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Enhancing 802.11n Physical LayerUsing Beamforming

A Research Submitted in Partial fulfillment for the Requirements of the Degree of B.Sc. (Honors) in Electronics Engineering

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بسم الله الرحمن الرحيم

قال تعالى:

(اللَّهُ نُورُ السَّمَاوَاتِ وَالأَرْضِ مَثَلُ نُورِهِ كَمِشْكَاةٍ فِيهَا مِصْبَاحٌ الْمِصْبَاحُ فِي زُجَاجَةٍ الزُّجَاجَةُ كَأَنَّهَا كَوْكَبٌ دُرِّيٌّ يُوقَدُ مِن شَجَرَةٍ مُّبَارَكَةٍ زَيْتُونَةٍ لّا شَرْقِيَّةٍ وَلا غَرْبِيَّةٍ يَكَادُ زَيْتُهَا يُضِيءُ وَلَوْ لَمْ تَمْسَسْهُ نَارٌ نُّورٌ عَلَى نُورٍ يَهْدِي اللَّهُ لِنُورِهِ مَن يَشَاء وَيَضْرِبُ اللَّهُ الأَمْثَالَ لِلنَّاسِ وَاللَّهُ بِكُلِّ شَيْءٍ عَلِيمٌ) **صدق الله العظيم**

آية رقم 35 من سورة النور

To our beloved mothers and fathers….

Acknowledgement

First and foremost, we are very thankful to Allah for granting us the success and the ability to complete this project and for all the knowledge we acquired during the making of this work.

We would like to express our deep sense of respect and gratitude toward our supervisor *Dr.Jacqueline John George*for the valuable guidance, advices and her patience with us. Her willingness to motivate us contributed tremendously to our project.

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Last but not least, we would like to take this opportunity to thank our parents for their support and encouragementto reach this level in our life.

Abstract

Beamforming in general is a signal processing technique used in sensor arrays for directional signal transmission or reception. This is achieved by combining elements in a phased array in such a way that signals at particular angles experience constructive interference while others experience destructive interference.Such technologyis specified in the IEEE 802.11n specification and takes advantage of the multiple transmit antennas available in a multiple input, multiple output (MIMO) system.

Since the 802.11n suffers a lot of interference sources which decrease the signal to noise and interference ratio (SNIR) and also due to the fading and multipath problems, adaptive beamforming algorithms can stand out as an efficient solution to the above problems.

In this thesis MATLAB software was used to design a graphical user interface to test the performance oftwo types of adaptive beamforming algorithms;the Blind approach and the Non-Blind approach. The algorithm that resulted in a better performance was simulated in the 802.11n system using MATLAB SIMULINK.The results showed that adding beamforming techniques improve the performance of the system.

المستخلص

تشكيل الاشعاع بصورة عامة هو تقنية مستخدمة في أنظمة الهوائيات الذكية في ارسال الاشعاع في اتجاه معين و الغاء باقي الاتجاهات. يمكن استخدام هذه الهوائيات في صورة مصفوفة بحيث قد تتعرض الى تداخل او تشويش خارجي سواء كان هدام او بناء و من ثم التخلص منه عن طريق تصفير اتجاهاته. هذه التقنية معرفة في نظام (IEEE 802.11n) بجانب تقنية الهوائيات المتعددة في المرسل و المستقبل MIMO ( ).

يواجه نظام (IEEE 802.11n) العديد من التداخلات الخارجية و العوائق التي تؤثر سلبا في الاشارة المرسلة و نتيجة لذلك تقل نسبة الاشارة الى التدخل الخارجي بصورة كبيرة (SNIR) . تبرز خوارزميات تشكيل الاشعاع كطريقة فعالة لحل المشاكل المذكورة.

قمنا باختبار هذه الخوارزميات بواسطة برنامج الماتلاب باستخدام نظام واجهة المستخدم(GUI)و كما تم عمل مقارنة بين طرق التشكيل العمياءو طرق غير العمياء من عدة اعتبارات و تم الحصول على نتائج واعدة و من ثم قمنا باختيار افضل خوارزمية و طبقناها في نظام 802.11n بواسطة برنامج الماتلابسيميولينكمثبتة مدى التحسين الذي تستطيع القيام به تقنية تشكيلالاشعاع في نظام (IEEE 802.11n).

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List of Symbols

$AF(\emptyset)$	Antenna Array Factor.
***B*rx**	Receiver Filters Bandwidth.
***b*pl**	Number of Bits of the Payload.
***B*ts**	Number of Bits of the Training Sequence.
C	Steering Vector.
***C*r**	Coding Rate.
***CW*min**	Minimum Contention Window.
***CW*opt**	Optimum Contention Window.
D	Destination Node.
$E(\mathrm{w}, \varphi)$	Antenna System Field Pattern in the Azimuth Plane.
$F_d(\varphi)$	Equivalent Power Gain Pattern in the Azimuth Plane.
$G(\varphi)$	Antenna Power Gain pattern in the Azimuth Plane.
g	Weight Vector for the Terms of the Cost Function.
gl	Weight for the *l*-th Term of the Cost Function.
H	Complex Conjugate Transpose of a Vector or Matrix.
Hs(r)	Magnetic Complex Field.
i(w)	Cost Function.
j	Imaginary Unit.
j(w)	Mean Square Norm.
n(t)	Noise Signal
***N*rx**	Number of Receiving Antennas of a MIMO System.
***N*tx**	Number of Transmitting Antennas of a MIMO System.
***n*des**	Number of Desired Sources.
***n*int**	Number of Interferers.

***n*tx**	Number of Transmitting Sources.
***P*des**	Received Desired Signal Power.
***P*int**	Received Interference Power.
***P*rx**	Total Received Power.
***P*tx**	Transmitted Power.
R	Covariance Matrix
$\boldsymbol{R_a}$	Auxiliary Array Correlation Matrix
$\boldsymbol{r_{ma}}$	Cross Correlation between Auxiliary and main Arrays
$\boldsymbol{R_r}$	Reference Signal Covariance Matrix.
***R*t**	Radius of the Area Occupied by the Entire Network.
Rxx	Array Correlation Matrix.
SINRout	SINR at the Antenna System Output.
$\boldsymbol{\gamma LMS}$	LMS Step Size for the LMS Algorithm.
$\boldsymbol{\delta_{im}^{K}}$	Kronecker Delta.
$\boldsymbol{\lambda}$	Wavelength.
y(t)	Output of the Array.
α	Inter-Element Phase Shift.
w(*i*)	Vector of Antenna Array Excitations at Time Instant *i*.
X(t)	Input Signal.

Abbreviations

AP	Access Point
BER	Bit Error Rate
BSS	Basic Service Set
CMA	Constant Modulus Algorithm
DOA	Direction of Arrival
IDFT	Inverse Direct Fourier Transform
LAN	Local Area Network
LCMV	Linearly Constrained Minimum Variance
LMS	Least Mean Squares
LOS	Line of Sight
LS-CMA	Least Squares Constant Modulus Algorithm
MAC	Medium Access Control
MIMO	Multiple Input Multiple Output
MSE	Mean Square Error
MUSIC	Multiple Signal Classification
MVDR	Minimum Variance Distortionless Response
OFDM	Orthogonal Frequency Division Multiplexing
PER	Packet Error Rate
QAM	Quadrature Amplitude Modulation.
QPSK	Quadrature Phase Shift Keying.
RLS	Recursive Least squares
SDM	Spatial Division Multiplexing
SMI	Sample Matrix Inversion
STBC	Space Time Block Coding

Chapter One

Introduction

1.1 Background

Over the last decade, wireless communication networks have achieved major success and emerged as the key technology for enabling the mobile revolution. The speed, capacity and robustness of wireless communication keep improving every day, but several challenges remain. WLANs have become an important last-mile technology for providing internet access within homes and enterprises. In such indoor deployments, the wireless channel suffers from significant multipath scattering and fading that degrades performance. Indoor wireless networks operating in the 2.4 - 5 GHz spectrum have become popular last mile internet access networks using standards such as IEEE 802.11, WiMAX, etc.

More recently, several experimental works have started investigating the practical benefits of the smart antennas in indoor and outdoor wireless networks and are reporting promising results. Most works have focused on improving the link performance by coping layer through physical mechanisms.

Beamforming is a smart antenna technology that adjusts the transmissions at the transmitter to reinforce the signals received through multiple paths at the receiver. However, doing this requires the accurate estimation of the channel coefficients at the receiver and its knowledge at the transmitter which Wi-Fi clients are incapable of doing. The ability to modify the signal in a way that signal components get reinforced by the multipath channel has led to the popularity of smart antennas and their adoption in several standards. It is a closed-loop technique and it uses the channel information at the Tx to modify the transmitted signal such that the signals received through the multiple paths are reinforced at the Rx thereby improving the link signal to interference and noise ratio (SINR).

Consequently, the resulting beam pattern may not have the single main lobe structure (pointing in the direction of the Rx) of a directional antenna but results in better performance in multipath rich environments [3].

1.2 Problem Statement

802.11 band suffers from different types of interference at the indoor environment. The high gain of interference which causes the weakness of signal to interference and noise ratio (SINR) makes the throughput less than wired LANs. More further the fading and multi path affect the link performance.

1.3 Proposed Solution

In order to achieve greater performance in the physical layer the beamforming technique with multiple input –multiple output technology (MIMO) can provide such enhancement and can result in higher performance.

1.4 Objectives

The objectives of this thesis are;

- To compare the different adaptive beamforming algorithms.
- To use beamforming algorithm to improve the 802.11n link performance.
- To simulate the beamforming technique on 802.11n system model.

1.5 Methodology

MATLAB software will be used to design a Graphical User Interface to compare the performance of two adaptive beamforming approaches; the Blind and Non-Blind. The approach that provides the best performance will be tested in the physical layer of the 802.11n model using SIMULINK.

1.6 Thesis Outlines

This thesis consists of five chapters as follow;

Chapter One: Introduction.

Chapter Two: Literature Review.

Chapter Three: Adaptive Beamforming.

Chapter Four: Simulation and Results.

Chapter Five: Conclusion and Recommendations.

Chapter Two

Literature Review

2.1 Introduction

In wired networking, the biggest innovation of the last two decades was the introduction of Ethernet switching, which dramatically increased network capacity by moving from relatively large collision domains (a multi-port hub) to minimum-sized collision domains (a single port). Wireless LANs have offered great benefits to network users, primarily in the form of mobility, but in return have expanded the collision domain from an Ethernet switch port to the coverage area of an access point [3].

The IEEE 802.11 series of standards for WLAN has shown great success since it started in the late 1990s (also known as Wi-Fi). Nowadays, almost every laptop or smart phone has a built-in WLAN card. However, until a recent time, these WLANs have been mainly used for internet browsing, email, and other light load applications. Today, more is needed from the wireless technology; users want to be able to stream HD videos, music, or transfer large amounts of data. These demands require changes to the technology. Researches has been made covering this area and proved that some smart antennas technologies such as Beamforming and its application in the form of multi-user MIMO in 802.11 has the potential to change how networks are built and increase capacity well beyond the headline rate of the network equipment. In essence, multi-user MIMO works by taking advantage of beamforming to send frames to spatially diverse locations at the same time, building the first standardized version of an 802.11 “switch.”[3]

2.2 Related Works

A lot of researcheshave been done in this area such as;

- In [1] the author discussed how multiple antennas are gaining increased interests because of their dramatic increase in capacity and speed of data transmissions. The author gave a brief look in multiple antenna techniquesin wireless communication system with the main focus on MIMO (Multiple-Input Multiple Output).
- In [2] the author represented three types of antenna arrays geometries in wireless communication systems and showed how these antenna arrays react when used with different smart antenna's algorithms such as LMS and RLS.
- In [3] the authors discussed the advantages of the IEEE 802.11n over the previous technologies and how it's still compatible with the other standards, the authors also represented the technical aspects of the IEEE 802.11n and showed how technologies like the multiple-input multiple output (MIMO) technology can provide a dramatic improvements in so many different aspects.
- In [4] the author discussed the adaptive beamforming technique and investigated some adaptive beamforming blind algorithms like the constant modulus algorithm (CMA) and the least square constant modulus algorithm (LS-CMA) and other Non-blind algorithms like the Least Mean Squares (LMS) and the Recursive Least Squares (RLS) ,the author also made a comparison between the convergence time in both approaches.
- In [5] the authors discussed some blind algorithms (CMA and LS-CMA) and other non-blind algorithms (SMI, LMS and RLS) and made a comparison between their performance and some

parameters such as the convergence rate, nulling the multi-path and the number of iterations.

2.3 Overview on 802.11

IEEE 802.11 is a set of media access control (MAC) and physical layer (PHY) specifications for implementing wireless local area network (WLAN) computer communication in the 2.4, 3.6,5, and 60 GHz frequency bands[3].

The 802.11 family consists of a series of half-duplex over-the-air modulation techniques that use the same basic protocol. 802.11b was the first widely accepted one, followed by 802.11a, 802.11g and 802.11n. The 802.11a operates in the 5 GHz band with a maximum net data rate of 54 Mbit/s while the 802.11b standard has a maximum raw data rate of 11 Mbit/s. Devices using 802.11b experience interference from other products operating in the 2.4 GHz band. The 802.11g standard works in the 2.4 GHz band (like 802.11b), but uses the same OFDM based transmission scheme as 802.11a. It operates at a maximum physical layer bit rate of 54 Mbit/s as shown in table (2.1).
802.11n is an amendment that improves upon the previous 802.11 standards by adding multiple-input multiple-output antennas (MIMO). 802.11n operates on both the 2.4 GHz and the lesser-used 5 GHz bands. Support for 5 GHz bands is optional. It operates at a maximum net data rate from 54 Mbit/s to 600 Mbit/s. 802.11n established major improvements in both performance and reliability and also managed to have backward compatibility with 802.11a and 802.11b/g equipment[5][8].

Table 2.1: IEEE802.11 a/b/g/n parameters

IEEE WLAN standard	Physical Layer	Modulation Technique	Space dimension	Channel bandwidth	frequency
802.11b	11Mbps	DSSS/CCK	1	20MHz	2.4GHz
802.11a	54Mbps	OFDM	1	20MHz	5GHz
802.11g	54Mbps	DSS/CCK/OFDM	1	20MHz	2.4GHz
802.11n	600Mbps	DSS/CCK/MIMO-OFDM	1,2,3 or 4	20MHz/40MHz	2.4GHz/5 GHz

2.4 IEEE 802.11n Standard

In October 2009, the IEEE 802.11n was published to public. Most importantly, the MAC of IEEE802.11n brought in MIMO-OFDM technique [3]. By implementing spatial diversity using array antennas in the OFDM system, the signal quality is improved and the multipath capacity is increased. The effective transmission speed is dramatically increased with carrier frequencies of 2.4GHz and 5GHz as shown in table (2.2).

The IEEE802.11n amendment clearly describes MIMO-OFDM in high throughput mode. In order to raise throughput of the entire network, IEEE802.11n optimizes MAC protocol, with some improvements. It supports a modified OFDM technique. By using higher maximum code rate and wider bandwidth, the OFDM of 802.11a/g is expanded.

IEEE802.11n improves throughputs and transmission rate. The protocol applies 2.4GHz and 5GHz frequency bands, as well as the bandwidth of 20MHz and 40MHz as illustrated in table 2. Utilizing the improvement of

MIMO technique, IEEE 802.11n supports Space-time Block Coding and Beam Forming. The protocol supports 4*4:4 antennas layout, which means the maximum number of transmitting antennas, is 4, the maximum number of receiving antennas is 4, and there are up to 4 data streams.

MIMO not only enhances the capability of receivers to extract useful information from transmitting signals with exploiting the multipath signals diversity. Moreover, Spatial Division Multiplexing (SDM) used in MIMO can realize transporting multipath independent signals on the same frequency. Apart from the mentioned properties, IEEE 802.11n has very good backward compatibility. It offers a kind of mixed mode, and allows IEEE 802.11a or IEEE 802.11g to be embedded in the transmission frame [3].

Table 2.2: Main parameters of IEEE 802.11n protocol

Carrier Frequency	2.4GHz/5GHz
Modulation Type	BPSK/QPSK,16 QAM,64 QAM
Bandwidth	20MHz/40MHz
Coding Technique	LDPC/Convolutional Code
Number of antennas	1Tx, 2Tx,3Tx,4Tx
Spatial Streams	1,2,3,4
Peak Data Rate	600Mbps(4 spatial streams, 40MHz bandwidth)
Training Sequence Length	1.6 µs

2.4.1 IEEE 802.11n Transmitter

The IEEE 802.11n transmitter is shown in figure (2.1). By using multiple antennas at the transmitter and the receiver, both the throughput and the range of the reception can be improved (MIMO).

The transmitter is composed of Scrambler, Encoder, parser, FEC encoder, Stream parser, Interleaver, Constellation mapper, Space time block encoder, Spatial mapper, IDFT, Guard insertion and Windowing.

