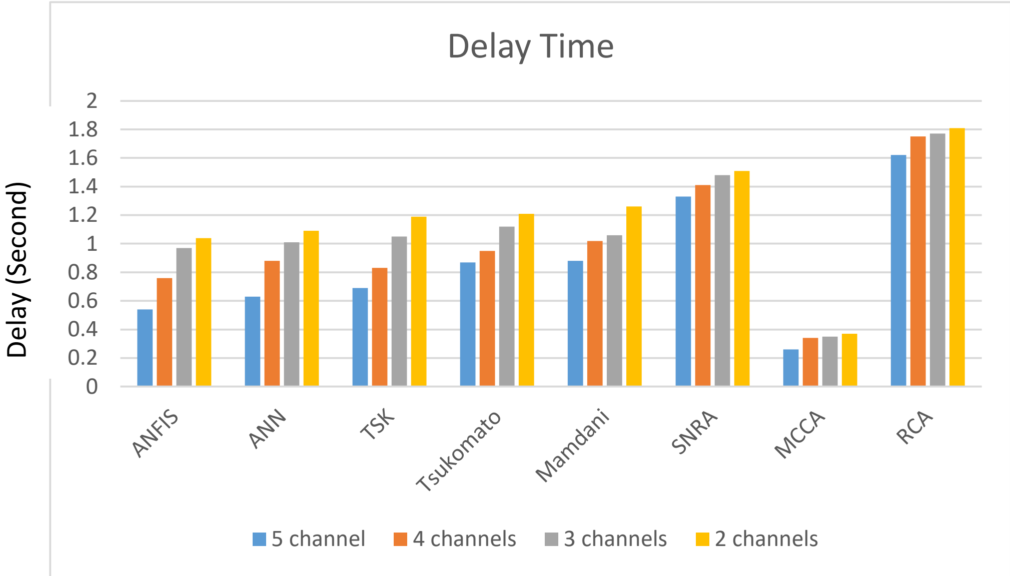


Figure (4.14) Comparison of delay time among different techniques

4.9 Other Experimental

4.9.1 A Different Number of Radio Channels.

In this study, the effect of increasing the number of radio channels on the throughput of the cognitive network, Figure (4.15) shows a comparison between the different decision-making methods for a different number of available radio channels, where the number of different channels is used in ascending order (2, 3, 4, 5, 6,7,8,9,10). The minimum number of channels was 2, and the largest number of channels was 10.

As it becomes clear from the results, the network throughput begins to rise with the increase in the number of available radio channels, as there is a greater possibility of finding channels available for a longer period and in a larger number. This leads to increased network throughput, as there are fewer transfers between channels and also less waiting time to find a new or available network. It was also noted that the throughput of most methods begins with stability, and the increase becomes small compared to the increase in the number of available channels.

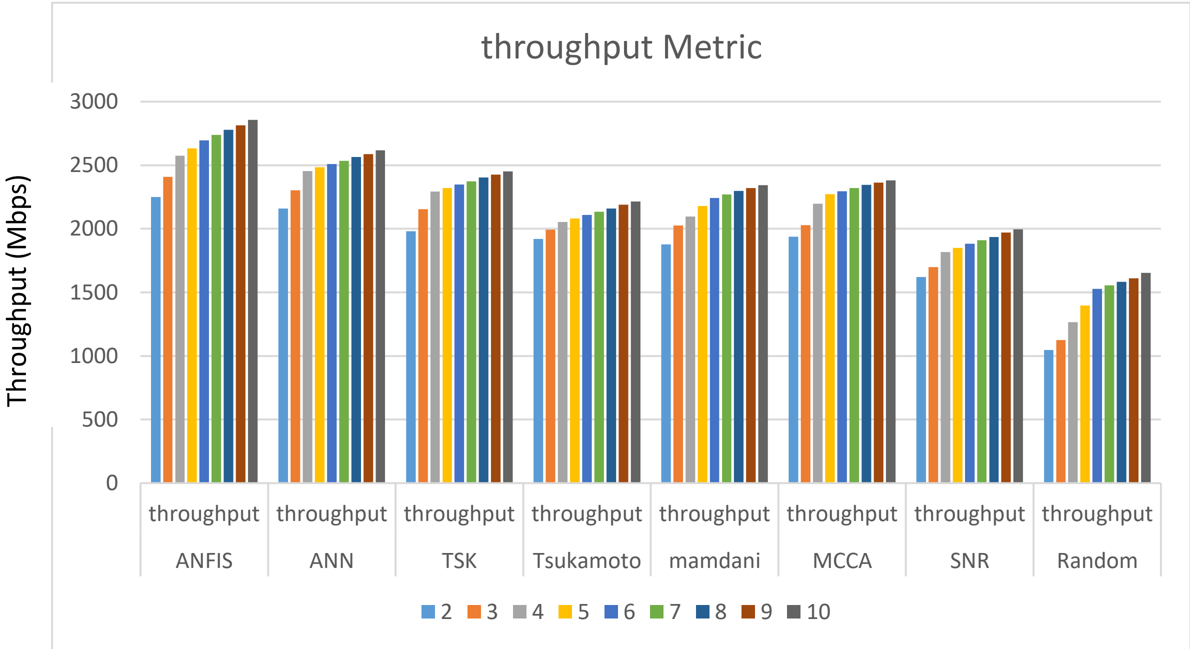


Figure (4.15) Comparison of throughput among different techniques

4.9.2 A Different Number of SUs.

To study the effect of using a different number of secondary users on the throughput of the cognitive network, we will design a cognitive network based on the central model.

