Neuro-Fuzzy Based Adaptive Coding and Modulation for Performance Improvement in OFDM Wireless Systems

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DECLARATION

This thesis is my original work and has not been submitted for award of a degree in any other University.

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This thesis report has been submitted for examination with our approval as the University Supervisors.

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Dr. Kibet Langat

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In addition, I would like to take this opportunity to give special thanks to my supervisors, Prof. Elijah Mwangi and Dr. Kibet Langat for the advice, direction, support, guidance and mentorship in course of my studies. I also cannot forget my colleagues and friends especially Kibrom Kidanu, Tedros Salih, Gebrehiwot Kalayu and Tesfamichael Gebreslassie for their moral support.

DEDICATION

This thesis work is dedicated to my family, especially my dad and mom for their sacrifices made my studies.

ABSTRACT

In a limited radio spectrum, the future wireless technologies are supposed to deliver multimedia services such as video, data, and audio with a high data rate and virtually error free communication. The performance of radio signals that propagate through the wireless channel is limited by multipath fading, noise and interference and thus affect the signal quality. Adaptive coding and modulation (ACM) plays a vital role in improving the performance of wireless communication by adapting its transmission parameters such as coding rate and modulation order based on the quality of the wireless channel.

Adaptive coding and modulation with Orthogonal Frequency Division Multiplexing (OFDM) systems allow the efficient use of available bandwidth to maximize data rate. In ACM techniques, both code rate and modulation order are varied dynamically to adapt the time-varying channel to improve capacity and reduce bit error rate (BER) in contrast to fixed systems that either enhance spectral efficiency or minimize BER. Due to the complexity and the uncertainty of the wireless channel, the conventional adaptive techniques, do not cope with the changing environment. Soft computing techniques, which do not require highly non-linear mathematical models, are commonly used to control and model uncertain systems. The fuzzy logic-based ACM is good in decision-making in an uncertain environment and performs better than adaptive and non-adaptive techniques but cannot learn from training examples. The neuro-fuzzy based approach combines the merits of both neural networks and fuzzy logic system. The neuro-fuzzy system grasps the learning capability of the artificial

neural networks to enhance the intelligent system's performance using a priori knowledge.

A special neuro-fuzzy method termed adaptive network based fuzzy inference system (ANFIS) is used as the model in our proposed algorithm. In this thesis, a neuro-fuzzy based adaptive coding and modulation for OFDM wireless systems is proposed and simulated in MATLAB environment. By analyzing the simulation results, the neuro-fuzzy based model shows an average of 25.03% data rate/spectral efficiency improvement compared to the existing fuzzy logic model. It also shows that, the proposed approach outperforms compared to neural networks, adaptive and non-adaptive techniques such that the BER and total transmit power remain under certain thresholds.

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LIST OF ABBREVIATIONS AND ACRONYMS

ACM	Adaptive Coding and Modulation
ADC	Analogue to Digital Convertor
ANFIS	Adaptive Neural based Fuzzy Inference System
ANN	Artificial Neural Networks
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BPSK	Binary Phase Shift Keying
BTS	Base-station Transceiver System
CP	Cyclic Prefix
D	Dimensional
DAC	Digital to Analogue Convertor
DVB-S	Digital Video Broadcasting-Satellite
FDMA	Frequency Division Multiple Access
FEC	Forward Error Correcting
FFT	Fast Fourier Transform
FIS	Fuzzy Inference System
FPGA	Field Programmable Gate Array
GUI	Graphical User Interface
I/O	Input Output
IFFT	Inverse Fast Fourier Transform
ISI	Inter-Symbol Interference
LTE	Long Term evolution

M-PSK	M-ary Phase Shift Keying
M-QAM	M-ary Quadrature Amplitude Modulation
OFDM	Orthogonal Frequency Division Multiplexing
P/S	Parallel to Serial
PSK	Phase Shift keying
QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
SNR	Signal-to-Noise Ratio
TSK	Takagi-Sugeno System
VHDL	VHSIC Hardware Description Language
WiFi	Wireless Fidelity
WiMAX	Worldwide Interoperability for Microwave Access

CHAPTER ONE

INTRODUCTION

This chapter provides a brief introduction to the background of the study, problem statement and objectives of the research work. In addition, a justification of the work, the scope and organization of the thesis are also presented.

1.1. Background

The emerging new electronic devices require improved wireless technologies to process large amount of information at higher data rates. A radio spectrum is used for data sharing to allow devices to effectively communicate with each other. The available radio spectrum is a limited resource and is usually shared among its users resulting in signal interference. In order to overcome such interference between users, the transmitted power is kept at a minimum level. Keeping both the frequency spectrum and transmitted power at low levels provides a limit to the data rate. Spectrally efficient data transmission schemes are becoming more common requirement for wireless communication that share the scarce spectrum to increase its performance. An adaptive coding and modulation is used to enhance spectral efficiency in wireless systems.

The adaptive modulation and coding (ACM) is a technique employed to combat the effects of time-varying channel conditions imposed by fading, interference and noise on wireless communications. The performance of coding and modulation techniques can be improved by adapting the transmission parameters such as code rate and modulation order to the time-varying channel conditions. The purpose of this transmission adaption is to increase the spectral efficiency, reduce BER and conserve the transmitted power [1]. The quality of channel should be estimated first to identify the best coding rate and modulation order.

In ACM techniques, selection of the desired coding rate and modulation order depends on the estimated SNR and/or calculated BER as shown in Figure 1.1. When the estimated signal-to-noise ratio (SNR) is high, then a higher modulation order with higher coding rate can be used to increase spectral efficiency [2, 3]. In other words, if the BER is low and SNR is high, a higher coding rate and modulation order such as 3/4 coding rate and 256QAM can be employed. On the other hand, during worst channel condition, lower coding rate and modulation order like BPSK and 1/4 code rate is used to maintain link availability. Thus, the purpose of adaptive transmission method is to improve the spectral efficiency and transmission link availability by increasing the channel capacity over the communication channel and to reduce the environmental interferences.

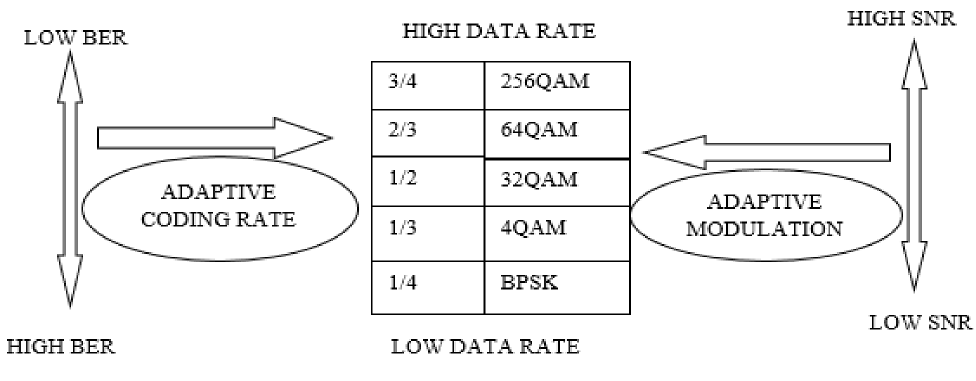

Figure 1.1 Coding and modulation scheme selection mechanism

The future wireless systems are supposed to deliver high data rate transmission with error free communication. The high data rate transmission may result in Intersymbol Interference (ISI) that reduce the quality of communication. The ISI occurs when the transmitted signal arrives at the receiver with a delayed and attenuated version. In order to cancel such multipath distortion, an Orthogonal Frequency Division Multiplexing (OFDM) technique is used.

The OFDM is a commonly used multiple carrier modulation(MCM) technique in wireless radio communications. In OFDM technique, a signal with high capacity is divided into many low capacity streams and then each data stream is modulated with different orthogonal subcarriers. The OFDM is a special form of spectrally efficient MCM technique, that employs densely spaced orthogonal sub-carriers and overlapping spectrums. Hence, the available bandwidth is used very efficiently without causing the ISI [4]. In adaptive coding and modulation technique, the transmission parameters are adapted to exploit the variations of the wireless channel for OFDM systems. These techniques are commonly employed over several wireless communication systems, such as LTE, IEEE 802.11n (WiFi) and IEEE 802.16 (WiMAX) standards to provide higher data rate. Depending on the quality of the channel, each subcarrier of the OFDM technique can be modulated and encoded with different coding rate and modulation order to maximize the throughput. In a WiMAX technology, a mobile user can provide the base station with feedback on the downlink channel quality and for the uplink, estimation of the channel quality is done by the base station based on the received signal fidelity. Thus, selection of the desired coding rate and modulation order is an important concern to have an enhanced system performance for OFDM systems.

In wireless communication system, adapting transmission parameters is done based on the quality of channel. In fixed coding and modulation scheme, the OFDM system uses single coding rate and modulation order so that either spectral efficiency or BER is improved. However, for an adaptive coding and modulation technique, both coding rate and modulation order are varied dynamically to behave on the time-varying channel to improve capacity and reduce BER. Since condition of the wireless channel is varying with time, an intelligent adaptive technique, which is good in decision-making, is required. In other words, due to complexity, uncertainty and adaptive nature of the wireless channel, the conventional non-intelligent systems cannot cope with an adaptive environment. Soft computing techniques are preferred over the adaptive and fixed coding and modulation techniques in decision-making to approximate and improve real world problems.

The most efficient soft computing systems used for decision-making in wireless communications are fuzzy logic, neural networks and neuro-fuzzy systems. The conventional adaptive coding and modulation techniques uses the *if-else* statements to select the desired modulation order and coding rate based on the received SNR and/or BER. However, the ordinary hardware decision-making techniques has limitations in predicting the exact quality of the channel and selecting the appropriate transmission parametrs. For example, when the received SNR is considered 0 to 10dB as ‘low’, and if the estimated input SNR is 10.1dB then it will not be considered as low SNR despite it is low. However, by using the soft-computing techniques in decision-making can improve the system performance.

Thus, by employing the neuro-fuzzy based approach in decision-making system, the ACM can be varied efficiently with the time changing conditions of channel to maximize throughput while maintaining target BER. In this research work, a neuro-fuzzy based adaptive coding and modulation is proposed to improve the performance of OFDM wireless systems that takes estimated SNR, BER, modulation order and coding rate as inputs to select the desired modulation order and coding rate as output. In addition to this, a comparison to other techniques such as fuzzy systems and adaptive techniques show the superiority of neuro-fuzzy system.

1.2. Problem Statement

The performance of electromagnetic radio waves that propagate through the wireless channel are limited by multipath fading, noise and interference. The undesirable behaviour of the wireless channel condition impact signal attenuation and distortion and hence affects signal fidelity. The adaptive modulation and coding technique with OFDM systems is used to dynamically adjust the transmission parameters based on the channel condition to improve spectrum efficiency with target BER [1]. In this way selection of the desired coding rate and modulation order is an important concern to have an enhanced system performance for OFDM systems. When a modulation and coding rate with a high spectral efficiency is chosen during bad channel condition, the BER is enhanced. On the other hand, selecting transmission parameters with a low spectral efficiency might waste the capacity of the system during good channel condition. Consequently, the throughput of the system cannot be optimized. The ordinary hardware decision-making system, which is inefficient algorithm, is controlled by plain of *if-else* control statements. The fuzzy logic control model has been found to be a good replacement for adaptive techniques. However, the design process of the fuzzy logic is a trial and error approach in determining the appropriate fuzzy rules and parameter tuning for the controller. Such an approach requires a large number of repetitions, and is therefore, time consuming and tedious. The neural networks have the learning and adapting capability; however, it requires adequate prior human knowledge to be initialized. Using neuro-fuzzy approach, solves the fuzzy logic and neural networks weaknesses and improves the system data rate/spectral efficiency.

1.3. Objective of the Study

1.3.1. Main Objective

The main objective of this thesis is to enhance the performance of OFDM wireless systems using neuro-fuzzy logic in adaptive coding and modulation scheme to determine the desired modulation order and coding rate in time-varying channel conditions that maximize the spectral efficiency while meeting a target BER.

1.3.2. Specific Objectives

The specific objectives of the study are as follows:

i. To investigate and identify parameters of adaptive modulation and coding scheme for performance improvement in OFDM systems

ii. To design a neuro-fuzzy system that maximize the data rate of ACM for wireless systems

iii. To analyze the performance of the proposed approach for the OFDM systems through comparison with the existing models using MATLAB

1.4. Justification

Adaptive modulation and coding is being employed in WiFi, WiMAX and DVB-S wireless technologies, however, due to uncertainty and time-varying conditions of the wireless channel, an intelligent decision-making system is required to exactly predict the desired next modulation order and coding rate based on the quality of the channel. The use of artificial intelligence techniques, for instance neural networks, fuzzy logic and neuro-fuzzy has shown great potential in this field. With the involvement of soft computing, imprecise, uncertain, missing information and complex ill based systems, which have direct application in many engineering problems have become much easier to be implemented. Thus, in this work the neuro-fuzzy system is used to maximize spectral efficiency and improve QoS for a time- varying wireless systems.

1.5. Scope of Work

The aim of this research is to develop a neuro-fuzzy system based adaptive coding and modulation for performance improvement in OFDM wireless communication. A perfect knowledge of the channel and stationary channel impulse response during the OFDM frame is assumed. The research is done based on the practical OFDM specifications on an adaptive coding and modulation techniques. This thesis is limited to developing and simulating a model using MATLAB fuzzy logic toolbox.

1.6. Organization of the Thesis

The thesis records a detailed approach of the use of neuro-fuzzy for performance improvement in wireless systems. The organization of the thesis is as follows:

Chapter 2 covers the literature review and brief introduction of adaptive and non-adaptive techniques in OFDM systems. In addition, soft computing-based techniques such as fuzzy logic, neural networks and neuro-fuzzy in relation to adaptive coding and modulation for wireless systems are discussed in this chapter.

In chapter 3 the methodology of proposed neuro-fuzzy based adaptive modulation and coding for OFDM system is explained.

Chapter 4 present the performance comparison of the simulation results of the proposed scheme to other existing models such as fuzzy logic and adaptive techniques, and discussion of the results.

Chapter 5 gives the conclusion and recommendation of the thesis.

1.7. Note on Publication

A paper entitled "Neuro-fuzzy Based Adaptive Coding and Modulation for Performance Improvement in OFDM Wireless Systems" has been published in the International Journal of Applied Engineering Research. The paper is based on the research work presented in this thesis. A copy of the published paper is attached in the Appendix B.

CHAPTER TWO

LITERATURE REVIEW

2.1. Adaptive Coding and Modulation for OFDM Systems

Wireless radio communication is a rapidly emerging technology, and new mechanisms to provide high capacity and improved quality of service are to be developed. One of the challenges in the random behaviour of the wireless channel is that it leads to signal attenuation, distortion and errors. Adaptive modulation and coding scheme plays a vital role in time-varying channel conditions to deliver enhanced data communications by adapting its transmission parameters. This section presents a review of adaptive and non-adaptive techniques and ACM analysis parameters to improve data transmissions.

2.1.1. Performance Analysis of Adaptive Coding and Modulation Schemes

i) SNR estimation

For an additive white Gaussian noise (AWGN) channel model, a randomly generated noise is added to the transmitted signal before its reception. In any communication system, the noise power should not be excessively large compared to the signal power in order to have a good quality of service signal reception. The signal-to-noise ratio is defined as the ratio of signal power P_r to noise power P_n within the spectrum/bandwidth of transmitted signal (2B) and noise power spectral density of N_o. The SNR in dB is given by [5].:

$$SNR(dB) = 10\log_{10}(\frac{P_r}{P_n}) \tag{2.1}$$

Alternatively, the received SNR is expressed as:

$$SNR = \frac{P_r}{N_o B} \tag{2.2}$$

ii) Channel model

In order to investigate the performance of any communication system, an accurate description of the wireless channel is important to address the environment in which the transmission is made. The additive white Gaussian noise refers to noise that distorts the transmitted information when it propagates through a wireless channel. It consists of uniform and continuous distribution over a given bandwidth. The AWGN wireless channel has the lowest BER and is preferred over Rayleigh and Racian channel models. It reflects the proper relationship between SNR and channel capacity achievable under specific target BER. In addition to this, it can easily compensate any other wireless channel model [5].

The information communication with high data rate over AWGN channel are limited by the random noise. A signal which is received in the interval $0<t<T$ can be given as:

$$r(t) = s(t) + n(t) \tag{2.3}$$

where $r(t)$ is the received signal, $s(t)$ is the transmitted signal and $n(t)$ is the sample of AWGN added at the channel with a known power spectral density. In practice, modelling of AWGN channel includes calculating the noise power from a given SNR and a known signal power. The information carrying signal is then added with a zero mean and unit variance noise before transmission.

iii) Channel coding

The channel coding (also called error correction) is a method of enhancing the BER performance in digital communication systems especially when the power of the system is fixed and limited. In forward error correction (FEC) redundant data or bits are added to the transmitted signal at the transmitter [6, 7]. This redundant data allows the receiver to detect and correct a limited number of errors incurred by the wireless channel during transmission. The most commonly used FEC is convolutional coding scheme. With proper channel coding and decoding techniques, information can be transmitted with a rate near the Shannon capacity but with a small probability of error. The channel coding consists of channel encoder and decoder at the transmitter and receiver respectively.

a) Convolutional encoder

The channel encoder contains shift registers which are used to temporarily store and operate shifting of input bits and exclusive-OR logic circuits that generate the encoded output. In general, the registers consist of *K* (each with *k*-bit input) stages and *n* linear function generators as shown in Figure 2.1.

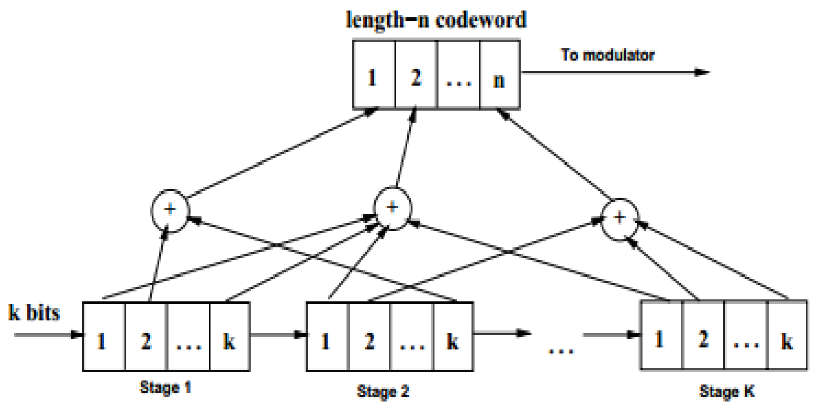

Figure 2.1 Convolutional encoder [8]

A convolutional channel encoder is specified by (*n*, *k*, *K*) or (*k/n*, *K*) elements. A channel encoder with input *k* bits and output *n* bits is said to have a rate of *k/n*. The *k/n* ratio refers to coding rate (R_c) of the system and *K* is the constraint length of the encoder. The range of code rate is between 0 and 1. The data rate can be increased by using higher coding rate, but it enhances the BER. Also increasing the constraint length of encoder increases the quality of service [9]. For example, an encoder with two bits output for every single bit input, i.e. for $k = 1$ and $n = 2$, is expressed as a code rate of 1/2 as shown Figure 2.2.

b) Viterbi decoding:

The Viterbi decoding algorithm is commonly applied in decoding the convolutionally encoded data at the receiver side [10]. It uses maximum likelihood decoding technique in order to recover the transmitted bits by a trellis diagram. The decoded information is recovered with either a hard decision or a soft decision. Hard and soft decisions decoding techniques depend on the quantization type employed at the receiver.

i. Hard decision: The received channel symbols are quantized to a single bit precision.

