Adaptive Radio Resource Management in Cognitive Radio Communications using Fuzzy Reasoning

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(Abstract)

As wireless technologies evolve, novel innovations and concepts are required to dynamically and automatically alter various radio parameters in accordance with the radio environment. These innovations open the door for cognitive radio (CR), a new concept in telecommunications. CR makes its decisions using an inference engine, which can learn and adapt to changes in radio conditions.

Fuzzy logic (FL) is the proposed decision-making algorithm for controlling the CR's inference engine. Fuzzy logic is well-suited for vague environments in which incomplete and heterogeneous information is present. In our proposed approach, FL is used to alter various radio parameters according to experience gained from different environmental conditions. FL requires a set of decision-making rules, which can vary according to radio conditions, but anomalies rise among these rules, causing degradation in the CR's performance. In such cases, the CR requires a method for eliminating such anomalies. In our model, we used a method based on the Dempster-Shafer (DS) theory of belief to accomplish this task. Through extensive simulation results and vast case studies, the use of the DS theory indeed improved the CR's decision-making capability. Using FL and the DS theory of belief is considered a vital module in the automation of various radio parameters for coping with the dynamic wireless environment.

To demonstrate the FL inference engine, we propose a CR version of WiMAX, which we call CogMAX, to control different radio resources. Some of the physical parameters that can be altered for better results and performance are the physical layer parameters such as channel estimation technique, the number of subcarriers used for channel estimation, the modulation technique, and the code rate.

In memoriam of Sarwat Shatila,
my beloved father.

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CHAPTER 1 **Introduction**

The global spread of wireless devices with mobile Internet access and the increasing demand of multimedia-based applications are fueling the need for wireless broadband networks. The need for wireless broadband network (WBNs) is driving much of the research and standardization activity. Most of these standards provide broadband wireless connectivity to fixed and mobile users through the use of OFDM (Orthogonal Frequency Division Multiplexing) for NLOS (Non-Line-of-Sight) communications [1]. IEEE 802.16 and 802.20 are standards for a broadband wireless access with promising features to support mobile Internet access. However, due the fast-changing radio environment and the demand for dynamic spectrum allocation mechanisms, these standards can benefit from cognitive radio (CR) for re-adjusting various radio parameters. The CR makes decisions based on its built-in inference engine, which can also, over time, learn from experience and adapt itself to different situations.

1.1 Problem Statement

In this work, we address a fundamental question: How can the physical layer's radio resources be dynamically allocated using the cognitive radio for a WBN? This question may appear simple but requires answering many other questions.

- *What parameters can be changed?* Using a cognitive radio changes the radio parameters to cope with the surrounding radio environment. The cognitive engine dynamically alters these radio parameters to achieve the required system performance or to meet certain objectives, such as maximizing system throughput or capacity. These tasks can be completed very quickly with little or no human intervention.

- *What reasoning methods should be applied?* Different AI (Artificial Intelligence) techniques can be used for CR reasoning. For certain wireless conditions, some AI techniques are more suitable than others for addressing specific problems. The chosen technique should minimize both complexity and processing time.

- *What decision-making algorithms must be developed?* Decision-making algorithms play a key role in a dynamic, fast-changing radio environment. Decisions should be made quickly, easily, and automatically. The CR should predict future actions with the information previously made available. The amount of stored data should be minimized to reduce system latency while analyzing stored data.

- *How is the effective of such systems to be measured?* We expect that the cognitive radio can make great improvements in a wireless network's overall system. These improvements can be measured using different metrics in accordance with the parameter being altered.

- *How can such concepts be implemented?* Such concepts can be implemented with the introduction of a cognitive-radio-based version of the wireless system used. The architecture design should be simple and should reduce latency. The addition of cognition should positively impact the overall system performance.

We choose to answer these fundamental questions by using 802.16 (WiMAX) as the wireless technology and applying a cognitive engine to upgrade 802.16 into a cognitive radio system. This upgrade involves developing a core engine that is capable of configuring the system parameters to minimize error probability, to increase data rates, to allocate resources, and to make intelligent decisions about other parameters. We propose a simple reasoning engine based on fuzzy logic for decision-making and a comprehensive system architecture for a cognitive WiMAX radio. The design of such a system could impact the IEEE 802.16m (Mobile WiMAX) and could be a developmental step toward a generic architecture that allows for control of existing standards.

We propose a system architecture based on the cognitive radio concept as shown in Figure 1.1. The objective of this new architecture, which we called *cognitive radio for microwave access* (CogMAX), is to improve WBN performance by continuously changing important parameters at the physical layer. The key element is the decision and learning process of the cognitive radio, which is the core of the cognitive engine. By configuring these parameters, the overall system performance can improve to meet challenges and can quickly make decisions regarding adjusting different physical parameters to meet the fast-changing radio environment.

The CogMAX architecture consists of three interfaces along with the cognitive engine, which are the heart of the proposed cognitive radio system. The application interface is responsible for providing information to applications using our system, without those applications having to deal with the associated network and system requirements. This includes location-based services, authentication services, and mobility management services. To guarantee users' requirements and quality of services are met, the application interface will use information the cognitive engine provides regarding the channel state and the network conditions. The air interface is responsible for sensing and estimating channel state information and monitoring spectrum usage and availability. Bi-directional communications are performed between the air interface and the cognitive engine. The network interface is responsible for setting the network configurations and monitoring its performance. The cognitive engine itself is composed of several modules as seen in Figure 1.1. More architectural details will be described in Chapter 3.

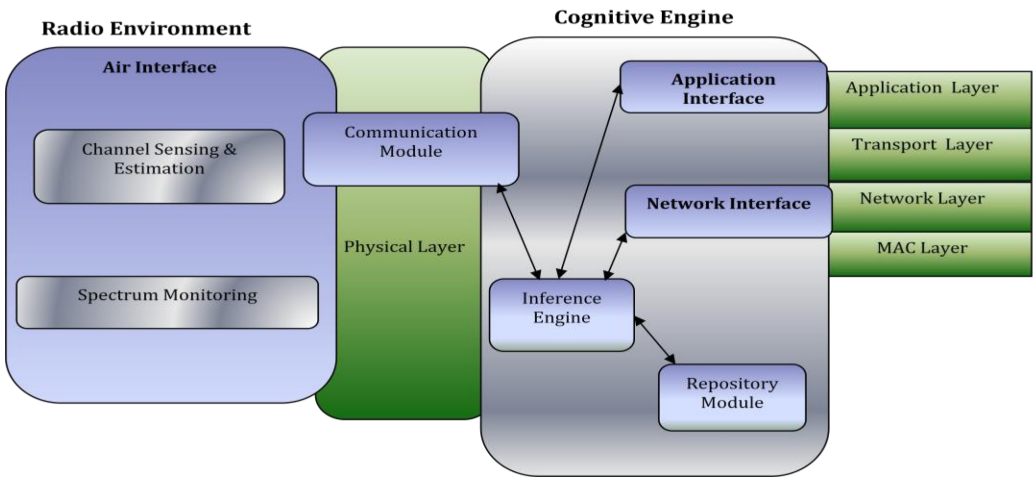

Figure 1.1 CogMAX System Architecture

The inference engine is used for learning and decision-making. Artificial intelligence (AI) techniques, such as case-based reasoning, neural networks, and hidden Markov models, are applicable techniques for reasoning and decision-making in the cognitive engine. Every technique has its advantages and disadvantages. For example, the most commonly used technique for the cognitive engine is case-based reasoning (CBR). Though this technique is simple, it may require a time-consuming search through the cases database to find the closest match. Furthermore, the search process could yield two closely matched cases with ambiguous actions. Neural networks are another technique that could be used and have a high ability for training and adaptation but also a high processing time to train the weights and a sensitivity to the quality of the training data. Similarly, the hidden Markov model can yield good decisions but faces basic problems in decoding,recognition, training and learning [3]. Table 1.1 summarizes the strengths and limitations of some of the commonly used AI techniques for cognitive radio.

Table 1.1 Strengths & Limitations of Common AI Techniques used for the Cognitive Radio

Technique	Strengths	Limitations
Case-Based Reasoning	1- Simple and close to human thinking 2- Allows learning in the absence of domain knowledge	1- Large storage space required to store all cases 2- Lack of sound and complete method to obtain a multiple solution for a multi-objective problem. Example: maximizing throughput and minimizing power consumption (contradicts). 3- Selection of similarity measure between a new and old case
Neural Networks	1- Low memory usage 2- Fast output 3- Excellent for classification 4- Identifies new patterns	1- Poor for unchangeable factors (like cost of CR) 2- High processing complexity 3- Untraceable output 4- Training required
Rule-Based Reasoning	1- Simply implemented 2- Includes relevant features that make up the rules 3- Good for unforeseen situations	1- Addition or deletion of rules can cause redundant and conflicting rules 2- Requires perfect knowledge base (not always available)
Hidden Markov Model	1- Prediction from experience 2- Good for classification	1- Training process can be computationally complex 2- Requires good training sequence
Genetic Algorithm	1- Parallel processing, which can be good for large problem spaces 2- Scarce domain knowledge	1- High processing time

Introducing a cognitive radio version of a WBN (Figure 1.1) helps improve the WBN's overall system performance. In general, some reconfigurable parameters (in the MAC and physical layers) in a WBN can be altered using cognitive radio techniques without human intervention. For example, a WBN currently uses proximity as the driver to change the modulation and oding techniques; a better approach is to use a cognitive engine (CE) with additional observations to decide on modulation and coding. In this case, the cognitive engine collects channel information from the environment and saves it as a channel profile at the WBN base station (BS). The channel profile and the distance of the user from the BS are factors that determine the selection of modulation/coding techniques at runtime. The CE monitors the channel characteristics, revises the channel profile, and performs distance calculations. Based on the inference (reasoning) level, user velocity, and rules governing operation, the CE decides upon the modulation/coding techniques and sets the rules that govern the OFDM power and bit allocations for every sub-carrier. This cycle is repeated continuously. This work supports self-tuning networks that minimize maintenance costs to service providers and should eventually lead to self-deploying and self-organizing WBNs.

We aims to investigate the appropriate WBN configurable physical parameters that can be adapted (such as modulation type, number of subcarriers, code rate, and channel estimation techniques) and configured using a cognitive WBN standard. Fuzzy logic is used as inference to alter various radio parameters according to experience gained from different environmental conditions. Fuzzy logic requires a set of rules for decision-making, and these rules can vary according to the radio conditions, but anomalies arise among these rules, causing degradation in the CR performance. In such cases, the CR requires a method for eliminating such anomalies. The method chosen to accomplish this task in our model is the Dempster-Shafer (DS) theory of belief.

Fuzzy logic transforms heterogeneous and qualitative information into homogeneous membership values, which can then be processed through a proper set of fuzzy inference rules. For environments in which uncertainty, incompleteness, and heterogeneity are present and in which decisions are made based on incomplete inputs—all of which describe the dynamic radio environment—fuzzy logic can be an excellent choice. In addition, mobility requires quick decision-making and learning capabilities, and fuzzy logic meets these demands. Fuzzy logic's occasional inaccuracy can be reduced through the CE's learning process. Like CBR, fuzzy logic requires minimal storage space to store all training cases and thus decreases latency. Unlike other AI techniques, fuzzy logic's decision-making offers a sense of reality. Most AI techniques offer a single decision chosen from mutually-exclusive potential responses, even in situations in which a combination of multiple potential responses is actually more accurate.. For example, if we consider a "tall" person to be more than 2 meters in height, then other AI techniques would consider 199cm as "short," but fuzzy logic would linguistically consider this person as "not that tall." As the person's height increases, fuzzy logic would assign the person more to the set of "tall" people and increase the person's grade of membership to the "tall" set. The cognitive engine, designed, automatically creates the rules and makes decisions according to the present and past states of any configurable parameter.

1.2 Contributions

This dissertation presents three novel contributions in the study of cognitive radio, wireless communications, and signal processing for communications.

1. The CogMAX system architecture dynamically enables cognitive techniques for altering radio parameters and thereby achieves enhancement in performance and efficient utilization of spectrum.
2. The proposed fuzzy c-mean clustering (FCM) techniques perform the reasoning and decision-making required in cognitive radio systems. These techniques (with validity techniques and online testing and fitting) are validated to generate dynamic policies used in altering the radio parameters. The proposed FCM techniques result in cognitive engine algorithms that

- dynamically change the type and the number of fuzzy logic membership functions (trapezoidal, triangular, Gaussian, and so on), according to learning and experience from the radio environment,
- automatically adapt the membership functions through the experience gained and the amount of data stored, and
- automatically generate rules for the fuzzy engine.

3. A method for removing anomalies of the generated rules. Specifically, Dempster-Shafer (DS) theory of belief is used to evaluate the relevance of the generated rules and to eliminate anomalies that might arise from the generation of too many rules. This method is validated and tested with CogMAX's inference engine and is applied to minimize spectrum efficiency.

With these contributions, we were able to

- estimate the channel type through FL reasoning along with a comparison to the CR's most commonly used AI inference technique (i.e., CBR) and change the method of channel estimation in WiMAX to match the channel characteristics,
- alter the modulation, code rate, and number of subcarriers using the proposed cognitive engine, which is based on linguistic and uncertainty reasoning, and
- dynamically allocate spectrum to users for more spectrum utilization.

1.3 Publications

1. H. Shatila, M. Khedr, and J. Reed, "Channel Estimation for WiMaX Systems using Fuzzy Logic Cognitive Radio*," WOCN 2009, Cairo-Egypt.*

2. H. Shatila and M. Khedr, "CogMAX- A Cognitive Radio Approach for WiMAX Systems," *IEEE/ACS International Conference on Computer Systems and Applications*, Rabaat-Morocco, May, 2009.

3. H. Shatila, M. Khedr, and J. Reed, "Adaptive Resource Management for a Vague Environment Using Cognitive Radio," *IEEE ICCSIT*, Chengdu-China, July, 2010.

4. H. Shatila, M. Khedr, and J. Reed, "Adaptive Modulation and Coding for WiMAX Systems with Vague Channel State Information using Cognitive Radio," *SPECTS 2010*, Ottawa, Canada, July, 2010.

5. H. Shatila, M. Khedr, and J. Reed, "Opportunistic Channel Allocation Decision Making in Cognitive Radio Communication," *International Journal of Communications System*. Reviewed: September, 2011; Revised: October, 2011; Accepted: December, 2011, to be published.

6. H. Shatila, M. Khedr, and J. Reed, "Enhancing the Performance of Cognitive Radio Systems Using a Joint Fuzzy Believe Theory," *PHYCOM Special Issue on Cognitive Radio*. Submitted: February, 2012, under revision.

1.4 Outline

This dissertation contains nine chapters. Background information regarding WiMAX standards and cognitive radio is provided in Chapter 2. A detailed explanation of the proposed system architecture along with some recent related work is presented in Chapter 3. The fuzzy C-mean clustering (FCM) technique and the Dempster-Shafer (DS) theory of belief are explained in

Chapter 4. Channel type and estimation of the proposed design as well as a comparison of the use of fuzzy logic (FL) and case-based reasoning (CBR) as inference are presented in Chapter 5. Chapter 6 discusses the use of a fuzzy logic reasoning engine to determine the number of pilot subcarriers that can be used for channel estimation. Chapter 7 proposes an algorithm, based on the FCM theory, to dynamically allocate radio resources. Chapter 8 proposes an algorithm for spectrum utilization for GSM (Global Systems for Mobile Communications) cellular technology. Finally, Chapter 9 includes conclusions and future work.

CHAPTER 2 **Background**

This chapter is an introduction to cognitive radio and we will use the WiMAX system as an example for WBN. We discuss some benefits of using WiMAX, as well as some WiMAX physical layer parameters that could be configured by our system. Applications and capabilities of the cognitive radio are also mentioned in this chapter along with some of the current related work related to the inference engine.

2.1 WiMAX Standard

WiMAX is a wireless MAN technology that provides broadband wireless connectivity to fixed and mobile users [2]. WiMAX is based on adaptive modulation with OFDM and has impressive capabilities especially in NLOS environments [1]. These technologies can potentially be used to provide backhaul in many networks such as IEEE 802.11 hotspots, cellular networks, and WLANs to the Internet. The mobile standard of WiMAX means that it can provide broadband wireless access in a mobile (fast varying) environment. WiMAX base stations can serve their subscribers without the need of LOS (Line of Sight) connection. A WiMAX base station can serve multiple numbers of users due to the large amount of available bandwidth. It can also be used as a solution for last-mile connection, especially to users who cannot get connected to broadband services through cable or DSL (Digital Subscriber Line). WiMAX base stations can cover a large range and can reach areas where traditional wireless broadband access is not possible.

As stated in [4] "*although the term WiMAX is only a few years old, 802.16 has been around since the late 1990s, first with the adoption of the 802.16 standard (10–66 GHz) and then with*

802.16a (2–11 GHz). Although the work on IEEE 802.16 standard started in 1999, it was only during 2003 that the standard received wide attention when the IEEE 802.16a standard was ratified in January". Although this standard has been around for a while, it is continuing to evolve. Eventually "intelligence" will be a part of the WiMAX standard.

WiMAX standard currently includes two versions: *802.16-2004* and *802.16e* [4], as shown in Figure 2.1. 802.16-2004 uses OFDM to serve large number of users in a time division technique in a cyclic method, but done so extremely quickly so that users have the perception that they are always transmitting/receiving [1, 4]. In case of 802.16e (mobile WiMAX), where user mobility is an important issue, WiMAX utilizes OFDMA (Orthogonal Frequency Division Multiple Access) and can serve multiple users simultaneously by allocating sets of subcarriers to each user. 802.16m standard will have an advanced air interface with data rates of 100 Mbit/s for mobile applications and 1 Gbit/s for fixed applications, cellular, macro and micro cell coverage, with currently no restrictions on the RF bandwidth (which is expected to be 20 MHz or higher).

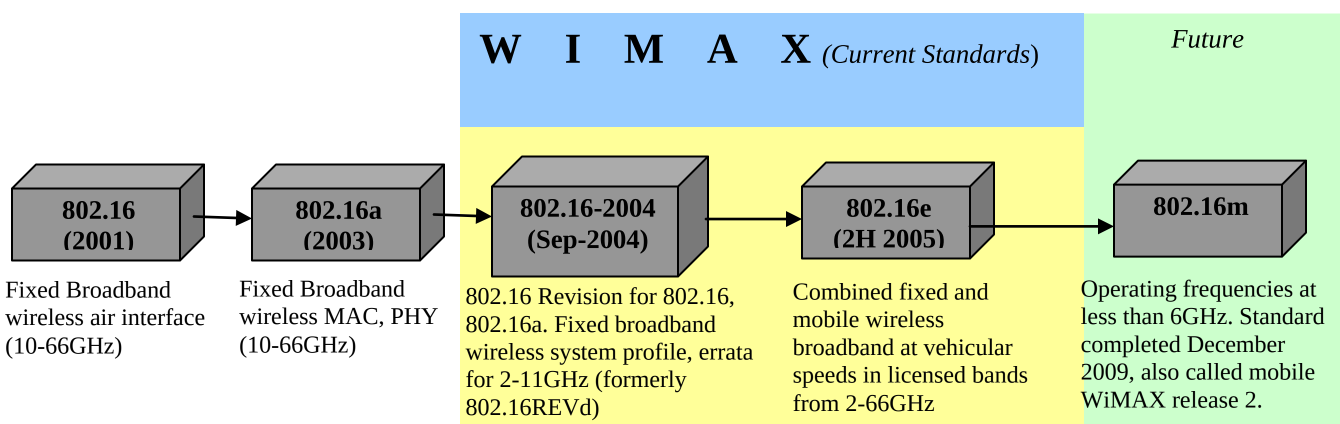

Figure 2.1 WiMAX Standards

IEEE 802.16-2004 is a fixed wireless access technology; it is designed to provide wireless DSL technology in areas where service providers cannot extend broadband cables or DSL. IEEE 802.16e (mobile WiMAX) is similar to IEEE 802.16-2004 but with a new additional function, which is mobility. It allows users to move around, while being served with broadband wireless services.

2.1.1 Benefits of WiMAX

WiMAX offers a lot of benefits. WiMAX base stations provide higher throughput at long ranges (up to 50 km) [4]. Scaling up system capacity is easily achieved by adding new sectors with more channels, thus increasing cell capacity. WiMAX offers coverage area in NLOS situations. In addition, WiMAX offers a decent quality of service capability. WiMAX offers a wide range of services from real time to non-real time, each with its required QoS parameters and ranges. WiMAX is very cost-effective [2]. Using WiMAX for wireless broadband access can cost service providers less than using broadband cables or DSL. WiMAX can be used as a last-mile solution to different kinds of networks. It can reach subscribers that are living in areas without cables or a DSL infrastructure. WiMAX is a new technology that will provide wireless broadband connectivity to everyone and everywhere!

2.1.2 WiMAX Physical Layer Parameters

Currently the two versions of the 802.16, the IEEE 802.16-2004 (Fixed WiMAX) and the 802.16e (Mobile WiMAX), use OFDM (Orthogonal Frequency Division Multiplexing) where orthogonal subcarriers are used to transmit traffic [5]. This technique is spectrally efficient; it combats the ICI (Inter-Carrier Interference) and ISI (Inter-Symbol-Interference). OFDMA is widely used at the physical layer for mobile WiMAX. In [1, 5], the authors describe the concept of scalable OFDMA (S-OFDMA) for WiMAX, which will have the flexibility to use a wide range of bandwidth. This flexibility is an important issue in spectrum allocation and usage model requirements [1]. As seen from Table 2.1, scalability is adjusted by changing the number of subcarriers used (FFT size) while keeping the sub-carrier frequency spacing at 10.94 kHz. The system bandwidths for two of the initial planned profiles being developed by the WiMAX Forum Technical Working Group for Release-1 are 5 and 10 MHz (highlighted in the table).

Parameters	**Values**			
System Channel Bandwidth (MHz)	1.25	5	10	20
Sampling Frequency	1.4	5.6	11.2	22.4
FFT Size	128	512	1024	2048
Number of Sub-Channels	2	8	16	32
Sub-carrier Frequency Spacing	10.94 kHz			
Useful Symbol Time (T_b=1/f)	91.4 microseconds			
Guard Time (T_g=T_b/8)	11.4 microseconds			
OFDMA Symbol Duration (T_s=T_b+T_g)	102.9 microseconds			
Number of OFDMA Symbols (5ms Frame)	48			

Table 2.1 OFDMA Scalability Parameters [1]

"*Adaptive modulation and coding (AMC), Hybrid Automatic Repeat Request (HARQ) and Fast Channel Feedback (CQICH) were introduced with Mobile WiMAX to enhance coverage and capacity for WiMAX in mobile applications*" [1]. Different combinations of modulation schemes and coding are used in WiMAX. Mobile WiMAX, QPSK, 16QAM and 64QAM, along with different code rates, are supported and mandatory in the DL (Downlink), whereas the UL (Uplink) and 64QAM is optional. Convolutional Code (CC) and Convolutional Turbo Code (CTC) are used as coding techniques in mobile WiMAX. Block Turbo Code and Low Density

Parity Check Code (LDPC) are supported as optional features [5]. Table 2.2 summarizes the different UL and DL modulation and coding schemes in mobile WiMAX.

		DownLink (DL)	**Uplink (UL)**
Modulation		QPSK, 16QAM, 64QAM	QPSK, 16QAM, *64QAM*
Code Rate	CC	1/2, 2/3, 3/4, 5/6	1/2, 2/3, *5/6*
	CTC	1/2, 2/3, 3/4, 5/6	1/2, 2/3, *5/6*

Table 2.2 Codes and Modulation in Mobile WiMAX [1]

2.2 Cognitive Radio

Defining cognitive radio can be a very difficult and a controversial task, though it was a term first defined by Mitola in [6] as "*A radio that employs model based reasoning to achieve a specified level of competence in radio-related domains*." It was also defined in Haykin in [7] as "*An intelligent wireless communication system that is aware of its surrounding environment (i.e., outside world), and uses the methodology of understanding-by-building to learn from the environment and adapt its internal states to statistical variations in the incoming RF stimuli by making corresponding changes in certain operating parameters (e.g., transmit-power, carrier-frequency, and modulation strategy) in real-time, with two primary objectives in mind:*

- *Highly reliable communications whenever and wherever needed.*
- *Efficient utilization of the radio spectrum".*

The six important key functions of a cognitive radio are:

- **Awareness** (The capability to know and understand the surrounding)
- **Intelligence** (Ability to conclude by reasoning (infer) upon information got from the surroundings)

- **Learning** (Gaining more knowledge from reasoning and judging more accurately)
- **Adaptability** (Changing its mode of operation and behaviors to surroundings)
- **Reliability** (Providing its functions seamlessly)
- **Efficiency** (Preserving and managing resources)

In addition to the above functions, we have another important function and that is **Reconfigurability.** For reconfigurability, a cognitive radio looks to s*oftware-defined radio* to perform this task. For cognitive functionality the cognitive radio looks to *signal-processing and machine-learning procedures* for their implementation.

2.2.1 Cognitive Tasks and Cognitive Cycle

According to Haykin [7], the three fundamental cognitive tasks are:

1. *Radio-scene analysis, which encompasses the following:*
   - *Estimation of interference temperature of the radio environment.*
   - *Detection of spectrum holes.*
2. *Channel identification, which encompasses the following.*
   - *Estimation of channel-state information (**CSI**).*
   - *Prediction of channel capacity for use by the transmitter*
3. *Transmit-power control and dynamic spectrum management.*

The above three fundamental tasks constitute the basic cognitive Cycle (Figure 2.2). Tasks (1 and 2) are carried out in the receiver, whereas task (3) is carried out in the transmitter. It should be noted that the transmitter and receiver should work in harmony. In order for that to happen, we need a *feedback channel* connecting the receiver to the transmitter. The receiver is enabled to convey information on the performance of the forward link to the transmitter through the feedback channel. Therefore, the cognitive radio is an example of a *feedback communication system*.

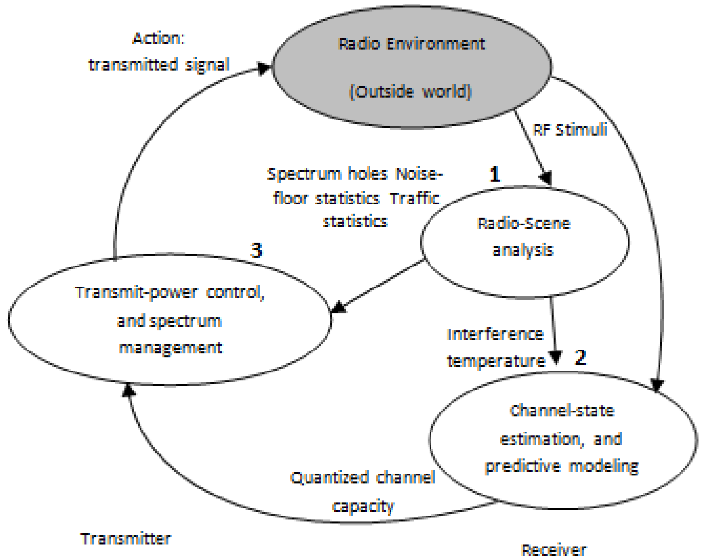

Figure 2.2 Basic Cognitive Cycle [7]

Cognitive radio can be defined in different ways, according to the expectations of the functionality that a CR will exhibit. Mitola introduced a number of cognitive functionalities in [6]. As a reference for how a cognitive radio could achieve these levels of functionality, Mitola introduces the cognition cycle, shown in Figure 2.3. According to the description by Neel in [8] of the cognitive cycle introduced by Mitola [6]; in the cognition cycle, a radio gathers information about its operating environment (**Outside world**) through observation. The process of evaluation comes next (**Orient**), to determine the importance of the collected information. Based on this valuation, the radio defines its **Plan** and **Decides** in such a way that would improve the valuation (this is the normal path that a cognitive radio will take during normal conditions). If a waveform change is deemed necessary, the radio then implements the alternative (**Act**) by adjusting its resources and performing the appropriate signaling. The radio can also go for an immediate (**Act**) depending on the evaluation of the observation made. These changes are reflected in the **Outside World** through the interference profile presented by the cognitive radio. As part of this process, the radio uses these observations and decisions to improve the operation of the radio (**Learn**), perhaps by creating new modeling states, generating new alternatives, or creating new valuations. There are different ways that can be used for learning; some of these ways will be defined at the end of this report.

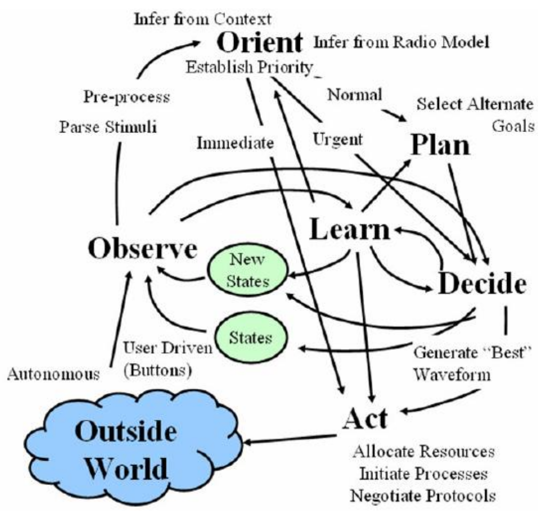

Figure 2.3 Cognitive Cycle [6]

2.2.2 Dynamic Spectrum Utilization

A cognitive radio is the key to solving the problem of fixed spectrum utilization through *Dynamic Spectrum Access*. "*Cognitive radio techniques can provide the capability to use or share the spectrum in an opportunistic manner.*"[9]. Through dynamic spectrum access techniques, the cognitive radio will detect the best available channel for the user to operate in. According to [9] the cognitive radio will enable the user to:

- Determining the availability of portions of the spectrum and detect the presence of licensed users when a user operates in a licensed band. (***Spectrum Sensing***).

- Select the best available channel to provide user’s communication requirements (***Spectrum Management***).
- Coordination of the channel access with other users (***Spectrum Sharing***).
- Leave the channel when a licensed user is detected (***Spectrum Mobility***)

The cognitive radio network shown in Figure 2.4 shows the large number of interactions between the different network functionalities. This leads us to the *cross-layer design* approach between the different network functions. For example in Figure 2.4, spectrum sensing and spectrum sharing cooperate with each other to enhance spectrum efficiency. For spectrum management and spectrum mobility functions to be carried requires cooperation between application, transport, routing, medium access and physical layer functionalities. In [10], the author proposes in his work fuzzy logic architecture for cross-layer optimization design for a cognitive radio. As stated in [10], that cross layer design for a cognitive network meets a number of challenges such as; *modularity*, which is modularity of the whole system architecture, i.e. allowing each radio component to be designed independently of each other and to be used interchangeably. *Interpretability*, *imprecision and uncertainty,* which is caused as most information is obtained by measurement and are subjected to errors in precision and accuracy. *Complexity and scalability*, this arises as the cognitive radio has to monitor all available resources in order to obtain the best solution to meet the users need. Cross-layer optimization can be sometimes unbearable as the number of layers involved increases. If the amount of information and parameters required exported by each layer are high and different in nature it can make the cognitive radio impractical. The solution that the author suggests to address all of the above challenges is to design a cross-layer architecture based on fuzzy logic controllers as a method for implementing cognitive cross layer engines. The author concludes after running his simulation that a cross layer design based on fuzzy logic results in a better overall system performance.

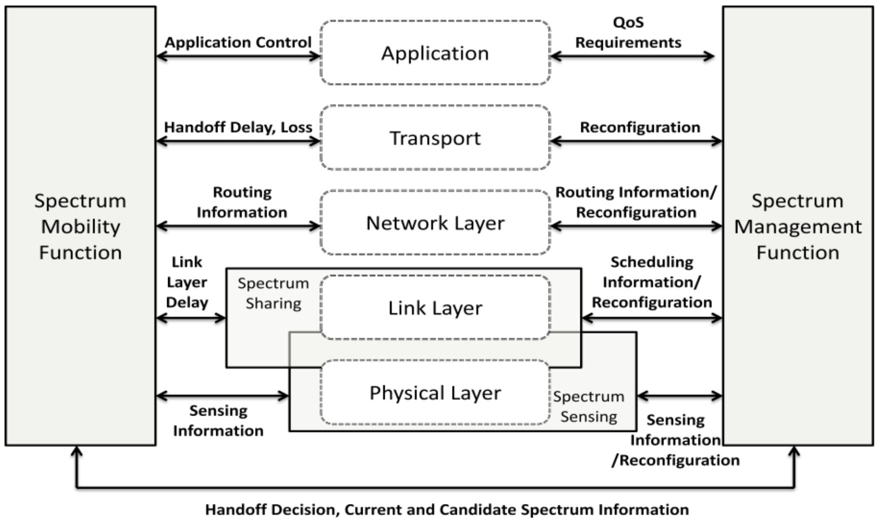

Figure 2.4 Cognitive Radio Network (Communication Functionalities) [9]

2.2.3 Capabilities of a Cognitive Radio

According to [7, 11], there are two main capabilities of a cognitive radio:

Learning and Decision Making: This is the ability of the radio to collect or sense information from the surrounding radio environment, decide upon the actions to take in certain situations, and learn from past experiences in order to perform better in new situations. To collect such information from a fast varying radio environment, and to avoid interference to other users, the radio needs very advanced techniques. It cannot simply be, for example, monitoring the power in some frequency band of interest. More sophisticated techniques are needed. Decision making is based on past experience and collected parameters from the environment.

Recently different artificial intelligence techniques used in the implementation of the cognitive engine have brought about the attention of many researchers. In [12] the authors introduced different AI techniques that could be used in the development of the cognitive engine (CE) for the cognitive radio. *Artificial neural* networks (ANN) were proposed in [12] to be used as the cognitive engine. Three types that were applicable with the cognitive radio were discussed; *Multi-Layer Linear Perception Network (MLPN)*, *Non Perception Network (NPN)* and *Radial Basis Function Network (RBFN)*. As proved in [12] a cognitive engine implemented using ANN to determine some radio parameters for different channel states met three goals; optimizing BER, maximizing throughput and minimizing transmit power. The work by Baldo [13], using ANN, to characterize real time achievable communication performance in CR proved to have a good modeling accuracy and flexibility for runtime modeling in various application and scenarios. In [14] the author also proposed an algorithm based on neural-networks as using GA (genetic algorithms) are not efficient when considering unchangeable parameters. Examples for unchangeable parameters are: the cost of the radio and the owner of the radio. In order to work with such parameter other AI algorithms should be used. The decision maker in this case will consider both changeable and unchangeable factors. Changeable and unchangeable information is the input of knowledge base and decision maker. In this case, the decision maker will evaluate the decision to get the best decision possible. The decision maker is a neural network. The author concluded at the end of his work that AI techniques, such as neural networks, could be a solution to get good decision especially when dealing with unchangeable factors.

Hidden Markov Model (HMM) could be also applied in the CR networks. In [15] the author used HMM to predict the vacant radio bands and proposed a model based on HMM-based DSA algorithm to use in the CR. In [16] and [17], Reed was able to prove that *rule-based reasoning*

CE showed the same results as a CE based on genetic algorithms but with less computational complexity. *Case based reasoning (CBR)* to be used for CE was also introduced by Reed in [18] and [19] and through simulation results Reed proved that CBR-CE achieved good and comparable results with less complexity but only after proper training/learning. In [20] author suggests the use of case based reasoning theory for decision making in the cognitive engine. The use of such a theory can be very efficient, especially in real time situations where a quick solution is required for the fast changing radio environment. The resulting sub-optimal parameter solution is “good” enough to support a QoS (quality of service) level quickly instead of finding the best parameter setting slowly. CBR also narrows the search space by just searching the local variables space including a similar stored case and does not have to search the whole variable space. As mentioned in this work, using CBR can cause a degradation in the overall performance because only a certain amount of cases can be stored. The paper proposed a new version of the cognition loop as shown in Figure 2.5, which somewhat similar to the Mitola’s Cognition cycle [6].