The proposed cognitive network consists of a fusion center, where all secondary users submit requests for spectral frequency access to this center.

The Fusion Center will determine the available spectral channels (idle channels) and assign them to secondary users according to the principle of queuing, as the first arrivals will serve before others.

The throughput in this system (central model) is calculated through the throughput rate (average) for all secondary users, as it represents the throughput of the cognitive network and not individual secondary user throughput.

The cognitive network that we will use consists of five channels with a fusion center and the number of secondary users consists of (2,3,4,5,6,7,8,9,10).

Figure (4.16) shows a comparison between the different decision-making methods with the use of a different number of secondary users.

The simulation results have shown that the throughput of the cognitive network decreases with the increase in the number of secondary users in the network for all the methods used.

Analyzing the reason for these results, it can be said that the increase in the number of secondary users with the constant number of channels in the network, will lead to increased competition in obtaining available resources (available radio channels), and as a result, the more secondary users there are, the more time is required to wait in the queue to access spectral channels by assigning available channels to secondary users by FusionCenter.

Thus, the throughput of all secondary users will decrease, and the delay time to find an available channel and switch to it, and then use this channel for transmission, will increase.

It was also noted that the fuzzy logic algorithms improved their performance by increasing the number of users compared to the ANNs algorithm.

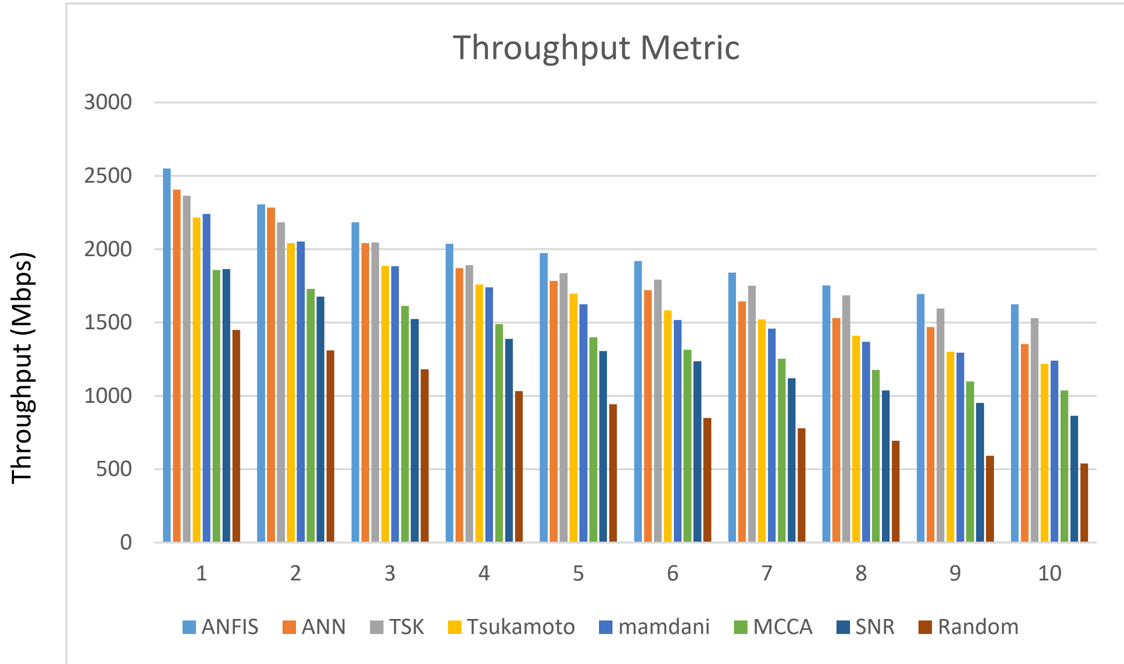


Figure (4.16) Comparison of throughput for all techniques with different number of SUs

4.9.3 Comparison the Results

A comparison with other related models should be made to evaluate our proposed model. In this dissertation, the model described in [19] is used for comparison.

The paper [19] propose scheme of fuzzy logic-based decision support system (FLB-DSS) that jointly deals with channel selection and channel switching to enhance the overall throughput of CRNs.

The evaluation measures throughput, handoffs and delay time are used to compare the two models.

Tables 4.10, 4.11, 4.12, 4.13 and 4.14 present a comparison of the scheme in [19], compared with the results obtained from the proposed system for ANFIS algorithm.

Table 4.10: Number of handoffs for proposed ANFIS algo. vs. the scheme in [21].

	No. of channels	No. of Handoffs	Properties of simulation
Scheme in [19]	5	10	Time : 50 (Sec) No. of SUs: 10.
Proposed ANFIS Algo.	5	8	

Table 4.11: Throughput for the proposed ANFIS algo. vs. the scheme in [21]. Throughput under varying number of licensed channels.