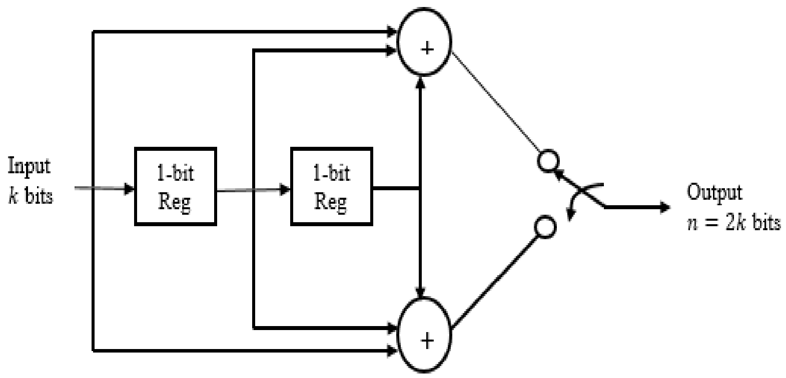

Figure 2.2 Half convolutional encoder **[11]**

ii. Soft decision: It used to quantize at least two bits of precision and performs better than hard decision.

iv) Modulation schemes

Modulation is a process of embedding the information message on to a carrier signal by changing its carrier phase, frequency or amplitude or combination of these. The commonly used modulation techniques are Phase Shift Keying (such as BPSK and QPSK) and M-ary Quadrature Amplitude Modulation (such as 8QAM and 256QAM) [8]. In QAM the information message is encoded in both the amplitude and phase of the carrier signal, whereas in PSK the phase of the carrier signal is allowed to vary with fixed amplitude. The QAM scheme is the most powerful modulation technique employed in most wireless system standards such as WiFi and WiMAX [12].

v) Bit error rate (BER) performance

In a radio communication, the transmitted signal may be affected by noise, interference, distortion and multipath fading resulting in undesirable errors at the receiver end. The bit error rate can be enhanced by increasing the transmit power, choosing a desired modulation order and by channel encoding schemes [8]. The BER is the rate of error that occurs during transmission of information bits. Assuming perfect coherent receiver detection and square signal constellation with size of *M,* the probability of bit error for M-ary QAM modulation scheme under AWGN channel is expressed as [8]:

$$BER = \alpha Q(\sqrt{\beta SNR}) \tag{2.4}$$

where $Q(z)$ is the complementary error function, α and β are constants given by:

$$\alpha = \frac{4(\sqrt{M}-1)}{\sqrt{M}\log_2 M}, \quad \beta = \frac{3\log_2 M}{(M-1)} \tag{2.5}$$

where SNR is the average received signal-to-noise ratio [8]. The Q function refers to the probability that a Gaussian variable x with zero mean and unit variance is more than z. It is given by [8]:

$$Q(z) = p(x > z) = \int_z^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx, \mathrm{x} > 0 \tag{2.6}$$

An alternative Q function obtained by Craig [8] is given as:

$$Q(z) = \frac{1}{\pi} \int_0^{\pi/2} \exp\left[\frac{-z^2}{2\sin^2\phi}\right] d\phi, \mathrm{z} > 0 \tag{2.7}$$

The BER of the OFDM system is expressed as a mean BER of each subcarrier.

$$BER_{OFDM} = \frac{1}{N} \sum_{i=0}^{N-1} \alpha \mathrm{Q}(\sqrt{\beta \mathrm{SNR}}) \tag{2.8}$$

vi) Capacity in AWGN channel

A channel with additive white Gaussian noise is expressed as: $y[i] = x[i] + n[i]$, where $x[i]$ is input to the channel, $n[i]$ is an AWGN random process and $y[i]$ is the channel output at time i. For a fixed transmission technique, the spectral efficiency is the maximum limit of information bits a wireless channel can support per second per unit bandwidth. The spectral efficiency measured in *bits/sec/Hz* over AWGN channel is given by Shannon's formula [8]:

$$\eta = \frac{C}{B} = \log_2(1 + SNR) \tag{2.9}$$

The Shannon's coding theorem shows encoding can be used to achieve a data rate that is close to capacity with small probability of error. For a given SNR and assuming ideal Nyquist pulses, the M-ary QAM spectral efficiency can be approximated as [13]:

$$\eta = (1 - P_b)^n mR_c \tag{2.10}$$

where P_b is the bit error rate, n is the number of bits in the block, m is the number of bits per symbol and R_c is the code rate.

2.1.2. Non-adaptive Techniques

Fixed transmission strategy is commonly used in improving spectral efficiency when the estimated SNR is sufficiently high and fixed. The non-adaptive techniques are designed for worst-case wireless channel conditions [8]. In fixed modulation scheme, a single constellation size is used to enhance data rate. In addition, by employing forward error correcting (FEC) codes, the amount of error that may be introduced in the wireless system can be reduced. For a fixed modulation and coding, a single code rate and modulation order such as 64QAM and 2/3 R_c is employed. However, since the wireless channel is varying with time, the SNR will not remain constant at all times. These fluctuations of SNR may lower the performance of wireless communication. Thus, fixed techniques are usually employed to improve either the throughput or BER.

2.1.3. Adaptive Techniques

In order to improve the performance of wireless communication system, different techniques that work with OFDM systems have been investigated. In this section review of adaptive modulation with fixed and adaptive coding techniques is presented.

i) Adaptive modulation

In adaptive modulation scheme, the constellation size is allowed to vary depending on the conditions of the wireless channel. Higher modulation orders are used to maximize the spectral efficiency during good channel condition [14]. However, the higher modulation schemes such as 64QAM have higher BER than lower modulation order schemes such as BPSK. When the channel condition is bad, a lower modulation order should be used to maintain the link availability.

Adaptive modulation has been used for high capacity data transmission when OFDM wireless system is used. An adaptive transmission for OFDM system is proposed in [15]. Estimation of SNR as a switching parameter is done for each subcarrier. The QoS for adaptive modulation is degraded when modulation order is changed to a higher size as the SNR increases. Different QAM modulation techniques for different types of channels studied in [16] show superiority in BER and spectral efficiency. Using inverse fast Fourier transform of size higher than 512 for OFDM systems, the BER comparison shows an improvement over fixed technique [17]. Moreover, an adaptive modulation for OFDM system is proposed in [18, 19]. A SNR based switching threshold range for different QAM under AWGN channel is proposed by [20] for OFDM system. The constellation size is varied to improve the performance of wireless communications in terms of BER and spectral efficiency.

ii) Adaptive coding and modulation

By estimating the wireless channel at the receiver and then feeding back estimated data to the transmitter, the transmission technique can be adapted based on the current channel condition as shown in Figure 2.3. Based on the quality of the channel, the transmitter adapts its coding and modulation schemes to improve throughput and maintain link availability [21].

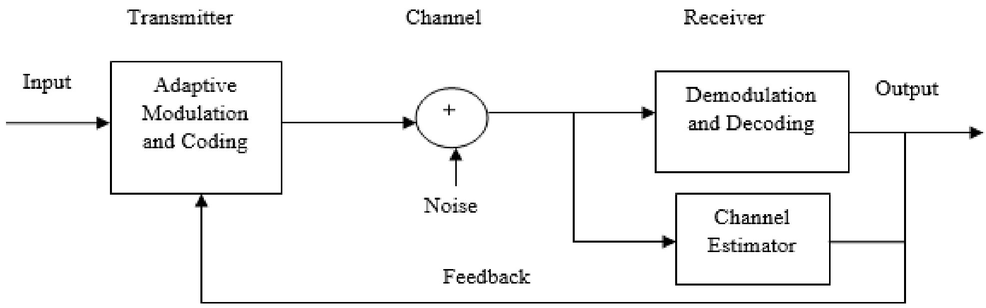

Figure 2.3 Adaptive system model

An adaptive modulation and coding for LTE wireless communication have been proposed by [22] to increase downlink capacity. In [23] an adaptive modulation and coding for OFDM systems was presented. In this scheme, the transmitter selects an appropriate constellation size and coding rate based on the measured SNR to maintain constant BER. Moreover, in [24] the performance of OFDM systems with and without adaptive modulation was investigated with respect to the BER and spectral efficiency of various digital modulations such as 4PSK and 16QAM. A significant improvement is shown on data rate and reduction in BER over the fixed transmission techniques.

2.1.4. OFDM Systems

In the Orthogonal Frequency Division Multiplexing (OFDM) technique, a signal with high capacity is divided into many low capacity streams and then each stream is modulated with different orthogonal subcarriers. Due to orthogonal nature of the subcarriers, the OFDM system is preferred over other multiplexing techniques and thus reduces the Intersymbol Interference (ISI) [4]. OFDM has been employed in several wireless technology standards such as LTE, IEEE 802.11n (WiFi) and IEEE 802.16 (WiMAX) to provide high data rates [25]. Figure 2.4 shows the block diagram for an OFDM system. The serial input symbols are converted to parallel symbols onto the subcarriers. The Inverse Fast Fourier transform (IFFT) is used to convert the frequency domain to time domain. These parallel subcarriers are sampled and combined to create an OFDM signal. After applying the digital signal processing based inverse fast Fourier transform, the OFDM signal can be expressed as [26]:

$$s(n) = \sum_{k=0}^{N-1} S(k) e^{j2\pi nk/N} \text{ , } 0 \le n \le N-1 \tag{2.11}$$

where $S(k)$ is the coded symbol at the k_{th} subcarrier, $s(n)$ is the time domain sample and N is the number of subcarriers of OFDM signals. In order to avoid the Intersymbol Interference (ISI), cyclic prefix is appended to the OFDM symbol [26]. Additive Gaussian noise is then added to the OFDM signal before transmission. The channel frequency domain response $H(k)$ with a finite impulse response of $h(n)$ is given by:

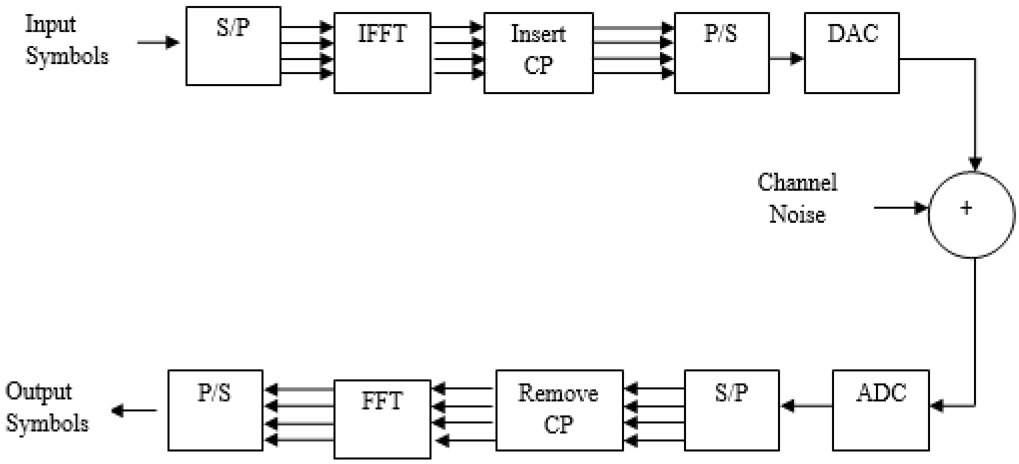

Figure 2.4 OFDM transmitter and receiver section

$$H(k) = \sum_{n=0}^{N-1} h(n) e^{-j2\pi nk/N}, \ 0 \le k \le N-1 \tag{2.12}$$

At the receiver side, the analogue received signal is converted to a digital format then the cyclic prefix is removed. Finally, the FFT system is applied to convert the time domain signal to the frequency domain signal. The frequency domain of the received symbol after the fast Fourier transform system is given by:

$$Y(k) = H(k)S(k) + w(k), \ 0 \le k \le N-1 \tag{2.13}$$

where, *Y(k)* is received OFDM symbol, *H(k)* is frequency response of the channel and *w(k)* is the channel noise. The received SNR for each subcarrier with overall signal-to-noise ratio, γ is given by:

$$\gamma_k = |H(k)|^2 \gamma \tag{2.14}$$

In adaptive OFDM system transmission, the same modulation and coding rate is employed to all subcarriers for the same block data [16]. The desired coding and modulation order to be used by the transmitter for its next OFDM block transmission is selected based on the current wireless channel quality. The instantaneous estimated

SNR is then used as a switching threshold for various coding and modulation techniques [17].

2.2. Soft Computing Based Techniques for Adaptive Modulation and Coding Schemes

Due to the complexity and uncertainty of the wireless channel, the conventional hard computing techniques cannot cope with the adaptive environment. The soft computing methods do not require mathematical models unlike the conventional techniques. Also, it is often used to model complex, uncertain and incomplete systems. Thus, the soft computing techniques are preferred over adaptive and non-adaptive systems in time-varying conditions of the channel to approximate and improve real world problems. The most powerful soft computing techniques are fuzzy logic, neural networks and neuro-fuzzy systems. A brief overview and related works of these techniques are presented in this section. In addition, the knowledge gaps are also identified.

2.2.1. Fuzzy Logic System

Fuzzy logic-based systems are useful in decision-making by incorporating expert knowledge. The fuzzy logic systems allow for partial membership to a particular set for an object unlike the classical logic set theory that only takes two cases (e.g. 1 or 0, ON or OFF). The fuzzy logic inference system (FIS) performs numerical computation using membership functions for modeling of fuzzy set linguistic variables. The fuzzy logic is useful for imprecise, uncertain information and complex-ill based systems and incorporates human experience based on *if-then* fuzzy rules in decision-making [27].

i) Fuzzy inference system structure

The basic structure of a FIS is shown in Figure 2.5. Basically, the fuzzy inference system consists of five components used to implement a fuzzy algorithm and resolve all of the associated vagueness. These are:

a) a fuzzification interface that converts the crisp input into corresponding fuzzy sets using membership functions such as trapezoidal, bell or gaussian shapes;
b) a rule base which consist of selection for fuzzy logic rules;
c) a fuzzy set database that defines the fuzzy set membership functions used in fuzzy rules;
d) an inference engine or reasoning mechanism which performs the inference procedure upon the rules to derive output or conclusion; and
e) defuzzification interface that converts back the fuzzy sets to crisp output using center of gravity, mean of maximum or bisector area.

ii) Types of fuzzy inference system

There are three commonly used types of fuzzy system, namely [28]:

a) Mamadani fuzzy system: - the output of this model are fuzzy sets.
b) Singleton fuzzy system: - the complexity of defuzzification of a linguistic variable may be simplified by using singleton membership function to the output parameter.
c) Takagi-Sugeno(TKS) fuzzy system: - the output of this TKS model is a linear function of the input variables plus a constant term.

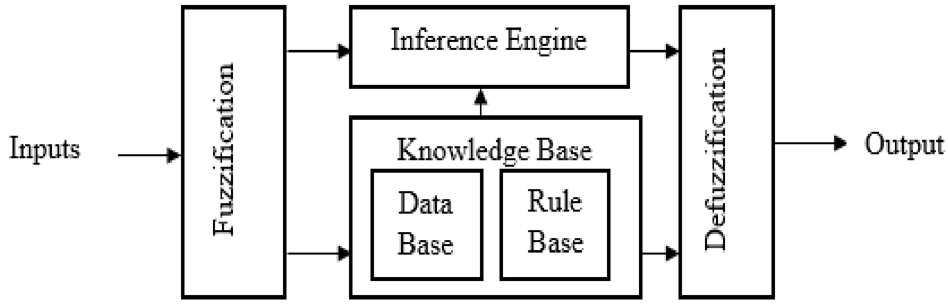

Figure 2.5 Structure of fuzzy logic system

Since the development of fuzzy logic concept, it has been used for modelling and making decisions in various wireless communication systems. Diverse solutions have been given on the problem of selecting the appropriate transmission parameters such as coding rate and modulation scheme for OFDM wireless communication systems based on the quality of the channel using fuzzy logic approach.

A fuzzy logic based adaptive modulation to improve the performance of OFDM systems in a changing channel condition is presented in [29]. In this work, the SNR and modulation order are used as inputs to the fuzzy system to control the next modulation order for the transmitter and receiver blocks. The fuzzy systems target in decreasing the BER even in condition when signal-to-noise ratio increases. An improvement in BER and throughput is shown over adaptive and non-adaptive techniques.

In [30] a modified adaptive modulation implementation for performance enhancement using a fuzzy based system is presented. By feeding back the best modulation scheme to the modulator and demodulator of the OFDM, the overall efficiency of the system was improved. Fixed modulation gave good results when the channel conditions were fixed, but the modified adaptive modulation by using the fuzzy logic gives improved performance of the wireless communication to time-varying environment condition. The results showed that the fuzzy logic system enhances the performance of OFDM in terms of spectral efficiency and BER by adapting to the channel condition.

An adaptive coding and modulation scheme using fuzzy logic for OFDM wireless communication to provide a better tradeoff between spectral efficiency and bit error rate is done by [31]. Firstly, an OFDM system is constructed under AWGN channel model. The BER is then calculated for each SNR while varying the modulation scheme in OFDM system. The calculated SNR and BER are used as input to the fuzzy logic system to determine the next modulation order as an output. Thus, the modulation technique that gives a better BER for a particular SNR was studied. The smoothness of the 3D rule surface proved that the rules are set very precisely and switching of the ACM can be done effectively. Thus, the performance of the fuzzy logic ACM is better than the fixed and ordinary adaptive coded modulation systems.

Seshadri [32] presented fuzzy logic based adaptive modulation for OFDM system to improve performance of the system capacity in a Rayleigh channel fading. The system was simulated using MATLAB and the performance of OFDM tested under various channel conditions. Fuzzy logic system was applied in decision making to improve the performance of adaptive modulation in terms of spectral efficiency and BER. The fuzzy logic system consisted of SNR and modulation scheme as inputs to decide the correct modulation order that would match with the current channel condition. The results showed that for OFDM systems the fuzzy rule based adaptive modulation performs better than the non-fuzzy logic based adaptive modulation.