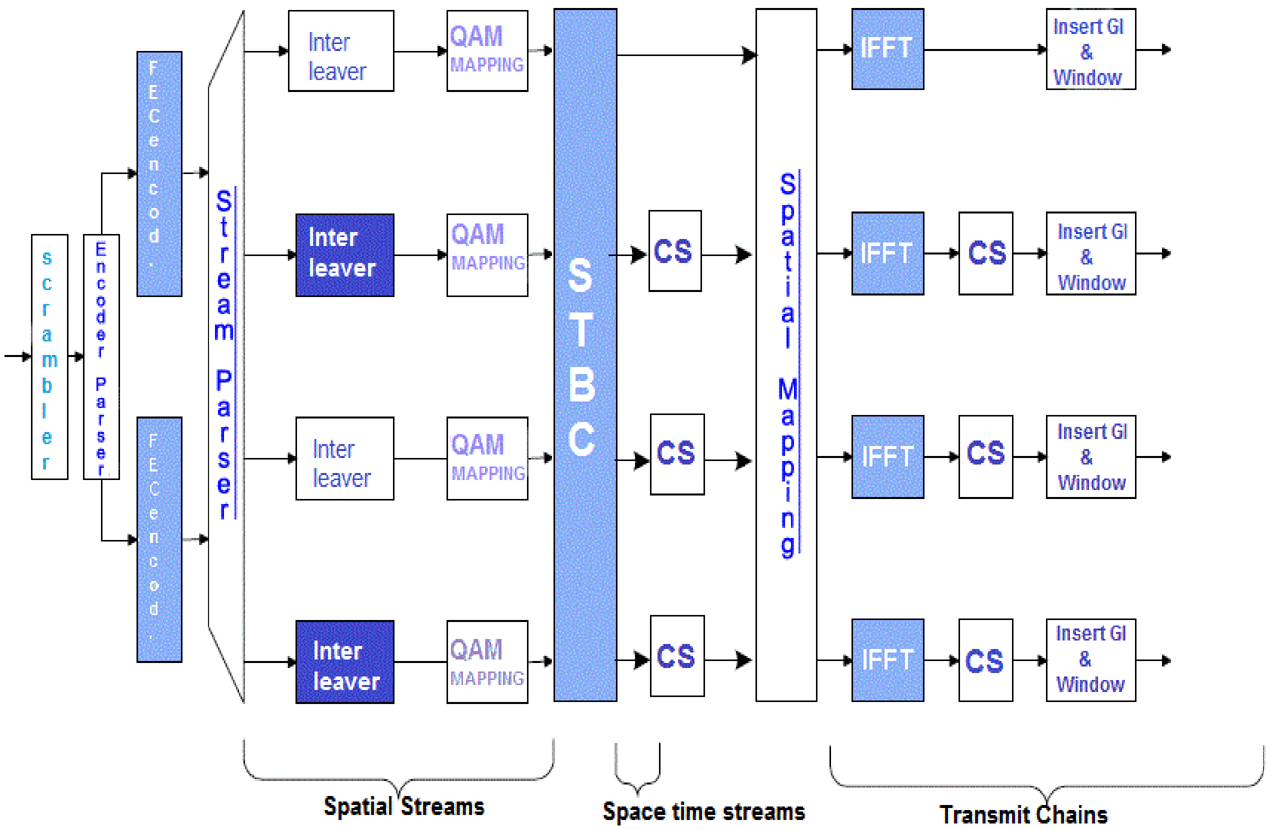

Figure 2.1: 802.11n transmitter

- The **scrambler** scrambles the data to prevent long sequences of zeros or ones.
- **Encoder parser** de-multiplexes the scrambled bits among NES (number of FEC encoders) FEC encoders.

- **FEC encoder** encodes the data to enable error correction-an FEC encoder may include a binary convolution encoder followed by a puncturing device, or an LDPC encoder.
- **Stream parser** divides the outputs of the encoders into blocks that are sent to different interleaver and mapping devices. Bits to the input of these interleavers are called as spatial streams.
- If BCC encoding is to be used, the **interleaver** interleaves the bits of each spatial stream (changes order of bits) to prevent long sequences of adjacent noisy bits from entering the BCC decoder.
- Constellation mapper maps the sequence of bits in each spatial stream to constellation points (complex numbers).
- Constellation points from Nss (spatial streams) are spread into Nsts (space time streams) using a space time block code, whereby Nss less than Nsts.
- The **spacial mapper** maps space time streams to transmit chains. This may include one of the following:
    I. Direct mapping: constellation points from each space time stream are mapped directly onto the transmit chains (one-to-one mapping).
    II. Spatial expansion: constellation points multiplied by matrix will expand the points to produce the input for all the transmit chains.
    III. Beam forming: It is similar to spatial expansion, where vector of constellation points from all the space time streams are multiplied by a matrix of steering vectors.
- **Inverse Discrete Fourier Transform (IDFT):** converts a block of constellation points to a time domain block.

- **Windowing** smoothes the edges of each symbol to increase spectral decay.

2.4.2 802.11n with MIMO

802.11n with MIMO is an extension of the earlier standard that adds the use of multiple antenna techniques at the physical layer. The IEEE ratified the 802.11n standard in September 2009, but the physical layer details have been finalized for years. The way 802.11n uses multiple antennas is quite different than earlier standard which called 802.11a/g access points (APs) that had multiple antennas sticking out of the box. Those APs would typically choose the best antenna to send or receive a packet, but still use a single antenna at a given moment. In terms of wireless signal processing, they are still SISO systems [3].

With 802.11n, multiple antennas at the transmitter and/or receiver are used at the same time (and on the same frequency band). To enable this, transmitters and receivers must have multiple RF processing chains to go with their multiple antennas; the techniques used are signal processing techniques implemented in the physical layer hardware with some amount of high-level control available to the driver. This processing is the hallmark of a MIMO system represented in figure (2.3).

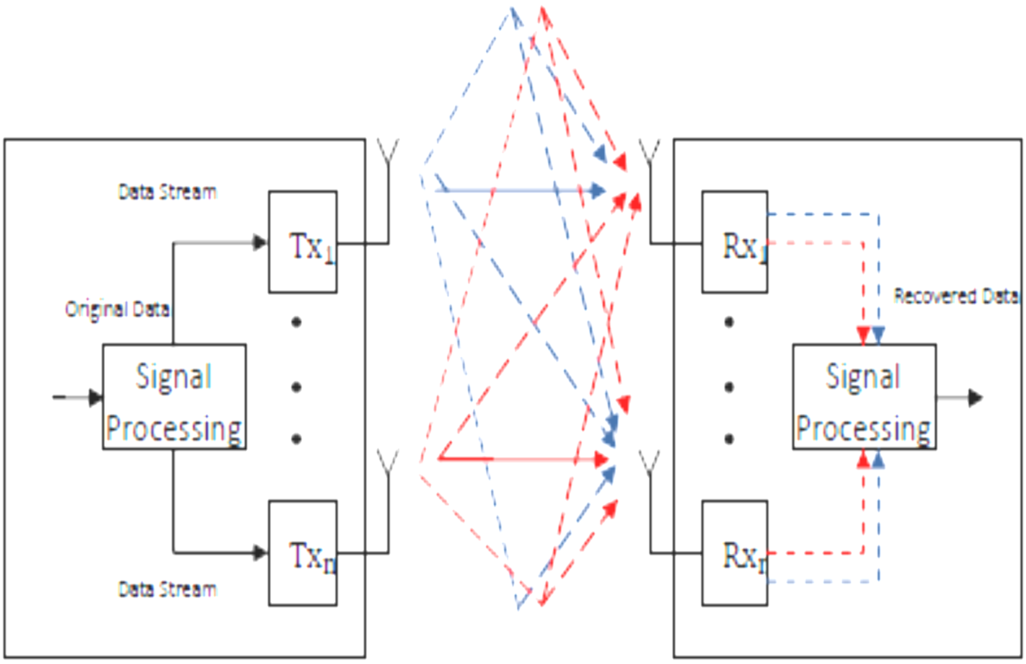

Figure 2.2: MIMO Wireless Communication System

MIMO is an important part of the IEEE802.11n standard and is also widely used in today's wireless communication. MIMO can also provide better capacity and potential of improved reliability compared to single antenna channels. And the combination of MIMO and OFDM is a very effectual way to achieve high efficiency spectral wideband systems.

To put the role of multiple antennas in 802.11n in context, consider that the highest data rate in 802.11a/g is 54 Mbps and the highest data rate in 802.11n is 600 Mbps. This is an increase of a factor of 11. Of this, a factor of four comes from the use of four antennas. This forms the bulk of the increase and is easily the largest single factor. Another factor of two comes from simply using double width channels of 40 MHz instead of 20 MHz. The remaining improvement, about 40%, comes from tweaking the OFDM and coding constants to shave overhead [6].

Multipath propagation can lead to fading problems. Components with the same phase will be added constructively, while components with opposite phase will be added destructively.For a MIMO configuration system as shown in figure (2.4) there are two ways to solve the problem, Spatial Diversity and Spatial Multiplexing.Spatial Diversity is the idea that, in case the antennas are spaced apart enough, the fading problem will occur independently. By always selecting the antenna with the best channel, or (better) combining the one with appropriate weights, the probability of a poor reception (signal outage) is dramatically reduced. The communication will be more stable, but the data rate can't be increased so much this way. Spatial multiplexing, on the contrary, increases the data rate but do not make the transmission system more robust. The data will be separated into several streams, and then these streams will be transmitted independently through separate antennas. Because they share the same channel, it is possible that during the transmission they will mutually affect each other. To solve the problem, the receiver can either make channel estimation or broadcast the channel performance through a special feedback loop. Since there are several parallel channels transmitting independent streams at the same time, the capacity can be increased several times [6].

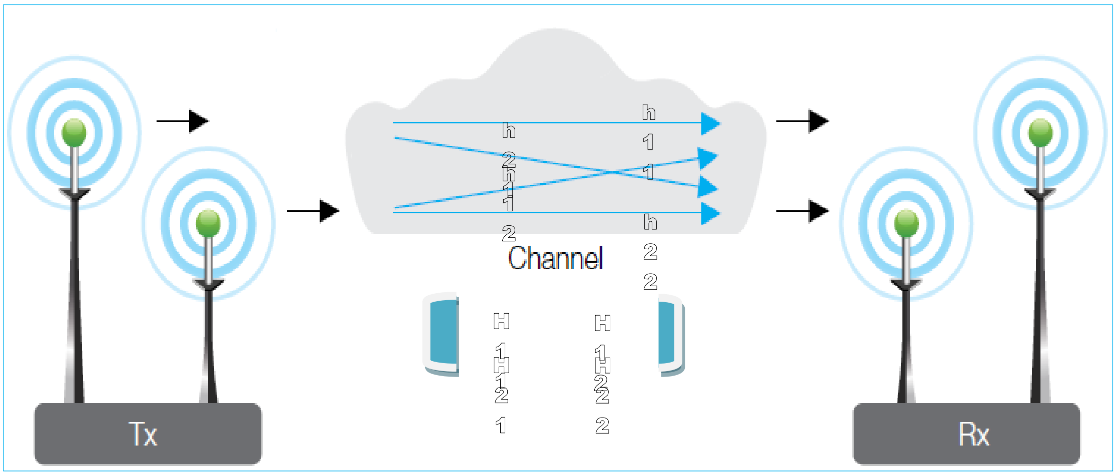

Figure 2.3: MIMO 2x2 antenna configuration

2.5 MIMO Geometries Models

The multiple input multiple output (MIMO) system consists of a number of elements which are arranged in different geometries (like Linear, Circular etc.,) and whose weights are adjusted with signal processing techniques and evolutionary algorithms to exploit the spatial parameters of wireless channel characteristics under noisy environment. [4]

2.5.1 Linear Array Geometry

For the array shown in Figure (2.4) the array factor, for a linear array of N elements with an inter-element spacing d, the array factor is given by:

$$AF(\theta) = \sum_{n=0}^{N-1} \omega_n e^{jnkdcos(\theta)} \quad (2.1)$$

Where:

ω = complex array weight at element n.

θ = angle of incidence of electromagnetic plane wave from array axis.

k = wave number (2π/λ).

λ = wavelength.

Let M be the number of plane waves, impinging on the array from directions (θ_1, θ_2,....,θ_m), as shown in Fig.2.4. The received signal at the element can be given as:

$$x_n(t) = \sum_i^M S_i(t) e^{-j(i-1)nkdsin(\theta_i)+n_n(t)} (2)$$

Here S1 (t) is the desired signal, M (t) is the interference signal and $n_n(t)$ is the noise signal received at the element.

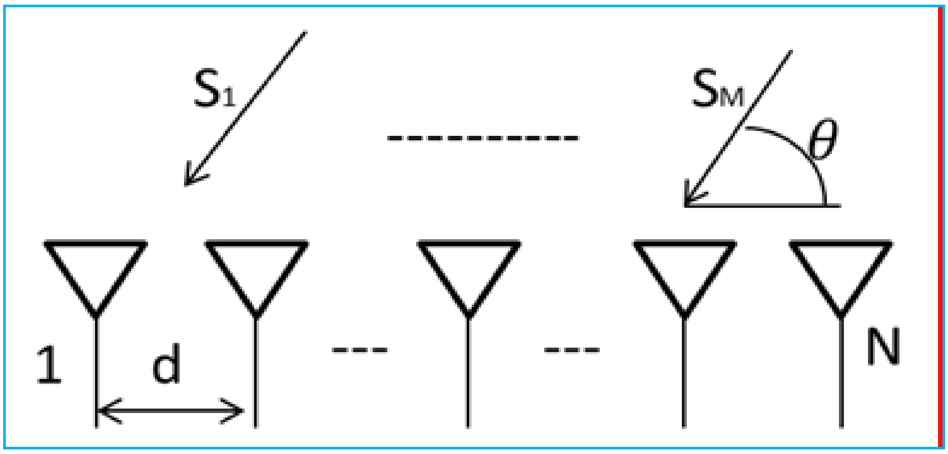

Figure 2.4: Linear array geometry

2.5.2 Circular Array Geometry

Figure (2.5) shows a circular array of N elements in the x-y plane. The nth array element is located at the radius 'a' with the phase angle∅n [4]. To direct the peak of the main beam in the ($\emptyset_0$,θ_0) direction, the array factor is given by:

$$AF=\sum_{n=1}^N \omega_n e^{-jka[\sin(\theta)\cos(\emptyset-\emptyset_n)-\sin(\theta_0)\cos(\emptyset-\emptyset_n)]} (3)$$

Where

ω_n = excitation coefficients (amplitude and phase) of nth element.

$\emptyset_n$ = 2п (n/N) = angular position of nth element on x-y plane.

ϴ = angular position of nth element on y-z plane.

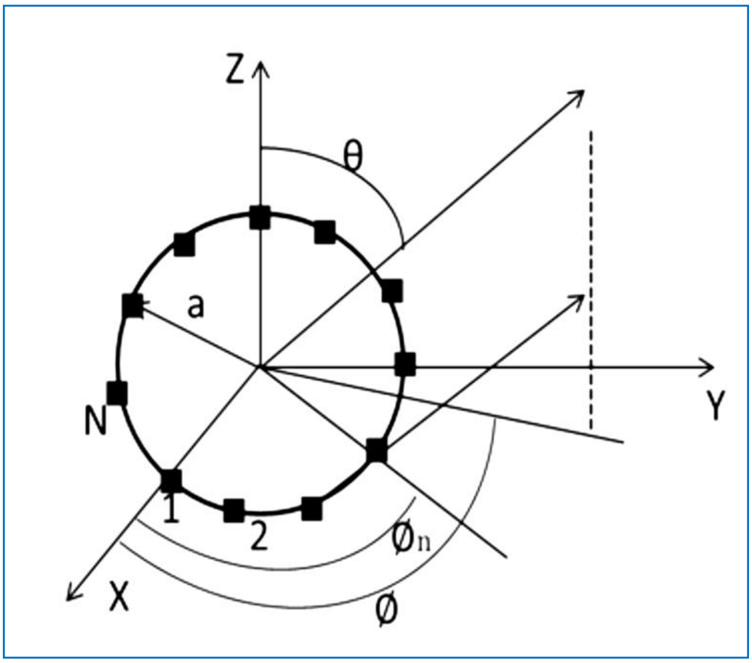

Figure 2.5: Circular array geometry of N elements

2.5.3 Planar Array Geometry

Figure (2.6) depicts a rectangular array in the x-y plane. The planar array can be viewed as M linear arrays of N elements or N linear arrays of M elements each. The pattern multiplication principle is used to find the pattern of the entire geometry [4].The array factor is given by:

$$\sum_{m=1}^{M}\sum_{n=1}^{N}\omega_{mn}e^{j[(m-1)(\varphi x+\beta x)+(n-1)(\varphi y+\beta y)]} \quad (4)$$

Where:

$$\varphi x = kdxsin\theta cos\varphi$$

φy =kdysinθsinφ

βx = -$kdxsin\theta cos\varphi$

βy = -$kdysin\theta sin\varphi$

βx&βy are phase delays, which are used to steer the beam in desired direction.

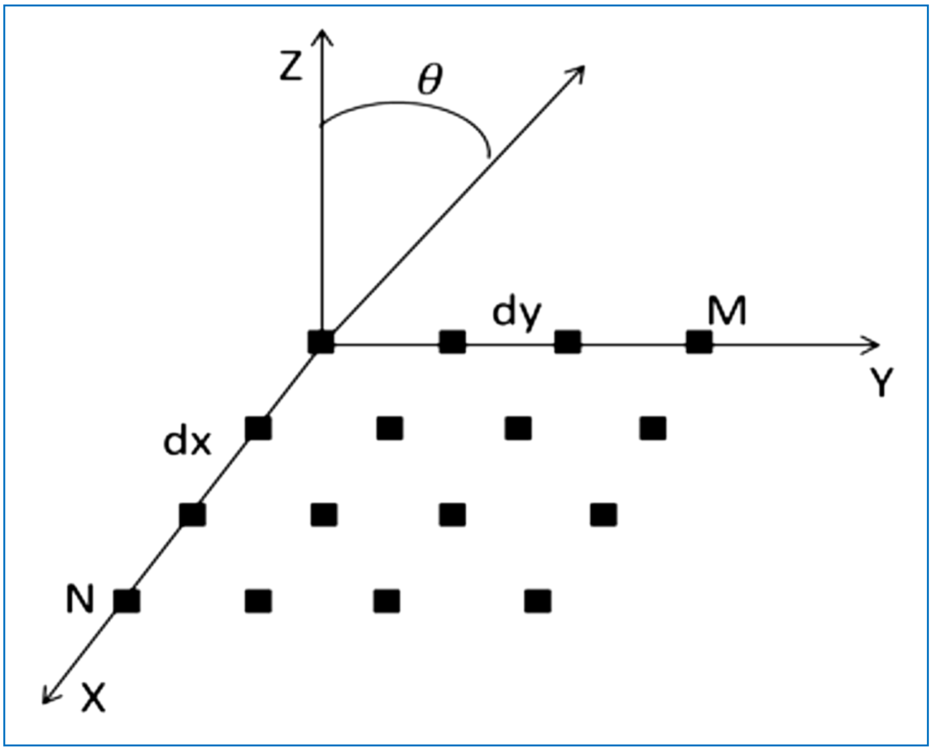

Figure 2.6: Planar array geometry

Chapter Three

Adaptive Beamforming

3.1 Introduction

Adaptive Beamforming is a technique in which an array of antennas is exploited to achieve maximum reception in a specified direction by estimating the signal arrival from a desired direction (in the presence of noise) while signals of the same frequency from other directions are rejected. This is achieved by varying the weights of each of the sensors (antennas) used in the array it is generally accomplished by phasing the feed to each element of an array so that signals received or transmitted from all elements will be in phase in a particular direction. The phases (the inter-element phase) and usually amplitudes are adjusted to optimize the received signal [5].