`	No. of SUs	Throughput (Mbit)	Properties of simulation
Scheme in [19]	30	2250	Time : 50 (Sec)
Proposed ANFIS Algo.	30	2306	

Table 4.12: Throughput for the proposed ANFIS algo. vs. the scheme in [21]. Throughput under varying number of SUs.

	No. of channels	Throughput (Mbit)	Properties of simulation
Scheme in [19]	5	600	Time : 50 (sec)
Proposed ANFIS Algo.	5	1624	

Table 4.13: Time consumed for channel selection in the proposed ANFIS algo. vs. the scheme in [21]. Time consumed in channel selection under varying transmission times.

	Time of simulation	Delay time (sec)	Properties of simulation
Scheme in [19]	125	8	No. of SUs: 10 No. of PUs: 5
Proposed ANFIS Algo.	125	4.3	

Table 4.14: Time consumed for channel selection in the proposed vs. the conventional scheme. Time consumed in channel selection under varying number of licensed channels.

	No. of channels	**Delay of time (sec)**	**Properties of simulation**
Scheme in [19]	5	7	Time: 50 (sec) No .of SUs: …
Proposed ANFIS Algo.	5	2.6	

The comparison between the scheme in [19] and the proposed algorithm in the tables (4.10,11,12,13 and 14) shows that the proposed algorithm has an advantage in some of the measures used (throughput, handoffs and delay time).

Chapter Five

Conclusion and Suggestions for future works

5.1 Conclusions

This dissertation introduces an approach to decision-making-based-different techniques to enhance the channel selection of CRNs. This dissertation focused on selecting the suitable available channels with a CRNs environment. Also, this dissertation focused on channel selection and compared two spectrum sensing models (cooperative, and non-cooperative).

Matlab code is used for simulating the proposed approach and comparing the results between FIS algorithms, Neural networks, and benchmark algorithms with data transmitters throughput, Handoffs, and delay time terms, and the improvement channel selection in CRNs. All results show that the network performance of the proposed approach can be enhancing the efficiency of the decision-making of the cognitive radio network. Several conclusions have been found through the development and implementation of the proposed approach:

1. The number of parameters and the nature of these parameters play an important role in improving the decision-making process in choosing the best channels.
2. In this work, many decision-making techniques were implemented to select the best channel for secondary users in cognitive radio networks, where the fuzzy neural network (ANFIS) algorithm has proven its superiority over the rest of the fuzzy inference systems (FIS) and also the artificial neural network (ANN) algorithm in the metrics of throughput and handoffs between channels.
3. The power of signal and signal-to-noise ratio attributes in radio channels represent important attributes that help in decision-making for channel value (important).

4. The cooperative sensing model showed better results compared to the non-cooperative model, as it helped improve the performance and productivity of the cognitive radio network.
5. Other radio channel attributes (bandwidth, distance, spectrum demand, and idle time) are used to improve available channel selection.
6. Three methods of fuzzy inference system were used, where fuzzy rules were used for the selected parameters, and two sets of fuzzy rules were created, one for each set of parameters.
7. The present approach has improved the selection of radio channels by using different techniques of decision making, Where the (ANFIS) algorithm showed a remarkable superiority over the rest of the techniques.
8. Thus, the cooperation model helps to enhance the cognitive radio network and adds more information that allows secondary users (SUs), to find the best channel selection from the range of available channels.

5.2 Future Works

For future works, some suggestions can be viewed as follows:

1. The proposed approach can apply to real radio channel datasets like 4G LTE or 5G that have different characteristics.
2. A hybrid approach of interweaving and underlay can be used to improve the performance of the CRNs.
3. Experiment with different sets of parameters for radio channels, and analyze the results obtained.
4. Different scenarios of the cognitive radio network can be tested, and the performance results of these different scenarios can be analyzed.
5. The parameters (attributes) selected (extraction) from channel state information (CSI) in this dissertation will be manually, and it can be developed into the dynamic in future works.
6. Work on developing fuzzy logic algorithms, by developing the inputs of these algorithms and also developing fuzzy logic rules, to improve their ability to make decisions with more accuracy.
7. Using different types of neural network algorithms such as long-term memory (LTM) neural networks to improve the ability of cognitive radio networks to make decisions and choose the best radio channels with a minimum of time and memory to up to date of channel information.
8. Using a different set of weight combinations for the parameters used in making the decision, and then comparing them to find the best combination of weights.

REFERENCES

References

[1] M. M. Mabrook, H. A. Taha, and A. I. Hussein, "Cooperative spectrum sensing optimization based adaptive neuro-fuzzy inference system (ANFIS) in cognitive radio networks," *J. Ambient Intell. Humaniz. Comput.*, no. 0123456789, 2020, doi: 10.1007/s12652-020-02121-9.

[2] L. YC, *Dynamic Spectrum Management*. Springer, Singapore, 2020.

[3] W. Wang, "Spectrum Sensing for Cognitive Radio," pp. 10–12, 2009, doi: 10.1109/IITAW.2009.49.