An adaptive modulation based on non-data aided SNR estimation is presented in [33] for OFDM systems using fuzzy logic. The developed fuzzy logic takes imaginary and real parts of the received signals to estimate the SNR from the noise and interference channel condition and existing modulation scheme from the database available in the receiver memory in order to control the new modulation order. Based on this, the receiver sends a feedback signal to the transmitter to adjust modulator to adapt to the time- varying channel condition. The performance of adaptive modulation such as bit error rate and data transmission capacity of the wireless OFDM system was found to be superior than ordinary adaptive and non-adaptive systems.

Moreover, an adaptive coding and modulation that adapts code rate and modulation type using fuzzy logic approach in OFDM system was proposed by [34] to improve the capacity in an OFDM systems with a fixed transmit power and target BER for each subcarrier. The fuzzy logic considered SNR and BER as inputs to control the output. It is shown that fuzzy logic is a more powerful method for utilizing the channel capacity and bit error rate when the BER of 10^{-2}, 10^{-3}, and 10^{-4} are considered.

In [35] adaptive coding and modulation using fuzzy logic for OFDM systems is presented. The authors investigated a new scheme to adapt coding rate and modulation order using fuzzy logic system to improve the throughput with a fixed target BER and transmit power for each subcarrier of OFDM system. The simulation results showed that fuzzy logic is more preferable than the ordinary adaptive coded modulation.

An adaptive resource allocation for OFDM systems using fuzzy and neural networks was proposed by [36]. The transmission parameters such as coding rate, power and modulation scheme are adapted based on the time varying channel conditions in order to maximize the data rate while meeting the BER constraint. The BER and SNR are used as input parameters to the fuzzy controller and neural networks to select the desired coded modulation under AWGN channel model. The fuzzy logic controller chooses the best and optimum code-modulation pair for the OFDM system based on the estimated BER and measured SNR to maximize data rate and reduce BER.

An intelligent link adaption technique [37] and adaptive resource allocation using fuzzy and product codes for OFDM systems by [38] is proposed. Both coding rate and modulation order are allowed to vary and the decision is made using fuzzy logic. The QoS and SNR were used to maximize the throughput of the wireless system. A significant improvement is shown using soft computing intelligent systems compared to the adaptive and non-adaptive coding and modulation schemes.

2.2.2. Neural Network Based Algorithms

An artificial neural network (ANN) is an intelligent system developed for the purpose of information processing, which has a similar characteristic with biological neural systems. The ANN is commonly used to process information, which are non-linear, complex and incomplete. The neurons which are interconnected by weights are used to mimic the human brain. The neural network that resembles the human brain, has the capability for learning, optimization abilities and adapt themselves to behave with the changing environment by adjusting the weights between the layers [28].

The most popular architectures of neural networks are Radial basis function neural network (RBFNN), Multi-layer perceptron (MLP) network and neuro-fuzzy network. RBFNN is a multilayer feed forward network that consists of three interconnected layers: input layer, hidden layer as well as output layer. In RBFNN, radial basis functions are used as activation functions for each hidden layer of the neural network. The output of the RBFNN is the weighted linear superposition of the radial basis functions. RBFNN based adaptive modulation in OFDM systems was proposed in [39] to learn the features of M-QAM before recovering the original signal under noisy environment. An adaptive resource allocation for OFDM systems using fuzzy and neural networks were proposed by [36]. The transmission parameters such as coding rate, power and modulation scheme are adapted based on the time-varying channel conditions in order to maximize the data rate and reduce BER.

2.2.3. Neuro-Fuzzy Approach

Neuro-fuzzy system is an artificial intelligence system that combines both fuzzy logic and neural networks. It takes advantage of fuzzy logic systems (e.g. *if-then* rules and ease of incorporating expert human knowledge available in linguistic forms) and neural networks (e.g. learning capabilities, optimization abilities). Neural networks require adequate prior human knowledge to be initialized whereas fuzzy logic needs the fuzzy inference rules and parameter membership functions to be adjusted. In a fuzzy based system, the fuzzy rules and membership functions are obtained by trial and error; this makes design of fuzzy systems a time-consuming task. The hybrid system uses back propagation learning technique of neural networks to train and automatically update membership functions. It improves the predictive capability of a system working in uncertain, imprecise and noisy environments.

i) Adaptive Network based Fuzzy Inference System

A special neuro-fuzzy method termed Adaptive Network based Fuzzy Inference System (ANFIS) [40] is used as the model in our proposed algorithm. The ANFIS comprises the fuzzy logic component as well as the neural networks. The fuzzy logic system considers imprecision and uncertainty of a system while neural networks takes the adaptability and learning capability of the system.

ii) Neuro-fuzzy (ANFIS) structure

The ANFIS structure illustrated in Figure 2.6 is based on the type 3 fuzzy inference system. Takagi and Sugeno's (TKS) rule-based fuzzy *if-then* rules are used in type-3 FIS. For simplicity, considering x and y as inputs and z as an output, the TKS rule is given by:

$$If\ x\ is\ A\ and\ y\ is\ B\ then\ z = f(x, y) \tag{2.15}$$

where A and B are fuzzy sets and $f(x, y)$ is crisp function. The function $f(x, y)$ is a polynomial of the input antecedent variables x and y. In this system, the output for each rule is obtained by adding constant value to the linear combination of the input variables. The final output is then calculated by taking the weighted average of each rule's output.

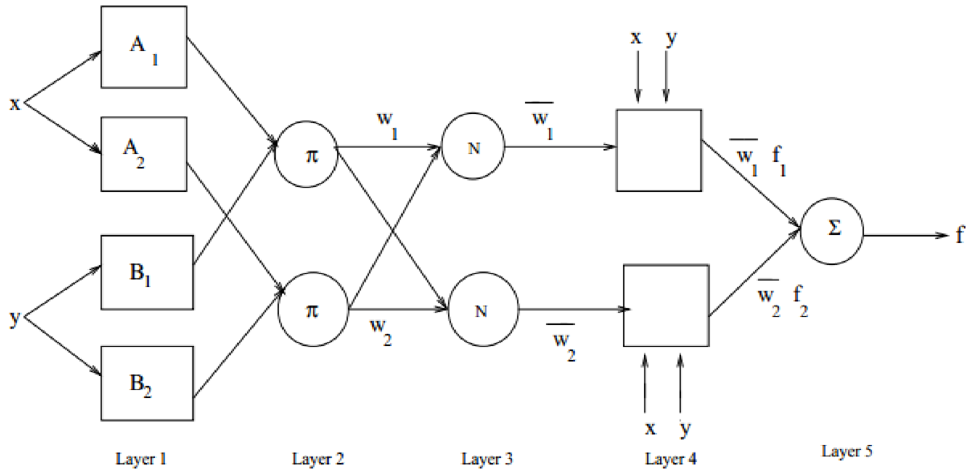

Figure 2.6 Type-3 ANFIS structure

Usually $f(x, y)$ is assumed to be a first-degree polynomial then a linear Sugeno fuzzy model is formed. For this case, with two rules it can be expressed as:

$$\begin{aligned} &Rule\ 1: if\ x\ is\ A_1\ and\ y\ is\ \ B_1\ then\ \ f_1 = p_1x + q_1y + r_1 \\ &Rule\ 2: if\ x\ is\ A_2\ and\ y\ is\ \ B_2\ then\ \ f_2 = p_2x + q_2y + r_2 \end{aligned} \tag{2.16}$$

where x and y are input parameters, A_1, A_2, B_1, B_2 are membership functions, f_1 and f_2 are output linear functions, and p_1, p_2, q_1, q_2, r_1 and r_2 are the consequent parameter set determined during training of the neuro-fuzzy system.

The ANFIS structure consists of five layers corresponding to various functions. Each layer of the Type-3 ANFIS structure is presented as follows [40]:

Layer 1: Every node in the first layer is an adaptive node with a function given as:

$$O_i^1 = \mu_{A_i}(x) \tag{2.17}$$

where O_i^1 is the output of the ith node in the first layer, x is input to the node i, A_i is the linguistic variable associated with the bell-shaped node function and μ_{A_i} is the grade membership function of A_i and is given by:

$$\mu_{A_i}(x) = \frac{1}{1 + (\frac{x - c_i}{a_i})^{2b_i}} \tag{2.18}$$

where $\{a_i, b_i, c_i\}$ is the premise parameters set that define membership functions

Layer 2: Each node in this layer is a fixed circle node labeled by π and determines the firing strength of a rule by multiplying the incoming signals (membership functions). The firing strength of each fuzzy rule for this layer is given by:

$$O_i^2 = w_i = \mu_{A_i}(x) \times \mu_{B_i}(x) \tag{2.19}$$

Layer 3: This layer is a fixed node used to compute the ratio of the ith rule's firing strength to the total of the firing strengths, which is normalized value and is given by:

$$O_i^3 = \overline{w_i} = \frac{w_i}{w_1 + w_2} \tag{2.20}$$

Layer 4: Each node in this hidden layer is an adaptive node with a function given by:

$$O_i^4 = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), i = 1,2,... \tag{2.21}$$

where $\overline{w}_i$ is the output of the layer 3 and $\{p_i, q_i, r_i\}$ is the consequent parameter set.

Layer 5: This is the output layer with a circle node labeled by $\sum$ and determines the overall output by summing all the incoming signals, i.e.

$$O_i^5 = \sum_i \overline{w_i} f_i \tag{2.22}$$

The output of the neuro-fuzzy system is expressed as:

$$O_{\mathrm{i}}^{5} = \frac{\sum_i \mu_{\mathrm{Ai}}(x) f_i}{\sum_i \mu_{\mathrm{Ai}}(\mathrm{x})} \tag{2.23}$$

iii) Hybrid learning algorithm

In order to train the ANFIS, a hybrid learning technique which is a combination of least squares and gradient descent methods is used [41]. During the forward pass, each node output goes forward until the last layer and the design parameters are determined by the least square method. In the backward pass, the error signals propagate to the backward to update the premise parameters/membership functions by gradient descent technique. Thus, the least squares method and gradient descent technique are used to optimize design parameters and update the membership functions respectively. The output f in Figure 2.6 can be expressed as:

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ f &= \overline{w_1} f_1 + \overline{w_2} f_2 \\ f &= (\overline{w_1} x) p_1 + (\overline{w_1} y) q_1 + (\overline{w_1}) r_1 + (\overline{w_2} x) p_2 + (\overline{w_2} y) q_2 + (\overline{w_2}) r_2 \end{aligned} \tag{2.24}$$

where f is the linear output function and p_1, p_2, q_1, q_2, r_1 and r_2 are the design parameters set determined during the ANFIS training.

An intelligent system based adaptive modulation for OFDM system was proposed by [42]. This proposed system takes modulation order and SNR as inputs to control the next modulation order. The performance of this system was analyzed in terms of mean square error, time taken and accuracy during training of the manual data. However, the developed system didn't show its performance relating to the BER and spectral efficiency, which are the main requirements of a wireless communications. An intelligent system that considers the real inputs which reveal the nature of the wireless channel is required to improve the performance of the wireless communications.

2.2.4. Research Gaps

After a comprehensive review of the existing literature, the following gaps have been identified in the area of adaptive coding and modulation for OFDM wireless systems.

i) There is a limited research done on both adaptive coding and adaptive modulation as applied to OFDM wireless communication. It can be envisaged that employing coding rate to the adaptive modulation, the performance of wireless radio data transmission can be improved.

ii) The efficiency of the intelligent system in OFDM depends on the exact number of input parameters used to develop intelligent system. By increasing the number of inputs (i.e. including BER and coding rate) to these systems, the performance of wireless communication could be improved.

iii) There is limited work done towards ANFIS in both adaptive modulation and coding for OFDM systems. Due to limitations of fuzzy systems, more emphasis is required towards ANFIS by considering the real inputs that describe the nature of wireless channel.

2.2.5. Summary of Literature Review

From the literature review, it can be concluded that the soft computing techniques particularly fuzzy logic and neuro-fuzzy systems has an interesting preference over fixed and adaptive modulation schemes in OFDM wireless communications. These are commonly used in decision-making systems for random time-varying wireless channel conditions. Developing neuro-fuzzy system for both adaptive coding and modulation techniques is still a major issue for wireless communication. The fuzzy based performance of the wireless system proposed by [34, 37, 38] is improved in this research by applying neuro-fuzzy based system controller. Moreover, the performance of OFDM systems presented by [42] is also enhanced by incorporating adaptive FEC coding to the wireless OFDM system.

Therefore, in this research work, adaptive coding and modulation techniques for OFDM system using neuro-fuzzy logic with SNR, BER, modulation order and coding rate as inputs and data rate as the output are considered in order to enhance the performance of the wireless communication in terms of data rate and BER over time-varying channel conditions.

CHAPTER THREE

METHODOLOGY

3.1. Introduction

This chapter discusses the simulation model employed in this research work. An adaptive coding and modulation scheme-based controller using neuro-fuzzy system to achieve desired BER performance and channel data rate is investigated. In order to adapt the transmission of information over a time-varying channel, at first neuro-fuzzy system controller is applied to decide the desired modulation type and coding rate to maximize data rate at the receiver end while achieving the target BER. The transmitter then adapts its coding rate and constellation size based on the quality of the channel to improve the performance of wireless systems. The proposed block diagram is shown in Figure 3.1.

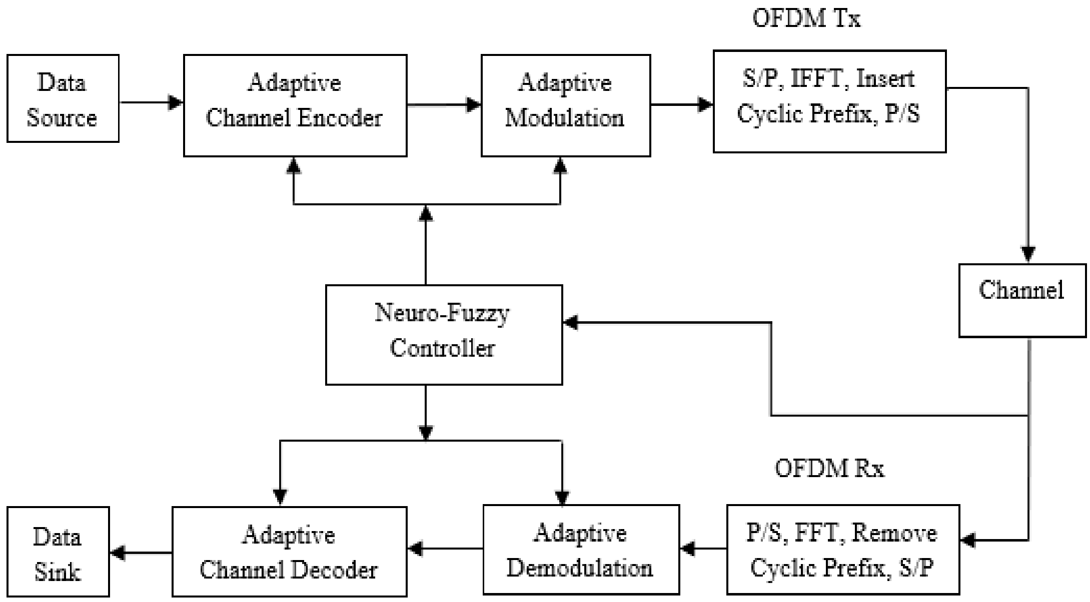

Figure 3.1 Proposed block diagram

3.2. Implementation of Adaptive Coding and Modulation for OFDM Systems

Based on the proposed block diagram shown in Figure 3.1, the randomly generated data source is encoded using a feed-forward convolutional encoder with different coding rates and then the convolutionally encoded data is modulated by M-QAM and M-PSK. The encoded and modulated symbols are fed to the OFDM transmitter. In the OFDM transmitter section, the first part is the conversion of serial symbol into parallel format and modulation by subcarriers. In the second part, inverse FFT is used to map the frequency domain to time domain. In this MATLAB simulation, the *ifft* function with a 256-point FFT is employed. A cyclic prefix is then added to the OFDM signal to avoid multipath delay that may give rise to ISI despite small loss of transmission energy as well as data rate. Lastly, after conversion back to serial, Gaussian noise is added to the OFDM signal.

At the receiver side, after conversion of the analogue signal back to a digital format, the cyclic prefix is removed and then FFT is applied to convert the received signal to frequency domain. An adaptive demodulator and channel decoder are then used for de-mapping and removal of redundant bits added for error correction, respectively. In practice, the system is unable to reproduce the transmitted data exactly due to the noise introduced in the wireless channel. There may be some bits received in error. The BER is calculated for each SNR by varying coding rate and modulation order in OFDM system based on the system parameters shown in Table 3-1. The comparison of the performance of BER for adaptive modulation and coding techniques is investigated.

Table 3-1 System parameters

Schemes	**Parameter values**
SNR	0 to 35dB
BER	10^{-6} to 0.01 bits/sec/Hz
Modulation scheme	BPSK, QPSK, 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, 512QAM
FFT size	256
Data rate or spectral efficiency	0.25 to 6.75 bits/sec/Hz
Cyclic prefix	1/4
Convolutional coding rate	1/4, 1/3, 1/2, 2/3, and 3/4
Convolutional constraint length	3
Channel model	AWGN

3.3. Design of Neuro-Fuzzy Based Adaptive Coding and Modulation

Neuro-fuzzy incorporates the benefits of both a fuzzy inference system (FIS) and neural network by utilizing neural learning methods in adjusting the membership function parameters and the structure of the FIS. Using this hybrid soft computing method, an initial fuzzy logic model with its input parameters is first obtained from the input-output data of OFDM system. Neural network is then applied to update the initialized fuzzy rules and membership functions to create the final neuro-fuzzy method for the OFDM wireless systems. In this neuro-fuzzy approach, back propagation learning and least squares method is used to update membership functions and optimize design parameters respectively. The general neuro-fuzzy approach system flowchart is shown in Figure 3.2.

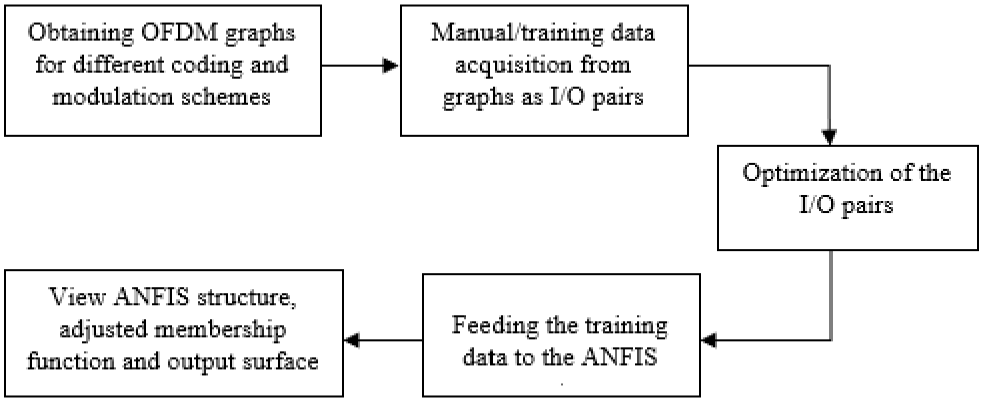

Figure 3.2 Neuro-fuzzy based system model flowchart

3.3.1. Generation of I/O Data Pairs

The proposed neuro-fuzzy system is trained by manual data generated from the simulations of adaptive coding and modulation for OFDM systems. Figure 3.3 shows selection mechanism of the desired coding rate and modulation order intersection pairs that fulfill different target bit error rate values such as 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3}, 10^{-2} demands. These pairs are obtained by drawing a straight line from the given SNR to the target quality of service points. The output is taken as the product of code-modulation pairs.