Beamforming basically uses the idea that, though the signals emanating from different transmitters occupy the same frequency channel, they still arrive from different directions. This spatial separation is exploited to separate the desired signal from the interfering signals. In adaptive beamforming the optimum weights are iteratively computed using complex algorithms based upon different criteria [3]. The array factor for an N-element equally spaced linear array is given as:

$$AF(\emptyset) = \sum_{N=0}^{N-1} A_n e^{jn(\frac{2\pi d}{\lambda} cos\emptyset + \alpha)} \quad (3.1)$$

Where N represents the number of antennas and $A_n$represents the array element. Figure (3.1) shows four elements linear array antenna where AF is the array factor for the equally spaced linear geometry.

Variable amplitude excitation is used. The inter-element Phase shift is given by:

$$\alpha = -\frac{2\pi d}{\lambda 0} cos\emptyset_0 \quad (3.2)$$

Where φ_0 is the desired beam direction. At wavelength λ_0 the phase shift corresponds to a time delay that will steer the beam to φ_0.

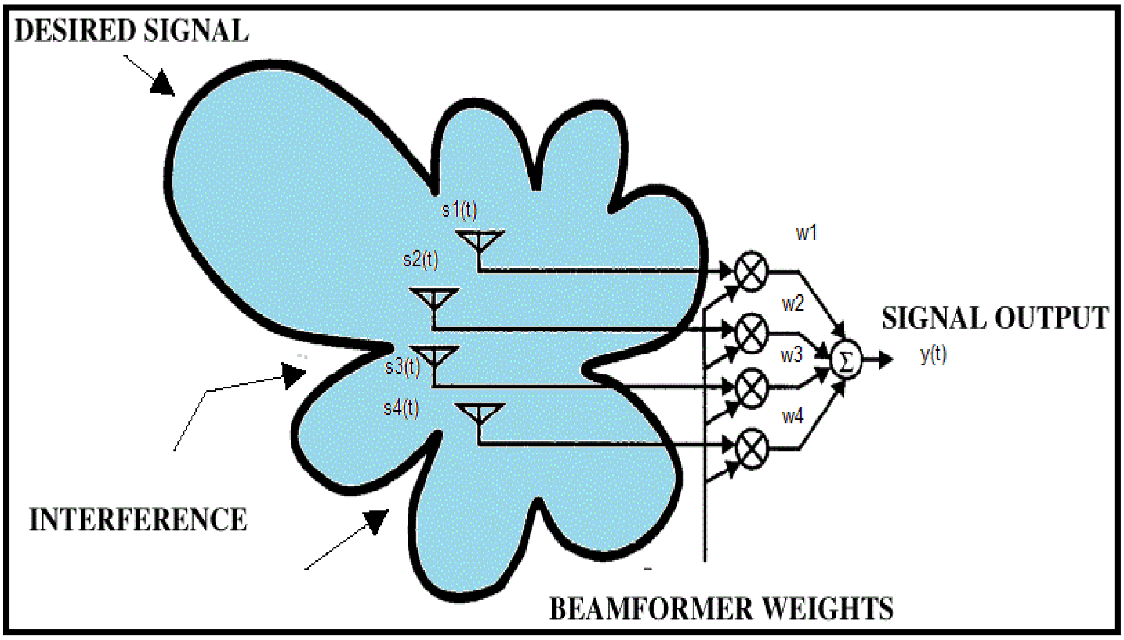

Figure 3.1: An Adaptive Array System

The output of the array y(t) with variable element weights is the weighted sum of the received signals Si(t) at the array elements and the noise n(t) the receivers connected to each element. The weights iteratively computed based on the array output y(t) reference. Signal d(t) that approximates the desired signal, and previous weights. The reference signal is approximated to the desired signal using a training sequence or a spreading code, which is known at the receiver. The format of the reference signal varies and depends upon the system where adaptive beamforming is implemented [2][5]. The reference signal usually has a good correlation with the desired signal and the degree of correlation influences the accuracy and the convergence of the algorithm. The array output is given by:

$y(t) = W^H X(t)$(3.3)

Where X(t) is the input signal.

3.2 Traditional Adaptive Beamforming Approaches

The following sections explains various traditional beamforming approaches [5].

3.2.1 Side Lobe Cancellers

This simple beamformer is shown in figure 3.2. It consists of a main antenna and one or more auxiliary antennas. The main antenna is highly directional and is pointed in the desired signal direction. It is assumed that the main antenna receives both the desired signal and the interfering signals through its side lobes. The auxiliary antenna primarily receives the interfering signals since it has very low gain in the direction of the desired signal. The auxiliary array weights are chosen such that they cancel the interfering signals that are present in the sidelobes of the main array response.

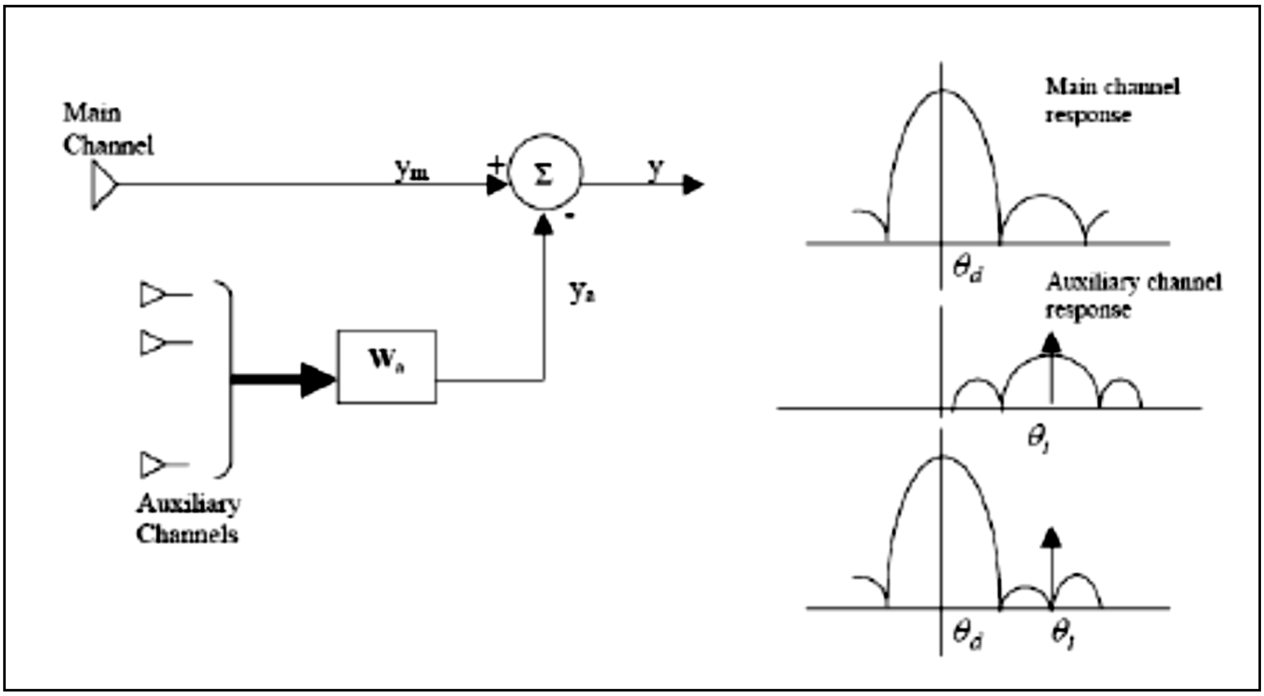

Figure 3.2: Sidelobe canceller beamforming

If the responses to the interferers of both the channels are similar then the overall response of the system will be zero, which can result in white noise. Therefore the weights are chosen to trade off interference suppression for white noise gain by minimizing the expected value of the total output power.

The optimum weights in figure (3.2) which correspond to the sidelobe canceller's adaptive component are:

$W_a = Ra^{-1} r_{ma}$(3.4)

$R_a = E\{X_a X_a^H\}$is the auxiliary array correlation matrix and the vector r_{ma} is the cross correlation between auxiliary array elements and the main array.

This technique is simple in operation but it is mainly effective when the desired signal is weaker compared to the interfering signals since the stronger the desired signal gets (relatively). Its contribution to the total output power increases and in turn increases the cancellation percentage. It can even cause the cancellation of the desired signal.

3.2.2 Linearly Constrained Minimum Variance (LCMV)

Most of the beamforming techniques discussed require some knowledge of the desired signal strength and also the reference signal. These limitations can be overcome through the application of linear constraints to the weight vector. LCMV spatial filters are beamformers that choose their weights so as to minimize the filter's output variance or power subject to constraints. This criterion together with other constraints ensures signal preservation at the location of interest while minimizing the variance effects of signals originating from other locations[5][7].

In LCMV beamforming the expected value of the array output power is minimized as follows:

$$E\{|y|^2\} = w^H R_x w \text{minimizes subject to } C^H w = f;$$

Where Rx denotes the covariance matrix of x(t), C is the constraint matrix which contains K column vectors and is the response vector. The optimum weights are given by:

$$w_{opt} = {R_x}^{-1} C (C^H {R_x}^{-1} C)^{-1} f \quad (3.5)$$

This beamforming method is flexible and does not require reference signals to compute optimum weights but it requires computation of a constrained weight vector.

3.2.3 Null Steering Beamforming

Unlike other algorithms null steering algorithms do not look for the signal presence and then enhance it, instead they examine where nulls are located or the desired signal is not present and minimize the output signal power. One technique based on this approach is to minimize the mean squared value of the array output while constraining the norm of the weight vector to be unity [5].

$$min_w \, w^H R w \text{Subject to } w^H C = 1 \quad (3.6)$$

The matrix A, a positive-definite symmetric matrix serves to balance the relative importance of portions of the weight vectors over others. The optimum weight vector must satisfy the following equation:

$Rw = -\lambda Aw$ (3.7)

Where:

H is a Complex conjugate transpose of a vector or matrix.

R is the covariance matrix

C is the steering vector

3.2.4 Sample Matrix Inversion (SMI) Algorithm

In this algorithm the weights are chosen such that the mean-square error between the beamformer output and the reference signal is minimized.[5] The mean square error is given by

$$E\lfloor\{r(t) - w^H x(t)\}^2\rfloor = E[r^2(t)] - 2w^H R_r + w^H R_m w \qquad (3.8)$$

Where x(t) is the array output at time t; r(t) is the reference signal;R_m is the signal covariance matrix;R_r is the reference signal covariance matrix. The weight vector, for which equation (8) becomes minimum, it is obtained by setting its gradient vector with respect to, to zero

$$\nabla_w\{E\lfloor\{r(t) - w^H x(t)\}^2\rfloor\} = -2R_r + 2R_m w = 0 (3.9)$$

Therefore,

$w_{opt} = {R_m}^{-1} R_r$(3.10)

The optimum weights can be easily obtained by direct inversion of the covariance matrix. This algorithm requires a reference signal and is computational intensive. It is definitely faster than LMS.

3.3Adaptive Beamforming Approaches

Adaptive algorithms can be classified into two categories; Non-Blind Adaptive algorithms and Blind Adaptive Algorithms [5].

Non-blind adaptive algorithms need statistical knowledge of the transmitted signal in order to converge to a weight solution. This is typically accomplished through the use of a pilot training sequence sent over the channel to the receiver to help identify the desired user. On the other hand, blind adaptive algorithms do not need any training, hence the term "blind". They attempt to restore some type of characteristic of the transmitted signal in order to separate it from other users in the surrounding environment. Figure (3.3) shows an illustration of an adaptive beamforming system.

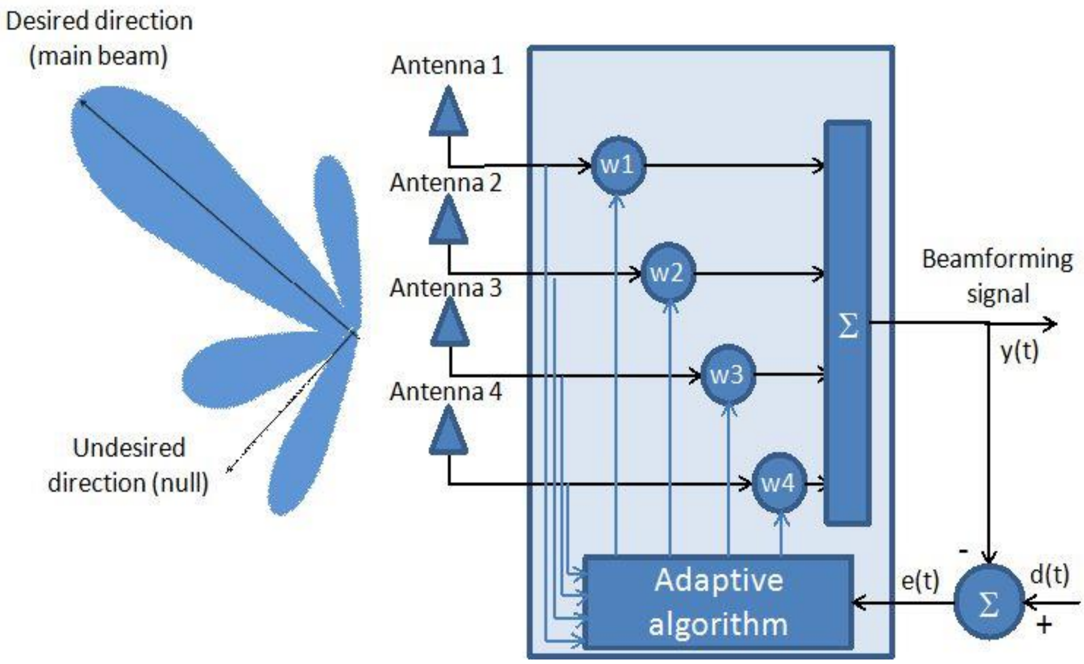

Figure 3.3: Adaptive Beamforming system

3.3.1 Non-Blind Adaptive Beamforming Algorithms

Non-blind adaptive algorithms require a training sequence, d(k) in order to extract a desired user from the surrounding environment. This in itself is undesirable for the reason that during the transmission of the training sequence, no communication in the channel can take place. This dramatically reduces the spectral efficiency of any communications system. Additionally, it can be very difficult to understand the statistics of the channel in order to characterize a reasonable estimate of d(k) needed to accurately adapt to a desired user. With this in mind, the following summarizes the basic concepts of non-blind adaptive algorithms [5][7].

1. **Adaptive Sample Matrix Inversion (SMI)**

In practice, the mobile channel environment is constantly changing making estimation of the desired signal quite difficult. These frequent changes will require a continuous update of the weight vector, which would be difficult to produce for reasons already stated

Sample Matrix Inversion (SMI) is an estimate to the Weiner solution through the use of time averages. Suppose K time samples of the received signal are taken to form an input data matrix, X, defined by:

$$X = [\bar{x}(1), \bar{x}(2), \cdots, \bar{x}(K)] \quad (3.11)$$

An estimate of the N*x*N covariance matrix is given by:

$$\hat{R}_{xx} = \frac{1}{K}\sum_{k=1}^{K} \bar{x}^*(k)\bar{x}^T(k) \quad (3.12)$$

Which can be expressed in matrix form as:

$$\hat{R}_{xx} = \frac{1}{K} X^* X^T \quad (3.13)$$

Likewise the estimate of the Nx1 cross-correlation vector can be expressed as:

$\hat{r}_{xd} = \widehat{\frac{1}{K}\left(X\bar{d}^{T}\right)}^{*}$(3.14)

Where: $\hat{d}$ is the desired signal vector given by:

$\bar{d} = [d(1), d(2), \dots, d(K)]$(3.15)

Then the estimated optimum weight vector is given by:

$\hat{\hat{w}} = \hat{R}xx^{-1}\hat{\hat{r}}_{xd}$(3.16)

Where $\hat{R}xx$ is the array correlation matrix.

The SMI method is a particularly desirable algorithm to determine the complex weight vector due to the fact that the convergence rate is usually greater than a typical LMS adaptive array and is independent of signal powers, AOA's and other parameters and it operates at its best when the number of elements in the adaptive ray is small [4].

2. Least Mean Squares (LMS)

The LMS algorithm estimates the gradient of the error signal, e(k), by employing the method of steepest descent, which is summarized below. Let k w represent the Nx1 weight vector at time sample k. The weight vector can be updated at time sample k+1 by offsetting k by some small quantity which drives the weight vector one step closer to the bottom of the performance surface [5]. This small quantity is the value of the error gradient for time sample k, which is given as:

$$\bar{w}(k+1) = \bar{w}(k) + 2\mu E[\bar{x}(k)d^{*}(k) - \bar{x}(k)\bar{x}^{H}(k)\bar{w}(k)]\text{(3.17)}$$

$$=\bar{w}(k+1) = \bar{w}(k) + 2\mu E[\bar{x}(k)\{d(k) - y(k)\}^*] \qquad (3.18)$$

$$=\boldsymbol{\bar{w}(k+1) = \bar{w}(k) + 2\mu E[\bar{x}(k)e^*(k)]} \qquad (3.19)$$

Dropping the expectation operator in equation (3) allows the algorithm to update the weights as the data are sampled, which is given by:

$$\bar{w}(k+1) = \bar{w}(k) + 2\mu\bar{x}(k)e^*(k) \qquad (3.20)$$

Where: μ is the gradient constant.

