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Bit Error Rate (BER) Enhancement of Space Time Block Coding (STBC) Based on Channel Estimator

A Thesis
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بِســـــْمِ اللَّهِ الرَّحْمَـٰنِ الرَّحِيمِ

﴿قَالُواْ سُبْحَانَكَ لاَ عِلْمَ لَنَا إِلاَّ مَا عَلَّمْتَنَا إِنَّكَ أَنتَ الْعَلِيمُ الْحَكِيمُ﴾

صَدَقَ اللّهُ الْعَلِيُّ الْعَظِيمُ

من سورة البقرة اية﴿32﴾

Dedication

I dedicate this work to the teacher of this nation and the one who sent a mercy to the worlds, our Prophet Muhammad, may God's prayers and peace be upon him and his family, and his good and pure family.

Secondly, I would like to dedicate this work to:

Great Lady … My Mother, who taught me that the highest success in life is the fulfillment of my ambition and without her constant prayers and encouragement; I would not have been able to reach this stage.

To

Great heart … My Father, who taught me that the Largest task can be accomplished if it is done Step by Step.

To

Helper and supporter … My brothers, my sisters.

To

My dear husband… for his patience, encouragement and support for me.

To

My beloved son … who adorned my life by his birth during my journey to perform this work and which made me struggle to complete this work.

To

All those who contributed even a word in the success of this work.

2021

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Next, I would like to express my gratitude to my family for their Sincere prayer and supplication to God and their continued support and encouragement to me who was the main cause of reaching this goal.

Also, I would like to thank the staff of Electrical Engineering Department at University of Babylon, for providing the support needed to complete this thesis.

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ABSTRACT

STBC systems are used in most modern wireless communication systems, including WiMAX, DVB-NGH, WiFi, HSPA+, LTE, 4G and 5G. MIMO systems with space time coding are a potential technique for increasing data rates and improving wireless communications reliability.

The main goal of this work is to provide STBCs for multiple transmit antennas and multiple receive antennas using semi-blind of channel estimation, improve BER performance, reduce decoding time.

This work proposed a technology for decoding STBC by using blind source separation (BSS), to enhance the BER performance for MIMO STBC channel estimator by using semi-blind independent component analysis (ICA) method, the kurtosis-based source extraction technique is achieved by using real imaginary decomposition (R-Im) of maximum ratio combiner (MRC) to evaluate the problem of the sign and the source ambiguity and by combined the kurtosis based on ICA with WCA and HIWOPSO independently to get a low complexity, fast speed, good BER performance decoder that can operate with any MIMO STBC is produced.

The MATLAB 2018 software was used to model the system's performance. The simulation results show that the performance of WCA-Kurtosis is better than the performance of the LS algorithm for transmit and receive antennas in 2×1, 2×2, 2×4,4×2, and 4×4 by 0.8, 1.6, 1, 2, and 2 dB, respectively, at the frame length of the 1024, and the performance of the HIWOPSO-Kurtosis is better than the performance of the LS algorithm for transmit and receive antennas in 2×1, 2×2, 2×4, 4×2, and 4×4 by 0.8, 1, 0.8, 2.1 and 4.2

dB, respectively. The simulation results demonstrate that the proposed channel estimation technique is feasible and effective, with only a small difference in performance between the estimated and known channel parameters, The results show that at 4×4, the HIWOPSO is the best algorithm because the proposed channel approaching to the known channel performance and get away the LS at a rate of 4.2 dB, and also the WCA algorithm achieved the best result at 4 × 4 at a rate of 2 dB than the LS, but HIWOPSO has more iterations than the WCA, whereas the Kurtosis-ICA achieved the best result at 2 × 2 and the worst result at 4 × 4, and this indicates that the proposed algorithms (WCA and HIWOPSO) can deal with matrices of large dimensions and with high accuracy and small iteration to reach the optimal solution.

Table of Contents

List of Abbreviations

ACO	Ant Colony Optimization
AWGN	Additive White Gaussian Noise
BEM	Block Element Modifier
BER	Bit Error Rate
BSS	Blind Source Separation
CSI	Channel State Information
GA	Genetic Algorithm
HIWOPSO	Hybrid Invasive weed optimization particle swarm Optimization
ICA	Independent Component Analysis
IWO	Invasive Weed Optimization
LS	Least Square
MIMO	Multiple-Input Multiple-Output
MI	Mutual Information
MMI	Minimizing Mutual Information
MRC	Maximum ratio Combiner
MSE	Mean Square Error
OFDM	Orthogonal Frequency Division Multiplexing
OSTBC	Orthogonal Space Time Block Code
PSO	Particle Swarm Optimization
QPSK	Quadrature Phase Shift Keying
R-Im	Real Imaginary
SNR	Signal to Noise Ratio
STBC	Space Time Block Code
STC	Space Time Coding
STTCs	Space-Time Trellis Codes
WCA	Water Cycle Algorithm

List of Symbols

Symbol	Description
H_{mrc}	Coefficient Channel Matrix of MRC
T_{co}	Coherence Time
p	Column Transmission Matrix
w	De-maxing Vector
f_d	Doppler Frequency Shift
$G_{N_t}^{H}$	Encoding Matrix
$\widetilde{U}$	Estimated Source
W	Estimator Matrix
G_{N_t}	Generate Matrix
c_1, c_2	Learning Coefficients
M	Mixing Matrix
$\vec{X}_{River}^{i}$	New River Site
$\vec{X}_{Stream}^{i+1}$	New Stream Site
T	Non-linear Modulation Factor
$Kurt(u)$	Normalized Kurtosis
N_p	Number of Pilot Symbol
n_r	Number of Receiver Signal
n_s	Number of Source
N_{sr}	Number of Stream
NSn	Number of Streams Which Flow to the Specific Rivers or Sea.
N_r	Number of receive Antennas
N_t	Number of Transmitter Antennas
x_i	PDF of Estimated Signals
C	Random Number Between 1-2
r_1 , r_2	Random Values Between 0-1
i_{th}	Received Antenna Coefficient

R	Received Mixture
Z_{mrc}	Received Signal for MRC
k	Row Transmission Matrix
U	Source Signal
f_c	Carrier Frequency
h_{ij}	The Complex Channel Fading Coefficient
x^t	The Inductor of The Fundamental Resonant Circuit
W_i	The ith Plant
S_j	The Locations of Seeds
v	The Relative Motion Velocity
d_{max}	Tiny Integer Around Zero
z^t	Total Length of The Wire
Z_p	Training Symbol in Receiver Side
X_p	Training Symbol in Transmitter Side
j_{th}	Transmitted Antenna Coefficient
v_i	Velocity Of the Particle
C	Light Velocity
θ	The Direction of Arrival of the Received Signal Wave
$\emptyset(u)$	Nonlinear Function

List of Figures

List of table

Chapter One
Introduction

Chapter One

Introduction

1.1 Motivation

In the wireless communication business, the multiple-input multiple-output (MIMO) channel has recently become a hot topic. The received signal in a MIMO channel is generally corrupted by the channel characteristics. In order to recover the transmitted bits, the channel effect must be assessed and modified in the receiver [1]. The channel response may generally be calculated using training or pilot symbols that are known to both the transmitter and the receiver. In order to keep track of the time-varying channel characteristics, the pilot symbols must be entered as often as the coherence time. On the other side, training symbols slow down throughput, making such systems useless when bandwidth is restricted. The process of calculating channels is the most difficult task in any wireless communication system. The estimation of a channel process offers crucial information about the numerous interactions that happened as signals burst through the channel. It is then employed in accurate signal decoding and demodulation, as well as leveling procedures. The total performance of wireless communications, such as bit error rate (BER), signal-to-noise ratio (SNR), and amplitude, is dependent on accurate estimation of channel characteristics in the receiver. More recently, on the MIMO signal reception system, the minimum bit error rate on the receiver side has been combined with channel estimate utilizing a number of estimation approaches [1].

Channel estimation has been studied and written about by a number of researchers. As a result, various techniques for wireless channel estimation problems have been proposed and implemented to provide channel state information (CSI). In the receiver side, the efficiently advanced techniques of channel estimation that have recently evolved for use in MIMO communication systems are presented, thus, a large amount of noise in a signal can be blocked. Estimating methods for MIMO may be divided into three groups [2].

1- Blind of Channel Estimation:

The receiver in this technique has no prior knowledge of the CSI. This type does not require a training symbol, allowing it to deliver complete throughput. However, the blind estimator's main two flaws are its enormous complexity and latency.

2- Non-Blind of Channel Estimation:

In this method, the receiver is aware of the CSI. This can be accomplished by utilizing an additional receiving antenna or a longer training sequence period, both of which limit throughput and add to system complexity.

3- Semi- Blind of Channel Estimation:

This technique requires fewer of pilots that reduce the efficiency of transmission. In comparison to a non-blind estimator, a semi-blind estimator requires fewer pilots, known as training codes, and their performance during modification may be superior. When the length of the experimental chain is long, good performance is obtained, but transmission efficiency is reduced. For example, in semi blind channel estimation approaches based on periodic training, signal sets, first order statistics are a sequence need for the inherent information known to the signal conveyed.

ICA (independent component analysis) is a crucial technique. ICA is a technique that can separate distinct sources from these linear mixes without knowing how they were mixed. As a result, it should be used in blind receivers to recognize transmitted symbols without the need for any training [3, 4]. ICA is a basic statistics tool to perform Blind Source Separation (BSS) [5], but the main problem in ICA algorithm is phase ambiguity and order ambiguity. Therefor used the semi blind for channel estimation. The ICA contains many algorithms such as kurtosis, Fast ICA and minimum mutual information (MMI). The main goal of these algorithms is extract independent components by maximize the negentropy, minimizing mutual information, or using Maximum probability (ML) [6,7].

The Real Imaginary (R- Im) decomposition of the maximum ratio combiner (MRC) model is used to reduce calculation complexity of complex number[8].

The maximum ratio combiner is the optimal decoder for flat fading AWGN channels [8], in theory is an ideal combination across fading channels as a scheme for diversity in the communication system.

The ICA technique is only applied to MRC signals don't on MIMO channel there in order to obtain the joint decoder and estimate for MIMO Rayleigh fading channels

1.2 Problem Statement

The STBC decoder contains two important parts channel estimation and decoder, all statistical methods dealing with a complex number are usually unfavorable and result in poor performance. When the signal is detected, orthogonal space time block code (OSTBC) receivers assume the full knowledge of the channel; however, to estimate the channel it usually needs to send a training sequence. The major drawback of a training-based system is that spectral efficiency is lowered, resulting in a lower usable data rate; in Blind's estimation. It is important to use optimal technique to Performance improve and increasing the speed work and Increased efficiency when dealing with a larger number of receivers.

1.3Literature survey

The drive for this work is that you have an excellent technique that can be applied to increase the performance of channel estimation process which is a very difficult task in any wireless communication system. To study MIMO channel estimation technique, it is necessary to review most of the relevant previous work as follows:

J. Kennedy, R. Eberhart, (1995) [9], detailed the application of particle swarm optimization to nonlinear functions, and examined the applications of the two different approaches. One of the new paradigms described in this work is an optimization method called particle swarm optimization (PSO). The concept of paradigm benchmarking is discuss-ed, as well as a number of applications, such as nonlinear function optimization and neural network training.

V. Tarokh and H Jafarkhani, (1999) [10], A novel transmission paradigm based on multiple transmitting antennas was developed, in which data was encrypted using STBC and then encrypted into split streams sent concurrently. It turns out that using several transmitting antennas with STBC offers excellent performance with practically no additional processing.

A.R. Mehrabian and C. Lucas, (2006) [11], offers a new numerical stochastic optimization technique based on weed colonization. IWO is used to solve an engineering challenge involving the optimization and tweaking of a robust controller. The findings of the experiments show that IWO produces superior outcomes than other techniques. In conclusion, IWO's performance is adequate for all of the test functions.

J. Vía, I. Santamaría and J.Pérez," (2009) [12], provide standard blind channel estimation. This technique relies solely on statistics order second (SOS) and the estimate is obtained as the main and important driver of the problem of generalized eigenvalues, if the channel is identifiable. Second, the technique proposes a new transition to solve the defects associated with the blind channel problem.

K .Bagadi and S. Das , (2010) [13], present their method for estimating the channel at experimental frequencies using the Least Square estimation algorithms and MIMO- OFDM and SISO -OFDM performance based on BER and MSE. They proved that MMSE performed better than LS but most complex than LS for MIMO using experimental carriers.

M.S. Ullah, M.J. Uddin, (2011) [14], MIMO channel is created with multiple antenna array elements at both ends of the wireless connector. All these MIMO technologies are based on the correct processing of the Alamouti scheme and signals of the method of combining the maximum ratio that is transmitted and received by a set of antennas. Simulation results show very high bit error rate performance even for low signal-to-noise ratios.

F. Delestre, (2011) [15], A new co-channel iterative technique and signal detection technology are proposed for SFBC_OFDM and STBC_OFDM systems. The symbols in OFDM are divided into groups, which are assigned a set of experimental sub-carriers and these are used to initiate the channel of estimation method. The specific data codes in each set of OFDM codes are decrypted simultaneously in order to improve the decoding duration for encoding.

M.N. Seyman and N. Taşpinar, (2011) [16], provide the optimal particle swarm (PSO) to improve the position and strength of comb type experimental tones that are used for estimation in the lower square channel (LS) in MIMO-OFDM systems. To improve the experimental tones, the upper limit of MSE is used as the target function of PSO. According to the simulation results, PSO is an effective solution for designing experimental tones.

A. Sadollah, H. Eskandar and A. Bahreinineja ,(2012) [17], introduce the water cycle algorithm (WCA), a novel optimization approach that may be used to solve a variety of restricted optimization and engineering design issues. The suggested method's core principles and ideas are drawn from nature and are based on observations of the water cycle process and how rivers and streams flow to the sea in the actual world.

A. Devasia, R. Reddy ,(2013) [18], provided a channel estimation of semi blind method which is a combination for blind of estimation and channel training estimation based on a lower square. The linear prediction method is used to estimate the blind constraint and the method of least -square (LS) for matrix estimation, which is used to find the semi-blind estimate. The results can be show that when using training data with the same number, the semi-blind channel estimate provides a lower volume of MSE and BER compared to LS.

S.P. Jadhav and V.S. Hendre, (2013) [19], The BER characteristics of various in transmit and in receive antennas are simulated in the MATLAB toolbox. Accurate bit error rate (BER) analysis of fading channels with maximum collection ratio (MRC) and incomplete channel estimation at reception are provided. It can show that an MRC-based receiver is a good option as it can remove some ISI and reduce total noise power. The results show that the BER rate decreases with increasing antenna configurations $m \times n$.

T. Ahmed, M.S. Anower, M.Z.I. Sarkar and M.M Ali, (2013) [20] closed expressions of the probability of error for these modulations are derived with MRC, allow undefined values of channel gain correlation matrix. Performance results show analysis assuming different future configurations and scattering scenarios provided give valuable insight. In the performance of the MRC in Rayleigh fading scenarios for gossiping of isotropic and non-isotropic properties Distributions**.**

SA Kadhim, (2014) [21], gives an introduction to the basic concepts of training based channel estimator and explains the implementation of least square error (LS) channel estimator with diagonal and orthogonal training matrix. The kurtosis based source extraction method based on using real imaginary (R-Im) decomposition of MRC was fully described. Finally the benefit of using at least four training symbols for initialization de-mixing vector and removing source ambiguity was illustrated.

M. Kashoob and Y. ZakharovMember, (2016) [22], proposed a selective symbol-by symbol optimal detection for a single-user MIMO OFDM. which compared the performance of the proposed detector with that of a detection with the reweighted LMMSE channel estimator Simulations indicate that selective optimum detection outperforms reweighted LMMSE channel estimation.

Z. Hosseini and A. Jafarian, **(2016) [23],** offered a hybrid method for global optimization based on invasive weed optimization and particle swarm optimization, where the suggested hybrid algorithm starts by searching for solutions using IWO and PSO algorithms, then using the best one as the input to the mutation function. The result of the mutation is compared to the input, and the best one is chosen as the new seed. The suggested hybrid outperformed other well-known algorithms in an experiment based on benchmark functions and non-parametric ranking.

L. Chang , (2018) [24], developed a fast forward-backward estimation (FFBE) method for multiple input- multiple output (MIMO) space time-block code (STBC) orthogonal frequency -division multiplexing (OFDM) systems. Computer simulations demonstrate the effectiveness and accuracy of the proposed FFBE in channel estimation.

N.S Ali, K.K. Abdalla and S.A Kadhim ,(2020) [25], provide the alamouti MIMO-STBC decoder's BER performance enhancement utilizing mutual information technique. The BER performance of a traditional MRC decoder for MIMO STBC systems based on the LS channel estimator was examined, and a novel method for decoding MIMO STBC based on a new model for MIMO-STBC was developed. The MRC is represented as a noisy linear mixing system in this model.

K. K. Abdalla, and S. A. K. Alrufaiaat, (2020) [26], present a new robust decoding approach based on Fast ICA Algorithm for four transmitters MIMO STBC System, where Fast ICA Algorithm is utilized as a BSS technique to create a new suggested decoder. This method assumes that the de-mixing vector has a single value that optimizes Negative Entropy measurement in every mixing system. This paper suggested a new MIMO STBC model based on the representation of the maximum ratio combiner as a linear mixing system.

M.S. Bendelhoum and M.R. Lahcene, (2021) [27], Space time block codes (STBC) with different antenna systems are presented and evaluated and BER performance of STBC and space time trellis code (STTC) solutions is compared using different configurations, where proved that the TCM scheme implemented over AWGN and Rayleigh channels may significantly improve performance of the transmission system.

S.A.K. Alrufaiaat and A.Q.J. Althahab, (2021) [28], offer a novel blind source separation (BSS) technique for decoding a MIMO-STBC, in which a global particle swarm optimization method (GPSO) is coupled with one source extraction Kurtosis based BSS to produce a high speed/low complexity MIMO-STBC decoder.

1.4 Aims of the work

The goals of this work are:

1- Improving the BER performance for MIMO-STBC channel estimator by using ICA semi-blind method and reduce a computational complexity of the detection in MIMO-STBC systems by using real imaginary (R- Im) decomposition.

2- Solving the source and sign ambiguity problem of ICA algorithm by using suitable initialization based on pilot symbols.

3- Performance improve and increasing the data rate of channel estimation Using kurtosis-based ICA algorithm by utilized two important algorithms first, the water cycle algorithm (WCA) and second, a hybrid algorithm based on the invasive weed optimization and the particle swarm optimization (HIWOPSO).

1.5 The Work Out line

Chapter 1 gives a synopsis of this thesis's beginning. This contains research background and the aims of work. Chapter 2 introduce an overview of MIMO systems as well as the fundamentals of STBC.at beginning, the chapter covers channel theory for systems utilizing various diversity methods. Then, Encoder STBC is discussed of details and the performances are evaluated assuming that Information of Channel State (CSI) is known for the receiver and that data is transmitted through MIMO flat Rayleigh fading channel. Further, Quasi-Orthogonal of Space-Time Block Coding was introduced. Chapter3 described the suggested system of MIMO-STBC channel estimation and discuss two proposed algorithms WCA and HIWOPSO and its effect on improving BER. Chapter 4 shows the results and discussion of the proposed techniques and Comparison between the performances of algorithm used. Finally, Chapter 5 introduces the conclusions of the thesis and their future works.

Chapter Two

MIMO Channel for Wireless Communication Systems

Chapter Two

Theory background of MIMO Channel in Wireless Communication Systems

2.1 Introduction

This chapter discusses the introduction of the main concepts for MIMO-STBC channel system and interprets the implementation of STBC encoder decoder. There are two main parts used in STBC decoder, the first is the channel- estimator and the second is the maximum ratio combiner. MIMO (multiple inputs, multiple outputs) is an antenna technology for wireless communications in which multiple antennas are used at both the source (transmitter) and the destination (receiver). The antennas at each end of the communications circuit are combined to minimize errors, optimize data speed and improve the capacity of radio transmissions by enabling data to travel over many signal paths at the same time. Creating multiple versions of the same signal provides more opportunities for the data to reach the receiving antenna without being affected by fading, which increases the signal-to-noise ratio and error rate.

2.2 MIMO Communication System

MIMO is often used for high-bandwidth communications where it's important to not have interference from microwave or RF systems. For example, it's frequently used by first responders who can't always rely on cell networks during a disaster or power outage or when a cell network is overloaded. Before MIMO, there were other types of advanced antenna technology with different configurations - most commonly, multiple input, single output (MISO) and single input, multiple outputs (SIMO). MIMO builds on these technologies. In its various configurations, MIMO has a number of advantages over MISO and SIMO advanced antenna technologies:

1. MIMO enables stronger signals. It bounces and reflects signals so a user device doesn't need to be in a clear line of sight.

2. Video and other large-scale content can travel over a network in large quantities. This content travels more quickly because MIMO supports greater throughput.

3. Many data streams improve visual and auditory quality. They also decrease the chance of lost data packets.

MIMO is a primary tool for advancing all aspects of wireless communications. It plays a substantial role in 5G technology and is influencing how users interact with these technologies daily. These influences include the following :

- **High network capacities.** Data travels to more users through the deployment of 5G New Radio (5G NR). MU-MIMO and 5G NR enable more users to access data at the same frequency and time rates.
- **More coverage.** Users can soon expect high-speed data wherever they are, even at the edge of service areas. Using 3D beam forming, the coverage adapts to the user's movement and location.
- **Better user experience (UX).** Watching videos and uploading content is easier and faster. Massive MIMO and 5G technology transform UX.

By boosting the capacity of radio frequency (RF) systems, MIMO creates a more stable connection and less congestion. The 3rd Generation Partnership Project (3GPP) added MIMO with Release 8 of the Mobile Broadband Standard. MIMO technology is used for Wi-Fi networks and cellular fourth-generation (4G) Long-Term Evolution (LTE) and fifth-generation (5G) technology in a wide range of markets, including law enforcement, broadcast TV production and government. It also can be used in wireless local area networks (WLANs) and is supported by all wireless products with 802.11n

There are various categories of MIMO techniques; the first one aimed to improve the power efficiency by maximizing spatial diversity, the second one aimed optimize data speed and improve the capacity of radio transmissions by enabling data to travel over many signal paths at the same time. The main function of MIMO system is to improve the signal quality and reduction on Bit Error Rate (BER) using multiple transceiver antennas. [29].

2.3 Basic MIMO Channel Model

The traditional single antenna communication system lacks the required spatial that is degree of freedom that is provided by multiple antennas. In MIMO communication systems, the presence of multiple antennas can be of great advantage. The spatial degree of freedom provided by these antennas can be appropriately harnessed to boost the capacity and expand the system's coverage through optimal scheduling of multiple users to simultaneously share the spatial channel. As illustrated in Figure 2.1, this model contains N_t antennas at the transmitter side and N_r antennas at the receiver side. For each sub channel attenuation, phase shift and delay between j_{th} transmitter and the i_{th} receiver was represented by complex value h_{ij}. This value denoted by channel fading coefficient [2].