Table 3-2 shows a sample of I/O data pairs that are obtained as a function of SNR, BER, modulation order and coding rate to select the best modulation and coding rate to maximize the spectral efficiency of the wireless system. All the input-output data pairs are not important only those that maximize the throughput are taken based on the spectral efficiency optimization.

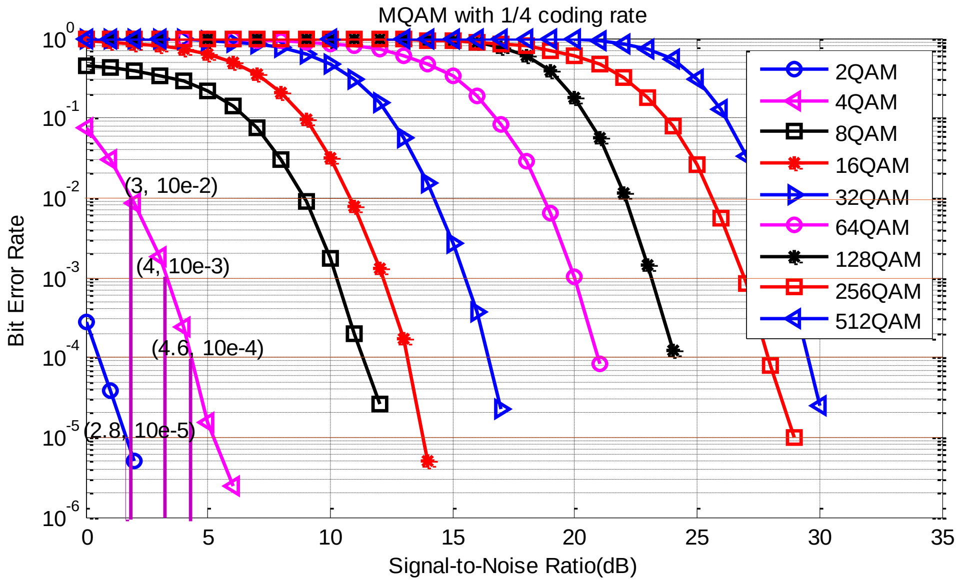

Figure 3.3 Generation of I/O pairs for different modulation schemes with 1/4 code rate

Table 3-2 Sample of input-output pairs obtained from simulation

Inputs				**Output**
Received SNR (dB)	**Target BER**	**Modulation schemes**	**Coding rate**	**Max Spectral efficiency (bits/sec/Hz)**
1.7	10^{-4}	2QAM	1/3	0.33
4.8	10^{-3}	4QAM	1/2	1
14.7	10^{-2}	16QAM	3/4	3
19.6	10^{-3}	32QAM	2/3	3.33
27.4	10^{-5}	64QAM	3/4	4.5
28.6	10^{-4}	128QAM	3/4	5.25
31	10^{-2}	256QAM	2/3	5.33
35	10^{-6}	512QAM	3/4	4.5

3.3.2. Spectral Efficiency Optimization

Assuming fixed transmit power, optimization of spectral efficiency (η) for adaptive coding and modulation is given by [43]:

$$max\ \eta = R_c \log_2(M) \text{ such that } \overline{BER}(\bar{\gamma}) \leq BER_T \tag{3.1}$$

where $\bar{\gamma}$ is average SNR, R_c is code rate, $\overline{BER}$ is average BER, BER_T is target BER and *M* is modulation order. A communication link should normally operate at or below a certain target BER. To maximize the throughput of the adaptive coding and modulation scheme, the following are to be considered:

i) For the same BER and SNR, better throughput is selected

ii) For the same throughput, less modulation and coding rate is chosen that demand less SNR

iii) The lookup table scheme may not have complete number of data pairs, then those missed parts are completed by the expert knowledge.

3.3.3. Neuro-Fuzzy Architecture for Adaptive Coding and Modulation

In this research work, a special neuro-fuzzy method termed Adaptive Network based Fuzzy Inference System (ANFIS) is used for modelling purpose. To implement and test the ANFIS system, MATLAB fuzzy logic toolbox has been selected as a development tool. It consists of a fuzzy logic designer, membership function editor, rule editor, neuro-fuzzy designer, rule and surface viewers.

The fuzzy logic designer is a GUI tool that shows general information of a fuzzy inference system. The membership function editor displays and edits all of the membership functions associated with all of the input and output variables. The rule editor allows a designer to build the fuzzy rules automatically. The rule viewer gives the better description and interpretation of all the FIS rules. The neuro-fuzzy designer is used to load FIS training data, save the trained FIS, open a new Sugeno-type system, generate the FIS, view the ANFIS structure or any other GUIs to interpret the trained FIS model. The output surface viewer represents a mapping of input variables to output variable.

3.3.4. ANFIS System for Training Process

The architecture of the ANFIS used to maximize the spectral efficiency has been developed and investigated as shown in Figure 3.4. It consists of five layers corresponding to various functions. The proposed model is trained with SNR, BER, coding rate and modulation order as inputs and data rate as an output which are generated from simulations of the OFDM system using parameters depicted in Table 3-1. Both the fuzzy logic system principles and learning capabilities of neural networks are being employed to construct ANFIS. At the initial stage, a basic fuzzy logic system controller is built to utilize the linguistic fuzzy rules. Then, the IO data pairs are used to train the ANFIS controller. The stages involved in the ANFIS training process are:

i) loading the I/O training data;

ii) generate an initial fuzzy inference system model;

iii) view FIS model structure;

iv) select FIS model optimization method (hybrid method);

v) choose the training epochs and training error tolerances;

vi) train ANFIS and view adjusted membership functions and output surface.

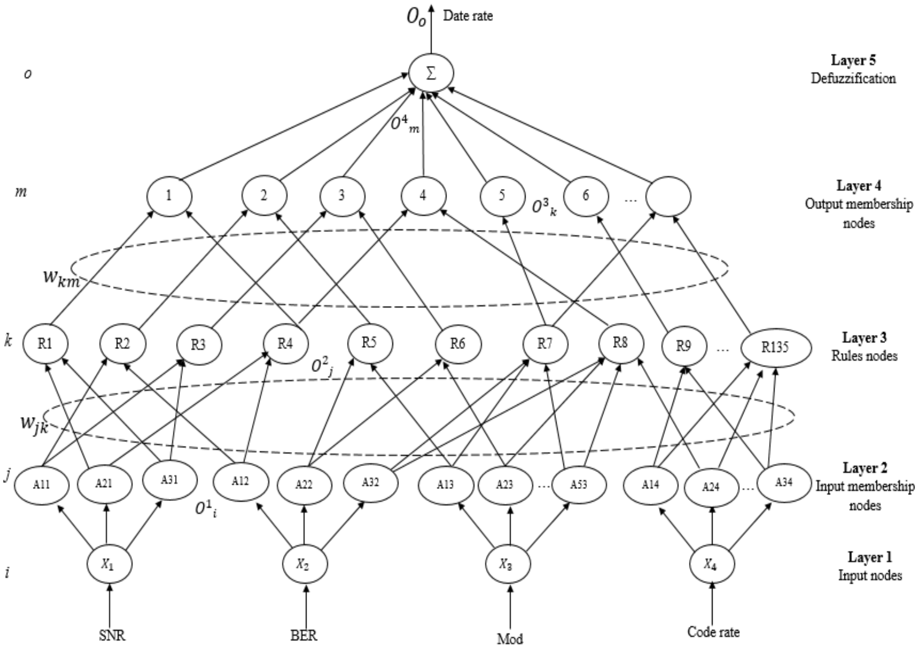

Figure 3.4 ANFIS structure with four inputs and one output

The range of fuzzy variables for the BER input values given by 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3} and 10^{-2} should be spaced equally and quantifiable. To get this a logarithmic operation is performed as given in the following equation:

$$\begin{aligned} BER &= \log_{10} 10^{-p}, \; p = 2,3,..,6 \\ BER &= -p \end{aligned} \tag{3.2}$$

In this proposed neuro-fuzzy based ACM, 135 first order Sugeno-type fuzzy inference rules have been constructed as follows:

The general rule:

$$\begin{gathered} \textit{IF } x_1 \textit{ is } A_{i1} \textit{ AND } x_2 \textit{ is } A_{i2} \textit{ AND } x_3 \textit{ is } A_{i3} \textit{ AND } x_4 \textit{ is } A_{i4} \textit{ THEN} \\ f_i = p_i x_1 + q_i x_2 + t_i x_3 + s_i x_4 + r_i \end{gathered} \tag{3.3}$$

The specific rules:

$$\begin{gathered} \textit{IF } x_1 \textit{ is } A_{11} \textit{ AND } x_2 \textit{ is } A_{12} \textit{ AND } x_3 \textit{ is } A_{13} \textit{ AND } x_4 \textit{ is } A_{14} \textit{ THEN} \\ f_1 = p_1 x_1 + q_1 x_2 + t_1 x_3 + s_1 x_4 + r_1 \end{gathered} \tag{3.4}$$

IF x_1 *is* A_{21} *AND* x_2 *is* A_{22} *AND* x_3 *is* A_{23} *AND* x_4 *is* A_{24} *THEN*

$$f_2 = p_2 x_1 + q_2 x_2 + t_2 x_3 + s_2 x_4 + r_2$$

where:

i) p_i, q_i, t_i, k_i and r_i are design parameters,

ii) f_i are the outputs within the fuzzy area specified by the fuzzy logic rules,

iii) A_{ij} are the fuzzy sets/membership functions for each input variables, and

iv) x_i is the input parameters to the neuro-fuzzy system and $i = 1,2,3, \ldots$

Layer 1-Input node: Each node in this layer is an input node, that corresponds to one input parameter. These nodes bypass the input signals to the layer 2. The proposed fuzzy sets for the input variables SNR, BER and code rate are *low, medium* and *high* and that of modulation order is *very low, low, medium, high,* and *very high.* The output of the neuron *i* in the input node is obtained as:

$$O_i^1 = f_i^1(net_i^1) = net_i^1 \tag{3.5}$$

where net_i^1 is the *i*th input to the node of layer one

Layer 2- Input membership layer: Each node in this layer acts a linguistic label of one of the input variables in input node, i.e., specifies the membership functions for each input parameters. The generalized bell membership function is used to represent each fuzzy set variables. The output of neuron *j* in the layer 2 is given by:

$$O_j^2 = f_j^2(net_j^2) = \frac{1}{1+(\frac{x-c_j}{a_j})^{2b_j}} \tag{3.6}$$

where a_j, b_j and c_j are parameters set that define shapes of *j*th membership function.

Layer 3-Rule layer: Each node in this layer calculates the firing strength of a rule via multiplication. Each node takes four inputs, to form 135 nodes in layer 3 and creates a fuzzy rule for all input variables. The output of the neuron *k* is obtained as follows:

$$\begin{aligned} O_k^3 &= f_k^3(net_k^3) = net_k^3 \\ net_k^3 &= \prod_j w_{jk}^3 \, y_j^3 \end{aligned} \tag{3.7}$$

where y_j^3 is *j*th input to the node layer 3 and w_{jk}^3 is assumed to be unity.

Layer 4-Output membership function: Neurons in this layer represent fuzzy sets used in the consequent fuzzy inference rules. An output membership neuron receives inputs from the corresponding fuzzy rule neuron and combines them by using the fuzzy operation union. The output of neuron *m* is given by:

$$\begin{aligned} O_m^4 &= f_m^4(net_{km}^4) = \max(net_{km}^4) \\ net_{km}^4 &= o_k^3 w_{km} \end{aligned} \tag{3.8}$$

where w_{km} is the output action of the *m*th output associated with *k*th rule.

Layer 5- Defuzification layer: in Layer 5 the sum-product composition is used to find the defuzzified output, i.e., crisp value. It calculates the output as the weighted average of the centroids of all output membership functions.

$$\begin{aligned} O_o &= f_o^5(net_o^5) = net_o^5 \\ net_o^5 &= \frac{\sum_{m,} O_m^4 a_{cm} b_{cm}}{\sum_m O_m^4 b_{cm}} \end{aligned} \tag{3.9}$$

where a_{cm} and b_{cm} are centers and widths of the output fuzzy sets respectively. The values of b_{cm} is assumed unity.

The Sugeno type FIS editor with four inputs and one output is shown in Figure 3.5. The neuro-fuzzy system takes the SNR, BER, code rate and modulation order as inputs in order to control the data rate or spectral efficiency in a wireless communication.

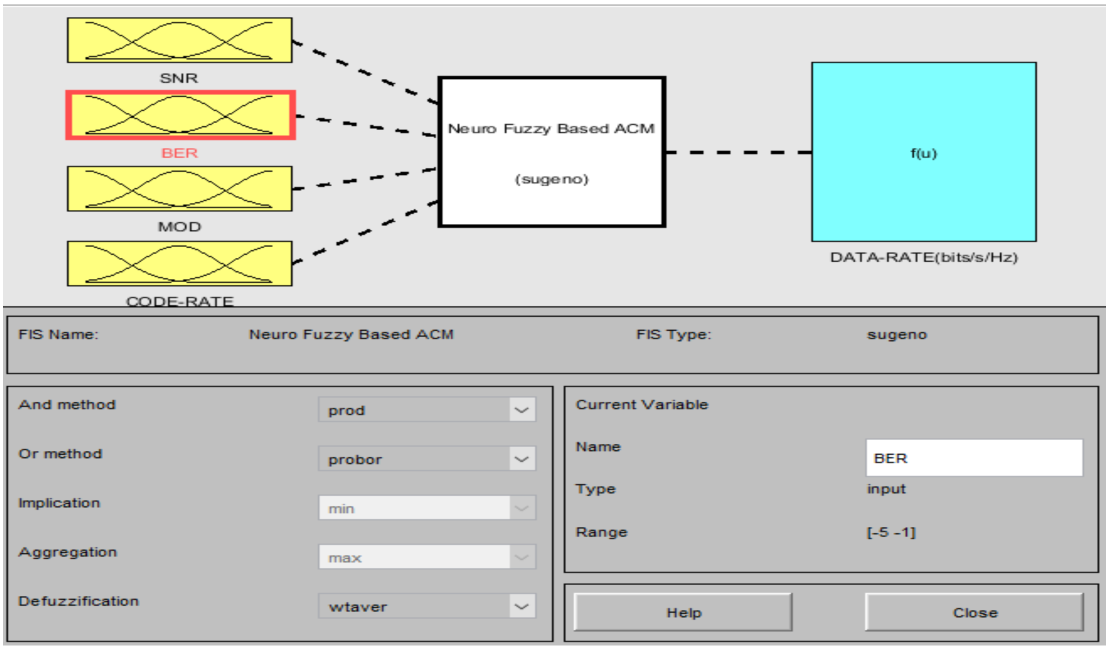

Figure 3.5 Sugeno type FIS with 4 inputs and one output

In a fuzzy logic system, the fuzzy sets of each input variable are specified by membership functions. A membership function is a curve that maps each input element to a membership value between 0 and 1. In the ANFIS system, because of its smoothness, a bell shape membership is considered for all IO variables. The number of membership functions is chosen so as to cover the entire input space. For SNR input, low, *medium* and *high* membership functions are considered as shown in Figure 3.6.

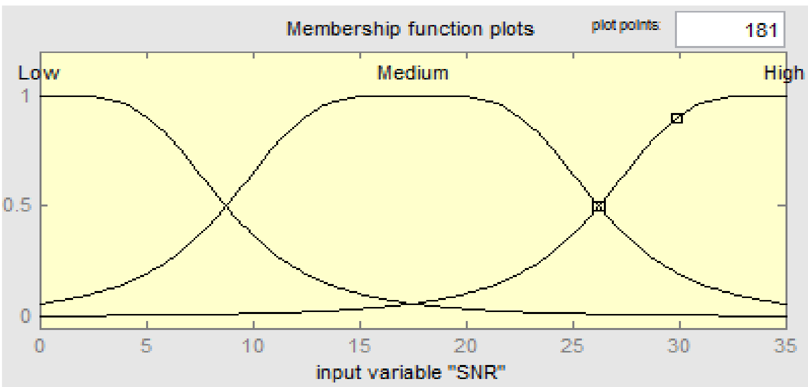

Figure 3.6 Membership function of input SNR

Using Equation 3.2 the range of input variable for BER is given as -6 to -2 and the membership functions namely *low*, *medium* and *high* are considered as shown in Figure 3.7.

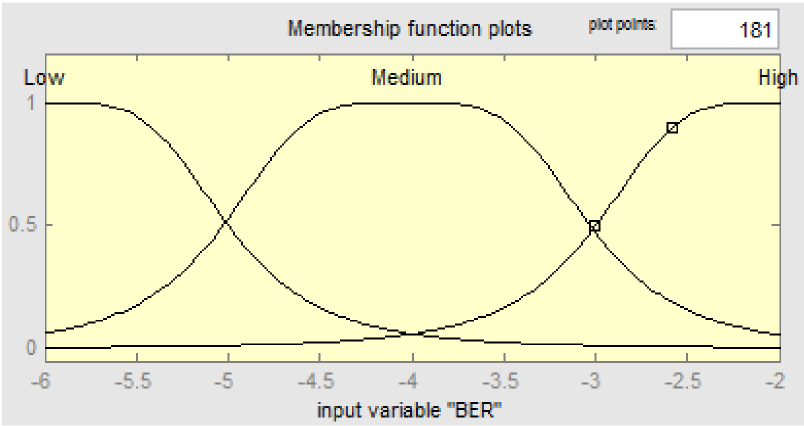

Figure 3.7 Membership function of input BER

For the modulation order input, five membership functions are taken namely *very low, low, medium, high, and very high* as shown in Figure 3.8. The modulation schemes are BPSK, QPSK, 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, 512QAM with 1, 2, 3 to 9 number of bits per each modulation scheme respectively.