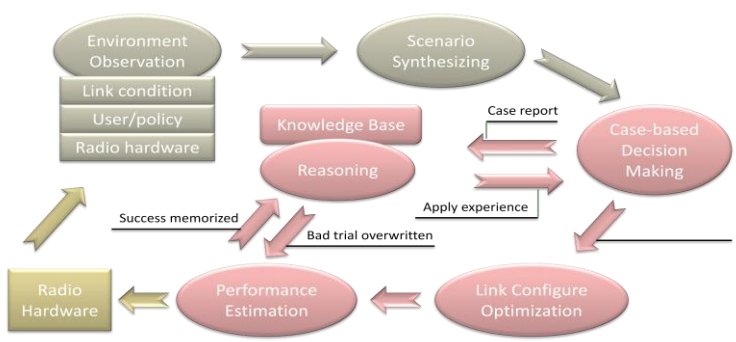

Figure 2.5 Cognition Loop [20]

The author in [21] proposes a fuzzy based approach to make an effective spectrum handoff decision. This approach of using fuzzy logic for decision making and will be adopted in my research. Fuzzy logic can be used for different decision making in a WiMAX system, for example determining the type of modulation technique, assigning different number of subcarriers to users, overall controlling different physical layer parameters in order to improve the system performance. The author focuses on the usage of the secondary (unlicensed) user too, as long as the user does not interfere with the primary user (licensed). The interference is measured with respect to a certain threshold. When the secondary user interference exceeds that threshold the spectrum handoff is performed. The author uses fuzzy logic to decide when spectrum handoffs are done. The proposed model is mainly based on two FLC (Fuzzy Logic Controllers) as shown in Figure 2.6. The first FLC estimates the distance between the primary and secondary users, i.e. the power, which the SU will transmit in order to not interfere with the neighbour primary users. The second FLC will be in charge of handoff decisions. As shown in Figure 2.6., the inputs to the first FLC will be SNR_{PU} (signal to noise ratio primary user) and SS_{PU} (signal strength received at SU from PU). The output of the FLC is the P_{SU} (secondary user transmission power). The second FLC as shown in Figure 2.6 will have three inputs: P_{SU} (secondary user transmission power), SSPU (signal strength received at the SU) and bit rate of SU, R_{SU}. The output of the FLC will be HO indicator (decides whether handoff has to be realized or not) and MOD_{PSU} indicator (indicates whether SU transmission power should be modified and how). The author concluded through simulation that this proposed approach outperforms a solution based on fixed thresholds in terms of spectrum handoffs rate interference temperature measured at the PU receiver. Besides the fact that the author concluded that the use of fuzzy logic in decision making was a good model, as decisions are made based on incomplete, qualitative and vague information available at the SU.

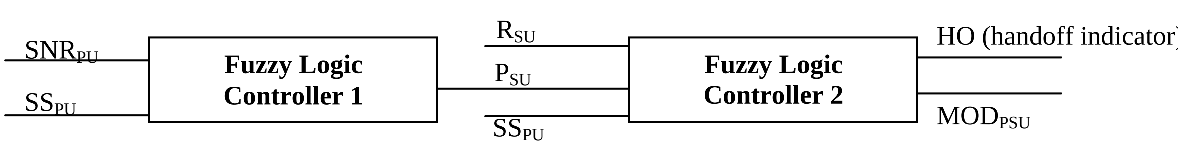

Figure 2.6 Block Scheme of Fuzzy-Based Spectrum Handoff Algorithm

Another approach introduced in [22], proposes a generic cognitive framework for autonomous decision making regarding the multiple, conflicting and operational objectives to face the time varying environment. This proposed model involved two stages: *preliminary initialization* and *operational phase*.

In the preliminary phase, all cognitive engine configuration alternatives are graded and ranked. The grading system is made to convey the match of an alternative with regard to the optimization objectives. In other words, the best-graded alternative is the alternative with the best solution as it provides all imposed constraints. After the grading process, all cognitive engine alternatives are ranked as to form what the author calls *optimality scale (OS).*

The second stage proposed is the operational phase, which is the decision making stage. The author proposes an algorithm called the RALFE (reason and learn from experience), which is based on trial/error approach of the problem in hand. This algorithm is responsible for three learning systems, and through these three learning systems the decision is taken. The first learning system is the PSE (performance scale explorer), and its main objective is to predict the highest compatible rank. The second learning system is the optimality predictor (OP) and this is in charge of estimating the correctness and/or the optimality of the PSE predictions. The last learning system is the compatibility checker and this is requested by the RALFE algorithm when the design is difficult. The author proved through case studies that the designed cognitive radio can learn a wide range of design problems. The designed cognitive engine takes multiple objectives into account and can adapt the trade off between them online. In comparison with [14, 22] I propose to use Fuzzy logic for decision making and learning to alter the different parameters. Using fuzzy logic for decision making enables fast decisions (on-line) and achieves good decisions for unchangeable factors [14].

Reconfigurability: This capability allows dynamic programming of the cognitive radio in order to meet its needs from the surrounding environment. The cognitive radio can be programmed to transmit and receive on different frequencies to avoid interference.

As described in Section 2.2.2, the ultimate objective of the cognitive radio is to detect available spectrum through cognitive capability and reconfigurability. The problem arises as the spectrum is fully occupied with users, so the main idea is to share the spectrum among different licensed users without interfering with each other's transmission as illustrated in Figure 2.7. The cognitive radio also helps in using unused spectrums, which we referred to as spectrum holes. A detection of another licensed user in this band will make the cognitive radio move to another spectrum band to avoid interference between users. The cognitive radio can stay in the same band but it alters the modulation technique or transmission power level in order to avoid interference.

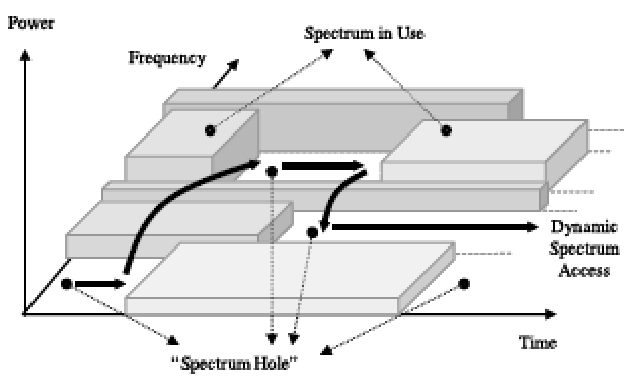

Figure 2.7 Spectrum Hole (White Space) [9]

2.2.4 Common Applications of Cognitive Radio

Figure 2.8 shows some important common applications of a cognitive radio.

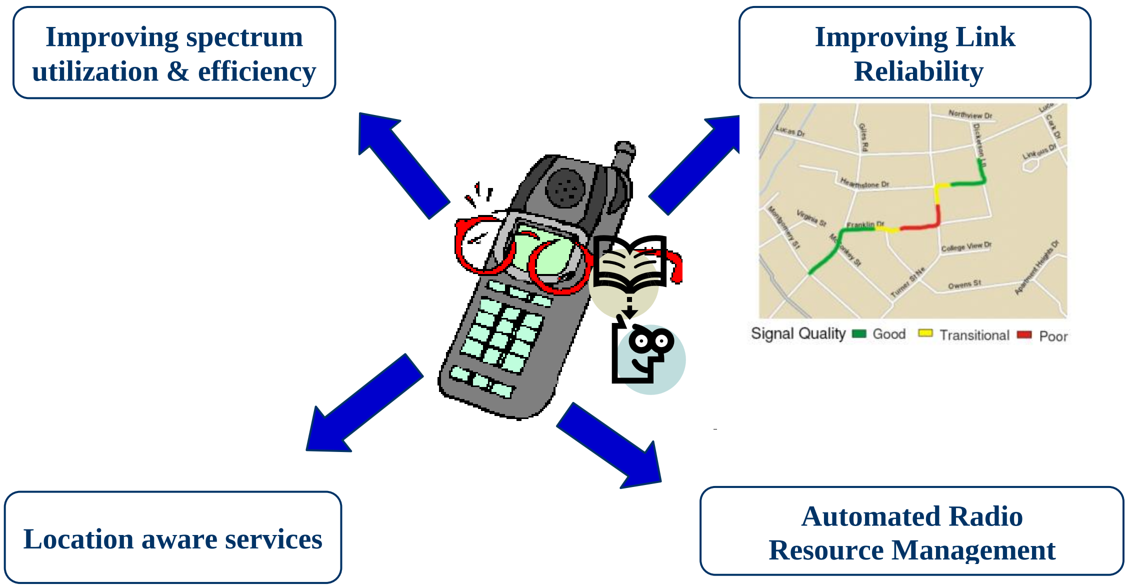

Figure 2.8 Common Applications of a Cognitive Radio.

Improving spectrum utilization & efficiency

As discussed earlier, a cognitive radio can be used to improve spectrum utilization through *Dynamic Spectrum Access*. As mentioned in [23] opportunistic spectrum utilization enhances capacity by the implementation of *dynamic frequency selection algorithm*.

Improving Link Reliability [8]

A cognitive radio has the ability to learn from past experience. This ability can help future decisions to improve link reliability. For example if a user mobile station was to follow a certain path to reach a particular destination every day (shown in Figure 2.8), and this path has locations were the signal drops below a certain threshold (shown in red), then the cognitive radio can learn from this daily experience and can take action to improve the coverage at these detected coverage gaps. For example, this can be done through changing the signal characteristics at certain coverage gap locations. The same concept can be done by a cognitive radio in the base station. In this case, the cognitive radio can detect coverage gaps in locations covered by the base station. The exchange of past experience among cognitive mobile stations can also improve link reliability.

Automated Radio Resource Management [8]

Service providers usually have a tough job in adjusting radio parameters of their network based on post deployment. To make full and efficient use of their network, radio parameters should be frequently re-tuned and adjusted. As the network grows larger in size the job becomes a nightmare. A cognitive radio can be used to automatically adjust these radio parameters by observing and learning the network. The cognitive radio adjusts the radio parameters to best suit the need of a particular deployment. The use of a cognitive radio in such cases lessens the burden on network engineers.

Location aware services

Location aware services are services can be adapted based on the current user's location. A cognitive radio can be used to detect the location of the user and supply him with the available services in this particular location.

Aspects of Cognitive radio

The document presented in [24] introduces the SON (self organizing network) concept in a mobile network as well as self-deploying femto-cells. The SON actually has the same concept as the cognitive radio where learning from past experience can cause the SON to function in the closed-loop manner mentioned in the document. During the learning process, the SON operates in the open-loop manner and under supervision from the O&M (Operations and Maintenance) personal. As more practical scenarios are noticed and then this open loop manner turns to the closed loop manner of operation where the SON starts making its own decisions. Such a concept can be used also with different Nodes present in the network, especially for self-healing. For example, nodes like RNC's (Radio network controller), where sometimes restarting a specific board in the H/W or loading the RNC from an older CV (Configuration Version) can solve the problem, and of course such a feature can control all of this. The document [24] shows different cases where the SON is used.

An introduction to WiMAX and the cognitive radio was introduced in this chapter. The benefits and uses of WiMAX and the cognitive radio was also briefly discussed. Some of the reconfigurable WiMAX physical layer parameters were mentioned to get an idea of what physical parameters can be altered by the cognitive radio to improve WiMAX performance. A review of current work regarding the Learning and decision making in a cognitive radio was also introduced.

CHAPTER 3 **CogMAX Architecture and Related Work**

This chapter proposes the system architecture that will be described, which can target different WBN standards especially 802.16m (Mobile WiMAX). Our main target, as mentioned previously, is the inference (reasoning engine) of the cognitive radio which will also be discussed. This chapter also demonstrates different learning techniques for the cognitive radio. The choice of the learning technique can be vital in the improvement of the overall system performance. An introduction to fuzzy logic, which we will target for the design of the cognitive engine, is detailed and described with current related work.

3.1 Overview of the MAC (Media Access Control) Layer

A wireless network operates in a shared medium. Each subscriber in the network should be able to access this medium and each subscriber should be able to use the services that he subscribed with a certain QoS. The MAC allows subscribers to access the medium.

The MAC layer in WiMAX supports different functions. Some of the important functions that a MAC layer supports are: QoS provisioning, call admission, scheduling, and fragmentation/segmentation of packets [25]. The MAC layer is also responsible for handling different types of services, real and non-real time. The MAC layer should cope with the harsh and changing physical environment, where it contends with different physical phenomena like fading and interference. The 802.16 standard states that the MAC in WiMAX should have the ability to be connected to different types of backhaul networks such as, asynchronous transfer mode (ATM) and IP based networks [25]. MAC also provides a dynamic range of throughput to a specific user, by dynamically allocating resources to this user. According to [25], the MAC layer in WiMAX is divided into *convergence-specific* (CS) and *common part sublayers* (CPS) as shown in Figure 3.1. Convergence-specific (CS) sublayers are used to map the transport-layer specific traffic to a MAC, which is flexible enough to efficiently carry any traffic type. Because the MAC layer of WiMAX must support various backhaul networks such as asynchronous transfer mode (ATM) and IP based networks, the CS needs to be able to handle a mapping from different types of transport-layer traffic to a MAC formatted connection (or multiple connections) [25]. The MAC is connection-oriented [25]; each service, including the connectionless service, is mapped to at least one connection. Each connection is identified by a 16-bit connection identifier (CID). This sublayer classifies the service data units (SDUs) to a proper connection with specific QoS parameters.

The common part sublayer (CPS), as its name suggests, is independent of the transport mechanism, and responsible for fragmentation and segmentation of MAC service data units (SDUx) into MAC protocol data units (PDUs), QoS control, and scheduling and retransmission of MAC PDUs.

The Physical layer in WiMAX is responsible for different functions as seen in Figure 3.1. Some of the important parameters that can be altered to improve the overall system performance were shown previously in Chapter 2.

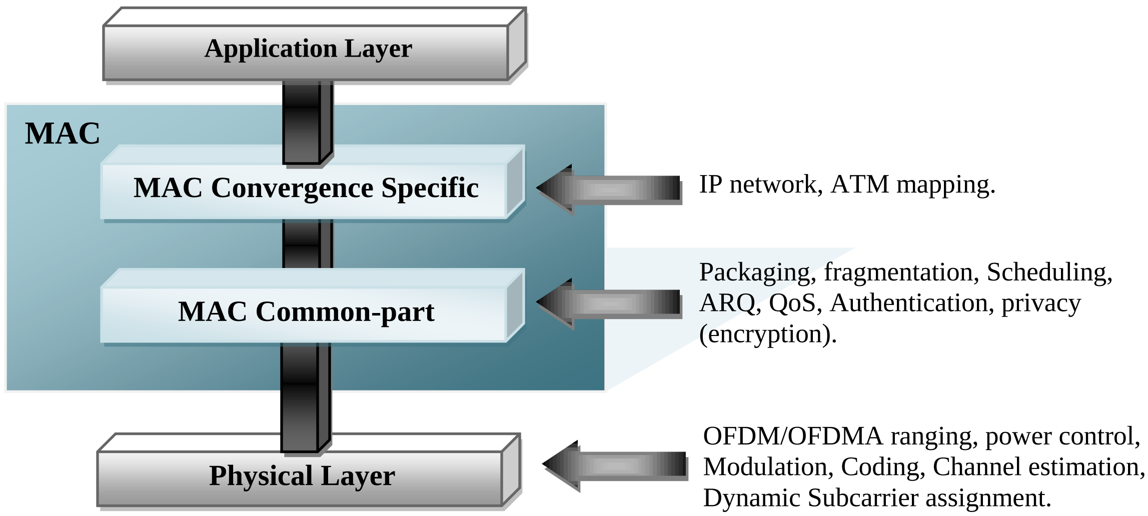

Figure 3.1 WiMAX MAC and Physical Layer

3.2 Proposed Architecture Design

The proposed CogMAX architecture is shown in Figure 3.2. The main blocks of this architecture are:

I. Air Interface

II. Network Interface

III. Application Interface

IV. Cognitive Engine

Blocks in Figure 3.2 are interactive with each other, in the sense that they depend on one another. The cognitive engine is the heart of the CogMAX system. The air interface is responsible for spectrum monitoring in order to find frequency gaps in the spectrum that can be used by unlicensed users. This is done by interacting with the communication block in the cognitive radio, which is linked to the cognitive engine. It is also responsible for channel sensing and estimation. The output from the air interface block is used by the communication module in the cognitive radio to do channel estimation, estimate the type of channel, determining type of modulation to be used, choosing number of subcarriers, select code rate, etc. so there exist a bi-directional communications between the air interface and the cognitive engine. This bi-directional communication is essential for the cognitive engine to perform channel estimation based on the number of pilots used and the channel type.

The application interface is responsible for providing information to applications using the proposed system without dealing with the associated network and system requirements. This includes location based services, authentication services, and mobility management services. The application interface will use information provided from the cognitive engine about the channel state information and about network conditions to guarantee users' requirements and quality of services. The network interface is responsible for setting the network configurations and monitoring its performance. For example, channel estimation parameters are passed on from the communication module to the reasoning engine to decide the channel type. After deciding the type of channel present, the number of pilots can then be determined through the cognitive engine. Considering WiMAX to be the standard used, then the communication module controls some important OFDM parameters of the WiMAX system such as:

- Guard time and symbol duration
- Subcarrier spacing
- Modulation type for each subcarrier
- Type of forward error correction coding

The choice of these parameters will be influenced by:

- Available bandwidth
- Required bit rate
- Delay spread
- Doppler values

The communication module handles the adaptive modulation and coding scheme (AMC). AMC is the primary method for which the quality of wireless transmission is maintained. WiMAX supports a variety of modulation and coding schemes. WiMAX defines seven combinations of modulation and coding rate [1] that can be used to achieve various trade-offs of data rate and robustness, depending on channel and interference conditions.

A primary function of the communications module is dynamic resource allocation [26]. DSA (Dynamic subcarrier assignment), as used by OFDMA, improves data rate and as data rate is a function of power allocation, it is expected that adaptive power allocation (APA) also plays a role in improving the system data rate [26]. Carrier power is allocated on a per-frame or burst level basis. DSA/APA has an efficient dynamic controller in the communication module. As seen from Figure 3.2 the communication module collects channel information through channel sensing and estimation in the air interface. This information is used in the channel estimation process. Through this estimation, parameters like Doppler Frequency, Delay Spread, Coherence BW, Coherence time and SNR (signal to noise ratio) are determined. These parameters can be used as input to the reasoning engine to determine the type of channel.

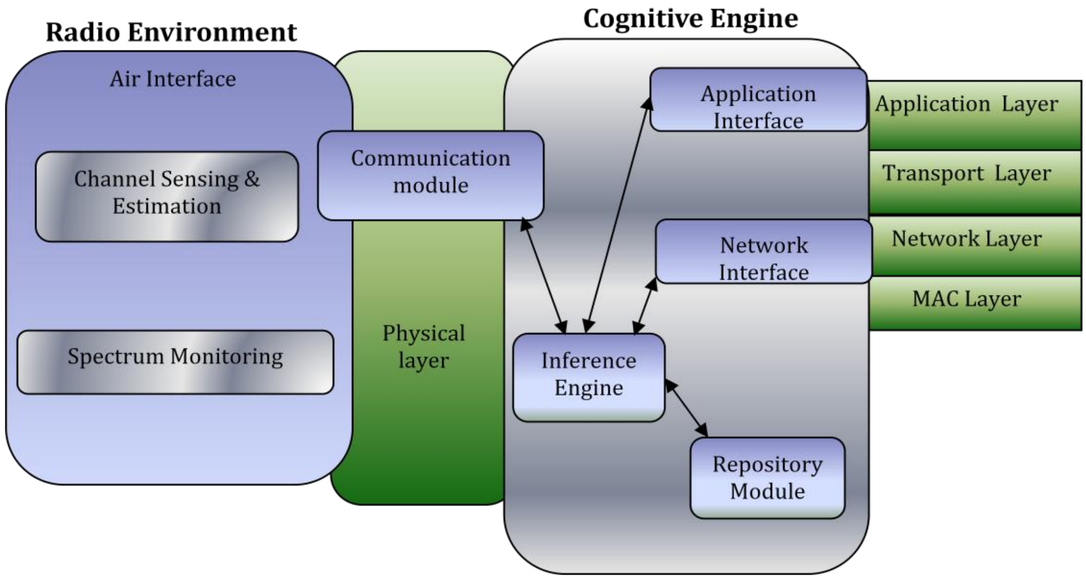

Figure 3.2 CogMAX System Architecture

3.3 The Inference Engine

Inference (reasoning) engine is the core of the cognitive radio. The inference engine is responsible for decision making and the learning process. The inference engine selects the most appropriate rule at a certain condition. Figure 3.3 shows the inference cycle of the cognitive engine (CE) at the BS (base station). It starts by generating the rules required to guarantee the successful operation of the BS under the current channel/users profiles. Rule generation is to come up with constraints to satisfy QoS, performance…etc. Rules can be of two types:

1. **Offline rules** (Initial stored rules are generated during the setup phase)
2. **Generated rules** (They are based on initial rules but, through the learning step in the cognitive radio they are modified, so they are practically rules generated by the CR).

Using these rules, the CE performs its reasoning algorithm, which may be based on Bayesian networks, fuzzy, and/or other types of inference. The CE will – decide: If the rules to be fired will result any conflicts with the QoS, reserved resources, schedule operation and perform a conflict resolution procedure to select one of them, all of which is done by the policy reasoner. Finally, it will apply the policies (policy enforcement) the will guarantee the requirements of users and the good operation of the BS.

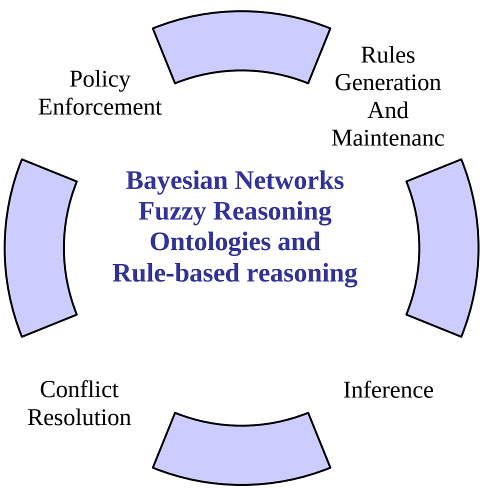

Figure 3.3 Cognitive Inference Engine

3.3.1 Learning in Cognitive Radio

Learning is the "*act, process, or experience of gaining knowledge or skill*" [27]. Learning is important to improving cognitive radio because it is necessary to understand the performance. Learning systems require observations to draw conclusions. Some of the well-known AI (Artificial Intelligence) learning techniques for CR [28] are:

Case-based Learning: This technique is useful in dynamically changing environment where knowledge is limited and experience is rich.

Knowledge-based Learning: This technique is useful for tackling new, unpredicted problems not used at the time of training.

Search Engine-based Learning: This technique tries to find the best-fit rule for a given training example.

Hidden Markov Models: This technique is used to model complicated statistical processes; it is commonly used for pattern matching. It is easy to scale, and has the ability to do prediction based on previous past experience.

Artificial Neural Networks: This technique has the ability to describe a multitude of functions; it can be scaled easily and it is excellent for classification problems. It can also identify new patterns.

Fuzzy Logic: Good for device control with unclear quality boundaries.

Cooperative Learning: Enables distributed learning and more reliable, comprehensive situation awareness, relaxes requirement of individual nodes, and reduces network cost.

3.4 Fuzzy Logic

Fuzzy logic is a multi-level logical concept that is simple and efficient and is used to find exact solutions from vague, unclear and noise inputs. Fuzzy set differs from the traditional set theory in the sense that an element can belong with a certain degree to a specific membership function. This degree of membership is referred to as the membership value, and is represented using a real value [0,1] [10]. A set ***A*** in a universe ***U*** has a membership function:

$$\mu_A : U \rightarrow [0,1] \tag{1}$$

For every $u \in U$ has a grade of membership function $u_A(u)$. Membership functions used can be trapezoidal, triangular, Gaussian…etc. Figure 3.4 shows three triangular membership functions (small, medium and large) used as input.

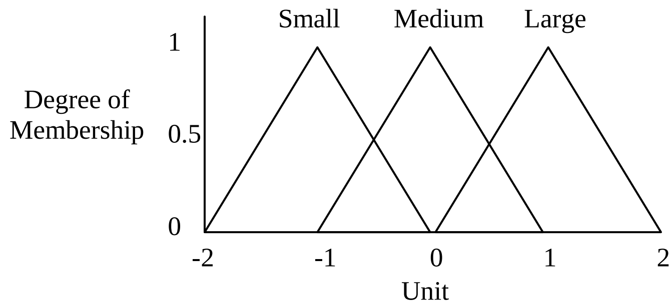

Figure 3.4 Small, Medium and Large (Linguistic Representation) Membership Functions

Fuzzy logic can be used for inference (reasoning). Predicates in fuzzy logic have a partial degree of truth. The grading level of the degree of truth is represented from [0, 1]. For example, the grade of truth of predicate ***P*** (i.e. "***x is A***") can be represented by $u_P = u_A(x)$. Traditional logic operators are used in order to modify the truth-value of the predicates. Traditional logic operators that are used are $\neg$(NOT), $\vee$(OR), and $\wedge$(AND). For example [10]:

$$u_{\neg P} \overset{\Delta}{=} 1 - u_P \tag{2}$$

$$u_{P_1 \wedge P_2} \overset{\Delta}{=} \min(u_{P_1}, u_{P_2}) \tag{3}$$

$$u_{P_1 \vee P_2} \overset{\Delta}{=} \max(u_{P_1}, u_{P_2}) \tag{4}$$

A fuzzy controller is used for inference in fuzzy logic. The control action of the controller is determined through fuzzy reasoning. Figure 3.5 shows a block diagram of a fuzzy controller. Since the input and output of the fuzzy controller have exact values, fuzzification and defuzzification are used to translate these exact values to and from their respective fuzzy representation.

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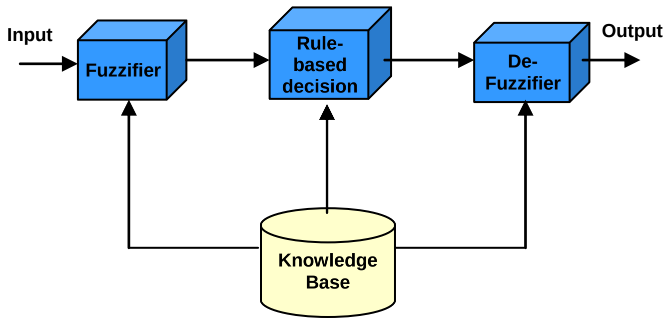


Figure 3.5 A Fuzzy Controller.

At the ***fuzzifier,*** the inputs are transferred into their fuzzy representation. The membership value of each input is got. The ***knowledge-base*** defines the relationship between input/output parameters. It also defines the input and output fuzzy representation understood by the fuzzy controller. Each input and output parameter is characterized by three main items in the knowledge-base:

- Universe: domain over which the variable can assume values.
- Set of linguistic attributes (“labels”) that compose its quantitative representation.
- For each label, a membership function is defined.

The ***rule-based decision*** is the heart of the Fuzzy Logic controller and it contains the set of the *if-then* rules. The following example in [10] was demonstrated to clearly explain the decision making step in the fuzzy controller. Suppose you have two input variables X,Y and one output variable Z and their respective linguistic attributes are X_1, X_2 for X, Y_1, Y_2 for Y and Z_1, Z_2 for Z. Then defining two rules (for example) can be:

- If X is X_1 AND Y is Y_1 then Z is Z_1.
- If X is X_2 AND Y is Y_2 then Z is Z_2.

Also let x, y be the exact values of X, Y.

The first step is to calculate α_i for each of the given rule [10]:

$$\alpha_1 = u_{X_1}(x) \wedge u_{Y_1}(y) \tag{5}$$

$$\alpha_2 = u_{X_2}(x) \wedge u_{Y_2}(y) \tag{6}$$

Then we calculate:

$$u'_{Z_1} = \alpha_1 \wedge u_{Z_1} \tag{7}$$

$$u'_{Z_2} = \alpha_2 \wedge u_{Z_2} \tag{8}$$

The final step is to determine the maximum of the above modified membership functions i.e.

$$u_Z = u_{Z_1} \vee u_{Z_2} \tag{9}$$

The defuzzification (***defuzzifier)*** is the process of determining an appropriate output value to be used as an actual output. One of the most used techniques is the centre of area (COA) [10].

Let us consider the example of a fuzzy controller, that were described in [29], which smoothly slows or stops a train that is traveling at any speed and at any distance from the station. The input variables considered in this case will be the train speed and the distance from the station. The output variable will be the train throttle and train brake. Figure 3.6 represents the membership functions of the input variables.

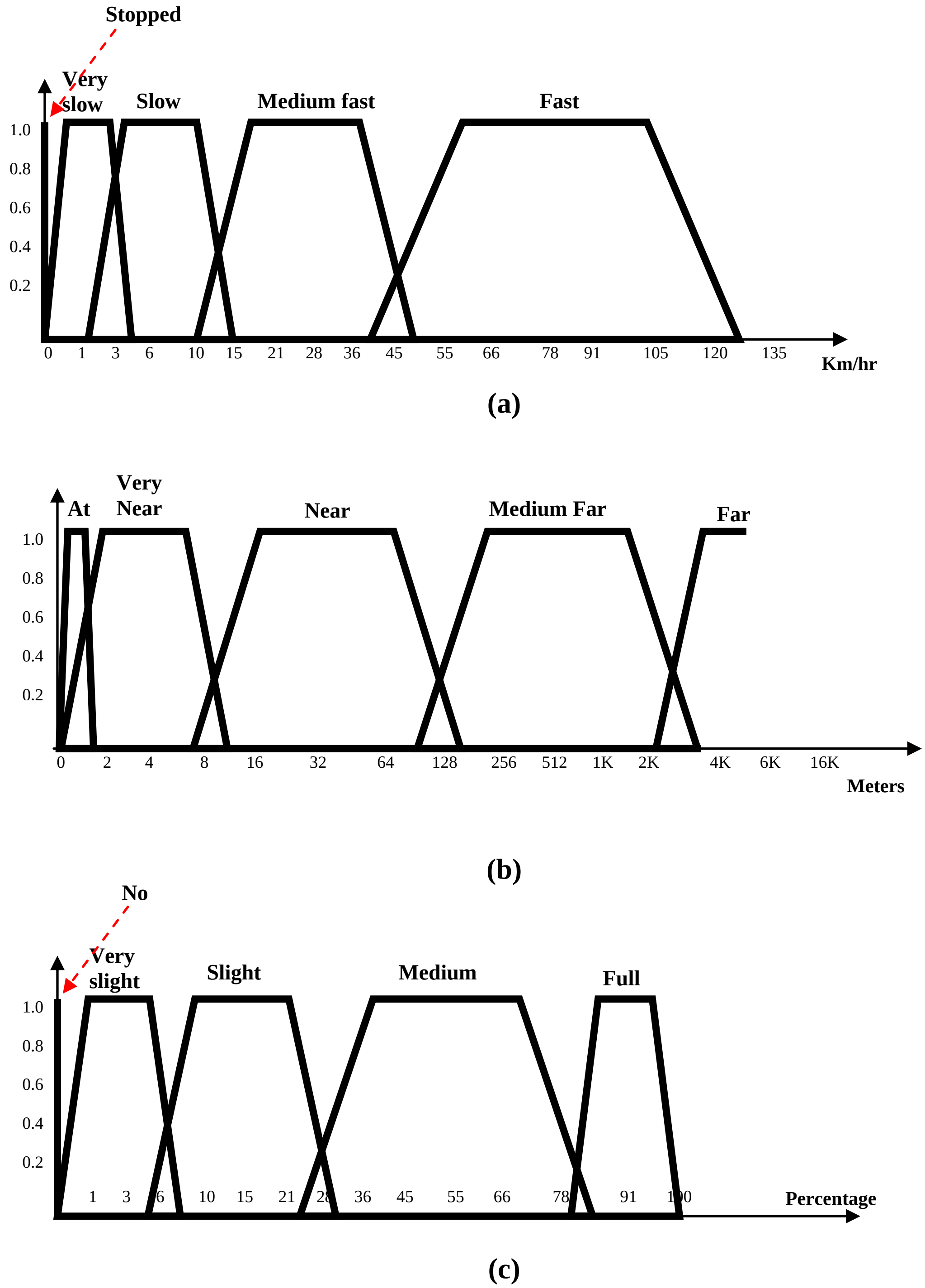


Figure 3.6 (a) Membership Functions for Speed. (b) Membership Functions for Distance (c) Membership Functions for Brake and Throttle.

The next step is to construct the rules that will lead to the decision making and thus the output. In order to make it simple, the rule based representation, in this case will be represented in the form of a matrix showing the different combinations between the inputs and the outputs. Table 3.1 illustrates this matrix representation.

Distance / **Speed**	At	Very Near	Near	Medium Far	Far
Stopped	Full Brake No Throttle	No Brake Very slow Throttle			
Very Slow	Full Brake No Throttle	Medium Brake No Throttle	No Brake Slow Throttle		
Slow	Full Brake No Throttle	Medium Brake No Throttle	No Brake Very slow Throttle		
Medium fast				No Brake Medium Throttle	No brake Full Throttle
Fast				No Brake Medium Throttle	No brake Full Throttle

Table 3.1 Fuzzy Rule Base Matrix

Table 3.1 is constructed using if-then rules and as an example, the shaded matrix entry in the table is:

IF (speed) is (stopped) AND IF (distance) is (at) THEN (full brake).

IF (speed) is (stopped) AND IF (distance) is (at) THEN (no throttle).

Now let's consider an input of:

Speed=2Km/hr

Distance= 1m

In this case, four membership functions are activated, two for speed and two for distance. Graphically this is represented by Figures 3.7 and 3.8.

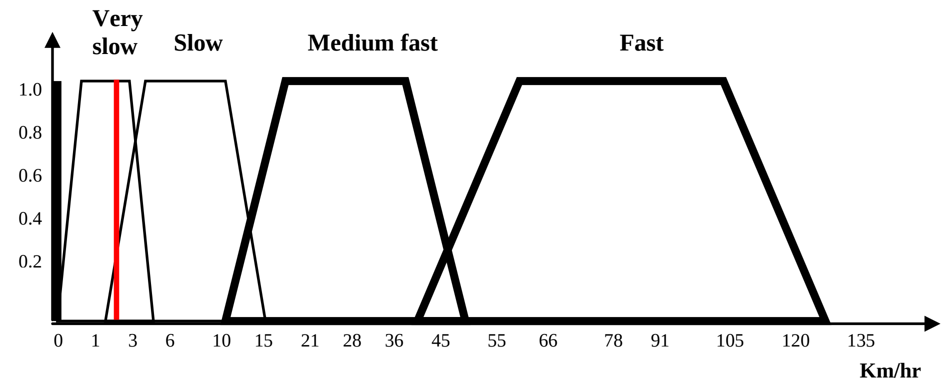


Figure 3.7 At Speed=2Km/hr Two Membership Functions are Activated, Very Slow (Value=1.0) and Slow (Value=0.2)

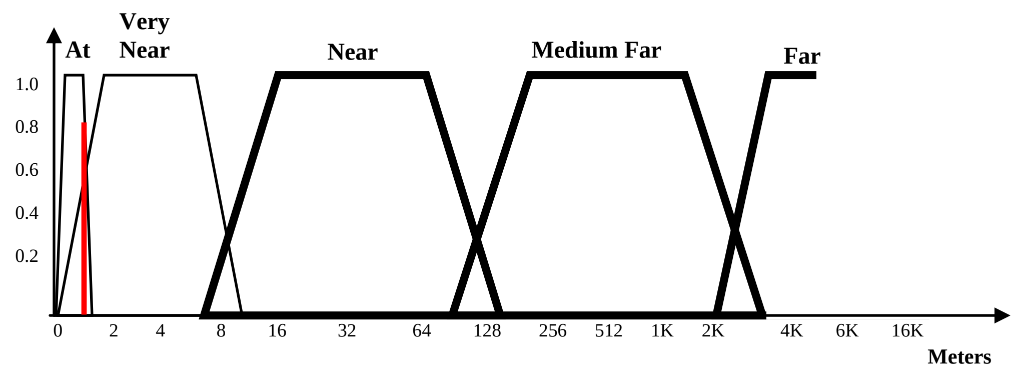


Figure 3.8 At Distance=1m Two Membership Functions are Activated, at (Value=0.8) and Very Near (Value=0.4)

Mathematically this is represented by:

- **For Speed**: $u_{\text{very slow}}(2)=1.0$, $u_{\text{slow}}(2)=0.2$

- **For Distance**: $u_{\text{very near}}(1)=0.4$, $u_{\text{at}}(1)=0.8$.

The next step is to combine the membership values together using AND (min) for each rule combination, this will yield four rules as shown in Table 3.2.

Distance / Speed	At	Very Near	Near	Medium Far	Far
Stopped	Full Brake No Throttle	No Brake Very slow Throttle			
Very Slow	**1** Full Brake No Throttle	**3** Medium Brake No Throttle	No Brake Slow Throttle		
Slow	**2** Full Brake No Throttle	**4** Medium Brake No Throttle	No Brake Very slow Throttle		
Medium fast				No Brake Medium Throttle	No brake Full Throttle
Fast				No Brake Medium Throttle	No brake Full Throttle

Table 3.2 The Four Activated Rules

The four rules are:

Rule 1: $u_{\text{very slow}}$ AND u_{at}=min (1.0, 0.8)=0.8.

Rule 2: u_{slow} AND u_{at}=min (0.2, 0.8)=0.2.

Rule 3: $u_{\text{very slow}}$ AND $u_{\text{very near}}$=min (1.0, 0.4)=0.4.

Rule 4: u_{slow} AND $u_{\text{very near}}$=min (0.2, 0.4)=0.2.

The next step is to determine the output values from the output membership functions. We will only determine the output value for the percentage of the break as the same methodology that will be used to determine the percentage of throttle.

Rules 1 and 2 are associated with the full brake membership function, whereas rules 3 and 4 are related to the med. brake membership function. The full brake membership function is intersected at 0.8 and 0.2 and the medium brake membership function is intersected at 0.4 and 0.2. The areas of these intersections are shaded and shown in Figure 3.9.