[4] H. Tang and S. Watson, "Cognitive radio networks for tactical wireless communications," 2014. [Online]. Available: https://publications.gc.ca/collections/collection_2015/rddc-drdc/D68-2-185-2014-eng.pdf.

[5] H. Tang and S. Watson, "Cognitive radio networks for tactical wireless communications," no. December, 2014.

[6] W. Jouini, C. Moy, and J. Palicot, "Decision making for cognitive radio equipment: Analysis of the first 10 years of exploration," *Eurasip J. Wirel. Commun. Netw.*, vol. 2012, pp. 1–16, 2012, doi: 10.1186/1687-1499-2012-26.

[7] A. Kaur, P. Aryan, and G. Singh, "Cognitive Radio , Its Applications and Architecture," vol. 4, no. 11, pp. 98–102, 2015.

[8] K. S. Y. N. Trivedi, "Spectrum Sensing Techniques Based on Last Status Change Point Estimation for Dynamic Primary User in Additive Laplacian Noise," *Wirel. Pers. Commun.*, no. 0123456789, 2021, doi: 10.1007/s11277-021-08984-1.

[9] S. Nandakumar, T. Velmurugan, and U. Thiagarajan, "Efficient Spectrum Management Techniques for Cognitive Radio Networks for Proximity Service," *IEEE Access*, vol. 7, pp. 43795–43805, 2019, doi: 10.1109/ACCESS.2019.2906469.

[10] A. Musa, H. Bany, R. Halloush, and K. A. Darabkh, "Spectrum management

with simultaneous power-controlled assignment decisions in cognitive radio networks," no. November 2018, pp. 1–10, 2019, doi: 10.1002/cpe.5224.

[11] J. Zou, L. Huang, X. Gao, and H. Xiong, "Joint Pricing and Decision-Making for Heterogeneous User Demand in Cognitive Radio Networks," *IEEE Trans. Cybern.*, vol. 49, no. 11, pp. 3873–3886, 2019, doi: 10.1109/TCYB.2018.2851620.

[12] D. Giral, C. Hernández, and E. Rodríguez-Colina, "Spectrum decision-making in collaborative cognitive radio networks," *Appl. Sci.*, vol. 10, no. 19, 2020, doi: 10.3390/app10196786.

[13] M. S. Gupta and K. Kumar, "Application aware networks ' resource selection decision making technique using group mobility in vehicular cognitive radio networks," *Veh. Commun.*, vol. 26, p. 100263, 2020, doi: 10.1016/j.vehcom.2020.100263.

[14] Y. Teekaraman, H. Manoharan, A. R. Basha, and A. Manoharan, "Hybrid Optimization Algorithms for Resource Allocation in Heterogeneous Cognitive Radio Networks," *Neural Process. Lett.*, 2020, doi: 10.1007/s11063-020-10255-2.

[15] S. Jang, C. Han, K. Lee, and S. Yoo, "Reinforcement learning-based dynamic band and channel selection in cognitive radio ad-hoc networks," pp. 1–25, 2019.

[16] J. Ma, T. Nagatsuma, S. Kim, and M. Hasegawa, "A Machine-Learning-Based Channel Assignment Algorithm for IoT," *2019 Int. Conf. Artif. Intell. Inf. Commun.*, pp. 1–6, 2019.

[17] R. Saifan, A. M. Msaeed, and K. A. Darabkh, "Probabilistic and deterministic path selection in cognitive radio network," *IET Commun.*, vol. 13, no. 17, pp. 2767–2777, 2019, doi: 10.1049/iet-com.2019.0748.

[18] V. Zuniga, L. Camunas-Mesa, B. Linares-Barranco, T. Serrano-Gotarredona,

and J. M. De La Rosa, “Using neural networks for optimum band selection in cognitive-radio systems,” *ICECS 2020 - 27th IEEE Int. Conf. Electron. Circuits Syst. Proc.*, pp. 0–3, 2020, doi: 10.1109/ICECS49266.2020.9294894.

[19] A. Ali *et al.*, “Hybrid Fuzzy Logic Scheme for Efficient Channel Utilization in Cognitive Radio Networks,” *IEEE Access*, vol. 7, pp. 24463–24476, 2019, doi: 10.1109/ACCESS.2019.2900233.

[20] D. Daši´c, N. Ili´, M. S. Stankovi´, M. Vuˇceti´, and M. B. Miroslav Peri´c 1, “Distributed Spectrum Management in Cognitive Radio,” no. Cm, pp. 1–20, 2021.

[21] F. Javaid, A. Wang, M. Usman, H. Zameer, and I. Ashraf, “A dual channel and node mobility based cognitive approach to optimize wireless networks in coal mines,” *J. King Saud Univ. - Comput. Inf. Sci.*, vol. 34, no. 4, pp. 1486–1497, 2022, doi: 10.1016/j.jksuci.2022.02.016.

[22] A. KACHROO, “STATISTICAL ANALYSIS AND CHANNEL MODELING IN NEXT,” 2021, [Online]. Available: https://hdl.handle.net/11244/330827.