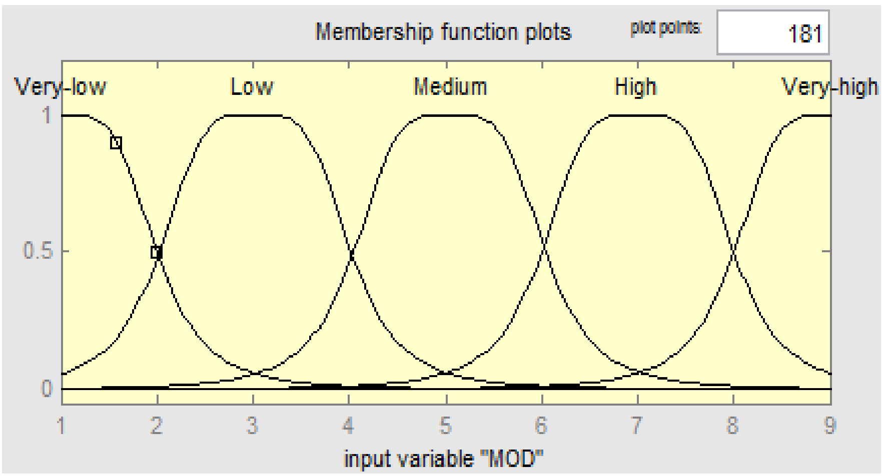

Figure 3.8 Membership function of input modulation order

Figure 3.9 shows the membership functions of the input variable code rate with a range of 0.25 to 0.75. It contains *low, medium* and *high* membership functions. The output of the neuro-fuzzy model has only one membership function i.e. *data rate*.

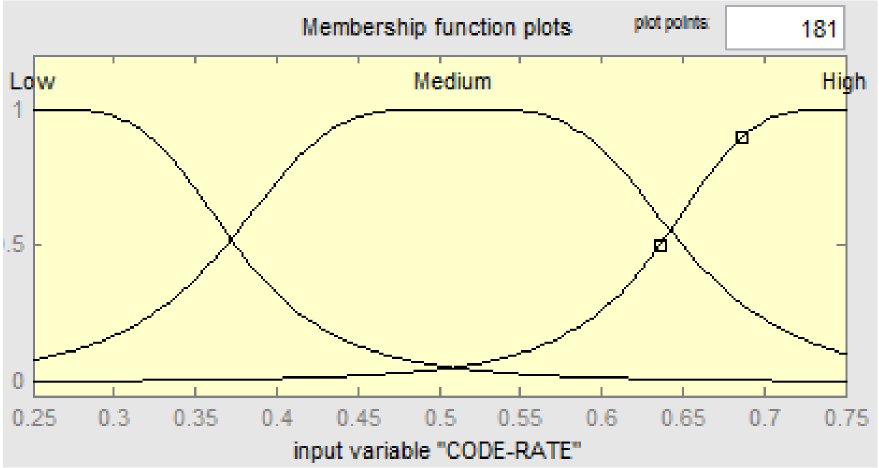

Figure 3.9 Membership function of input code rate

CHAPTER FOUR

RESULTS AND DISCUSSION

This research work is done by simulation on a MATLAB environment. In this simulation, a perfect knowledge of the channel transfer function at the receiver is assumed. At any point of distance, the power of the signal is assumed to be more than that of the noise signal, i.e. the SNR is assumed greater than 0dB. Also, the channel impulse response is assumed to be invariant during an OFDM frame block.

4.1. ACM Performance Results for OFDM Systems

4.1.1. BER Results

In this section, BER vs SNR plots for different modulation schemes are investigated with various code rates under AWGN channel. Each curve in these graphs represents the BER performance of a specific modulation and code pair. The results show that BER decreases sharply with the increase in the SNR. The lower modulation and coding techniques provide better performance with less SNR. On the other hand, when the received SNR is high, a higher modulation order and coding rate schemes are employed.

In Figure 4.1 the BER versus SNR variations for each modulation schemes (such as BPSK, QPSK, 8QAM to 512QAM) are plotted with FEC 1/4 code rate. The higher modulation orders such as 128QAM are operated for a higher SNR wireless communication system.

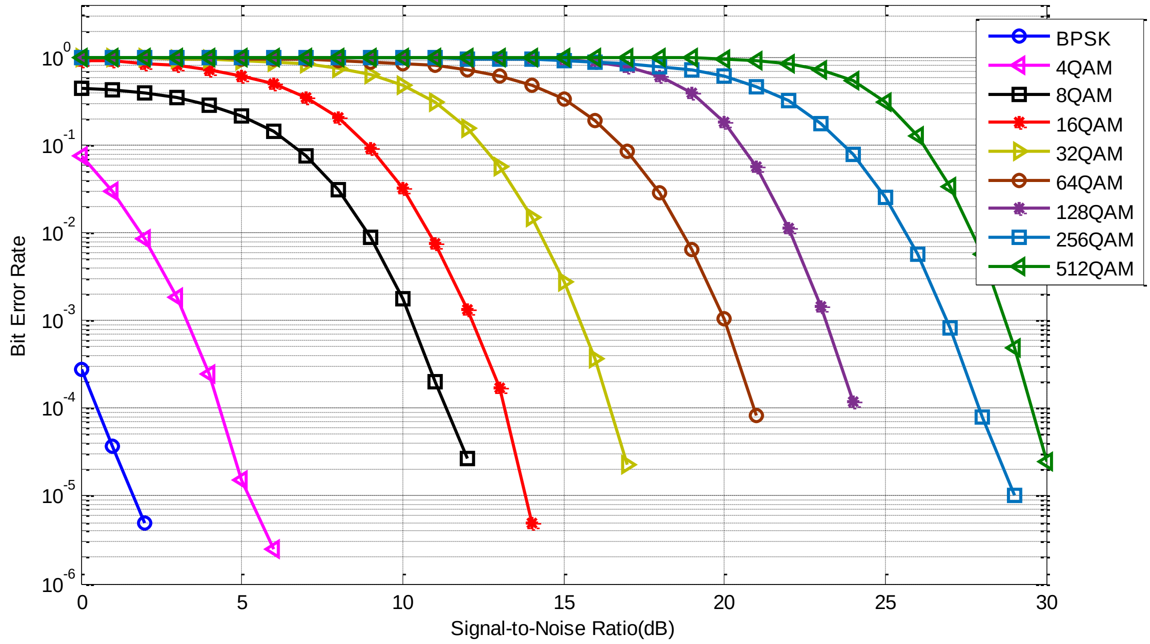

Figure 4.1 BER Vs SNR for different M-ary QAM with 1/4 code rate

Figure 4.2 shows SNR vs BER graphs for different M-ary QAM with 1/3 coding rate. To fulfill a target QoS, higher SNR is required with 1/3 coding rate compared to FEC of 1/4 coding rate.

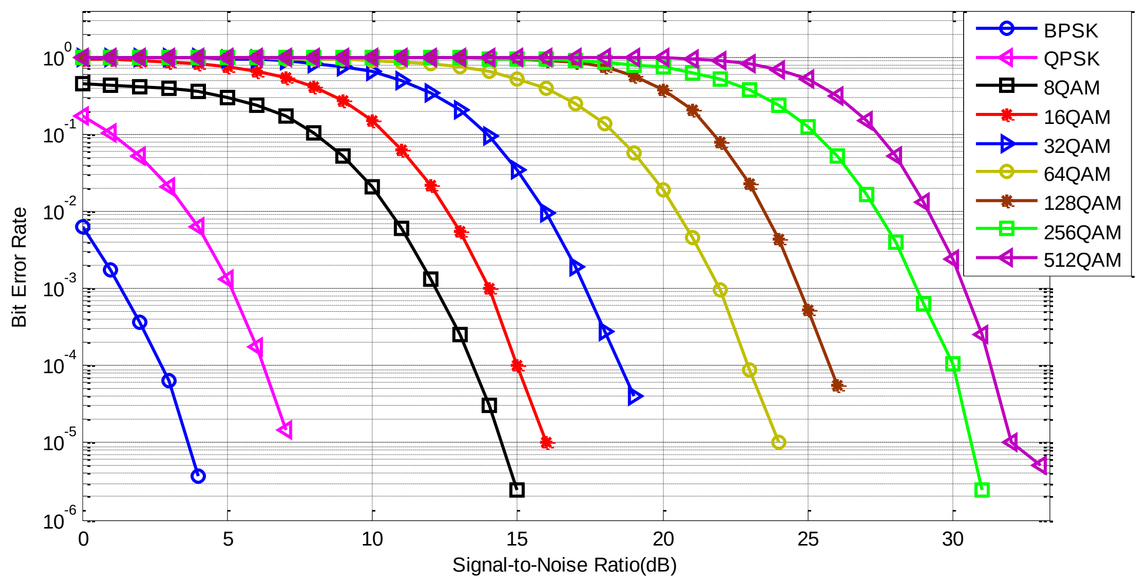

Figure 4.2 BER Vs SNR for different M-ary QAM with 1/3 code rate

The BER performance for various modulation schemes with 1/2 coding rate under AWGN channel are shown in Figure 4.3. The BER curves indicate that by increasing the code rate increases the required SNR to operate for a system.

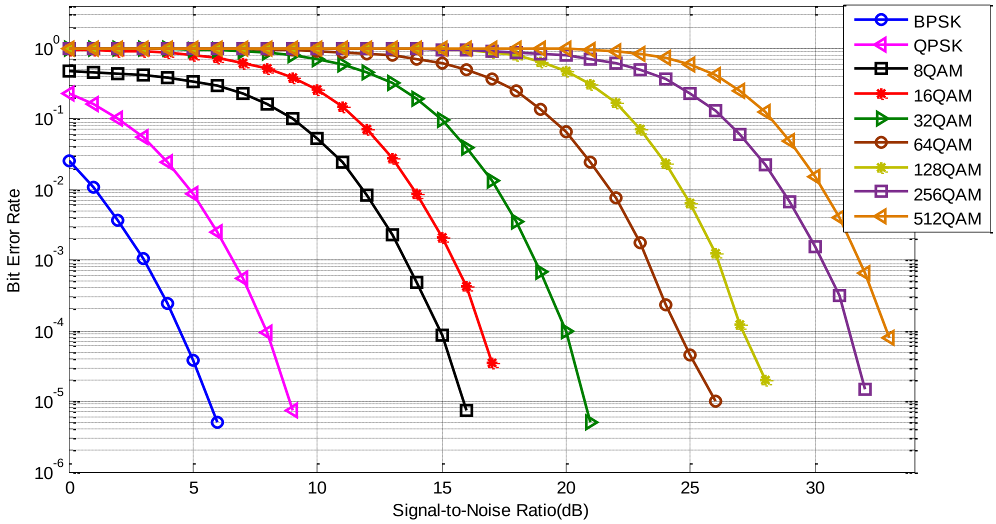

Figure 4.3 BER Vs SNR for different M-ary QAM with 1/2 code rate

The BER performance comparison for different modulation schemes using rate 2/3 and 3/4 convolutional codes is shown in Figure 4.4 and Figure 4.5 respectively.

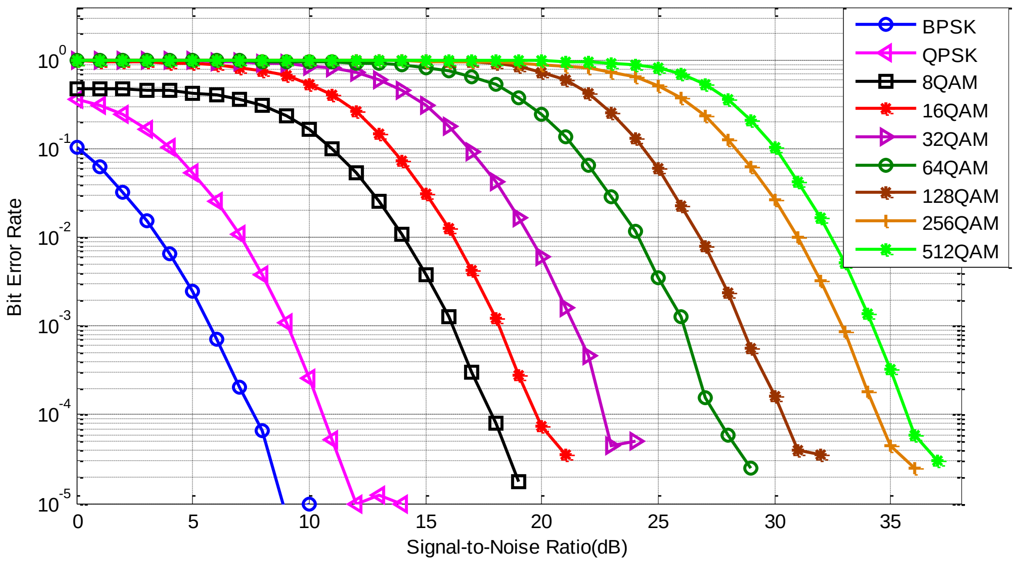

Figure 4.4 BER Vs SNR for different M-ary QAM with 2/3 code rate

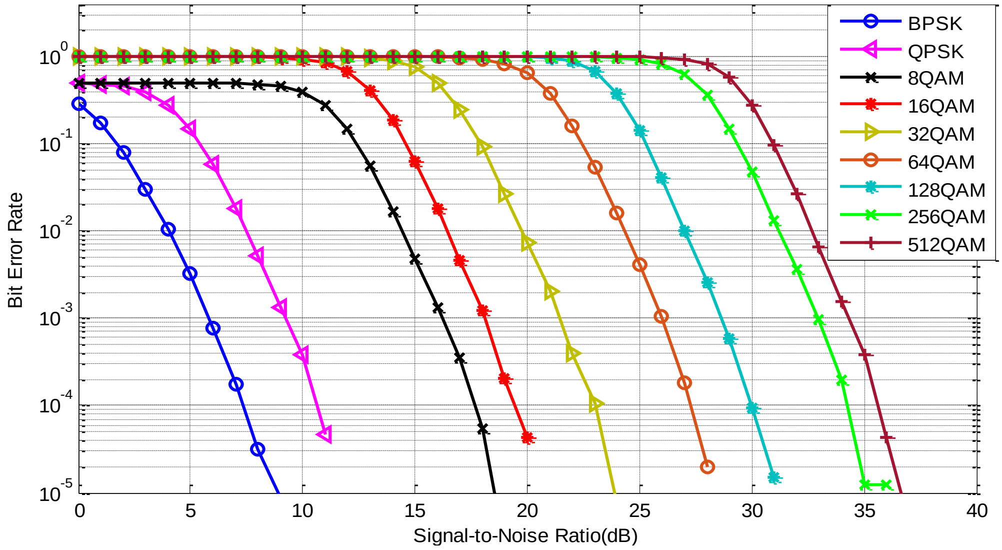

Figure 4.5 BER Vs SNR for different M-ary QAM with 3/4 code rate

The selection of the modulation order and coding rate depends on the quality of the wireless channel. The bandwidth efficient modulation and coding techniques are used during a good channel condition. On the other hand, lower coding and modulation scheme are used to improve the BER performance for less SNR. For example, for SNR of 20dB and target BER of 10^{-4}, 16QAM with 2/3 or 3/4 code rate can be employed to improve capacity and maintain link.

4.1.2. Effect of Channel Coding

The performance of an OFDM system is degraded when a FEC convolutional encoder is not employed. The FEC coding rate improves the BER performance of the system. Table 4-1 shows the required SNR to meet the target BER=10^{-3} for various constellation sizes with 1/4, 1/3, 1/2, 2/3, and 3/4 code rates. The higher modulation schemes require higher SNR. In addition, increasing the code rate increases the required SNR to meet the target QoS for each modulation order.

Table 4-1 Required SNR for a set of code rates for target BER=0.001

Modulation schemes	**Code Rate (R_C)**				
	1/4	1/3	1/2	2/3	3/4
BPSK	0.5dB	1.7dB	3dB	5.7dB	5.7dB
QPSK	3.2dB	5.2dB	6.5dB	9dB	9.3dB
8QAM	10.2dB	12.3dB	13.6dB	16.2dB	16.3dB
16QAM	12.2dB	14dB	15.5dB	18.2dB	18.3dB
32QAM	15.5dB	17.4dB	18.6dB	21.4dB	21.5dB
64QAM	20dB	22dB	23.4dB	26.2dB	26dB
128QAM	23.2dB	24.8dB	26.1dB	28.6dB	28.6dB
256QAM	26.9dB	28.7dB	30.3dB	32.9dB	33dB
512QAM	28.5dB	30.4dB	31.7dB	34.2dB	34.4dB

Figure 4.6 shows a graphical representation of the required SNR to meet the target BER of 10^{-3} for various modulation schemes with different code rates as tabulated in Table 4-1. The results indicate, the coding rate approaches to one for a higher SNR for a given modulation scheme. In other words, to meet a target BER, higher modulation and coding is used during a good channel condition.

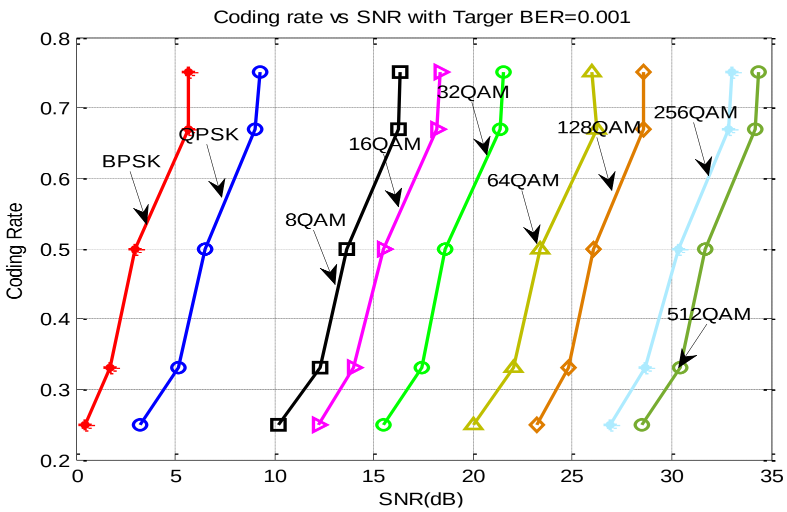

Figure 4.6 Code rate Vs SNR for different modulation schemes for target bit error rate=0.001

Table 4-2 shows the required SNR to meet target BER of 10^{-2} for various modulation orders with 1/4, 1/3, 1/2, 2/3, and 3/4 code rates. The results show for a higher coding and modulation, the required SNR is less as compared to lower modulation and coding.

Table 4-2 Required SNR for a set of code rates for target BER=0.01

Modulation schemes	**Code Rate (R_C)**				
	1/4	1/3	1/2	2/3	3/4
BPSK	-	-	1dB	3.4dB	4dB
QPSK	1.9dB	3.6dB	4.8dB	7dB	7.5dB
8QAM	8.9dB	10.6dB	11.8dB	14dB	14.5dB
16QAM	10.8dB	12.6dB	13.9dB	16.4dB	16.5dB
32QAM	14.4dB	16dB	17.3dB	19.6dB	19.7dB
64QAM	18.7dB	20.4dB	21.8dB	24.2dB	24.4dB
128QAM	22dB	23.5dB	24.7dB	26.7dB	27dB
256QAM	26.5dB	27.4dB	28.7dB	31dB	31.3dB
512QAM	27.7dB	29.1dB	30.3dB	32.5dB	32.6dB

Figure 4.7 shows the plots of the required SNR to meet the target BER of 10^{-2} for various modulation schemes with various code rates as tabulated in Table 4-2.