The LMS algorithm is a very desirable algorithm in many circumstances. One of its great weaknesses is its slow convergence rate.

3. Recursive Least Squares (RLS)

Contrary to the LMS algorithm, which uses the steepest descent method to determine the complex weight vector, the Recursive Least Squares (RLS) algorithm uses the method of least squares. The weight vector is updated by minimizing an exponentially weighted cost function consisting of two terms:

- Sum of weighted error squares.
- A regularization term.

  Together the cost function is given by:

$$\varepsilon(k) = \sum_{i=1}^{k} \lambda^{k-i} |e(i)|^2 + \delta\lambda^k \|\bar{w}(k)\|^2 \qquad (3.21)$$

Where: e(i) is the error function, and λ is called the forgetting factor, which is a positive constant close to, but less than one. In a stationary environment, λ = 1 corresponds to infinite memory. Expanding equation 3.23 and collecting terms, the weight summation of the covariance matrix for the received signal,

$\bar{w}(k) = \bar{w}(k-1) + \bar{k}(k)e^{*}(k)$(3.22)

At time sample k = 1, the initial conditions for the RLS algorithm can be described by:

- Set $\bar{w}(0)$ to either a column in vector of all zeros an NxN identity matrix,I.
- Setting k=0 in equation 4.27 yields : Φ(0) = δ I = P(0),

Where δ=small positive constant for high SNR.
large positive constant for low SNR.

3.3.2 Blind Adaptive Beamforming Algorithms

Blind adaptive algorithms do not need a training sequence in order to determine the required complex weight vector. They attempt to restore some type of property to the received signal for estimation. A common property between polar NRZ waveforms and DS-SS signals is the constant modulus of received signals [5][10].

1. Constant Modules Algorithm (CMA)

A typical polar NRZ signal possesses an envelope which is constant, on average. Using the constant modulus algorithm (CMA) which is a blind technique, the envelope of the adaptive array output, y(k), can be restored to a constant by measuring the variation in the signal's modulus and minimizing it by using the cost function [5][10].
A recursive update method to determine the proper weights by utilizing the method of steepest descent for the following cost function:

$J(k) = E[|y(k) - 1|^2]$ (3.23)

Taking the gradient of the above cost function yields:

$$\nabla\big(j(k)\big) = E\left[(|y(k) - 1|)\frac{\partial|y(k)|}{\partial\bar{w}^*(k)}\right] \quad (3.24)$$

$$\nabla\big(j(k)\big) = E\left[(|y(k) - 1|)\frac{\partial(y(k)y^*(k))^{1/2}}{\partial\bar{w}^*(k)}\right](3.25)$$

$$\nabla\big(j(k)\big) = E\left[(|y(k) - 1|)\frac{\partial\left(\bar{w}^H(k)\bar{x}(k)\bar{x}^H(k)\bar{w}(k)\right)^{1/2}}{\partial\bar{w}^*(k)}\right](3.26)$$

$$\nabla\big(j(k)\big) = \frac{1}{2}E\left[(|y(k) - 1|)\left(\bar{w}^H(k)\bar{x}(k)\bar{x}^H(k)\bar{w}(k)\right)^{-1/2}\frac{\partial\left(\bar{w}^H(k)\bar{x}(k)\bar{x}^H(k)\bar{w}(k)\right)}{\partial\bar{w}^*(k)}\right](3.27)$$

$$= \frac{1}{2}E\left[\bar{x}(k)\left[y(k) - \frac{y(k)}{|y(k)|}\right]^*\right] \quad (3.28)$$

$$J(k) = E[||y(k)|^p - 1|^q](3.29)$$

The p = 1, q = 2 solution is typical because it provides the deepest nulls of the four configurations and provides the best signal to interference noise ratio (SINR).

By decreasing the value of the step size parameter, a faster convergence is achieved. Likewise, due to the high correlation between the transmitted signal and its multipath component.

2. Least Squares Constant MODULUS Algorithm (LSCMA)

The constant modulus algorithm utilizes the method of steepest descent to adapt the weight vector. Additionally Agee [15] proposed an algorithm based upon the method of nonlinear least squares, also known as Gauss's method which states that if a cost function can be expressed in the form:

$$F(\bar{w}) = \sum_{k=1}^{k}|g_k(\bar{w})|^2 = |\bar{g}(\bar{w})|_2^2 \quad (3.30)$$

The weight vector can then be updated by adding this offset to the current weight vector:

$$\bar{w}(k+1) = \bar{w}(k) - \left[D\big(\bar{w}(l)\big)D^{H}\big(\bar{w}(l)\big)\right]^{-1}D\big(\bar{w}(l)\big)\bar{g}(\bar{w}(l)) \qquad (3.31)$$

The beam pattern for the LS-CMA algorithm is nearly symmetric. This is due to the fact that when computing the estimate of the covariance matrix, much of the phase information needed is eliminated when multiplying the two input data matrices.

3. Recursive Least Squares Constant Modulus Algorithm (RLS-CMA)

The newly developed Recursive Least Squares Constant Modulus (RLS-CMA) Algorithm combines adaptive beamforming using the constant modulus criterion via the RLS iterative update solution. This particular algorithm possesses the convergence properties of the RLS algorithm and the tracking capabilities of the CMA define the dynamic complex limited array output. Together they form an algorithm which is capable of restoring the modulus of the array output [5][13]. The RLS optimization technique provides a faster convergence rate than that of the CMA algorithm. However, the constant modulus cost function is non quadratic in the array weights, therefore making application of the RLS algorithm impossible .

The RLS-CMA algorithm attempts to modify the constant modulus cost function to allow use of the RLS algorithm for the special case where q = 2. Replacing the expectation operator with the exponential sum of weighted error squares yields a modified cost function for q = 2 given by:

$J(k) = \sum_{.}^{k} \lambda^{k-i}[|\bar{w}(k)\bar{x}(i)|^{p} - 1]^{2}$ (3.32)

The RLS-CMA weight is as follows:

$$\bar{w}(k) = \bar{w}(k-1) + \bar{k}(k)e^{*}(k) \quad (3.33)$$

The algorithm is much more capable of adapting to the proper weights without divergent error and issues with stability no matter what signals are incident upon the array. Its ability to measure the variations in the envelope of the array output is troubled when the two signals are highly correlated. Either way, it still provides a greater convergence rate than that of the CMA algorithm but lacks the ability to significantly decrease the contribution from interferers with equal modulus.

Chapter Four

Simulationand Results

4.1 Introduction

A comparison between both adaptive beamforming approaches is made using MATLAB software. The Non-Blind approach is represented by the least mean square error algorithm (LMS) while the blind approach is represented by the Constant modulus algorithm (CMA). The comparison is in terms of phase, magnitude response, magnitude response error and amplitude response depending on the number of antennas in the antenna array using 2 antennas and 4 antennas. Both algorithms provide different results according to the number of antennas, direction of signal and the direction of the noise.

The LMS with the minimum mean square error is implemented in the 802.11n Simulink model with different scenarios and is compared before using the technology of beamforming and after implementing the beamforming algorithm.

4.2 Graphical User Interface Design

Figure 4.1 shows the Graphical User Interface (GUI) designed using MATLAB software. It is designed to compare the performance of the beamforming algorithms; the blind and non-blind. In this GUI the user is required to enter the following parameters;

- Number of antennas: 2 or 4 antennas. This parameter identifies the number of corresponding antennas in the ad adaptive antenna array system.
- Direction of signal: Identifies the angle of the arriving received signal.
- Directions of noise sources: Identifies the angles of the unwanted signals passing by.

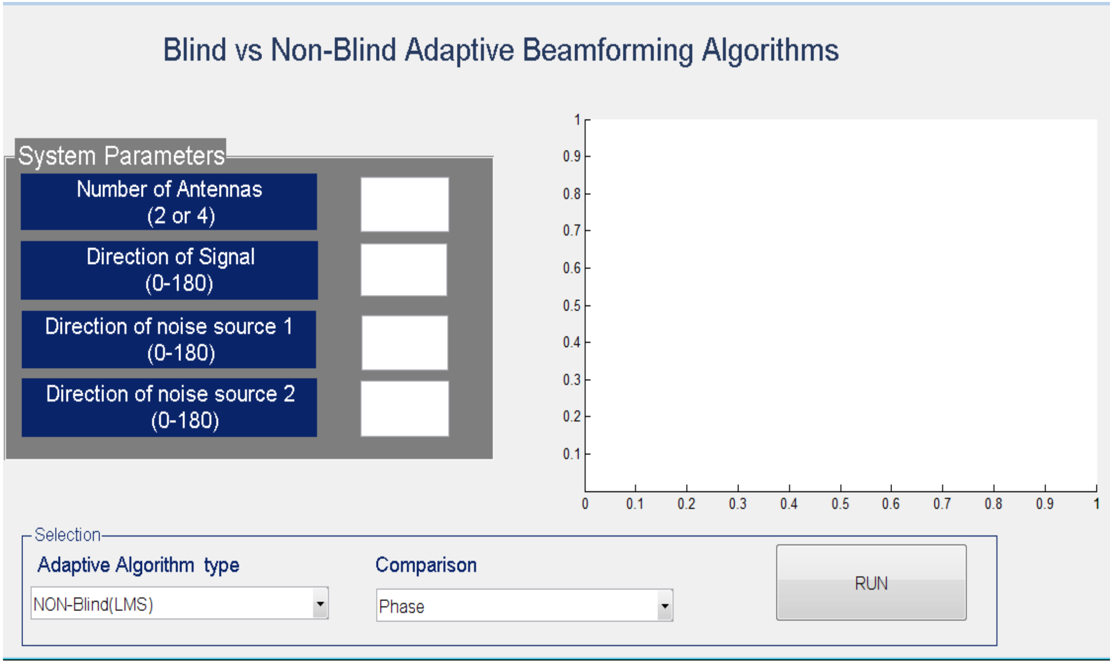

Figure 4.1: Graphical User Interface (GUI) Design

Table 4.1 GUI Parameters

Parameter	Unit
Number of samples	100
System noise variance	0.1
Direction of signal	35
Direction of the first noise source	0 degrees
Direction of the second noise source	-20 degrees
Desired signal amplitude	1

4.3 Graphical User Interface Results

The GUI designed was used to compare the performance of both adaptive beamforming approaches. The Non-Blind approach is represented by the least mean square error algorithm (LMS) algorithm while the blind approach is represented by the Constant modulus algorithm (CMA). The comparison is made in terms of; phase, magnitude response, magnitude response error and amplitude response. Two cases were considered in the simulation, one using 2 receiving antennas and the other using 4 receiving antennas.

When an array of 2 or 4 antennas is used with a separation of λ/2 (λ is the wavelength) there is a maximum of 3 nulls that can eliminate the interferers. The interference signals types are Gaussian white noise and zero mean with a sigma of 1 which are the extra system noise to all antennas.

4.3.1 Least Mean Squares (LMS)

1. **Phase**

Figures 4.2 and 4.3 show the phase of the LMS output when using 2 antennas and 4 antennas respectively.

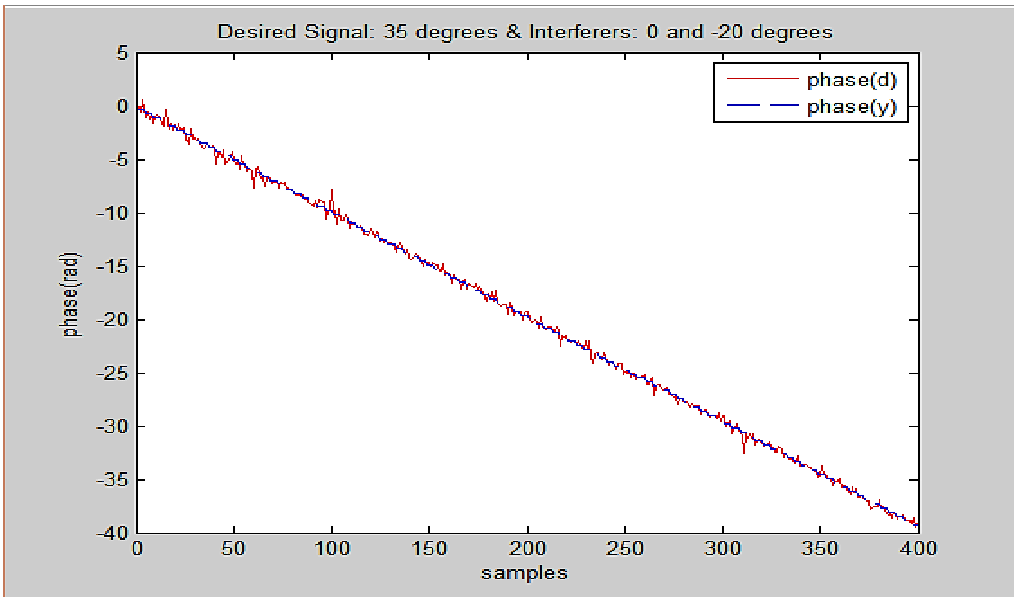

Figure 4.2: Phase of Desired Signal and LMS Output Using 2 antennas

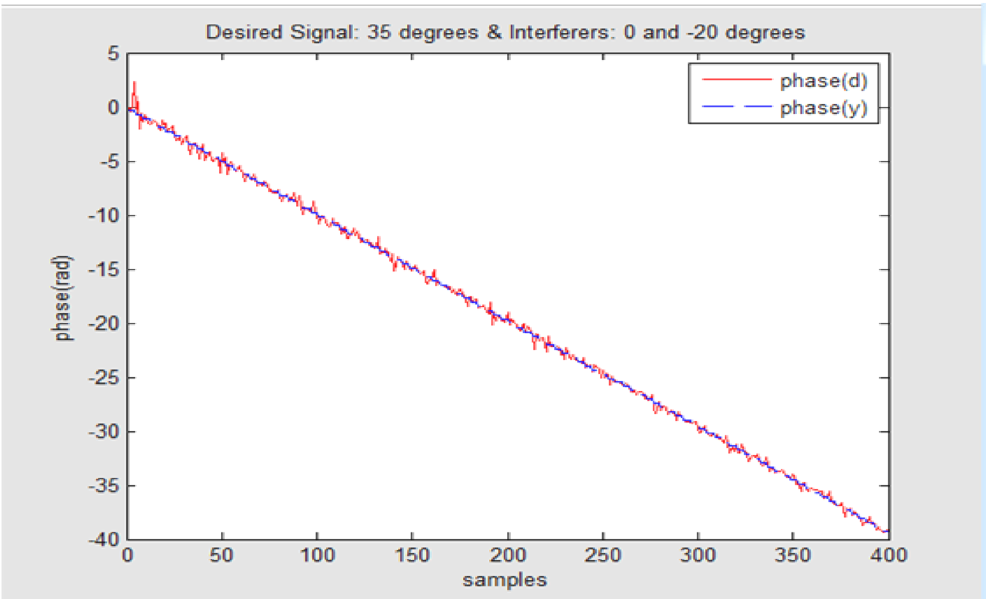

Figure 4.3: Phase of Desired Signal and LMS Output Using 4 antennas

Figures 4.2 and 4.3 show two lines; a red and a blue. The red represents the phase of the desired signal while, the blue represents the phase of the LMS output. The desired signal represents the first weight of the desired signal while the output is approximated to the desired signal using training sequence in equations (3.17), (3.18) and (3.19).

A more accurate result of the LMS output is produced and almost matched with the desired signal phase when using 4 antennas, while in two antennas a slightly phase difference occurs between the LMS output and the desired signal phase.

2. Magnitude Response

The LMS output converges around this magnitude of the desired signal. The convergence varies in both cases of using different antenna arrays when using 2 antennas and 4 antennas respectively. Figure 4.4 and 4.5 shows the magnitude response of the LMS output.