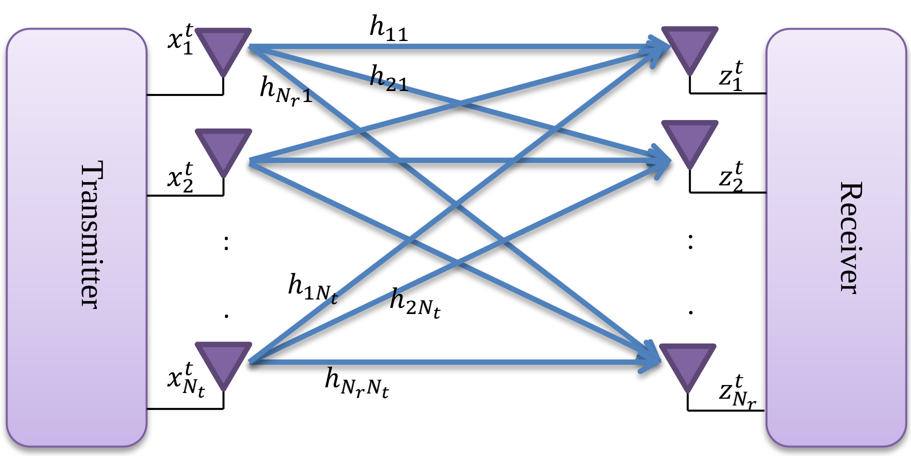


Figure 2.1 MIMO channel model [2]

There are several mathematical models to represent a noisy communication channel which are summarized in the Figure (2.2) [30].

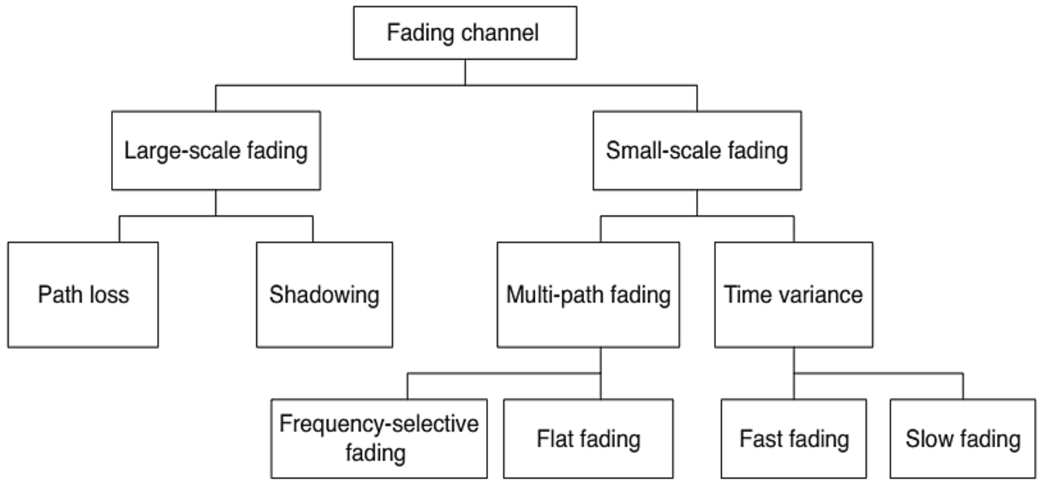


Figure 2.2 Classification of communication system channels [30].

fading refers to the fluctuations in signal strength when received at the receiver. Fading can be classified in to two types:

- Fast fading/small scale fading
- Slow fading/large scale fading

Fast fading refers to the rapid fluctuations in the amplitude, phase or multipath delays of the received signal, due to the interference between multiple versions of the same transmitted signal arriving at the receiver at slightly different times.

Slow Fading, the name slow fading itself implies that the signal fades away slowly. The features of slow fading are given below:

1. Slow fading occurs when objects that partially absorb the transmission lie between the transmitter and receiver.

2. Slow fading is so called because the duration of the fade may last for multiple seconds or minutes.

3. Slow fading may occur when the receiver is inside a building and the radio wave must pass through the walls of a building, or when the receiver is temporarily shielded from the transmitter by a building. The obstructing objects cause a random variation in the received signal power.

4. Slow fading may cause the received signal power to vary, though the distance between the transmitter and receiver remains the same.

5. Slow fading is also referred to as **shadow fading** since the objects that cause the fade, which may be large buildings or other structures, block the direct transmission path from the transmitter to the receiver.

The quasi-static, non-selective, Rayleigh fading channel model was utilized in this thesis. The channel response varies randomly between blocks under the quasi-static assumption, but it remains constant inside a transmission period, which is referred to as coherence time (T_{coh}) it is the time period during which the channel impulse response is coherent (remain invariant). Coherence time is inversely proportional to the maximum of Doppler frequency shift, $f_{d,max}$, which it is given by[31] :

$$T_{coh} \approx \frac{1}{f_{d,max}} \tag{2.1}$$

Doppler shift can be defining due to the relative motion between transmitter and receiver as the apparent change in frequency of the transmitted signal, which it is given by [32]:

$$f_d = \left(\frac{v}{C} f_c\right) \cos(\theta) = f_{d,max} \cos(\theta) \tag{2.2}$$

where v is the relative motion velocity, C is light velocity, f_c is the carrier frequency, and θ is the direction of arrival of the received signal wave.

During T_{coh} time the MIMO channel can be represented by linear system with coefficients matrix [2]:

$$H = \begin{pmatrix} h_{11} & \dots & h_{1Nt} \\ : & : & : \\ h_{Nr1} & \dots & h_{NrNt} \end{pmatrix} \tag{2.3}$$

Each channel fading coefficient h_{ij} is supposed to be independently identically distributed zero mean complex Gaussian random variables with unit variance [2].

The mechanism of data transmission through MIMO system can be represented by using matrix operation. At time t, if transmitted signals represented as column vector $X^t = \begin{bmatrix} x_1^t \\ : \\ x_{N_t}^t \end{bmatrix}$ and received signals as $Z^t = \begin{bmatrix} z_1^t \\ : \\ z_{N_r}^t \end{bmatrix}$ then:

$$Z^t = HX^t + noise \tag{2.4}$$

This equation represents mathematical model for noisy MIMO system where H is still constant through each block and varies randomly between block to block.

2.4 Space Time Code (STC)

STC is a method employed to improve the reliability of data transmission in wireless communication systems using multiple transmit antennas. STCs rely on transmitting multiple and redundant copies of a data stream to the receiver in order that at least some of them may survive the physical path between transmission and reception in a good enough state to allow reliable decoding.

Space time codes may be split into main two types:

- Space–time trellis codes (STTCs) distribute a trellis code over multiple antennas and multiple time-slots and provide both coding gain and diversity gain [33].
- Space–time block codes (STBCs) act on a block of data at once (similarly to block codes) and also provide diversity gain but doesn't provide coding gain [34].

Space–time line codes (STLCs) is a recently proposed as a symmetric transmission scheme of the STBCs. It also provides diversity gain even when there is no channel state information (CSI) at the receiver [35].

STC may be further subdivided according to whether the receiver knows the channel impairments. In coherent STC, the receiver knows the channel impairments through training or some other form of estimation. In noncoherent STC the receiver does not know the channel impairments but knows the statistics of the channel. In differential space–time codes neither the channel nor the statistics of the channel are available. In this chapter we will focus on the STBC.

2.5 Space Time Block Code

Space–time block coding is a technique used in wireless communications to transmit multiple copies of a data stream across a number of antennas and to exploit the various received versions of the data to improve the reliability of data transfer. The fact that the transmitted signal must traverse a potentially difficult environment with scattering, reflection, refraction and so on and may then be further corrupted by thermal noise in the receiver means that some of the received copies of the data may be closer to the original signal than others. This redundancy results in a higher chance of being able to use one or more of the received copies to correctly decode the received signal. In fact, space–time coding combines all the copies of the received signal in an optimal way to extract as much information from each of them as possible. This chapter focuses on channel estimation problem, where the training- based channel estimator and the implementation for the least square error (LS) channel estimator was illustrates. The improvement for semi blind channel estimation using deferent Independent Component Analysis (ICA) strategies [14].

2.5.1 Encoding Algorithm of STBC

A space–time block code is defined by N_t row by p column transmission matrix G_{Nt}. The entries of the matrix G_{Nt} are linear combination of the variables $S_1, S_2 \dots, S_k$ and their conjugates. The N_t of transmission antennas were used to separate different codes from each other. For example, G_2 represents a code which utilizes two transmit antennas and is defined by [36]:

$$G_2 = \begin{pmatrix} S_1 & -S_2^* \\ S_2 & S_1^* \end{pmatrix} \tag{2.5}$$

where $*$ denotes complex conjugate, this code is well known by Alamouti STBC [12].

Alamouti suggested a simple transmit diversity technique dedicated for flat fading wireless Communication channel based on two transmit antennas. The basic scheme proposed by Alamouti which is called "Space Time Block code" can be summarized by:

1. Assume that the transmitted sequence is { S_1 , S_2 , S_3 , S_4 , ... , S_n }.
2. In usual transmission, the symbol S_1 sends in the 1st time slot, then S_2 in the 2nd time slot and so on.
3. The transmission of S_1 and S_2 in the 1st time slot from the first and 2nd antenna simultaneously. In the next slot the values of $-S_2^*$ and S_1^* are sent from 1st and 2nd antenna. In the 3rd time slot S_3 and S_4 are sent from the 1st and 2nd antenna. In 4th time slot, S_4^* and S_3^* sent from the 1st and 2nd antenna and so forth slot. As example the encoding process of Alamouti can be illustrated as shown in Figure (2.3) where it assumes M- array modulation scheme is used [10].

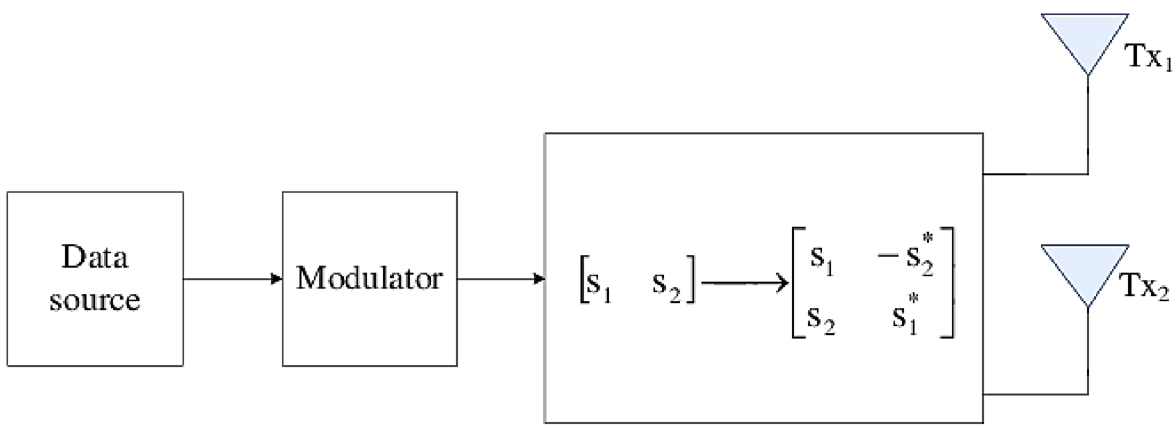


Figure (2.3) Block diagram of Alamouti space-time encoder [10]

Space-time block codes (STBC) are an extension to Alamouti scheme [36]. The key features of these codes are the orthogonally and full diversity that characterized by the number of transmit antennas. For each N_t -MIMO channel there is one (or more) specific STBC encoding matrix. The key feature of any STBC scheme that is the transmit sequences from the two transmit antennas are orthogonal, i.e. the encoding matrix should be specify the following condition $G_{N_t} \times G_{N_t}^H = \alpha I_{N_t}$ where α is scalar = $\sum_{i=1}^{k} |S_i|^2$ .The encoding rate for STBC can be found simply by dividing k/p (k is number of column as example in the G_{Nt}, p is number of row in G_{Nt}), for Alamouti STBC $k = p = 2$, that made encoding $rate = 1$ (full rate) [12] .

2.5.2 The STBC Decoder Using Maximum Ratio Combiner

To improve the performance of a communication system working in fading environment, Maximum Ratio Combining (MRC) technique with multiple receiving antennas is utilized. This method simply combines received signals from multiple channels to obtain the highest average signal-to-noise power ratio. on the other hand, the improvement in performance is comes at the cost of increasing the complexity of the mobile station. As explained in last section (2.5.1) Alamouti suggested the use of two transmitting antennas with an arbitrary number of antennas at the receiver assuming flat fading channel. The decoding procedure may be accomplished in two steps: first, the channel coefficients h_{ij} must be estimated using a channel estimator, and then the encoded signals S_1, S_2 ..., S_v must be calculated (using a maximum ratio combiner) (MRC). To illustrate the MRC operation, Alamouti STBC will be used as example. If we denoted coefficient matrix of $2 \times N_r$ MIMO channel as $\mathrm{H} = [\hbar_1 \quad \hbar_2]$ where $\hbar_{\mathrm{i}}$ is the i^{th} column of H matrix, then the received signals are: at $t = 1$ is:

$$\mathrm{Z}^1 = \begin{bmatrix} \mathrm{z}_1^1 \\ \vdots \\ \mathrm{z}_{N_r}^1 \end{bmatrix} = [\hbar_1 \quad \hbar_2] \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \end{bmatrix} + noise \qquad (2.6.a)$$

If channel coefficient is still constant (quasi-static channel), then the received signals at $t = 2$ is:

$$Z^2 = \begin{bmatrix} \mathrm{z}_1^2 \\ \vdots \\ \mathrm{z}_{N_r}^2 \end{bmatrix} = [\hbar_1 \quad \hbar_2] \begin{bmatrix} -S_2^* \\ S_1^* \end{bmatrix} + noise \qquad (2.6.b)$$

By using simple modification for Equation (2.6.b) can be rewrite it as:

$$(\mathrm{z}^2)^* = [-(\hbar_2)^* \quad (\hbar_1)^*] \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \end{bmatrix} + noise \qquad (2.6.c)$$

The main idea of MRC for deducing the value S_1, S_2 is ***combining*** the Equation (2.6.a) and Equation (2.6.c) to obtain:

$$\begin{bmatrix} \mathrm{Z}^1 \\ (\mathrm{Z}^2)^* \end{bmatrix} = \begin{bmatrix} \hbar_1 & \hbar_2 \\ -(\hbar_2)^* & (\hbar_1)^* \end{bmatrix} \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \end{bmatrix} + noise \qquad (2.6.d)$$

In general, for any G_{Nt} orthogonal STBC encoding matrix with v-input sample $\mathrm{S}_1, \mathrm{S}_2 \ldots, \mathrm{S}_v$ the MRC equation could be writing as:

$$\mathrm{Z}_{\mathrm{MRC}} = \mathrm{H}_{\mathrm{MRC}} * \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \\ \vdots \\ \mathrm{S}_v \end{bmatrix} + noise \qquad (2.7)$$

It can be denoted that $\mathrm{H}_{\mathrm{MRC}}$ is orthogonal matrix where:

$$(\mathrm{H}_{\mathrm{MRC}})^{\mathrm{H}}\ \mathrm{H}_{\mathrm{MRC}} = \|\ \mathrm{H}_{\mathrm{MRC}}\| \mathrm{I}_v \qquad (2.8)$$

where $\|\mathrm{H}_{\mathrm{MRC}}\|$ is norm of $\mathrm{H}_{\mathrm{MRC}}$. The input symbols of STBC encoder $\mathrm{S}_1, \mathrm{S}_2 \dots, \mathrm{S}_\mathrm{k}$ can be estimated by:

$$\begin{bmatrix} \check{S}_1 \\ \check{S}_2 \\ \vdots \\ \check{S}_k \end{bmatrix} \cong \frac{1}{\| \mathrm{H}_{\mathrm{MRC}} \|} (H_{MRC})^H \, Z_{MRC} \tag{2.9}$$

According to this equation, the performance of STBC is mostly determined by two factors.

Once, the channel estimator's quality and second, encoding rate (k/p) and number of receiver antennas N_r. Since the dimension of $\mathrm{H}_{\mathrm{MRC}}$ is (pN_r) rows by (k) columns, that mean the k-unknown values $(\check{S}_1, \check{S}_2 \dots, \check{S}_k)$ are estimated using equation 2.9.

2.5.3 Least Squares Channel Estimation Technique

The technique of channel estimate is a significant and difficult problem in wireless communication systems. A channel estimate technique provides sufficient information about any distortion delays, interferences, attenuations, and phase shifts that occur to the signals carried via the channel [5]. The least squares (LS) estimation is a common method for pilot-based channel estimation, as it offers good performance with reasonable complexity. If the receiver has no prior knowledge of the channel state information, this kind is known as a blind channel estimator. This method is not preferred in a communication system since it has two significant flaws, which are as follows [5]:

Once the phase ambiguity (It is unable to identify the precise sign of the estimated channel coefficient ($\mp\hbar_i$)), and second, the order ambiguity (It is unable to identify the precise order of channel coefficients). Furthermore, blind channel estimation necessitates a high level of computing complexity. The most common channel estimate technique is to use training or pilot symbols (X_t) that are known to the receiver side, as shown in Figure (2.4). To keep track of the time-varying channel properties, the pilot symbols must be put as often as the coherence time. However, training symbols degrade throughput, therefore such techniques are insufficient when bandwidth is limited. When the training symbols (Z_t and X_t) are provided, the Least Square (LS) approach is commonly employed for channel estimation where [37]:

$$Z_t = HX_{\mathrm{t}} + noise \tag{2.10}$$

The channel estimation of the least square technique is to find the estimated channel matrix $\breve{\mathrm{H}}$ in such a mothed that the minimized cost function $\left\| Z_t - \breve{H}X_t \right\|^2$that made:

$$\breve{H} = Z_{\mathrm{t}}(X_t)^{\dagger} \tag{2.11}$$

$(X_t)^{\dagger}$ is pseudo inverse of X_t which can be defined as [38]:

$$(X_t)^{\dagger} = X_t^H(X_tX_t^H)^{-1} \tag{2.12}$$

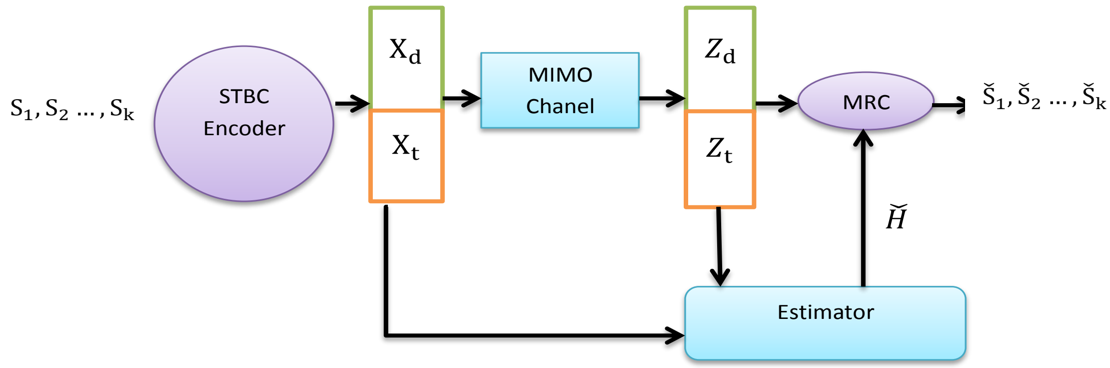


Figure (2.4) Channel estimation using pilot sequence

According to Equation (2.11), increasing the number of training symbols (N_t) improves the quality of channel estimation; but, because training symbols (X_t) must be sent in addition to data symbols (X_d), this method lowers transmission efficiencies [38].

One goal of this thesis is to figure out how to enhance channel estimate quality without increasing the number of training pilots. To get a semi blind channel estimator, a simple criterion based on utilizing $\breve{H}$ (calculated using LS estimator with minimal training pilot sequence) as the beginning value for a statistically based blind channel estimator is used. This criterion will alleviate the problems associated with blind channel estimators (phase and order ambiguities), as well as reduce computing complexity and speed up the estimate process.

2.5.4 Real Imaginary (R- Im) Decomposition for MRC

The following decomposition will be used to get rid of the complex number calculation for MIMO-STBC with N_t transmitter, N_r receiver and encoding $rate\ = k/p$. There are several methods of the Real_ Imaginary

(R- Im) decomposition for the MRC model: Source Decomposition, Signal Decomposition and Matrix Decomposition.

1 .Source Decomposition

Assume $\boldsymbol{S_i} = \boldsymbol{u_i} + \boldsymbol{j}\boldsymbol{u_{k+i}}$ is the i_{th} complex source, where $u_i$is the real portion of $\boldsymbol{S_i}$ and $\boldsymbol{u_{k+i}}$ is the imaginary component of $\boldsymbol{S_i}$. This decomposition will yield a set of $(n_s = 2k)$ real value sources organized as follows:

$$U = \begin{bmatrix} \boldsymbol{u_1} \\ \vdots \\ \boldsymbol{u_k} \\ \boldsymbol{u_{k+1}} \\ \vdots \\ \boldsymbol{u_{n_s}} \end{bmatrix} = \begin{bmatrix} Re\begin{Bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \\ \vdots \\ \mathrm{S}_\mathrm{k} \end{Bmatrix} \\ Im\begin{Bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \\ \vdots \\ \mathrm{S}_\mathrm{k} \end{Bmatrix} \end{bmatrix} \tag{2.13}$$

2. Signal Decomposition

In the same manner Z_{MRC} can decompose into n_r real value mixtures received signals (R), that arranged as following:

$$R = \begin{bmatrix} Re\{Z_{MRC}\} \\ Im\{Z_{MRC}\} \end{bmatrix} = \begin{bmatrix} \boldsymbol{r_1} \\ \boldsymbol{r_2} \\ \vdots \\ \boldsymbol{r_{n_r}} \end{bmatrix} \tag{2.14}$$

3. Matrix Decomposition

If consider a linear mixing system with input(n_s) of sources inputs $\boldsymbol{U}$ and output (n_r) of mixture received signals ($\boldsymbol{R}$), then the $n_r \times n_s$ mixing matrix $\boldsymbol{M}$ should look like this:

$$\boldsymbol{M} = \begin{bmatrix} \boldsymbol{Re\{H_{MRC}\}} & \boldsymbol{-Im\{H_{MRC}\}} \\ \boldsymbol{Im\{H_{MRC}\}} & \boldsymbol{Re\{H_{MRC}\}} \end{bmatrix} \quad (2.15)$$

The entire noisy real values mixing system is expressed as follows:

$$\boldsymbol{R = MU + noise} \quad (2.16)$$

The main feature of this decomposition of the mixing matrix is orthogonal, which means that the optimal un-normalized de mixing matrix W_{opt} should equal M^T, as illustrated in Figure (2.5).