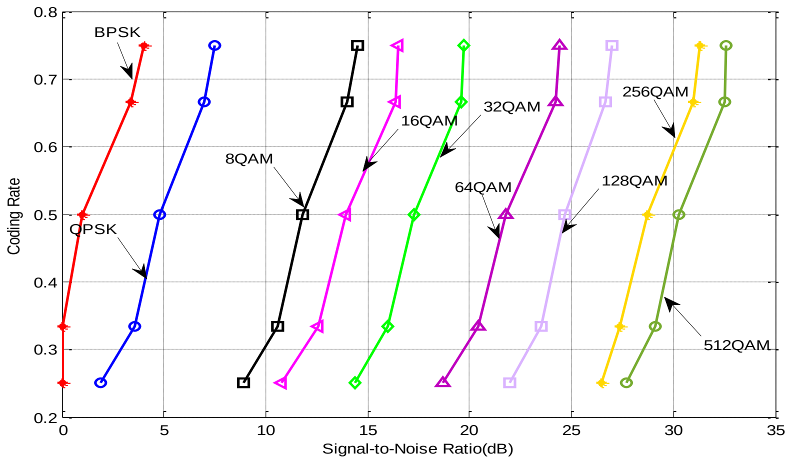

Figure 4.7 Code rate Vs SNR for different modulation schemes for target bit error rate of 10^{-2}

For a low QoS, less SNR is required compared to high QoS for the same code-modulation pair. For example, for 64QAM with 1/2 code rate, 23.4 dB and 21.8dB SNR is required to meet the bit error rate of 10^{-3} and 10^{-2}, as seen from Figures 4.6 and 4.7 respectively. Figure 4.8 shows the bit error rate comparison of 16QAM with different coding rates. For the same modulation order, the BER performance varies with coding rate. By reducing the code rate, less SNR is required to meet the desired target BER. The BER performance for the coded message is better compared to the un-coded information.

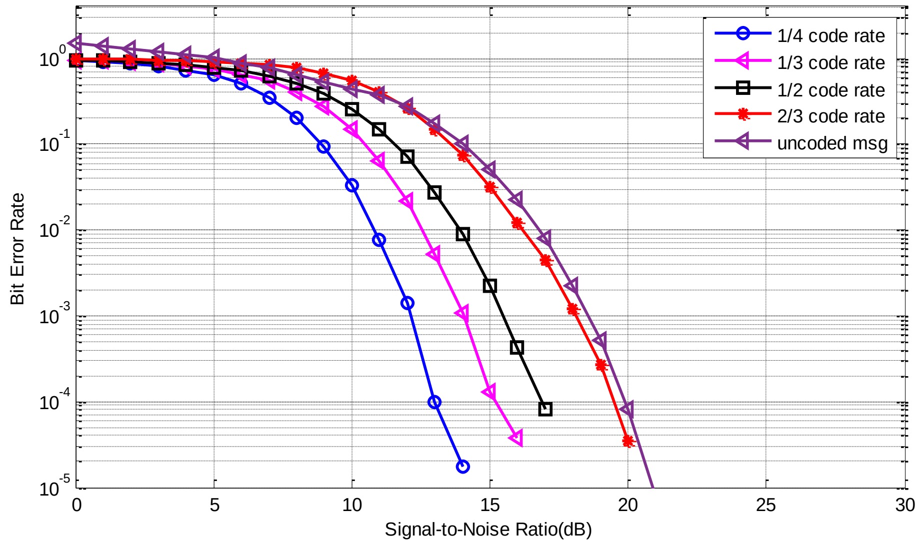

Figure 4.8 BER Vs SNR for 16QAM for different coding rates

4.1.3. Spectral Efficiency Results

The spectral efficiency with various SNR range for different modulation and coding techniques over AWGN channel is presented in this section. The range of SNR switching thresholds for various coding and modulation with target BER of 10^{-2} and 10^{-3} is shown in Table 4-3. These SNR values are used to select the appropriate code-modulation pair for the adaptive coding and modulation schemes.

Table 4-3 Range of SNR values that give a target BER of 10^{-3} and 10^{-2}

Modulation	QPSK	QPSK	QPSK	16QAM	16QAM	64QAM	256QAM
Code rate	1/4	1/2	3/4	1/2	3/4	3/4	3/4
Channel	**Range of SNR(dB)**						
BER=10^{-2}	<1.9	1-4.8	4-7.5	11.8-13.9	14.5-16.4	19.7-24.4	>31.3
BER=10^{-3}	0.5-3.2	3-6.5	5.7-9.3	13.6-15.5	16.3-18.2	21.5-26	>33

The spectral efficiency performance comparison with fixed and adaptive techniques with a target BER of 10^{-3} is shown in Figure 4.9 based on Table 4-3. The results show that, the spectral efficiency is proportional to the estimated SNR. In other words, the throughput is increased with increasing received SNR, however, after some values the spectral efficiency remain constant.

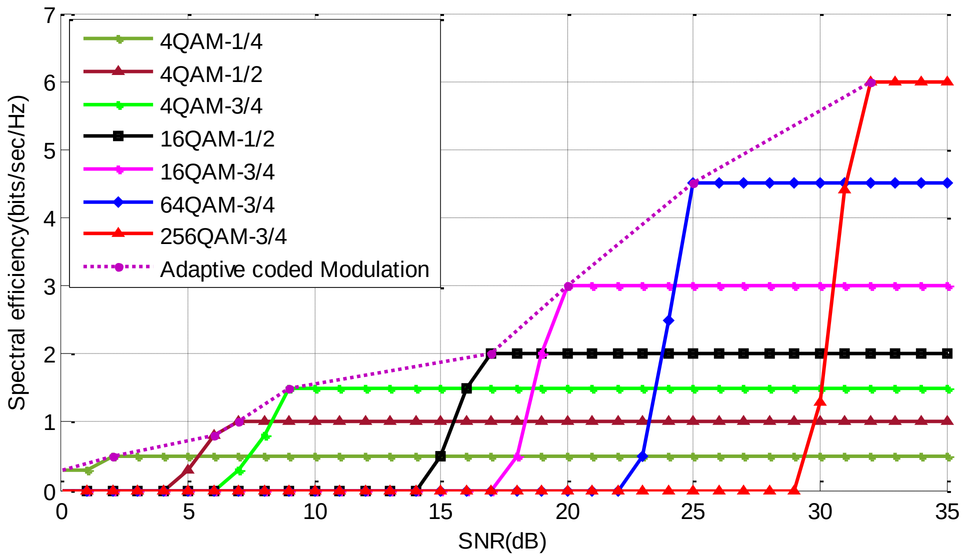

Figure 4.9 Spectral efficiency Vs SNR for BER of 10^{-3} for fixed and adaptive techniques

Figure 4.10 shows the spectral efficiency (bits/sec/Hz) performance comparison with fixed and adaptive techniques for a target BER of 10^{-2} based on Table 4-3. The spectral efficiency is higher when SNR with 3/4 coding rate for QPSK, 16QAM, 64QAM and 265QAM is more than 9dB, 18dB, 26dB and 30dB respectively. Moreover, increasing the constellation size (modulation order) with coding rate increase the performance of wireless systems. For example, 256QAM with 3/4 coding rate has higher throughput than the lower code-modulation pair schemes such as QPSK-3/4.

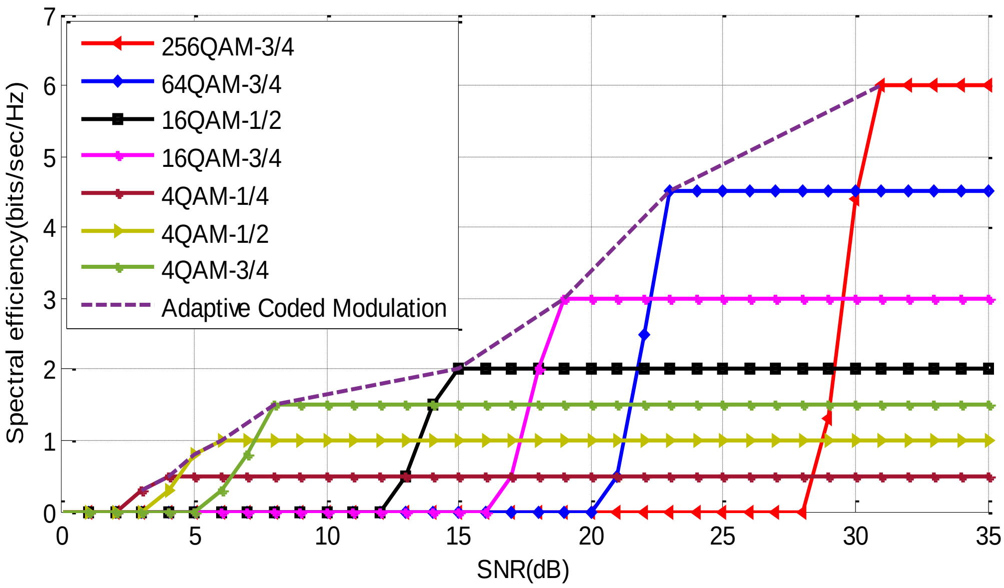

Figure 4.10 Spectral efficiency Vs SNR for larger BER of 10^{-2} for fixed and adaptive techniques

4.1.4. Parameter Selection to Maximize Spectral Efficiency

In this work, an OFDM system is simulated under an AWGN channel. The bit error rate is calculated for each given SNR. The given SNR are investigated for each modulation order and coding rate. Thus, the spectral efficiency of an adaptive modulation and coding scheme for OFDM wireless systems is dependent on the BER, SNR, coding rate and modulation order. The input and output parameters that are used to train the ANFIS system with their corresponding values are shown in Table 4-4.

$$\eta = f(BER, SNR, m, R_c) \tag{4.1}$$

where m is $log_2(M)$, M is the modulation/constellation size and R_c is the FEC convolutional coding rate.

Table 4-4 Neuro-fuzzy parameters and their corresponding values

	ACM Parameters	**Values**
Input Variables	SNR	0-35dB
	BER	10^{-6} to 10^{-2} bits/sec/Hz
	Modulation scheme	BPSK, QPSK, 8QAM, 16QAM, 32QAM, 64QAM, 128QAM, 256QAM, 512QAM
	Coding rate	1/4, 1/3, 1/2, 2/3, 3/4
Output Variable	Spectral efficiency	0.25 to 6.75 bits/sec/Hz

4.2. Neuro-Fuzzy Based Performance Results

Taking 10^{-5} as tolerance error and 50 as the number of epochs in the ANFIS training process the output is selected based on the constructed 135 fuzzy rules. Figure 4.11 shows the neuro-fuzzy based rule editor. In this system the *if-then* rules are used to make decision in data rate optimization. The ANFIS rule viewer is shown in Figure 4.12 and these gives a better description of all fuzzy rules. The first four columns indicate the membership functions of the input parameters and last column is the output data rate/spectral efficiency membership function.

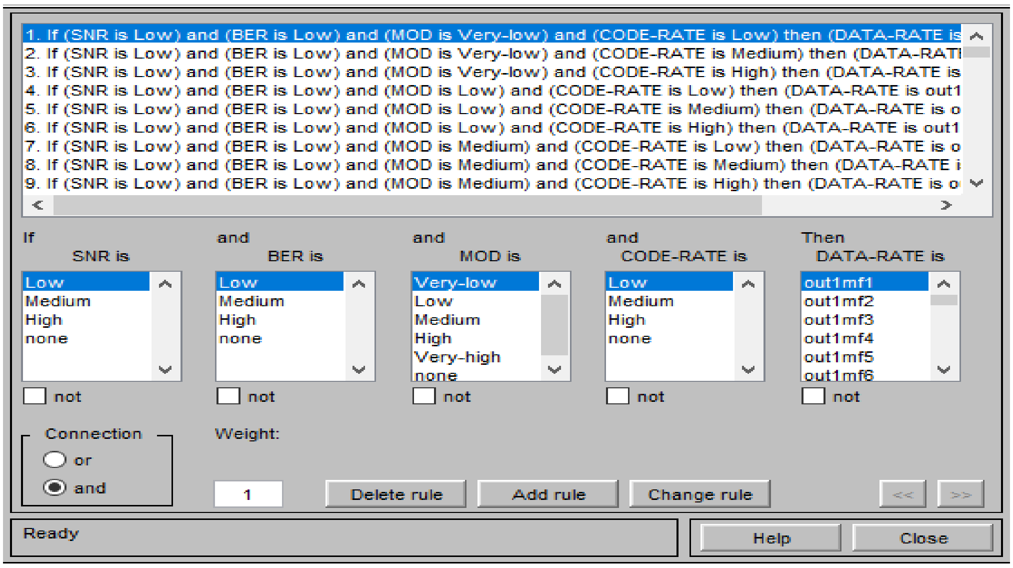

Figure 4.11 Rule editor of fuzzy inference system

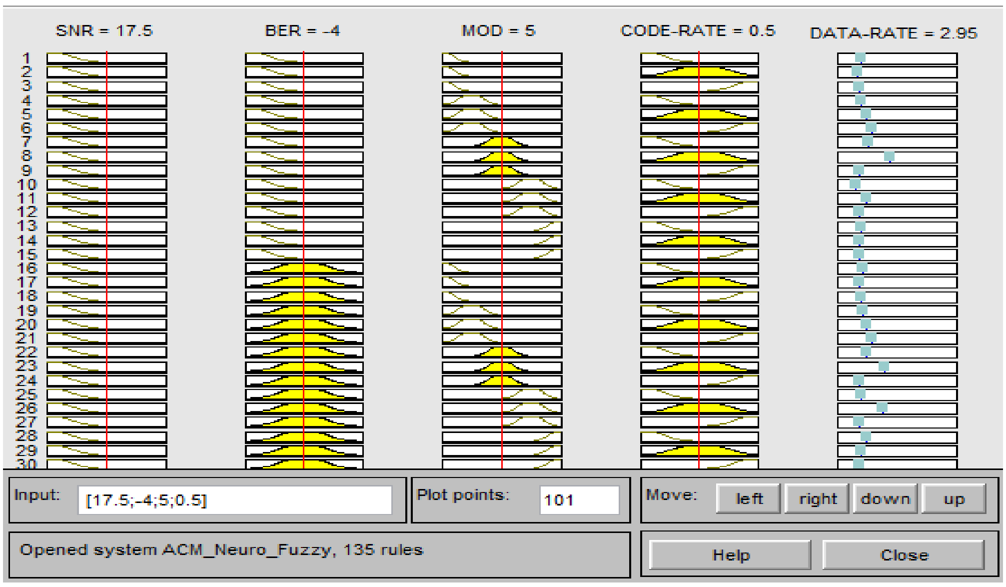

Figure 4.12 Rule viewer of fuzzy inference system

Figure 4.13 and 4.14 show different surface views. These 3D curves represent mapping of input variables against output variable. In other words, it dictates the smoothness and correlation between the input variables to select the desired output at a particular time depending on the quality of the channel. The surface view of combined effect for both SNR, and BER is shown in Figure 4.13. It indicates that by increasing the SNR the data rate is also increased. In addition to this, for a poor QoS, the spectral efficiency is higher compared to a low target BER. For a BER of 10^{-2} and SNR of 35dB, a data rate of 6.75 bits/sec/Hz can be achieved. Data rate can also be increased by increasing the modulation order and coding rate as shown in Figure 4.14. The surface colors indicate the level of the output. As shown in both figures, the yellow, light blue and dark blue colors show the data rate is high, average and low, respectively.

The neuro-fuzzy based adaptive modulation and coding scheme simulation results show a better performance over the works presented by [30, 44, 32]. In these investigations, a fuzzy logic system was used in decision-making to maximize the transmission data rate.

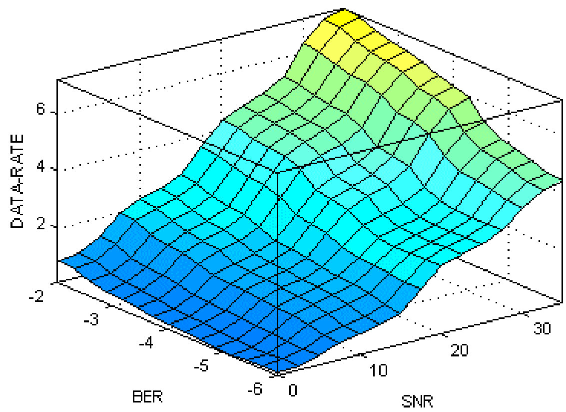

Figure 4.13 Surface view for BER Vs SNR

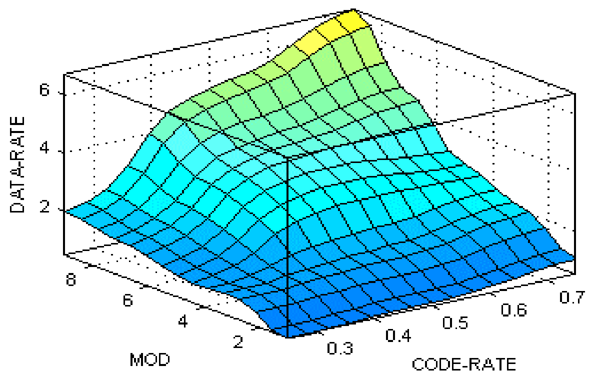

Figure 4.14 Surface view for MOD Vs CODE RATE

4.3. Performance Comparison of the ANFIS to Various Schemes

The proposed neuro-fuzzy controller based adaptive coding and modulation for OFDM system is simulated in MATLAB and compared to existing fuzzy logic models and adaptive techniques. Figure 4.15 shows the performance results of neuro-fuzzy based adaptive coding and modulation for different target quality of services such as 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3} and 10^{-2}. These results are taken from the surface view for BER Vs SNR shown on Figure 4.13. For a fixed quality of service, higher data rate is obtained by increasing SNR. For a low QoS, higher spectral efficiency can be achieved compared to high QoS at high SNR. For example, for an SNR of 35dB, a spectral efficiency of 6.75 and 4.5 bits/sec/Hz can be achieved for a target BER of 10^{-6} and 10^{-2}, respectively. Increasing the quality of service reduces the data rate that can be transmitted. Hence, the data rate is inversely proportional to the bit error rate.