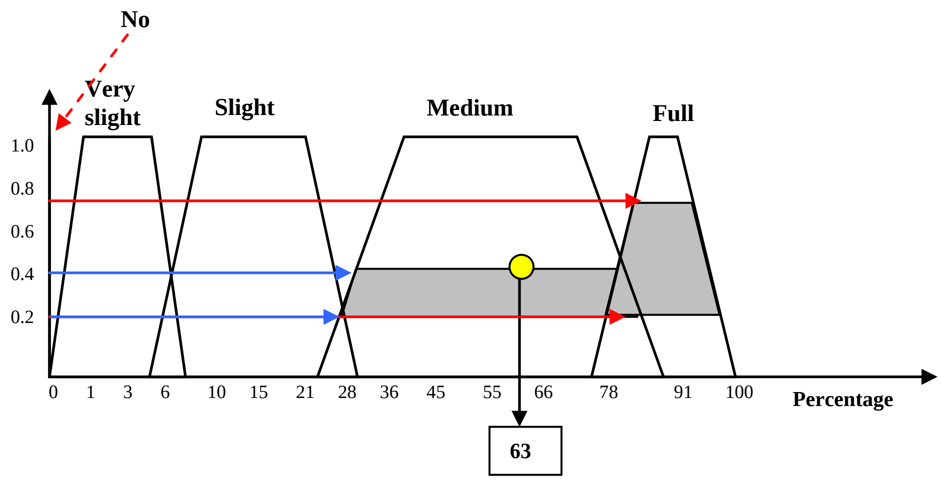


Figure 3.9 Areas of Intersection and Centroid

The last step is to determine the centroid (COA) to get the output brake percentage, this is calculated by [10]:

$$Output = \frac{\sum x_i u_A[x_i]}{\sum u_A[x_i]} \tag{10}$$

Where: $u_A[x_i]$ represents the membership function of element x_i in fuzzy set A.

Using equation 10 we get:

$$\text{Output}=\frac{0.4\times 28+0.8\times 85+0.2\times 26+0.2\times 76}{0.8+0.2+0.2+0.4}=\boldsymbol{63\%}$$

The result at the horizontal coordinates of the centroid (COA) along the x-axis gives an output value of 63% application of break. This approach can be similarly done for the defuzzification throttle.

3.4.1 Type 2 Fuzzy Logic

In the previous section we described type 1 fuzzy logic of fuzzy sets (T1FS), where the output is a crisp value. This section introduces type 2 fuzzy sets (T2FS), where the output has grades of membership functions that are fuzzy and not crisp. In other words there will not be a single value for the membership function for any "x" value, there will be a few. The values obtained need not be the same and so we can assign an amplitude distribution to all of the points. By doing this, we create a 3-D membership function. This means that there is uncertainty about the obtained value from the membership function. If all uncertainty disappears then a T2FS reduces to T1FS. Figure 3.10 shows the obtained output for a value "x", which is noticed to be a range of amplitudes [30].

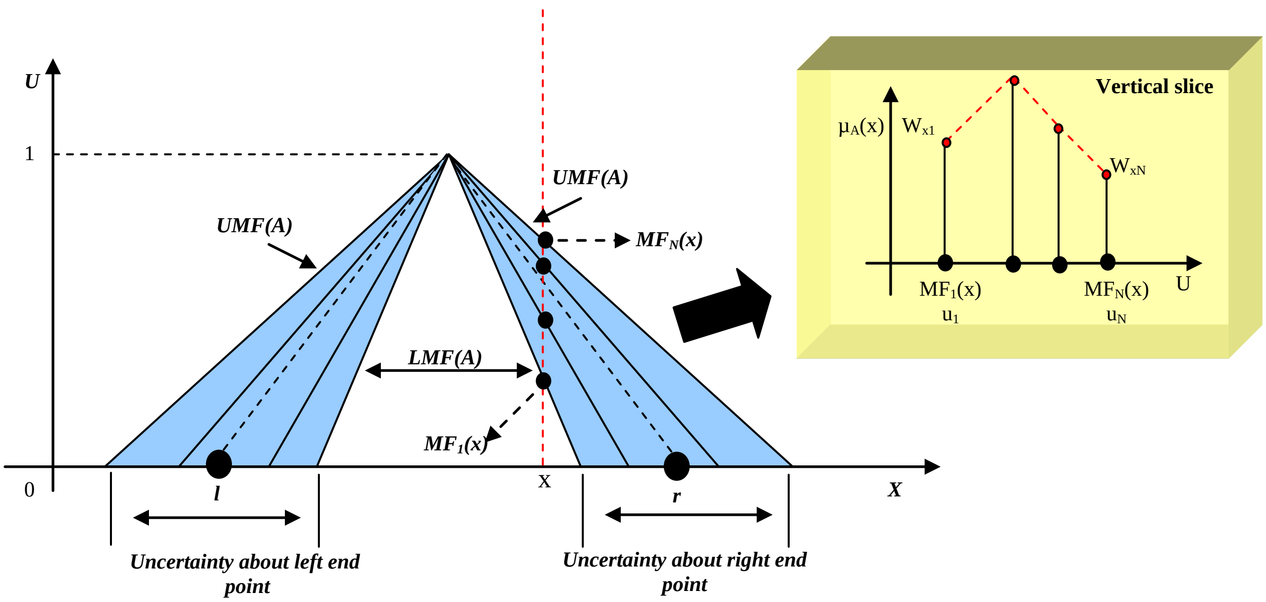


Figure 3.10 Triangular MFs (Membership Functions) when Base End Points (*l* and *r*) have Uncertainty Intervals Associated with Them. The Top Insert Depicts the Secondary MF (Vertical Slice) at *x*. UMF and LMF are the Upper and Lower Membership Functions.

Each of the possible MF grades has a weight assigned to it, say w_{x1}, $w_{x2}, \ldots, w_{xN}$ (see the top insert in Figure 3.10). These weights can be thought of as the *possibilities* associated with each triangle's grade at this value of *x*. Consequently, at each *x*, the collection of grades is a function $\{(MF_i(x), w_{xi}), i = 1,\ldots,N\}$ (called *secondary MF*). As it is not easy to sketch 3-D figures of a T2MF, another way to clear this is to plot its foot print uncertainty (FOU) on the 2-D domain of the T2FS as show in Figure 3.11 [30].

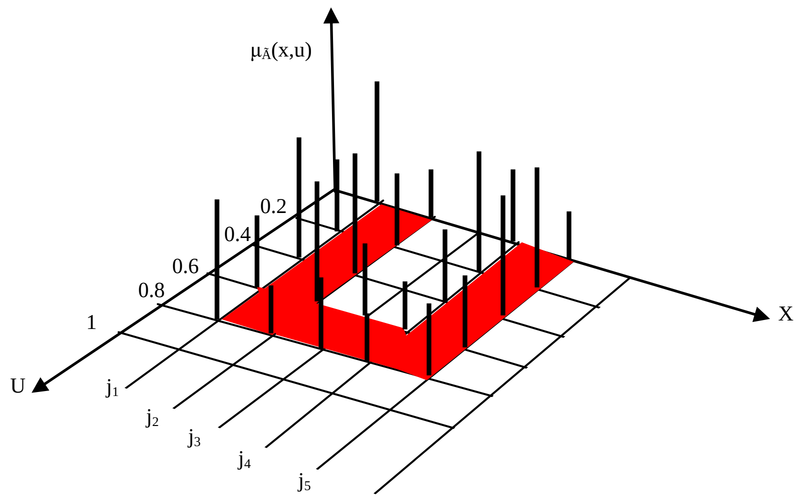


Figure 3.11 Foot Print Uncertainty (FOU) for Different Values of *x* Showing the set of Possible u Values (j_x), for Example for $x=3$ $j_3=[0.6, 0.8]$. J_x is Called the Primary Membership of *x* and is the Domain of the Secondary Membership Function. The Amplitude of the 'Sticks' is called a Secondary Grade

A type 2 fuzzy set, Ã, is characterized by a type-2 membership function $u_{\tilde{A}}(x,u)$, where

$x \in X \text{ and } u \in J_x \subseteq [0,1]$

$$\tilde{A} = \left\{ \left((x,u), u_{\tilde{A}}(x,u) \right) \mid \forall x \in X, \forall u \in J_x \subseteq [0,1] \right\} \tag{11}$$

Where: (x,u) is an intersection somewhere in the FOU $u_{\tilde{A}}(x,u)$ are the stick heights.

Ã can be also expressed as:

$$\tilde{A} = \int_{x \in X} \int_{u \in J_x} u_{\tilde{A}}(x,u)/(x,u) \qquad J_x \subseteq [0,1], \tag{12}$$

Where $\int\int$ denotes union of all admissible x and u values and can be replaced by Σ for discrete universes.

The fuzzy controller for T2FS has an extra block, as seen in Figure 3.12. It is the *type reducer*. The type reducer is responsible for centroid calculation that leads to T1FS called the type-reduced sets. There are mainly two ways to do type reduction; the first way is through the iterative Karnik-Mendel procedure to calculate the type-reduced fuzzy sets [30], while the second way is the Wu-Mendel uncertainty bounds method that has been employed to approximate the type-reduced set [31].

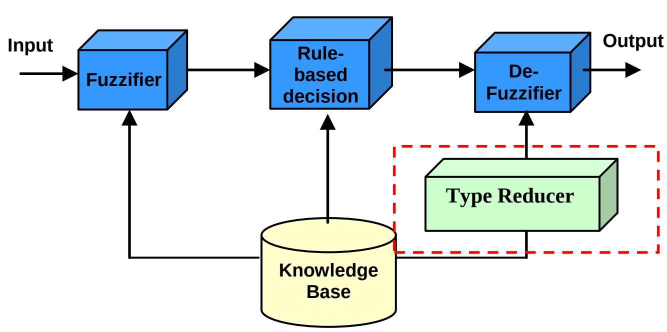


Figure 3.12 Type 2 Fuzzy Controller

3.5 Current Related Work

In our work, we propose the use of FL based on FCM (Fuzzy C-mean clustering) to automatically alter different radio parameters based on experience gained from the environment. FCM and its improvements [32-41] are important clustering methods and have been broadly used in many fields, such as pattern recognition, machine learning, data mining and so on. There is a good amount of clustering techniques that are present. For example, in [42] the K-mean algorithm is extended and the VFKM (Very Fast K-Mean) is introduced. The problem of clustering binary data streams was also introduced in [43]. An algorithm called AFCM is implemented to speed up the FCM by using a lookup table approach in [41]. FFCM (Fast FCM) algorithm is proposed in [34]. It is based on decreasing the number of distance calculations by checking the membership value for each point and eliminating those points with a membership value smaller than a threshold value. In addition, we incorporated the usage of Dempster Shafer (DS) theory of belief to tackle eliminate the anomalies that rise among the generated rules in the FL inference engine to improve the overall system performance. DS theory of evidence has attracted much attention in many fields, such as artificial intelligence research [44], multisensory networks [45], etc. DS was also used by the authors in [46] for the detection of the available spectrum for secondary transmission. In this novel algorithm, the credibility and uncertainty are calculated based on the local sensing result of cognitive radios, then fused at the fusion center using DS theory. DS was also used in spectrum utilization in [47] where a new distributed sensing scheme is proposed by considering the reliability of local spectrum sensing. The authors, in this case, quantify the channel condition between licensed user (LU) and secondary user (SU) with a parameter called "credibility" and the information gathered at an access point (AP) is made up of two parts: decision of each SU and its associated credibility. To effectively combine these results from different SU, they applied DS theory of evidence to final decision making at AP.

Lately, cognitive radio technology, used in spectrum utilization, has been encouraged by the Federal Communications Commission (FCC), due to scarce availability of frequency bands. The main issue that should be considered while using such technology is the interference caused by the transmission of the secondary to the primary user. The author in [48] proposes a technique that controls the power of the secondary users in a general situation with the purpose of acquiring the best spectrum utilization efficiency without causing any interference to primary users. The author in [49] proposed a scheme for power control but taking in consideration that primary users are active decision makers. In [50] and [51], for example, authors proposed schemes for power control among the secondary users. However, in these models the primary users were not considered as active decision makers, i.e. they don't actively participate in the spectrum sharing process.

This chapter introduced the proposed architecture design for the CogMAX along with its main operating blocks. Designing such system architecture of a cognitive radio for microwave access (CogMAX) enables using cognitive techniques for altering radio parameters to achieve enhancement in performance and efficient utilization of spectrum in a dynamic manner. Fuzzy logic was described in this chapter, along with some current related work on fuzzy logic.

In the next chapters, such an artificial intelligence technique will be used for decision making and learning capability of the inference engine.

CHAPTER 4 **Fuzzy C-mean Clustering and Dempster Shafer Theory of Belief**

In this chapter, we explain the theory behind FCM (Fuzzy C-mean Clustering). FCM will be used for clustering the training input data that will be used for the automatic generation of fuzzy membership functions and rules in the inference engine. In FCM, the initial number of clusters has recently been a wide point of research area. Some validity index tests had been proved to find the optimum number of cluster centers to be used in FCM for any input data samples. Some of them are explained in this chapter along with those that will be used in our proposed approach. The Dempster Shafer theory will be also explained, as it will be mainly used in the removal of any contradicting rules.

4.1 Basic Algorithm

To clearly explain FCM, we define the following notations. Let's consider that we have a set of objects, individuals, or data points to be clustered. In our case, these data points can represent parameters from the radio environment such as path loss value, power of the radio signal, SNR, Doppler frequency, channel delay spread…etc. Then the set of data points is denoted by $X=\{x_1, x_2,\ldots..x_p\}$ in which x_k, $(k=1,2,3\ldots.p)$ is a data point. Two basic concepts are needed in any clustering process, the first is the dissimilarity concept and the second is the cluster centre concept. To evaluate clustering of data we evaluate the nearness of the data given. This nearness is measured by finding the amount of dissimilarity between any two data points to be clustered. Dissimilarity between any arbitrary pair of data *x, x' that belongs to X* is denoted by *D(x,x')* which should be a real value and is symmetric:

$$D(x, x') = D(x', x) \qquad \forall x, x' \epsilon\ X \tag{13}$$

Small $D(x, x')$ means x, x' are near and a large $D(x, x')$ means x, x' are distant apart. We assume x is nearest to itself:

$$D(x, x) = \min_{x' \epsilon\ X} D(x, x') \tag{14}$$

Dissimilarity measure can be realized using the concept of metric, which is standard in many mathematical literatures. A metric *$m(x, x')$* defined on a space *S* satisfies the following axioms [52]:

(i) $m(x, x') \geq 0$ *and* $m(x, x') = 0 \Leftrightarrow x = x'$;

(ii) $m(x, x') = m(x', x)$;

(iii) $m(x, x') \leq m(x,z) + m(x',y)$.

One of the most common metrics used is the Euclidean metric:

$$d_2(x, y) = \sqrt{\sum_{j=1}^{p} (x^j - y^j)^2} = \|x - y\|_2 \tag{15}$$

Where: $x = (x^1, x^2, \ldots x^p)$ and $y = (y^1, y^2, \ldots y^p)$ are p dimensional vectors of R^p. and Euclidean norm is denoted by $\|x\|_2$ and Eucledian scalar product $\langle x, y \rangle = \sum_{i=1}^{p} x^i y^i$. We will omit the subscript and write $\|x\|$ instead of $\|x\|_2$.

Though, the most frequently used metric is the Euclidean space, we use squared metric as the dissimilarity measure and not the Euclidean metric d_2. The squared metric is generally used because in the presence of a very large data set, the processing time can be lower as the program does not have to calculate the square root for Euclidean Distance.

$$D(x, y) = d_2^2(x, y) = \|x - y\|_2^2 = \sum_{j=1}^{p} \left(x^j - y^j\right)^2 \tag{16}$$

The main scheme of using the c-mean algorithm is to classify X data points into disjoint subsets G_i *(i=1,2,3….c)* that are called clusters. For each cluster, a cluster centre υ_i *(i=1,2,3…c)* is found. The c-mean algorithm has the following procedure [52]:

(1) Generate random c initial center values υ_i *(i=1,2,3…c).*

(2) Allocate data points x_k ,*(k*=1,2,3….*N)* to the cluster of the nearest centre.

$$x_k \epsilon\ G_i \Leftrightarrow i = arg\ \min_{1 \le j \le c} D(x_k, \upsilon_i) \tag{17}$$

(3) Calculate new cluster centre as new centroids for each cluster.

$$\upsilon_i = \frac{1}{|G_i|} \sum_{x_k \epsilon\ G_i} x_k, \tag{18}$$

$where$ $|G_i|$ is the number of elements in G_i *(i=1,2,3….c).*

(4) Test convergence. If the test passes, the process stops, otherwise go back to step 2.

There are mainly two ways to test the convergence, that is:

(i) If no object changes its membership from previous membership obtained.

(ii) No cluster centre changes its position from the last position.

4.2 Optimization Formulation of Crisp C-mean Clustering

Let G=(G_1,G_2,……G_c) and V=($\upsilon_1, \upsilon_2, \ldots \ldots \upsilon_c$). Clusters G_1 and G_2 are disjoint and their union is the set of data points [52]:

$$\cup_{i=1}^{c} G_i \qquad G_i \cap G_{j=}\ \ (i \neq j) \tag{19}$$

Now consider the following function [52]:

$$J_{cm}(G,V) = \sum_{i=1}^{c} \sum_{x \in G_i} D(x, v_i) \qquad (20)$$

Where, $D(x, v_i) = \|x - v_i\|_2^2$.

$J_{cm}(G,V)$ is the first objective function to be minimized. This minimization process is an iteration procedure of attenuate minimization with respect to a number of different variables. As seen previously in the basic c mean algorithm that step 2 is equivalent to the minimization of the $J_{cm}(G,V)$ with respect to *G*, while *V* is fixed, while step 3 is equivalent to the minimization of $J_{cm}(G,V)$ with respect to *V* while *G* is fixed. This is an iteration procedure for minimization.

4.3 Fuzzy C-mean Algorithm

Fuzzy c-mean algorithm was introduced by Bezdek [52]. The crisp c-mean clustering is appended by additional variables representing membership functions. This is achieved by introducing an *NxC* membership matrix $U\ (u_{ki})\ (i \le k \le N,\ 1 \le i \le c)$ in which u_{ki} is a real value, where *N* is the number of data points and c are the number of clusters. let's consider u_{ki} is binary, that is, $u_{ki} = 0$ *or* 1,

$$u_{ki} = \begin{Bmatrix} 1 & (x_{k \epsilon G_i}) \\ 0 & (x_{k \notin G_i}) \end{Bmatrix} \qquad (21)$$

This means that each component of *U* shows membership/non-membership of a data point to the cluster. Thus equation (20) can be rewritten as

$$J_o(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{N} u_{ki} D(x_k, v_i) \qquad (22)$$

This is not correspondent to *J(G,V)* as *G* is a share of *X* while u_{ki} does not exclude multiple existence of an object to more than one cluster [53, 54]. Hence a constraint to *U* should be forced in order that an object belongs to one and only one cluster for all *k*. This constraint can be expressed as:

$$u_b = \left\{U = (u_{ki}): \sum_{j=1}^{c} u_{kj} = 1, 1 \leq k \leq N;\ u_{ki} \in \{0,1\}, 1 \leq k \leq N, 1 \leq i \leq c\right\} \quad (23)$$

Using u_b for minimization of the $J_o(U,V)$ will have to have two minimization steps [52]:

(i) $$\bar{U} = arg \min_{U \in u_b} J_o(U, \bar{V})$$

(ii) $$\bar{V} = arg \min_{V} J_o(\bar{U}, V)$$

$\bar{U}$ *and* $\bar{V}$ are the optimum *U*,*V* values. According to Bezdek [52], minimizing $J_o(U,V)$ can be done using dynamic programming or a genetic algorithm while considering some certain limitations. We will still proceed to fuzify the constraints u_b, i.e. allowing fuzzy memberships by relaxing the condition $u_{ki} \in \{0,1\}$ into the fuzzy one $u_{ki} \in [0,1]$ and so we replace u_b as follows:

$$u_f = \left\{U = (u_{ki}): \sum_{j=1}^{c} u_{kj} = 1, 1 \leq k \leq N;\ u_{ki} \in [0,1], 1 \leq k \leq N, 1 \leq i \leq c\right\} \quad (24)$$

In accordance the minimization steps will be:

$$\bar{U} = arg \min_{U \in u_f} J_o(U, \bar{V}) \quad (25)$$

$$\bar{V} = arg \min_{V} J_o(\bar{U}, V) \quad (26)$$

It is necessary to introduce non-linearity in U to obtain fuzzy memberships. For this Bezdek [52] and Dunn [55] introduced the non linear term $(u_{ik})^m$ into the objective function:

$$J(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ki})^m D(x_k, v_i), m > 1 \tag{27}$$

Let us consider the minimization of $J(U,V)$with respect to U under the constraint $\sum_{i=1}^{c} u_{ki} = 1$ using the Lagrange multiplier. Let the Lagrange multiplier be λ_k, $k=1,2,\ldots\ldots N$ and we put

$$L = J + \sum_{k=1}^{N} \lambda_k \left(\sum_{i=1}^{c} u_{ki} - 1\right) \tag{28}$$

For necessary conditions of optimality we differentiate with respect to u_{ki},

$$\frac{\partial L}{\partial u_{ki}} = m(u_{ki})^{m-1} D(x_k, v_i) + \lambda_k = 0 \tag{29}$$

We will assume that no $x_k = v_i$ and so $D(x_k, v_i) > 0$. We get

$$u_{ki} = \left[\frac{-\lambda_k}{mD(x_k, v_j)}\right]^{\frac{1}{m-1}} \tag{30}$$

Summing for $j=1,2,\ldots.c$ and using $\sum_{i=1}^{c} u_{ki} = 1$, we have

$$\sum_{j=1}^{c} \left[\frac{-\lambda_k}{mD(x_k, v_j)}\right]^{\frac{1}{m-1}} = 1 \tag{31}$$

Substituting for λ_k,

$$u_{ki} = \left[\sum_{j=1}^{c} \left(\frac{D(x_k, v_i)}{D(x_k, v_j)}\right)^{\frac{1}{m-1}}\right]^{-1} \tag{32}$$

Also we consider the minimization of $J(U,V)$with respect to V

$$\frac{\partial J}{\partial v_i} = 0 \tag{33}$$

Considering the Euclidean distance, where $D(x_k, v_i) = (x_k - v_i)^2$

$$\frac{\partial J}{\partial v_i} = -\sum_{k=1}^{N} (u_{ki})^m x_k + \sum_{k=1}^{N} (u_{ki})^m v_i = 0 \tag{34}$$

Therefore,

$$v_i = \frac{\sum_{k=1}^{N} (u_{ki})^m x_k}{\sum_{k=1}^{N} (u_{ki})^m} \tag{35}$$

4.3.1 Convergence Test

For the convergence of *J(U,V)*, one of the following can be used [52]:

(i) For a small positive number ε, judge that the solution of *U* is convergent if

$$\max_{k,i} | u_{ki} - \hat{u}_{ki} | < \varepsilon$$

Where *U* is the new solution and $\widehat{U}$ is the optimal solution.

(ii) For a small positive number ε, judge that the solution of *V* is convergent if

$$\max_{1 \le i \le c} | v_i - \hat{v}_i | < \varepsilon$$

Where *V* is the new solution and $\widehat{V}$ is the optimal solution.

(iii) Judge the solution is convergent when the value of the objective function is convergent.

(iv) Another criterion is also limiting the number of iterations.

4.4 Validity Test

To evaluate the correctness of clusters partitions as a result of applying the FCM algorithm, cluster validity index is used. The advantage of Cluster validity, besides measuring the soundness of the clusters, is that is also provides the number of clusters that should be used for optimum clustering. Optimum clustering is to define well compacted clusters with appropriate distance between cluster centers, in order to clearly assign each data point to a cluster. Thus, using cluster validity in our model will assist in determining the optimum number of clusters to be used as FCM algorithm initially starts by choosing a random number of clusters *c*. Several popular validity indexes were proposed in literature and we present here the most commonly used as follows:

(a) The first is the *partition coefficient (PC)* [52,56] and this is defined by:

$$PC(c) = \frac{1}{N}\sum_{i=1}^{c}\sum_{k=1}^{N} (u_{ki})^2 \tag{36}$$

Where, $\frac{1}{c} \leq PC(c) \leq 1$. We find the optimal $\hat{c}$ by solving $\max_{2\leq c\leq n-1} PC(c)$.

(b) Another validity index is the *partition entropy (PE)* [57,58] and is defined by:

$$PE(c) = -\frac{1}{N}\sum_{i=1}^{c}\sum_{k=1}^{N} u_{ki} log_2\, u_{ki} \quad (37)$$

Where, $0 \leq PE(c) \leq log_2 c$. We find the optimal $\hat{c}$ by solving $\min_{2\leq c\leq n-1} PC(c)$.

(c) A modification of the PC index was introduced in [59, 60],

$$MPC(c) = 1 - \frac{c}{c-1}\big(1 - PC(c)\big) \quad (38)$$

Where $0 \leq MPC(c) \leq 1$. We find the optimal $\hat{c}$ by solving $\min_{2\leq c\leq n-1} MPC(c)$.

(d) Validity function proposed in [61] was defined by

$$FS(c) = \sum_{i=1}^{c}\sum_{k=1}^{N} {u_{ki}}^{m}\, \|x_k - a_i\|^2 - \sum_{i=1}^{c}\sum_{k=1}^{N} {u_{ki}}^{m}\, \|a_i - \bar{a}\|^2 \quad (39)$$

$$FS(c) = J(u,a) + K_m(u,a) \quad (40)$$

Where $\bar{a} = \sum_{i=1}^{c} \frac{a_i}{c}$. *J(u,a)* is the objective of the FCM which measures the compactness and $K_m(u,a)$ measures the separation. We find the optimal $\hat{c}$ by solving $\max_{2\leq c\leq n-1} FS(c)$.

(e) The validity function proposed by [62] with m = 2 was modified by Pal and Bezdek in [63] was defined by:

$$XB(c) = \frac{\sum_{i=1}^{c}\sum_{k=1}^{N} {u_{ki}}^{m} \|x_k - a_i\|^2}{N \min\limits_{i,k}\|a_i - a_j\|^2} = \frac{J(u,a)/N}{Sep(a)} \tag{41}$$

J(u,a) is the compactness measure and *Sep(a)* is the separation measure. In general optimal $\hat{c}$ is got by solving $\max_{2\le c\le n-1} XB(c)$.

(f) The validity function proposed by Zahid in [64] was defined by

$$SC(c) = SC_1(c) - SC_2(c) \tag{42}$$

Where

$$SC_1(c) = \frac{\sum_{i=1}^{c}\|a_i - \overline{a_\iota}\|^2/c}{\sum_{i=1}^{c}(\sum_{k=1}^{N}(u_{ki}^{m})\,\|x_k - a_i\|^2/\sum_{k=1}^{N} u_{ki})} \tag{43}$$

And

$$SC_2(c) = \frac{\sum_{i=1}^{c-1}\sum_{l=i+1}^{c}\left(\sum_{\mathrm{k}=1}^{\mathrm{N}}(\min\,(\mathrm{u_{ki}},\mathrm{u_{kl}}))^2\right)/\sum_{k=1}^{N}\min(\mathrm{u_{ki}},\mathrm{u_{kl}})}{\sum_{k=1}^{N}\left(max_{1\le c\le u_{ki}}\right)^2/\sum_{k=1}^{N} max_{1\le c\le u_{ki}}} \tag{44}$$

SC_1 measures the ratio of separation and *SC_2* measures the ratio of compactness. Generally we find the optimal $\hat{c}$ by solving $\min_{2\le c\le n-1} SC(c)$.

(g) The fuzzy hpervolume Validity introduced in [65] was defined by

$$FHV(c) = \sum_{i=1}^{c}[\det\,(F_i)]^{1/2} \tag{45}$$

Where

$$F_i = \frac{\sum_{k=1}^{N} (u_{ki})^2 (x_k - a_k)(x_k - a_i)^T}{\sum_{k=1}^{N} (u_{ki})^m} \tag{46}$$

The matrix F_i is the fuzzy covariance matrix of cluster *i*. The optimal $\hat{c}$ by is got by solving $\min_{2\le c\le n-1} FHV(c)$.

4.4.1 Partition Coefficient and Exponential Separation Validity

A problem in noisy points is that sometimes, they can be identified as cluster centers using the previous validity index techniques whereas the validity index proposed by Wu and Yang [66] (*PCAES-partition coefficient and exponential separation*) for fuzzy clustering discards such noisy points from becoming cluster centers.

Wu and Yang first defined the PCAES for cluster *i* as [66]:

$$PCAES_i = \sum_{k=1}^{N} \left(\frac{{u_{ki}}^2}{u_M} \right) - \exp\left(-\min_{j \neq i} \frac{\left\{ \left\| a_i - a_j \right\|^2 \right\}}{\beta_T} \right) \tag{47}$$

Where;

$$u_{M=} \max_{1\le i\le c} \left\{ \sum_{k=1}^{N} {u_{ki}}^2 \right\} \;\; and \;\; \beta_T = \frac{\sum_{l=1}^{c} \|a_l - \bar{a}\|^2}{c} \tag{48}$$

Wu and Yang used the term of normalized partition coefficient (NPC) with $\sum_{k=1}^{N} \frac{{u_{ki}}^2}{u_M}$ for measuring the compactness for the cluster *i* relative to the most compact cluster which has the compactness measure u_M .

The separation measure for cluster *I* is measured using the following exponential type equation, as follows:

$$\exp\left(-\min_{j\neq i} \frac{\left\{\left\|a_i - a_j\right\|^2\right\}}{\beta_T}\right) \tag{49}$$

The compactness and separation for each cluster are restricted to:

$$0 < \frac{\sum_{k=1}^{N} u_{ki}^2}{u_M} \leq 1 \quad and \quad 0 < \exp\left(-\min_{j\neq i} \frac{\left\{\left\|a_i - a_j\right\|^2\right\}}{\beta_T}\right) \leq 1 \tag{50}$$

And the boundary for $PCAES_i$ are 1< $PCAES_i$<1, for all *i=1,2,…….c.*

If the value of $PCAES_i$ is large that means that cluster is compact inside and significantly separated from other *(c-1)* clusters [66]. While small values mean that the cluster is not compact. The *PCAES* is then defined as [66]:

$$PCAES(c) = \sum_{i=1}^{c} PCAES_i \tag{51}$$

$$= \sum_{i=1}^{c} \sum_{k=1}^{N} \left(\frac{{u_{ki}}^2}{u_M}\right) - \sum_{i=1}^{c} \exp\left(-\min_{j\neq i} \frac{\left\{\left\|a_i - a_j\right\|^2\right\}}{\beta_T}\right) \tag{52}$$

Obviously,

$$-c < PCAES(c) < c \tag{53}$$

Total compactness of the data set is shown by:

$$\sum_{i=1}^{c}\sum_{k=1}^{N}\left(\frac{{u_{ki}}^{2}}{u_M}\right) \tag{54}$$

Total separation of the data set is measured by:

$$\sum_{i=1}^{c}\exp\left(-\min_{j\neq i}\left\{\left\|a_i - a_j\right\|^2\right\}/\beta_T\right) \tag{55}$$

Maximum *PCAES(c)* will eventually yield a compact and well separated clusters.

Optimal $\hat{c}$ can be found by solving $\max_{2\leq c\leq n} PCAES(c)$ to produce a best clustering performance for the dataset *X*.

4.5 The Dempster Shafer Theory

Using the FCM process to find the optimum number of clusters and generate the corresponding membership functions does not prevent anomalies in the rules generated. Thus a concept is required to overcome these anomalies. In the past few years, belief functions has been an important issue for discussion amongst researchers. Belief functions have started to find their way in scientific and technological areas as well as educational enterprises. Theory of belief functions has become a primary tool for knowledge representation and uncertain reasoning in expert systems. In this chapter we introduce the Dempster-Shafer theory and present its basic concepts.

4.5.1 The Basic Concepts

The Dempster–Shafer theory originated from the concept of lower and upper probability induced by a multivalued mapping [67]. Glenn Shafer further extended the theory in his book [68] stating: "*A multivalued mapping from space S to space T associates each element in S with a set of element in T, i.e., $\Gamma : S \rightarrow 2^T$. The image of an element s in S under the mapping is called the granule of s, denoted as G(s). The multivalued mapping can also be viewed as a compatibility relation between the spaces S and T. A compatibility relation C between S and T characterizes the possibilistic relationship between their elements. An element s of S is compatible with an element t of T if it is possible that s is an answer to S and t is an answer to T at the same time and the granule of s is the set of all elements in T that are compatible with s*".

$$G(s) = \{t | t \in T, sCt\} \tag{56}$$

Knowing the probability distribution of space S and the compatible relation that exists between *S* and *T*, BPA (*basic probability assignment)* of space *T* which is denoted by $2^{T} \rightarrow [0,1]$, is:

$$m(A) = \frac{\sum_{G(s_i)=A} p(s_i)}{1 - \sum_{G(s_i)=} p(s_i)} \tag{57}$$

where the subset A is also called a focal element.

The belief measure of a set *B* is then defined by [67, 68]:

$$Bel(B) = \sum_{A \subset B} m(A) \tag{58}$$

Whereas the plausibility of *B* is given by [67, 68],

$$Pl(B) = \sum_{A \subset B \neq} m(A) \tag{59}$$

From this, we conclude that the interval *[Bel(B), Pl(B)]* is the range of *B*'s probability, which is the lower probability and the upper probability of the set subject to those constraints.

The belief interval *[Bel(B), Pl(B)]* is the range of *B*'s probability considering an example [68], if *V* is a variable and its value is from a set *X*. Then Bel(B) is the degree belief that the value of *V* lies in set *B*.

$$Bel() = 0, \qquad Bel(X) = 1, \quad if\ B_1 \subset B_2 then\ Bel(B_2) \geq Bel(B_1) \tag{60}$$

Also Pl(B) is a degree of plausibility that the value of *V* lies in the set *B*.

$$Pl() = 1, \qquad pl(X) = 1, \quad if\ B_1 \subset B_2 then\ Pl(B_2) \geq Pl(B_1) \tag{61}$$

We will have always Pl(B) ≥ Bel(B) also,

$$Pl(B) = 1 - Bel(\bar{B})\ and\ Bel(B) = 1 - Pl(\bar{B}) \tag{62}$$

If Shafer Belief structure *m* represents *X* (a set of elements) and a collection of non-null subsets of *X*, A_i, *i=1,2,3…..n.* (focal elements) and with associated weights $m(A_i)$. then:

i- $m(A_i) \in [0,1]$

ii- $\sum_i m(A_i) = 1$

Lets consider *Bel*$_1$ and *Bel*$_2$ to be two belief functions of crisp sets over the same frame of discernment according to two independent evidential sources [68]. If $m1$ and $m2$ are the BPAs of *Bel*$_1$ and *Bel*$_2$, respectively, then the combined BPA is computed through *Dempster's rule of combination as [68]:*

$$m_1 \oplus m_2\,(C) = \frac{\sum_{A\cap B=C} m_1(A)m_2(B)}{1-\sum_{A\cap B=} m_1(A)m_2(B)} \tag{63}$$

In this chapter we introduced the basic concepts of the FCM technique and different validity test to determine the optimum number of clusters and cluster centres. Dempster Shafer theory of belief was also introduced and it will play a vital role in our proposed architecture in improving the performance and in removing contradicting rules that are generated in the inference engine.

CHAPTER 5 **Channel Type & Estimation in CogMAX**

This chapter shows how channel estimation is performed and used in the proposed cognitive radio for wireless broadband systems CogMAX. The cognitive engine designed in CogMAX uses fuzzy logic (FL) for decision making and learning. A comparison between using case based reasoning (CBR) and FL is also shown. The architecture proposed in section 3.2 is the main system architecture.

5.1 Introduction to Channel Estimation Techniques

OFDM is based on multicarrier communication techniques. Subcarriers are used for transmitting the information. The available bandwidth is divided into subcarriers with appropriate frequency spacing in order for these subcarriers to be orthogonal to one another. A base band OFDM symbol is generated first by modulating the input data stream using a well known modulation scheme. The data symbols generated are converted to parallel streams before the modulation process. The sampling of subcarriers is done at a rate of N/T_S, where N represents the number of subcarriers and T_S is the OFDM symbol duration. Frequency separation between each subcarrier is $2\pi/N$. Summing of samples on each subcarrier is performed to form an OFDM sample. For example the m^{th} sample of an OFDM symbol is given by [69]:

$$x_m = \sum_{n=1}^{N-1} X_n e^{\frac{j2\pi mn}{N}} \quad 0 \le m \le N-1 \tag{64}$$

Where X_n is the transmitted data symbol on the n^{th} carrier and N is the number of subcarriers.

All OFDM samples are summed together to form an OFDM symbol. This baseband OFDM symbol is modulated by a carrier to become a band pass signal, which will be transmitted to the receiver.