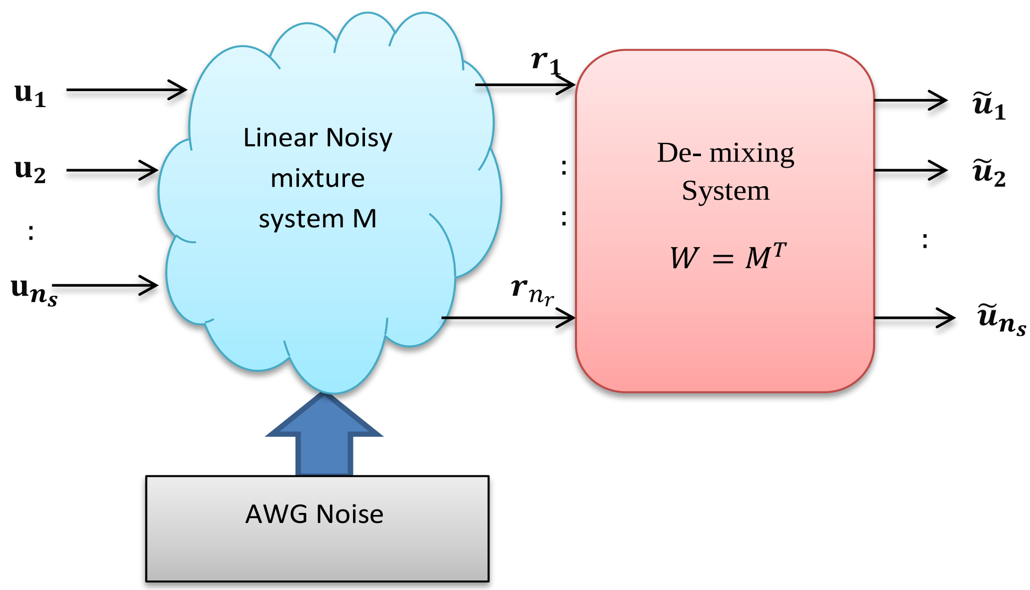
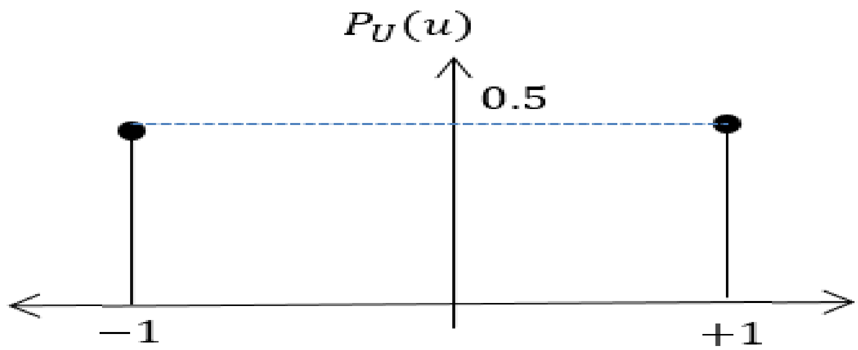


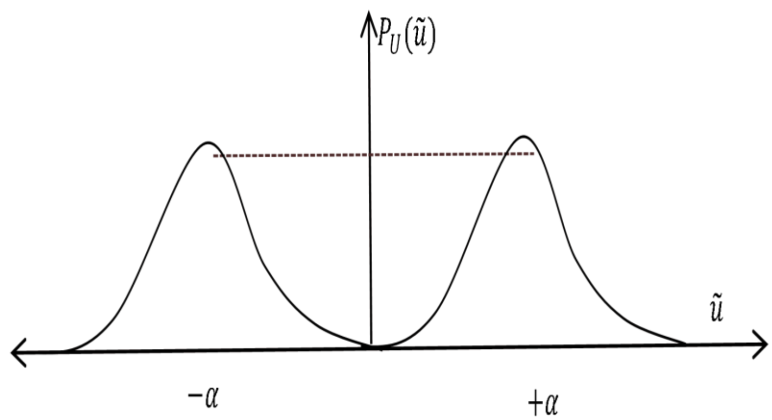
Figure 2.5 *R-Im* decomposition model for MIMO STBC

2.6 Statistical Analysis of the Model

A mathematical representation of a QPSK signal with a carrier amplitude of A_C is $S_i = \frac{A_c}{\sqrt{2}}\{(\mp 1) + j(\mp 1)\}$. After Source Decomposition all sources (normalized sources) are belong to two values $u_i \in \{-1, +1\}$. To put it another way, any source may be represented statistically as a discrete r.v. with two level binomial distributions as illustrated in Figure (2.6a):



(a)



(b)

Figure 2.6: (a) Probability Mass Function of a discrete r.v.u (b) is the Probability Density Function of $\tilde{u}$.

Note that $P_u(u=-1) = P_u(u=+1) = 0.5$ is assumed because in a communication system, any source encoding produces a binary signal (modulator input) with an equal likely distribution. The expected statistic for $\boldsymbol{U}$, according to traditional statistical computation analysis:

All sources are sub-Gaussian.

1- The variance is 0.5 and the mean value is 0.
2- For each source, the normalized Kurtosis is 2
3- The entropy for each source is 1.
4- Uncorrelated the All source.

Receiving signals R can be represented as a continuous r.v with a Gaussian distribution probability density function, according to central limit theory as shown in Figure (2.5b). The expected statistic for $\boldsymbol{R}$ are:

1) Because all sources and noise are zero, the mean value of R is zero.
2) Variance of $\boldsymbol{R}$ depending on noise variance (SNR value).
3) Entropy of $\boldsymbol{R}$ is greater than Entropy of $\boldsymbol{U}$.
4) All mixtures received signals are correlated signals.

The predicted signal can be approximated **as** $\boldsymbol{\tilde{u} = \alpha u + noise}$, because the de-mixing method isolates the mixture signals without reducing additive noise. The predicted PDF for estimated signal $\tilde{u}$ is based on the additive probity of the two variables is:

$$P_U(\tilde{u}) = P_U(u) \circledast P_{noise} \tag{2.17}$$

Where the convolution operation is $\circledast$ and P_{noise} is PDF of noise (zero mean Gaussian noise), The expected PDF of $\tilde{u}$ can be represent as shown in Figure (2.6.b).

2.7 ICA Channel Estimation Technique

Independent component analysis (ICA) is a computational method to solve blind source separation (BSS) problem. Different kinds of classic measure can be used for the estimation of non-gaussian sources by ICA. Independent component analysis (ICA) is a mathematical tool for extracting factors or components that underlie sets of random variables, measurement, or signals. A generative model is defined for the observed multivariate data by ICA, which is typically given in a large amount of data. In the model, the data variables are assumed to be linear or nonlinear mixtures of some latent variables. The mixing system is also unknown. The latent variables are supposed to be mutually independent and non-Gaussian. They are called the independent components of the observed data.

Source separation, blind signal separation (BSS) or blind source separation, is the separation of a set of source signals $\boldsymbol{U} = \begin{bmatrix} \boldsymbol{u_1} \\ \boldsymbol{u_2} \\ \vdots \\ \boldsymbol{u_{n_s}} \end{bmatrix}$ from a set of mixed signals $\boldsymbol{R} = \begin{bmatrix} \boldsymbol{r_1} \\ \boldsymbol{r_2} \\ \vdots \\ \boldsymbol{r_{n_r}} \end{bmatrix}$, without the aid of information (or with very little information) about the source signals or the mixing process. It is most commonly applied in digital signal processing and involves the analysis of mixtures of signals; the objective is to recover the original component signals from a mixture signal where [5]:

$$\boldsymbol{R} = \boldsymbol{MU} \tag{2.18}$$

where $\boldsymbol{M}$ is the $n_r \times n_s$ mixing matrix, n_r denotes the number of received signals, and n_s denotes the number of source signals. Consider a BSS linear system $\boldsymbol{W}$ ($n_s \times n_r$ matrix) with inputs as combinations of received signals $\boldsymbol{R}$ and outputs as the estimation of the independent sources $\breve{\boldsymbol{U}}$ where:

$$\breve{\boldsymbol{U}} = \boldsymbol{W}\boldsymbol{R} \tag{2.19}$$

Equation (2.14) represents the BSS all-unit version, which means that all sources will be extracted. As demonstrated in the preceding section, BSS suffer from: order, phase, and scalar ambiguity problems, which may be mathematically represented by a global de mixing matrix [39].

$$\boldsymbol{G} = \boldsymbol{W}\boldsymbol{M} = \boldsymbol{P}\boldsymbol{D} \tag{2.20}$$

where P is a $n_s \times n_s$ permutation matrix (order ambiguity) and D is a $n_s \times n_s$ diagonal matrix (phase and scalar ambiguity) [40].

If $\boldsymbol{M} = [\boldsymbol{m_1} \quad \boldsymbol{m_2} \quad \cdots]$ mixing matrix is orthogonal matrix (dot product between two columns = 0 ($\langle \boldsymbol{m_i}, \boldsymbol{m_j} \rangle = 0 \; if \; i \neq j$) then ***one unit*** version of BSS (extracting a single source $\boldsymbol{u_i}$) is presented as [41]:

$$\breve{\boldsymbol{u}} = \boldsymbol{w}\boldsymbol{R} \tag{2.21}$$

where $\boldsymbol{w}$ is de mixing vector.

If $\boldsymbol{w} = \boldsymbol{m_j}$, the estimated source is $\breve{\boldsymbol{u}} = \|\boldsymbol{m_j}\|\boldsymbol{u_j}$, however one unit BSS suffers from phase, order, and scalar ambiguity issues. The de mixing vector might be [42]:

$$\breve{\boldsymbol{u}} = \pm\alpha\boldsymbol{u_j} \tag{2.22}$$

where α is α is scalar. Scalar ambiguity can be eliminated by using suitable preprocessing to the receive mixture $\boldsymbol{R}$. The first preprocessing is to ***centering*** $\boldsymbol{R}$, i.e. subtract its mean vector E$\{\boldsymbol{R}\}$ and normalized its power so as each $\boldsymbol{r_j}$ a zero-mean, unit variance signal. Based on the same assumption estimated source signal $\breve{\mathbf{U}}$ is centered signal of $\boldsymbol{U}$, that mean the de mixing vector should be a unity vector i.e $\|\boldsymbol{w}\| = 1$ .This preprocessing simplify the ICA search algorithm for only unity vector . To complete the estimation **U** ,add the mean vector of E{$\boldsymbol{U}$} back to the centered estimates signal $\breve{\boldsymbol{U}}$ and multiply each component $\boldsymbol{u_j}$ by its power (in communication system, mean and variance of source ,modulated, signal is known)[42].

All BSS-ICA algorithms are based on the ***Central Limit theorem*** that states that "*the sum of independent random variables usually has a distribution that is closer to Gaussian than any of the two original random variables*". In other words, the fundamental concept to estimate de-mixing matrix, $\boldsymbol{w}$, bases on maximizing non-Gaussianty measuring of $\varphi(\boldsymbol{wR})$ where $\varphi(u\ )$ is nonlinear function depend on distribution function of source and cost function. In other words, BSS algorithm is adjust the parameters of the de mixing matrix w in order to minimization and/or maximization of one or more non- Gaussianty measuring to obtain the independence signal of its output. The ICA contains many algorithms are: Minimum mutual information (MMI), Fast ICA (negentropy) and Kurtosis. In this research, will focus only on the kurtosis-based ICA because of its advantages compared to the other two types in terms of speed of implementation and also the number of frames it needs is less than the rest [7].

2.7.1 Mutual Information

Mutual information (MI) is one of the best contrast functions for constructing blind separation algorithms since it has numerous invariant features from an information geometrical standpoint. Mutual Information (MI) is a natural measure of the reliance between random variables. If these random events are completely independent of one another, MI equals zero. MMI-ICA algorithm is the most complex ICA algorithms because its extract all units version where required huge calculation [43].

2.7.2 Fast ICA Algorithm

It is an efficient and popular algorithm for independent component analysis invented by Aapo Hyvärinen at Helsinki University of Technology. Like most ICA algorithms, FastICA seeks an orthogonal rotation of prewhitened data, through a fixed-point iteration scheme, that maximizes a measure of non-Gaussianity of the rotated components. Non-gaussianity serves as a proxy for statistical independence, which is a very strong condition and requires infinite data to verify. FastICA can also be alternatively derived as an approximative Newton iteration. FICA is very fast but it suffers from serious weakness point where its work only on long frame length (because it is use negative entropy as cost function) [20].

2.7.3 Kurtosis Based ICA

Kurtosis (or its absolute value) is commonly employed as a measure of non-Gaussianity in the ICA problem because to its computational and theoretical simplicity. Normalized kurtosis of real value (r.v u) may be calculated as [5]:

$$kurt(\boldsymbol{u}) = \frac{E\{\boldsymbol{u}^4\}}{(E\{\boldsymbol{u}^2\})^2} - 3 \qquad (2.23)$$

Theoretical analysis is simplified because kurtosis is zero for a Gaussian random variable, but for non-Gaussian random variables, kurtosis ≠ 0 [44].

Kurtosis-based ICA is often used for one-unit ICA (extracting a single source $\boldsymbol{u}$). The solution for a single unit ICA transformation ($\breve{\boldsymbol{u}} = \boldsymbol{w}\boldsymbol{R}$) may be reduced to an optimization problem that seeks the best n_r dimensional vector $\boldsymbol{w_{opt}}$ that optimizes absolute kurtosis measurement. In other words, absolute kurtosis is employed as a cost function to assess the quality of the mixing vector $\boldsymbol{w}$, where:

$$if\ \boldsymbol{w} = \begin{cases} \boldsymbol{w}_{opt} & \rightarrow \quad |kurt(\boldsymbol{wR})| \approx\ max \\ else & \rightarrow \quad |kurt(\boldsymbol{wR})| <\ max \end{cases} \tag{2.24}$$

There are two ways to solve optimization problem, Gradient Ascent/Decent Algorithm (GAA) and evolutionary search algorithm.

2.7.4 GAA for Kurtosis Based on Independent Component Analysis

The gradient is a first order optimization algorithm that seeks maximum/ minimum values for the function using the first order differential of cost function to update value of $\boldsymbol{w}$ recursively. First the value of $\frac{\partial\, kurt(\breve{\boldsymbol{u}})}{\partial \boldsymbol{w}}$ should evaluate, then $\boldsymbol{w}$ will be update recursively for each iteration (it) using:

$$\Delta\boldsymbol{w}_{it} = -\mu \frac{\partial\, kurt(\breve{\boldsymbol{u}})}{\partial \boldsymbol{w}} \tag{2.25}$$

where μ is the learning rate. .GAA lead to the well-known update formula [40]:

$$\boldsymbol{w}_{it+1} = \boldsymbol{w}_{it} - \mu\boldsymbol{\varphi}(\boldsymbol{u})\boldsymbol{R}^{\boldsymbol{T}} \tag{2.26}$$

where $\boldsymbol{\varphi}(\boldsymbol{u})$ is the nonlinear function.

The steps for one unit kurtosis-based ICA using only n_r received mixture signals $\boldsymbol{R} = \begin{bmatrix} \boldsymbol{r_1} \\ \boldsymbol{r_2} \\ \vdots \\ \boldsymbol{r_{n_r}} \end{bmatrix}$, where each signal is N_{samp} of samples

1- Initialize de-mixing vector: $\boldsymbol{w}^1 = [w_1 \;\; w_1 \;\; \ldots.. \;\; w_{n_r}]$.

2- $it = 1$ (Number of iteration)

3- Find extracted source: $\boldsymbol{u} = \boldsymbol{w}_{it}\boldsymbol{R}$, where $\boldsymbol{u}$ is one dimension vector with N_{samp} samples.

4- Evaluate the nonlinear function $\boldsymbol{\varphi}(\boldsymbol{u})$ for each element of $\boldsymbol{u}$.

5- Update the de-mixing vector using Equation (2.21).

6- Normalized the weighting vector using: $\boldsymbol{w_{it+1}} = \frac{\boldsymbol{w_{it+1}}}{\|\boldsymbol{w_{it+1}}\|}$

7- The algorithm can be stopped (go to step 8)

If:

1- it > maximum number of iterations.

2- or $\boldsymbol{w_{it+1}}$converge to specific value i.e:

$\left|1 - |\boldsymbol{w_{it}} \times (\boldsymbol{w_{it+1}})^T|\right| \leq Threshold$

Else: $it = it + 1$, Go to step 3.

8- At end of iteration specify which source was extracted and it sign.

2.8 MIMO Channel Encoder Optimization

The Optimization approach is one of the effective ways for determining the optimum answer in numerical problems. Only a few solutions are regarded the best in optimization, and they are referred to as the objective. Classical optimization approaches have several limitations when it comes to tackling complicated optimization issues. These flaws are largely dependent on their built-in search systems. These traditional optimization methods are heavily influenced by the selection of appropriate objectives, constraints functions, and variable types. They also do not provide a general solution technique that can be utilized to solve issues involving different types of variables, objective and constraint functions [17]. To address these shortcomings, a new approach known as Metaheuristic was created, which is based on artificial intelligence research conducted by researchers [17]. A metaheuristic is an algorithm that is meant to solve different sorts of challenging optimization issues without fully accommodating to each problem. The Greek word meta suggests that these approaches are higher-level heuristics. The following are the key characteristics of metaheuristic methods: They are nature-inspired (derived from nature's physics, behavior, and so on), stochastic components are an integral element of these approaches (including random variables). Metaheuristic algorithms combine various intelligent procedures and guide basic heuristic methods [32]. These algorithms are inspired from different things such as natural phenomena, natural selections and social behaviors and applied in solving the optimization problems. Examples of the recently metaheurtistc algorithms are Vortex search [31], WOA (whale optimization algorithm) [1], MBA (mine blast algorithm) [2], WCA (water cycle algorithm) [3], SFS (stochastic fractal search) [4] and HIWOPSO (A Hybrid Algorithm based on Invasive Weed Optimization and Particle Swarm Optimization for Global Optimization) [12]. In this work will Improve Kurtosis based ICA using two types of these algorithms: WCA and HIWOPSO.

2.8.1 Water Cycle Algorithm

Most of optimization algorithms mimic physical or biological processes. Some of the most famous of these algorithms are Ant Colony Optimization [ACO], Genetic-Algorithm [GA], Particle Swarm Optimization [PSO] and Bacterial Foraging Algorithm [BFA] and other algorithms. There is, however, no specific algorithm for achieving the optimum answer to all optimization issues. Some algorithms provide a better answer than others in certain situations. Similar to other metaheuristic algorithms, the water cycle algorithm (WCA) is an optimization algorithm inspired by the water cycle process and observation of how streams and rivers flow into the sea, has been proposed for finding better optimal solutions of power flow optimization problems [17].

The proposed method begins with an initial population so called the raindrops. First, assume that have rain or precipitation. The best individual (best raindrop) is chosen as a sea. Then, a number of good raindrops are chosen as a river and the rest of the raindrops are considered as streams which flow to the rivers and sea. Typically the WCA simulates the surface run-off process, i.e., one of the main phases in the water cycle process observed in nature, as updating formulation for generating new individuals during iterative optimization process [17]. In this research the water cycle algorithm was used to improve the efficiency of the LS algorithm, where kurtosis was used as an objective function to reach to the optimal solution.

2.8.2 Hybrid Algorithm based on Invasive Weed Optimization and Particle Swarm Optimization (HIWOPSO)

The PSO is another Metaheuristic method that has been used to optimize various issues. For improved answers, this algorithm employs the migratory method of birds and humans. Individuals in the PSO are referred to as particles, and each particle moves at a different speed in the searching space. Particles are scattered at random in the searching space, and their locations are modified based on the determined velocity [9]. These particles have a tendency to gravitate toward the best spots, causing them to seek a better position and discover the best one of the shortcomings of PSO that frequently falls to the local minimum fast, therefore missing out on better possibilities when dealing with multimodal functions [23].

IWO is a nature-inspired algorithm that is gaining popularity due to its efficient exploration and dissimilarity features, as well as its remarkable performance in addressing continuous optimization problems. In formal IWO, the seeds are evenly distributed over the search space. After all, if the searching space is too big, using this sort of distribution for searching is inefficient. In addition, parameter initialization is a critical duty in IWO, and trapping in the local solution is a likely occurrence. As a result, it was discovered that the effectiveness of an IWO algorithm in achieving success goals in issues is overly dependent on its starting parameters, which should be intelligently chosen based on the problem to be addressed. To address these issues, a hybrid IWO/PSO method for addressing continuous optimization problems is suggested and implemented in this work to improve the efficiency of the LS algorithm, where kurtosis was used as an objective function to reach to the optimal solution [11].

Chapter Three

MIMO-STBC Decoder Design

Chapter Three

MIMO-STBC Decoder Design

3.1 Introduction

This chapter described the suggested system of MIMO-STBC channel estimation and discuss two proposed algorithms WCA and HIWOPSO and its effect on improving BER.

In order to apply ICA algorithm in MIMO STBC, there are several steps that must be followed:

- MRC is first modeled as a mixing system.
- Real Imaginary (R- Im) decomposition is used to minimize the calculation complexity of complex numbers.
- The source and sign ambiguity problem of ICA algorithm were solved using suitable initialization based on pilot symbols.
- In this thesis, a simple (one source) criterion was devised to minimize the decoding delay by $\frac{1}{n_s}$ times, (n_s denotes the number of source signals). This chapter thoroughly describes the one unit ICA algorithms (Kurtosis-based ICA).
- Finally, WCA and HIWOPSO were combined Severally with Kurtosis-based ICA to provide a high speed / low complexity MIMO STBC decoder.

To validate the suggested methods, two MIMO-STBC systems with 2tx and 4tx transmitter are used as case studies. For each example, MRC was used, followed by (R- Im) decomposition, and lastly the search space dimension was completely defined.

3.2 Modeling the MRC of MIMO-STBC as a Mixing System

The generic equation for any MRC of MIMO STBC is:

$$\boldsymbol{Z_{MRC}} = \begin{bmatrix} \vec{Z}^{1}_{mrc} \\ \vdots \\ \vdots \\ \vec{Z}^{p}_{mrc} \end{bmatrix} = \boldsymbol{H_{MRC}} * \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_k \end{bmatrix} + \boldsymbol{noise} \quad (3.1)$$

As illustrated in Figure 3.1, this equation may be represented as a noisy linear mixing system with a complex mixing matrix H_{MRC}, where $S_1, S_2, \dots, S_k$ are complex source signals and Z_{MRC} is mixture complex signals. Because H_{MRC} is a unitary matrix, the best de mixing matrix is H^{H}_{MRC} .

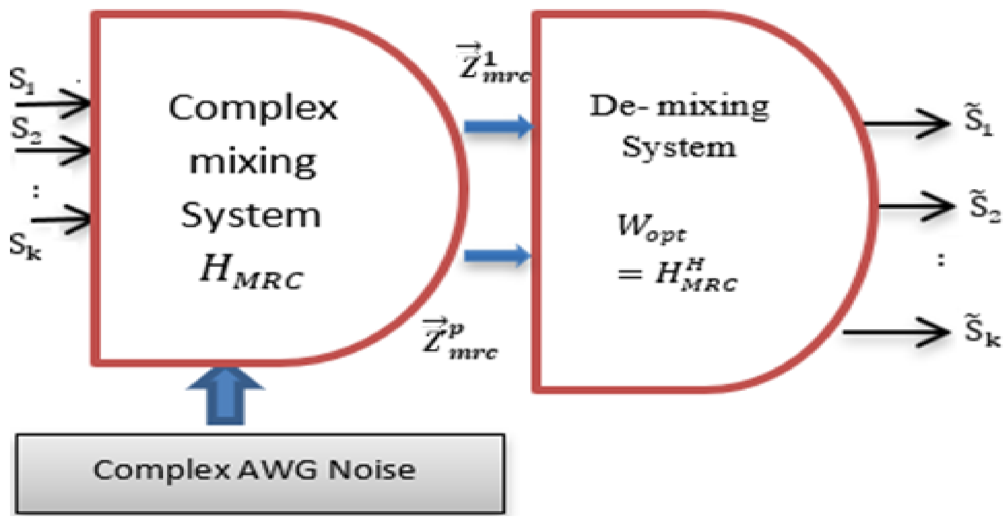


Figure 3.1 The MRC as a mixing system

Because the most statistical methods for dealing with complex numbers are ineffective and yield poor results hence, it shall employ the Real_ Imaginary (R- Im) decomposition for the MRC model.