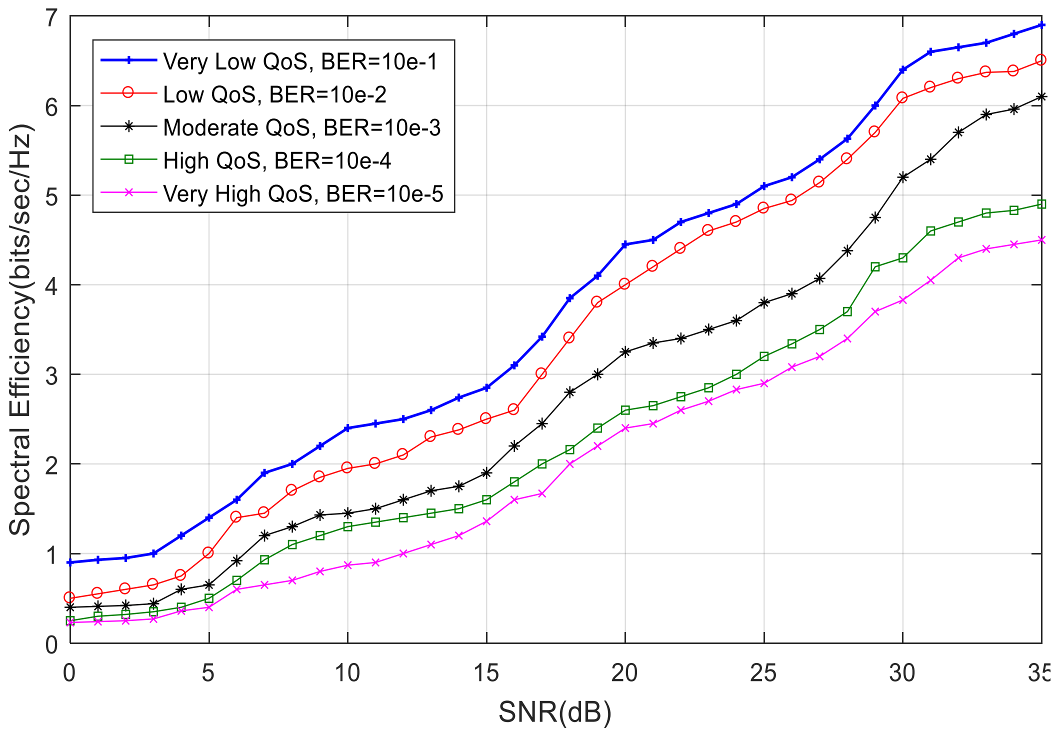

Figure 4.15 Neuro-fuzzy based performance comparison

The Shannon capacity given in Eqn. 2.9 is compared to upper and lower limits of the proposed approach shown in Figure 4.16. At 20dB SNR, a data rate of 6.8, 4.5 and 2.5bits/sec/Hz can be achieved for Shannon, neuro-fuzzy approach for QoS 10^{-2} and 10^{-6}, respectively.

Figure 4.17 shows the performance comparison of the proposed neuro-fuzzy based adaptive coding and modulation to neural networks and fuzzy logic system [34] [45], switching threshold based adaptive modulation [19], adaptive coded modulation and non-adaptive techniques [23]. The simulation results show that the proposed scheme perfoms better compared to the other techniques in terms of spectral efficency or data rate for a target BER of 10^{-2} and fixed trasnmit power. Thus, the overall data rate of the OFDM system is maximized by varying code rate and modulation scheme such that the BER and total transmitted power remain under certain thresholds.

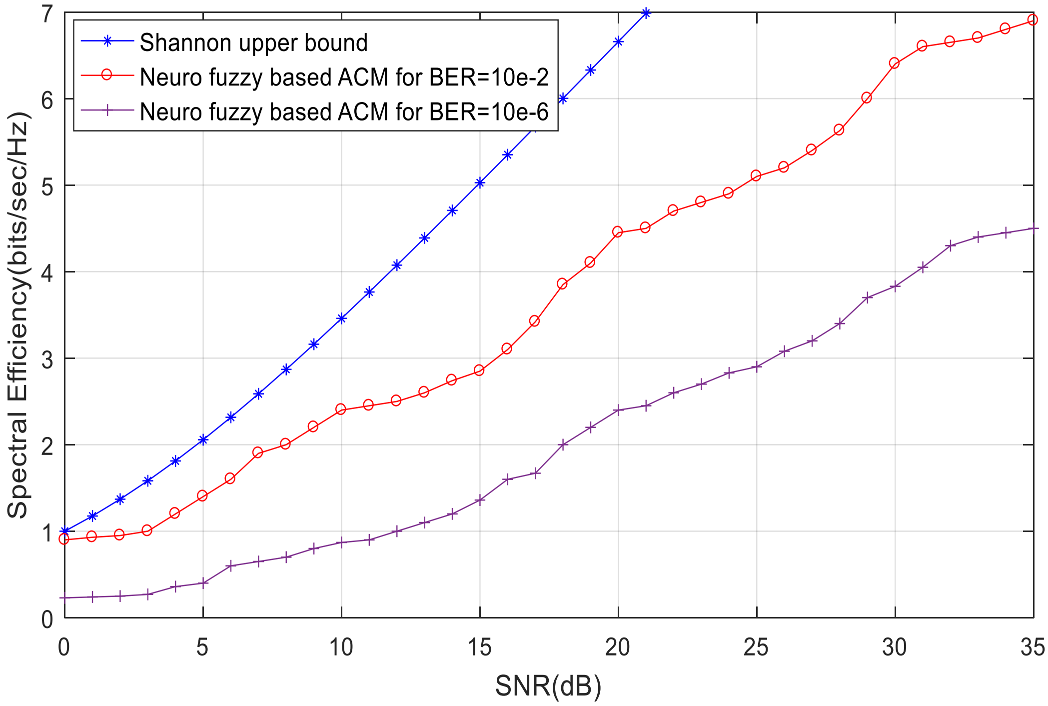

Figure 4.16 Comparsion of proposed approach to Shannon capacity

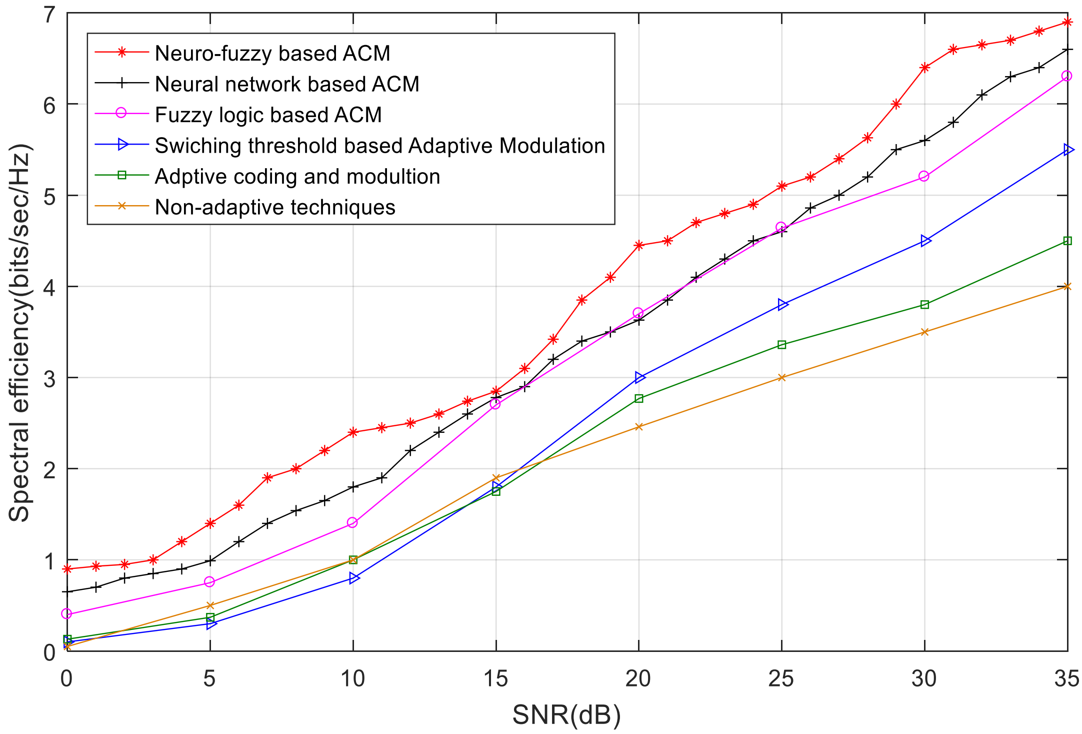

Figure 4.17 Spectral efficency Vs SNR for various schemes for target QoS of 10^{-2} and fixed transmit power

Table 4-5 shows the data rate comparison of the proposed scheme to different existing models for SNR 5dB, 15dB, 25dB and 35dB. At 35dB SNR, a neuro-fuzzy based adaptive coding and modulation shows superiority in spectral efficency of 0.15, 0.45, 1.25, 2.25, and 2.75 bits/sec/Hz compared to neural networks based ACM, fuzzy logic based ACM, switching threshold based adaptive modulation, adaptive coded modulation and non-adaptive techniques, respectively. By analazying the simulation results, the neuro-fuzzy model shows an average of 25.03% data rate improvement compared to the existing fuzzy logic model. It also shows that, the proposed approach outperforms compared to neural networks, adaptive and non-adaptive techniques such that the BER and total transmit power remain under certain thresholds.

Table 4-5 Data rate (bits/sec/Hz) comparison

Schemes	**5dB**	**15dB**	**25dB**	**35dB**
Neuro-fuzzy based ACM	1.4	2.85	5.1	6.75
Neural networks based ACM	0.99	2.78	4.6	6.6
Fuzzy logic based ACM	0.75	2.7	4.64	6.3
Switching threshold based AM	0.3	1.8	3.8	5.5
Adaptive technique	0.37	1.75	3.36	4.5
Non-adaptive systems	0.5	1.9	3	4

CHAPTER FIVE

CONCLUSION AND RECOMMENDATIONS

5.1. Conclusions

5.1.1. Adaptive Coding and Modulation for OFDM Systems

In this research, the performance of OFDM systems in terms of spectral efficiency and BER using various coding rates and modulation schemes under AWGN channel was analyzed and compared to fixed and adaptive techniques. The advantage of channel coding over the uncoded message is also studied. The BER performance is improved by using FEC coding rate. However, selecting lower code rate can reduce spectral efficiency. During good quality of channel, higher coding and modulation orders can be used to improve data rate. Since the frequency spectrum is limited, ACM is applied to efficiently use the available bandwidth. By comparing the performance within different modulation and coding schemes, it is shown that BER can be improved by using lower modulation and coding technique but with less spectral efficiency. The performance comparison of ACM schemes based on results shown on Figure 4.9 and 4.10 is summarized in Table 5-1.

Table 5-1 Summary of the proposed system performance

Code-modulation pair	BER performance	Spectral efficiency
4QAM-1/4	Low BER	Worst
16QAM-1/2	Higher BER	Low
64QAM-3/4	Good for higher SNR	Medium
256QAM-3/4	Worst for lower SNR	Good
Adaptive techniques	Maintain target BER	Good

5.1.2. Performance Comparison of Neuro-Fuzzy Logic to Various Schemes

In this research work, a neuro-fuzzy based adaptive coding and modulation for performance improvement in OFDM wireless systems is proposed and compared to other fuzzy models, adaptive techniques as well as fixed techniques. The performance comparison of spectral efficiency against SNR for various quality of services such as 10^{-6}, 10^{-5}, 10^{-4}, 10^{-3} and 10^{-2} is done. By using the learning ability of the neuro-fuzzy logic, the network is trained by the real data values that include SNR, BER, modulation order and code rate as inputs and data rate as output. The manual data is generated from simulation of the OFDM system for different coding rates and modulation schemes. As an efficient control mechanism, a neuro-fuzzy logic responds to an adaptive environment to decide the desired coding rate and modulation order to enhance system performance. In addition, neuro-fuzzy systems are suited for the situations that are imprecise, complex and missing certain information, also it can easily be implemented in hardware and it is suitable for real time systems. By analyzing the MATLAB simulation results, the neuro-fuzzy scheme shows an average of 25.03% data rate(bits/sec/Hz) improvement compared to the existing fuzzy logic model. In addtion to this, the proposed approach outperforms compared to neural networks, adaptive and non-adaptive techniques such that the BER and total transmit power remain under certain thresholds.

5.2. Recommendations and Future Work

The proposed scheme suits the WiMAX wireless standards in which fixed and mobile users having different QoS and data rate demands are privileged. The performance of the neuro-fuzzy approach can be further investigated for different FFT and cyclic prefix sizes. It can also be studied for Rayleigh and Rician fading channel noise models. Furthermore, the possibility of applying on-line learning method to track the variation of wireless channel can be investigated. A prototype model could also be implemented in VHDL code and downloaded to an FPGA.

REFERENCES

[1] G. Andera, "Adaptive Modulation and Coding for Fading Channel," in *Information Theory and Communications Workshop, Proceedings of the IEEE,* Kruger National Park, South Africa, June 1999.

[2] M. A. Islam, M. M. Rahman, F. Enam and H. Homyara, "Analysis of the Effect of Spectral Efficiency on Digitally Modulated OFDM Communication System over Realistic Channel Condition," *International Journal of Scientific & Engineering Research*, vol. 7, no. 1, pp. 1019-1024, 2016.

[3] T. Jaya, E. Gopinathan and V. Rajendran, "Comparison of BER Performance of Various Adaptive Modulation Schemes in OFDM Systems," *Indian Journal of Science and Technology*, vol. 9, no. 40, pp. 1-7, 2016.

[4] R. Rashmi and S. Sarala, "OFDM: Modulation Technique for Wireless Communication," *International Journal of Innovative Research in Advanced Engineering*, vol. 1, no. 1, pp. 1-5, 2015.

[5] T. Awon and M. Rahman, "Effect of AWGN and fading (Rayleigh and Rician) channels on BER Performance of a WIMax Communication System," *International Journal of Computer Science and Information Security,* vol. 10, no. 8, pp. 11-17, 2012.

[6] Z. Xinyu, "A Basic Research on Forward Error Correction," in *IEEE 3rd International Conference on Communication Software and Networks (ICCSN),* Xi'an, China, May, 2011.

[7] W. Huffman and P. Vera, Fundamentals of Error-Correcting Codes, Cambridge University Press, Feb. 2010.

[8] G. Andera, Wireless Communications, New York: Cambridge University Press, 2005.

[9] S. Dhaliwal, N. Singh and G. Kaur, "Performance Analysis of Convolutional Code Over Different Code Rates and Constraint Length in Wireless Communication," in *I-SMAC (IoT in Social, Mobile, Analytics and Cloud)(I-SMAC), 2017 International Conference on IEEE,* Palladam, India, Feb. 2017.

[10] F. G. David, "The Viterbi Algorithm: A Personal History," in *Viterbi Conference University of Southern California*, Los Angeles, March 2005.

[11] S. R. Theodore, Wireless Communications Principles and Practice, Prentice-Hall of India Private Limited, 2004.

[12] A. Islam, R. Mondal and Z. Hasan, "Performance Evaluation of Wimax Physical Layer under Adaptive Modulation Techniques and Communication Channels," *International Journal of Computer Science and Information Security, ,* vol. 5, no. 1, pp. 11-114, 2009.

[13] A. Mohammad, "Performance Evaluation of WiMAX/IEEE 802.16 OFDM Physical Layer," PhD diss., MS Thesis, Helsinki University of Technology, Espoo, Finland, 2007.

[14] S. Bhargavi, "Design and Implementation of an Efficient OFDM Transceiver Chain for WiMax," *International Journal of Engineering Research and Applications*, vol. 3, no. 1, pp. 992-997, 2013.

[15] S. A. Jumde, D. Lekariya and R. Mandavgane, "Adaptive Modulation for OFDM System using Convolutional Coding and BCH Coding," *International Journal of Engineering Science and Innovative Technology (IJESIT),* vol. 4, no. 4, pp. 132-139, 2015.

[16] A. Svensson, "Introduction to Adaptive QAM Modulation Schemes for Known and Predicted Channels," *Proceedings of the IEEE,* vol. 95, no. 12, pp. 2322-2336, 2007.

[17] N. Borkar and D. Bormane, "BER Performance of OFDM System with Adaptive Modulation," in *Complex Systems (ICCS), 2012 International Conference on IEEE*, Agadir, Morocco, 2012.

[18] A. Mewara and S. Sharma, "Adaptive Modulation Technique to Improve OFDM System," *Suresh Gyan Vihar University Journal of Engineering & Technology*, vol. 1, no. 2, pp. 17-21, 2015.

[19] J. Faezah and K. Sabira, "Adaptive Modulation for OFDM Systems," *International Journal of Communicaation Networks and Information Security*, vol. 12, pp. 1-8, 2009.

[20] Deepa and S. Singh, "An Adaptive Approach to Switching Coded Modulation in OFDM System under AWGN Channel," *International Journal for Scientific Research & Development*, vol. 2, no. 7, pp. 457-462, 2014.

[21] S. K. Lye, S. E. Tan, Z. W. Siew, H. Yew and K. K. Teo, "Analysis and Performance Measurement of Adaptive Modulation and Coding," in *Control System, Computing and Engineering (ICCSCE), 2012 IEEE International Conference on*, Penang, Malaysia, 2012.

[22] S. Hadi and T. Tiong, "Adaptive Modulation and Coding for LTE Wireless Communication," *In IOP Conference Series: Materials Science and Engineering, IOP Publishing*, vol. 78, no. 1, pp. 1-6, 2016.

[23] Y. Lei and A. Burr, "Adaptive Modulation and Code Rate for Turbo Coded OFDM Transmissions," in *Vehicular Technology Conference, 2007. VTC2007-Spring. IEEE 65th*, Dublin, Ireland, May 2007.

[24] T. Harivikram, R. Harikumar, C. Babu and P.Murugamanickam, "Adaptive Modulation and Coding Rate for OFDM Systems," *International Journal of Emerging Technology and Advanced Engineering*, vol. 3, no. 2, pp. 250-255, 2013.

[25] M. N. Rajesh, B. K. Shrisha, N. Rao and H. Kumaraswamy, "An analysis of BER comparison of various digital modulation schemes used for adaptive modulation," in *Recent Trends in Electronics, Information & Communication Technology (RTEICT), IEEE International Conference on*, Bangalore, India, May 2016.

[26] S. Nandi, N. Pathak, A. Nandi and M. Sarkar, "Performance Analysis of Cyclic Prefix OFDM using Adaptive Modulation Techniques," *International Journal of Electronics, Electrical and Computational System*, vol. 6, no. 8, pp. 214-220, 2017.

[27] T. Takagi and M. Sugeno, "Fuzzy Identification of Systems and its Application to Modeling and Control," in *IEEE Transactions on Systems, Man, and Cybernetics* , Jan.-Feb. 1985.

[28] B. Kosko, Neural Networks and Fuzzy Systems: A dynamic Systems Approach to Machine Intelligence, Englewood Cliffs, NY Prentice Hall., 1992.