ICI (Inter Carrier Interference) is caused when the multipath channel varies over an OFDM symbol time [70]. Loss of orthogonally is also considered a vital issue, and is mainly caused by the Doppler shift which in due causes a frequency offset. If an OFDM transmitter having N subcarriers and the duration for each data symbol is given by T', then the OFDM symbol duration would be given by $T_S = T'N$. OFDM combats ISI (Inter Symbol Interference), further improvement and decrease of the ISI effect can also be induced by inserting a guard time, this can be easily done by inserting a part of the OFDM symbol at the beginning of the symbol itself, this is *cyclic prefix (71).*

The use of OFDM in WBN along with the use of cyclic prefix cancels the effect of time dispersion [72]. However, fluctuations in amplitude and phase caused by the wireless channel on OFDM symbols require a good channel estimation technique to overcome such phenomena. The effect of the channel can be removed by using pilot symbols to estimate the phase and amplitude shifts caused by the channel. As it is not practical to send pilots on the entire OFDM bandwidth, pilot subcarriers are sent at certain frequencies or time intervals. The time-frequency occupancy in this case will look like a grid, where the pilots are placed at different points on this grid. The channel effect estimated by these pilot subcarriers is then used to determine the channel response for all the data subcarriers. Figure 5.1 shows example of the time-frequency grid with the pilot and data subcarriers arrangement. The example shown in Figure 5.1 represents four OFDM symbols.

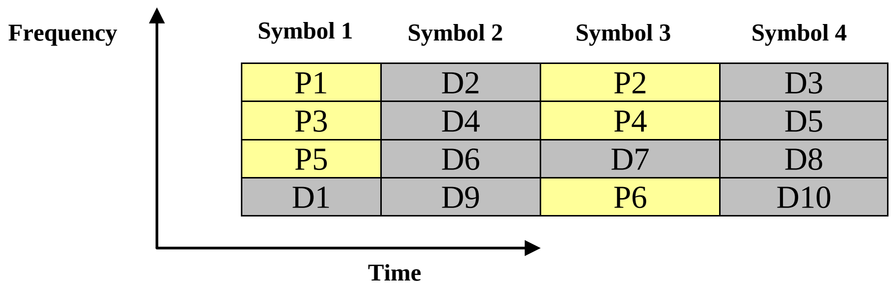


Figure 5.1 Time-Frequency Grid Showing Pilot (P) and Data Subcarriers (D) for Four OFDM Symbols

The arrangement of pilots consists of two types: ***Block-type*** and ***Comb-type*** arrangement [73]. The Block-type arrangement is mainly considered for slow, fading channels, where pilots are placed into all subcarriers of an OFDM symbol but within a specific period as shown in Figure 5.2a. Comb-type arrangements are used for medium or fast fading channels where pilots are placed at a specific subcarrier for each OFDM symbol as shown in Figure 5.2b.

A mix of both these types can be also used. The best placement of the pilot symbols for a changing wireless channel is a key research objective. This placement can be controlled by the cognitive radio. The spacing of the pilots should be determined with great care. The spacing of pilot tones (D_P) in the frequency domain will depend on the coherence bandwidth of the channel, which is related to the delay spread of the channel as in equation (65). According to the Nyquist sampling theorem the spacing should be small enough to detect the entire variations of the channel [73]. D_P is given by:

$$D_P \leq \frac{1}{\tau_{\max} \Delta d f} \tag{65}$$

Where, τ_{max} is the maximum delay spread of the channel. In order to track the channel in the time domain the pilot position (D_t) will then depend on the coherence time, which is related to the Doppler spread as in equation (66):

$$D_t \leq \frac{1}{2\,fd_{\max} T_f} \tag{66}$$

Where fd_{max} is the maximum Doppler spread and T_f is the OFDM symbol duration. In order to control the position of the pilots using the cognitive engine, the above two criteria should be taken in consideration. This will require fast decisions to determine the channel type, which is a key research objective.

In order to estimate the different channel response at the data subcarriers: first we estimate the channel response at the pilot subcarriers, second we estimate the channel response at the data subcarriers (this is done through interpolation). Two commonly used types of estimators; ***LS (Least Square)*** and ***LMMSE (Linear Minimum Mean Square Error)*** have been adapted. The interpolation techniques considered were the ***linear***, ***averaging*** and ***constant*** interpolators for 1-dimension and 2-dimension.

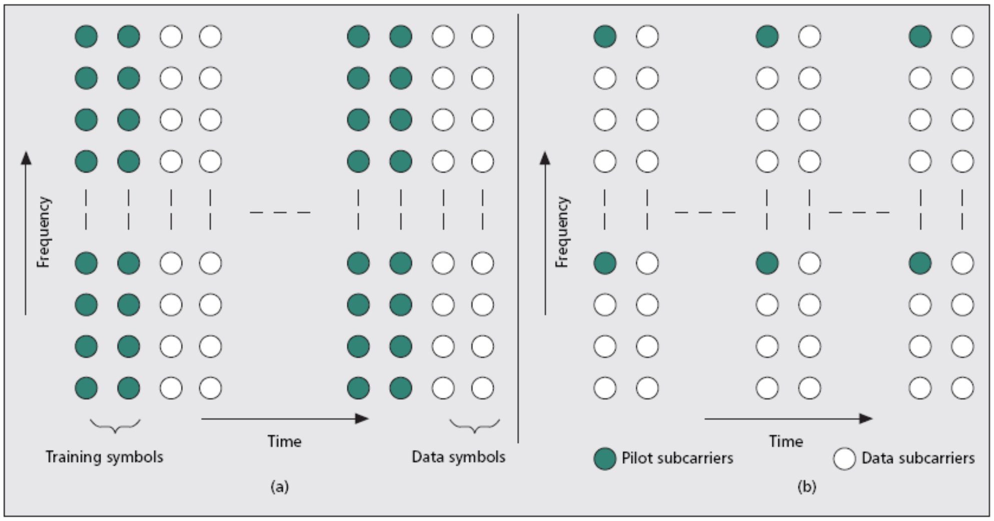


Figure 5.2 (a) Block Type (b) Comb Type Arrangement [74]

5.1.1 Estimators

The investigation considered two types of estimators; LS (Least square) and LMMSE (Linear Minimum Mean Square Error.

5.1.1.1 Least Square (LS)

The LS is considered to be the simplest and the least complex type of estimator. It is also used by many other estimation techniques as initial estimation of the channel because of its simplicity. No statistical knowledge of the channel is considered for the channel estimation using the LS technique [73]. If we consider an OFDM transmitted symbol X and the received signal Y then the LS estimate $\hat{h}_{LS}$ is given by [73]:

$$\hat{\mathrm{h}}_{LS}=\mathrm{X}^{-1}\mathrm{Y}=[\frac{\mathrm{y_o}}{\mathrm{x_o}} \;\; \frac{\mathrm{y_1}}{\mathrm{x_1}} \ldots\ldots \frac{\mathrm{y_{N-1}}}{\mathrm{x_{N-1}}}]^{\mathrm{T}} \tag{67}$$

If to consider the comb type pilot arrangement, the N_p pilot signals $X_p(m)$, $m=0,1,2\ldots N\text{-}1$ are uniformly inserted into $X(k)$. That is the total N subcarriers are divided into N_p groups, where for each group the first subcarrier is used for pilot transmission.

If the channel response vector of the pilot subcarriers is given by:

$$\boldsymbol{h}_p = \left[h_p(0)\ \ h_p(1)\ \ h_p(N_p - 1)\right] \tag{68}$$

and the received pilot signals are:

$$\boldsymbol{Y}_p = \left[Y_p(0)\ \ Y_p(1)\ \ Y_p(N_p - 1)\right] \tag{69}$$

Then $\mathbf{Y}_p$ can be expressed as :

$$\boldsymbol{Y}_p = \boldsymbol{X}_p.\boldsymbol{h}_p + \boldsymbol{I}_p + \boldsymbol{W}_p \tag{70}$$

Where,

$$\boldsymbol{X}_p = \begin{bmatrix} X_p(0) & 0 \\ 0 & X_p(N_p - 1) \end{bmatrix} \tag{71}$$

$\mathbf{I}_p$ is the vector of ICI and $\mathbf{W}_p$ is the Gaussian noise vector.

The LS estimation on the pilot signals is [73]:

$$\boldsymbol{h}_{p,ls} = \left[h_{p,ls}(0)\ \ h_{p,ls}(1)\ \ h_{p,ls}(N_p - 1)\right]^T \tag{72}$$

$$= \boldsymbol{X}_p^{-1}\boldsymbol{Y}_p \tag{73}$$

$$\left[\frac{Y_p(0)}{X_p(0)}\ \ \frac{Y_p(1)}{X_p(1)} \ldots\ldots \frac{Y_p(N_p-1)}{X_p(N_p-1)}\right]^T \tag{74}$$

This technique suffers from high mean-square error as no correlation is considered between frequency carriers and across OFDM symbols [73].

5.1.1.2 Linear Minimum Mean Square Error (LMMSE)

LMMSE is widely used for channel estimation for OFDM [74]. LMMSE uses additional information like the SNR (signal to noise ratio). The equation of this estimator is given in [74]. If we assume that we have the available LS estimates, and they are arranged in vector $\hat{P}$ (previously mention as $\boldsymbol{h}_{p,ls}$). Channel values have to be estimated from $\hat{P}$ are in vector h. The whole idea is to find the channel estimates $\hat{h}$ as a linear combination of LS estimates and $\hat{P}$. According to [75] the MMSE estimate of this problem is given by:

$$\hat{h}_{LMMSE} = R_{h\hat{P}}(R_{\hat{P}\hat{P}})^{-1}\hat{P} \tag{75}$$

Where: $R_{h\hat{P}}$ is the covariance matrix between h and noisy pilots $\hat{P}$ and $R_{\hat{P}\hat{P}}$ is the covariance matrix between noisy pilots $\hat{P}$. This is given by:

$$R_{h\hat{P}} = E\{h\hat{P}^H\} \tag{76}$$

and,

$$R_{\hat{P}\,\hat{P}} = E\{\hat{P}\hat{P}^H\} \tag{77}$$

$$= R_{PP}+\sigma_n^2(PP^H)^{-1} \tag{78}$$

Where σ_n^2 is the variance of the additive channel noise and $(.)^{\mathrm{H}}$ denotes the Hermitian transpose. For block type pilot channel estimation equation (75) can be rewritten as [75]:

$$\hat{h}_{LMMSE} = R_{hh}(R_{hh}+\sigma_n^2(PP^H)^{-1})\hat{P} \tag{79}$$

Let us assume that the variance of the channel attenuation in h are normalized to unity, i.e. $E\{|h^k|^2\} = 1$.

In order to further reduce the complexity we replace $(PP^H)^{-1}$ with its expectation $E\{(PP^H)^{-1}\}$ and that the all tones have similar signal constellation and equal probability, we well then have $E\{(PP^H)^{-1}\} = E\left\{\left|\frac{1}{P_k}\right|^2\right\} I$, where I is the identity matrix. Defining the average signal to noise ratio to be:

$$SNR = E\{|P_k|^2\}/\sigma_n^2 \tag{80}$$

The simplified estimator will then be [75]:

$$\hat{h}_{LMMSE} = R_{hh}(R_{hh}+\frac{\beta}{SNR}I)^{-1}\hat{P} \tag{81}$$

Where $\beta = E\{|P_k|^2\}E\left\{\left|\frac{1}{P_k}\right|^2\right\}$

LMMSE outperforms the LS techniques especially at low SNR [74]. However LMMSE suffers from high computational complexity.

5.1.2 Interpolators

After the channel estimation process of the pilot subcarriers, 1D or 2D interpolators are used to determine the channel response at the data subcarriers. As mentioned before, the linear-averaging and constant interpolators were used in 1D and 2D. The three types of interpolators are shown in Figure 5.3 in order to clearly illustrate the different techniques.

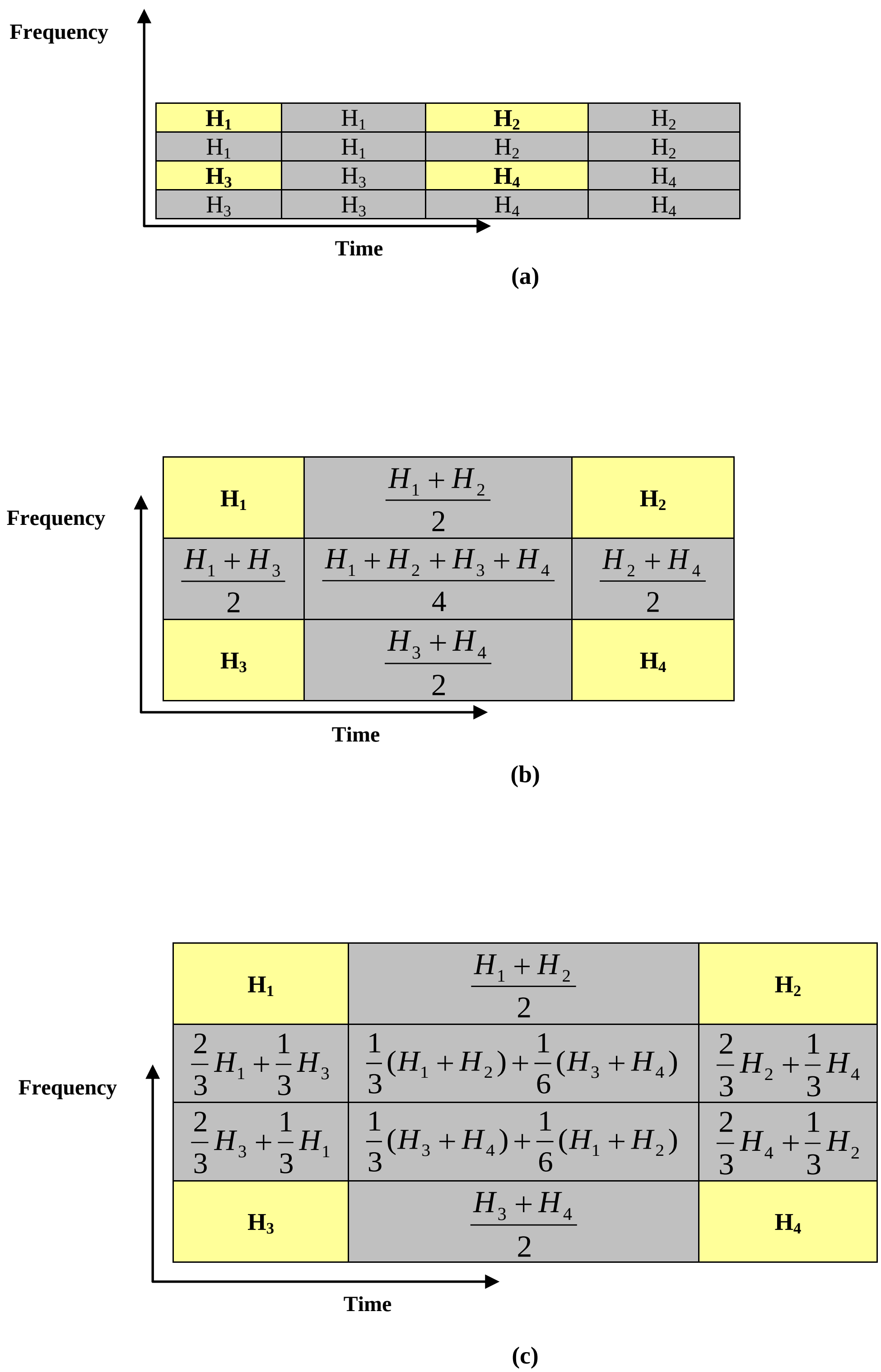


Figure 5.3 **(a)** Constant Interpolator**, (b)** Averaging Interpolator, **(c)** Linear Interpolator.

Figure 5.3a shows the constant interpolator, where the channel response at the pilot subcarriers remains the same for the next upcoming data subcarriers and changed only when a new pilot subcarrier is detected and its channel response is calculated. Figure 5.3b uses the averaging interpolator, where the average is taken between the channel responses of the pilot subcarriers. As seen from the Figure, the average is taken first of the horizontal direction, and then the vertical direction. Notice: to use such an interpolator, the receiver waits for the rest of the pilots subcarriers to arrive in order to calculate the average. Figure 5.3c explains the linear interpolation method where the channel response at the pilot subcarriers are use to linearly determine the response at different data subcarrier locations. This is also done in the horizontal direction first and then the vertical direction.

5.2 Determining Channel Type in CogMAX

The main algorithm used by the cognitive engine (CE) in our CogMAX system is shown in Figure 5.4. Four important parameters are estimated in the communication module through channel estimation and sensing in the air interface. These parameters are T_b (bit duration), τ (delay spread), f_d or B_d (Doppler spread) and B_s (Signal Bandwidth). Using these parameters the type of channel can be determined through the following if-then rules:

- If $(\tau/T_b)>1$ then channel is ***Frequency Selective***, otherwise channel is ***Flat Fading***.
- If $(B_d/B_s)>1$ then channel is ***Fast Fading***, otherwise channel is ***Slow Fading***

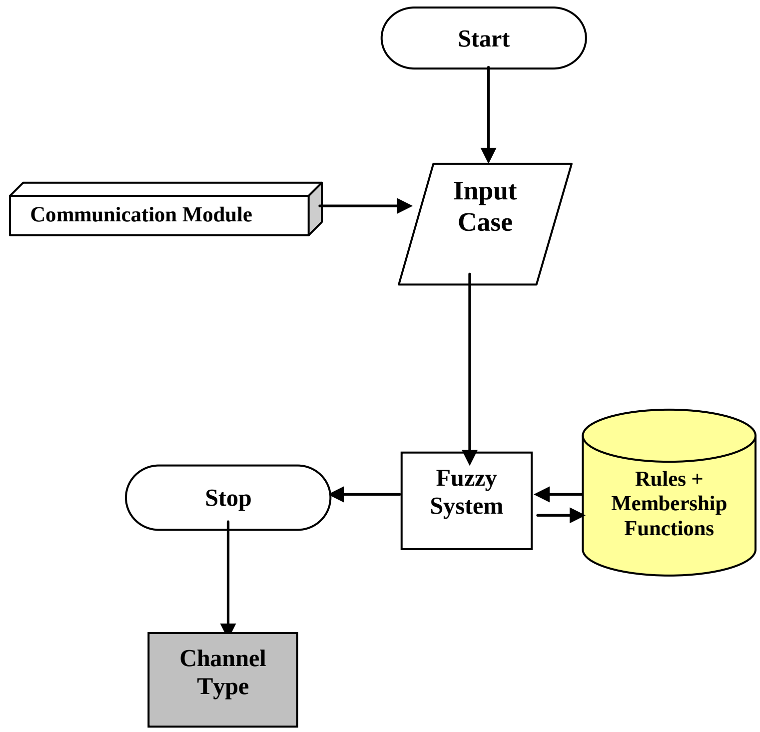


Figure 5.4 Simulation's Flowchart (Channel Type Determination in the CE)

5.2.1 Algorithm

Fuzzy Logic membership functions (Figure 5.6) are estimated from stored training data. The stored training data will be T_b (bit duration), τ (delay spread), f_d or B_d (Doppler spread) and B_s (Signal Bandwidth) along with their respective channel type. The stored data is used to determine the input and output membership function using the FCM algorithm described in chapter 4. The rules are also generated using FCM. Figure 5.6 a & b show the membership function generated for inputs and outputs. As seen from Figure 5.4, an input case or situation enters the fuzzy system and using the membership functions stored along with the set of rules stored the type of channel is determined. The membership functions can be made adaptive by considering each new case and result, hence the CE is *learning* from experience.

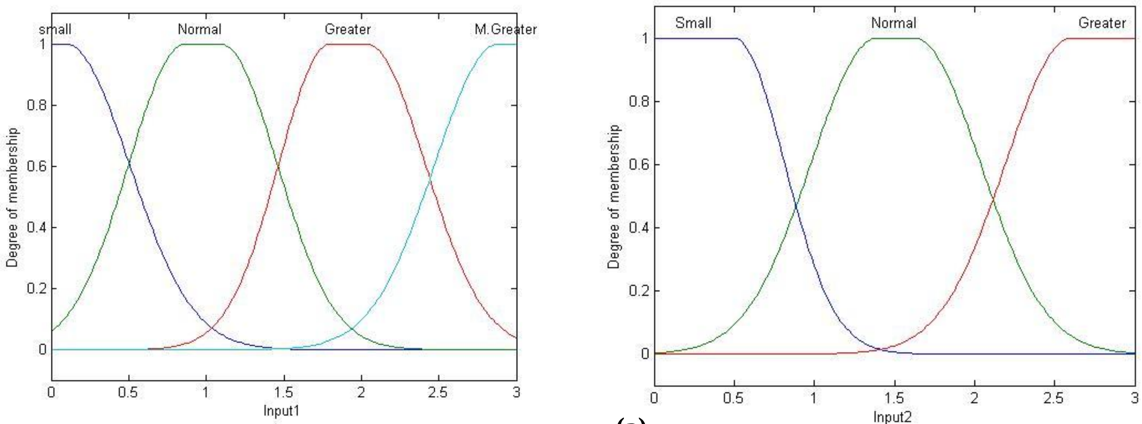
```
a=newfis('Channel Type');
% Add the first input variable
a=addvar(a,'input','Input1',[0 3]);
a=addmf(a,'input',1,'small','gauss2mf',[0.408 -0.144 0.408 0.0964]);
a=addmf(a,'input',1,'Normal','gauss2mf',[0.363 0.8619 0.363 1.096]);
a=addmf(a,'input',1,'Greater','gauss2mf',[0.3312 1.797 0.3762 2.037]);
a=addmf(a,'input',1,'M.Greater','gauss2mf',[0.4077 2.88 0.4077 3.12]);
% Add the second input variable
a=addvar(a,'input','Input2',[0 3]);
a=addmf(a,'input',2,'Small','gauss2mf',[0.312 -0.218 0.312 0.5017]);
a=addmf(a,'input',2,'Normal','gauss2mf',[0.4077 1.388 0.4077 1.628]);
a=addmf(a,'input',2,'Greater','gauss2mf',[0.408 2.603 0.0408 3.12]);

% Add the first output variable
a=addvar(a,'output','Output1',[0 3]);
a=addmf(a,'output',1,'Flat','gauss2mf',[0.408 -0.144 0.408 0.0964]);
a=addmf(a,'output',1,'Q.Flat','gauss2mf',[0.363 0.8619 0.363 1.096]);
a=addmf(a,'output',1,'Q.F.Selective','gauss2mf',[0.3312 1.797 0.3762
2.037]);
a=addmf(a,'output',1,'F.Selective','gauss2mf',[0.4077 2.88 0.4077 3.12]);
% Add the second output variable
a=addvar(a,'output','Output2',[0 3]);
a=addmf(a,'output',2,'Slow','gauss2mf',[0.312 -0.218 0.312 0.5017]);
a=addmf(a,'output',2,'Medium','gauss2mf',[0.4077 1.388 0.4077 1.628]);
a=addmf(a,'output',2,'Fast','gauss2mf',[0.408 2.603 0.0408 3.12]);
```

(a)

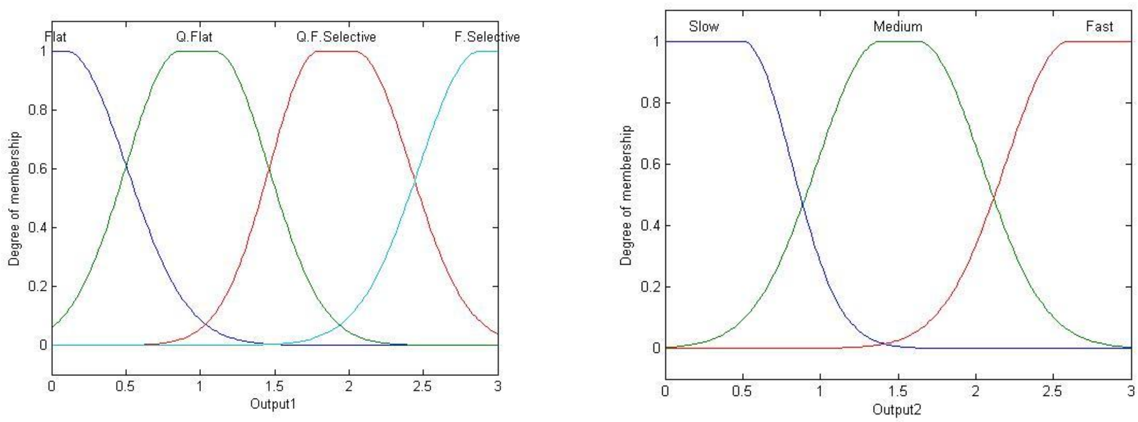
```
If (Input1 is Normal) and (Input2 is Normal) then (Output1 is Q.Flat)(Output2 is Medium) (1)
If (Input1 is Greater) and (Input2 is Greater) then (Output1 is Q.F.Selective)(Output2 is Fast) (1)
If (Input1 is small) and (Input2 is Normal) then (Output1 is Flat)(Output2 is Medium) (1)
If (Input1 is M.Greater) and (Input2 is Small) then (Output1 is F.Selective)(Output2 is Slow) (1)
If (Input1 is M.Greater) and (Input2 is Normal) then (Output1 is F.Selective)(Output2 is Medium) (1)
If (Input1 is Greater) and (Input2 is Normal) then (Output1 is Q.F.Selective)(Output2 is Medium) (1)
If (Input1 is Normal) and (Input2 is Small) then (Output1 is Q.Flat)(Output2 is Slow) (1)
If (Input1 is Greater) and (Input2 is Small) then (Output1 is Q.F.Selective)(Output2 is Slow) (1)
). If (Input1 is M.Greater) and (Input2 is Greater) then (Output1 is F.Selective)(Output2 is Fast) (1)
. If (Input1 is Normal) and (Input2 is Greater) then (Output1 is Q.Flat)(Output2 is Fast) (1)
2. If (Input1 is small) and (Input2 is Small) then (Output1 is Flat)(Output2 is Slow) (1)
```

(b)

Figure 5.5 (a) Code of the Generated Membership Functions. (b) Snapshot of the Fuzzy Engine Set of Rules



(a)



(b)

Figure 5.6 Showing **(a)** the Two Input Membership Functions Input1 (τ/T_b) and Input2 (B_d/B_s), **(b)** the Two Output Membership Functions for Determining whether the Channel is (Flat or Frequency Selective) and (Slow or Fast Fading), Q Stands for Quasi,

The simulation used cases for training and cases for testing. The cases for training were used to determine the membership functions for the fuzzy logic system using FCM. All the membership functions used in our case were determined to be flat Gaussian (m = 1.5). The reason was that in a Gaussian function, there is no abrupt change for transition but a smooth change beside that the membership functions considered were flat from the top to show that the output or input can be constant for a certain interval.

5.3 Comparison with Case Based Reasoning (CBR)

The training cases were considered to be the stored cases, which are obtained from previous knowledge. A search is done for every new case to determine the closest match from the stored cases. The search is carried out normally through all the stored cases, and the use of the Euclidean distance is performed to determine the closest match i.e., for every new case with inputs (τ/T_b) and (B_d/B_s) a whole search is done through the stored cases and the closest match is considered to be the one with the least Euclidean distance. The Euclidean distance is the root of the sum of the square of the difference between different input parameters. For example, if a search is done for an input $A_{11} = (\tau/T_b)_1$ and $A_{21} = (B_d/B_s)_1$ through N stored cases with $B_{1(1..N)}$ and $B_{2(1..N)}$, then the closest match is the one with the least below distance:

$$d_{ij}=\sqrt{(A_{i1}-B_{j1})^2+(A_{i2}-B_{j2})^2} \tag{82}$$

where,

i: index of the input.

j: index of the stored cases (1….N).

To compare between the CBR and the Fuzzy logic in the determination of the channel type, two important parameters were measured; time taken to reach a result and the error percentage of the result.

Shown in Figure 5.7, for 1000 cases, the fuzzy logic reasoning engine outperforms the CBR engine in both speed and error avoidance. Alternately, if the number of cases were to be reduced to 100 cases, as seen in Figure 5.8, the CBR engine performs faster than the Fuzzy logic engine but with more errors. Overall, the fuzzy logic reasoning engine performs better than the CBR engine as the number of stored cases would have to be large enough for a CBR engine to perform better. The results also show that for a fuzzy logic reasoning engine the variation of the error is much smaller than that of a CBR engine. This makes the Fuzzy logic engine more predictive in terms of error.

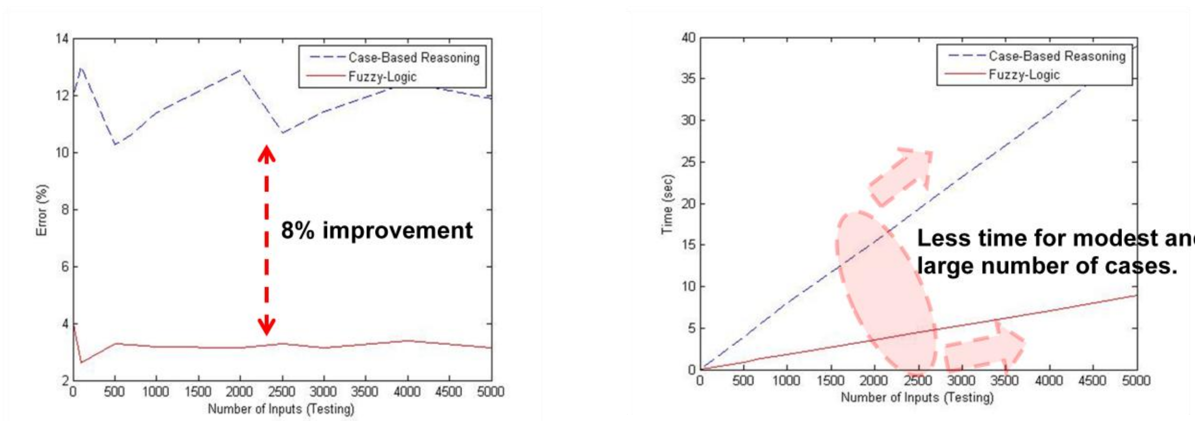


Figure 5.7 Comparison between CBR Engine and a Fuzzy logic Engine in Terms of the Error (%) and Time (sec), 1000 Cases Were Used for Training.

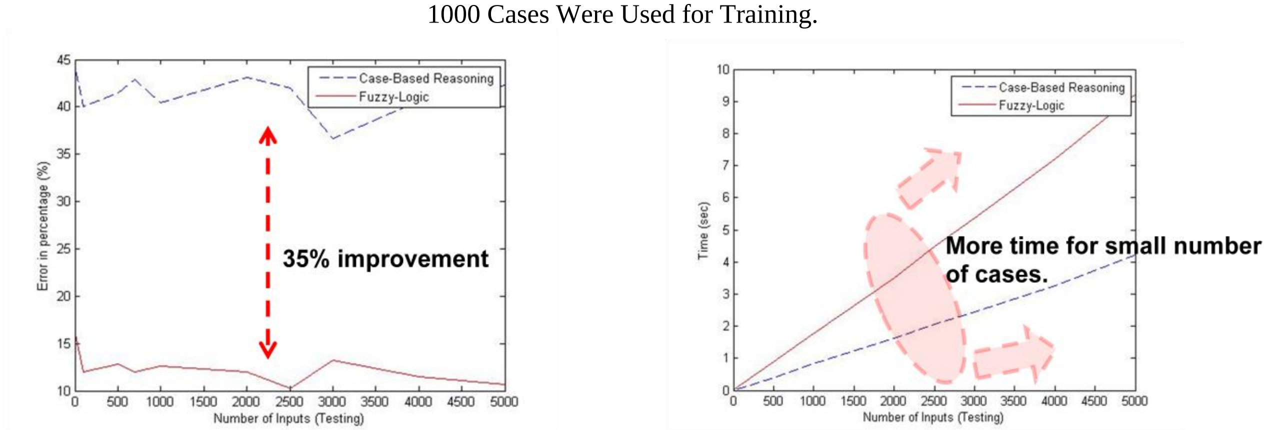


Figure 5.8 Comparison between CBR Engine and a Fuzzy Logic Engine in Terms of the Error (%) and Time (sec), 100 Cases Were Used for Training.

The results showed that fuzzy logic reasoning results in lesser errors than the case-based reasoning engine (CBR), i.e. 8% improvement for 1000 cases and 35% improvement for 100 case. It is obvious that for a lesser number of stored cases, the CBR will not perform well, due to the lack of information. Furthermore, the fuzzy system took less time for modest and large number of cases. Overall, a fuzzy reasoning engine gives better results than a case-based reasoning engine. In addition for fuzzy systems, there can be an adaptation of the membership function in accordance with the number of training cases, i.e, if I have more cases (knowledge) stored in my database then the membership functions can vary in *width* and *type* to achieve better results.

5.4 Channel Estimation in CogMAX

This section presents a pilot based channel estimation technique, where the pilot symbols are transmitted on the subcarriers. At the receiver, the channel transfer function is estimated from the pilot subcarriers samples. The channel transfer function of the unknown data symbols is then determined by interpolation. The number of pilots, placement of the pilots, and the type of interpolation greatly influences the quality of the channel estimate. The channel estimation techniques were described in section 5.1. Figure 5.9 shows the system for determining the type of channel and the number of pilots to be used in the CE. CE is made up of two FLRE (fuzzy logic reasoning engines (FLRE1 and FLRE2).

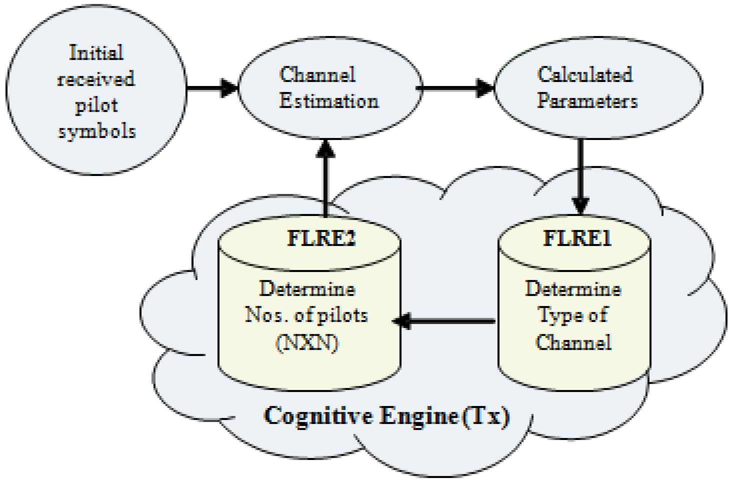


Figure 5.9 Channel Estimation System Main-Functions

The main algorithm for the proposed system is shown in Figure. 5.10. Four important parameters are calculated in the communication module (Figure 3.2) through channel estimation. These parameters are T_b (bit duration), τ (delay spread), B_d (Doppler spread) and B_s (Signal Bandwidth). Using these parameters, the type of channel can be determined through fuzzy logic reasoning (as shown in section 5.3). The main set of rules used in the fuzzy logic reasoning engine depends on the below states.

- If $(\tau/T_b)>1$ then channel is ***Frequency Selective***, otherwise channel is ***Flat Fading***.
- If $(B_d/B_s)>1$ then channel is ***Fast Fading***, otherwise channel is ***Slow Fading***

The membership functions are estimated for the inputs and outputs and a set of rules are put in order to determine the outputs from the inputs.

The number of pilot used (N^2) is then determined through FLRE2 as shown in Figure 5.9.