3.3 Proposed with Kurtosis-Based ICA

Since mixing matrix $\boldsymbol{M}$ is orthogonal matrix then ***one-unit*** version of ICA can be applied efficiently. Depending on initial value of de mixing vector w_{int} , ICA algorithm (GAA) will update the w_{int} until it reaches the nearest optimum point that maximize the non Gaussianity measured of $\varphi(wR)$as shown in Figure (3.4). Take advantage that in any communication system there are a pilot symbols present as harder in each frame used for synchronization, estimation and equalization issues. These symbols can be used to obtain prior knowledge for channel coefficient using LS estimator as described in chapter two. MRC matrix H_{MRC}^{LS} can be constructed using H_{LS} then R- Im decomposition can be applied for H_{MRC}^{LS} to obtain prior knowledge for mixing matrix $\boldsymbol{M}$ which we symbolize it by M_{LS}:

$$M_{LS} = \begin{bmatrix} Re\{H_{MRC}^{LS}\} & -Im\{H_{MRC}^{LS}\} \\ Im\{H_{MRC}^{LS}\} & Re\{H_{MRC}^{LS}\} \end{bmatrix} \tag{3.2}$$

In order to extract $\boldsymbol{u_1}$ we should set initial value for demixing vector equal to first column of M_{LS} , In same manner to extract $\boldsymbol{u_2}$, we should set initial value for de-mixing vector equal to ***second*** column of M_{LS} and so on. Finally, after all sources $\boldsymbol{u_1}, \boldsymbol{u_2}, \ldots, \boldsymbol{u_{n_s}}$ have been extracted, then original complex source signal can be obtained by:

$$S_i = \boldsymbol{Re}\{\boldsymbol{S_i}\} + j\boldsymbol{Im}\{\boldsymbol{S_i}\} \tag{3.3}$$

Since $\boldsymbol{Re}\{\boldsymbol{S_i}\} = \boldsymbol{u_i}$, $\boldsymbol{Im}\{\boldsymbol{S_i}\} = \boldsymbol{u_{k+i}}$ and $\boldsymbol{u_i} = \boldsymbol{w_i R}$ then**:**

$$S_i = (\boldsymbol{w_i} + j\boldsymbol{w_{k+i}})\boldsymbol{R} \quad i = 1,2,..,k \tag{3.4}$$

In this thesis we invented a simple criterion that can be used to extract sources $\boldsymbol{u_2}, \boldsymbol{u_3}, \ldots, \boldsymbol{u_{n_s}}$ directly without using ICA algorithm. We called this strategy by one ***source extraction***. The idea of this strategy that: since optimum de mixing vector or first source w_1 related to the first column of $\boldsymbol{M}$ that made w_2 is related to second column of $\boldsymbol{M}$ and so on. after applying R- Im decomposition to Z_{MRC}, n_r mixed signals $(\boldsymbol{r_1}, \boldsymbol{r_2}, \ldots, \boldsymbol{r_{n_r}})$ are obtained. The same procedures described in section 2.7.4 will be used to estimate $\boldsymbol{u_1}$, with the starting value set as the first column of M_{LS}, as illustrated in Figure (3.2).

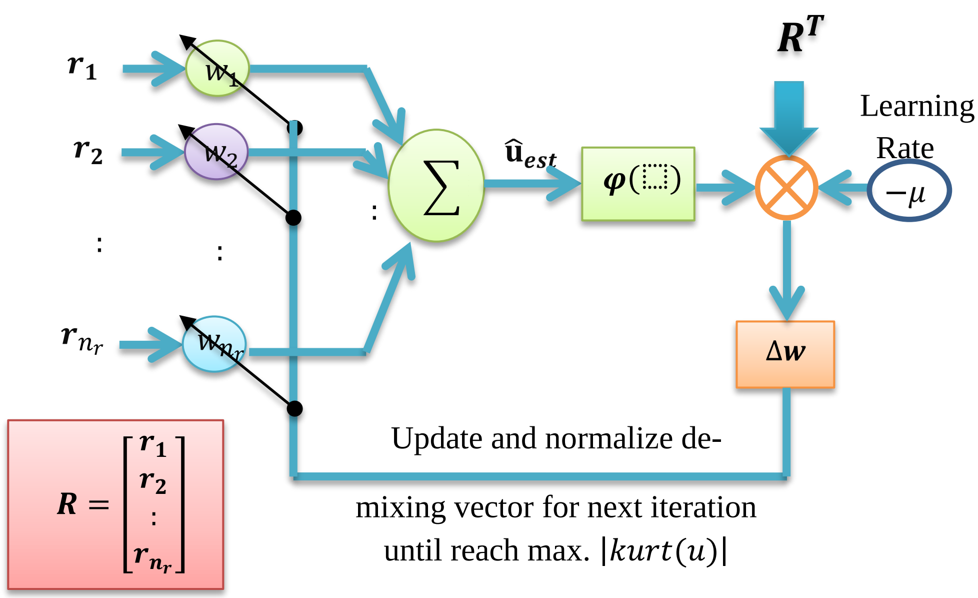


Figure 3.2 Kurtosis-based ICA for MIMO-STBC

It discovered that the best nonlinear function for QPSK modulation is as follows:

$$\varphi(\boldsymbol{u}) = \frac{\boldsymbol{u}}{E\{\boldsymbol{u}^2\}} - \frac{\boldsymbol{u}^3}{E\{\boldsymbol{u}^4\}} \tag{3.5}$$

At the end of the iteration, the de mixing vector will be presumed to be $\boldsymbol{w_1}$. The other de mixing vectors $\boldsymbol{w_2}, \boldsymbol{w_3}, \dots, \boldsymbol{w_{n_s}}$ may be calculated intuitively utilizing the structure of the MIMO-STBC mixing matrix (one source extraction criteria).

Finally, using Equation (3.4), transmitted signals $\boldsymbol{S_1}, \boldsymbol{S_2}, \dots, \boldsymbol{S_k}$ are immediately decoded in one step. As a result, this decoding technique is known as combined decoding and estimation for MIMO- STBC. In addition to improving BER performance, the approach shortens the decoding process by lowering decoding delay time and computing complexity.

3.4 Improve Kurtosis based ICA using Water Cycle Algorithm (WCA)

In this section we try to combine one unit kurtosis ICA optimization -problems, with a high dimensional search- space, using classical algorithms of optimization. Most of optimization algorithms mimic physical or biological processes. However, there is no specific algorithm in order to achieve the best solution of all optimization problems.

As discuss in chapter two, ICA can be simplified to optimization problem that searches for optimum n_r dimensional vector $\boldsymbol{w_{opt}}$ which maximizes the absolute kurtosis measuring. GAA lead to the update the weight by $\mu\boldsymbol{\varphi}(\boldsymbol{u})\boldsymbol{R}^{\boldsymbol{T}}$. But the problem of GAA that it's too slow to reach optimum value. In other hand WCA is motivated from the simulation of the social behavior that cooperative to seek optimum position .The fundamental concepts and ideas which underlie the WCA is inspired by nature and based on the observation of water cycle process and how rivers and streams flow to the sea in the real world. The WCA mimics the flow of rivers and streams towards the sea and derived by the observation of water cycle process. Assume that there are some rain or precipitation phenomena. An initial population of design variables (population of streams) is randomly generated after raining process. where the best individual (i.e., the best stream), classified in terms of having the minimum cost function (for minimization problem), is chosen as the sea Then, a number of good streams (i.e., cost function values close to the current best record) are chosen as rivers, while all other streams flow to the rivers and sea. The WCA can be simplified in Figure 3.5

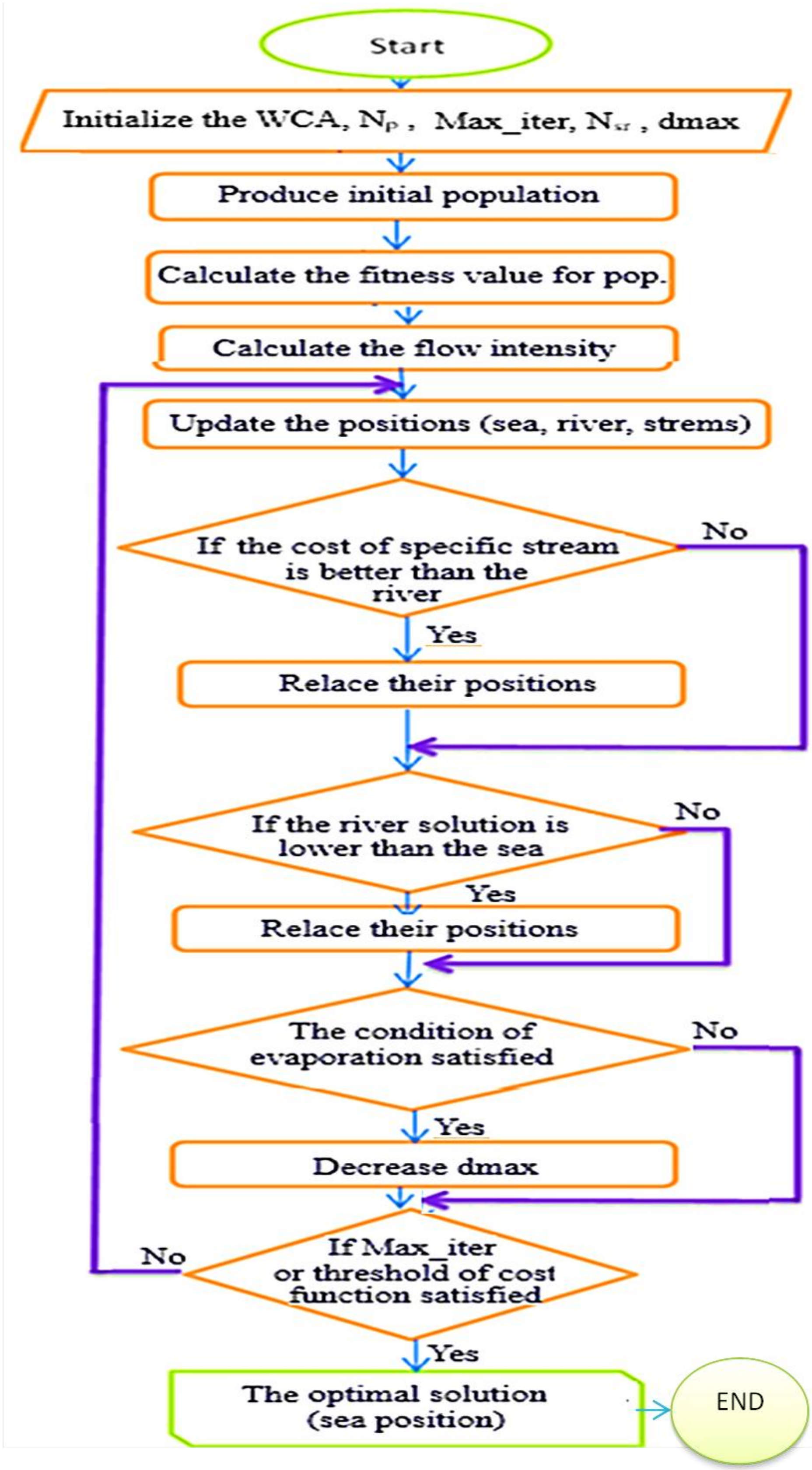


Figure 3.5 Water cycle algorithm [17]

Starting the optimization method necessitates the formation of an initial population, which is representing by a matrix of streams of size $N_{pop} \times N$, Hence, this matrix, which is generated randomly, is given by:

$$total\ pop. = \begin{bmatrix} sea \\ River_1 \\ River_2 \\ \vdots \\ Stream_{N_{sr}+1} \\ Stream_{N_{sr}+2} \\ \vdots \\ . \\ Stream_{N_{POP}} \end{bmatrix} = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_N^1 \\ x_1^2 & x_2^2 & & x_N^2 \\ \vdots & & \ddots & \vdots \\ x_1^{N_{POP}} & x_2^{N_{POP}} & \cdots & x_N^{N_{POP}} \end{bmatrix} \qquad (3.6)$$

where N_{pop} and N are the total population number and the number of design variables, respectively. For continuous and discrete issues, each of the decision variable values (x_1, x_2... x_N) can be expressed as a floating-point number (real values) or as a predetermined set.The cost of a stream is determined by evaluating the cost function (C), which is given by:

$$C_i = \mathrm{Cost}_i = f\,(x^i_1, x^i_2, \ldots, x^i_N),\ i = 1, 2, .., N_{pop} \qquad (3.7)$$

The cost function of N_{pop} is absolute kurtosis (that given in Eq. (2.23)) for each individual.

N_{pop} are generated in the initial stage. The sea and rivers are then chosen from a group of the best individuals N_{sr} (minimum values). In actuality, N_{sr} is the sum of the number of rivers and a single sea. A rest of population is viewed as a stream that runs into rivers or directly into the sea. Each river receives water from streams based on the size of the flow. As a result, the quantity of water that enters the river and/or the sea fluctuates from one stream to another. Rivers also flow to the sea that is the most sloped region.

As we discuss the initialization problem in section (3.4), the initial sea position should equal to the first column of M_{LS}, then the other population (the position of streams and rivers) are generated randomly around the initial position of sea where distance doesn't exceed ±1 initial value This distance is terrifying enough that the exploring space does not reach the maximum points of the neighbor.as shown in Figure 3.6.

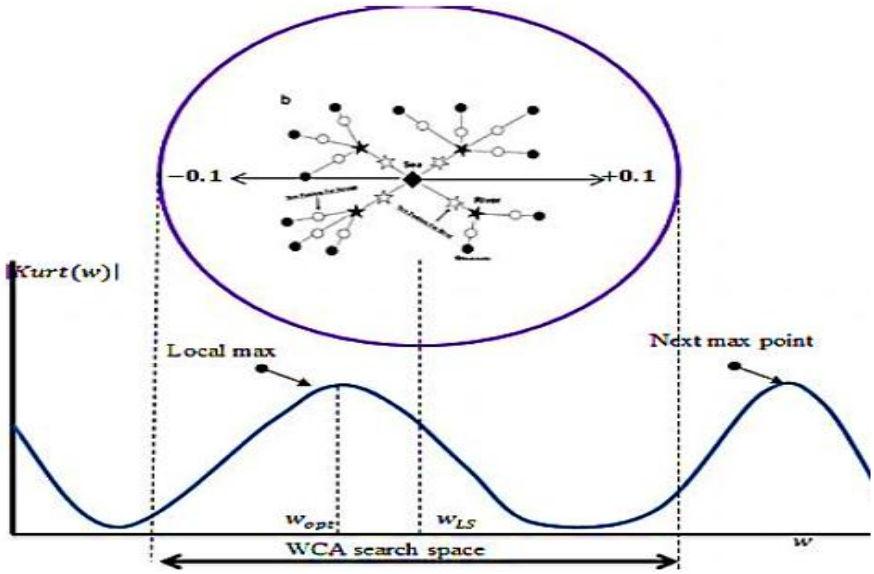


Figure 3.6 Initialization for WC algorithm

To assign streams to rivers and the sea based on the intensity of the flow, use the following formula:

$$Cost_i = f(stream_i) = f(x_1, x_2, x_3, \dots, x_N) \tag{3.8}$$

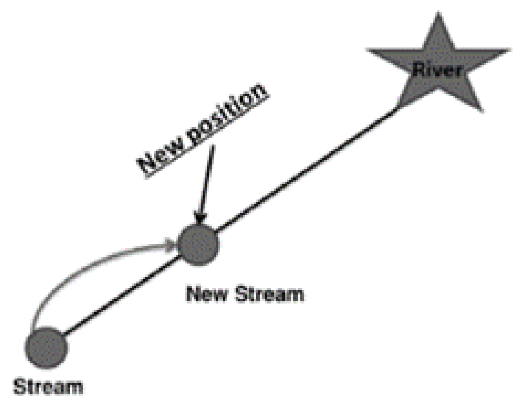
where *i = 1, 2, 3… N*

The designated streams for sea and each river are calculated using the following equations [17]:

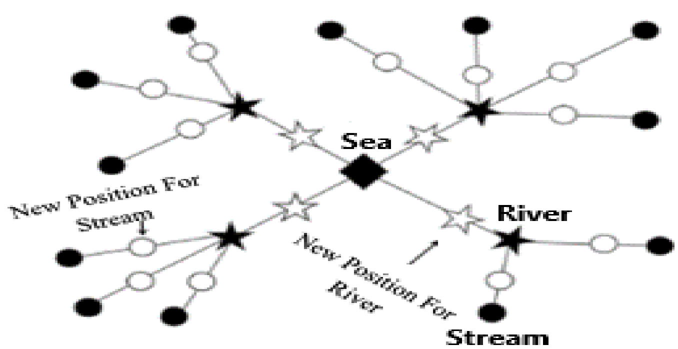
$$C_n = Cost_n - Cost_{N_{sr}+1}\ ,\ n = 1,2,3,\dots,N_{sr} \tag{3.9}$$

$$NS_n = round\left\{\left|\frac{Cost_n - Cost_{N_{sr}}+1}{\sum_{i=1}^{NSR} C_n}\right| \times N_{Streams}\right\} \tag{3.10}$$

where NS_n is the number of streams which flow to the specific rivers or sea. Figure 3.7 shows The WCA Optimization



(a)



(b)

Figure 3.7 the WCA Optimization (a) Streams flowing into a specific river and (b) WCA Optimization schematically[17].

Figure 3.7 (a, b) shows a schematic representation of a stream moving towards a specific river and the WCA optimization method with circles, stars, and diamonds representing streams, rivers, and the sea, respectively. The white (empty) shapes represent the new locations of streams and rivers.

For WCA's exploitation phase the following new stream and river sites have been proposed [17]:

$$\vec{X}_{Stream}^{i+1} = \vec{X}_{Stream}^{i}(t) + rand \times C \times \left(\vec{X}_{sea}^{i}(t) - \vec{X}_{Stream}^{i}(t)\right) \quad (3.11)$$

$$\vec{X}_{Stream}^{i+1} = \vec{X}_{Stream}^{i}(t) + rand \times C \times \left(\vec{X}_{River}^{i}(t) - \vec{X}_{Stream}^{i}(t)\right) \quad (3.12)$$

$$\vec{X}_{River}^{i+1} = \vec{X}_{River}^{i}(t) + rand \times C \times \left(\vec{X}_{sea}^{i}(t) - \vec{X}_{River}^{i}(t)\right) \quad (3.13)$$

where t is the iteration index, $1 < C < 2$ (where 2 is the best value for C), where rand is the uniformly distributed random integer between the numbers 0 and 1. Eqs. (3.11) and (3.12) are for the streams that run into sea and their comparable rivers. If the solution of stream is better than of its connected river the places of river and stream are swapped (i.e., the stream transforms into a river, and the river transforms into the sea). A river and the sea can be exchanged in a similar way. To avoid early (immature) convergence to local optima, the evaporation process operator is also introduced (exploitation phase evaporation is the process by which sea water evaporates when rivers/streams flow into it. This causes fresh precipitation. As a result, the determination must be done if the river/stream is close enough to the sea for evaporation to occur. For this reason, the evaporation condition between a river and the sea is measured using the following criterion:

$$if \left\|\vec{X}_{sea}^{i} - \vec{X}_{River}^{i}\right\| < d_{max}\,, i = 1,2,3,\dots,N_{SR} - 1 \quad (3.14)$$

where d_{max} is a tiny integer around zero.

The rainy process is employed after evaporation, and fresh streams emerge in diverse locations. Indeed, the evaporator operator is in charge of the exploratory phase in the WCA. To designate new positions of newly created streams, a uniform random search is utilized. A big d_{max} number discourages future searches, but a lower value encourages search intensity near the sea. As a result, d_{max} determines the intensity of the search near the water (i.e., best obtained solution). The value of d_{max} decreases adaptively as seen below [17]:

$$d_{max}^{i+1} = d_{max}^{i} - \frac{d_{max}^{i}}{Max\ Iteration} \tag{3.15}$$

where $t = 1, 2 \ldots Max\_iter$

To ensure that update equations not exceed the exploring space should use hard threshold function by assume that the variance of cost function for all population ≤ threshold = 10^{-5}.

There are two ways to end the evolution process:

1- The first one: if all population converge into single position (variance of cost function for population position ≤ threshold = 10^{-5})

2- The second: if number of iterations ≥ max. Iteration.

In the evolution step optimum solution for WCA (after iteration stopped) is $\boldsymbol{w_{opt} = sea}$.

3.5 Improve Kurtosis Based ICA Using HIWOPSO

The PSO evolved from the migratory behavior of birds and humans living in small and big groups. The birds employ a strategy for locating food and migrating that has been incorporated into this algorithm. Only the birds know their distance from food with this approach, but they don't know where the food is, thus following the other nearby birds is the best way to survive. The PSO algorithm is comprised of the following major steps: Each bird within the algorithm is called the particle, and each particle has a fitness value, and the fitness value indicates how important this particle compared to the rest of the particles, where process carried out with the help of a function called the fitness function. The particles are initially randomly scattered in the search region, then PSO begins the process with these particles. Particles only follow the one that is closer to the target and has a higher fitness value throughout this seeking process. Each particle has a velocity, which is denoted by v_i and computed using Eq. (3.16):

$$v_i[t+1] = wv_i[t] + c_1 r_1\left(x_{p,best}[t] - x_i[t]\right) + c_2 r_2(x_{g,best}[t] - x_i[t]) \qquad (3.16)$$

The D-dimensional searching space Particles are under the effect of personal ($pbest_i^t$) and swarm experiences ($g\ best_i^t$) and the position is updated by Eq. (3.17).

$$x_i[t+1] = x_i[t] + v_i[t+1] \qquad (3.17)$$

In Eq. (3.16) and (3.17), x_i represents the i^{th} particle of the population, c_1 and c_2 are the learning coefficients, r_1 and r_2 are random values between [0 1], w is the inertia weight, and v_i is the i^{th} member of particles velocity. $pbest_i^t$ and $gbest_i^t$ are the personal best and generation best, respectively.

- **PSO algorithm**

1. Initialize location x_i and velocity v_i of *n* particles.
2. Find *gbest* from min {*f(x_1),.., f(x_n)*} (at t=0).
3. **While** (criterion)
4. **for** *i=1,2, 3, …,n* do
5. Generate anew velocity v_i^{t+1}using Eq. (3.21).
6. Calculate new location x_i^{t+1}=$x_i[t] + v_i[t + 1]$
7. Evaluate objective function (kurtosis) at new location x_i^{t+1}.
8. If x_i^{t+1} is better than $pbest_i^t$ **then**
9. Set x_i^{t+1} to be $pbest_i^t$
10. **end if**
11. **end for**
12. Find the generation best $gbest_i^t$from particles $pbest_i^t$
13. Iter=iter +1(pseudo time or iteration counter)
14. **end while**
15. Output the final result *gbest*.