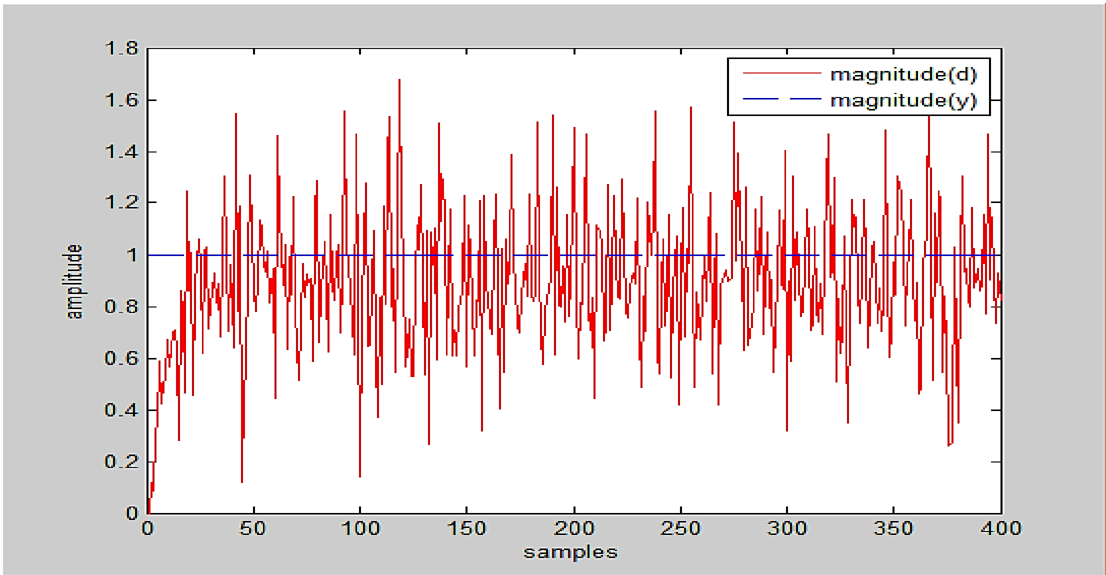

Figure 4.4: Magnitude of the Desired Signal and LMS Output Using 2 antennas

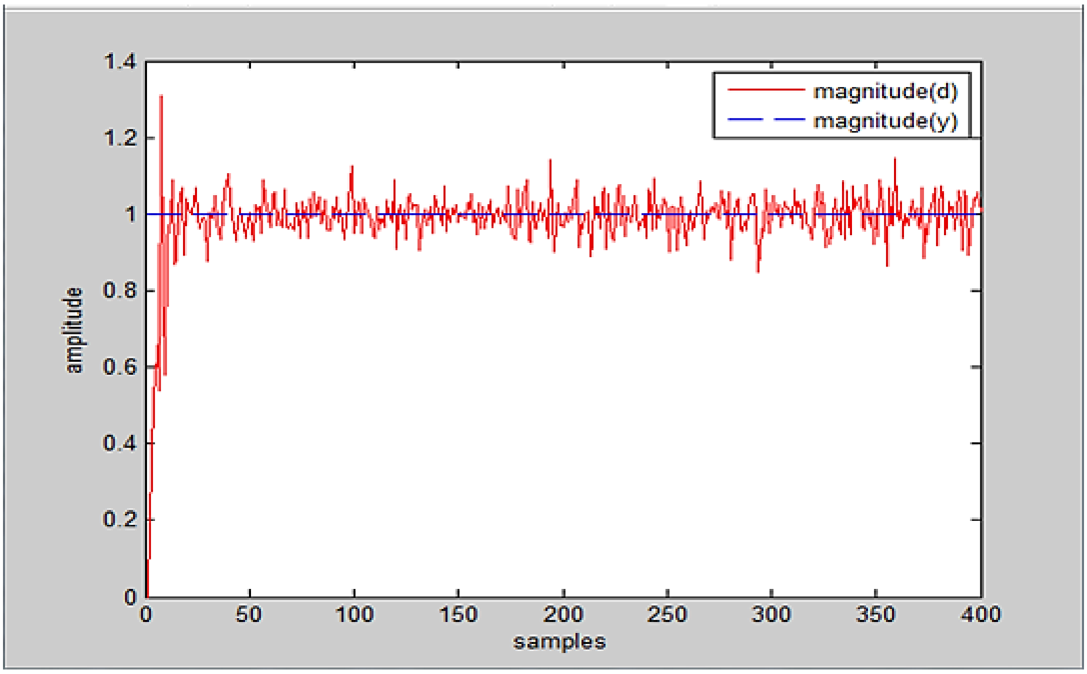

Figure 4.5: Magnitude of Desired Signal and LMS Output Using 4 antennas

Figures 4.4 and 4.5 show that using four antennas resulted in a better magnitude response and a good estimation of desired signal than when using two antennas.

Figure 4.6 and 4.7 shows the error of the LMS output when using 2 antennas and 4 antennas respectively.

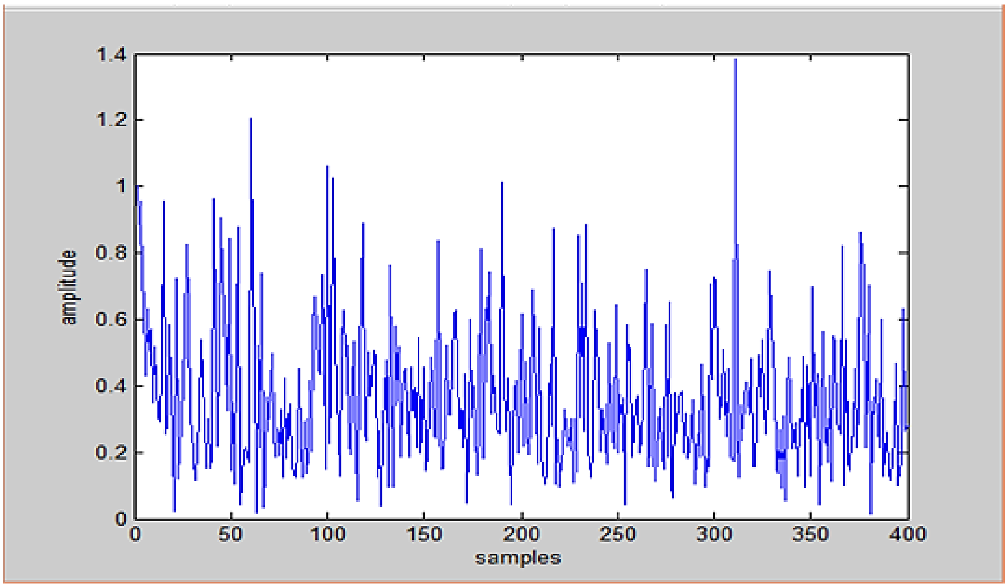

Figure 4.6: Error between desired signal and LMS output in case of 2 antennas

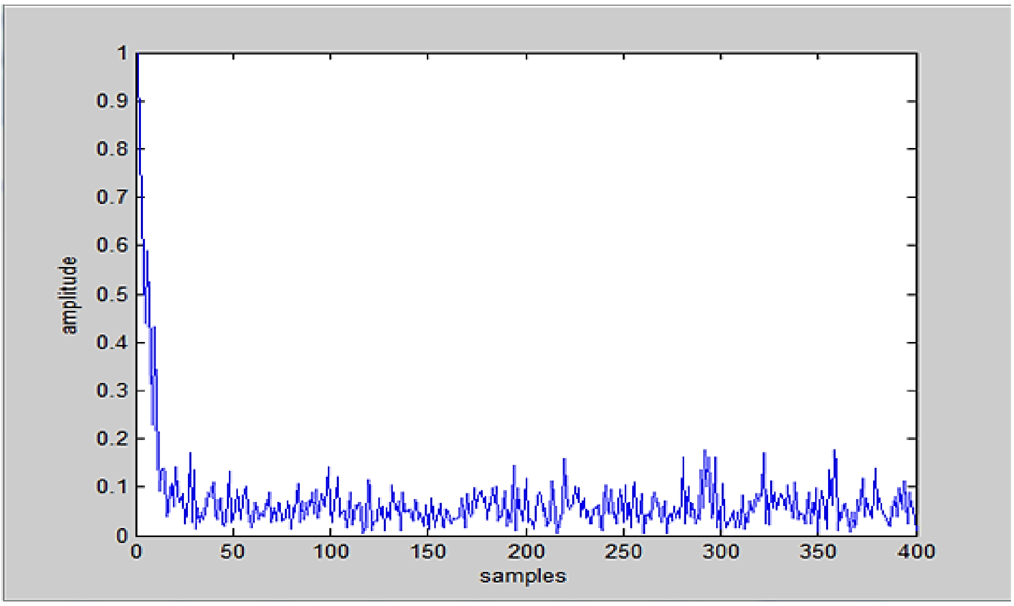

Figure 4.7: Error between desired signal and LMS output in case of 4 antennas

In figure (4.7) the estimation of the desired signal is made by using 4 antennas which decreases the error between the desired signal and LMS output while in figure (4.6) we see that the error between the desired signal and output is more when we use 2 antennas.

3. Amplitude Response

The amplitude response is tested after beamforming with LMS algorithm directions of signal sources and noise sources. Figure 4.8 and 4.9 shows the amplitude response when using 2 and 4 antennas respectively.

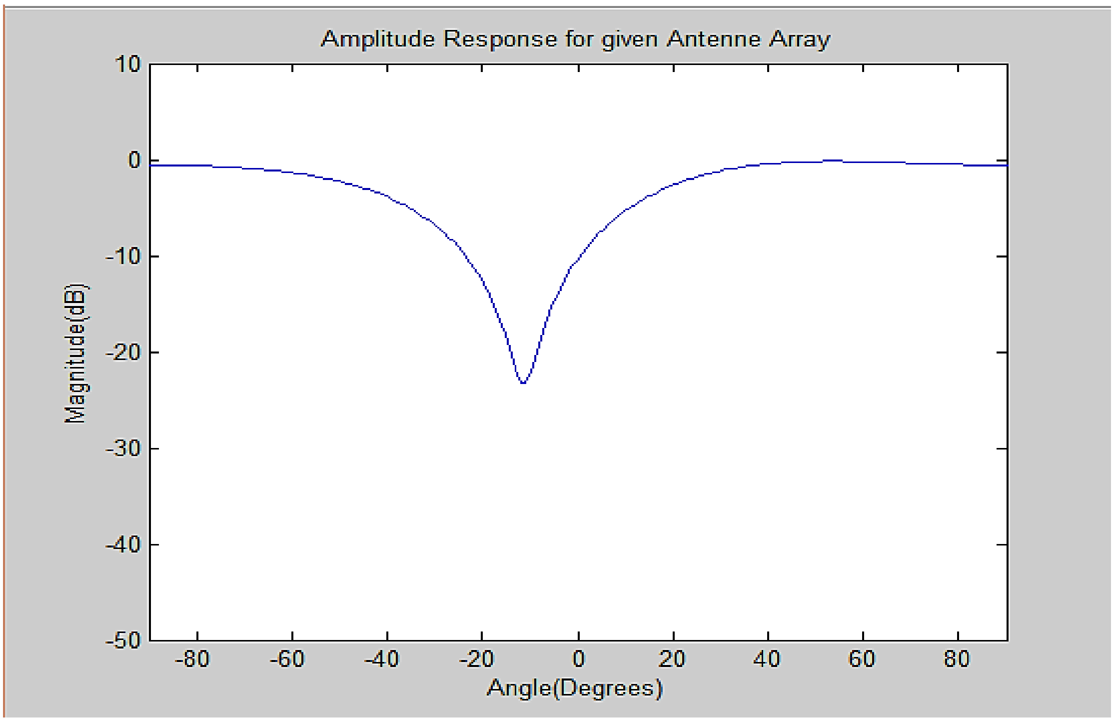

Figure 4.8: Amplitude response after beamforming using 2 antennas

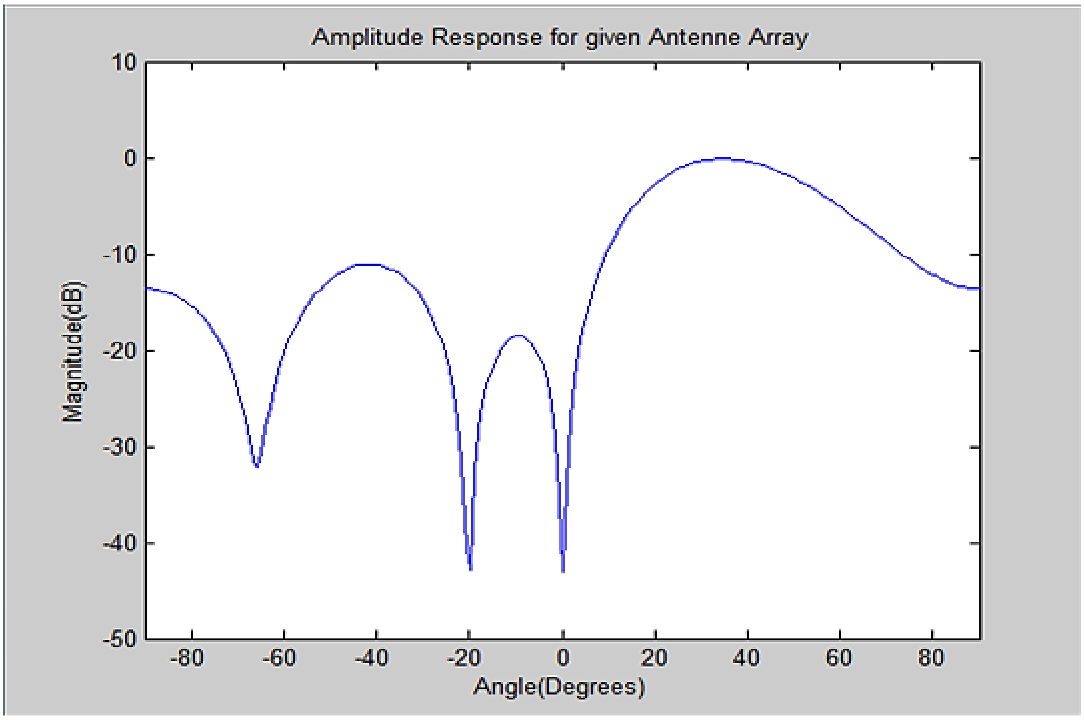

Figure 4.9: Amplitude response after beamforming using 4 antennas

Figure (4.8) shows the amplitude response of LMS algorithm by using 2 antennas while figure (4.9) shows the amplitude response of LMS algorithm by using 4 antennas. The amplitude response in case of using 4 antennas is very good and nulling of the noise sources (0, -20 degree) is closely accurate and the power is sufficiently directed to the direction of the signal source (35degree). On the other hand when using 2 antennas the nulling is approximately between the two sources of noise (0, -20 degree) and less accurate, using 4 antennas resulted in a better performance than 2 antennas.

4.3.2 Constant Modulus algorithm (CMA)

1. Phase

Figures 4.10 and 4.11 show the phases of the desired signal and CMA output when using 2 antennas and 4 antennas respectively. The red line in the figures represents the phase of desired signal while the blue represents the phase of the CMA output.

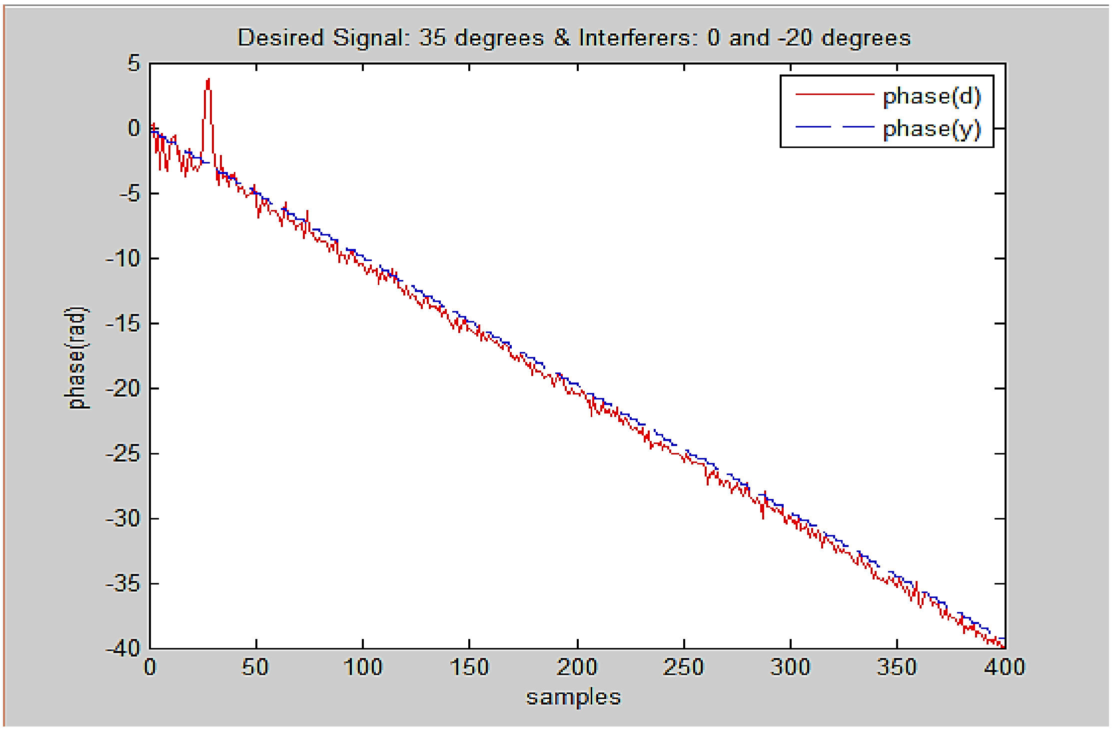

Figure 4.10: Phase of desired signal and CMA output using 2 antennas

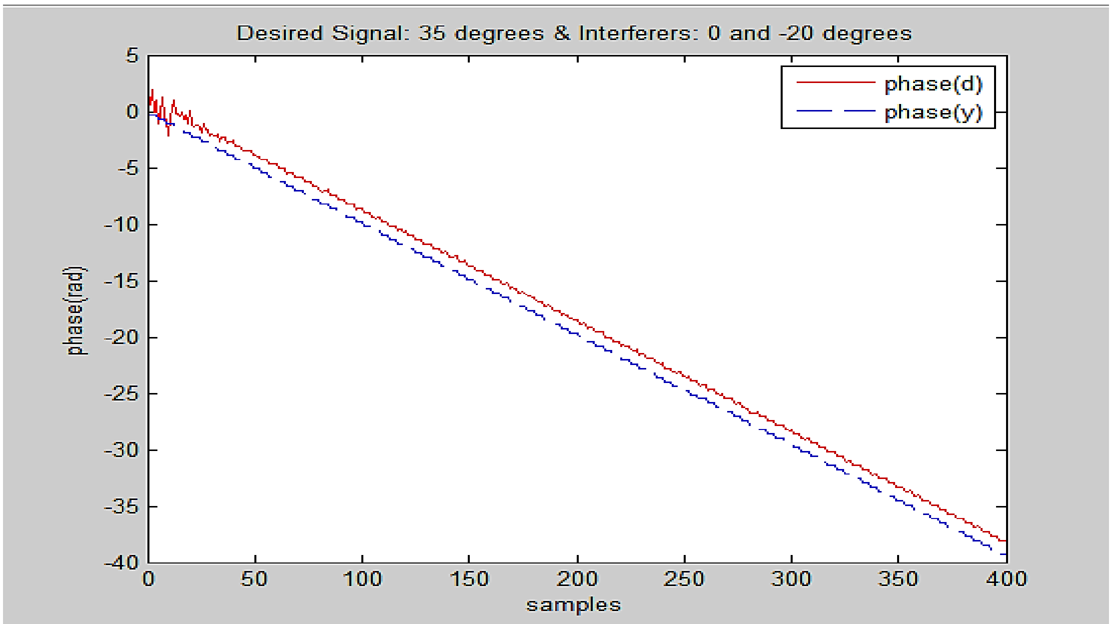

Figure 4.11: Phase of desired signal and CMA output using 4 antennas

In case of using CMA with 2 antennas in figure (4.10) there is a little difference between the desired signal and CMA output as same as the case of 4 antennas shown in figure (4.11), so as a result there is no much difference between those two cases in terms of phase.