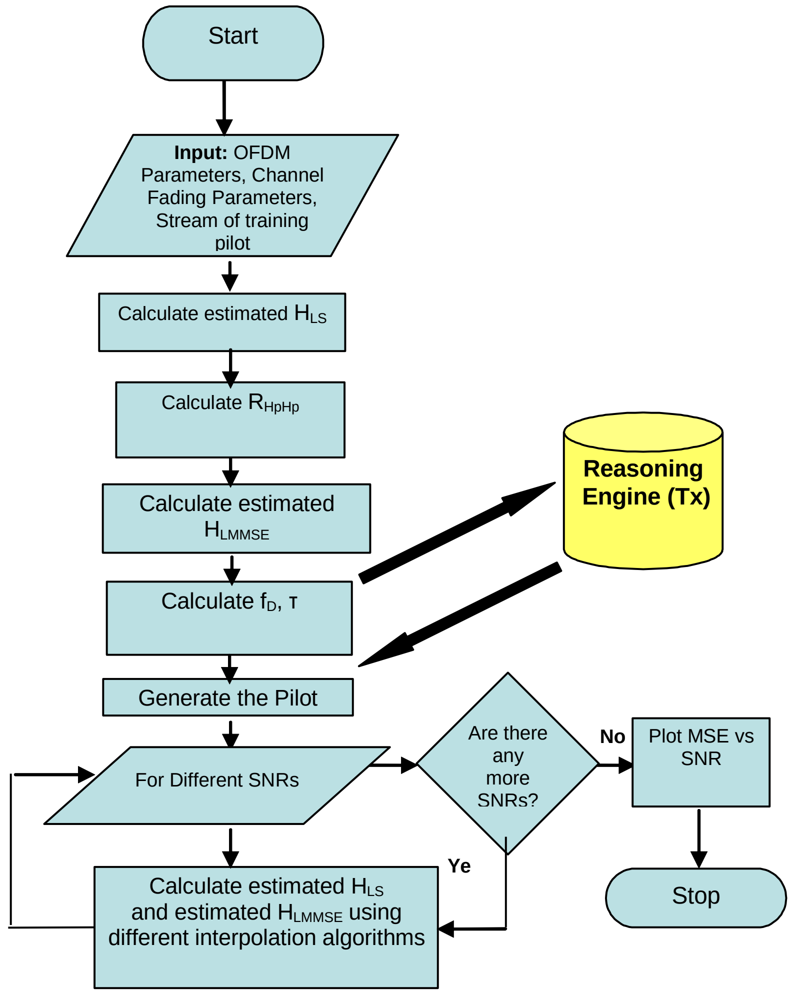
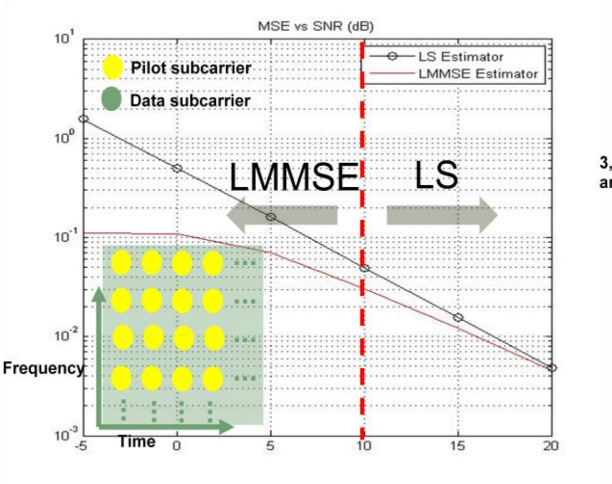
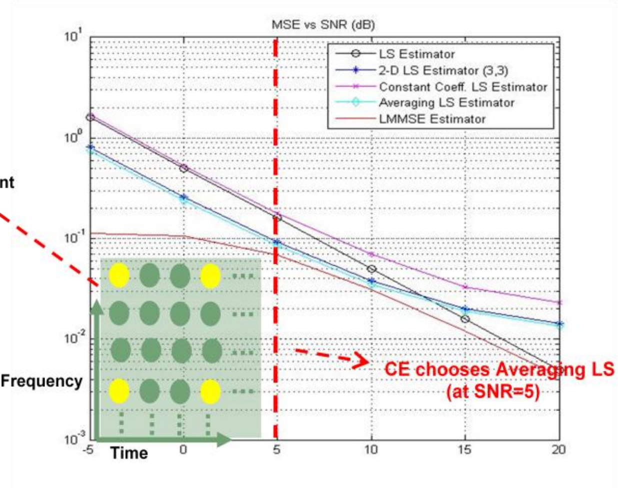


Figure 5.10 Simulation's Flowchart (Channel Estimation)

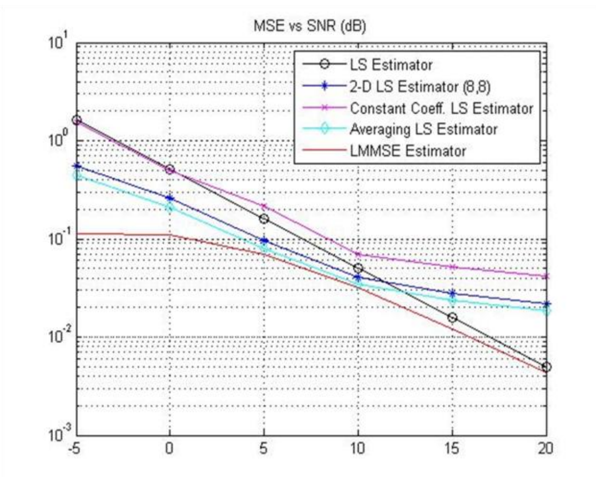
As shown in Figure 5.10, as the channel conditions changes the CE will alter the number of pilots used for channel estimation. Figure 5.11 shows the different techniques used for channel estimation with different number of pilots, showing that changing the number of pilots can change the channel estimation.



Number of Subcarriers=124, Rayeligh Channel (4 paths), AWGN, Doppler Frequency= 50Hz, Stream of Training Pilots, T_S=1/10000, SNR=-5 to 20 dB.



Number of Subcarriers=124, Rayeligh Channel (4 paths), AWGN, Doppler Frequency= 50Hz, D_t=3, D_f=3, T_S=1/10000, SNR=-5 to 20 dB.



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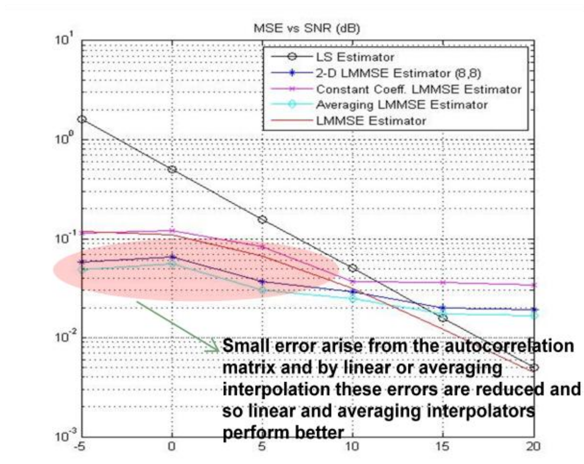
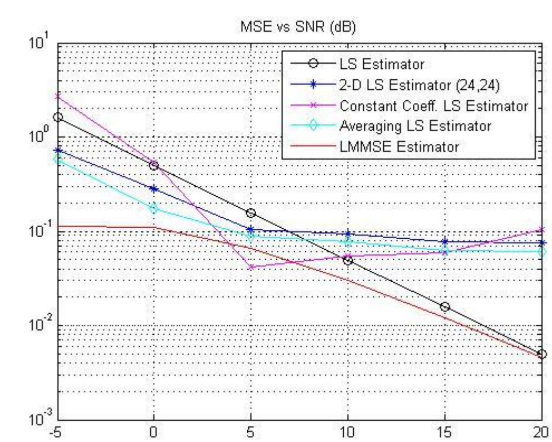


Number of Subcarriers=124, Rayeligh Channel (4 paths), AWGN, Doppler Frequency= 50Hz, D_t=8, D_f=8, T_S=1/10000, SNR=-5 to 20 dB.



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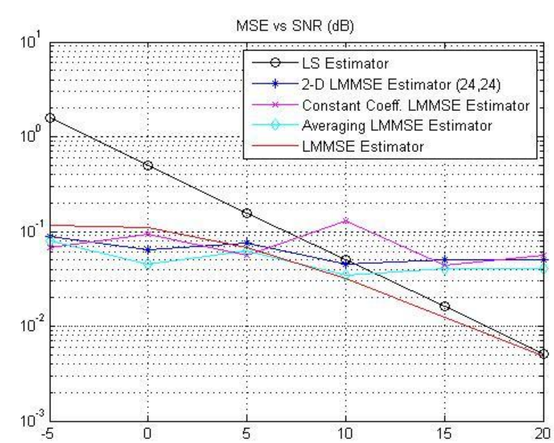
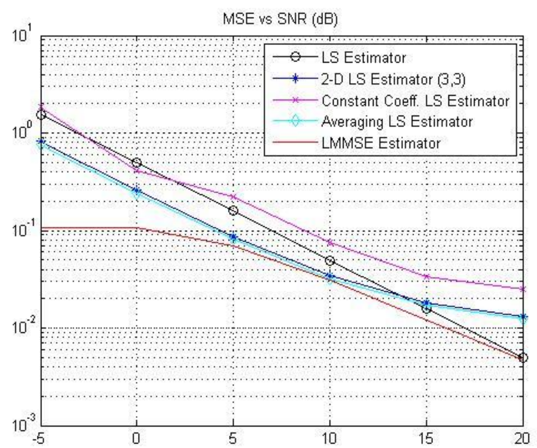


Number of Subcarriers=124, Rayeligh Channel (4 paths), AWGN, Doppler Frequency= 60Hz, D_t=24, D_f=24, T_S=1/10000, SNR=-5 to 20 dB.



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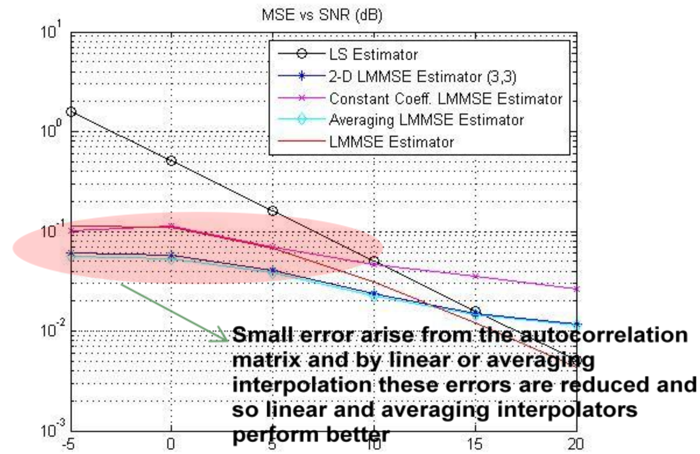


Number of Subcarriers=124, Rayeligh Channel (4 paths), AWGN, Doppler Frequency= 100Hz, D_t=3, D_f=3, T_S=1/10000, SNR=-5 to 20 dB.

Figure 5.11 Different Channel Estimation Techniques with Different Number of Pilot Assignment

5.4.1 Algorithm for Channel Estimation

1- Initial stream of pilot symbols are sent.

2- H_{LS} and H_{LMMSE} are determined from the received pilot symbols.

3- Doppler spread and delay spread are determined.

4- Using T_b (bit duration), τ (delay spread), B_d (Doppler spread) and B_s (Signal Bandwidth) the channel type is estimated using the channel type FL system described in Section 5.2. This is shown as FLRE1 in Figure 5.9.

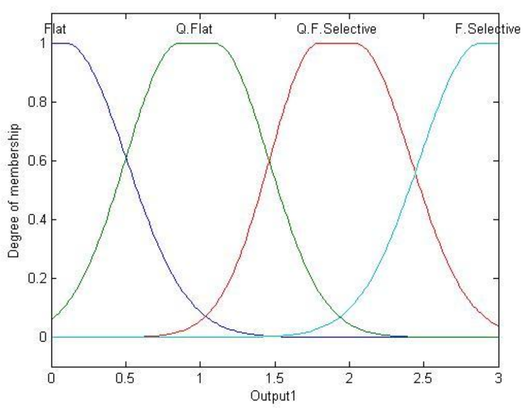
5- The output membership function of FLRE1 is the input to FLRE2 (Figure 5.12).

6- The output member ship function at FLRE2 is a ratio between the numbers of pilot subcarriers to total subcarriers. The output membership function is shown in Figure 5.13.

7- A set of rules are generated from inputs and output membership functions, i.e. between the channel type membership functions and the number of pilot membership function using c-mean clustering and training data.

8- The output will be the number of pilots to be used for channel estimation. These numbers of pilots will then be used for the next channel estimation. The result is then used for the next channel estimation (as shown in Figure 5.9).

9- If the channel condition changes then the parameters will in turn change causing a change in the channel type and so a change in the number of pilots used for channel estimation. This results in having an adaptive number of pilot system for channel estimation according to the channel conditions using fuzzy logic reasoning.



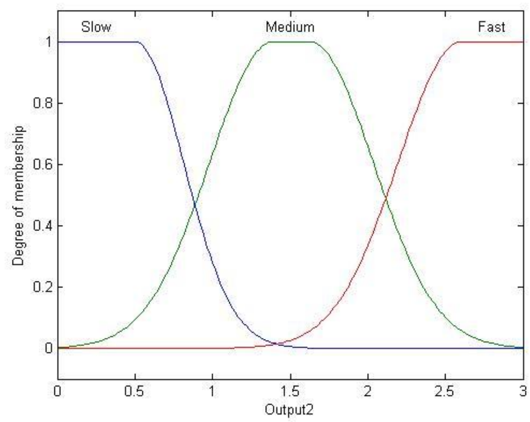
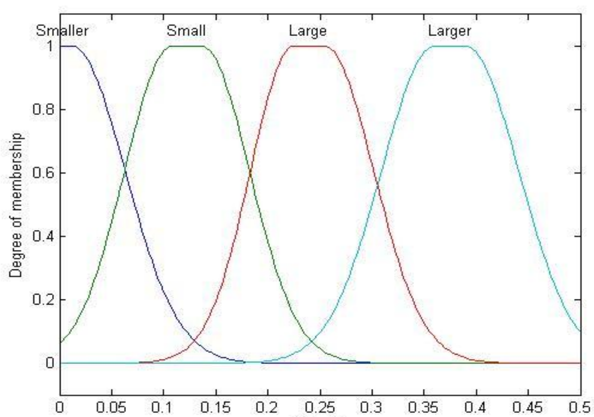


Figure 5.12 Output of FLRE1 (Input to FLRE2)



Number of Pilot Subcarriers/Total subcarriers

Figure 5.13 Output Membership Showing the Ratio Between the Number of Pilot Subcarriers to the Total Subcarriers (Output of FLRE2)

The estimation process involved the determination of the channel type through a fuzzy logic reasoning engine (FLRE). The numbers of pilots estimated are placed uniformly along the time and frequency in the time-frequency grid. The type of channel is also determined through the cognitive engine, which is used in the determination of the number of pilots. So in order to do channel estimation a *chain* of FLREs is used (in our case 2 FLREs).

The result shows that as the channel condition changes, the numbers of pilots change, in order to properly estimate the channel. As the channel grows more valuable, pilots will be sent in order to overcome the fast varying channel. Different channel estimation techniques were introduced. Estimation was done on the sent pilot symbols; where as for the rest of the data sent interpolators were used. Fuzzy logic is used as reasoning engine. FL uses membership functions to determine the type of channel and the number of pilots. The use of FL is crucial especially when the decision is at the boundaries of two channel states.

CHAPTER 6 Adaptive Resource Management for a Vague Environment Using Cognitive Radio in WiMAX

In Chapter 5, we discussed the use of fuzzy logic reasoning in a CR to determine the number of pilot subcarriers that can be used for channel estimation. We introduced the idea of using a chain of fuzzy reasoning engines to determine the type of channel and the number of pilot subcarriers. In this chapter, we present a system that is capable of adapting important resources (type of modulation, code rate, and number of subcarriers) for blurred channel conditions. The system in this chapter is mainly designed for WiMAX, The approach depends upon using cognitive radio for decision-making, which uses fuzzy logic for reasoning. To maintain a good system throughput without wasting available bandwidth, the cognitive engine controls the type of modulation, code rate, and number of subcarriers. The results show that new combinations of modulation type, code rate, and number of subcarriers should be considered in WiMAX since, in most cases, these combinations outperform the standard in error probability and spectral efficiency, especially in a dynamic radio environment. Figure 6.1 shows the basic blocks of such a chain of fuzzy reasoning engines.

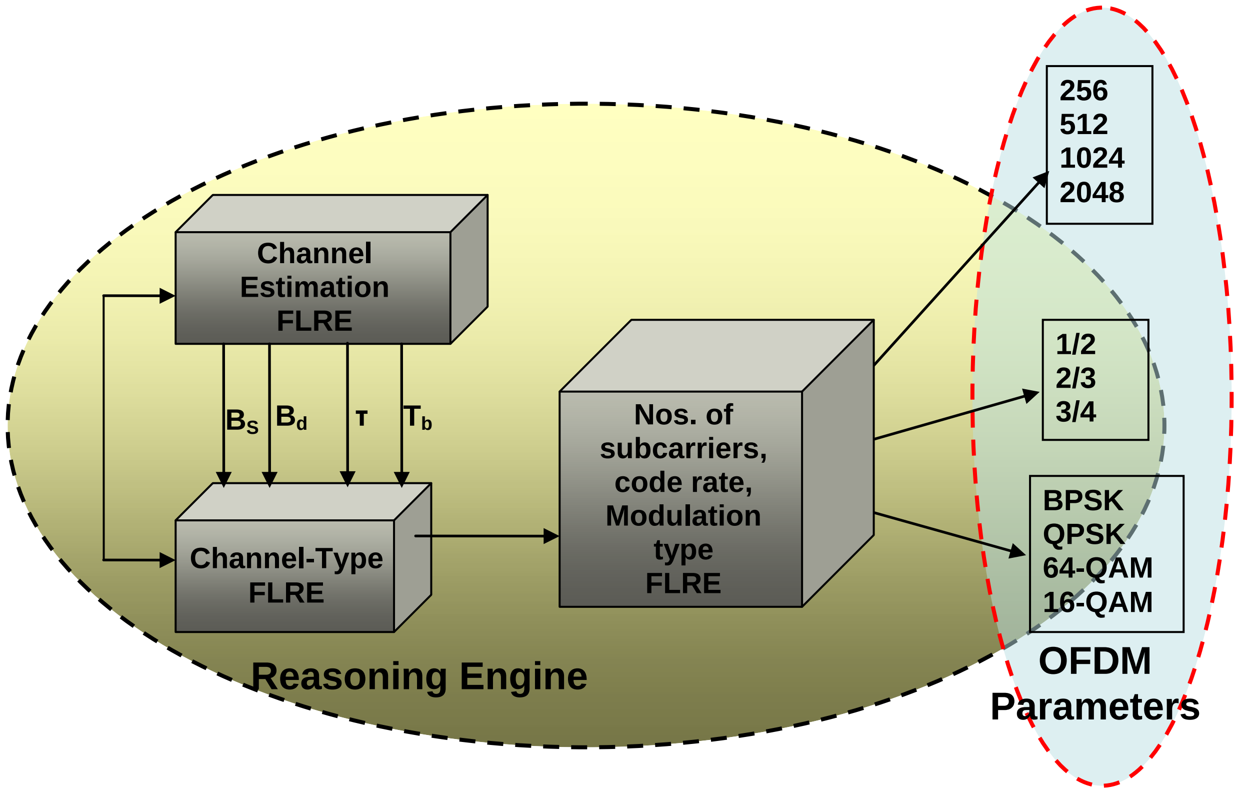


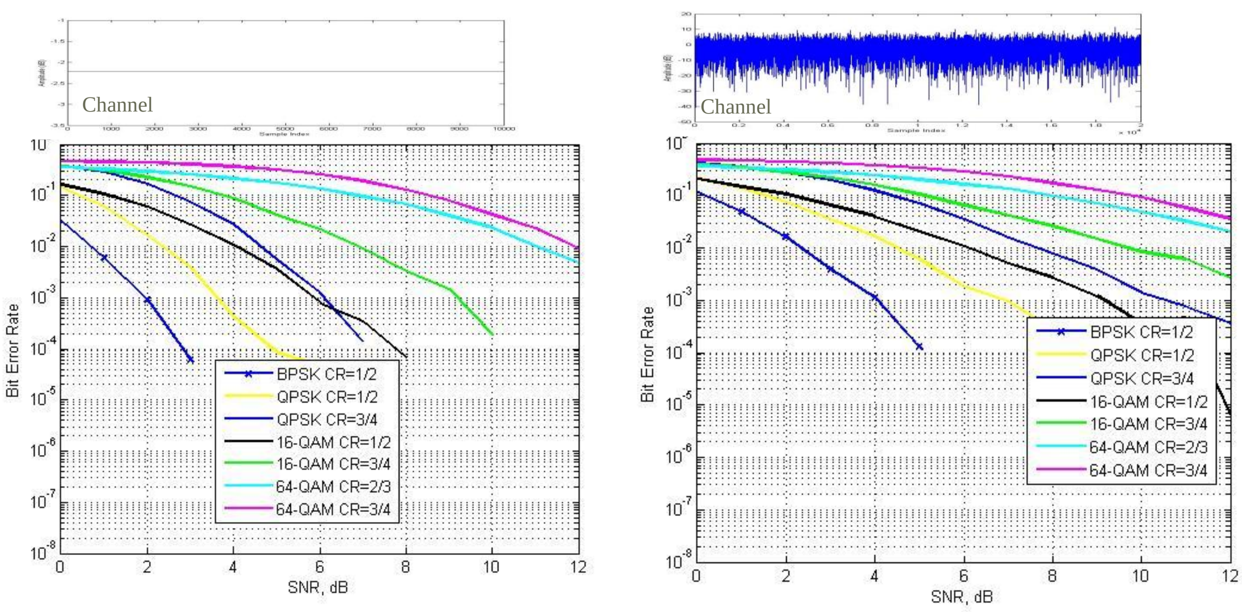
Figure 6.1 Basic Blocks of the Chain of FLREs for the Determination of Modulation Technique, Code Rate, and Numbers of Subcarriers in WiMAX

Table 6.1 shows the seven different modulation type and code rate combinations that WiMAX defines for achieving various trade-offs among data rate and robustness, depending on channel and interference conditions. Through an adaptive modulation and coding scheme (AMC), WiMAX switches from one combination to another in accordance with the radio environment through adaptive modulation and coding scheme (AMC). The allowed modulation schemes in the downlink (DL) and uplink (UL) are binary phase shift keying (BPSK,) quaternary PSK (QPSK), 16-quadrature amplitude modulation (16-QAM), and 64-QAM [4].

WiMAX delivers high throughput at long ranges with a high level of spectral efficiency that is also tolerant of multipath. Dynamic adaptive modulation allows the base station to trade-off throughput for range. For example, if the base station cannot establish a robust link to a distant subscriber using the highest order modulation scheme, 64-QAM, the modulation order is reduced to 16-QAM or QPSK, which reduces throughput but increases the effective range.

Table 6.1 Modulation and Coding Schemes for WiMAX [1]

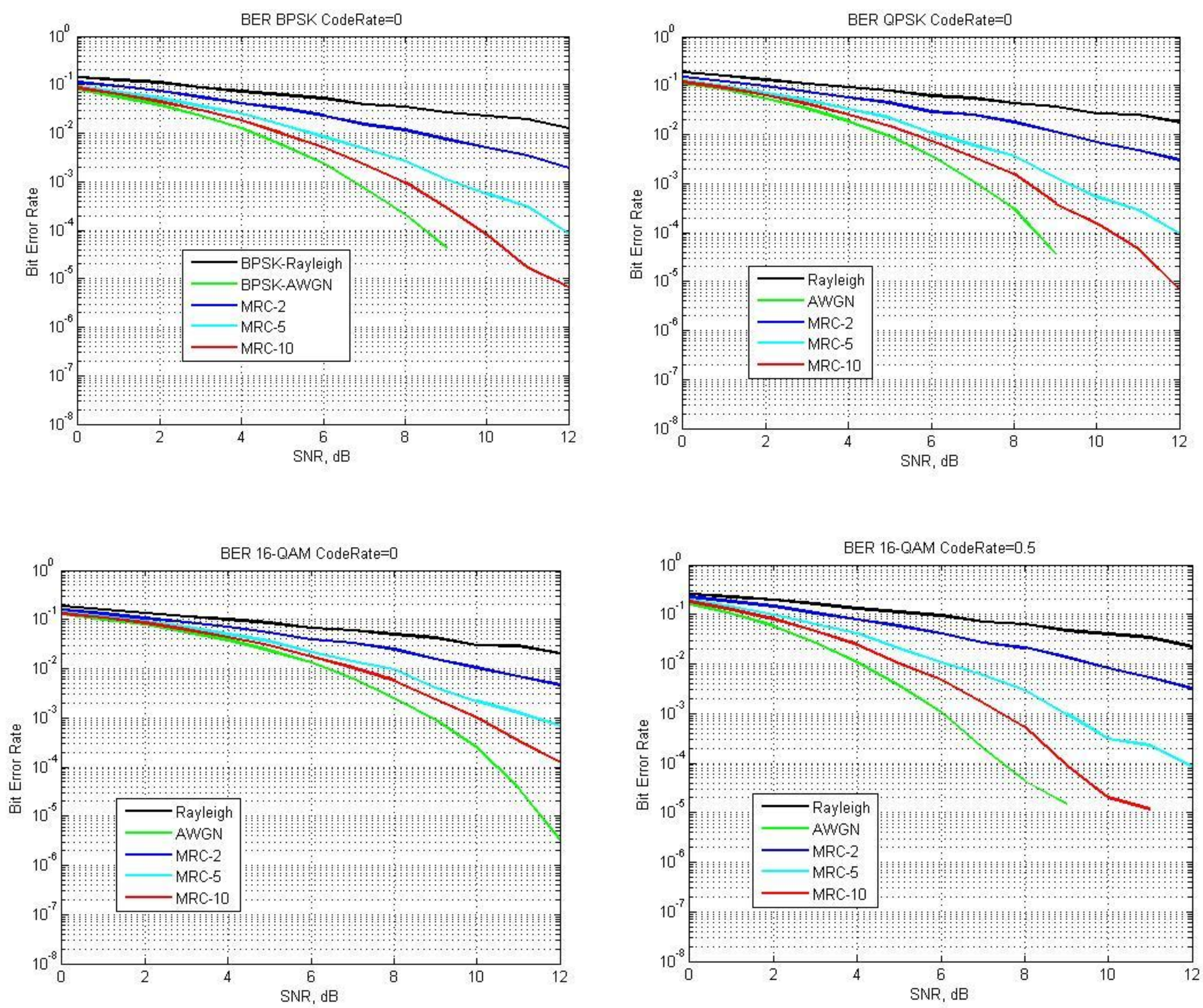
Rate ID	Modulation rate	Coding
0	BPSK	1/2
1	QPSK	1/2
2	QPSK	3/4
3	16QAM	1/2
4	16QAM	3/4
5	64QAM	2/3
6	64QAM	3/4



(a) (b)

Figure 6.2 The Seven WiMAX Combinations for a (a) Flat Slow-Fading Channel and (b) Frequency-Selective Fast-Fading Channel. (The number of samples used were 10000 and MRC paths = 3.)

As Table 6.1 shows, WiMAX has seven different combinations of modulation type and coding rate. Figure 6.2 shows the seven WiMAX combinations in various channel conditions. The diversity technique used is MRC (maximum ratio combining). The number of signal paths used for MRC was altered to improve the performance. Figure 6.3 shows some simulation results of altering the signal paths in MRC. The simulation shows that altering the modulation type and code rate affects the performance and proves that the selection of the modulation technique, code rate, and number of subcarriers is of great importance and affects the performance of the WiMAX system.



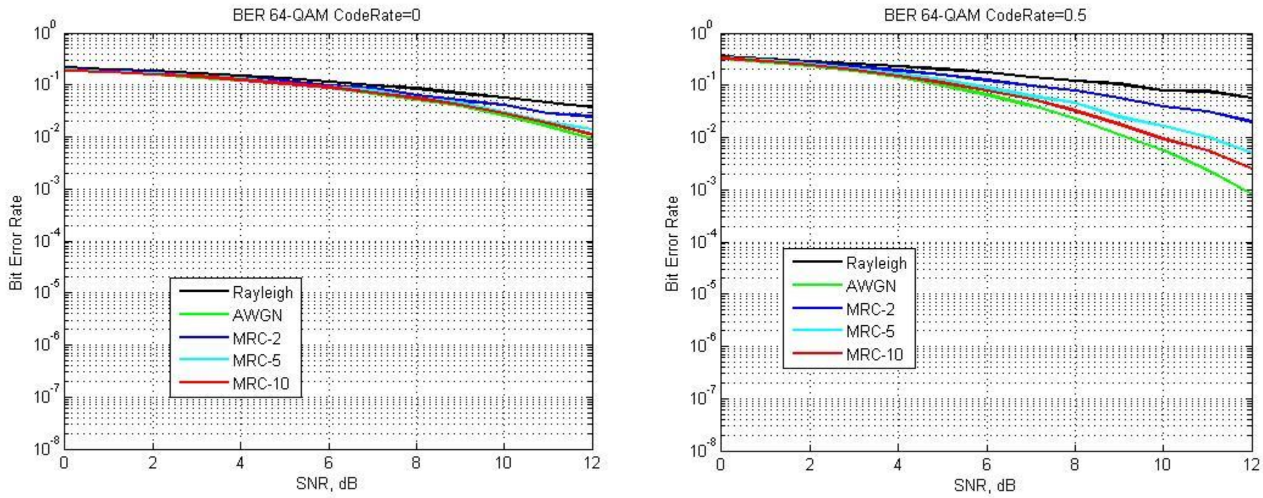


Figure 6.3 Different Modulation Techniques along with MRC and Code Rate

As seen from the main blocks in Figure 6.1, the output from the channel-type FLRE will be used as an input to the FLRE that decides on the number of subscribers used, the code rate, and the modulation technique to be applied. We use a fuzzy-based adaptive resource allocation algorithm that switches between the different modulation, coding, and number of subcarrier combinations, depending on the estimated channel type and SINR, which are estimated at the receiver and are reported to the transmitter through a feedback channel. FLRE performs resource allocation at the transmitter. The modulation and coding level is selected such that the BER remains below a desired performance threshold. Also, the number of subcarriers is selected such that the channel is changed to a flat-fading channel, thus having a constant estimated channel SINR for all the COFDM symbol durations.

6.1 Proposed Adaptive Algorithm

The following algorithm describes the design steps of the FLRE used for the determination of the modulation type, code rate and number of subcarriers for a WiMAX system.

Step 1 (Channel Fuzzification): Using previously stored channel information training data, the receiver applies the fuzzy C-mean clustering procedure (discussed in Chapter 5) to determine the appropriate membership functions that represent the channel type.

Step 2 (Resource Fuzzification): The previously stored channel information training data is sent back to the transmitter, which will apply the same procedure to determine the membership functions that represent the modulation technique, coding rate, and number of subcarriers.

Step 3 (Rule Generation and Deployment): Based on Steps 1 and 2, the transmitter generates a set of fuzzy rules that will connect the type of the channel and SINR with the allocated resources in terms of modulation order, coding rate, and number of subcarriers.

Step 4 (Resource Allocation): The rules are then generated from the clusters created in Steps 1 and 2 and ensure that the level of modulation, the coding rate, and the number of subcarriers used is suitable for transmitting the required data. The inference engine compares the measured SINR in each subcarrier with the different modulation orders, and the highest modulation level that satisfies the required BER is chosen.

6.2 Input and Output Membership Functions

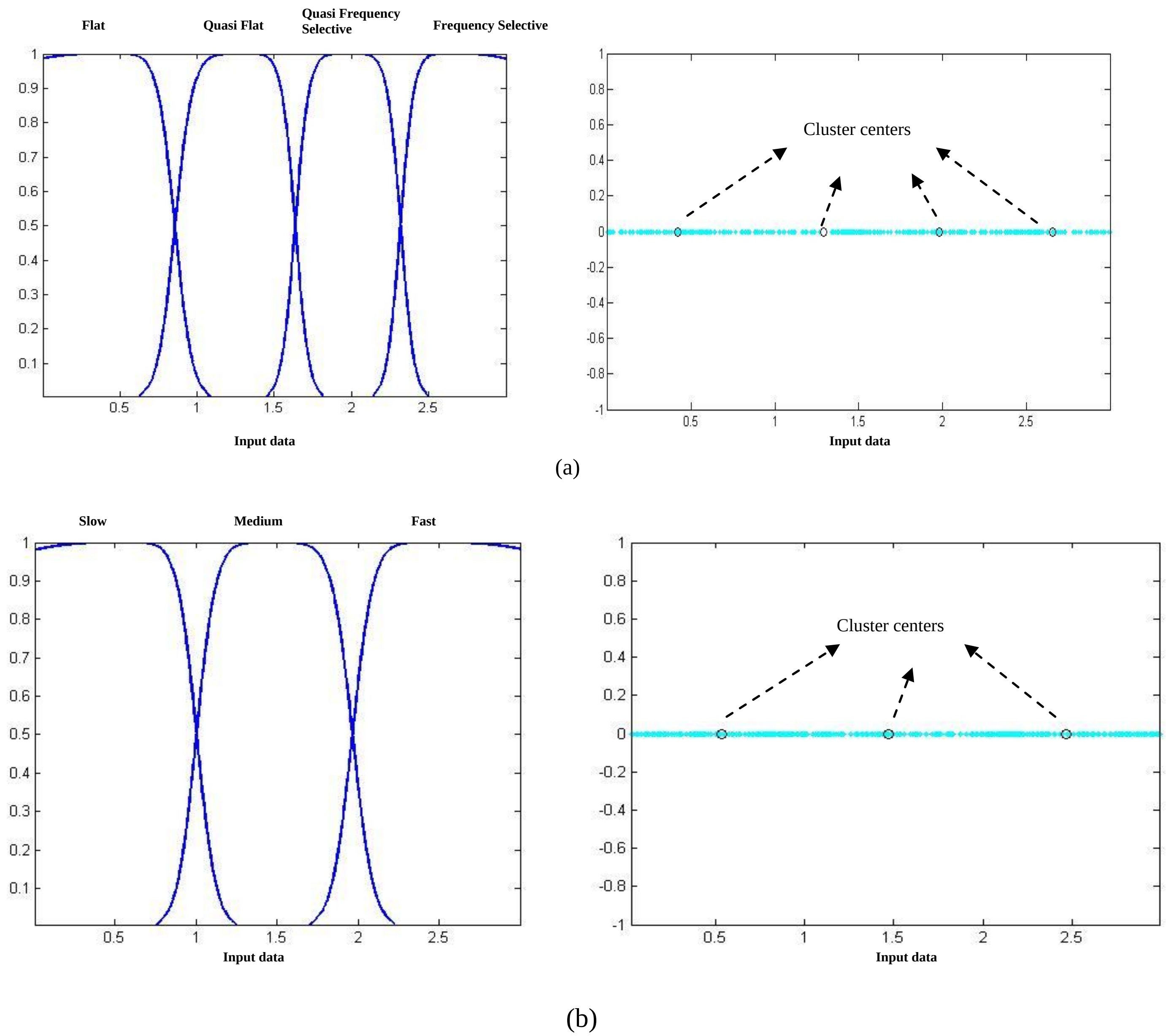
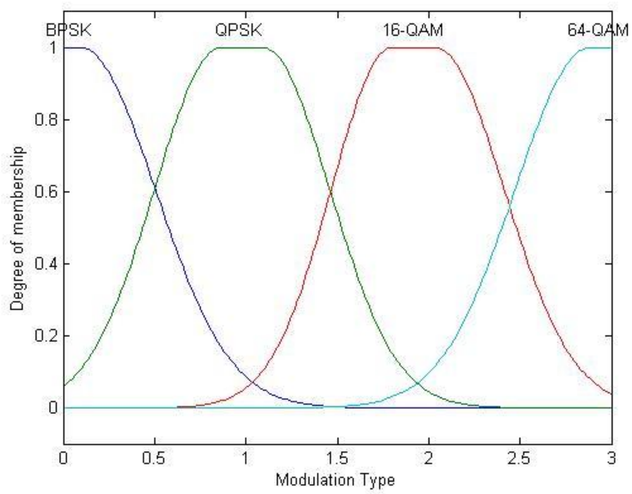
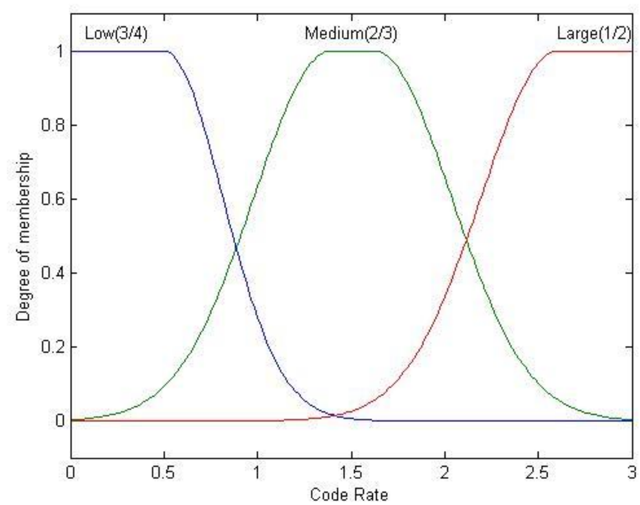


Figure 6.4 Clustered Inputs Membership Functions Forming the Channel Types using FCM: (a) Selectivity, (b) Fading

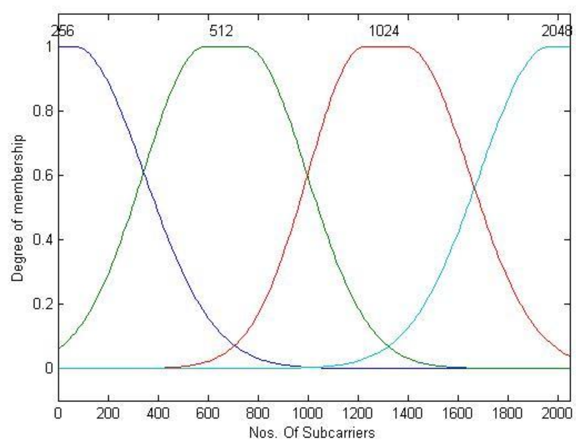
Two inputs are used in Step 1 of the adaptive resource management algorithm. The first input represents the selectivity of the channel, and the second input represents the rate of fading (Figure 6.4). The fuzzy C-mean clustering grouped the selectivity of the channel (τ/T_b) into four membership functions, *flat, quasi-flat, quasi–frequency-selective and frequency selective channels*, and the fading rate (B_d/B_s) was fuzzified into *slow-, medium-, and fast-fading channels.* The output of Step 2 is illustrated in Figure 6.5, which shows that the fuzzy C-mean clustering groups the modulation types into four groups associated with the three coding rates and four groups of the number of subcarriers. The proposed FLRE, along with the clustered inputs, describe the type of channel. The generated rules shown in Table 6.2 form the whole fuzzy logic inference engine. Twelve rules are defined with twenty-four different outputs.