All these steps of PSO algorithm can be summarized as following flowchart as presented in the Figure 3.8:

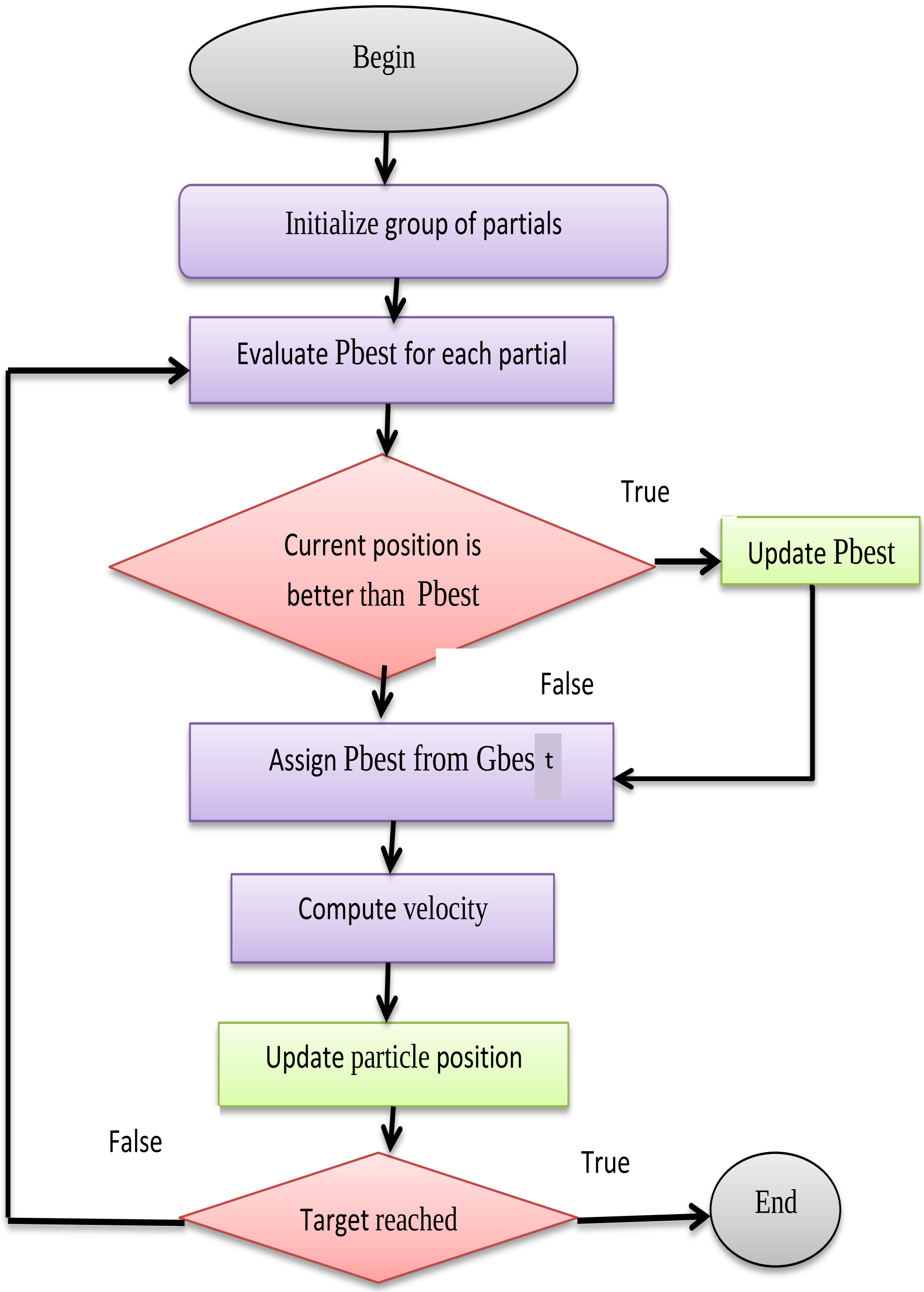


Figure 3.8 PSO algorithm [23]

- **IWO algorithm**

Mehrabian and Locus pioneered invasive weed optimization, which is one of the population-based optimization methods derived from weed colonial behavior. The IWO method is a very simple and yet effective algorithm for finding the optimum solution of the objective function, which is constructed based on the natural and fundamental properties of weeds in a colony such as reproduction, growth, and survival competition. When compared to other algorithms, IWO is simpler and has a sufficient ability and convergence rate to the global optimal solution of the objective function. Some of the key characteristics of this algorithm that distinguishes it from others include replication, spatial distribution, and exclusive competition. The following method explains the simulating weed behavior steps. According to [11].

Step 1: Initial population production: a population of N_0 seeds is randomly distributed in an n dimensional space.

Step 2: Reproduction: each seed grows and turns into mature plant and then, begins seed production for newer generation. The amount of seeds produced by a plant increases linearly between two possible values of minimum (S_{min}) and maximum (S_{max}) possible amounts of produced seeds. The amount of produced seeds for the i^{th} plant in every repeat is dependent on its goal value (F_i), its best (F_{best}) and worst (F_{worst}) goal values in that repeat and it is calculated with the following equation:

$$Numseed(i) = [S_{min} + (S_{max} - S_{min})\,\frac{f - f_{wrost}}{f_{best} - f_{wrost}}] \tag{3.18}$$

Step 3: In this stage, the randomness and assimilation of the algorithm are connected. The seeds are dispersed in a d dimensional search space using a normal distribution with a zero mean and a variance of $N(0, \sigma_t)^d$, The seeds will be near the breeder plant in this stage. Although the standard deviation reduces from the starting amount ($\sigma_{initial}$) to the final amount (σ_{final}) in each iteration, non-linear variation of standard deviation produces excellent results in the simulations, as shown below:

$$\sigma_t = ((T - t)/T)^n \times \left(\sigma_{initial} - \sigma_{final}\right) + \sigma_{final} \tag{3.19}$$

where n is the non-linear modulation factor and Trepresents the maximum number of repetitions associated to (t). The locations of seeds (S_j) for the i^{th} plant (W_i) are determined in this status as follows:

$$S_j = W_i + N(0, \sigma_t)^d, 1 \leq j \leq numseed(i) \tag{3.20}$$

Step 4: Exclusive competition: after many repetitions, the number of plants generated by fast reproduction reaches its maximum value (W_{max}), at which point each plant is allowed to produce seeds in line with the reproduction technique. The seeds are allowed to spread in search space using the distribution space technique; once the seeds locate their place, they establish a colony with their parent plants. Then, members with lower propriety are removed until the total number of members reaches the maximum allowable figure. The parent plants mix with their children in this technique, and the plants with the greatest propriety from the group are kept and permitted to be replaced. This crowd control technique will be enforced on future generations until the end of time.

Step 5: End, if the criterion satisfied, otherwise, return to Step 2.

- **HIWOPSO Algorithm**

The swarm intelligence is some kind of artificial intelligence which has been established based on group behaviors in decentralized and self-organizing systems. These systems usually included population of the simple agents that interact locally with each other and their environment. Some samples of this system that can be mentioned are ant groups, birds flock, fishes flock, bacterize bulk and animal's herd. In order to use of swarm intelligence, will merge the PSO with IWO global optimization methods and present a unique hybrid algorithm based on both techniques, dubbed HIWOPSO. Because PSO includes Swarm intelligence, it may give a more diverse population for IWO, allowing it to identify better sites by drawing on prior experiences. To prevent trapping in local solutions and substantially exploring the broad region, the mutation function was utilized, which was applied for examining other areas and giving them a chance. The proposed technique is evaluated on benchmark functions and compared to other well-known methods. In order to use of swarm intelligence, it needs to use the behavior of these systems in the proposed method. So PSO algorithm has been using with IWO algorithm to give the behavior of swarm intelligence to agents of IWO algorithm and use it in guiding the solution of the problems to the goal. The HIWOPSO algorithm can be simplified in the Figure 3.9:

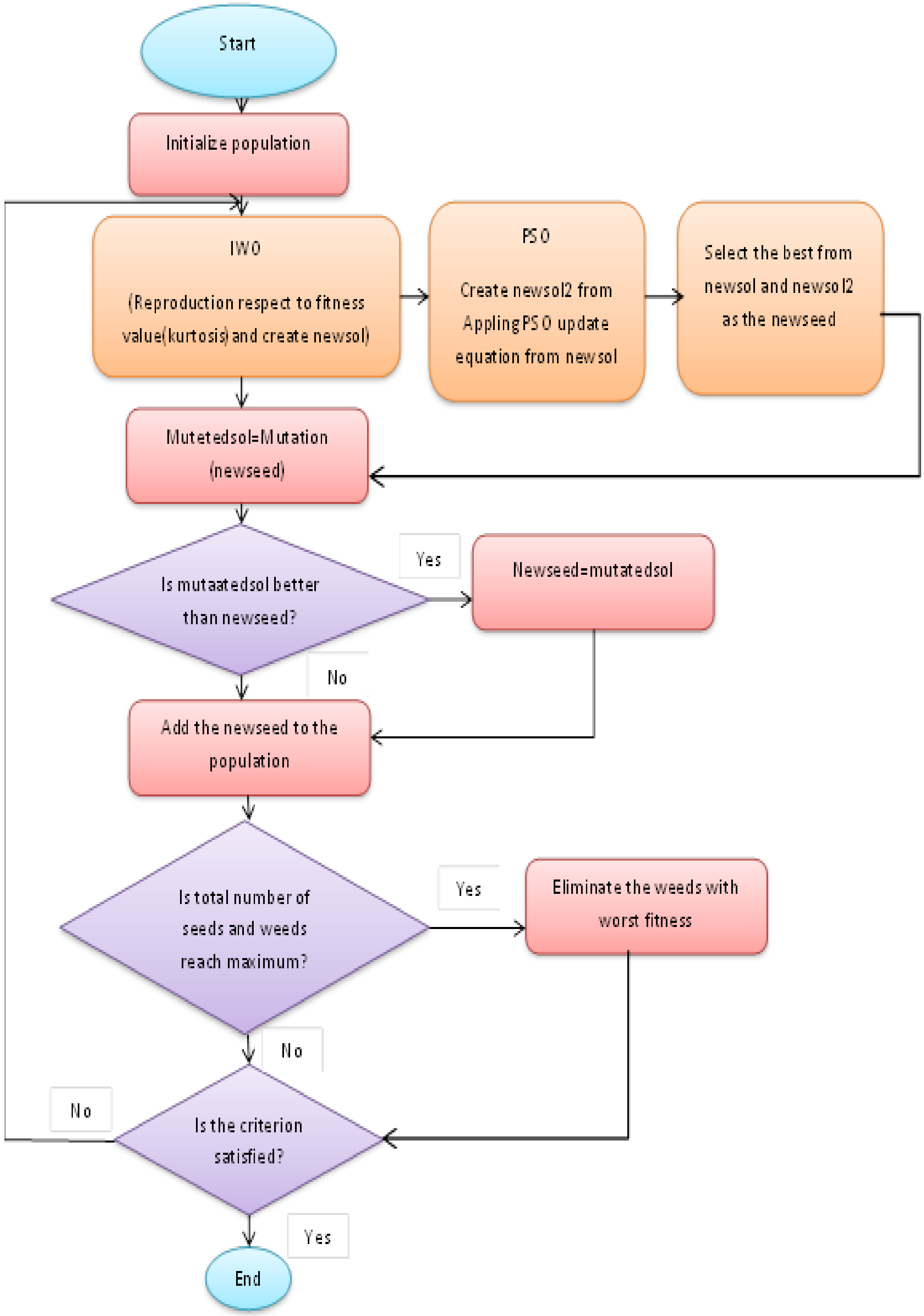


Figure 3.9 HIWOPSO algorithm [23]

As previously mentioned, in IWO algorithm, each father (weed) produces some child (seed) that these Childs distribute around the father with a kind of normal distribution. In proposed hybrid method, this distribution could be based on some kind of normal distribution or guided through the goal by using the swarm intelligence and previously experience of father. Using the previously experiences is like this, if each weed (w_i) could give good result, it stores the result as the experience in the experience memory and these experiences inherited to this weed Childs and used in guiding the solutions of the problem like the PSO algorithm. Each child in proposed method (HIWOPSO) inherited two things from their father are the velocity (v_i) and experience (w_p). The main process of proposed method is like this: first, the population with size npop0 of weeds (w_i) are distributed randomly around the searching space and their position is initialized randomly. The cost of each weed is computed from the position which calculated previously and at the Start, the value of velocity is zero (v_i= 0). First, the experience of each weed is the value which previously initialized to the position and cost for each weed. After producing population with size of npop0, algorithm enters to the main iteration loop which at start has a section for computing the number of producing child for each weed by Eq. (3.19) and also the velocity for each weed is computed like the following equation:

$$w_i^{t+1} = w.w_i^t + c_1.r_1.\left(w_{pi}^t - w_i^t\right) + c_2 + r_2.(w_{best\ i}^t - w_i^t) \qquad (3.21)$$

where w_i is the population weed, w_p is personal experience, and w_{best} is the global best, and the other variables are given in the PSO algorithm.

This equation is the same as the PSO velocity update equation. For each $w_{i,}$ a loop is formed, and one solution is generated by the seed distribution formula in IWO (newsol) Eq. (3.22) and another solution is generated by PSO (newsol2) Eq (3.23).

$$Newsol = w_i + N(0, \sigma_t)^d \tag{3.22}$$

$$Newsol2 = w_i + v_i \tag{3.23}$$

New solutions (newsol and newsol2) are compared, and if newsol2 outperforms newsol, the newsol value is replaced with the newsol2 value. The newsol is compared to the w_i experience, and if it is better than the w_p it is set as the w_i experience, and if it is better than the global best, the global best is updated with the newsol.

As mentioned earlier in WCA to ensure that update equations not exceed the exploring space should use hard threshold function by assume that the variance of cost function for all population ≤ threshold = 10^{-5}.

there are two ways to end the evolution process:

1-The first one: if all population converge into single position (variance of cost function for population position ≤ threshold=10^{-5})

2-The second: if number of iterations ≥ max Iteration (npop0).

In the evolution step optimum solution for HIWOPSO (after iteration stopped is $\boldsymbol{w_{opt} = weed}$.

3.6 Maximum Ratio Combiner for 2tx and 4tx and MIMO-STBC System

1- $N_t = 2$

The following is the generator for two transmitter antennas:

$$G_2 = \begin{bmatrix} S_1 & -S_2^* \\ S_2 & S_1^* \end{bmatrix} \tag{3.24}$$

If the coefficient matrix of $2 \times N_r$ MIMO channel is indicated as $\mathrm{H} = [\hbar_1 \quad \hbar_2]$ and $\hbar_{\mathrm{i}}$is the i_{th} column of the H matrix, then the received signals are: at time t=1 is:

$$\mathrm{Z}^1 = \begin{bmatrix} \mathrm{z}_1^1 \\ \vdots \\ \mathrm{z}_{N_r}^1 \end{bmatrix} = [\hbar_1 \quad \hbar_2] \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \end{bmatrix} + noise \tag{3.25.a}$$

If the channel coefficient remains constant (quasi-static channel), the received signals at t=2 are:

$$Z^2 = \begin{bmatrix} \mathrm{z}_1^2 \\ \vdots \\ \mathrm{z}_{N_r}^2 \end{bmatrix} = [\hbar_1 \quad \hbar_2] \begin{bmatrix} -S_2^* \\ S_1^* \end{bmatrix} + noise \tag{3.25.b}$$

By using simple modification for Equation (2.25.b) can be rewrite it as:

$$(\mathrm{Z}^2)^* = [-(\hbar_2)^* \quad (\hbar_1)^*] \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \end{bmatrix} + noise \tag{3.25.c}$$

The fundamental idea of MRC for determining the value S_1, S_2 is to combine Equations (3.25.a) and (3.25.b) to obtain:

$$\begin{bmatrix} \mathrm{Z}^1 \\ (\mathrm{Z}^2)^* \end{bmatrix} = \begin{bmatrix} \hbar_1 & \hbar_2 \\ -(\hbar_2)^* & (\hbar_1)^* \end{bmatrix} \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \end{bmatrix} + noise \tag{3.25.d}$$

The MRC equation might be written as follows:

$$\mathrm{Z}_{\mathrm{MRC}} = \mathrm{H}_{\mathrm{MRC}} * \begin{bmatrix} \mathrm{S}_1 \\ \mathrm{S}_2 \\ \vdots \\ \mathrm{S}_\mathrm{k} \end{bmatrix} + noise \tag{3.26}$$

2. $N_t = 4$

The generator for four transmitter antenna is:

$$G_4 = \begin{bmatrix} S_1 & S_2 & S_3 & S_4 \\ -S_2 & S_1 & -S_4 & S_3 \\ -S_3 & S_4 & S_1 & -S_2 \\ -S_4 & -S_3 & S_2 & S_1 \\ {S_1}^* & {S_2}^* & {S_3}^* & {S_4}^* \\ -{S_2}^* & {S_1}^* & -{S_4}^* & {S_3}^* \\ -{S_3}^* & {S_4}^* & {S_1}^* & -{S_2}^* \\ -{S_4}^* & -{S_3}^* & {S_2}^* & {S_1}^* \end{bmatrix} \tag{3.27}$$

The input signals S_1, S_2 , S_3 *and* S_4 are combined using a maximum ratio combiner (MRC) for four transmit antennas. Let us define the channel coefficient matrix as $H = [\,\hbar_1 \quad \hbar_2 \quad \hbar_3 \quad \hbar_4]$ When $\hbar_l$ is the l^{th} row of the H matrix, then the received signals are: at t=1 is:

$$Z^1 = \begin{bmatrix} z_1^1 \\ z_2^1 \\ z_3^1 \\ z_4^1 \end{bmatrix} = [\,\hbar_1 \quad \hbar_2 \quad \hbar_3 \quad \hbar_4] \begin{bmatrix} S_1 \\ S_2 \\ S_3 \\ S_4 \end{bmatrix} + noise \tag{3.28.a}$$

and t=2 if channel still constant then

$$Z^2 = \begin{bmatrix} z_1^2 \\ z_2^2 \\ z_3^2 \\ z_4^2 \end{bmatrix} = [\,\hbar_1 \quad \hbar_2 \quad \hbar_3 \quad \hbar_4] \begin{bmatrix} -S_2 \\ S_1 \\ -S_4 \\ S_3 \end{bmatrix} + noise \qquad (3.28.b)$$

By using suitable modification Equation (3.28.b) can be rewrite as

$$Z^2 = [\hbar_2 \quad -\hbar_1 \quad \hbar_4 \quad -\hbar_3 \quad] \begin{bmatrix} S_1 \\ S_2 \\ S_3 \\ S_4 \end{bmatrix} + noise \qquad (3.28.c)$$

3.7 Dimensions of the Search Space for 2N t and 4N t MIMO-STBC Systems

1. $\boldsymbol{N_t = 2}$

If frame length =L (complex source signal frame is $S_1, S_2, .., S_L$), then there are two encoded signal X_1 and X_2 each one is L symbols (encoding rate=1),second the Dimension of channel coefficient matrix H is $N_r \times 2$,There are N_r encoded received signals: Z_1 , Z_2 … Z_{N_r} each one is L symbols, the dimension of H_{MRC} is $2N_r \times 2$.Finally MRC construct $2N_r$ signal: Z_{MRC} each one is $\frac{L}{2}$ symbols.

After (R- Im) Decomposition: There are 4 source signals $\boldsymbol{u_1}, \boldsymbol{u_2}, \boldsymbol{u_3}$ *and* $\boldsymbol{u_4}$ each one is L real values. The dimension of mixing matrix $\boldsymbol{M}$ is $n_r \times 4$ where $n_r = 4N_r$. There are n_r observed signals $\boldsymbol{r_1}, \boldsymbol{r_2}$, *and* $\boldsymbol{r_{n_r}}$ each one is $\frac{L}{2}$ values.

The dimension of the ICA WCA and HIWOPSO search space for one unit is $n_r = 4N_r$ dimensional vector (de mixing vector $\boldsymbol{w}$).

2. $N_t = 4$

If frame length =L (complex source signal frame is $S_1, S_2, \ldots, S_L$) then there are four encoded signal X_1 , X_2 , X_3 and X_4 each one is L symbols (encoding rate=1), the Dimension of channel coefficient matrix $\boldsymbol{H}$ is $N_r \times 4$. There are N_r encoded received signals: Z_1 , Z_2 , Z_3 , $Z_4 \ldots$ Z_{N_r} each one is L symbols .The dimension of Z_{MRC} is $8N_r \times 4$. Finally, the MRC construct $8N_r$ signal: Z_{MRC} each one is $\frac{L}{2}$ symbols.

After (R- Im) Decomposition: There are 8 sources $\boldsymbol{u_1}, \boldsymbol{u_2}, \boldsymbol{u_3}$ $\boldsymbol{u_4}, \boldsymbol{u_5}, \boldsymbol{u_6}$, $\boldsymbol{u_7}$ *and* $\boldsymbol{u_8}$each one is L real values. The dimension of mixing matrix M is $n_r \times 8$, where $n_r = 16N_r$ and there are n_r observed signals r_1, r_2, r_3, r_4,*and* r_{n_r} each one is $\frac{L}{2}$ values.

For one unit ICA WCA and HIWOPSO search space dimension is $n_r = 16\, N_r$ dimensional vector (de mixing vector $\boldsymbol{w}$).