[29] R. Srihari, K. Hymavathi and K. Shiva, "Fuzzy Adaptive Coded Modulation in Wireless Network using Bit Error Rate," *International Conference on Emerging Trends in Engineering, Science and Management*, pp. 611-619, 2017.

[30] K. Singh, "Fuzzy Logic Based Modified Adaptive Modulation Implementation for Performance Enhancement in OFDM Systems," *International Journal Intelligent Systems and Applications*, vol. 8, no. 5, pp. 49-54, 2016.

[31] Deepa and S. Singh, "A Fuzzy Logic Approach to Adaptive Coding and Modulation in OFDM," *International Journal of Enhanced Research In Science Technology & Engineering*, vol. 3, no. 9, pp. 181-192, 2014.

[32] S. Sastry and M. Babu, "Adaptive Modulation for OFDM System using Fuzzy Logic Interface," in *Software Engineering and Service Sciences (ICSESS), 2010 IEEE International Conference on*, Beijing, China, 2010.

[33] K. S. Sastry, "Fuzzy Logic Based Adaptive Modulation Using Non Data Aided SNR Estimation for OFDM System," *International Journal of Engineering Science & Technology*, vol. 2, no. 6, pp. 2384-2392, 2010.

[34] A. Rahman, I. Qureshi and A. Malik, "A Fuzzy Rule Base Assisted Adaptive Coding and Modulation Scheme for OFDM Systems," *Journal of Basic and Applied Scientific Research*, pp. 4843-4853, 2012.

[35] A. Rahman, I. Qureshi and M. Muzaffar, "Efficient Link Adaptation in OFDM Systems using a Hybrid Intelligent Technique," in *Hybrid Intelligent Systems (HIS), 2013 13th International Conference on IEEE*, Gammarth, Tunisia, Dec. 2013.

[36] R. Atta, I. Qureshi, A. Malik and M. Naseem, "A Real Time Adaptive Resource Allocation Scheme for OFDM Systems Using GRBF-Neural Networks and Fuzzy System," *The International Arab Journal of Information Technology,* vol. 11, no. 6, pp. 590-598, 2014.

[37] A. Rahman, M. Salam, M. Naseem and M. Muzaffar, "An Intelligent Link Adaption Scheme for OFDM based Hyperlans," in *Soft Computing and Pattern Recognition (SoCPaR), 2013 International Conference of IEEE*, Hanoi, Vietnam, Dec. 2013.

[38] A. Rahman, I. M. Qureshi and M. T. Naseem, "Adaptive Resource Allocation for OFDM Systems using Fuzzy Rule Base System Water-filling Principle and Product Codes," in *Intelligent Systems Design and Applications (ISDA), 2012 IEEE 12th International Conference on*, Kochi, India, Nov. 2012.

[39] P. Kaur, K. Singh and H. Kaur, "Adaptive Modulation of OFDM by using Radial Basis Function Neural Network," *International Journal of Advanced Research in Computer and Communication Engineering,* vol. 3, no. 6, pp. 6886-6888, 2014.

[40] S. Jang, "ANFIS: Adaptive Network based Fuzzy Inference System," *IEEE transactions on systems, man, and cybernetics*, vol. 23, no. 3, pp. 665-685, 1993.

[41] S. Haykin, Neural networks: A Comprehensive Foundation, Tsinghua University Press., 2001.

[42] V. Priya, Y. Ponjenifer and A. R. Benoe, "Adaptive Modulation of OFDM by Using Neuro-Fuzzy Method," *International Journal of Advanced Research Trends in Engineering and technology (IJARTET),* vol. 2, no. 19, pp. 81-84, 2015.

[43] G. D. Sworo, R. Measel, M. Kam and K. Dandekar, "Optimization of Adaptive Modulation and Coding Techniques for OFDM Systems," in *Signal Processing and Communication Systems (ICSPCS), 2011 IEEE 5th International Conference on,* Honolulu, HI, USA, Dec. 2011.

[44] K. Nagar and K.Sharma, "Adaptive OFDM Implementation Using Fuzzy Inference System," *International Journal of Advanced Research in Computer Science and Software Engineering (IJARCSSE),* vol. 3, no. 7, pp. 309-314, 2013.

[45] A. Rahman, I. Qureshi and M. Muzaffar, "Adaptive Coding and Modulation for OFDM systems using Product Codes and Fuzzy Rule Base System," *International Journal of Computer Applications*, vol. 35, no. 4, pp. 41-48, 2011.

APPENDICES

APPENDIX A: MATLAB Programme Codes

Matlab code for adaptive coding and modulation for OFDM systems with 1/4, 1/3 and 1/2 coding rate

```
% This code is prepared by Temalow Seife
% Department of Electrical Engineering
% Pan African University
% September 2017
% Simulation of adaptive coding and modulation for OFDM systems with 1/4, 1/3
% and 1/2 coding rate.
clc;
clear all;
close all;
% ofdm specifications
N = 256; % fft size
n = 256; % number of data subcarriers
CP=1/4;%cyclic prefix
nbits = 256; % number of bits per OFDM block
nblocks = 10^2; % number of ofdm blocks
% specify the range of signal-to-noise ratio in dB
SNR=[0:40];
% linear SNR
lin_snr=10.^(SNR./10);
% number of iterations
niter=5;
color_vec1 = ['b-','r-','k-','r-','g-', 'k-','r-','b-'];
% Modulation orders
M=[2 4 ];
% constraint length of the encoder
constlen=3;
% check the correct constellation size
for i=1:length(M)
   if ((rem(M(i),2)~=0)|| M(i)<2 || M(i)>512 )
       error('wrong modulation order')
   end
end
% Input the convolutional coding rate
code_rate=input('input the coding rate(1/4, 1/3, 1/2)');
```

```
%check the correct coding rate
if (code_rate~=1/4 && code_rate~= 1/3 && code_rate ~=1/2)
        error('Enter the correct coding rate')
end
%selection of the polynomial for the encoder
switch(code_rate)
       case 1/4
        codegen=[6 5 7 4];
       case 1/3
        codegen=[6 5 7];
       case 1/2
        codegen=[6  7];
 end
%Effective signal-to-noise ratio
SNR_eff = 10*log(lin_snr) + 10*log10(N/(N+N*CP));
for i=1:length(M)
 BER=zeros(1,length(SNR_eff));
for snr=1:length(SNR_eff)
    total_ber=0;
    for runs=1:niter
        % Data manupulation for the encoder input
        msg = randi([0 1],25600,1);%nbits*nblocks random data
        msg1=size(msg, 1);
        num_bits=msg1;
        num_bytes=num_bits/8;%number of byte
        % polynomial to trellis structure
        t = poly2trellis(constlen, codegen);
        % convolutionally encode binary data.
        code = convenc(msg,t);
        % Modulatation of the encoded message
        if (M(i)<=4)
        h=modem.pskmod(M(i));
        else
        h=modem.qammod(M(i));
        end
        ymod=modulate(h, code);
        y=ymod';
        % OFDM transmitter section
        s3=size(y,2);
        j=ceil(s3/N);
        %serial to parallel conversion of symbols
```

```
y=reshape(y,j, N);
% Applaying IFFT,
ifft_sig=ifft(fftshift(y.'));
ifft_sig=transpose(ifft_sig);
size_sig=size(ifft_sig)
% Appending cylic prefix
xt = [ifft_sig(:,[193:256]) ifft_sig];
%total bits per iteration
total_bits=size(xt, 1)*size(xt, 2);
% Concatenating multiple symbols to form a long vector
ynew=reshape(xt.',1,total_bits);
% Adding AWGN channel noise
ncode = awgn(ynew,snr, 'measured'); % Adding noise
ynoise=ncode;
% Receiver
% formatting the received vector into serial symbols
ncode=reshape(ncode.',size(xt,2), size(xt,1));
ncode=transpose(ncode);
% Removing the cyclic prefix
yt = ncode(:,[65:320]);
%Converting to freqency domain
fft_sig=fftshift(fft(yt.'));
fft_sig=transpose(fft_sig);
ff=size(fft_sig)
% Parallel to serial conversion for modulation
fft_sig=reshape(fft_sig, 1, j*N).';
% demodulation
if (M(i)<=4)
w=modem.pskdemod(M(i));
else
w=modem.qamdemod(M(i));
end
z=demodulate(w, fft_sig);
% Quantize to prepare for soft-decision decoding.
dec=[0.01, 0.1, 0.3, 0.5, 0.7, 0.9, 0.999];% decision points
qcode = quantiz(z,dec);
% Traceback length
tblen = 46;
delay = tblen;
% Convolutionally decode binary data using Viterbi algorithm
decoded = vitdec(qcode,t,tblen,'cont','soft',3);
```

```
        % Compute bit error rate and number of bit errors
        [number,ratio] = biterr(decoded(delay+1:end),msg(1:end-delay));
        total_ber=total_ber+ratio;
    end % number of niter loop
    % compute average BER
    BER(snr)=total_ber/(niter);
end % snr loop
% Plot graphs
semilogy(SNR(1:end),BER(1:end),'-b*','lineWidth',1.2,  'MarkerSize',7);
axis([0 40 10^-6 1])
legend('2QAM','4QAM', '8QAM', '16QAM','32QAM', '64QAM', '128QAM',
'256QAM','512QAM');
grid on
hold on
xlabel('Signal-to-Noise Ratio(dB)')
ylabel('Bit Error Rate')
title('SNR vs BER')
end
```

Matlab code for adaptive coding and modulation for OFDM systems with 2/3, and 3/4 coding rates

```
% This code is prepared by Temalow Seife
% Department of Electrical Engineering
% Pan African University
% September 2017
% Simulation of adaptive coding and modulation for OFDM systems with 2/3, and
3/4 coding rates.
clc;
clear all;
close all;
% ofdm specifications
N = 256; % fft size
n = 256; % number of data subcarriers
CP=1/4;%cyclic prefix
nbits = 256; % number of bits per OFDM block
nblocks = 10^2; % number of ofdm blocks
% specify the range of signal-to-noise ratio in dB
SNR=[0:40];
% linear SNR
lin_snr=10.^(SNR./10);
```

```
% number of iterations
niter=5;
color_vec1 = ['b-','r-','k-','r-','g-', 'k-','r-','b-'];
% Modulation orders
M=[2 4 ];
% constraint length of the encoder
% check the correct constellation size
for i=1:length(M)
    if ((rem(M(i),2)~=0)|| M(i)<2 || M(i)>512 )
        error('wrong modulation order')
    end
end
% Input the convolutional coding rate
code_rate=input('input the coding rate(2/3, 3/4)');
%check the correct coding rate
if (code_rate~=2/3 && code_rate~= 3/4)
     error('Enter the correct coding rate')
end
%Effective signal-to-noise ratio
SNR_eff = 10*log(lin_snr) + 10*log10(N/(N+N*CP));
for i=1:length(M)
 BER=zeros(1,length(SNR_eff));
for snr=1:length(SNR_eff)
    total_ber=0;
    for runs=1:niter
        % Data manupulation for the encoder input
        msg = randi([0 1],25600,1);%nbits*nblocks random data
        msg1=size(msg, 1);
        num_bits=msg1;
        num_bytes=num_bits/8;%number of byte
        %selection of the polynomial for the encoder
        switch(code_rate)
        case 2/3
         constlen=[3 3];
         codegen=[7 6 7  ; 7 4 5 ];
        case 3/4
          constlen=[3 3 3];
          codegen=[7 6 4 5;3 5 7 6;5 4 7 3];
          msg = randi([0 1],26112,1);
          msg1=size(msg, 1);
        end
```

```
% polynomial to trellis structure
t = poly2trellis(constlen, codegen);
% convolutionally encode binary data.
code = convenc(msg,t);
% Modulatation of the encoded message
if (M(i)<=4)
h=modem.pskmod(M(i));
else
h=modem.qammod(M(i));
end
ymod=modulate(h, code);
y=ymod';
% OFDM transmitter section
s3=size(y,2);
j=ceil(s3/N);
%serial to parallel conversion of symbols
y=reshape(y,j, N);
% Applaying IFFT,
ifft_sig=ifft(fftshift(y.'));
ifft_sig=transpose(ifft_sig);
% Appending cylic prefix
xt = [ifft_sig(:,[193:256]) ifft_sig];
%total bits per iteration
total_bits=size(xt, 1)*size(xt, 2);
% Concatenating multiple symbols to form a long vector
ynew=reshape(xt.',1,total_bits);
% Adding AWGN channel noise
ncode = awgn(ynew,snr, 'measured'); % Adding noise
ynoise=ncode;
% Receiver
% formatting the received vector into serial symbols
ncode=reshape(ncode.',size(xt,2), size(xt,1));
ncode=transpose(ncode);
% Removing the cyclic prefix
yt = ncode(:,[65:320]);
%Converting to freqency domain
fft_sig=fftshift(fft(yt.'));
fft_sig=transpose(fft_sig);
ff=size(fft_sig)
% Parallel to serial conversion for modulation
fft_sig=reshape(fft_sig, 1, j*N).';
```

```
        % demodulation
        if (M(i)<=4)
        w=modem.pskdemod(M(i));
        else
        w=modem.qamdemod(M(i));
        end
        z=demodulate(w, fft_sig);
        % Quantize to prepare for soft-decision decoding.
        dec=[0.01, 0.1, 0.3, 0.5, 0.7, 0.9, 0.999];% decision points
        qcode = quantiz(z,dec);
        % Traceback length
        tblen = 46;
        delay = tblen;
        % Convolutionally decode binary data using Viterbi algorithm
        decoded = vitdec(qcode,t,delay,'trunc','soft',3);
        % Compute bit error rate and number of bit errors
        [number, ratio]=biterr(decoded,msg);
        total_ber=total_ber+ratio;
    end % number of niter loop
    % compute average BER
    BER(snr)=total_ber/(niter);
end % snr loop
% Plot graphs
semilogy(SNR(1:end),BER(1:end),'-m*');
axis([0 40 10^-5 1])
grid on
hold on
xlabel('Signal-to-Noise Ratio(dB)')
ylabel('Bit Error Rate')
title('SNR vs BER')
end
```

Matlab code for BER comparison for 16QAM with different coding rates

```
% This code is prepared by Temalow Seife
% Department of Electrical Engineering
% Pan African University
% September 2017
% BER comparison for 16QAM with different coding rates
clc;
% specify the range of signal-to-noise ratio in dB
```

```
SNR=[0:30];
% linear SNR
lin_snr=10.^(SNR./10);
% number of iterations
nruns=5;
% Modulation orders
M=16;%M=2 is BPSK, M=4 is QPSK and for M>4 is M-ary QAM
% check the correct constellation size
for i=1:length(M)
   if ((rem(M(i),2)~=0)|| M(i)>512)
      error('wrong modulation order')
   end
end
% Input the convolutional coding rate
code_rate=input('input the coding rate(1/4, 1/3, 1/2, 2/3)');
if (code_rate~=1/4 && code_rate~= 1/3 && code_rate ~=1/2 && code_rate~=2/3)
      error('Enter the correct coding rate')
end
% ofdm specifications
N = 256; % fft size
n = 256; % number of data subcarriers
CP=1/4;%cyclic prefix
nbits = 256; % number of bits per OFDM block
nblocks = 10^2; % number of ofdm blocks
%Effective siganl-to-noise ratio
SNR_eff = 10*log(lin_snr)+ 10*log10(n/N) + 10*log10(N/(N+N*CP));
for i=1:length(code_rate)
 BER=zeros(1,length(SNR_eff));
for snr=1:length(SNR_eff)
   total_ber=0;
   for runs=1:nruns
      % Data manupulation for the encoder input
      msg = randi([0 1],25600,1);%nbits*nblocks
      msg1=size(msg, 1);
      num_bits=msg1;
      num_bytes=num_bits/8;%number of byte
      % Convolutionally encoding data
        if code_rate == 1/4
            constlen=3;% constraint length
            codegen=[6 5 7 4];% polynomial of the encoder
        elseif code_rate == 1/3
```

```
        constlen=3;
        codegen=[6 5 7];
    elseif code_rate == 1/2
        constlen=3;
        codegen=[6  7];
    elseif code_rate == 2/3
        constlen=[3 3];
        codegen=[7 6 7  ; 7 4 5 ];
    else
        constlen=3;
        codegen=7;
    end
% polynomial to trellis structure
t = poly2trellis(constlen, codegen);
code = convenc(msg,t); % onvolutionally encode binary data.
% Modulatation of the encoded message
h=modem.pskmod(M);
ymod=modulate(h, code);
y=ymod';
% OFDM transmitter section
s3=size(y,2);
j=ceil(s3/N);
%serial to parallel conversion of symbols
y=reshape(y,j, N);
% Applaying IFFT,
% ifft_sig=ifft(y.').';
ifft_sig=ifft(fftshift(y.')).';
size_sig=size(ifft_sig)
% Appending cylic prefix
xt = [ifft_sig(:,[193:256]) ifft_sig];
total_bits=size(xt, 1)*size(xt, 2);
% Concatenating multiple symbols to form a long vector
ynew=reshape(xt.',1,total_bits);
% Adding AWGN channel noise
ncode = awgn(ynew,snr, 'measured'); % Adding noise
ynoise=ncode;
% Receiver
% formatting the received vector into serial symbols
ncode=reshape(ncode.',size(xt,2), size(xt,1)).';
%Removing the cyclic prefix
yt = ncode(:,[65:320]);
```

```
        %Converting to freqency domain
        fft_sig=fftshift(fft(yt.')).';
        ff=size(fft_sig)
        % Parallel to serial conversion for modulation
        fft_sig=reshape(fft_sig, 1, j*N).';
        % demodulation
        w=modem.pskdemod(M);
        z=demodulate(w, fft_sig);
        % Quantize to prepare for soft-decision decoding.
        dec=[0.01, 0.1, 0.3, 0.5, 0.7, 0.9, 0.999];% decision points
        qcode = quantiz(z,dec);
        tblen = 46; delay = tblen; % Traceback length
        % Convolutionally decode binary data using Viterbi algorithm
        if (code_rate>0.5)
           decoded = vitdec(qcode,t,delay,'trunc','soft',3);
           [number, ratio]=biterr(decoded,msg);
        else
           decoded = vitdec(qcode,t,tblen,'cont','soft',3);
           % Compute bit error rate and number of bit errors
           [number,ratio] = biterr(decoded(delay+1:end),msg(1:end-delay));
        end
         total_ber=total_ber+ratio;
    end % number of runs loop
    % compute average BER
    BER(snr)=total_ber/(nruns/2);
end % snr loop
% Plot graphs
semilogy(SNR,BER);
axis([0 30 10^-6 1.4])
legend('1/4 code rate','1/3 code rate', '1/2 code rate', 'Uncoded msg');
grid on
hold on
xlabel('Signal-to-Noise Ratio(dB)')
ylabel('Bit Error Rate')
title('Comparison of 16QAM with different coding rate')
end
```