(a)



(b)



(c)

Figure 6.5 Proposed FLRE Outputs Showing the (a) Type of Modulation, (b) Code Rate, and (c) Number of Subcarriers

6.3 Rules

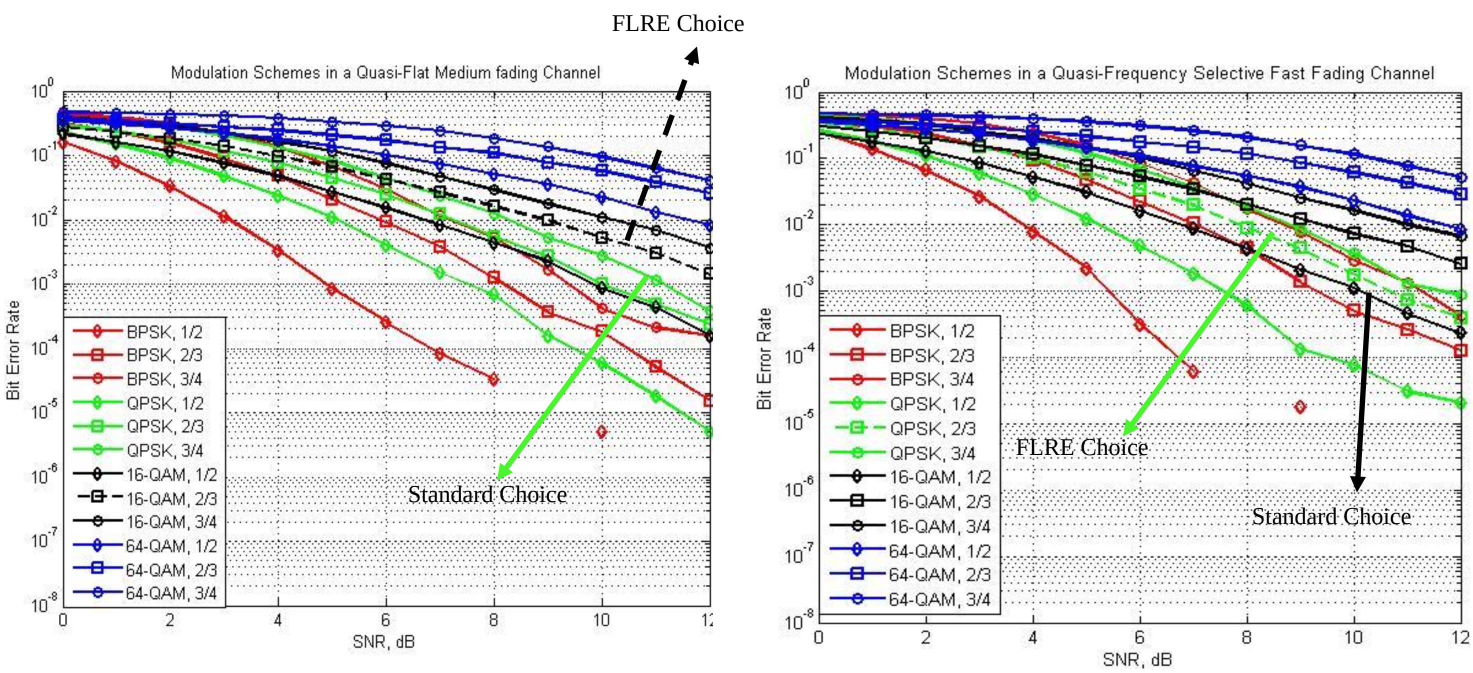
These are the rules generated through the FLRE, which is done through FCM clustering of the input and output training data.

Table 6.2 Generated Rules of the FLRE

Rule #	**Selectivity**	**Fading**	**Channel**	**Subcarriers, Modulation, Code rate**
1	Flat	Slow	Bad	256, 64-QAM, 3/4
			Good	256, 64-QAM, 3/4
2	Flat	Medium	Bad	256, 64-QAM, 2/3
			Good	256, 64-QAM, 3/4
3	Flat	Fast	Bad	1024, 64-QAM, 1/2
			Good	1024, 64-QAM, 2/3
4	Frequency-Selective	Slow	Bad	512, BPSK, 3/4
			Good	512, QPSK, 2/3
5	Frequency-Selective	Medium	Bad	1024, BPSK, 2/3
			Good	1024, QPSK, 1/2
6	Frequency-Selective	Fast	Bad	2048,BPSK,1/2
			Good	2048,QPSK,1/2
7	Quasi–Frequency-Selective	Slow	Bad	512, 16-QAM, 3/4
			Good	512, 64-QAM, 3/4
8	Quasi–Frequency-Selective	Medium	Bad	1024, QPSK, 3/4
			Good	1024, 16-QAM, 3/4
9	Quasi–Frequency-Selective	Fast	Bad	1024, QPSK, 2/3
			Good	1024, 16-QAM, 2/3
10	Quasi-Flat	Slow	Bad	256, 64-QAM, 2/3
			Good	256, 64-QAM, 3/4
11	Quasi-Flat	Medium	Bad	512, 16-QAM, 2/3
			Good	512, 64-QAM, 2/3
12	Quasi-Flat	Fast	Bad	1024, QPSK, 2/3
			Good	1024, 16-QAM, 2/3

6.4 Simulation Results

For simulation, we used 20000 samples transmitted in different channel conditions, which depend on the channel type FLRE. Monte-Carlo's simulation was performed for the all-different FLRE combination. The Doppler spread and delayed channel paths were changed in accordance with the channel type needed. The diversity technique uses MRC (maximum ratio combining) [76]. The simulation was performed for mainly two kinds of channels: quasi–frequency-selective fast-fading and quasi-flat medium-fading. The BER was calculated for all different combinations of the proposed FLRE, and spectral efficiency was compared between the results of the FLRE and the WiMAX standard.



(a) (b)

Figure 6.6 Modulation Schemes of FLRE for (a) Quasi-Flat Medium-Fading and (b) Quasi–Frequency-Selective Fast-Fading Channels The dotted curve represents the FLRE choice.

Figure 6.6a shows the different modulation schemes for a quasi-flat medium-fading channel. According to the designed FLRE, the choice for a bad channel will be 16-QAM with code rate

2/3. The standard slightly outperforms the FLRE for some SNR in terms of BER because the standard would choose QPSK and a 3/4 code rate. If the channel is good, i.e., few subcarriers face less degradation in amplitude due to the attenuation from channel, then the FLRE would choose 64-QAM and a 2/3 code rate and will cause an increase in spectral efficiency. Figure 6.6b shows the different modulation schemes for a quasi–frequency-selective fast-fading channel. The choice of the FLRE will be QPSK and a 2/3 code rate (for a bad channel), which outperforms, in terms of BER for all SNRs, the WiMAX standard's choice of 16-QAM and a 1/2 code rate. If the channel is good, the FLRE would choose 16-QAM and a 2/3 code rate and thus increase spectral efficiency.

6.4.1 Spectral Efficiency

Figure 6.7 shows the spectral efficiency for a target BER of 10^{-2} for both kinds of channels. FLRE simulation was run when all subcarriers where assigned the same modulation scheme (whether the channel was good or bad), which was considered to be a bad channel in our run. The results proved that, in some cases, the FLRE system outperforms the WiMAX standard in terms of spectral efficiency.

Figure 6.7 shows that nearly no difference in spectral efficiency is evident between the proposed adaptive resource management algorithm and WiMAX, mainly because the channel is nearly a standard, well-known channel. Figure 6.7b illustrates different results, specifically at higher SNR and in a channel that slightly deviates from the standard, known channels.

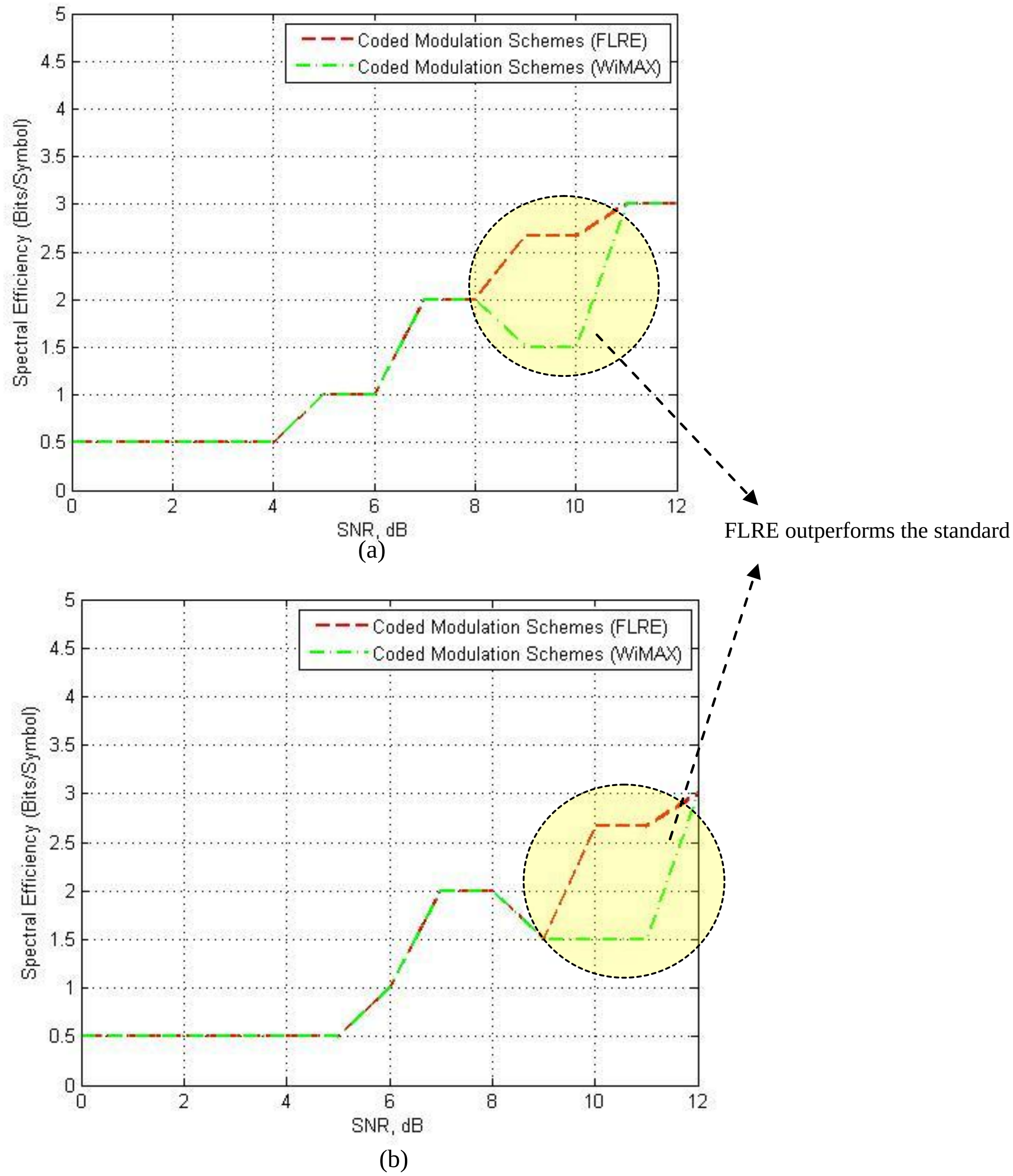
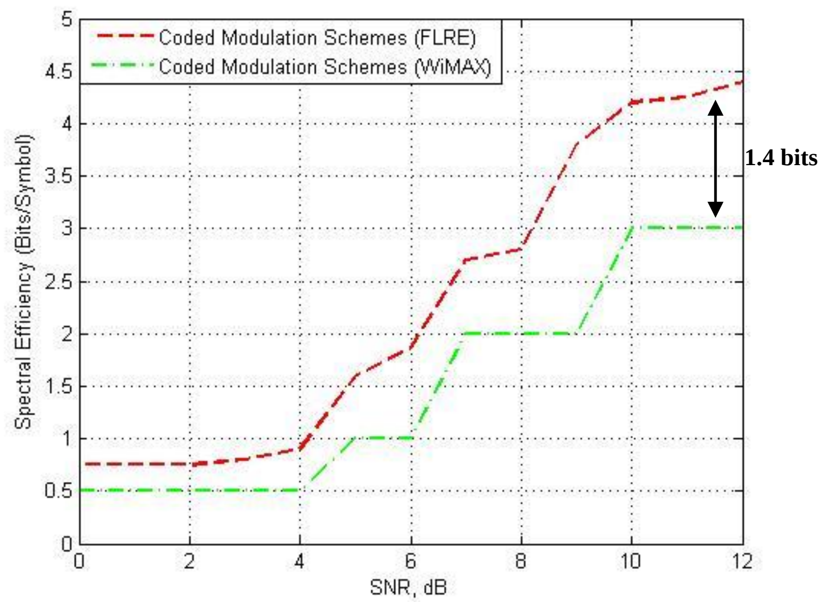
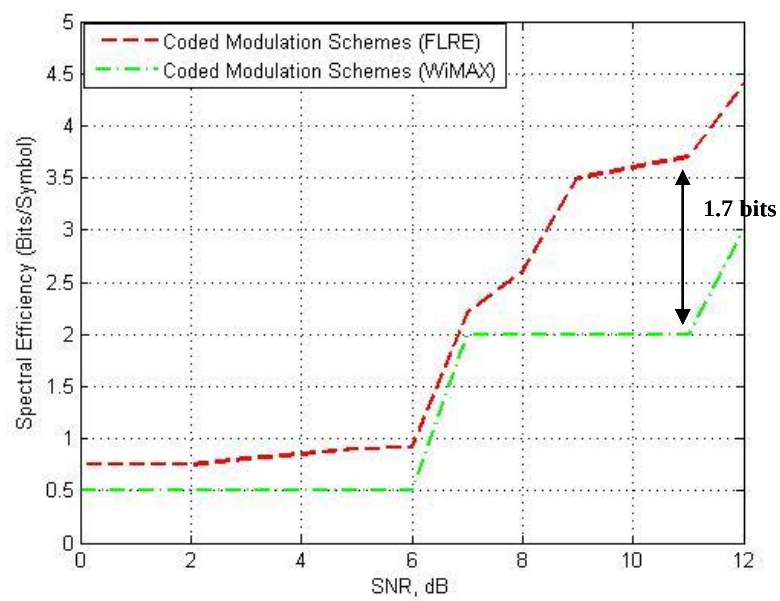


Figure 6.7 Comparison Between FLRE and WiMAX Spectral Efficiencies for Coded Modulation Schemes for (a) Quasi-Flat Medium-Fading and (b) Quasi–Frequency Selective Fast Fading Channels (Target BER = 10^{-2})

As stated, adaptive resource management in the FLRE is to assign different modulation schemes to subcarriers facing the same channel. The assignment depends upon whether the system considers the channel to be bad or good. According to the rules in Table 6.2, for each channel type, two modulation schemes are available, and the choice between them depends upon whether the channel is good or bad. If we consider that each subcarrier will be assigned a modulation scheme in that sense, then, for a certain channel, subcarriers would be assigned different modulation schemes rather than a specific scheme as in WiMAX.



(a)



(b)

Figure 6.8 Comparison Between FLRE and WiMAX Spectral Efficiencies for Coded Modulation Schemes for (a) Quasi-Flat Medium-Fading and (b) Quasi–Frequency-Selective Fast-Fading Channels (Target BER = 10^{-2}, Modulation Scheme Assignment is Per Subcarrier)

Figure 6.8 shows the spectral efficiency for FLRE and WiMAX per subcarrier. The results in Figure 6.8 prove that the proposed adaptive resource management algorithm outperforms the WiMAX standard in all SNR ranges. Thus, in vague wireless channel characteristics, using cognitive radio for adaptive resource allocation will increase spectral efficiency over that of the WiMAX standard.

6.5 Conclusion

In this chapter, we proposed a cognitive radio framework for adapting various resource management in vague channels. We compared our results with WiMAX standards. The framework is based on using a fuzzy logic reasoning engine for imperfect and vague channel state information that channel estimation techniques provide. The framework features a modular design and a generic, technology-independent knowledge representation based on fuzzy logic. The proposed reasoning engine’s performance has been evaluated via simulation and is compared with the WiMAX standard. The performance evaluation involved scenarios explicitly designed to highlight specific issues, particularly imperfect channel state information, imprecise channel types, and fading characteristics. The investigation also examined the transition region in which decision is highly unpredictable.

The results show that the proposed FLRE may perform significantly better than standard WiMAX in terms of both spectral efficiency and BER for the two channel type scenarios chosen in our simulation. Simulation also shows that the adaptation of the FLRE yielded even better results in terms of spectral efficiency. Future research may include the automation of generated rules according to the present set of training data as well as broadening the analysis presented in this chapter to include scenarios in which adaptive fuzzy membership functions are required.

CHAPTER 7 Dynamic Resource Allocation Algorithm

The algorithm discussed in this chapter was developed to allocate radio resources dynamically and was based on the FCM theory described in Chapter 4. In [77], the author uses machine learning in a cognitive radio to overcome the changing nature of the wireless environment. Machine learning will use a set of training data as input for the cognitive radio's learning and action. In our proposed algorithm, the set of training data is used to construct the FL system's input and output membership functions for the radio parameters in hand. A set of rules is also constructed for the FL system. Learning makes the cognitive radio robust to various situations and environmental conditions. In [78], the authors suggest a learning scheme for detecting frequency vacancies for use by secondary unlicensed users transmission. This approach was compared to other approaches that use energy detectors and proved to yield better CR system throughput. In our work, we simulate the efficient spectrum utilization (in Chapter 8) through FL reasoning with training data that were used to set up the FL system's rules and input/output membership functions. "Y. Huang, J. Wang, and H. Jiangin in [79] & G. Quer, H. Meenakshisundaram, B. Tamma, B. S. Manoj, R. Rao and M. Zorzi [80]" propose a Bayesian network (BN) approach to optimizing the radio configuration in a continuously changing wireless environment. The authors in [79] used SNR (signal to noise ratio) as the input (which changes according to the environment) and the modulation type and code rate of an IEEE 802.11a system as the output. Through simulation, they proved the feasibility of using BNs for cognitive learning. In [81], the authors compare a simple immune theory with genetic algorithm for CR reasoning. The immune theory uses prior knowledge of the practical problem at hand and, when used with the genetic algorithm, reduces (and thereby speeds up) the CR's search process. The fuzzy logic reasoning when used in this case will be very beneficial because no search is required.

Our goal is to design a cognitive radio that can make opportunistic decisions and that has a learning capability so that it can control different radio parameters in wireless communication. We are considering an algorithm general enough to control *any* radio parameters, rather than a specific parameter. For example, if we consider a WiMAX system, we can use parameters like Doppler frequency, delay spread, bit duration, and signal bandwidth as inputs to determine the channel type (Chapter 5). Modulation type, code rate, and number of subcarriers can also be used to determine the number of pilots that can be used in channel estimation (Chapter 6). All of these inputs and outputs in our proposed technique will be transferred into membership functions from stored training data. The FL rules will also be obtained using these training data. The proposed technique will be applied in the next chapter for spectrum utilization. Flow chart shown in Figure 7.1 shows the process, the pseudo-code is illustrated in pseudo-code 1 of Appendix A.

The algorithm starts by using a set of stored inputs and their respective output radio parameter values, collected from previous radio state conditions, as training data. The training data is clustered using FCM clustering, and PCEAS clustering is used as the cluster index to get the best combination of cluster number (c) and fuzzy weighting component (m); this process is repeated for each input or output to get all the membership functions of the input and output radio parameter values. Knowing any physical phenomena for our system will reduce the clustering complexity because the number of inputs to be clustered will be reduced, thereby reducing the dimension and the FCM clustering technique's complexity. The generated rules and cluster dimension will reduce, and the CE will make decisions more quickly. Once this process is completed, we start generating the rules to be used in the cognitive engine.

7.1 Algorithm Without the Dempster-Shafer Theory

The flow chart in Figure 7.1 describes the fuzzy logic reasoning engine used for the allocation of radio resources dynamically without the removal of contradicting rules.

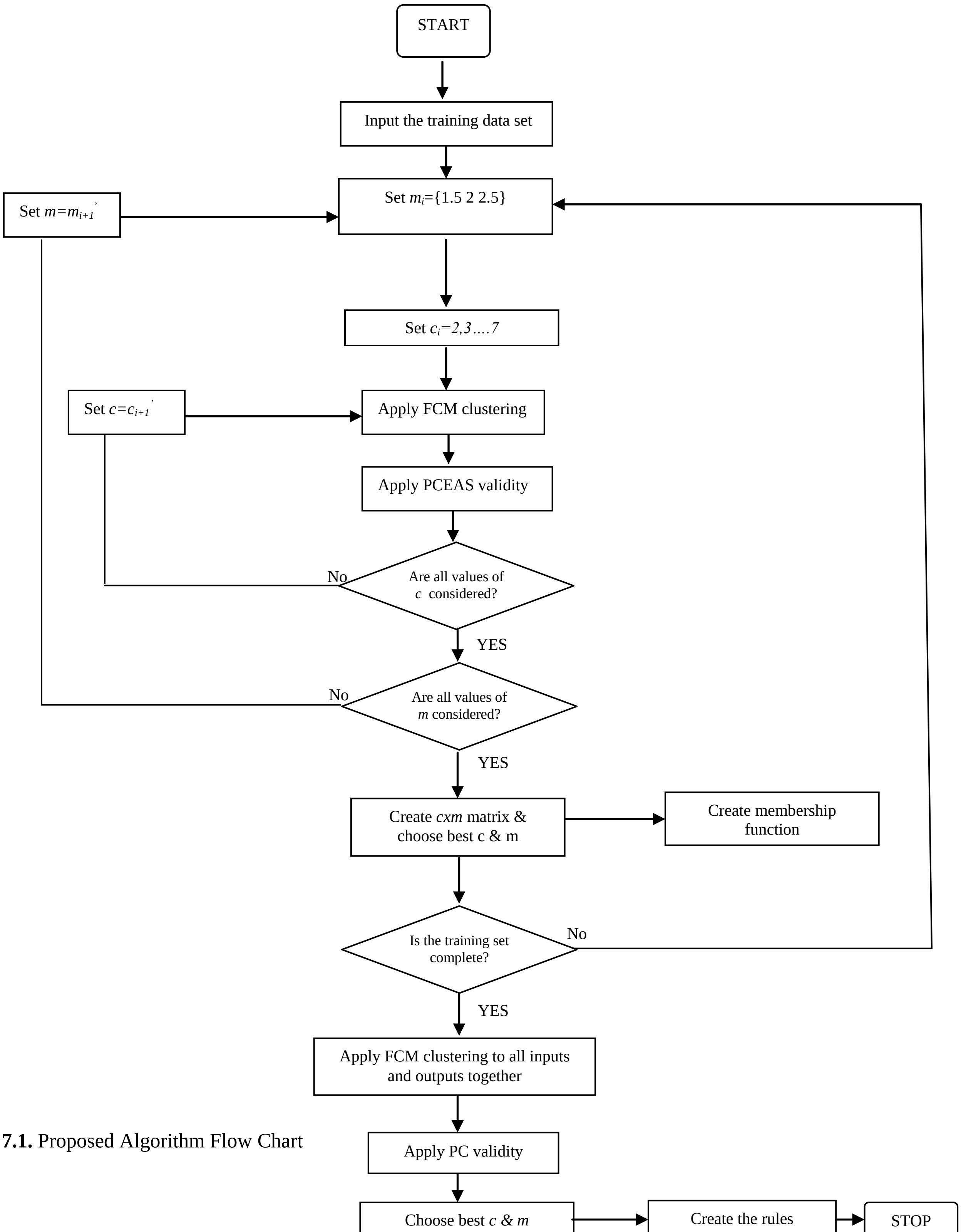


Figure 7.1. Proposed Algorithm Flow Chart

7.2 Algorithm Steps

Step 1: Check the training data that will be used for training the inference engine.

Let’s consider an example in which we have two inputs and two outputs captured from the radio environment. These inputs and outputs are cases captured and stored in the CR. The inputs can be, for example, the exponent power of the path loss and the phase offset of the received signal, which, when combined, can provide two consequence outputs, such as indices to actions to be taken. So, if we consider that these outputs are stored in a form of records, then each record will have two input values with their respective two output values. These records are the X data sets mentioned in the previous section.

2.3757	2.2349	3.0000	3.0000	
1.1740	1.8230	2.0000	2.0000	
1.3659	1.8442	2.0000	2.0000	
2.4243	1.5021	3.0000	2.0000	**Record**
0.5153	0.0067	2.0000	1.0000	
1.2851	2.2991	2.0000	3.0000	
2.1094	1.2810	3.0000	2.0000	
Inputs		Outputs		

Figure 7.2 Stored Records Showing Two Inputs and Two Outputs

Step 2: Assign membership functions to the inputs and outputs.

Regarding the input, the next step is to follow the FCM clustering algorithm, described in equations (13) to (35) in Chapter 4. To choose the best match of membership function to the input and output data sets, *m* and *c* will be changed to reach the best membership functions. PCAES validity of equation (47) is therefore used.

Figure 7.3 shows four types of cluster validity index (PC, MPC, PE and PCAES, defined in Chapter 4) for input x_1. The figures are plotted for seven clusters and $m = \{1.5, 2, 2.5\}$ for forty FCM iterations as the convergence test. For inputs and outputs, we use PCAES as cluster validity. The results show that optimal m is at $c = 3$ and $m = 1.5$.

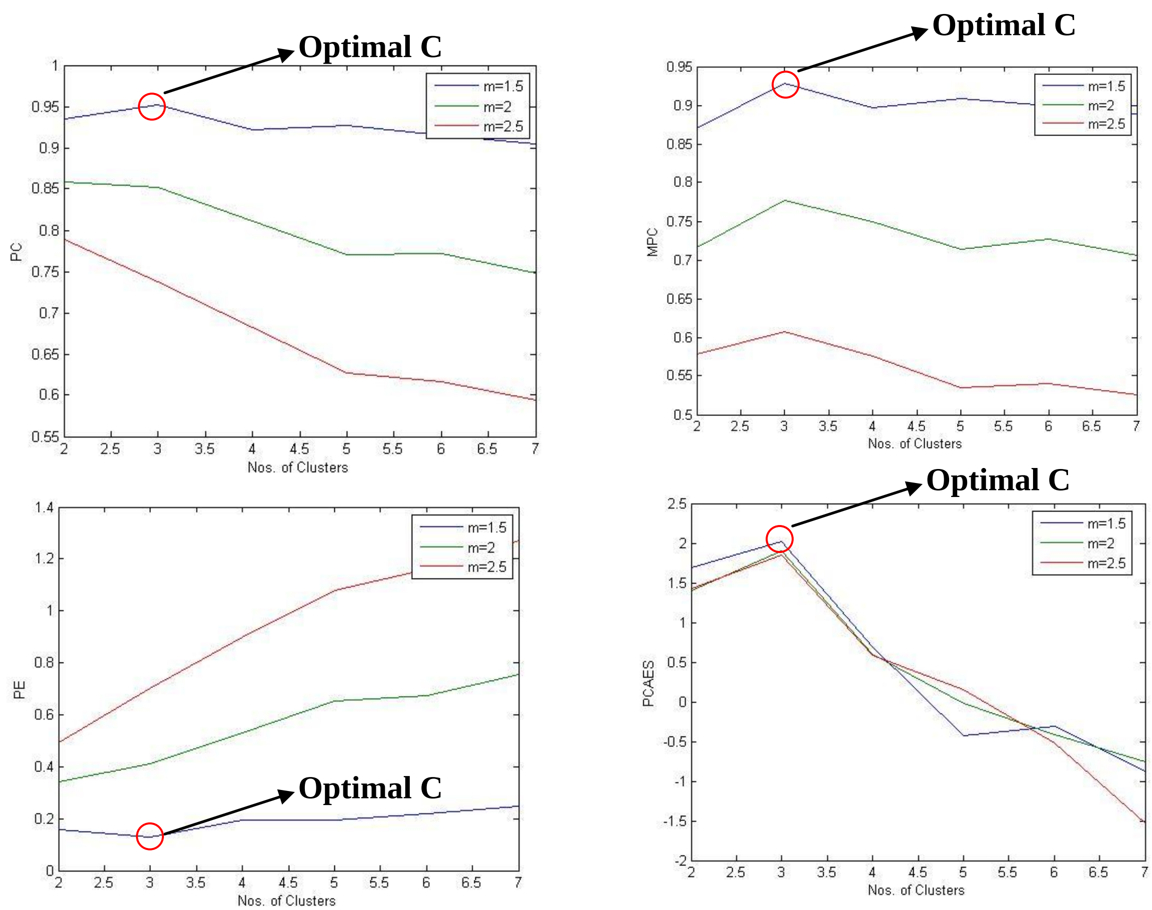


Figure 7.3. Input = x_1, $0 \leq x_1 \leq 3$, m = (1.5,2,2.5), FCM Iterations = 40 (PC, MPC, PE, and PCAES validity test)

Figure 7.4 illustrates the variation of m for $c = 3$. Notice that for $m = 1.5$ we have a flat Gaussian membership function, for $m = 2$ we have a Gaussian membership function, and for $m = 2.5$ we have a triangular membership function. Thus, we can conclude that as m varies, the shape of membership function changes. The width of the membership function depends on the input data set. A change in the input data set can cause an increase or a decrease in the membership function width.

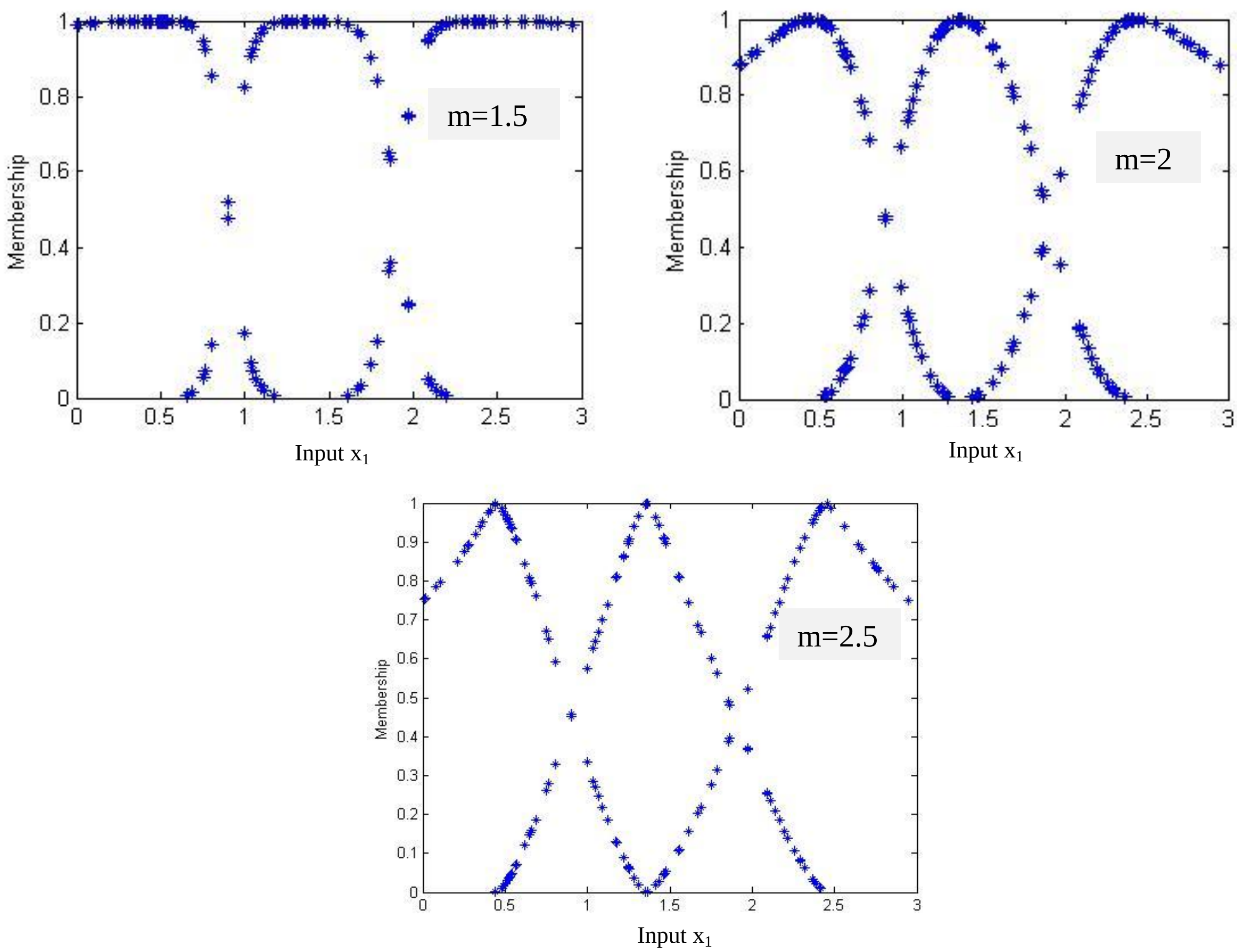


Figure 7.4. Membership Functions of x_1, $0 \le x_1 \le 3$, m = (1.5, 2, 2.5), c = 3, FCM Iterations = 40

Figures 7.5 and 7.6 show the membership function of the two inputs x_1 and x_2. Notice that x_2 has Gaussian membership functions. The two inputs may have different types of membership functions because the membership functions depends completely on the training data set.

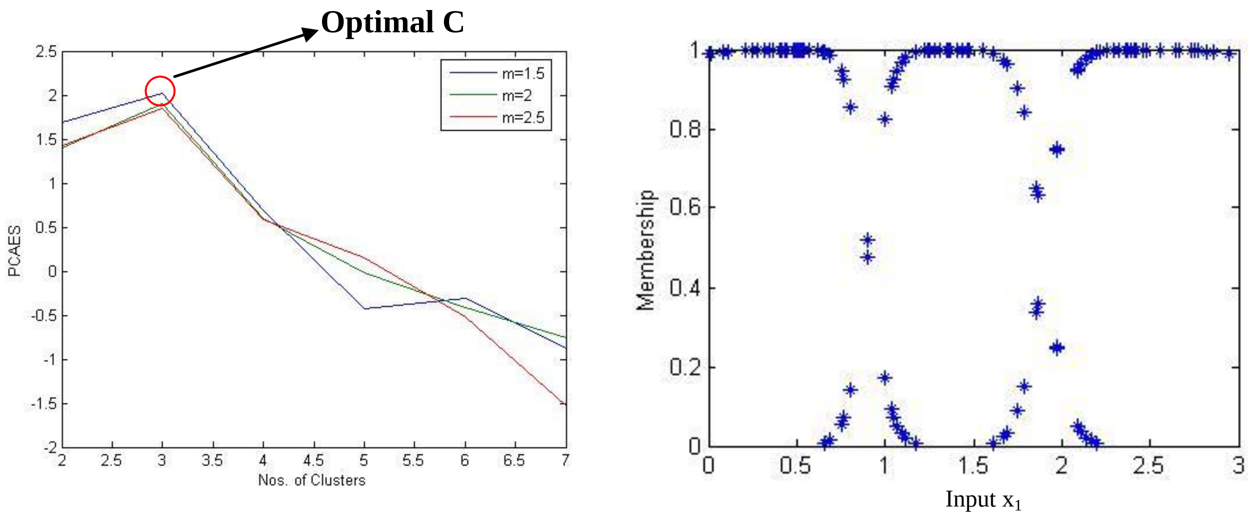


Figure 7.5. Optimum Membership Functions for x_1 at c=3, m=1.5, centers={0.4487, 1.3654, 2.4367}

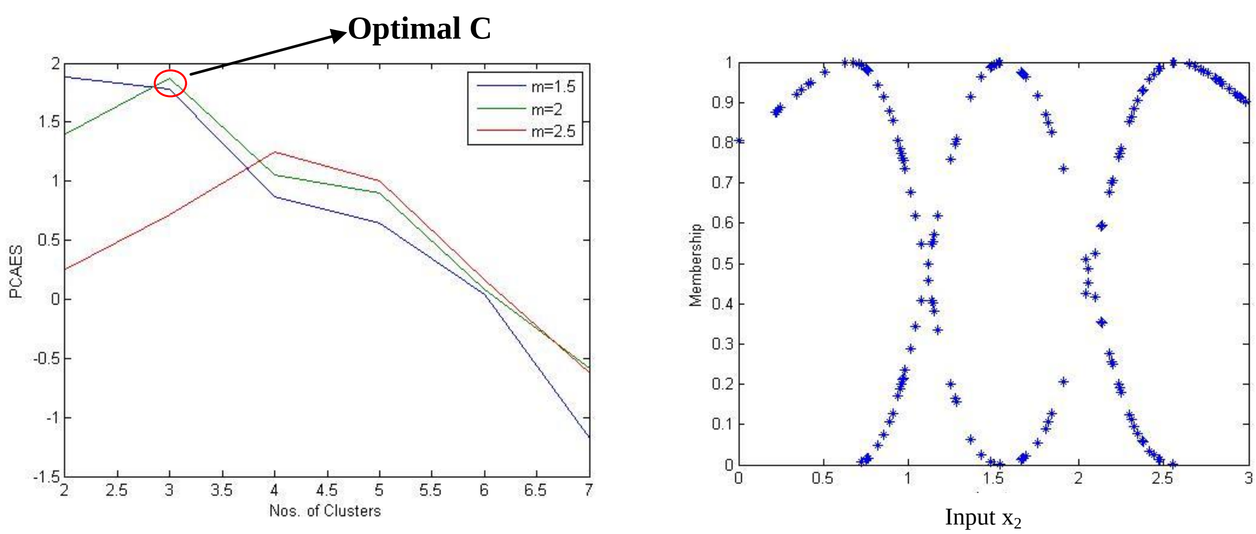


Figure 7.6. Optimum Membership Functions for x_2 at c=3, m=2, centers={0.6570, 1.5556, 2.5823}

We use a cubic spline curve fitting, which is the smoothest curve that exactly fits a set of data points, to get the proper shape of the membership functions of the inputs x_1 and x_2, and we illustrate this in Figure 7.7.