[23] C. T. C. Trapp and D. K. Kanbach, “Green entrepreneurship and business models : Deriving green technology business model archetypes,” *J. Clean. Prod.*, vol. 297, p. 126694, 2021, doi: 10.1016/j.jclepro.2021.126694.

[24] M. Ranasinghe and M. N. Halgamuge, “Review: Effective Solutions for Challenges in Cognitive Radio Networks,” no. January, 2019, doi: 10.4018/978-1-5225-7458-3.ch005.

[25] A. Popescu, “Cognitive radio networks,” *Cogn. Radio Networks*, pp. 1–6, 2012, doi: 10.1145/2479957.2479965.

[26] J. Mitola and G. Q. Maguire, “Cognitive radio: making software radios more personal,” *IEEE Pers. Commun.*, vol. 6, no. 4, pp. 13–18, 1999, doi: 10.1109/98.788210.

[27] P. Sandeep, “A Comparative Analysis of Optimization Techniques in Cognitive Radio (QoS),” *Int. J. Eng. Adv. Technol.*, vol. 6, no. 3, pp. 97–102,

2017.

[28] A. G. Fragkiadakis, E. Z. Tragos, and I. G. Askoxylakis, “A survey on security threats and detection techniques in cognitive radio networks,” *IEEE Commun. Surv. Tutorials*, vol. 15, no. 1, pp. 428–445, 2013, doi: 10.1109/SURV.2011.122211.00162.

[29] A. U. Makarfi, R. Kharel, K. M. Rabie, O. Kaiwartya, X. Li, and D. T. Do, “Reconfigurable intelligent surfaces based cognitive radio networks,” *2021 IEEE Wirel. Commun. Netw. Conf. Work. WCNCW 2021*, 2021, doi: 10.1109/WCNCW49093.2021.9419976.

[30] Z. Wei, S. Member, and Z. Feng, “Three Regions for Space – Time Spectrum Sensing and Access in Cognitive Radio Networks,” vol. 64, no. 6, pp. 2448–2462, 2015.

[31] B. J. Hamza and W. K. Saad, “Improving Spectrum Sensing Under Impact of Noise Uncertainty Factor to Detect Primary User Traffic for Cognitive Radio System Improving Spectrum Sensing Under Impact of Noise Uncertainty Factor to Detect Primary User Traffic for Cognitive Radio System,” no. February, 2021, doi: 10.1088/1742-6596/1804/1/012002.

[32] S. S. Oyewobi, K. Djouani, and A. M. Kurien, “A review of industrial wireless communications, challenges, and solutions: A cognitive radio approach,” *Trans. Emerg. Telecommun. Technol.*, vol. 31, no. 9, pp. 1–26, 2020, doi: 10.1002/ett.4055.

[33] I. F. Akyildiz, W. Y. Lee, M. C. Vuran, and S. Mohanty, “NeXt generation/dynamic spectrum access/cognitive radio wireless networks: A survey,” *Comput. Networks*, vol. 50, no. 13, pp. 2127–2159, 2006, doi: 10.1016/j.comnet.2006.05.001.

[34] W. Zhang, *Handbook of cognitive radio*, vol. 1–3. Springer Nature Singapore, 2019.

[35] G. Singh, Shweta Pandit, *Spectrum Sharing in Cognitive Radio Networks: A*

Survey, vol. 40, no. June. 2012.

[36] F. R. Yu, *Cognitive Radio Mobile Ad Hoc Networks*, Springer. New York , Dordrecht: Springer New York Dordrecht, 2011.

[37] K. Du, P. Wan, Y. Wang, X. Ai, and H. Chen, "Spectrum sensing method based on information geometry and deep neural network," *Entropy*, vol. 22, no. 1, p. 94, 2020, doi: 10.3390/e22010094.

[38] P. J. Smith, R. Senanayake, P. A. Dmochowski, and J. S. Evans, "Distributed spectrum sensing for cognitive radio networks based on the sphericity test," *IEEE Trans. Commun.*, vol. 67, no. 3, pp. 1831–1844, 2019, doi: 10.1109/TCOMM.2018.2880902.

[39] G. Kakkavas, K. Tsitseklis, V. Karyotis, and S. Papavassiliou, "A Software Defined Radio Cross-Layer Resource Allocation Approach for Cognitive Radio Networks: From Theory to Practice," *IEEE Trans. Cogn. Commun. Netw.*, vol. 6, no. 2, pp. 740–755, 2020, doi: 10.1109/TCCN.2019.2963869.

[40] G. Caso, M. T. P. Le, L. De Nardis, and M. Di Benedetto, "Handbook of Cognitive Radio," *Handb. Cogn. Radio*, no. May, 2017, doi: 10.1007/978-981-10-1389-8.

[41] M. T. Masonta, M. Mzyece, and N. Ntlatlapa, "Spectrum decision in cognitive radio networks: A survey," *IEEE Commun. Surv. Tutorials*, vol. 15, no. 3, pp. 1088–1107, 2013, doi: 10.1109/SURV.2012.111412.00160.

[42] R. Aguilar-gonzalez and V. Ramos, "Spectrum Decision Mechanisms in Cognitive Radio Networks," *Emerg. Wirel. Commun. Netw. Technol.*, pp. 271–296, 2018, doi: 10.1007/978-981-13-0396-8.