Chapter Four

Simulation Results

Chapter Four

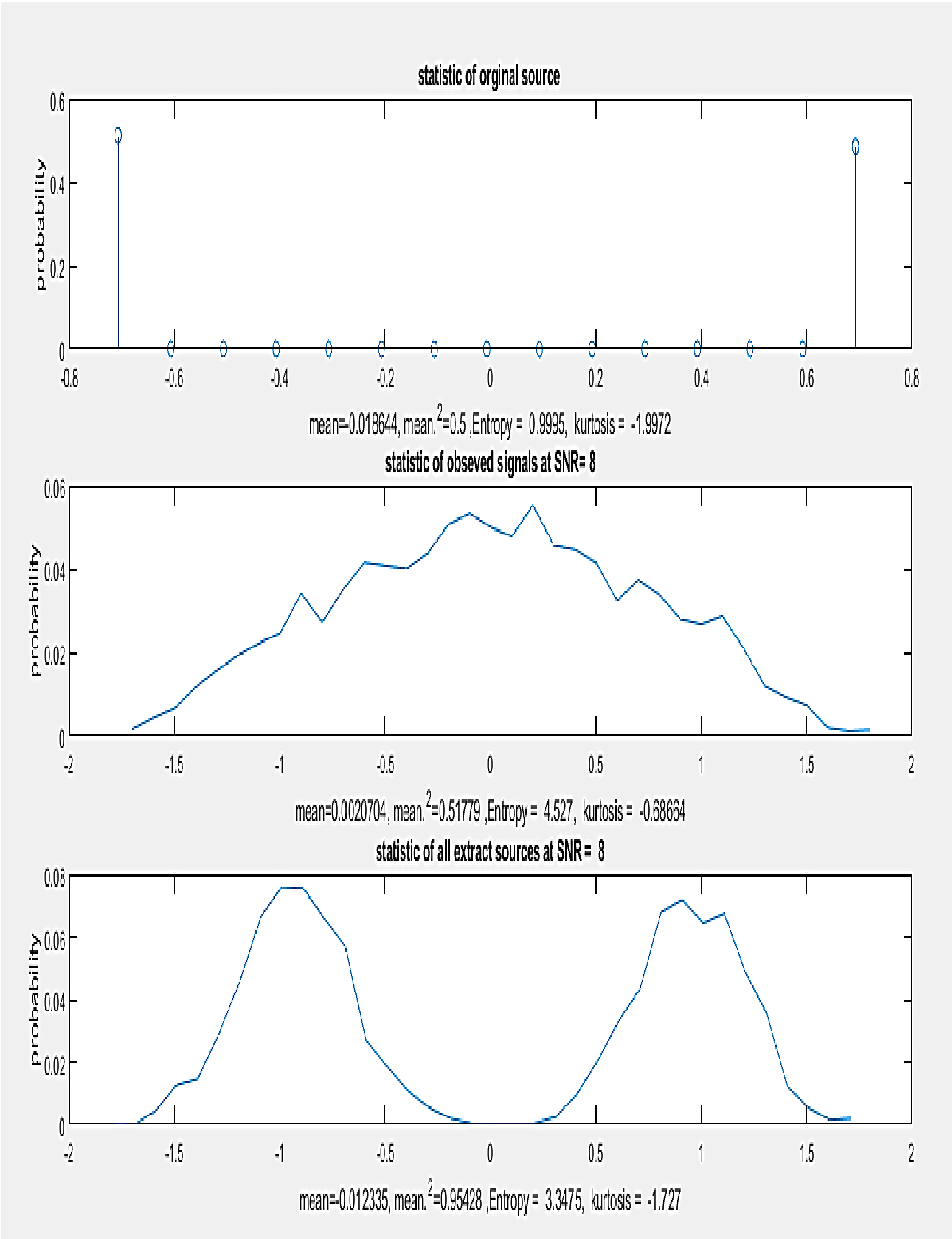
Simulation Results

4.1 Introduction

In this chapter, the QPSK - STBC (2× 1, 2×2, 2×4, 4×2 and 4×4) MIMO channel was implemented using the MATLAB-2018 software. The decoding and estimating performances are analyzed using the BER and the number of iterations. In this work, a random data generator produces digital information bits (frame by frame), where the frame length changes based on the state The QPSK modulator was used to modulate these frames, resulting in the different amount of the symbols for each frame. The first N_t values will be used as the training symbols, with the remaining frame length N_t encoded by the STBC encoder serving as the data symbol. Two and four antennas are presented in this thesis for transmitting encoded signals over a MIMO STBC Rayleigh fading channel, The received signal is mixed with its complex AWGN. The training symbols are used to compute the channel estimate coefficient in the LS channel estimation. At the receiver end, the MRC is being used to decode the other received symbols, which are then transmitted to the QPSK demodulator. In order to calculate a BER for the given SNR, the coded bits are compared to the original data bit frame. Second, simple criteria based on the use of H_{LS} (calculated channel coefficient using a LS estimator with restricted experimental sequence of training) is used as the beginning value of the statistically based blind channel estimator to produce a semi blind channel estimator. The performance of channel estimation for MIMO STBC was described using eight parameters: number of transmitter antennas, number of receiver antennas, SNR, BER, the number of iterations, numeral of frame, number of symbols/frames, and number for pilot.

4.2 Statistical Analysis for ICA algorithms Semi-blind Channel Estimator

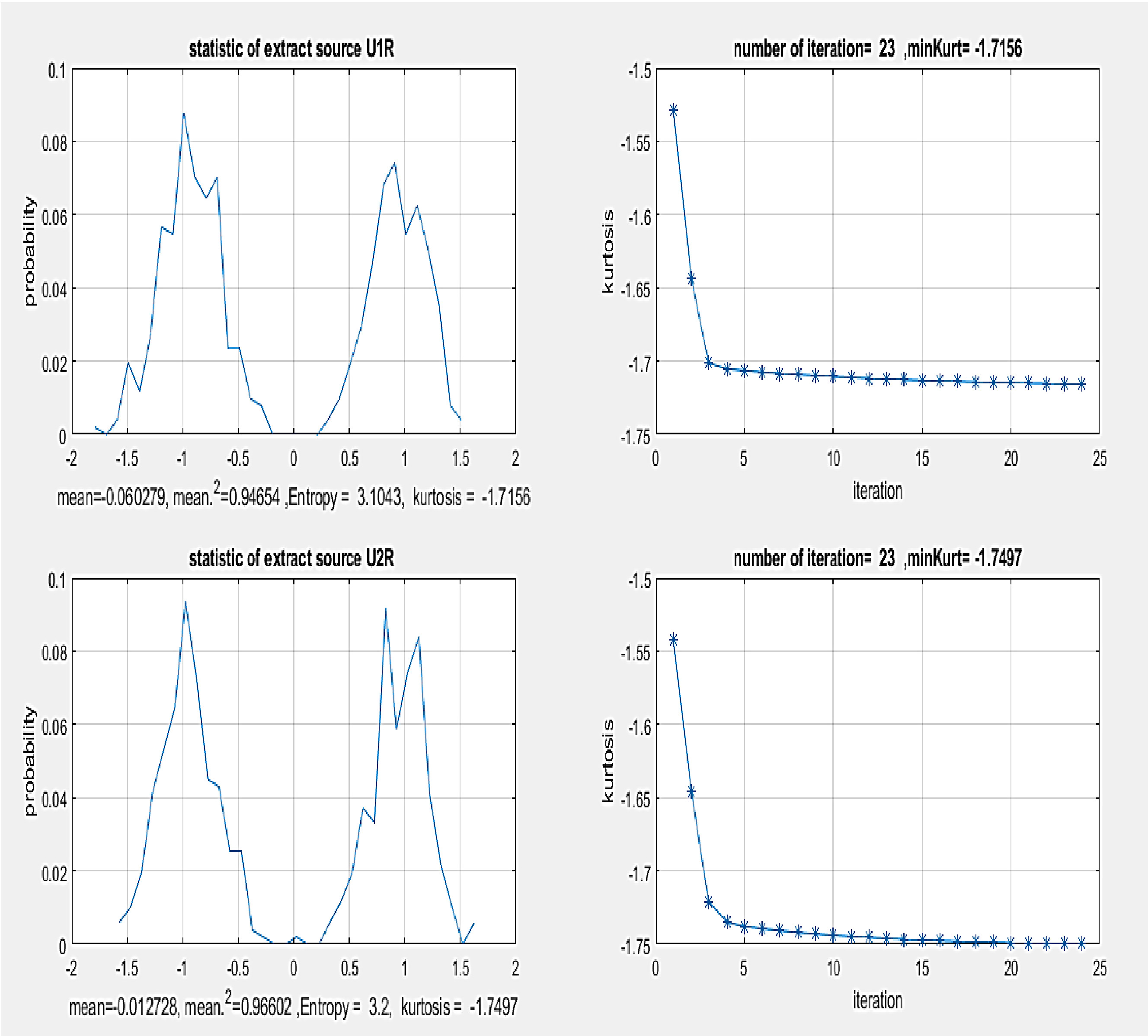
In this part, each source may be statistically represented as a discrete with two level binomial distributions that are close to Gaussian with normalized kurtosis of -2, zero mean vale, and half variance, as predicted in section (3.4). According to central limit theory, mixes of received signals are represented as continuous signals with a probability density function of Gaussian distribution. Due to the fact that the de-mixing method isolates the mixed signals without lowering the additive noise, the estimated signal neared the Gaussian distribution. The confirmation uses Kurtosis Based ICA to apply mixing algorithms for real and imaginary sources to each source. Figure 1 depicts the sources (4.1)



(a) The statistic of original source

Table 4.1: Statistical results of original source

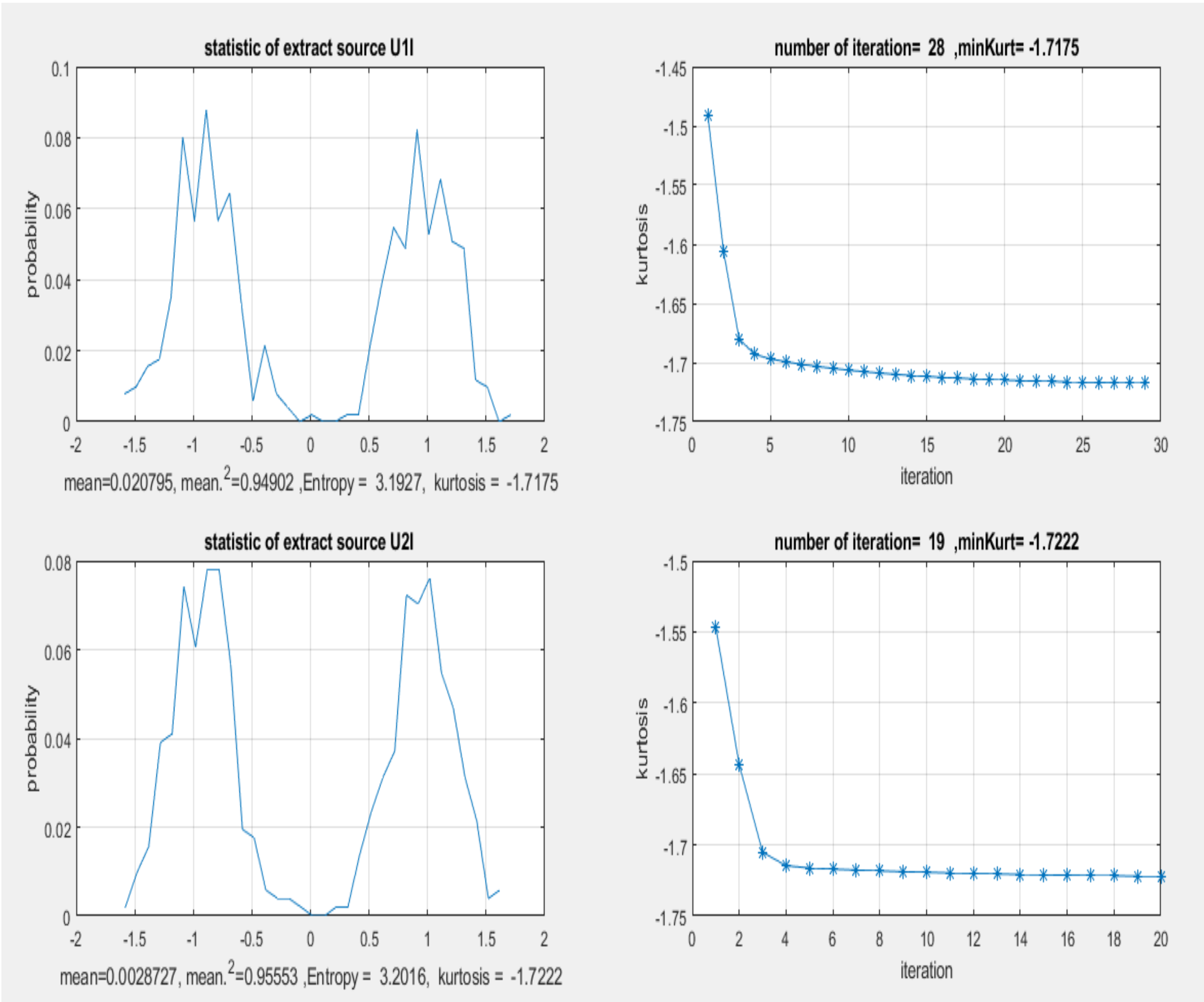
	Mean	Entropy	kurtosis
Original source	**0.018664**	**0.995**	**-1.9972**
Observed source	**0.0020704**	**4.527**	**-0.68664**
Extract source	**0.01235**	**3.3475**	**-1.727**



(b) Statistic of extracted real source

Table 4.2: Statistical results of extracted real source

	mean	Entropy	kurtosis	iteration
U1R	0.060279	3.1043	-1.7156	23
U2R	0.012782	3.2	-1.7497	23



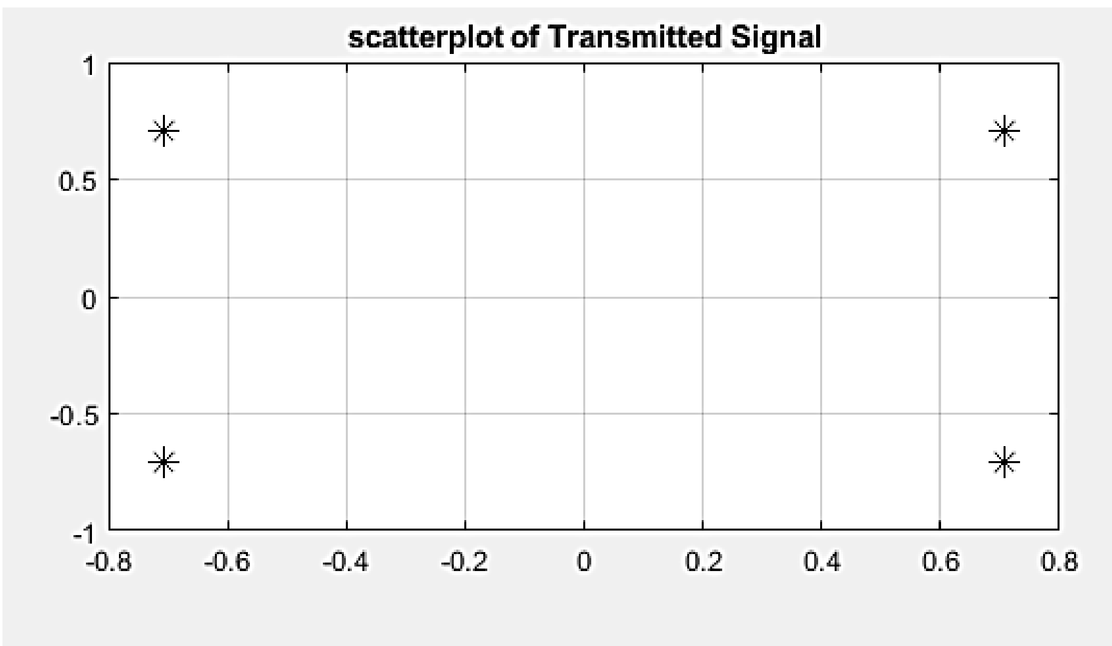
(c) Statistic of extracted imaginary source

Figure (4.1) Statistical Analysis of Mixing Model

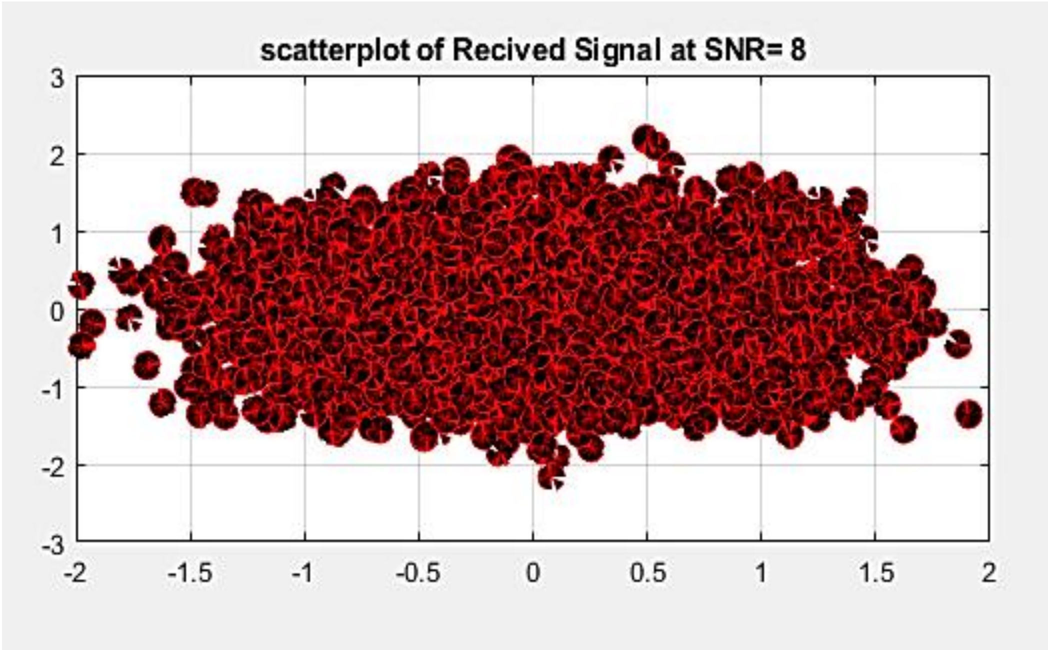
Table 4.3: Statistical results of extracted imaginary source

	mean	Entropy	kurtosis	iteration
U1I	0.020795	3.1927	-1.7175	28
U2I	0.95553	3.2016	-1.7222	19

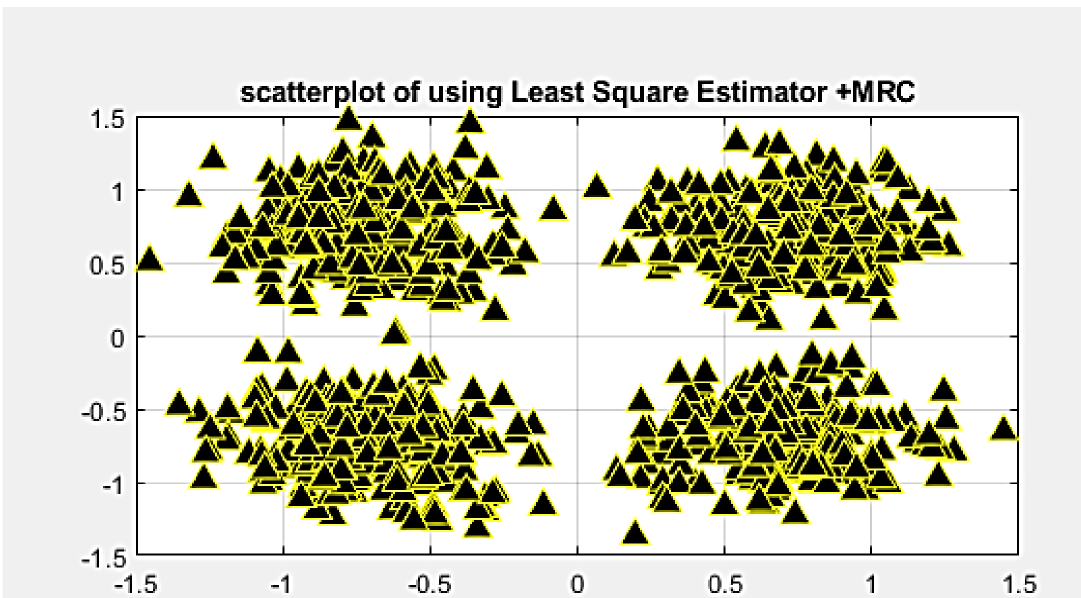
Typically, in communication systems, the scatter plot is used to assess system performance using the standard technique LS and the suggested method kurtosis-based ICA, as shown in Figure 4.2.