2. Magnitude Response

Figures 4.12 and 4.13 show the magnitude response of the CMA output when using 2 antennas and 4 antennas respectively.

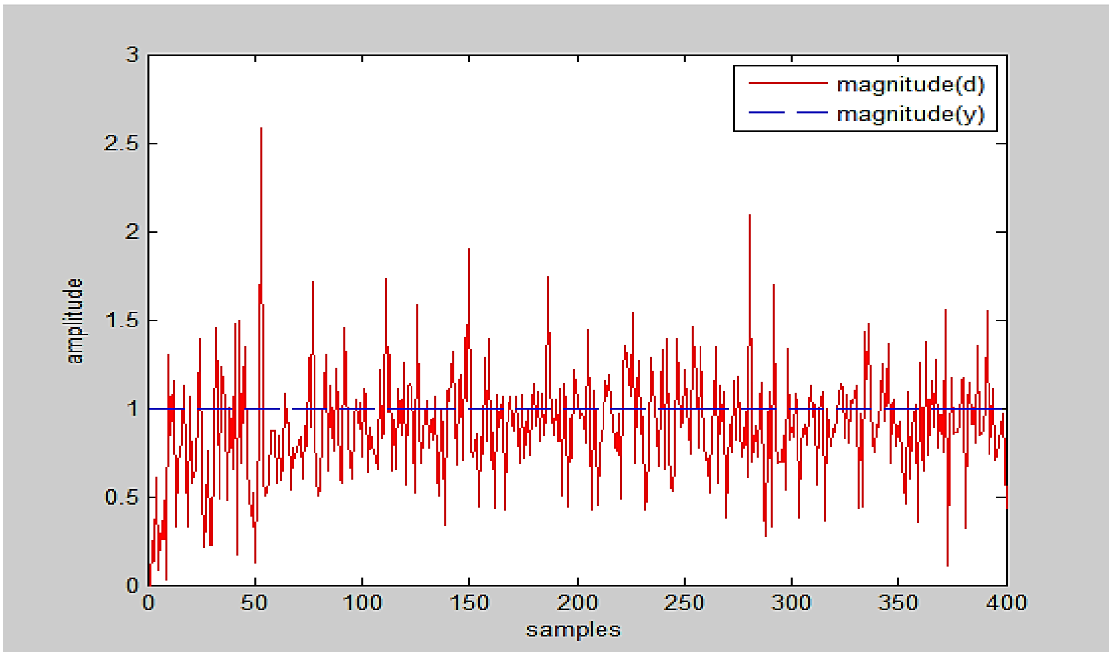

Figure 4.12: Magnitude of desired signal and CMA output by using 2 antennas

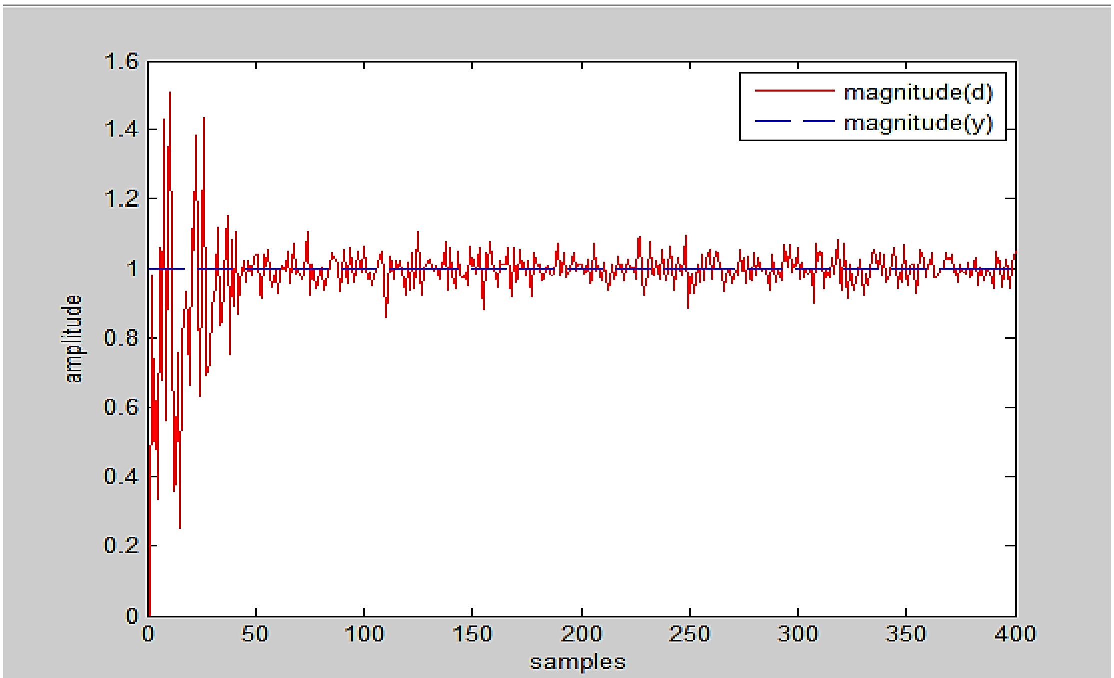

Figure 4.13: Magnitude of desired signal and CMA output by using 4 antennas

Figure (4.12) shows that using 2 antennas results in a large difference between the CMA output and the desired signal. In contrast figure(4.13) shows using 4 antennas results in the desired output being close to the CMA output which reflects a respectfully good estimation.

Figures 4.14 and 4.15 show the error of the CMA output when using 2 antennas and 4 antennas respectively.

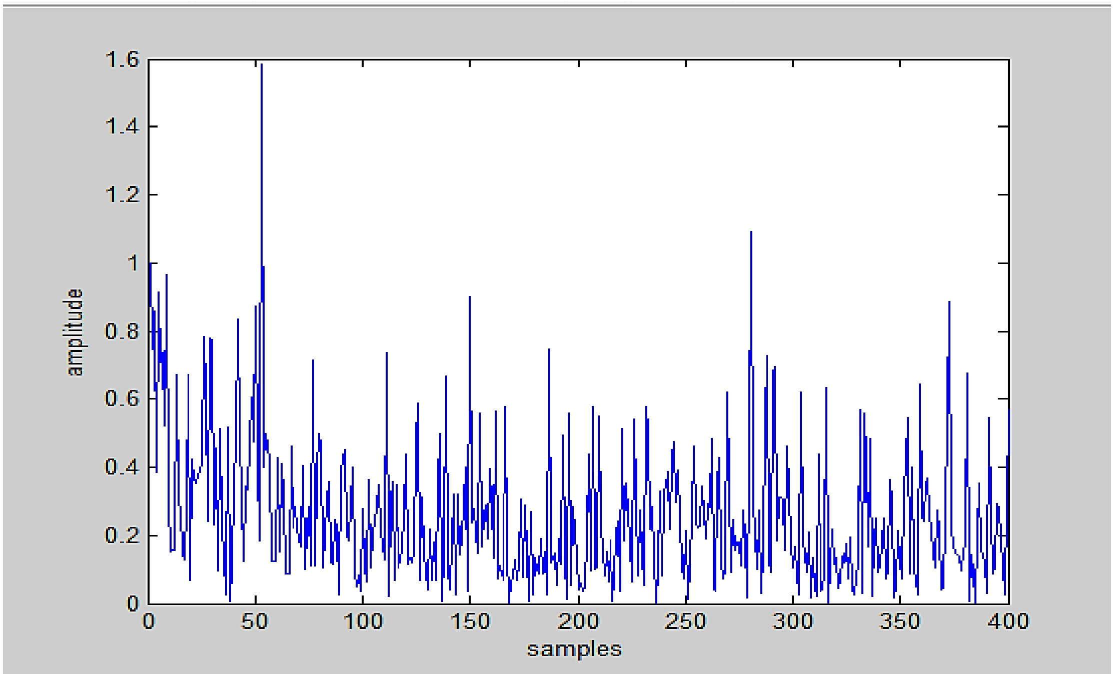

Figure 4.14: Error between desired signal and CMA output by using 2 antennas

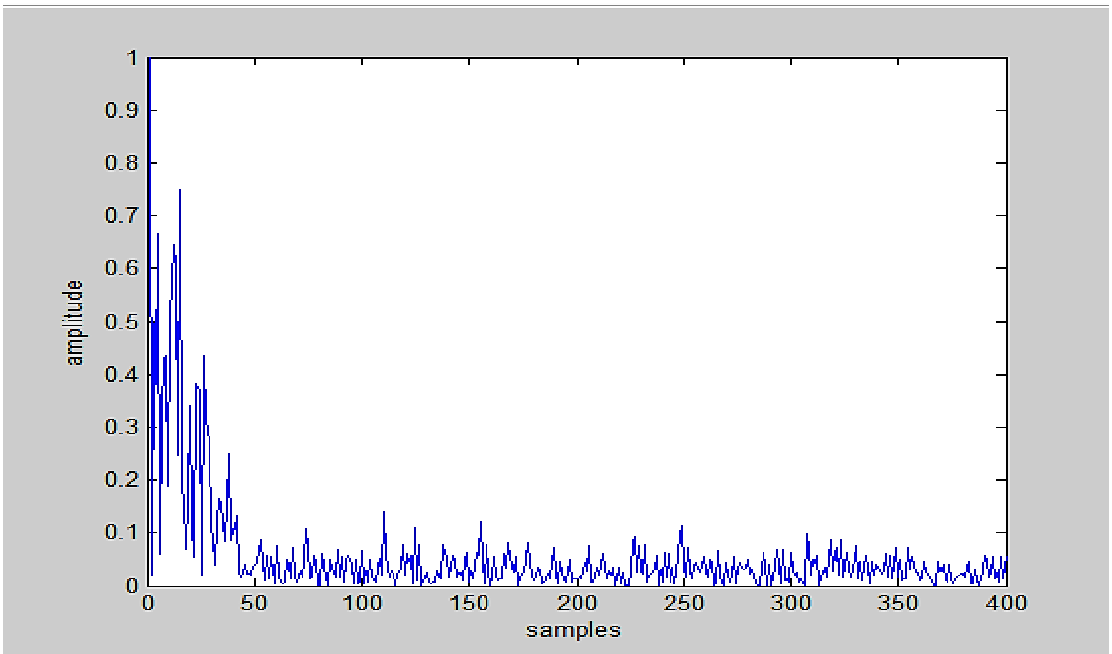

Figure 4.15: Error between desired signal and CMA output by using 4 antennas

Figures (4.14) and (4.15) illustrate the error between the desired signal estimated and CMA output. In figure (4.14) we see that the error reaches higher values when using 2 antennas compared to the error in case of using 4 antennas as illustrated in figure (4.15).

3. Amplitude Response

Figures 4.16 and 4.17 show the amplitude response when using 2 and 4 antennas respectively.

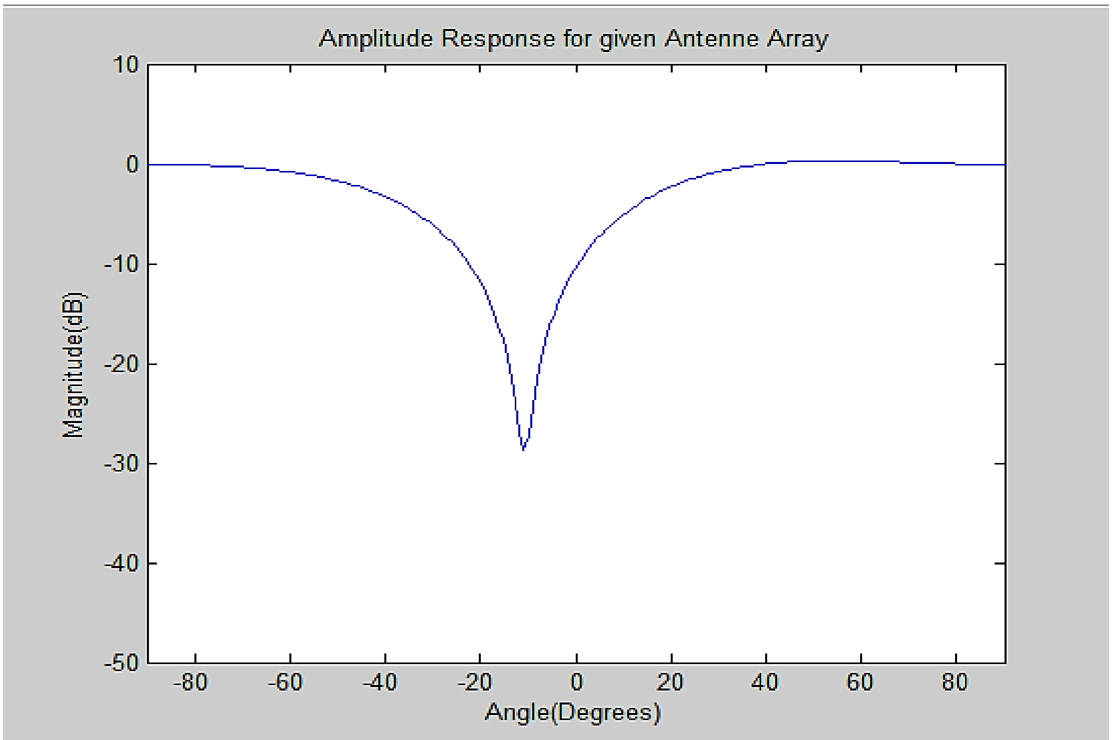

Figure 4.16: Amplitude response after beamforming using 2 antennas

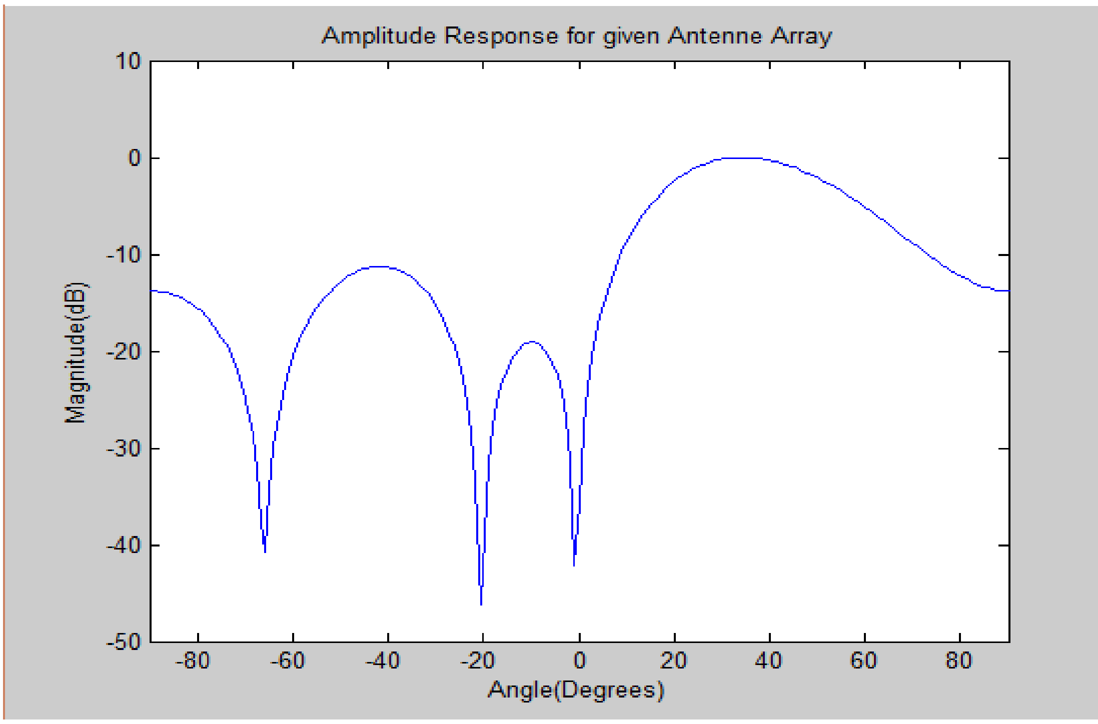

Figure 4.17: Amplitude response after beamforming using 4 antennas

In figure (4.16) when using 2 antennas the nulling is approximately between the two sources of noise (0, -20 degree) and obviously less efficient then the four antennas case. On the other hand figure (4.17) shows the amplitude response of CMA algorithm using 4 antennas. The amplitude response in case of using 4 antennas is very good and nulling of the noise sources (0, -20 degree) is quite impressive, also the power is directed to the direction of the signal source.

4.4 802.11n SIMULINK Model

The simulation model developed in MATLAB/SIMULINK is useful to describe performance verification of the IEEE 802.11n standard as shown in figure 4.18. This model has been made available from the Mathworks MATLAB central without beamforming. The beamforming technique is added into the basic model to provide the potential of increasing signal strength at the receiver with optimal efficiency. Note that the channel used for this simulation reflects a typical office-type environment.