[43] I. Christian, S. Moh, I. Chung, and J. Lee, "Spectrum mobility in cognitive radio networks," *IEEE Commun. Mag.*, vol. 50, no. 6, pp. 114–121, 2012, doi: 10.1109/MCOM.2012.6211495.

[44] C. Sudhamani and M. Satya Sai Ram, "Energy Efficiency in Cognitive Radio Network Using Cooperative Spectrum Sensing," *Wirel. Pers. Commun.*, vol.

104, no. 3, pp. 907–919, 2019, doi: 10.1007/s11277-018-6059-9.

[45] A. Thakur and R. Kumar, "A Review on Spectrum Mobility for Cognitive Radio Networks," vol. 4, no. 5, 2015.

[46] P. S. Yawada and M. T. Dong, "Intelligent Process of Spectrum Handoff/Mobility in Cognitive Radio Networks," vol. 2019, no. Article ID 7692630, p. 12, 2019, doi: s https://doi.org/10.1155/2019/7692630.

[47] J. J. Priyangu Shaya Sarmah, "Dynamic Spectrum Access for Cognitive Radio Networks," *Int. J. Sci. Eng. Technol. Res.*, vol. 4, no. 6, 2015, [Online]. Available: http://docplayer.net/29045402-Dynamic-spectrum-access-for-cognitive-radio-networks.html.

[48] S. Kandeepan, G. Baldini, and R. Piesiewicz, "UWB Cognitive Radios," in *Novel Applications of the UWB Technologies*, no. June 2014, 2011, pp. 211–236.

[49] M. J. Shilpa Merin Babya, "A Comparative Study on Various Spectrum Sharing Techniques," *Procedia Technol.*, vol. 25, no. Raerest, pp. 613–620, 2016, doi: 10.1016/j.protcy.2016.08.152.

[50] A. Goldsmith, S. A. Jafar, I. Maric and S. Srinivasa, "Breaking Spectrum Gridlock With Cognitive Radios: An Information Theoretic Perspective," *Proc. IEEE, vol. 97, no. 5, pp. 894-914*, vol. 97, no. 5, pp. 894–914, 2009.

[51] A. A. Khan, S. M. I. Rahman, and M. Ahmed, "Research Challenges of Cognitive Radio," vol. 1, no. 3, pp. 1–4, 2012.

[52] S. Lacheta and G. Tiwari, "Challenges and Opportunities of Cognitive Radio Networks," vol. 63, no. 163, pp. 26–28, 2019.

[53] V. T. Nguyen, F. Villain, and Y. Le Guillou, "Cognitive Radio RF : Overview and Challenges," vol. 2012, 2012, doi: 10.1155/2012/716476.

[54] B. B. A Dalvi, P Swamy, Meshram, "Challenges of Spectrum Sensing Techniques for Cognitive Radio," *Icwet 2011*, vol. February 2, pp. 972–973, 2011.

[55] B. A. Attar, H. Tang, A. V Vasilakos, F. R. Yu, and V. C. M. Leung, "A Survey of Security Challenges in Cognitive Radio Networks : Solutions and Future Research Directions," vol. 100, no. 12, 2012.

[56] A. Umbert, O. Sallent, J. Pérez-Romero, J. Sánchez-González, D. Collins, and M. Kist, "An experimental assessment of channel selection in cognitive radio networks," *IFIP Adv. Inf. Commun. Technol.*, vol. 520, pp. 78–88, 2018, doi: 10.1007/978-3-319-92016-0_8.

[57] A. Borany, "Decision-making approach in Cognitive Radio using Tsukamoto and Mamdani FIS," vol. 2021, no. Bicits, pp. 144–148, 2021.

[58] W. Jouini, C. Moy, and J. Palicot, "On decision making for dynamic configuration adaptation problem in cognitive radio equipments : a multi-armed bandit based," no. June 2014, 2010.

[59] A. Alkhayyat, F. Abedi, A. Bagwari, P. Joshi, H. M. Jawad, and S. N. Mahmood, "Fuzzy logic , genetic algorithms , and artificial neural networks applied to cognitive radio networks : A review," vol. 18, no. 7, 2022, doi: 10.1177/15501329221113508.

[60] W. Pedrycz, *Fuzzy Control and Fuzzy Systems*. Research Studies Press Ltd.24 Belvedere Road Taunton, Somerset TA1 1HDUnited Kingdom, 1993.

[61] A. J. Eradus, W.J., Scholten, H., Udink ten Cate, "An optimized fuzzy inference system for oestrus detection in dairy cattle," *1st Int. Symp. Neuro-Fuzzy Syst. '96. Conf. Rep.*, 1996, doi: 10.1109/ISNFS.1996.603835.

[62] K. Hwang *et al.*, "An Autonomous Coil Alignment System for the Dynamic Wireless Charging of Electric Vehicles to Minimize Lateral Misalignment," 2017, doi: 10.3390/en10030315.

[63] L. O. Batista *et al.*, "Fuzzy neural networks to create an expert system for detecting attacks by SQL Injection .," pp. 8–21, 2018, doi: 10.5769/J201801001.