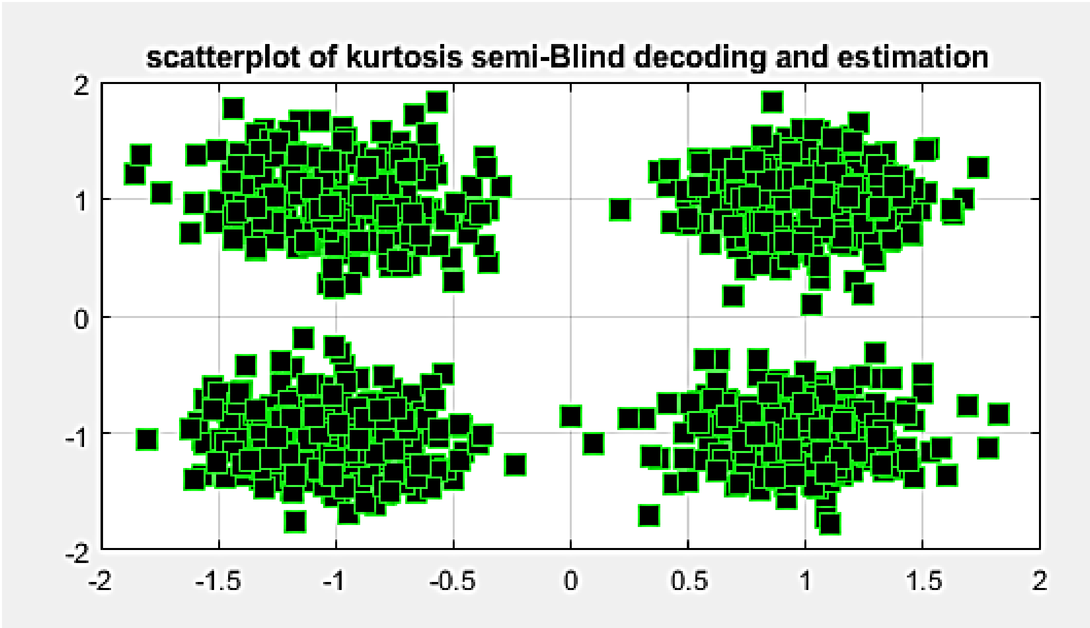
(a) Scatterplot of transmission signal



(b) Scatterplot of Received signal



(c) Scatterplot of least square estimator +MRC



(d) Scatterplot of kurtosis semi-Blind decoding and estimator

Fig 4.2 Scatter plot for method of estimation and transmit signal

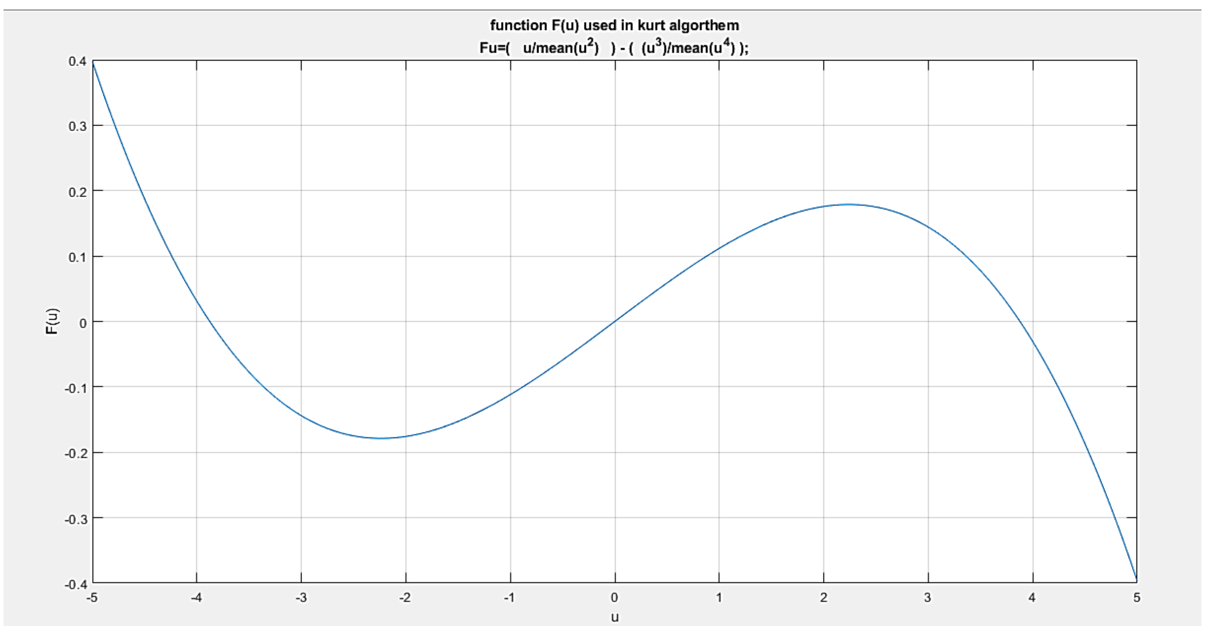
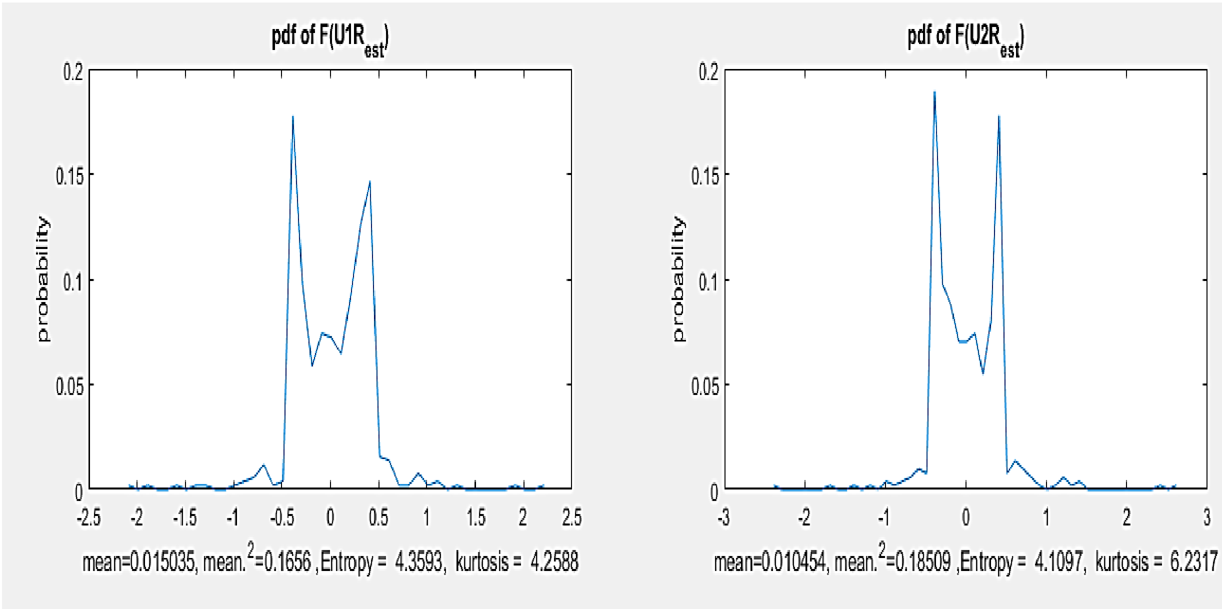
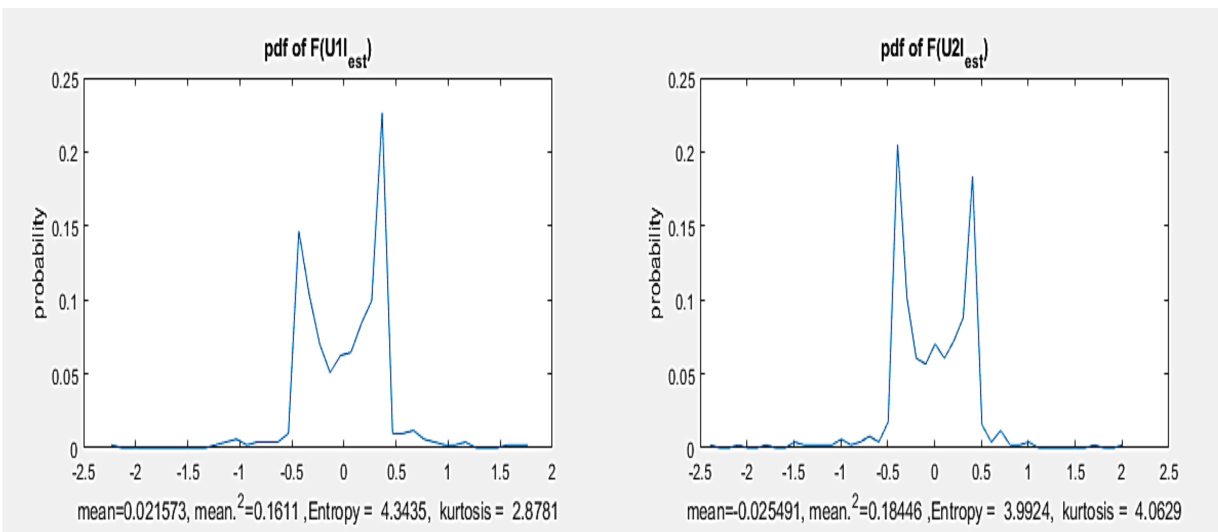


Figure 4.3 Nonlinear function of kurtosis



(a) pdf of real estimated source



(b) pdf of imaginary estimated source

Figure 4.4 pdf of F(U)

The simulation result in this subsection describes how to get a global vector for each source. In the case of g_blind source extraction, the starting value of w is equal to the random value, hence the retrieved source is unknown. In the case of semi-blind source extraction, the starting value of *w* is equal to the $\boldsymbol{M_{LS}}$ value, making it easy to identify the value and sign of each source and compare it to blind source extraction after a few attempts.

Table 4.4 Comparison between blind and semi blind

Number of iterations	global vector		w * M
35	g_blind		-1.3325 -0.0026155 0.018544 0.0087988
23	Semi- blind	g1	1.3387 0.0055725 -0.0201 -0.0075182
23		g2	0.022385 1.34 -0.0088874 -0.0056524
28		g3	-0.029622 -0.0003974 1.3377 -0.0065487
19		g4	-0.017299 0.0010598 0.0020063 1.3314

The bit error rate value of above case is:

BER_kurt = 4.8828e-06

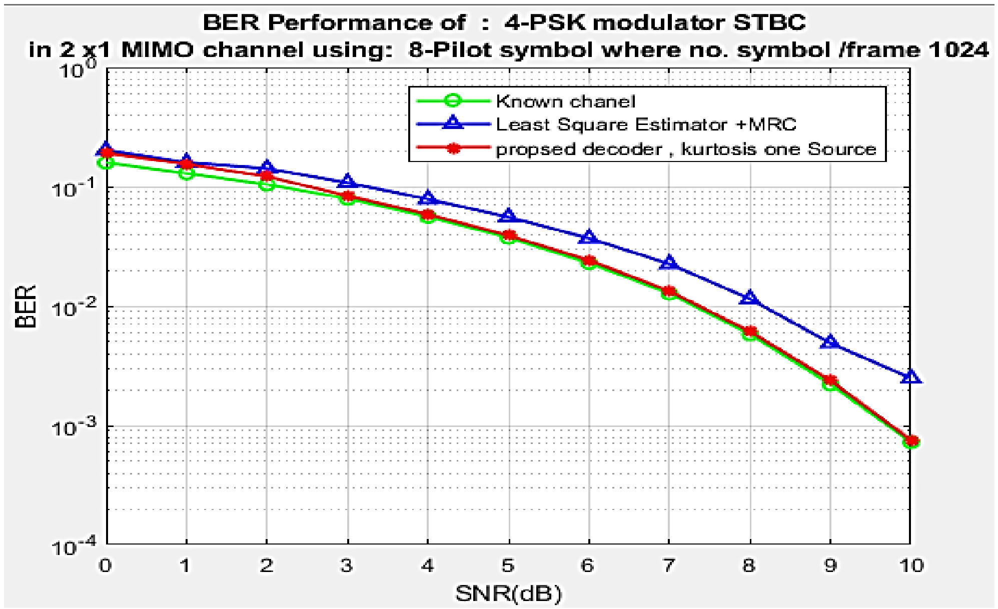
BER_LS= 1.4648e-05

4.3 BER performance of kurtosis-based ICA Algorithm

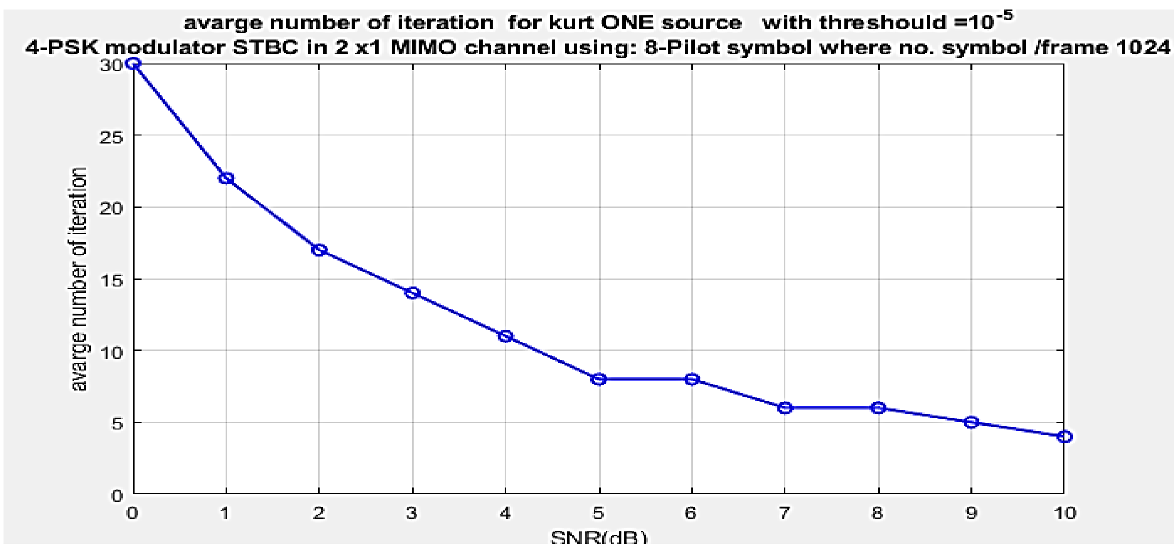
To test the performance of kurtosis-based ICA algorithm, the configuration of antennas has been selected as $(2 \times 1,\ 2 \times 2,\ 2 \times 4,\ 4 \times 2\ and\ 4 \times 4)$ with training symbol (N_t) =8 and the number of samples/frames = 1024.

A- $\mathbf{2 \times 1}$, $\boldsymbol{N_t}$ =8:

Using kurtosis-based ICA with number of samples/frames = 1024, the simulation result is shown in Figure (4.5. a, b)



(a)



(b)

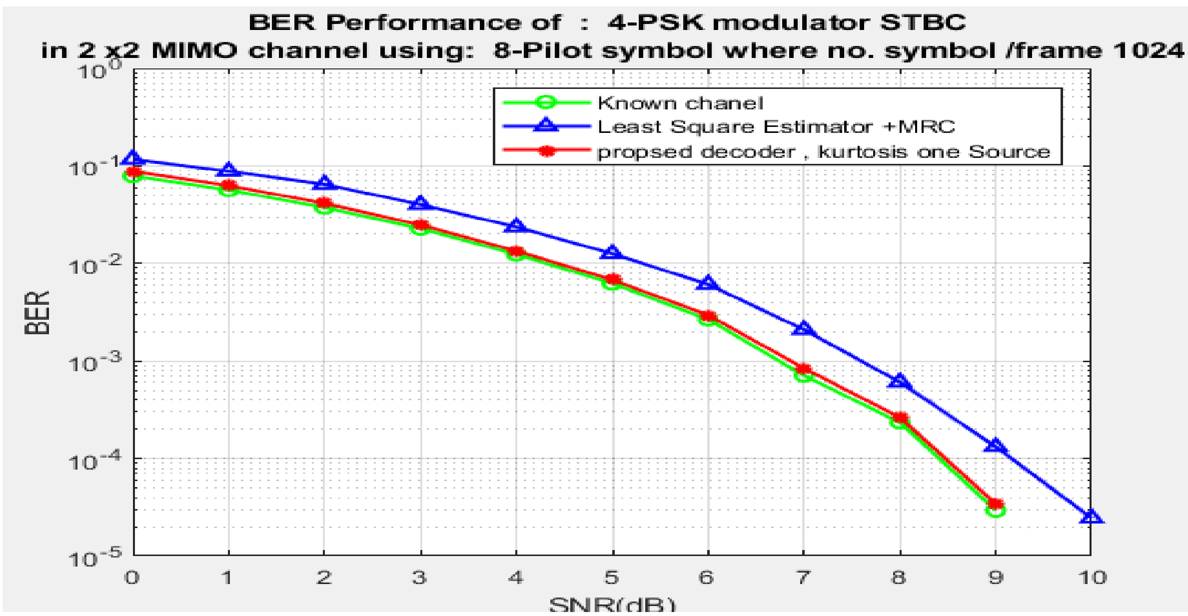
Figure (4.5(a)) 2×1BER performance of one source kurtosis-based ICA, (b) average number of iterations for kurtosis one source

Figure (4.5.a,b) presents the MIMO-STBC channel estimation by using kurtosis-based ICA algorithm that achieves the improvement with only

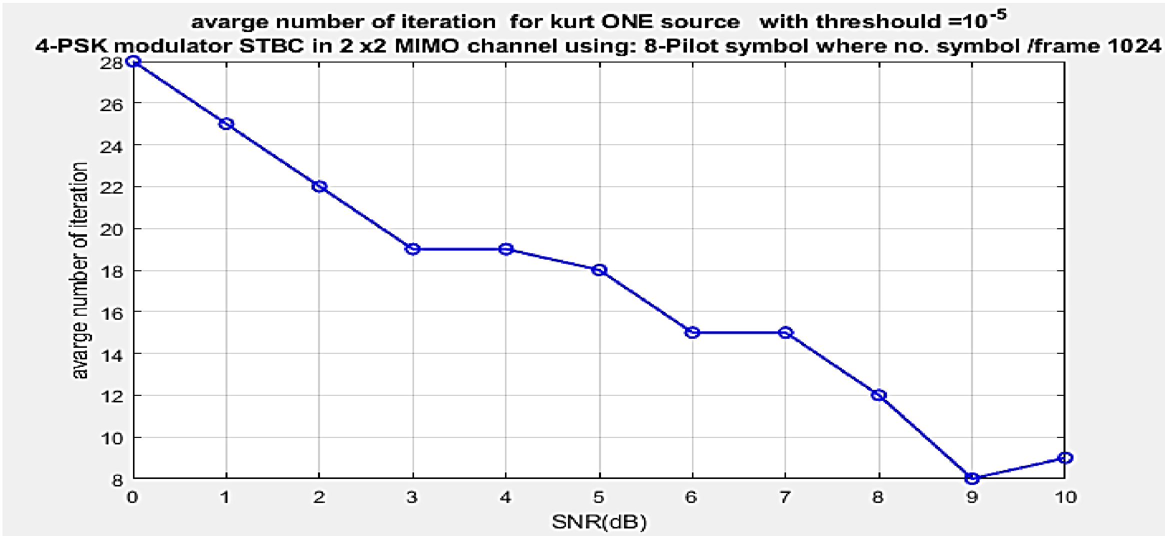
0.6dB and shows the number of iterations gradually decrease. It has better performance when compared with the LS case where X_t is known at the receiver.

B- 2×2, N_t =8:

By using kurtosis-based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.6.a, b)



(a)



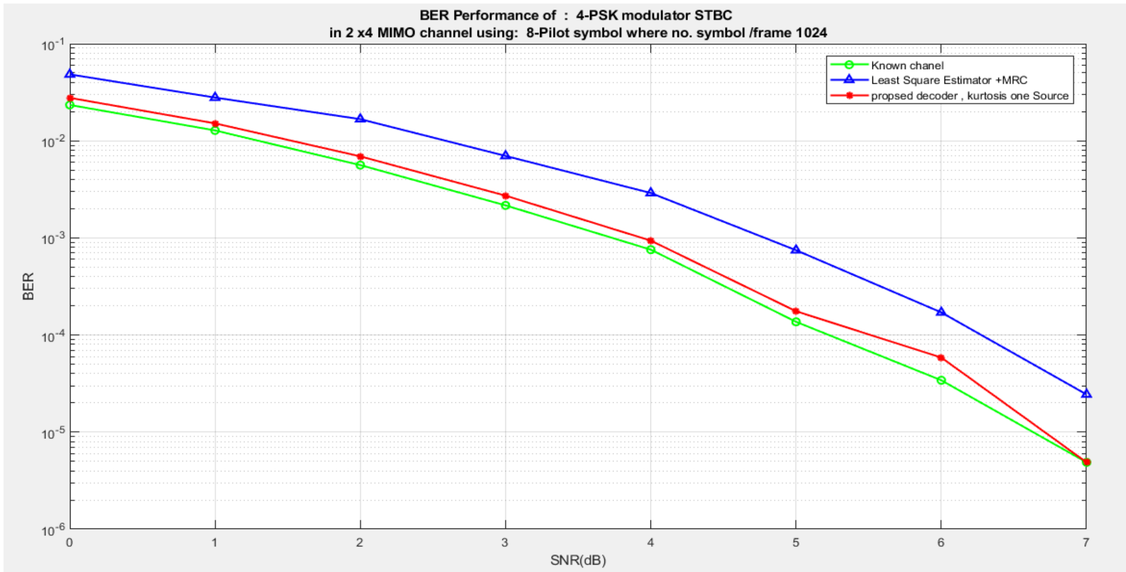
(b)

Figure (4.6) (a) 2×4 BER performance of one source kurtosis-based ICA (b) average number of iterations for kurtosis one source

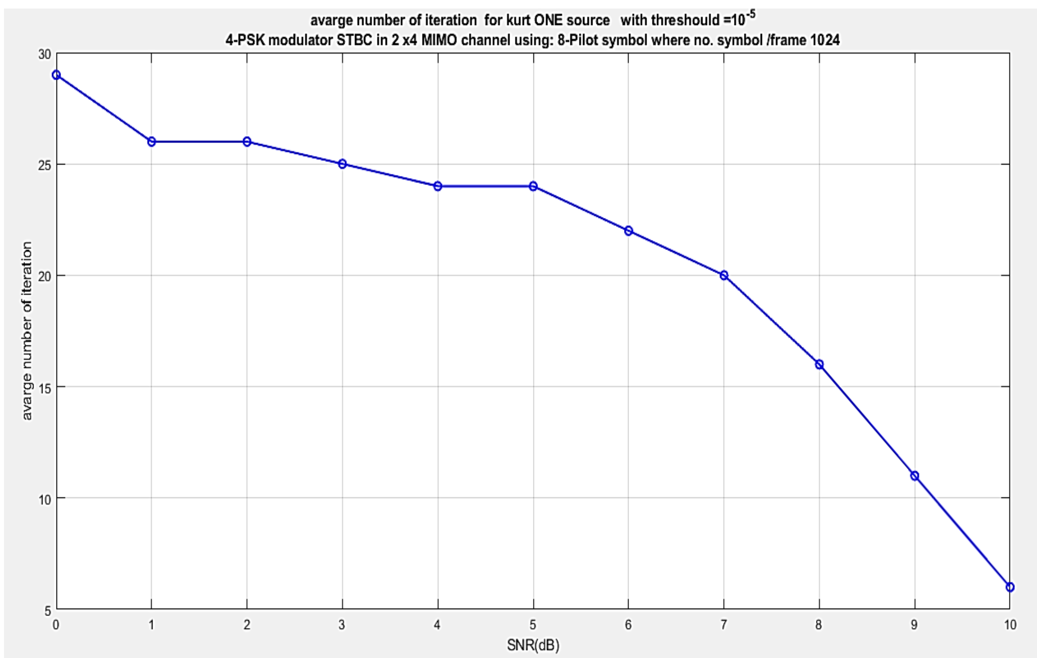
Figure (4.6 a, b) presents the MIMO-STBC channel estimation by using kurtosis-based ICA algorithm that achieves the improvement with only 0.8dB and shows the number of iterations gradually decreases. It has better performance when compared with the LS case where X_t is known at the receiver.

C- $\mathbf{2 \times 4}$, $\boldsymbol{N_t}$ =4:

By using kurtosis-based ICA and number of samples/frames =1024, the simulation results are shown in Figure (4.7.a,b)



(a)



(b)

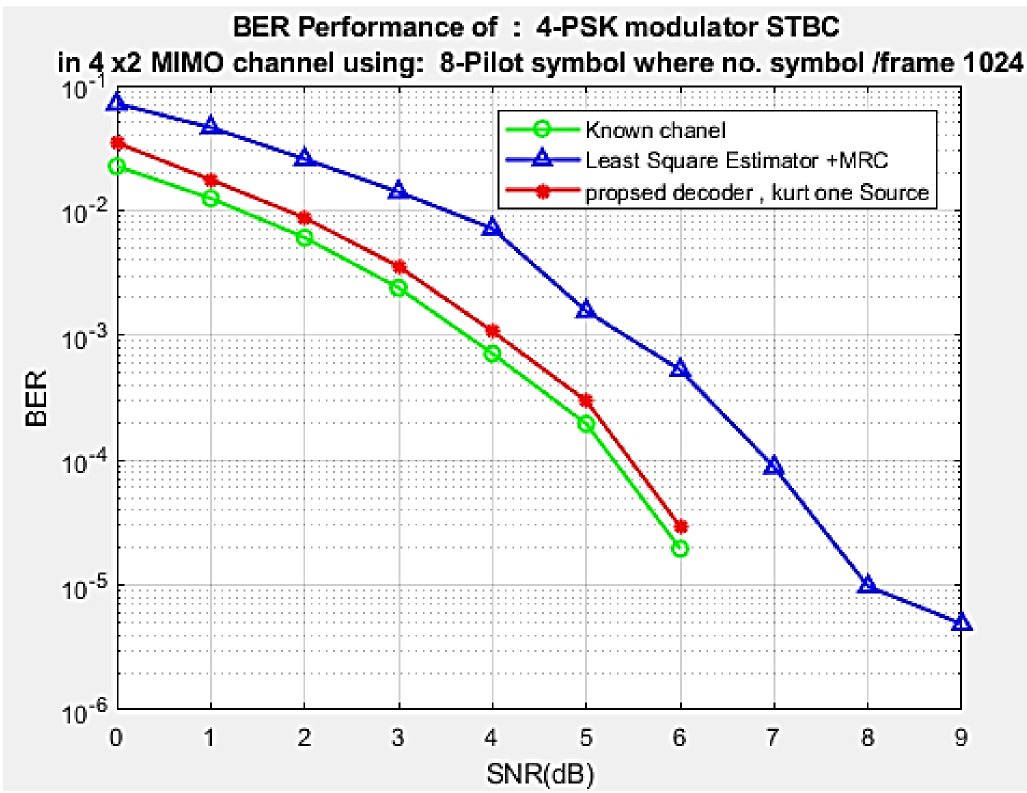
Figure (4.7) (a) 2× 4 BER performance of one source kurtosis-based ICA (b) average number of iterations for kurtosis one source

Figure (4.7a, b) shows the MIMO-STBC channel estimation by using kurtosis-based ICA algorithm that achieves the improvement with only 0.8

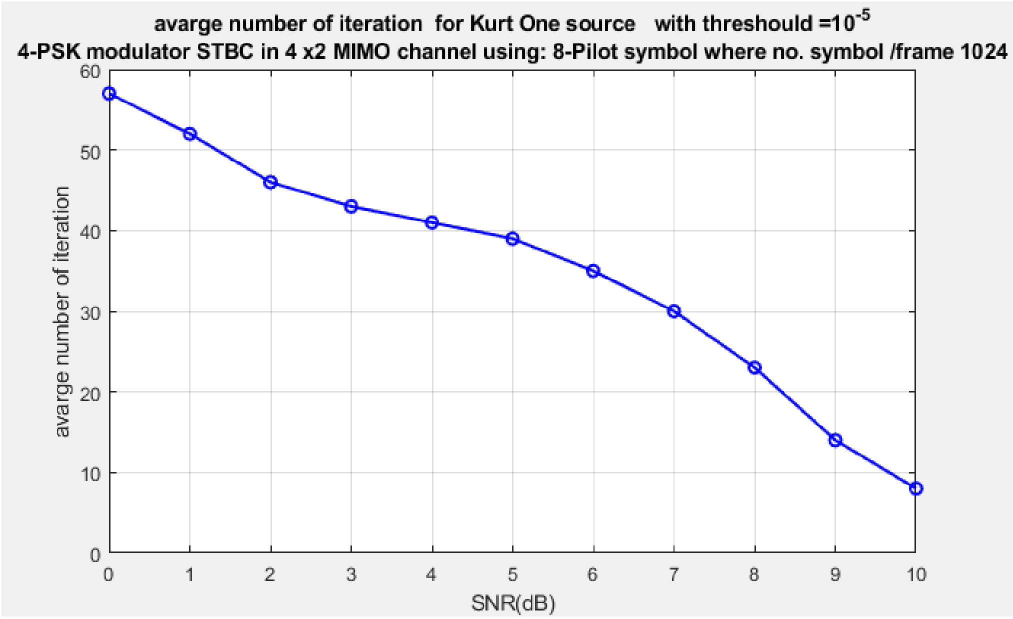
dB and shows the number of iterations gradually decrease. It has better performance when compared with the LS case where X_t is known at the receiver.