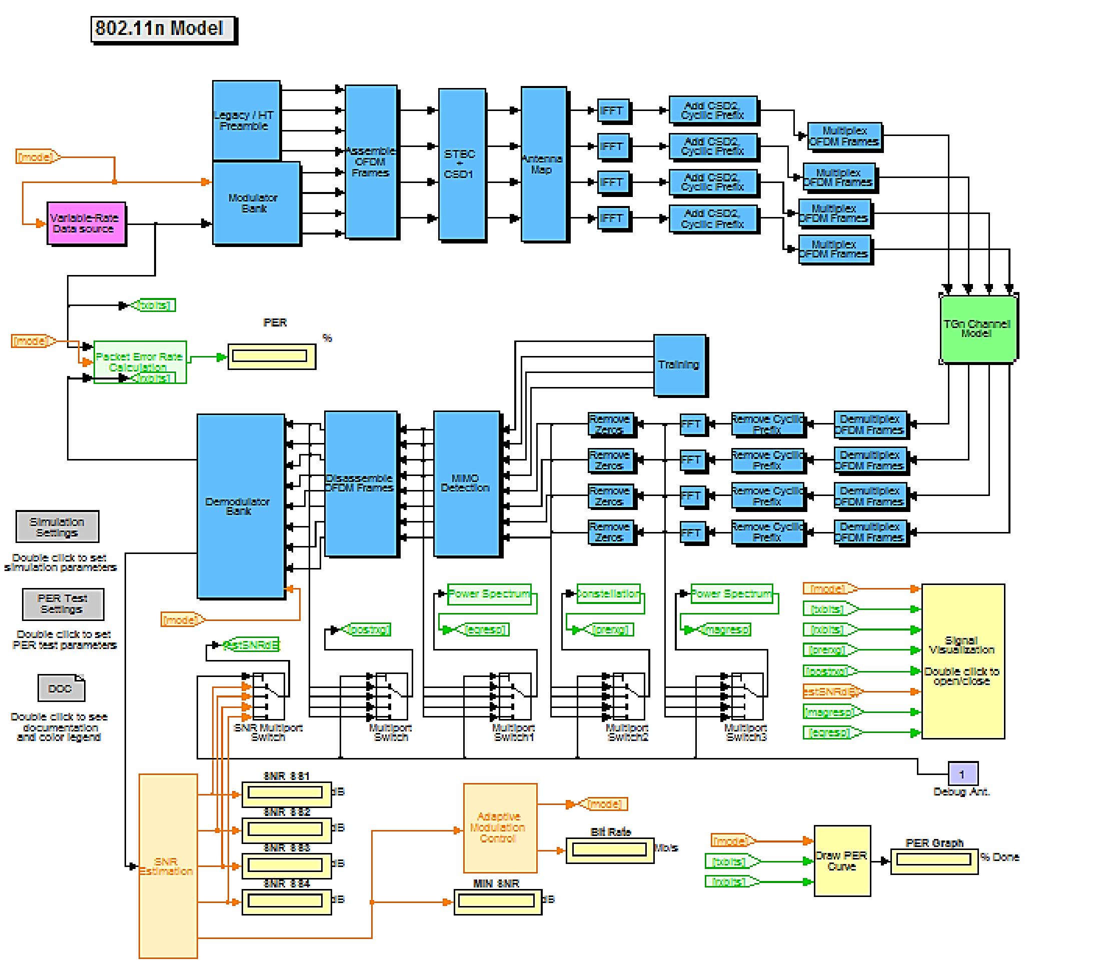

Figure 4.18: MATLAB/SIMLINK Block Diagram for the IEEE 802.11n Standard

Table 4.2 shows the assumptions considered in the simulation.

Table 4.2: Simulink Parameters

Parameter	Unit
Antenna Matrix	2X2
Channel Bandwidth	20MHz
Guard Interval	800ns
Modulation	64-QAM
Number of Packets	442
Data Payload Size	1000 Bytes

Table 4.3 shows the modulation coding scheme MCS corresponding parameters.

Table 4.3: MCS Parameters

MCS Index	**Spatial Streams**	**Modulation Type**	**Coding rate**
14	2	64-QAM	3/4
15	2	64-QAM	5/6

4.5 Simulink Results

The snapshots were taken randomly during the process. The two modulation code schemes MCS-15 and MCS-14 were simulated in the 802.11n model with and without beamforming technology to analyze the system in both cases.

1. Modulation code schemes MCS-15

Figures 4.19 and 4.20 show the simulation results of the modulation code schemes MCS-15 without and with beamforming respectively.

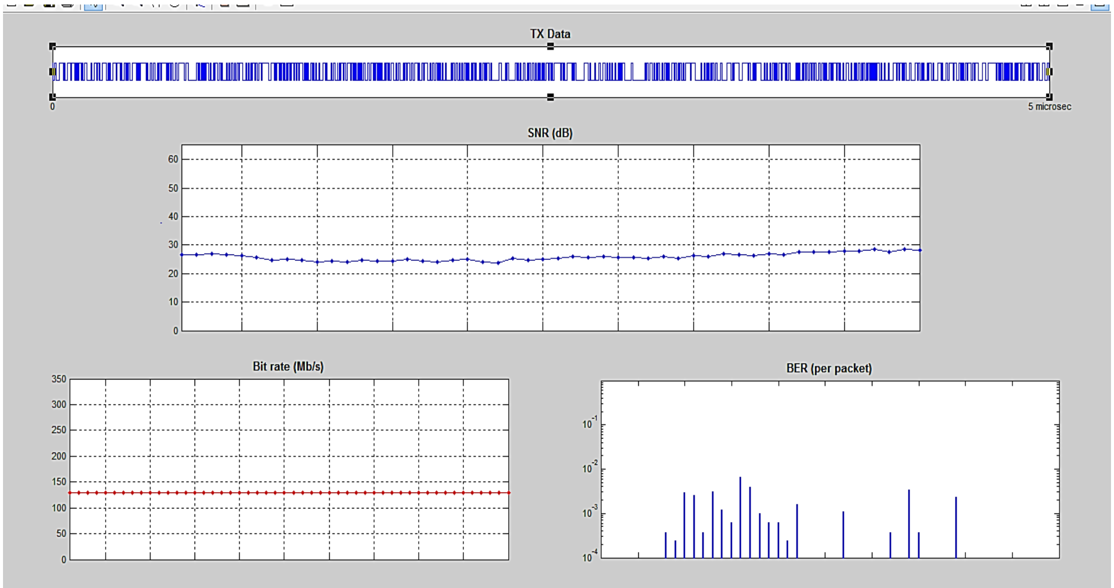

Figure 4.19: Simulation results for MCS15 without Beamforming

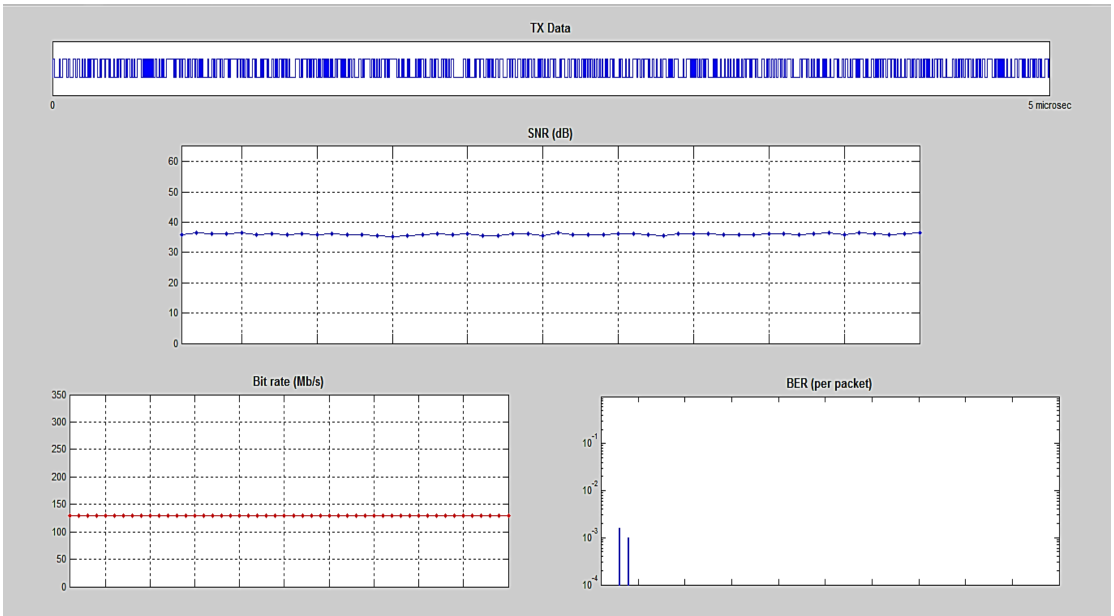

Figure 4.20: Simulation results for MCS15 with Beamforming

Figures 4.19 and 4.20 show an increase in SNR increases from (20-30) dB to (30-40) dB when beamforming technique is used. The figures also show that using beamforming technique reduces the BER. The results also show that the bit rate is 130Mb/s in both cases.

Figures 4.21 and 4.22 show the packet error rate PER vs. SNR values without and with using beamforming technique

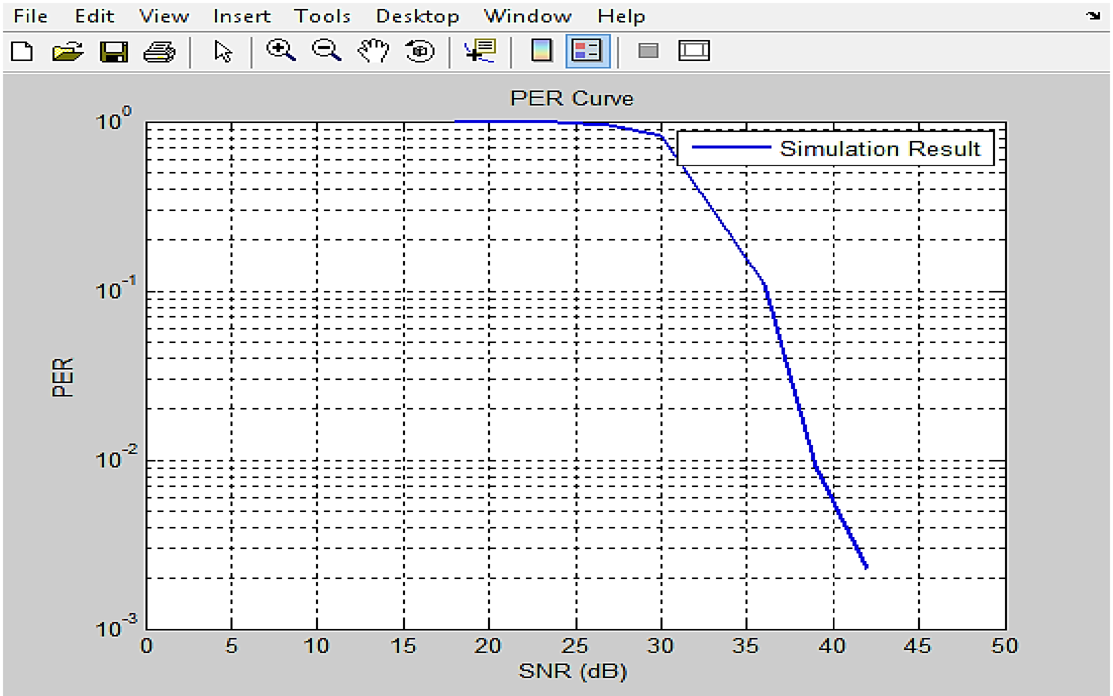

Figure 4.21: Packet Error Rate without Beamforming

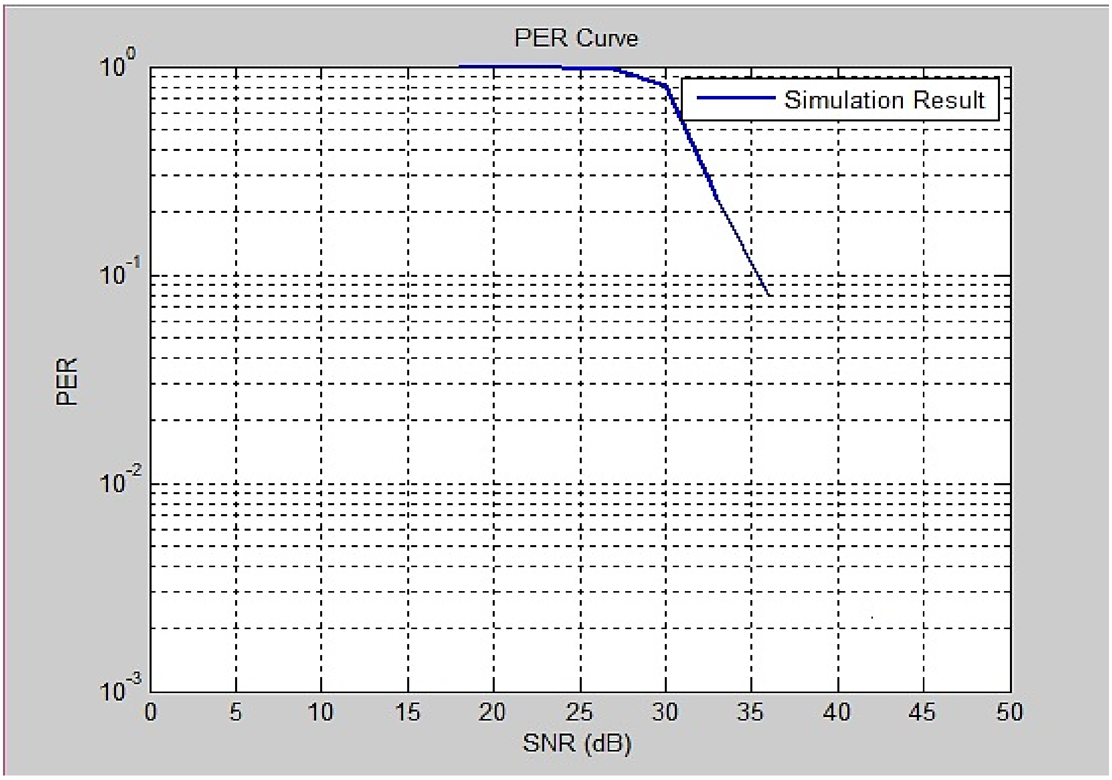

Figure 4.22: Packet Error Rate with Beamforming

Figures 4.21 and 4.22 show a decrease in the PER when using beamforming techniques. The results show that with beamforming an SNR>37 results in no packets being dropped while for a system without beamforming it requires a SNR > 42 for no packets to be dropped.

2. Modulation code schemes MCS-14

Furthermore, another scenario is studied when the MCS-14 is applied with the beamforming technology.

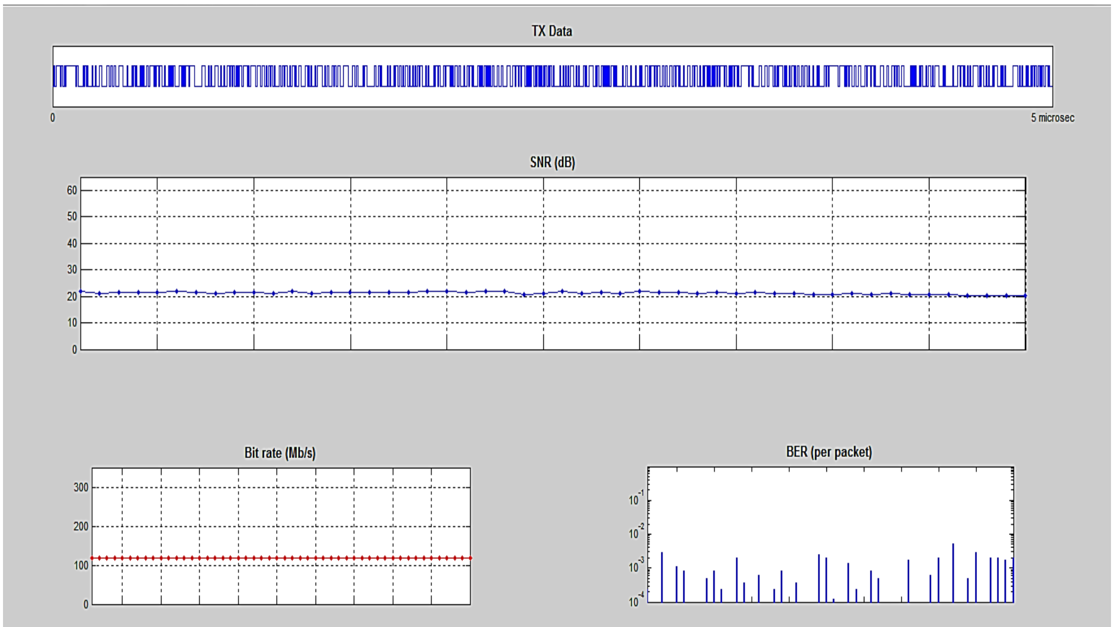

Figure 4.23: Simulation Results for MCS14 without Beamforming

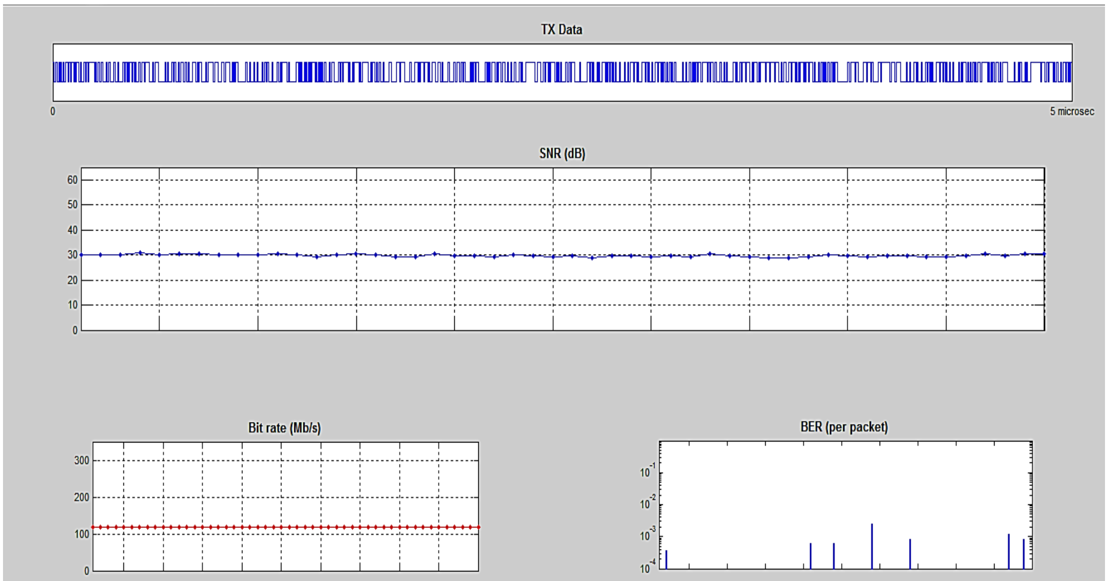

Figure 4.24: Simulation Results for MCS14 with Beamforming

Figures 4.23 and 4.24 show an increase in SNR increases from (20-30) dB to (30-40) dB when beamforming technique is used. The figures also show that using beamforming technique reduces the BER. The results show that the bit rate is minimized to 117 Mb/s compared to the 130Mb/s in MCS 15.