[64] Abbas Daftari, "New Approach in Prediction of Soil Liquefaction," 2015.

[65] J. Chen, Q. H. Do, T. V. A. Nguyen, T. Thanh, and H. Doan, "Forecasting Monthly Electricity Demands by Wavelet Neuro-Fuzzy System Optimized by Heuristic Algorithms," 2018, doi: 10.3390/info9030051.

[66] E. Biglieri, A. J. Goldsmith, L. J. Greenstein, N. Mandayam, and H. V. Poor, *Principles of Cognitive Radio*. Cambridge University Press, 2013.

[67] J. Lundén, V. Koivunen, and and H. V. Poor, "Spectrum Exploration and Exploitation for Cognitive Radio," no. April, pp. 123–140, 2015.

[68] Y. Chen, Y. Ge, Z. Song, and M. Lv, "Decision-Making Optimization of TMT : A Simulated Annealing Algorithm Analysis," vol. 2010, no. September, pp. 363–368, 2010, doi: 10.4236/jssm.2010.33042.

[69] G. Mazzuto and C. Stylios, "Empower Fuzzy Cognitive Maps Decision Making abilities with Swarm Intelligence Algorithms," *2019 IEEE Int. Conf. Syst. Man Cybern.*, pp. 2602–2607, 2019.

[70] N. Colson, A. Kountouris, A. Wautier, and L. Husson, "Cognitive Decision Making Process Supervising the Radio Dynamic Reconfiguration," *IEEE Xplore*, doi: 10.1109/CROWNCOM.2008.4562503.

[71] P. Pourbaba, S. Ali, K. B. S. Manosha, and N. Rajatheva, "Multi-Armed Bandit Learning for Full-Duplex UAV Relay Positioning for Vehicular Communications," no. August, 2019, doi: 10.1109/ISWCS.2019.8877122.

[72] P. Sharma, "Basic Introduction to Convolutional Neural Network in Deep Learning," *Analytics Vidhya*, 2022. https://www.analyticsvidhya.com/blog/2022/03/basic-introduction-to-convolutional-neural-network-in-deep-learning/.

[73] Hung Tien Le and Thoi Trung Nguyen, "ANFIS for building cooling load estimation," *AIP Conf. Proc. 2420, 020015*, vol. 2420, 2021.

[74] M. Laciak and J. Kaˇ, "Comparison of Different Approaches to the Creation of a Mathematical Model of Melt Temperature in an LD Converter," 2022.

[75] B. J. Mitola, "Architecture Evolution," vol. 97, no. 4, 2009.

[76] M. López-benítez, *Overview of Recent Applications of Cognitive Radio in Wireless Communication Systems*, Handbook o. Springer Nature Singapore., 2018.

[77] R. T. and A. Akkerman, “Machine Learning,” *Encycl. ofSocial Netw. Anal. Min.*, pp. 846–1023, 2014, doi: 10.1007/978-1-4614-6170-8.

[78] M. D. Mueck, S. Srikanteswara, and B. Badic, “Spectrum Sharing : Licensed Shared Access (LSA) and Spectrum Access System (SAS),” *white Pap.*, p. 26, 2015, [Online]. Available: https://www.intel.com/content/dam/www/public/us/en/documents/white-papers/spectrum-sharing-lsa-sas-paper.pdf.

[79] X. Zhang and W. Wang, “Carrier Aggregation for LTE-Advanced Mobile Communication Systems,” no. January 2015, 2010, doi: 10.1109/MCOM.2010.5402669.

[80] J. Zhang, M. Wang, M. Hua, T. Xia, W. Yang, and X. You, “LTE on License-Exempt Spectrum,” *IEEE Commun. Surv. Tutorials*, vol. 20, no. 1, pp. 647–673, 2018, doi: 10.1109/COMST.2017.2771485.

[81] S. Thalanany, M. Irizarry, and N. Saxena, “License-Assisted Access Considerations,” no. June, pp. 106–112, 2017.

[82] H. E. Kwon *et al.*, “Licensed-Assisted Access to Unlicensed Spectrum in LTE Release 13,” vol. 2016, 2016.

[83] M. Labib, V. Marojevic, J. H. Reed, A. I. Zaghloul, and V. Tech, “Extending LTE into the Unlicensed Spectrum : Technical Analysis of the Proposed Variants,” vol. 2009, no. December 2009, 2011.

[84] A. Hulkkonen, J. Ylitalo, A. Roivainen, and K. Technologies, “Application of Cognitive Radio Techniques to Satellite Communication,” no. October, 2012, doi: 10.1109/DYSPAN.2012.6478178.

[85] T. Ayyasamy, “Satellite Communication with the Merge on Television Communication,” vol. 6, no. 14, pp. 1–3, 2018.

[86] K. Lee and J. G. Park, "Intelligent Cognitive Radio Ad-Hoc Network : Planning , Learning and Dynamic Configuration," p. 10(3):254, 2021, doi: https://doi.org/10.3390/electronics10030254.

[87] R. P. Sirigina, "Cognitive Radio for Aeronautical Communications : A Survey Cognitive Radio for Aeronautical Communications : A Survey," no. August 2017, 2016, doi: 10.1109/ACCESS.2016.2570802.