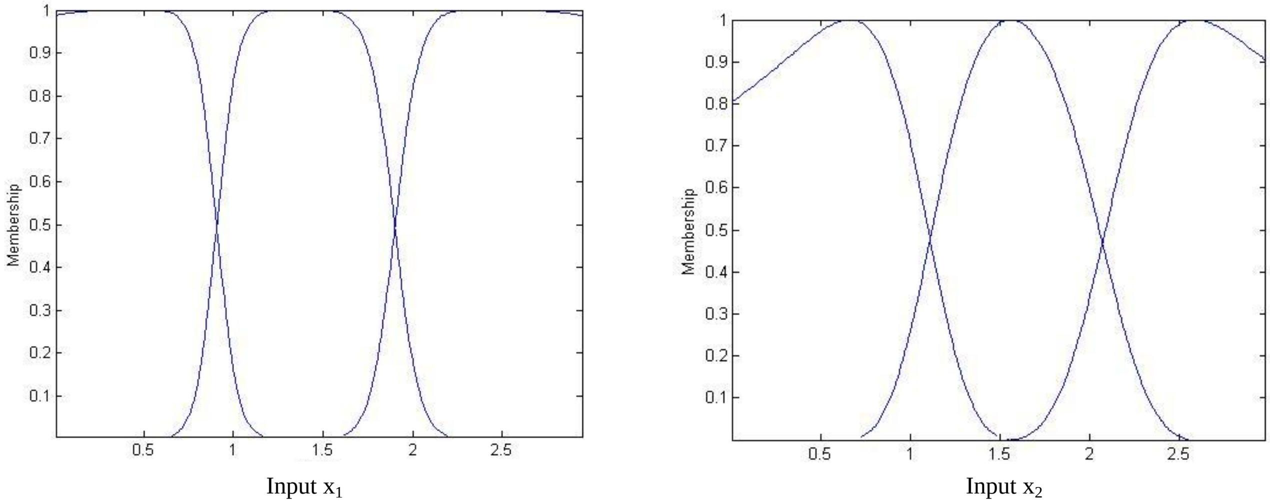


Figure 7.7. Membership Functions of Inputs x_1 and x_2 Using Cubic Spline Curve Fitting

Similarly, the output sets will follow the same process, and the resulting memberships are shown in Figure 7.8.

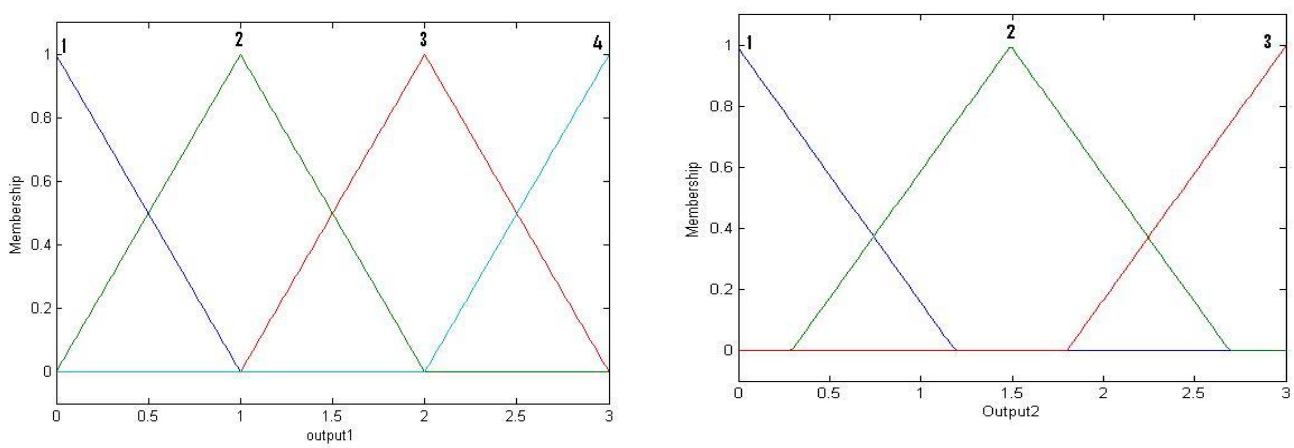


Figure 7.8. Output Membership Functions

Step 3: Generate the rules

The generation of the rules follows the same steps as the generation of the input membership functions. As discussed before, we have two inputs and two outputs. Generating the rules will use FCM at m = 1.5 with PC (equation 36) as cluster validity. In this case, FCM clustering will be performed for all inputs and outputs together, i.e., we will have four-dimensional FCM clustering (equations (13)–(32)). Figure 7.9 shows the optimal c = 16. This means that the inputs and outputs are clustered into sixteen different clusters with sixteen different cluster centers. Each cluster center will represent a single rule. In other words, we end up with sixteen different rules.

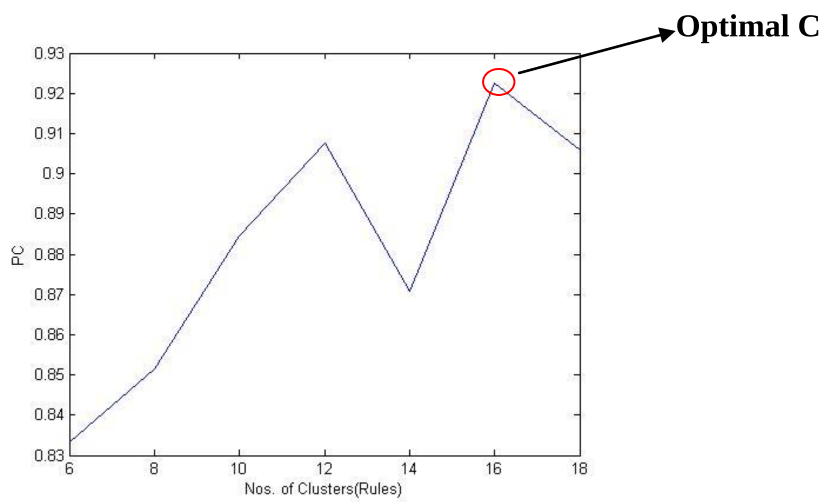


Figure 7.9. Optimal C = 16 (PC Validity), Number of Rules = 16

The rules generated after FCM clustering (and after rounding the O/Ps) are as follows.

0.2358	2.5544	1.0000	3.0000
0.7241	0.5631	2.0000	1.0000
2.6345	1.6129	4.0000	2.0000
1.1202	1.0173	2.0000	2.0000
1.2596	2.5771	2.0000	3.0000
1.6874	0.4079	3.0000	1.0000
2.1991	2.5351	3.0000	3.0000
2.0273	1.0202	3.0000	2.0000
1.1262	1.7119	2.0000	2.0000
2.7381	0.3930	4.0000	1.0000
0.7601	2.2686	2.0000	3.0000
0.3635	1.2707	1.0000	2.0000
1.6658	1.4748	3.0000	2.0000
2.7776	2.7387	4.0000	3.0000
0.6137	1.0507	2.0000	2.0000
2.3076	1.6985	3.0000	2.0000

The if-then rules are obtained using the cluster centers of Figure 7.7 and 7.8 with their respective membership grade to inputs and outputs. The if-then rules are:

If input1=C1 and Input2=C3 then output1=C1 and output2=C3
If input1=C1 and Input2=C1 then output1=C2 and output2=C1
If input1=C3 and Input2=C2 then output1=C4 and output2=C2
If input1=C2 and Input2=C1 then output1=C2 and output2=C2
If input1=C2 and Input2=C3 then output1=C2 and output2=C3
If input1=C2 and Input2=C1 then output1=C3 and output2=C1
If input1=C3 and Input2=C3 then output1=C3 and output2=C3
If input1=C3 and Input2=C1 then output1=C3 and output2=C2
If input1=C2 and Input2=C2 then output1=C2 and output2=C2
If input1=C3 and Input2=C1 then output1=C4 and output2=C1
If input1=C1 and Input2=C3 then output1=C2 and output2=C3
If input1=C1 and Input2=C2 then output1=C1 and output2=C2
If input1=C2 and Input2=C2 then output1=C3 and output2=C2
If input1=C3 and Input2=C3 then output1=C4 and output2=C3
If input1=C1 and Input2=C1 then output1=C2 and output2=C2
If input1=C3 and Input2=C2 then output1=C3 and output2=C2

7.3 Algorithm with Dempster-Shafer Theory

To use the Dempster-Shafer theory to remove contradictory rules, an additional step (Step 4) will be used in addition to those described in Section 7.2. Figure 7.10 shows the flow chart used when using the DS theory to remove the contradictory rules. Pseudo-code is illustrated in pseudo-code 2 of Appendix A.

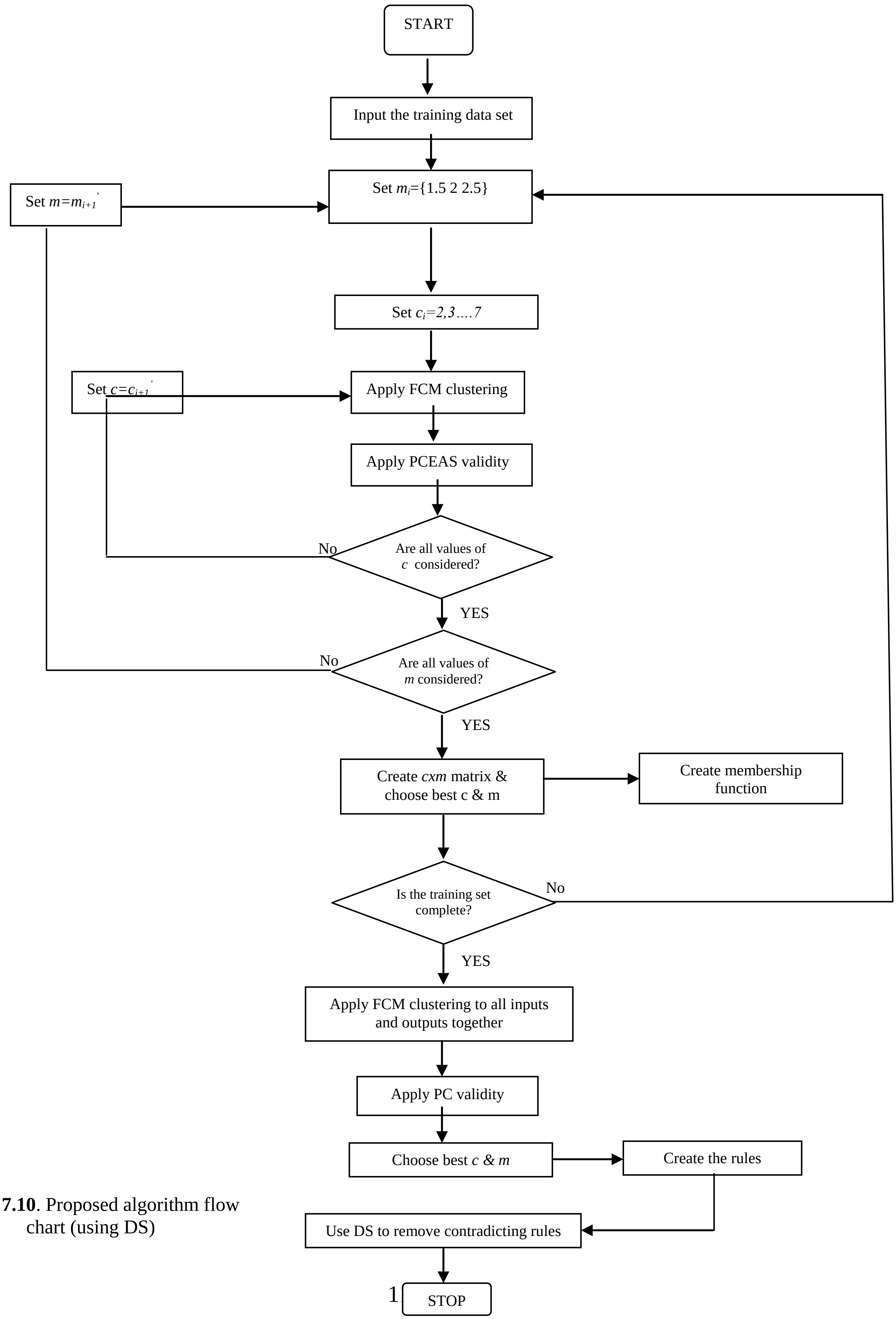


Figure 7.10. Proposed algorithm flow chart (using DS)

Step 4: Remove contradicting rules. The Dempster-Shafer theory will be used for the removal of contradicting. Figure 7.11 shows the set of rules obtained after clustering, and some rules contradict, i.e., result in the same output. Sixteen rules are obtained using FCM, and after applying the Dempster-Shafer theory, we have eleven rules. Contradiction can be in the inputs and outputs; in other words, different inputs can yield the same outputs, or different outputs can be related to different inputs. For example, Rules 4, 9, and 15 are contradicting, yielding the same output. According to the algorithm for removal of contradicting rules, the following is applied.

Rule 4: $m_{121} = \mu_{2x=1.2102}$ and $\mu_{1y=1.0173}$
Rule 9: $m_{222} = \mu_{2x=1.1262}$ and $\mu_{2y=1.7119}$
Rule 15: $m_{311} = \mu_{1x=0.6137}$ and $\mu_{1y=1.0507}$

m_{111}=0.9813x0.661=0.6486

m_{222}=0.9837x0.9484=0.9329

m_{311}=0.9976x0.5993=0.5978

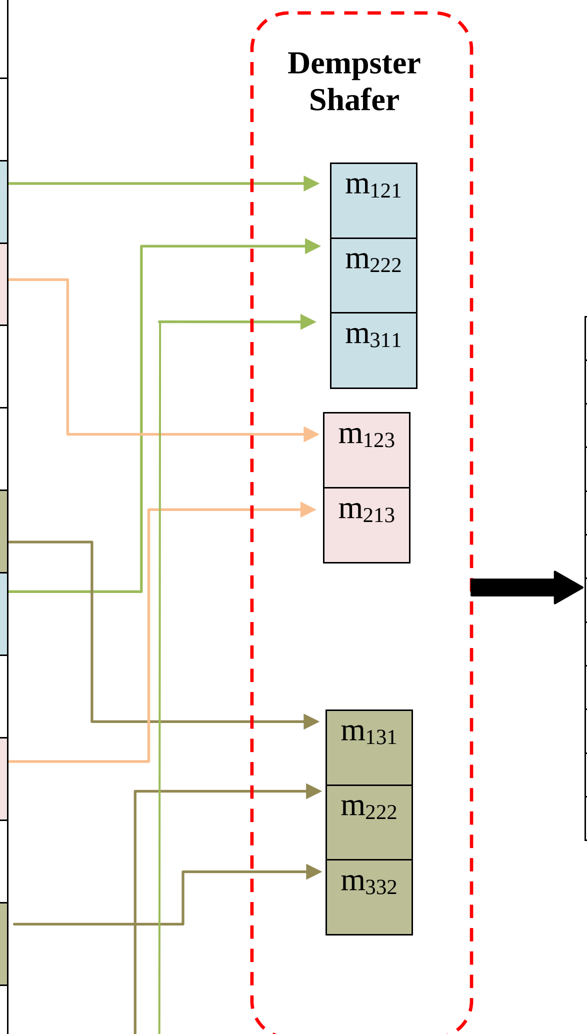
$$\sum m_{IWV} = 2.1793$$

After normalization,

$m'_{111} = 0.2976$, $\boldsymbol{m'_{222} = 0.4280}$,, $m'_{311} = 0.2743$

where $\boldsymbol{m'_{222}}$ has the highest value, so Rules 4 and 15 are removed. Similarly, Rules 11, 8, and 13 will be removed.

R	I/P1	I/P2	***O/P1***	***O/P2***
1	1	3	***1***	***3***
2	1	1	***2***	***1***
3	3	2	***4***	***2***
4	2	1	***2***	***2***
5	2	3	***2***	***3***
6	2	1	***3***	***1***
7	3	3	***3***	***3***
8	3	1	***3***	***2***
9	2	2	***2***	***2***
10	3	1	***4***	***1***
11	1	3	***2***	***3***
12	1	2	***1***	***2***
13	2	2	***3***	***2***
14	3	3	***4***	***3***
15	1	1	***2***	***2***
16	3	2	***3***	***2***



R	I/P1	I/P2	***O/P1***	***O/P2***
1	1	3	***1***	***3***
2	1	1	***2***	***1***
3	3	2	***4***	***2***
5	2	3	***2***	***3***
6	2	1	***3***	***1***
7	3	3	***3***	***3***
9	2	2	***2***	***2***
10	3	1	***4***	***1***
12	1	2	***1***	***2***
14	3	3	***4***	***3***
16	3	2	***3***	***2***

Figure 7.11 Removal of Contradicting Rules using DS (Different Inputs Yielding the Same Output)

The same procedure will be applied to the outputs to remove the contradicting inputs. The number of rules, after applying the Dempster-Shafer theory, will reduce from eleven to nine, as shown in Figure 7.12.

R	I/P1	I/P2	***O/P1***	***O/P2***
1	1	3	***1***	***3***
2	1	1	***2***	***1***
3	3	2	***4***	***2***
5	2	3	***2***	***3***
6	2	1	***3***	***1***
7	3	3	***3***	***3***
9	2	2	***2***	***2***
10	3	1	***4***	***1***
12	1	2	***1***	***2***
14	3	3	***4***	***3***
16	3	2	***3***	***2***

R	I/P1	I/P2	***O/P1***	***O/P2***
1	1	3	***1***	***3***
2	1	1	***2***	***1***
3	3	2	***4***	***2***
4	2	3	***2***	***3***
5	2	1	***3***	***1***
6	2	2	***2***	***2***
7	3	1	***4***	***1***
8	1	2	***1***	***2***
9	3	3	***4***	***3***

Figure 7.12. Removing of contradicting rules using DS (same inputs yielding different outputs)

7.4 Conclusion

This proposed algorithm designs a fuzzy logic reasoning engine that can make decisions based on the fuzzy logic engine. The fuzzy logic engine, as described, consists of membership functions and a set of rules that were obtained through previously stored cases in the CR. If a large number of cases are stored, the FLRE's decision-making will be more accurate but will require more processing time. As the number of cases decreases, the processing time is reduced, which may lead to the FLRE making an inaccurate decision. The Dempster-Shafer theory was used to remove contradicting rules, which can cause the FLRE to make inaccurate decisions. The FLRE is also very simple, its learning and decision-making is less complex than that of neural networks, and its processing time is less than case based reasoning's. The main drawback of such an algorithm is that the stored data (cases) must be very accurate and must be able to obtain the FLRE's membership functions and rules.

CHAPTER 8 **Performance and Simulation**

8.1 Proposed Scheme for Spectrum Utilization

Cognitive radio has recently been commonly used for spectrum sensing [82]. As a case study, we will apply our proposed approach on the GSM cellular network to fully utilize that network's spectrum. The presented scheme uses FL for reasoning in the cognitive radio for detection of spectrum holes and hence uses these holes for secondary user transmission, which leads to better spectrum utilization [83, 84]. In [83], the authors propose a genetic algorithm to overcome the throughput and delay optimal scheduling problems, which the Federal Communications Commission (FCC) confines to certain constraints during efficient spectrum utilization. We considered GSM cellular technology in our scheme shown in Figure 8.1. No dedicated resources were assigned for handoffs; all resources are available for initiation or handoff of a call. The designed FLRE detects the presence of spectrum holes for secondary initiation or handoff of a call.

PU1	**PU2**	**SU1**	**PU3**	**PU4**	**PU5**	**SU2**	

Figure 8.1. GSM Band (Cellular Technology), Full Rate (Eight Time Slots) TDMA Uplink Channel (BW=200 KHz), PUs=5, SUs=2, Empty Time Slot=1

8.1.1 System Scenarios

Our system considers various scenarios, which are shown in Figure 8.2.

- Primary initiation (PI) of a call occurs when a call is initiated from a primary user (licensed).
- Secondary initiation (SI) of a call occurs when a call is initiated from a secondary user (unlicensed).

- Secondary handoff (SH) occurs when a primary user attempts to access the same resource (time slot) as that of a secondary user.

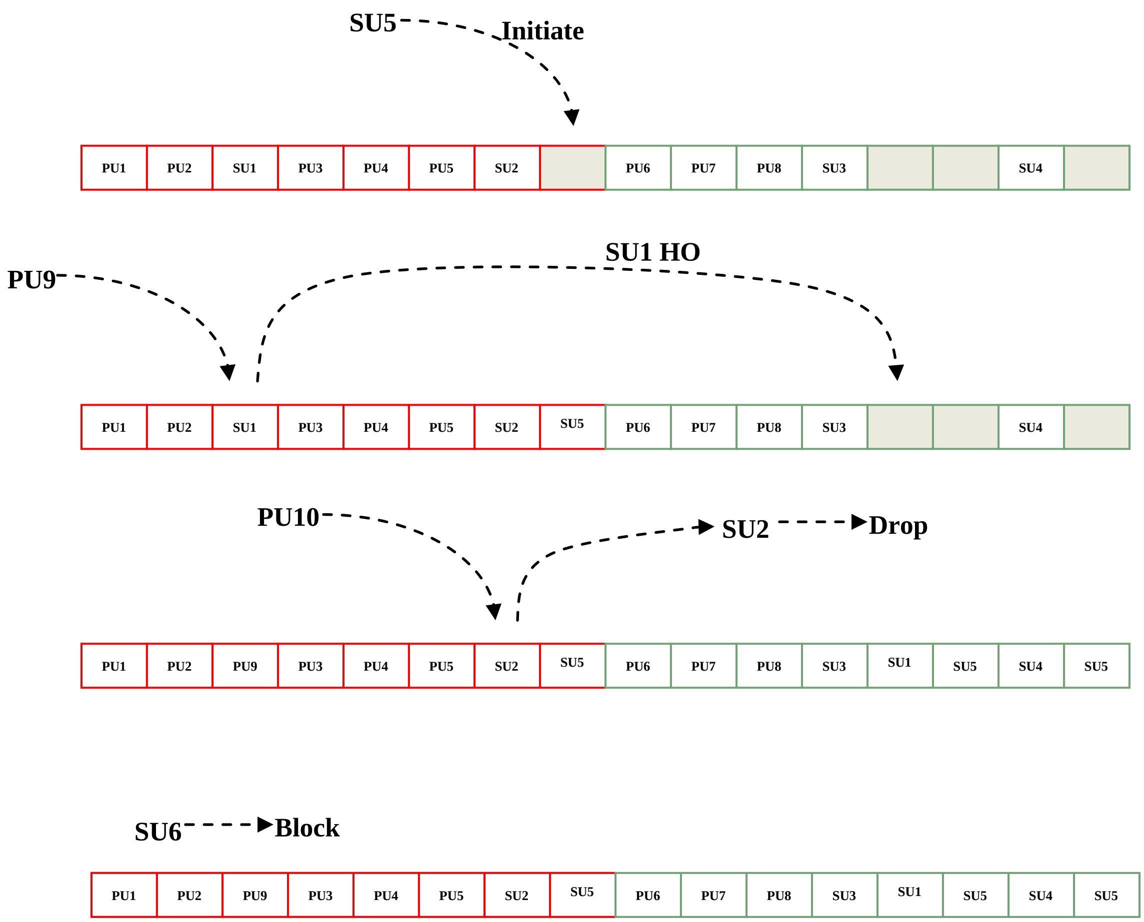


Figure 8.2. Two GSM Bands (a) SU5 Initiated Call, (b) SU1 is performing a hand-off to a white space in another band (c) PU10 occupying SU2 space, while SU2 is dropped. (d) SU6 blocked, no spectrum holes.

These scenarios result in two different situations for a secondary (unlicensed) user: due to the unavailability of a time slot, the secondary user's call is either blocked or dropped.

8.2 Simulation without the Dempster-Shafer Theory

In our simulation, we considered ten GSM bands, each band with eight time slots. The same GSM base station is serving primary and secondary users. The FLRE will be located in the base station. The arrival rate of primary and secondary users follows Poisson's distribution, and the time for each call follows the exponential distribution. The FLRE selects the empty time slot for secondary user transmission, i.e., the availability of spectrum holes, in any one of the ten bands. The FLRE, shown in Figure 8.3, considered 2000 training sample in the form of two inputs: path loss (PL) experienced by primary users in band and mobile station (MS) power of primary users in band (keeping in mind there are no secondary users at initiation). The FLRE will decide, according to the PL and MS power, the availability of a time slot for secondary user transmission in any one of the bands.

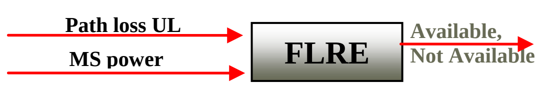


Figure 8.3 Designed FLRE

The PL and MS power were obtained from statistical readings from Vodafone-Egypt. These statistics are shown in Figures 8.4 and 8.5, which show the accumulated MS power and PL of all MSs for a single base station for all bands (ten bands in our case). Figure 8.6 shows the spectrum utilization of the GSM band during peak and non-peak hours. The utilization at peak hours is around 30% and at non-peak hours is around 5% for a certain location averaged over one complete day. When the GSM network is serving more users, the spectrum will be better utilized, which will naturally happen at daily peak hours. During non-peak hours, secondary (unlicensed users) can use this band, thus achieving better spectrum utilization. The base station in this case will serve both primary and secondary users, keeping in mind that primary users are the priority users and that secondary users' calls can be handed off from one time slot to another to provide space for a primary user's call. The FLRE designed will decide the availability of the spectrum time slot for a secondary user's call during both peak and non-peak hours.

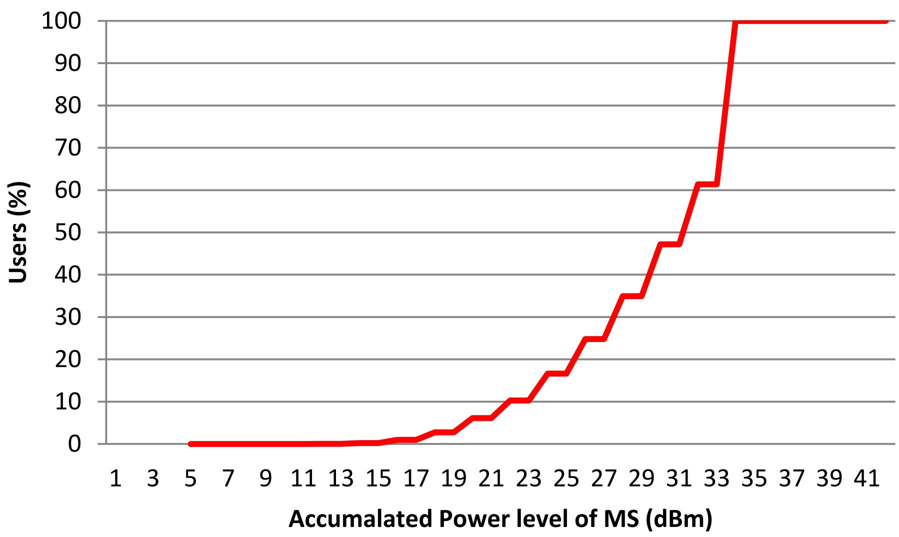


Figure 8.4 Accumulated Power Level of the Mobile Station in a Single GSM Band with Respect to the Percentage of Users Available at the Band (Vodafone-Egypt)

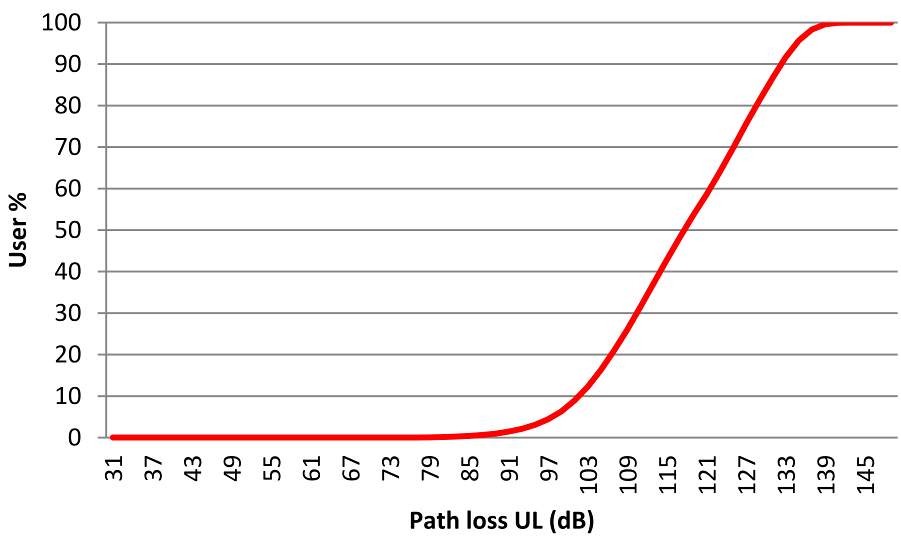


Figure 8.5 Path Loss for the UL in Decibels with Respect to the Users in Percentage for a Certain Location (Vodafone-Egypt)

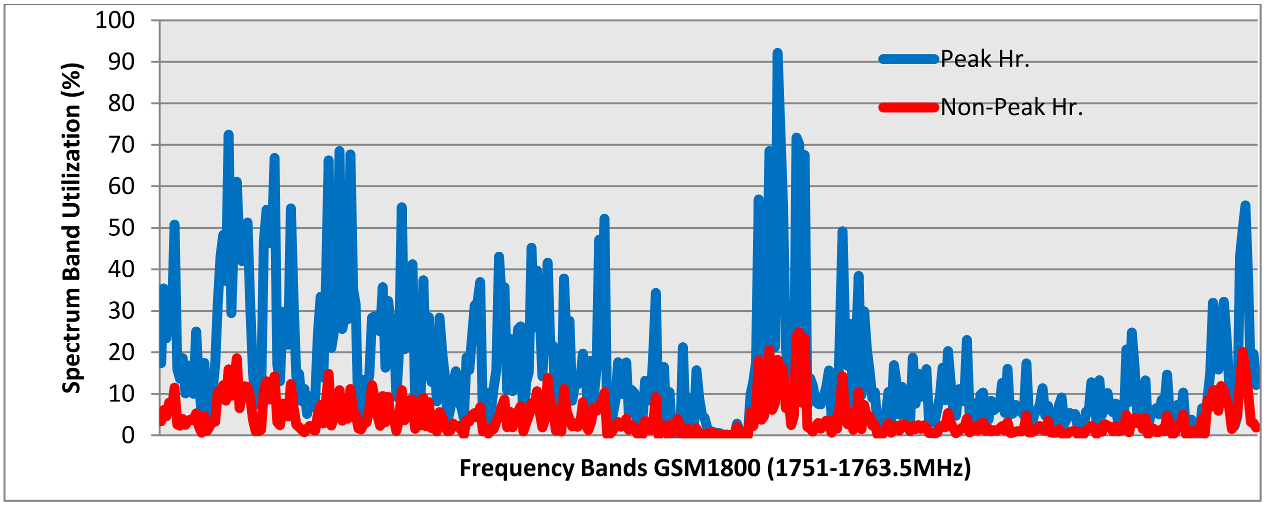


Figure 8.6. Traffic in Terms of Spectrum Utilization in Percentage in GSM Bands (Vodafone-Egypt) Showing Peak and Non-Peak Hours for a Certain Location Area

Using the proposed approach for the FLRE's design, we obtain the results shown in Figures 8.7 and 8.8 i.e., from the 2000 training samples (obtained from Vodafone) for the MS power and the PL and through FCM clustering, we determine the number of clusters to be used. Figures 8.7 and 8.8 show a snap shot of 200 samples (of the 2000 used) for the PL and MS power along with the cluster number obtained using FCM clustering and the PCAES validity test.

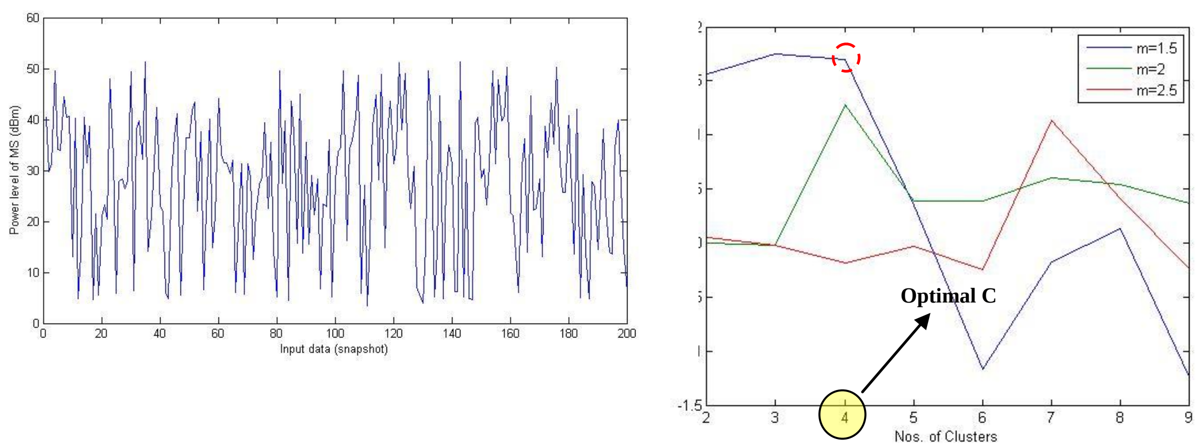


Figure 8.7 Power Level of MS (dBM) and Cluster Numbers After Using FCM Clustering and the PCAES Validity Test

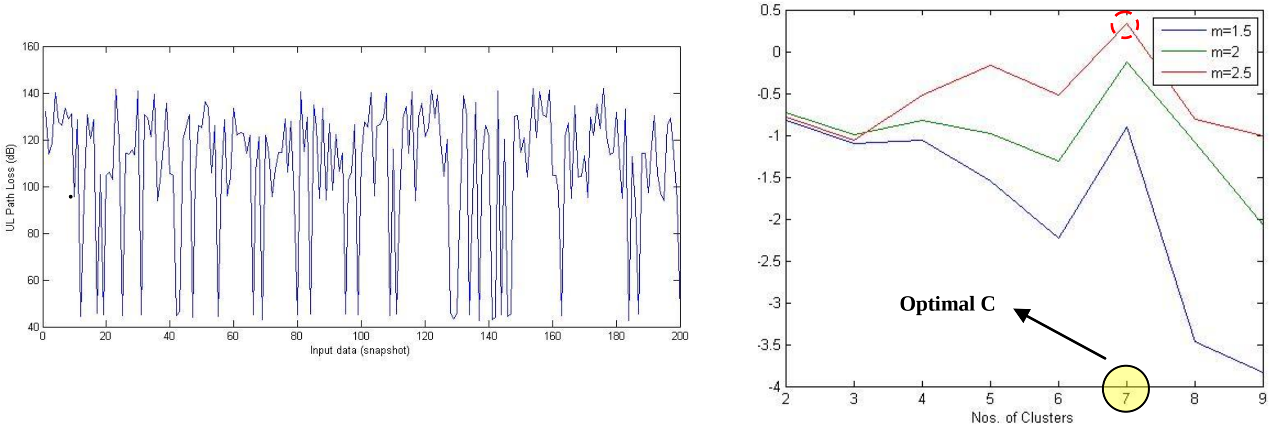


Figure 8.8 UL Path Loss (dB) and Cluster Numbers After Using FCM Clustering and the PCAES Validity Test

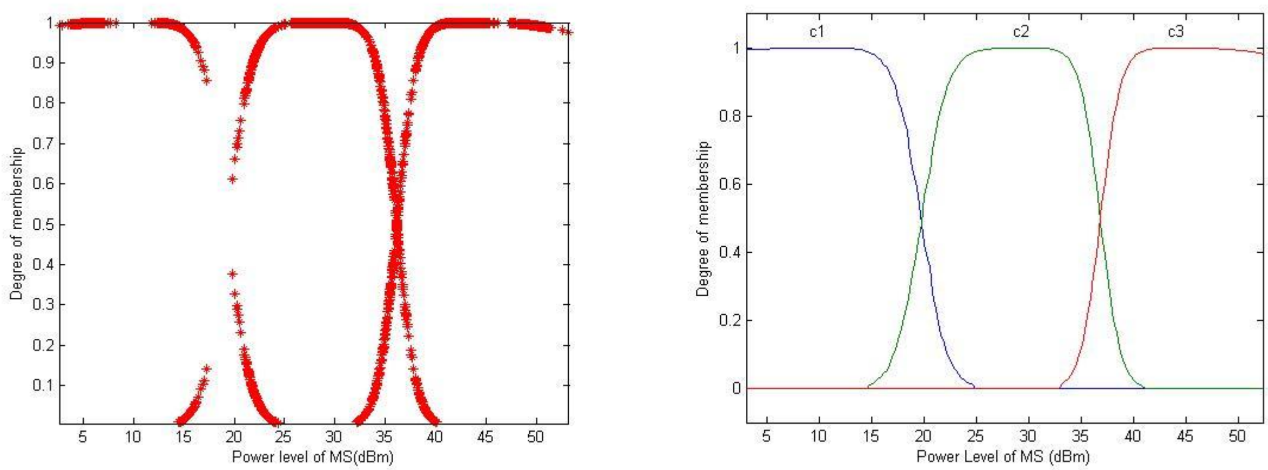


Figure 8.9. Power Level of MS Membership Functions

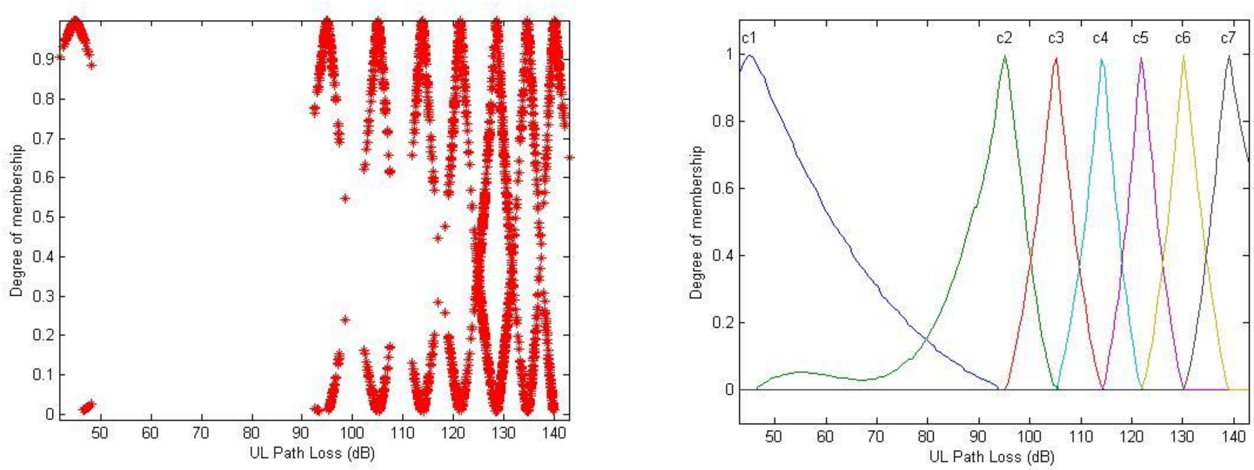


Figure 8.10 UL Path Loss Membership Functions

Figures 8.9 and 8.10 show the membership functions obtained for the two inputs using our proposed approach, and Figure 8.11 shows the output membership functions obtained.