Figures 4.21 and 4.22 show the packet error rate PER vs. SNR values without and with using beamforming technique respectively.

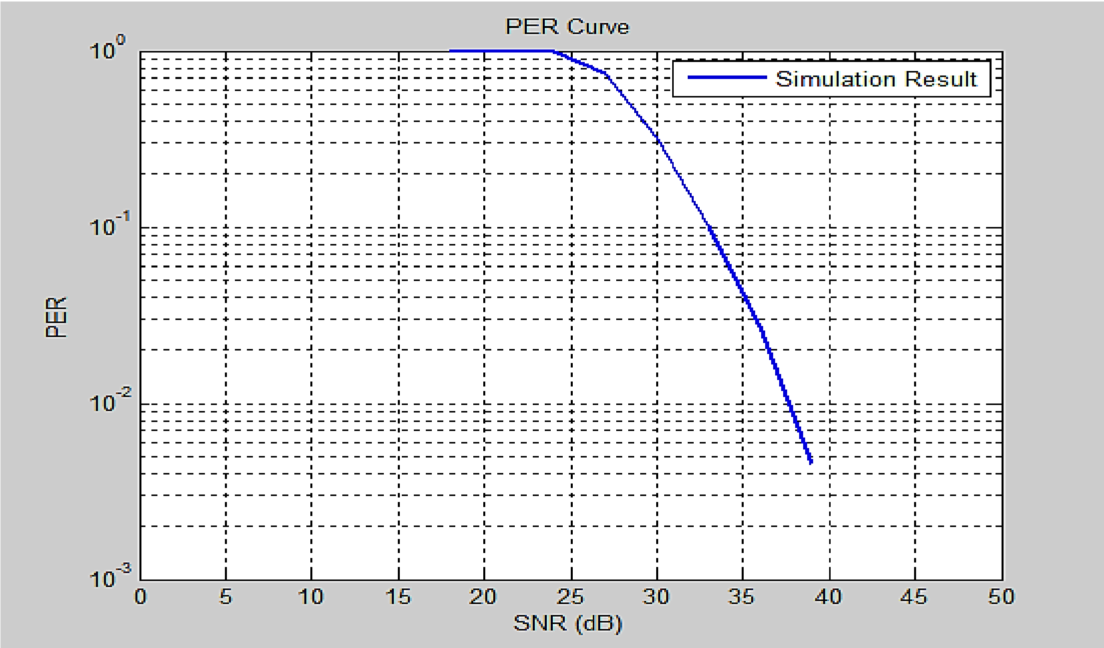

Figure 4.25: MCS14 Packet Error Rate without Beamforming

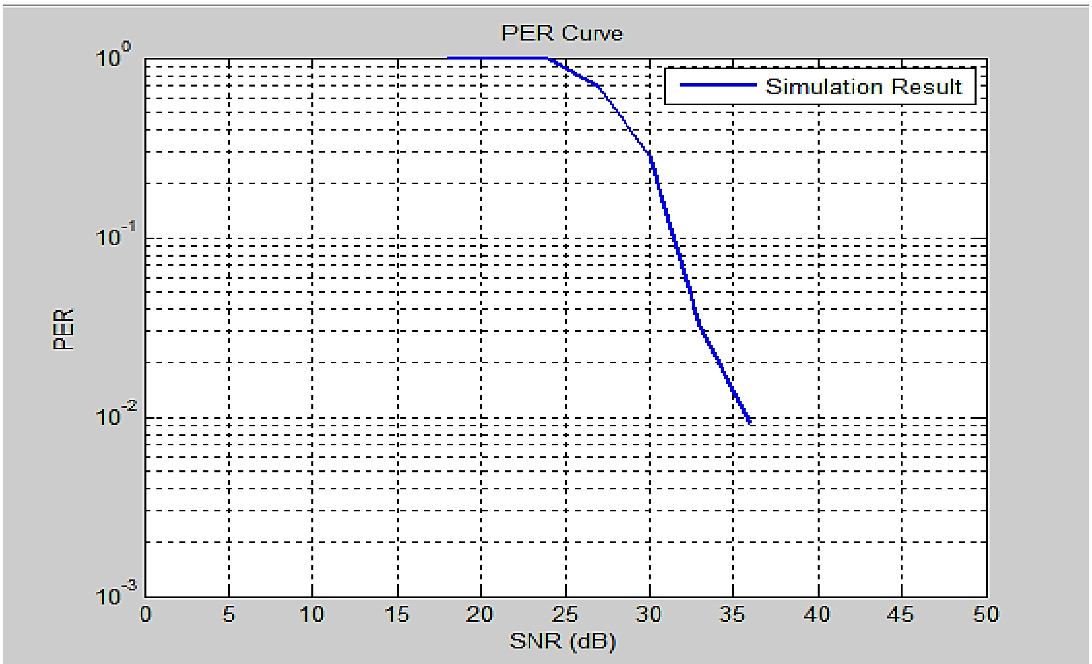

Figure 4.26:MCS14 Packet Error Rate with Beamforming

Figure 4.25 and 4.26 shows a decrease in the PER when using beamforming techniques. The results show that with beamforming an SNR>36 results in no packets being dropped while for a system without beamforming it requires a SNR > 39 for no packets to be dropped.

Chapter Five

Conclusion and Recommendations

5.1 Conclusion

Since the wireless communication suffers from different link effects the beamforming technique in its adaptive form has been widely studied to decrease these effects.

In this thesis MATLAB software was used to design a Graphical User Interface to compare the performance of two adaptive beamforming approaches; the Blind and Non-Blind. The Least Mean Squares (LMS) was selected as the non-blind approach while, the Constant Modulus Algorithm (CMA) as the blind approach.

The results from the GUI showed that CMA algorithm converges slower than LMS algorithm. During the efforts to simulate the CMA algorithm it was clear that the algorithm is less stable than the LMS algorithm.The LMS algorithm outperforms the CMA algorithm in nulling the interference signal sources and has less error between the desired signal and the output.

The LMS with its minimum mean square error was tested in a MATLAB/SIMULINK based simulation model for the 802.11n PHY layer.

The results from the SIMULINK showed that the selection of the beamforming techniques depends on the environment that the 802.11n operates in. Adding these algorithms improves the SNR while the packet error rate decreases and therefore enhances the overall link performance.

The results showed that adding beamforming techniques can make such an improvement to the performance of the system.

5.2 Recommendations

A lot of work has been done in this thesis but there is still room for improvement

- In this thesis CMA and LMS were simulated, it is recommended to testmore beamforming algorithms and their performance in the IEEE 802.11n model.
- In addition adaptive modulation and coding (AMC) can be effective when applied in the IEEE802.11n model.

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Appendices

A : MATLAB code for LMS algorithm

```
clc;
close all;
clear all;
% INITIALIZATIONS
NumofAntenna = input('Enter the number of antennas  (2 or 4 antennas): ');
 % Number of antennas in the array
NumofSamples = 100; % Number of bits to be transmitted
SigmaSystem = 0.1; % System Noise Variance
theta_x12 = input('Enter the direction of signal ');
theta_x=theta_x12 * (pi/180); % direction of signal x
theta_n12 = input('Enter the direction of noise source 1 ');
theta_n1=theta_n12* (pi/180); % direction of noise source 1
theta_n21 = input('Enter the direction of noise source 2 ');
theta_n2 = theta_21 * (pi/180); % direction of noise source 2
% TIME SETTINGS
theta = pi*[-1:0.005:1];
BitRate = 100;
SimFreq = 4*BitRate; % Simulation frequency
Ts = 1/SimFreq; % Simulation sample period
% GENERATE A COMPLEX MSK DATA TO BE TRANSMITTED
for k=1:NumofSamples
q=randperm(2);
Data(k)=-1^q(1);
end
Data = upsample(Data, SimFreq/BitRate); % Upsample data
t = Ts:Ts:(length(Data)/SimFreq); % Timeline
faz=(cumsum(Data))/8;
signal_x = cos(pi*faz)+j*sin(pi*faz); % The signal to be received
% GENERATE INTERFERER NOISE -> uniform phase (-pi,pi), gaussian amplitude
% distribution(magnitude 1)
signal_n1 = normrnd(0,1,1,length(t)).*exp (j*(unifrnd(-pi,pi,1,length(t))));
signal_n2 = normrnd(0,1,1,length(t)).*exp (j*(unifrnd(-pi,pi,1,length(t))));
% GENERATE SYSTEM NOISES for EACH ANTENNA -> uniform phase (-pi,pi),
gaussian
% amplitude distribution(magnitude 1)
noise = zeros(NumofAntenna, length(t));
fori = 0:NumofAntenna-1,
noise(i+1,:) = normrnd(0,SigmaSystem,1,length(t)).*exp (j*(unifrnd(-pi,pi,1,length(t))));
end;
% ARRAY RESPONSES for DESIRED SIGNAL (X) and INTERFERER NOISES (N1
and N2)
Kd = pi; % It is assumed that antennas are seperated by lambda/2.
response_x = zeros(1,NumofAntenna);
response_n1 = zeros(1,NumofAntenna);
response_n2 = zeros(1,NumofAntenna);
for k = 0:NumofAntenna-1,
response_x(k+1) = exp(j*k*Kd*sin(theta_x));
response_n1(k+1) = exp(j*k*Kd*sin(theta_n1));
response_n2(k+1) = exp(j*k*Kd*sin(theta_n2));
end;
% TOTAL RECEIVED SIGNAL (SUM of X.*Hx, N1.*Hn1 and N2.*Hn2)
x = zeros(NumofAntenna, length(t));
```

```
n1 = zeros(NumofAntenna, length(t));
n2 = zeros(NumofAntenna, length(t));
fori = 0:NumofAntenna-1,
x(i+1,:) = signal_x .* response_x(i+1); % received signal from signal source x
n1(i+1,:) = signal_n1 .* response_n1(i+1); % received signal from noise source n1
n2(i+1,:) = signal_n2 .* response_n2(i+1); % received signal from noise source n2
end;
signal_ns = (noise + n1+n2+x); % total received signal
% EVALUATUING WEIGHTs THOSE SATISFY BEAMFORMING at DESIRED
DIRECTION
y = zeros(1,length(t)); % output
mu = 0.05; % gradient constant
e = zeros(1,length(t)); % error
w = zeros(1,NumofAntenna); % weights
%LMS Algorithm
fori=0:length(t)-1,
y(i+1) = w * signal_ns(:,i+1);
e(i+1) = signal_x(i+1)-y(i+1);
w = w + mu *e(i+1)*(signal_ns(:,i+1))';
end;

% PLOTS

close all;
plot(phase(y),'r');
hold;
plot(phase(signal_x),'--b');
ylabel('phase(rad)');
xlabel('samples');
title('Desired Signal: 35 degrees & Interferers: 0 and -20 degrees')
legend('phase(d)','phase(y)')
hold off;
figure;
plot(abs(y),'r');
hold;
plot(abs(signal_x),'--b');
ylabel('amplitude');
xlabel('samples');
legend('magnitude(d)', 'magnitude(y)')
hold off;
figure;
plot(abs(e));
ylabel('amplitude');
xlabel('samples');
figure;
for k = 0:NumofAntenna-1,
response(k+1,:) = exp(j*k*Kd*sin(theta));
end;
% CALCULATE ARRAY RESPONSE
R = w*response;
plot((theta*180/pi), 20*log10(abs(R)));
title('Amplitude Response for given Antenne Array');
ylabel('Magnitude(dB)');
xlabel('Angle(Degrees)');
axis([-90,+90,-50,10]);
```

B : MATLAB code for CMA algorithm:

```
clc;
close all;
clear all;
% INITIALIZATIONS
NumofAntenna = input('Enter the number of antennas  (2 or 4 antennas): ');
 % Number of antennas in the array
NumofSamples = 100; % Number of bits to be transmitted
SigmaSystem = 0.1; % System Noise Variance
theta_x12 = input('Enter the direction of signal ');
theta_x=theta_x12 * (pi/180); % direction of signal x
theta_n12 = input('Enter the direction of noise source 1 ');
theta_n1=theta_n12* (pi/180); % direction of noise source 1
theta_n21 = input('Enter the direction of noise source 2 ');
theta_n2 = theta_21 * (pi/180); % direction of noise source 2
% TIME SETTINGS
theta = pi*[-1:0.005:1];
BitRate = 100;
SimFreq = 4*BitRate; % Simulation frequency
Ts = 1/SimFreq; % Simulation sample period
% GENERATE A COMPLEX MSK DATA TO BE TRANSMITTED
for k=1:NumofSamples
q=randperm(2);
Data(k)=-1^q(1);
end
Data = upsample(Data, SimFreq/BitRate); % Upsample data
t = Ts:Ts:(length(Data)/SimFreq); % Timeline
faz=(cumsum(Data))/8;
signal_x = cos(pi*faz)+j*sin(pi*faz); % The signal to be received
% GENERATE INTERFERER NOISE -> uniform phase (-pi,pi), gaussian amplitude
% distribution(magnitude 1)
signal_n1 = normrnd(0,1,1,length(t)).*exp (j*(unifrnd(-pi,pi,1,length(t))));
signal_n2 = normrnd(0,1,1,length(t)).*exp (j*(unifrnd(-pi,pi,1,length(t))));
% GENERATE SYSTEM NOISES for EACH ANTENNA -> uniform phase (-pi,pi),
gaussian
% amplitude distribution(magnitude 1)
noise = zeros(NumofAntenna, length(t));
fori = 0:NumofAntenna-1,
noise(i+1,:) = normrnd(0,SigmaSystem,1,length(t)).*exp (j*(unifrnd(-pi,pi,1,length(t))));
end;
% ARRAY RESPONSES for DESIRED SIGNAL (X) and INTERFERER NOISES (N1
and N2)
Kd = pi; % It is assumed that antennas are seperated by lambda/2.
response_x = zeros(1,NumofAntenna);
response_n1 = zeros(1,NumofAntenna);
response_n2 = zeros(1,NumofAntenna);
for k = 0:NumofAntenna-1,
response_x(k+1) = exp(j*k*Kd*sin(theta_x));
response_n1(k+1) = exp(j*k*Kd*sin(theta_n1));
response_n2(k+1) = exp(j*k*Kd*sin(theta_n2));
end;
% TOTAL RECEIVED SIGNAL (SUM of X.*Hx, N1.*Hn1 and N2.*Hn2)
x = zeros(NumofAntenna, length(t));
```

```
n1 = zeros(NumofAntenna, length(t));
n2 = zeros(NumofAntenna, length(t));
fori = 0:NumofAntenna-1,
x(i+1,:) = signal_x .* response_x(i+1); % received signal from signal source x
n1(i+1,:) = signal_n1 .* response_n1(i+1); % received signal from noise source n1
n2(i+1,:) = signal_n2 .* response_n2(i+1); % received signal from noise source n2
end;
signal_ns = (noise + n1+n2+x); % total received signal
% EVALUATUING WEIGHTs THOSE SATISFY BEAMFORMING at DESIRED
DIRECTION
y = zeros(1,length(t)); % output
mu = 0.05; % gradient constant
e = zeros(1,length(t)); % error
w = zeros(1,NumofAntenna); % weights
w = zeros(1,NumofAntenna); w(1)=eps; % weights
fori=0:length(t)-1,
y(i+1) = w * signal_ns(:,i+1);
e(i+1) = y(i+1)/norm(y(i+1))-y(i+1);
w = w + mu *e(i+1)*(signal_ns(:,i+1))';
end;

close all;
plot(phase(y),'r');
hold;
plot(phase(signal_x),'--b');
ylabel('phase(rad)');
xlabel('samples');
title('Desired Signal: 35 degrees & Interferers: 0 and -20 degrees')
legend('phase(d)','phase(y)')
hold off;
figure;
plot(abs(y),'r');
hold;
plot(abs(signal_x),'--b');
ylabel('amplitude');
xlabel('samples');
legend('magnitude(d)', 'magnitude(y)')
hold off;
figure;
plot(abs(e));
ylabel('amplitude');
xlabel('samples');
figure;
for k = 0:NumofAntenna-1,
response(k+1,:) = exp(j*k*Kd*sin(theta));
end;
% CALCULATE ARRAY RESPONSE
R = w*response;
plot((theta*180/pi), 20*log10(abs(R)));
title('Amplitude Response for given Antenne Array');
ylabel('Magnitude(dB)');
xlabel('Angle(Degrees)');
axis([-90,+90,-50,10]);
```