[88] B. Kamali, "AN OVERVIEW OF VHF CIVIL RADIO NETWORK AND THE RESOLUTION OF SPECTRUM DEPLETION The Present VHF Aeronautical Radio," *ntegrated Commun. Navig. Surveill. Conf. Proc.*, pp. F4-1-F4-8, 2010, doi: 10.1109/ICNSURV.2010.5503256.

[89] S. S. C. and M. G. Sudip Misra1, "Stochastic learning automata-based channel selection in cognitive radio/dynamic spectrum access for WiMAX networks," *Int. J. Commun. Syst.*, vol. 23, no. 5, pp. 633–652, 2014, doi: 10.1002/dac.

[90] Y. Song, Y. Fang, and Y. Zhang, "Stochastic channel selection in cognitive radio networks," *GLOBECOM - IEEE Glob. Telecommun. Conf.*, no. June, pp. 4878–4882, 2007, doi: 10.1109/GLOCOM.2007.925.

[91] T. Specification and E. Universal, "TS 136 213 - V13.3.0 - LTE; Evolved Universal Terrestrial Radio Access (E-UTRA); Physical layer procedures (3GPP TS 36.213 version 13.3.0 Release 13)," vol. 0, 2016, [Online]. Available: https://portal.etsi.org/TB/ETSIDeliverableStatus.aspx.

[92] J. Tlouyamma and M. Velempini, "Channel Selection Algorithm Optimized for Improved Performance in Cognitive Radio Networks," *Wirel. Pers. Commun.*, vol. 119, no. 4, pp. 3161–3178, 2021, doi: 10.1007/s11277-021-08392-5

الخلاصة

يتيح الراديو المعرفي باستشعار وكشف حالة القنوات اللاسلكية ، مما يسمح لأجهزة الإرسال والاستقبال اللاسلكية بتحديد القنوات المستخدمة وأيها غير مستخدمة. يعد التنقل إلى القنوات الفارغة مع تجنب القنوات المزدحمة هو الهدف الأساسي لأجهزة الراديو المعرفية. ونتيجة لذلك ، يتم تحسين استخدام الطيف مع تقليل التداخل مع المستخدمين الآخرين من خلال السماح ببث إشارات لعدة مستخدمين على قناة واحدة.

كانت هناك مرحلتان في تطوير هذه الدراسة، لقد طورنا في المرحلة الاولى نهجًا مباشرًا لنمذجة الشبكات الراديوية المعرفية لتشجيع إدارة أفضل للطيف من خلال استخدامه الانتهازي، في المرحلة الثانية ، نقترح استخدام ثلاث خوارزميات من نظام المنطق الضبابي (Mamdani، Tsukamoto، TSK) وخوارزميتين من الشبكات العصبية (ANN، ANFIS) لتحسين عملية اتخاذ القرار في اختيار أفضل القنوات المتاحة في الشبكة الراديوية. ومن اجل تحقيق ذلك تم اختبار نوعين من الانظمة هما النظام غير التعاوني والنظام التعاوني للمستخدمين الثانويين.

استخدام طريقة النمذجة المحددة في المرحلة الأولى كأساس. بعد تنفيذ جميع عمليات المحاكاة ، تم استخدام ثلاثة مقاييس للتقييم ، بما في ذلك معدل نقل الشبكة لوحدات البيانات ، وعمليات التسليم (الانتقال بين القنوات) ، ووقت التأخير(يتضمن وقت البحث و الاختيار ومن ثم الانتقال الى القناة المتاحة الجديدة). حيث تم إجراء مقارنة وتحليل لنتائج المحاكاة ، حيث أظهرت خوارزمية نظام الاستدلال العصبي الغامض التكيفي (ANFIS) ميزة وافضلية على بقية الخوارزميات وأيضًا على الخوارزميات المعيارية.

أثبتت النتائج أن خوارزميات ANFIS و TSK أعطت أفضل النتائج عند زيادة عدد القنوات مقارنة بالطرق الأخرى (ANNs ، والخوارزميات المعيارية)، كما أظهرت النتائج أن خوارزمية (MCCA) حققت أفضل النتائج في عدد عمليات التحويل مقارنة بباقي الخوارزميات، وخلصت الدراسة الى ان النتائج التي تم الحصول عليها تبين أن خوارزمية ANFIS قدمت نتائج أفضل من بقية الخوارزميات في نسبة الإنتاجية (كمية البيانات المتبادلة) بقيم مقبولة لبقية القياسات عند مقارنتها بباقي الطرق والخوارزميات الأخرى.

جمهورية العراق
وزارة التعليم العالي والبحث العلمي
جامعة بابل / كلية تكنولوجيا المعلومات
قسم البرمجيات

طريقة اختيار القناة في شبكه الراديو المعرفي باستخدام التضبيب و الشبكات العصبيه

أطروحة

مقدمة إلى مجلس كلية تكنولوجيا المعلومات في جامعة بابل والتي هي جزء من متطلبات الحصول على درجة الدكتوراه في تكنولوجيا المعلومات – البرمجيات

من قبل

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