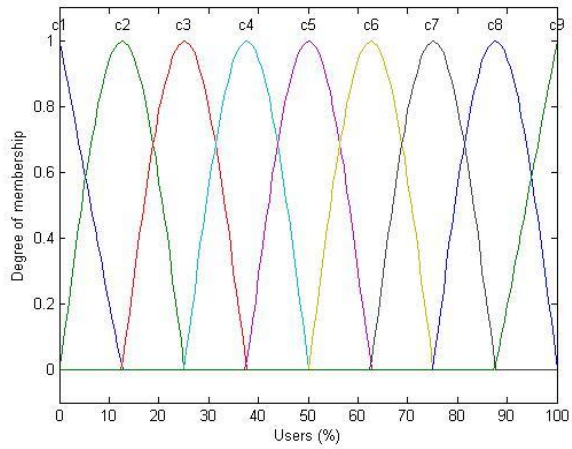
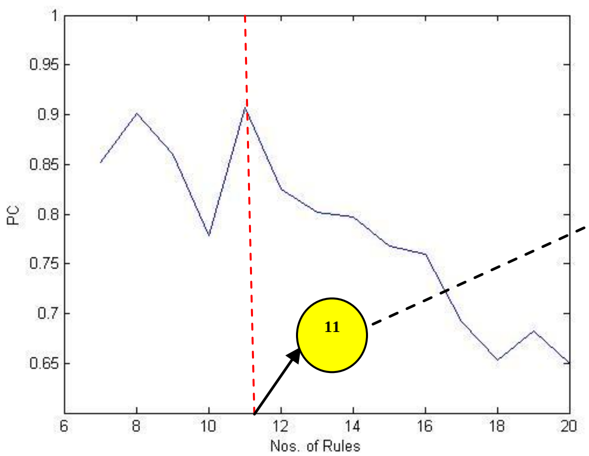


Figure 8.11. Output Membership Functions Showing the Percentage of User Available in a Band

After obtaining the membership functions of the outputs and inputs, the algorithm for the automatic generation of rules is then applied. Figure 8.12 clearly shows the number of rules generated for the 2000 input training samples by applying our proposed FCM approach to the input and output with the PC validity test. Some rules are repeated, but those are removed to result in nine rules, shown in Figure 8.13. Figure 8.12 shows that, after the clustering of all inputs and outputs together (i.e., forming *n*-dimensional clusters) and using the PC validity index, the result is eleven clusters, which are eleven rules. Each cluster (rule) is defined by three points (two inputs and one output). Using the membership functions of the inputs (Figures 8.9 and 8.10) and output (Figure 8.11) that we previously obtained, we can determine to which class (C) these points belong, and the rules table is as shown in the Figure 8.12. As shown in the rules table, Rule 1 (for example) states that if we have input 1 belonging to C2 and input 2 belonging to C6 then the output will be C6. In other words, any input data points can first be identified by the cluster to which it belongs, and, according to the rules table, the respective output is obtained.

The rules obtained depend greatly on the training data used because different training data gives results to different membership functions.



#	C	C	C
1	2	6	6
2	2	3	3
3	1	1	1
4	1	1	1
5	1	1	1
6	3	6	7
7	3	7	9
8	1	2	2
9	2	5	5
10	2	4	4
11	3	7	8

Figure 8.12. Automatic Generated Rules for the Proposed FLRE

Rule #	**MS power**	**PL**	**User Availability (%) in band**
1	C1	C1	C1
2	C3	C6	C7
3	C1	C2	C2
4	C2	C5	C5
5	C2	C6	C6
6	C3	C7	C9
7	C2	C4	C4
8	C3	C7	C8
9	C2	C3	C3

Figure 8.13. Rules for the Proposed FLRE

The number of training samples used alters the shape, size, and type of the membership functions generated, and a greater number of training samples offers more specific and accurate rules. Testing was performed for the designed FLRE with different samples and compared to the actual values (i.e., compared with the availability of the bandwidth for secondary user transmission). As the number of training data used increases, the FLRE's decision is more accurate. As seen from Figure 8.14, as the number of training samples reaches 2000, the decision is 100% accurate.

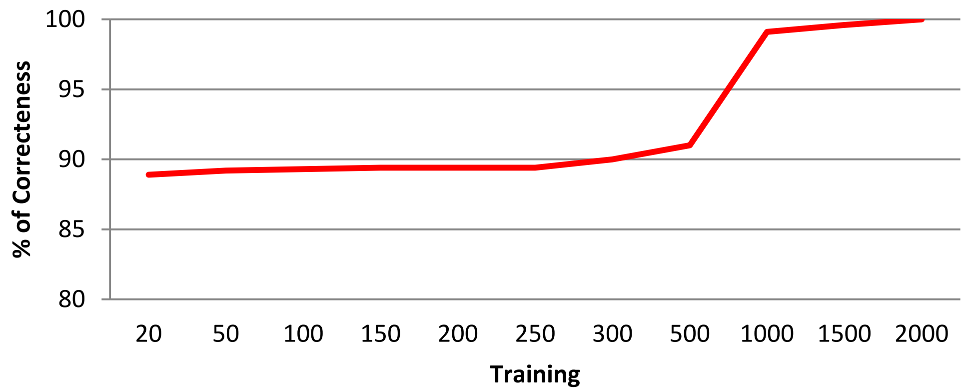


Figure 8.14 Percentage of Correctness of FLRE Output for Availability of Empty Slots With Respect to the Training Data

The designed FLRE decides upon the availability of the band (time slot) for secondary user transmission. Different scenarios were used and resulted in better spectrum utilization. Figure 8.15 clearly shows that we can make better usage of the spectrum in the presence of secondary user transmission.

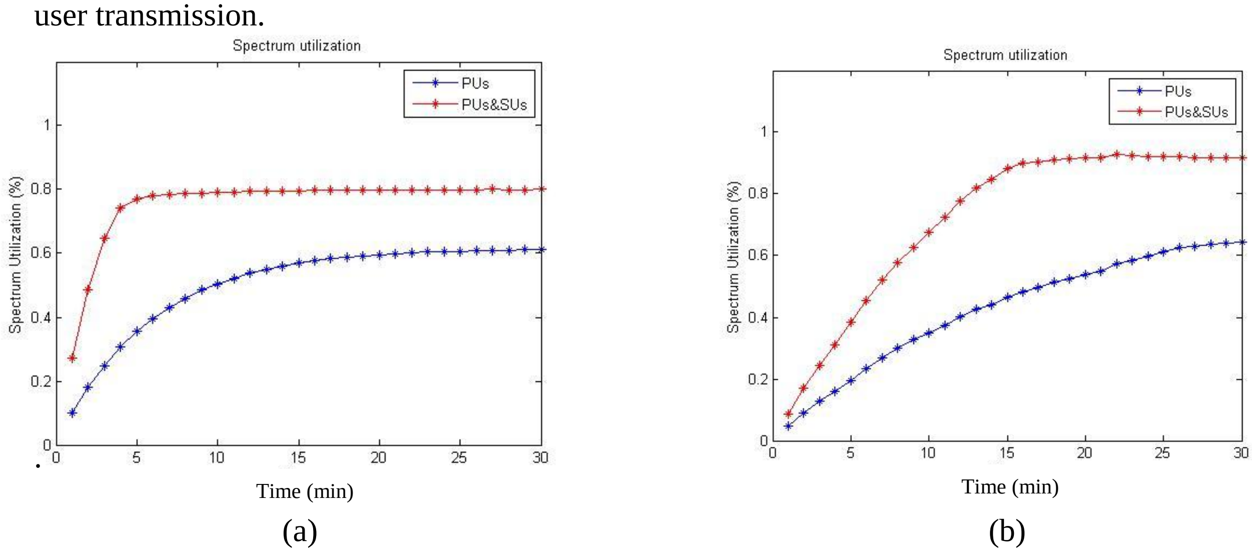


Figure 8.15. Utilization for primary users and primary & secondary users. (a) λ_P=10 calls/min, λ_S=20 calls/min MCT_P (mean call time)=5min, MCT_S (mean call time)=5min. (b) λ_P=4calls/min λ_S=4calls/min, MCT_P (mean call time)=15min, MCT_S (mean call time)=15min. λ is the call arrival rate (calls/min).

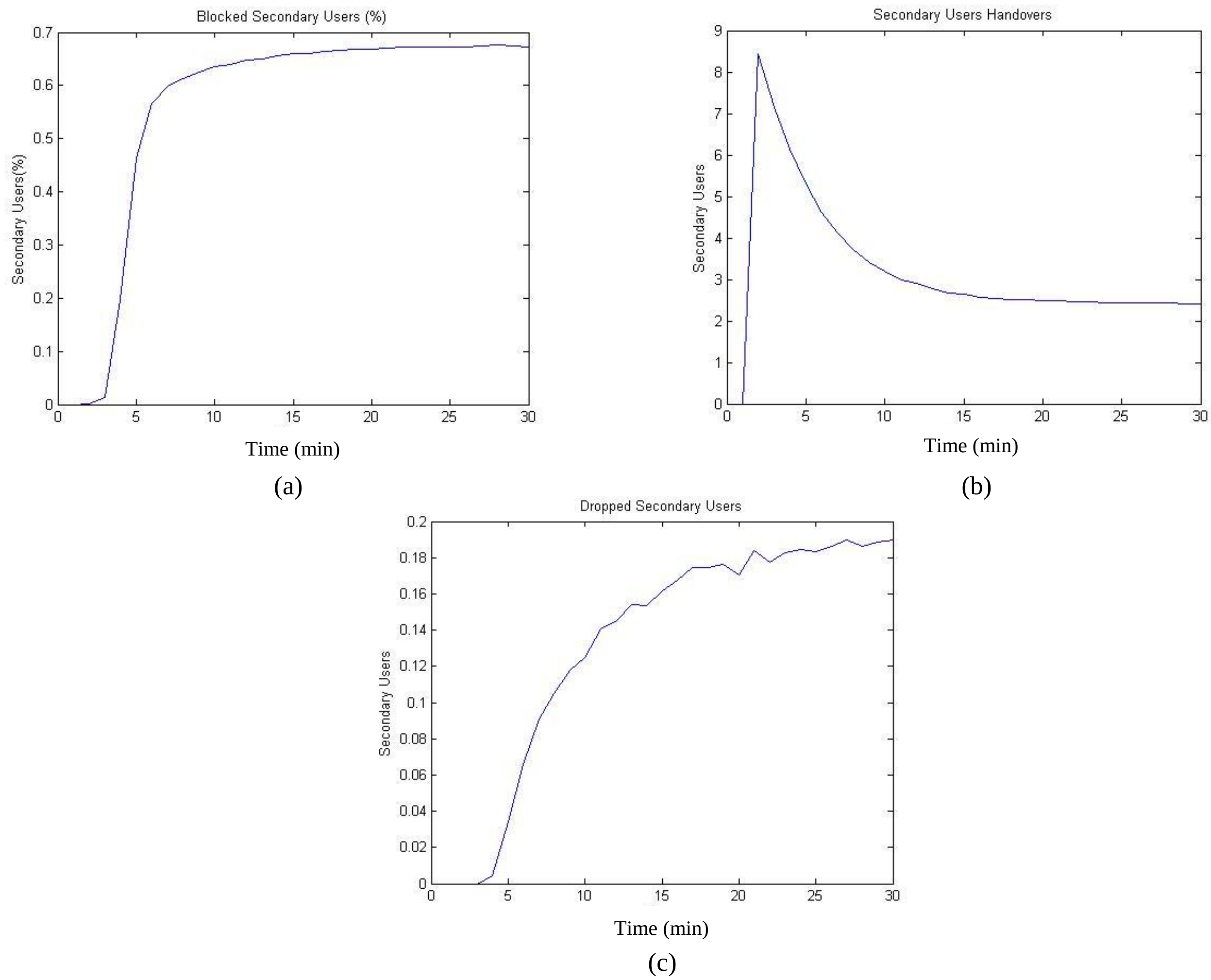


Figure 8.16. λ_P=10 calls/min, λ_S=20 calls/min MCT_P (mean call time)=5min, MCT_S (mean call time)=5min. (a) percentage of blocked secondary users (b) number of secondary users handoffs (c) number of dropped secondary users.

Figure 8.15 shows that spectrum is more efficiently used in our proposed approach. In Figure 8.15a, as time elapses the difference in percentage of spectrum utilization is around 25%, and, in Figure 8.15b, the difference is around 30%. The number of blocked secondary users, due to the full utilization of the spectrum at that time, has a maximum value of 0.68% (Figure 8.16a). The blockage of secondary users can be overcome by retrying for initiation of a secondary user's call, i.e., by giving the secondary user a hold time to initiate the call. Figure 8.16b shows the number of successful secondary user handoffs. The number of dropped secondary users' calls (Figure

8.16c) is very small (around 0.2%), which is acceptable for cellular technology (in which 1% is a good rate).

The number of training samples used alters the shape, size, and type of the membership functions generated. In addition, the rules are more specific and accurate when we use more samples for training. Testing was performed for the designed FLRE with different samples and compared to the actual values (i.e., compared with the availability of the bandwidth for secondary user transmission). As the number of training data increases, the FLRE's decision is more accurate. As shown in Figure 8.14, as the number of training samples reaches 2000, the decision approaches 100% accurate.

8.3 Simulation with the Dempster-Shafer Theory

Using the Dempster-Shafer theory of belief will remove all contradicting rules and thus reduce the number of rules the FLRE uses. Figure 8.17 contained two contradicting rules which need to be resolved.

Rule #	MS power	PL	User Availability (%) in band
1	C1	C1	C1
2	C3	C6	C7
3	C1	C2	C2
4	C2	C5	C5
5	C2	C6	C6
6	C3	C7	C9
7	C2	C4	C4
8	C3	C7	C8
9	C2	C3	C3

Figure 8.17 Rules Showing Contradiction

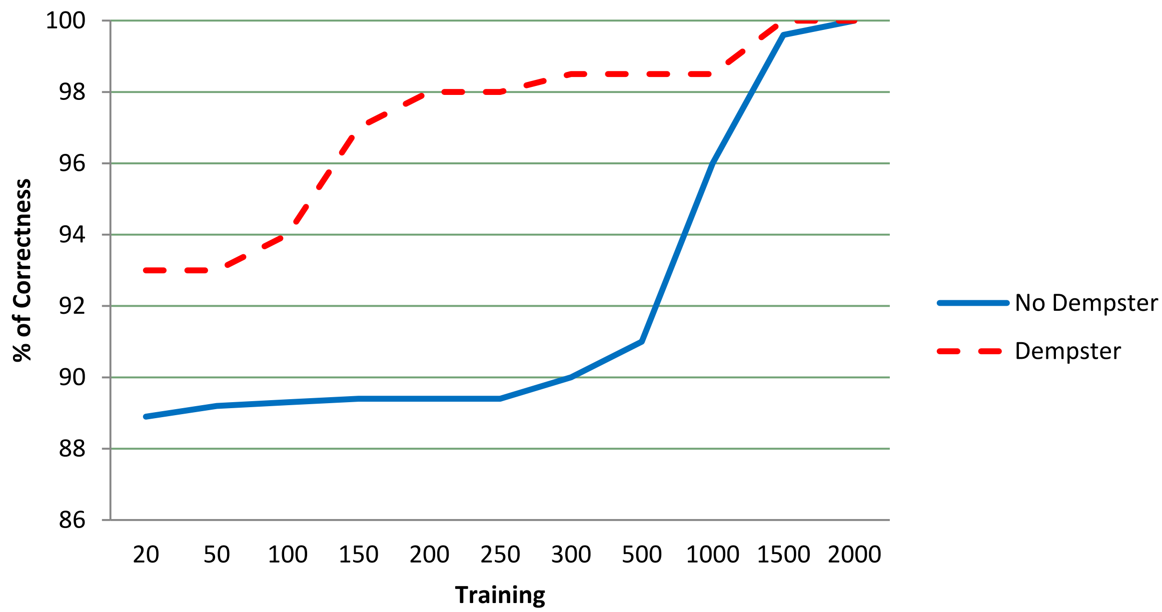
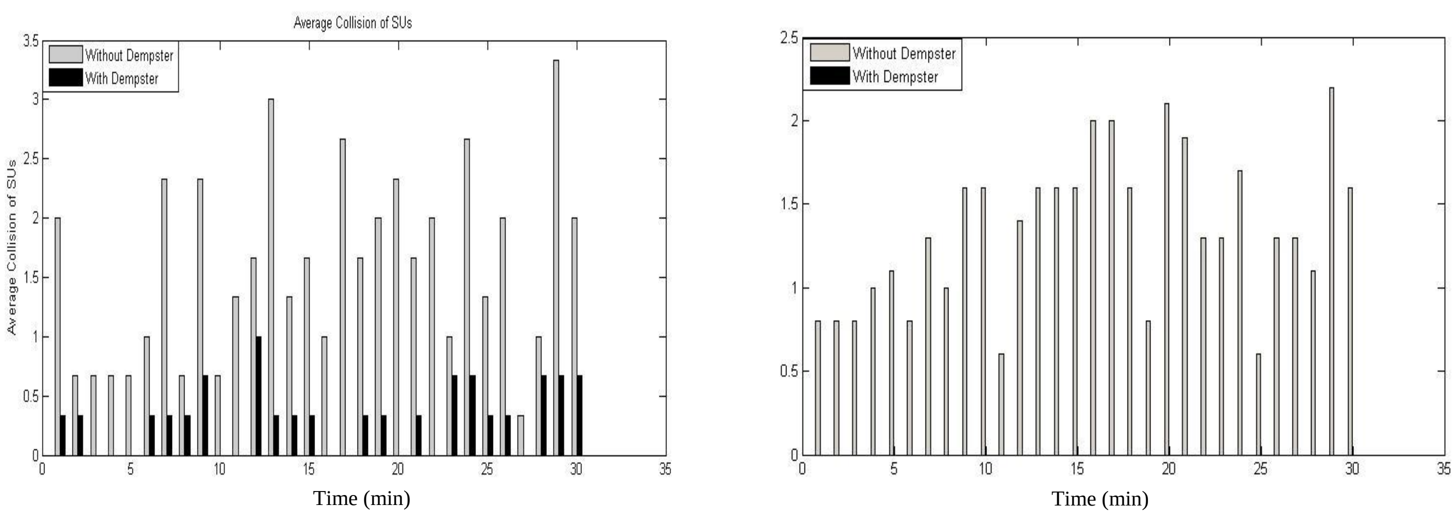


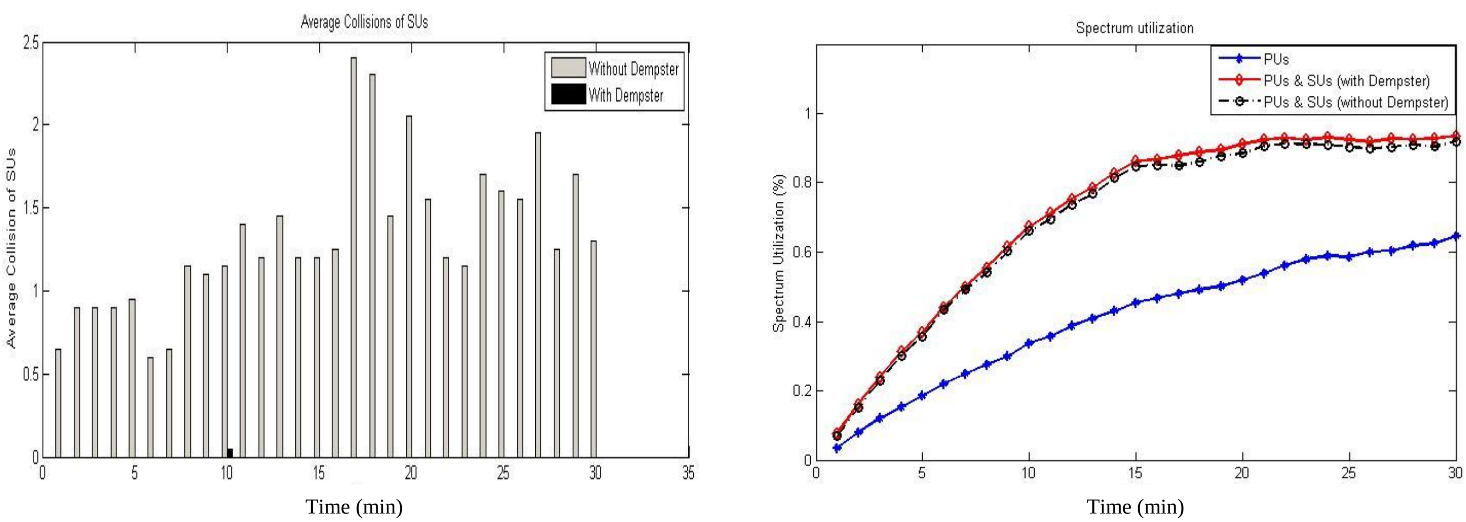
Figure 8.18 Percentage of Correctness of FLRE Output for Availability of Empty Slots with Respect to the Training Data, (a) Without using the Dempster-Shafer Theory to Remove Contradicting Rules, (b) Using the Dempster-Shafer Theory to Remove Contradicting Rules



(a) (b)

Figure 8.19 Average number of Collisions of SUs with PUs for FLRE (With and Without using the Dempster-Shafer Theory) Generated from (a) 100 training data samples and (b) 1000 training data samples. It is noticed that with Dempster at (b) it is equal to zero. λ_P=4 calls/min, λ_S=4calls/min MCT_P (mean call time)=15min, MCT_S (mean call time)=15min.

Figure 8.18 clearly proves that the removal of contradicting rules leads to better accuracy, i.e., the decision is more accurate even with fewer training samples. Using fewer training samples also means that the engine's processing time is quicker. The decision is inaccurate when a secondary user collides with a primary user. A collision is an unacceptable phenomenon during a primary user call. The use of the Dempster-Shafer theory in the removal of contradicting rules minimizes such collisions to the point of being insignificant. The collision between a primary user and a secondary user will also depend on the number of rules generated, which indirectly means that the collision depends on the type and number of the training data samples used. Figure 8.19 shows that using the Dempster-Shafer theory reduces the number of collisions for 100 training data samples and using the theory minimizes the number of collisions to zero for 1000 training data samples.



(a) (b)

Figure 8.20 Average number of collisions of SUs with PUs for FLRE (with and without using Dempster) generated from (a) 750 training data samples and (b) the spectrum utilization for 750 training data samples and parameters λ_P=4 calls/min, λ_S=4calls/min MCT_P (mean call time)=15min, MCT_S (mean call time)=15min.

Figure 8.20a shows the average collision of a secondary user's call with a primary user's call for a training data set of 750 samples. Using the Dempster-Shafer theory minimizes collisions. The spectrum utilization shown in Figure 8.20b also proves that spectrum utilization is improved when using DS because the decision-making accuracy is improved, so secondary user call transmission is possible, resulting in better utilization of the spectrum.

In this chapter, we introduced the use of our proposed FL approach for efficient spectrum utilization in a GSM network. Transmission of secondary users' calls in empty time slots in a GSM band was tested using the designed FLRE's decisions. The inputs to the FLRE engine were the PL and MS power, which were obtained from Vodafone Egypt. Simulations proved that increasing the amount of training data used for the design of membership functions and FLRE rules improves accuracy regarding secondary user channel selection and minimize collisions with a primary user's call. Also, the use of the Dempster-Shafer theory proved to be very efficient when using a small amount of training data.

CHAPTER 9 **Conclusion**

This dissertation proposed a cognitive radio for microwave access (CogMAX) system to improve WBN (wireless broadband network) performance by continuously altering important radio parameters at the physical layer. WiMAX was considered as a case study for the application of the proposed approach due to its wide adaptation and flexible parameters that can be dynamically changed using the cognitive engine. The cognitive engine, which controls the reasoning and decision-making of the proposed system as the inference engine, will be responsible for altering the various radio parameters that could lead to an overall improvement of the performance. We imposed the use of fuzzy logic for decision-making. Fuzzy logic requires a set of rules to be used for decision-making; these rules can vary according to the radio conditions. However, anomalies rise among these rules, causing degradation in the CR's performance. In such cases, the CR requires a method to eliminate such anomalies, so the Dempster-Shafer (DS) theory was applied. Spectrum utilization, one of the recent hot topics in wireless communications, was also considered in our research by applying our proposed approach to better utilize the spectrum band in the GSM cellular network.

9.1 Summary of Contributions

We identified various physical radio parameters that the CogMAX system could control. One of the main issues in our work was channel estimation, and the estimation process involved the determination of the channel type through a fuzzy logic reasoning engine. The numbers of pilots estimated are placed uniformly along the time and frequency grid. The type of channel is also determined through the cognitive engine, which is used in the determination of the number of pilots.

Adapting resource management for vague environments in wireless communication proved to be a major point of research recently. In our research, we presented a system capable of adapting important resources (type of modulation, code rate, and number of subcarriers) for vague channel conditions. The system in this work is demonstrated for WiMAX, which proved to be one of the prominent technologies in providing broadband wireless access (BWA) in metropolitan areas with a simpler installation and lower cost than the wired alternatives. The cognitive radio uses fuzzy logic for reasoning. The cognitive engine controls the type of modulation, code rate, and number of subcarriers to maintain a good system throughput without wasting available bandwidth. Fuzzy logic reasoning in the cognitive engine was chosen because it is well-suited for situations of uncertainty and of incomplete and heterogeneous information, all encountered in dynamic radio environments. The results proved flexible combinations of modulation type, code rate, and number of subcarriers should be considered in WiMAX since, in most cases, it outperforms the standard fixed settings in error probability and spectral efficiency, especially in a fast-changing radio environment.

In our research, we present an automated, opportunistic, decision-making and learning process for cognitive radio based on uncertainty reasoning algorithms. This novel approach is well-suited for dynamic wireless environments with vague, incomplete, and heterogeneous information. Theory and simulations prove that decision-making and learning of the cognitive radio based on the proposed approach cope with the changes in the radio environment. Simulation also proved that our approach provides accurate and precise decisions on allocating spectrum to mobile Internet users even in fast-varying radio conditions.

The dynamic spectrum access application was addressed to test our designed CR system. We tested the system on the GSM cellular technology by developing an algorithm that uses fuzzy c-mean clustering along with the Dempster-Shafer (DS) theory of belief as inference for a cognitive radio that alters radio parameters to yield better system performance. Fuzzy logic was used as the artificial intelligence algorithm applied. The Dempster-Shafer theory was used to remove the contradiction of rules for the fuzzy logic system. Spectrum utilization was the metric used to test the performance of our system. Simulation results proved that using fuzzy logic with FCM and the Dempster-Shafer theory yields better spectrum utilization than the standard GSM system. The use of the Dempster-Shafer theory also showed an improvement in spectrum utilization over non-use. Also, when the Dempster-Shafer theory was used to remove the contradiction of rules, collisions between primary users' calls and secondary users' calls were minimized, as was the number of rules (complexity) of the system.

9.2 Future Work

The CogMAX system and new fuzzy logic approaches our research introduced shows much promise. Several open problems and opportunities for carrying this work forward are listed here.

- Artificial Intelligence Techniques: In our proposed work, we used fuzzy logic reasoning for the cognitive engine. Other AI techniques can also be used and compared to the obtained results. Though case-base reasoning is the most common, Bayesian networks, neural networks, and hidden Markov Models can be also investigated to test their performance within the CogMAX framework.

- The MAC Layer: Our research targeted the physical layer, but future study can target the MAC layer. The MAC layer supports different though important functions, such as QoS provisioning, call admission, scheduling, and fragmentation/segmentation of packets. The MAC layer is also responsible for handling different types of services, both in real and non-real time. The MAC layer should cope with the harsh and changing physical environment, where it contends with different physical phenomena, like fading and interference. The MAC layer also provides a dynamic range of throughput to a specific user by dynamically allocating resources to this user. The investigation of joint optimization of the MAC and PHY layers is also an attractive research direction.

- Pilot Pattern for Channel Estimation: In our research, we were able to determine the number of pilots used for channel estimation. The pilot's arrangement was uniformly distributed along the time-frequency grid. Future work can target dynamically changing the pilot pattern, which could lead to a decrease of the number of pilots used and, hence, better utilization of the spectrum.

Appendix A Pseudo-codes

Pseudo-code 1

Algorithm

---

1. Input training data points.
2. Define I/Ps and O/Ps.
   I/Ps={x_1,x_2,x_3.......x_N}
   O/Ps={y_1,y_2,y_3.......y_M}
3. Let *m* be the fuzzy weighting component={1.5,2,2.5}
4. Let *c* be number of clusters={2,3,4,5,6,7}
5. Let *sizm* be the size of m array (=3)
6. Let *sizc* be the size of the number of clusters array (=6)
7. Get I/Ps Membership functions

```
for i=1:N
   for nc=1:sizc
     for nm=1:sizm
       apply FCM clustering (using c(nc) and m(nm))
       check PCAES validity.
       Let PI(nc,nm)=PCAES_i
      end
    end
  end
```

8. Get max(PI), get optimum c&m.
9. Get O/Ps Membership functions

```
for i=1:M
   for nc=1:sizc
     for nm=1:sizm
       apply FCM clustering (using c(nc) and m(nm))
       check PCAES validity.
       Let PO(nc,nm)=PCAES_i
      end
    end
  end
```

10. Get max(PO), get optimum c&m.
11. Generate the membership functions.
12. All input training point are to be clustered together.
13. Steps 3 to 10 are repeated but using PC validity
14. Create rules (Optimum c will represent the number of rules)

Pseudo-code 2

Algorithm

---

1. Input training data points.
2. Define I/Ps and O/Ps.
   I/Ps={x_1,x_2,x_3.......x_N}
   O/Ps={y_1,y_2,y_3.......y_M}
3. Let *m* be the fuzzy weighting component={1.5,2,2.5}
4. Let *c* be number of clusters={2,3,4,5,6,7}
5. Let *sizm* be the size of m array (=3)
6. Let *sizc* be the size of the number of clusters array (=6)
7. Get I/Ps Membership functions

```
for i=1:N
   for nc=1:sizc
     for nm=1:sizm
       apply FCM clustering (using c(nc) and m(nm))
       check PCAES validity.
       Let PI(nc,nm)=PCAES_i
      end
    end
  end
```

8. Get max(PI), get optimum c&m.
9. Get O/Ps Membership functions

```
for i=1:M
   for nc=1:sizc
     for nm=1:sizm
       apply FCM clustering (using c(nc) and m(nm))
       check PCAES validity.
       Let PO(nc,nm)=PCAES_i
      end
    end
  end
```

10. Get max(PO), get optimum c&m.
11. Generate the membership functions.
12. All input training points are to be clustered together.
13. Steps 3 to 10 are repeated but using PC validity
14. Create rules (Optimum c will represent the number of rules)
15. Remove Contradicting rules using DS.

Appendix B Acronyms

AI	Artificial Intelligence
ANN	Artificial Neural Network
AP	Access Point
APA	Adaptive Power Allocation
ATM	Asynchronous Transfer Mode
BER	Bit Error Rate
BN	Bayesian Network
BPA	Basic Probability Assignment
BPSK	Binary Phase Shift Keying
BS	Base Station
CBR	Case Based Reasoning
CC	Convolutional Coding
CE	Cognitive engine
CID	Connection Identifier
COA	Center of Area
CogMAX	Cognitive Radio for Microwave Access
CPS	Common Part Sublayers
CR	Cognitive Radio
CS	Convergence specific
CSI	Channel state Information
CTC	Convolutional Turbo Coding

CV	Configuration Version
DL	Down link
DS	Dempster Shafer
DSA	Dynamic Spectrum Access
DSL	Digital Subscriber line
FCC	Federal Communications Commission
FCM	Fuzzy C-Mean Clustering
FFT	Fast Fourier Transform
FHV	Fuzzy Hyper Volume
FL	Fuzzy Logic
FLC	Fuzzy Logic Controller
FLRE	Fuzzy Logic Reasoning Engine
GA	Genetic Algorithm
GSM	Global system for Mobile Communication
HMM	Hidden Markov Model
HO	Hand Over
ICI	Inter-Carrier Interference
IP	Internet Protocol
ISI	Inter-Symbol Interference
LAPC	Low Density Parity Check Code
LMMSE	Linear Minimum Mean Square Error
LOS	Line of Sight
LS	Least Square

LU	Licensed User
MAC	Media Access Control
MF	Membership Function
MLPN	Multi-Layer Linear Perception Network
MPC	Modified Partition coefficient
MRC	Maximum ratio combining
MS	Mobile Station
NLOS	Non Line of Sight
NN	Neural Network
NPC	Normalized Partition coefficient
NPN	Non Perception Network
O&M	Operations and Maintenance
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency Division Multiple Access
OP	Optimality Predictor
OS	Optimality Scale
PC	Partition Coefficient
PCAES	Partition Coefficient and Exponential Separation
PE	Partition Entropy
PI	Primary Initiation
PL	Path Loss
PSE	Performance Scale Explorer
PU	Primary User

QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
QPSK	Quadrature Phase Shift Keying
RALFE	Reason and Learn from Experiment
RBFN	Radial Basis Function Network
RNC	Radio Network Controller
SDU	Service Data Unit
SH	Secondary Hand-off
SI	Secondary Initiation
SINR	Signal to Interference Noise Ratio
SNR	Signal to Noise Ratio
S-OFDMA	Scalable-Orthogonal Frequency Division Multiple Access
SON	Self Organizing Network
SU	Secondary User
UL	Up Link
VFKM	Very Fast K-Mean
VT-MENA	Virginia Tech – Middle East and North Africa Region
WBN	Wireless Broadband Network
WIMAX	Worldwide Interoperability for Microwave Access

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