D- 4×2, N_t =8:

By using kurtosis-based ICA and number of samples/frames =1024, the simulation results are shown in Figure (4.8(a))



(a)



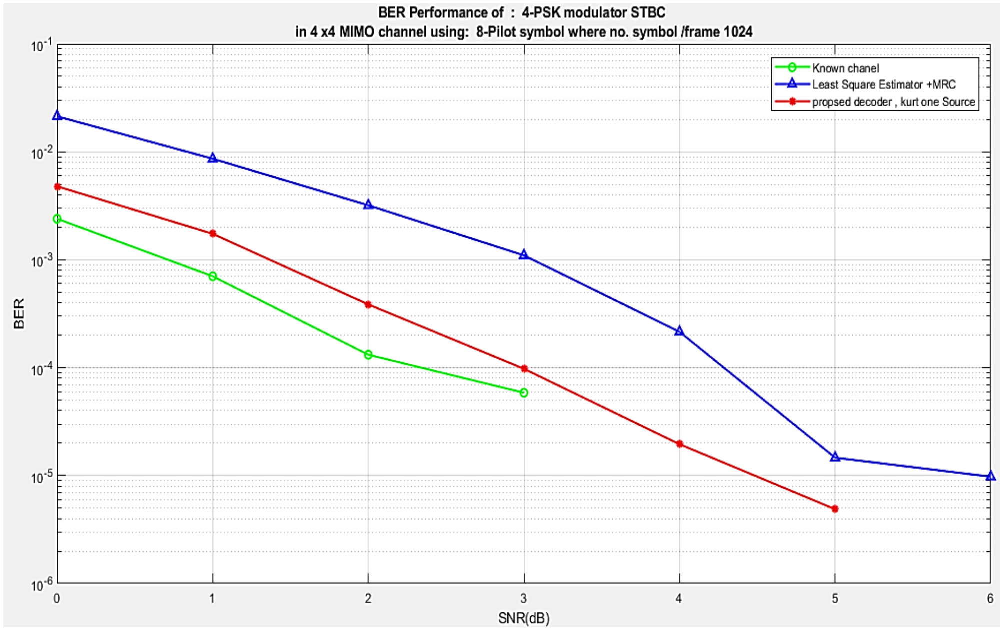
(b)

Figure (4.8) (a) 4×4 BER performance of one source kurtosis based ICA (b) average number of iterations for kurtosis one source

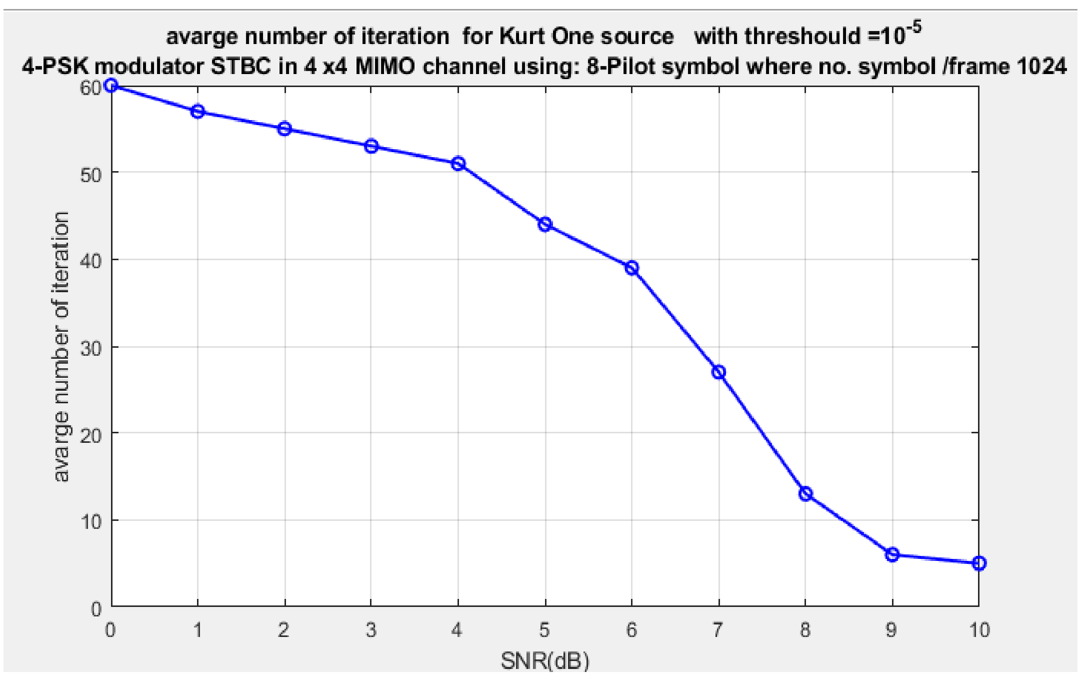
Figure (4.8. a,b) presents the MIMO-STBC channel estimation by using kurtosis based ICA algorithm that achieves the improvement with only 1.5 dB and shows the number of iteration gradually decrease. It has better performance when compared with the LS case where X_t is known at the receiver

E- 4×4, N_t =8:

By using kurtosis-based ICA and number of samples/frames =1024, the simulation results are shown in Figure (4.9.a, b)



(a)



(b)

Figure (4.9(a)) 4×4 BER performance of One Source Kurtosis Based ICA

(b) average number of iterations for kurtosis one source

Figure (4.9.a, b) presents the MIMO-STBC channel estimation by using kurtosis based ICA algorithm that achieves the improvement with only 1.2 dB and shows the number of iteration gradually decrease. It has better performance when compared with the LS case where X_t is known at the receiver

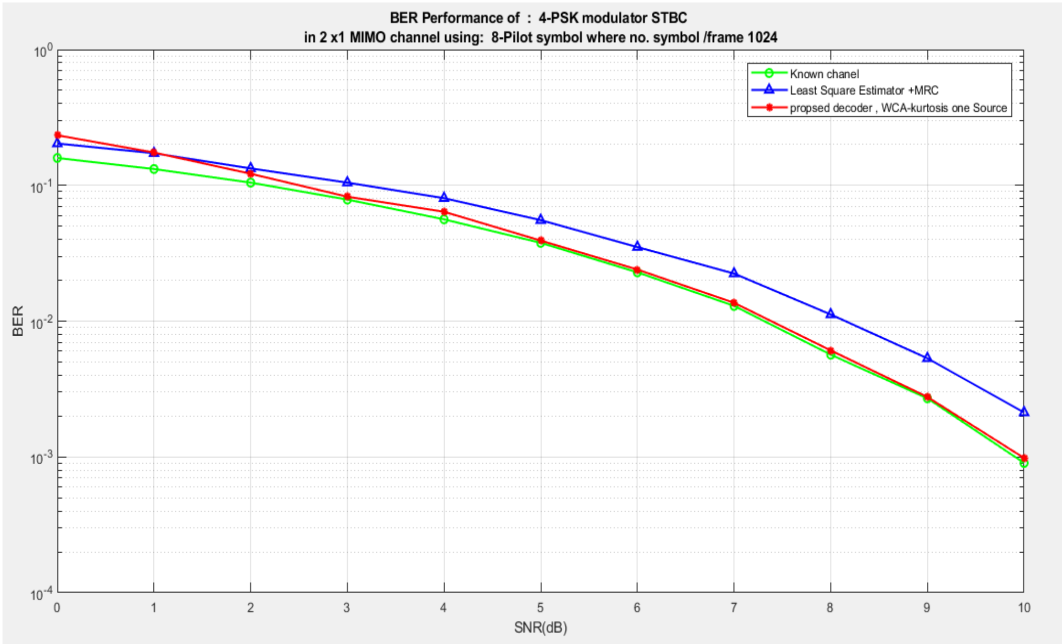
It's clear from above result that when use kurtosis ICA algorithm and when the number of transmitter N_t larger than number of receiver N_r, the result is better than when N_r larger than N_t where the proposed channel closer to the known channel in $2 \times 1, 2 \times 2, 2 \times 4, 4 \times 2$ and 4×4 sequentially where the better result get in 2×1 and the worst result get in 4×4 .

4.4 Comparison between BER performance of WCA-Kurtosis and Kurtosis

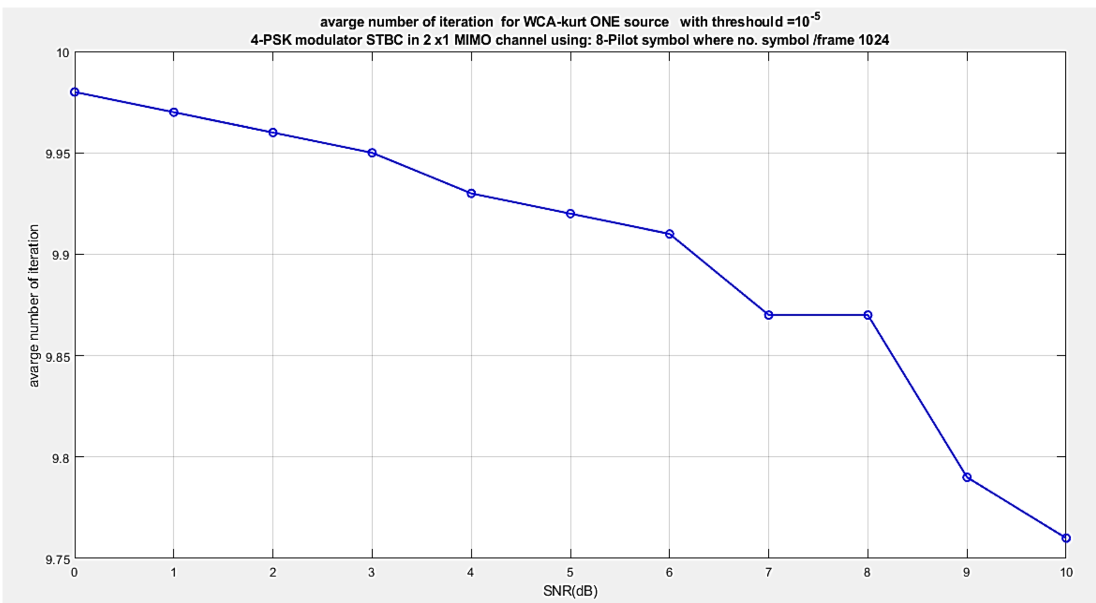
In this section, the BER performance of WCA-Kurtosis and kurtosis-ICA had been compared in terms of BER performance and average number of iterations:

A- $\mathbf{2 \times 1}$, $\boldsymbol{N_t}$ =8:

By using WCA-kurtosis based ICA and number of samples/frames = 1024, the simulation result is shown in Figure (4.10.a,b)



(a)



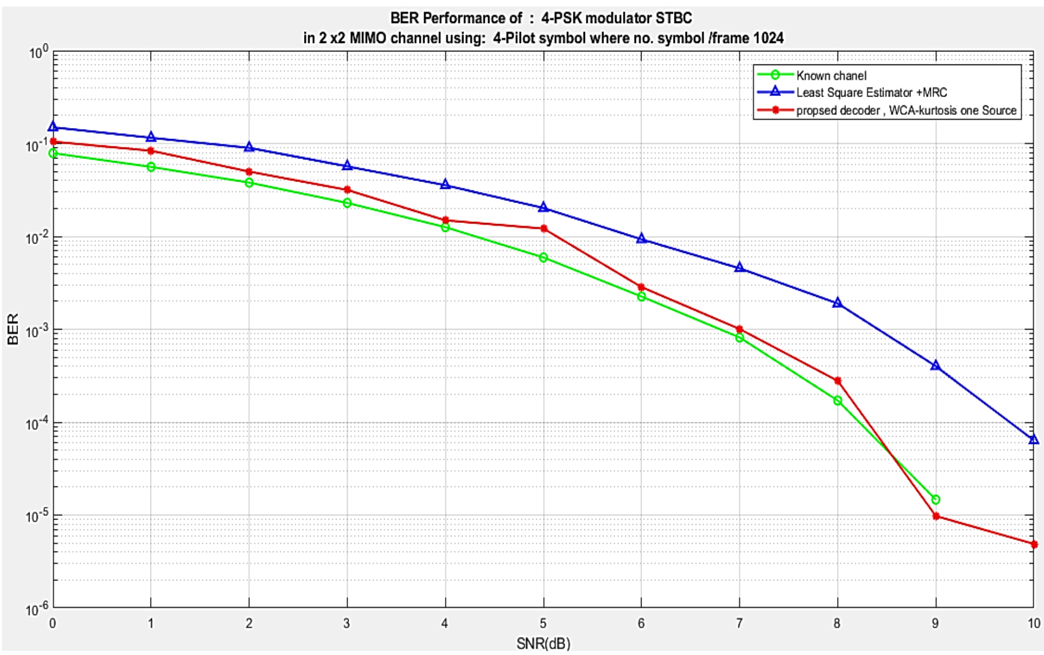
(b)

Figure (4.10(a)) 2×1 BER performance of one source WCA-kurtosis based ICA (b) average number of iterations for WCA-kurtosis one source.

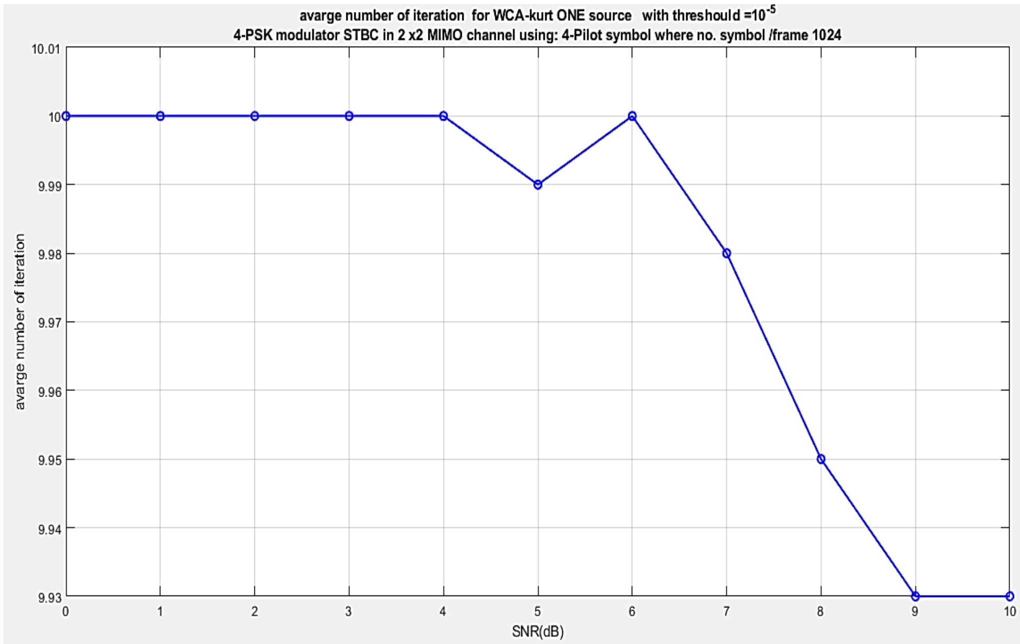
From the calculation of BER optimization at 10^{-2} for the two antennas at the transmitter, it show that the performance of the proposed algorithm using WCA-kurtosis is better than the performance of the LS algorithm by 0.8 dB at the length of the 1024 frame which is shown in Figure(4.10.a) The performance of the proposed algorithm using kurtosis-ICA shows 0.6 dB better than the LS algorithm in the 1024 frame length shown in Figure(4.5.a), and the number of iteration in WCA-kurtosis is less than in kurtosis-ICA as shown in Figure(4.10b)

B- $2 \times 2, N_t$ =8:

By using WCA-kurtosis based ICA and number of samples/frames =1024, the simulation results are shown in Figure (4.11 .a,b)



(a)



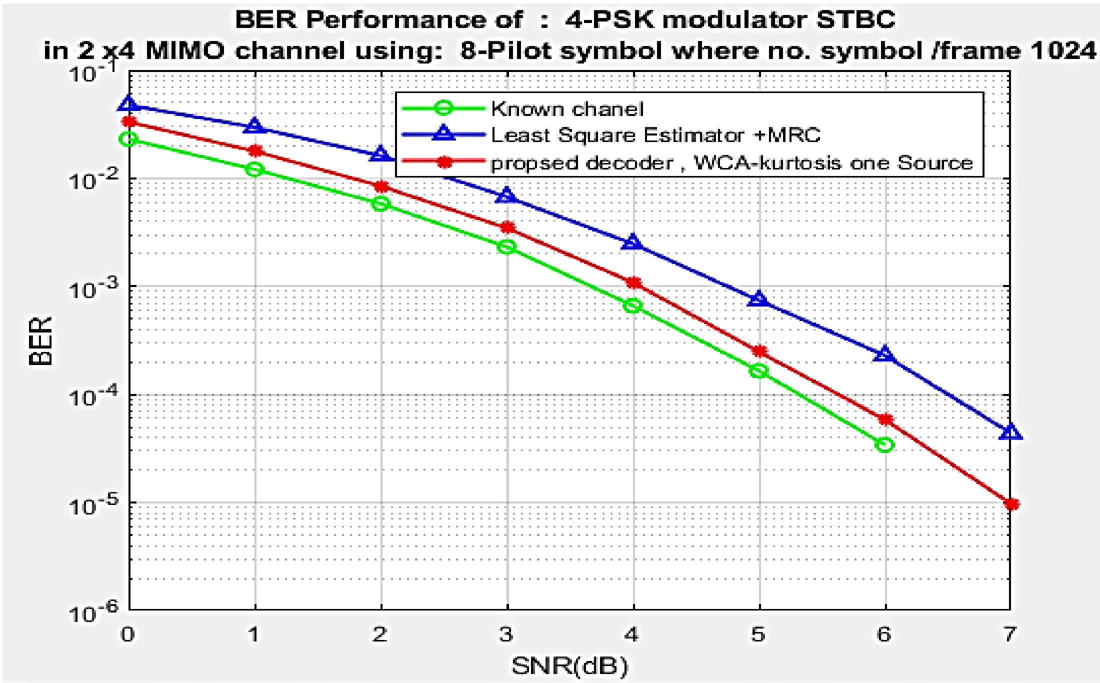
(b)

Figure (4.11(a)) $\mathbf{2 \times 2}$ BER performance of one source WCA-kurtosis based ICA (b) average number of iterations for WCA-kurtosis one source.

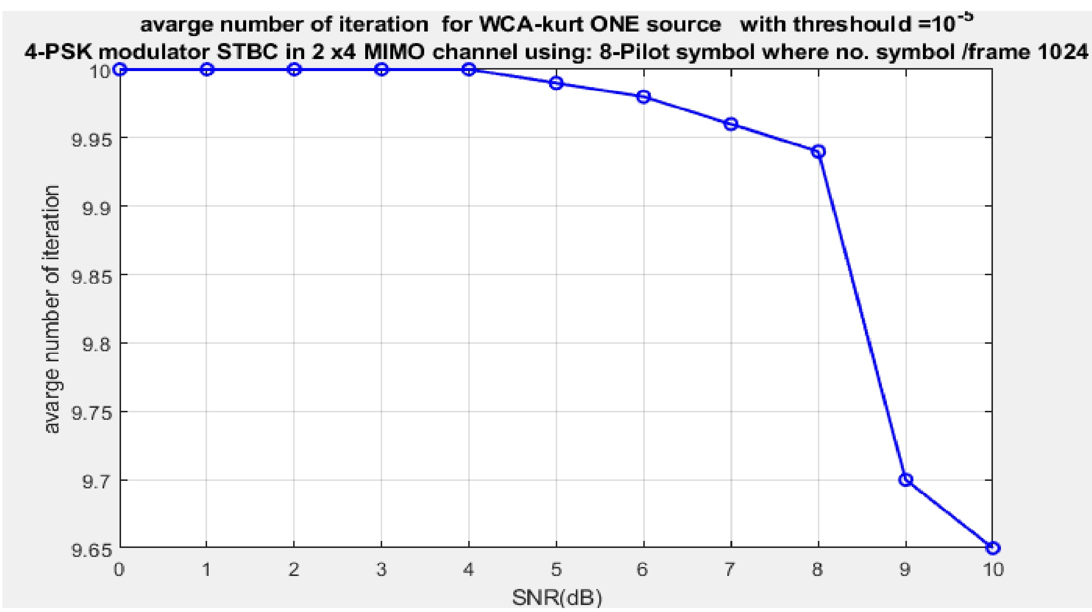
From the calculation of BER optimization at 10^{-4} for the two antennas at the transmitter, we show that the performance of the proposed algorithm using WCA-kurtosis is better than the performance of the LS algorithm by 1.6 dB at the length of the 1024 frame which is shown in Figure(4.11.a). The performance of the proposed algorithm using kurtosis-ICA shows 0.8db better than the LS algorithm in the 1024 frame length shown in Figure (4.6.a), and the number of iteration in WCA-kurtosis is less than in kurtosis-ICA as shown in Figure (4.11.b)

C- $\quad \boldsymbol{2 \times 4, N_t = 8}$

By using WCA-kurtosis based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.12.a,b)



(a)



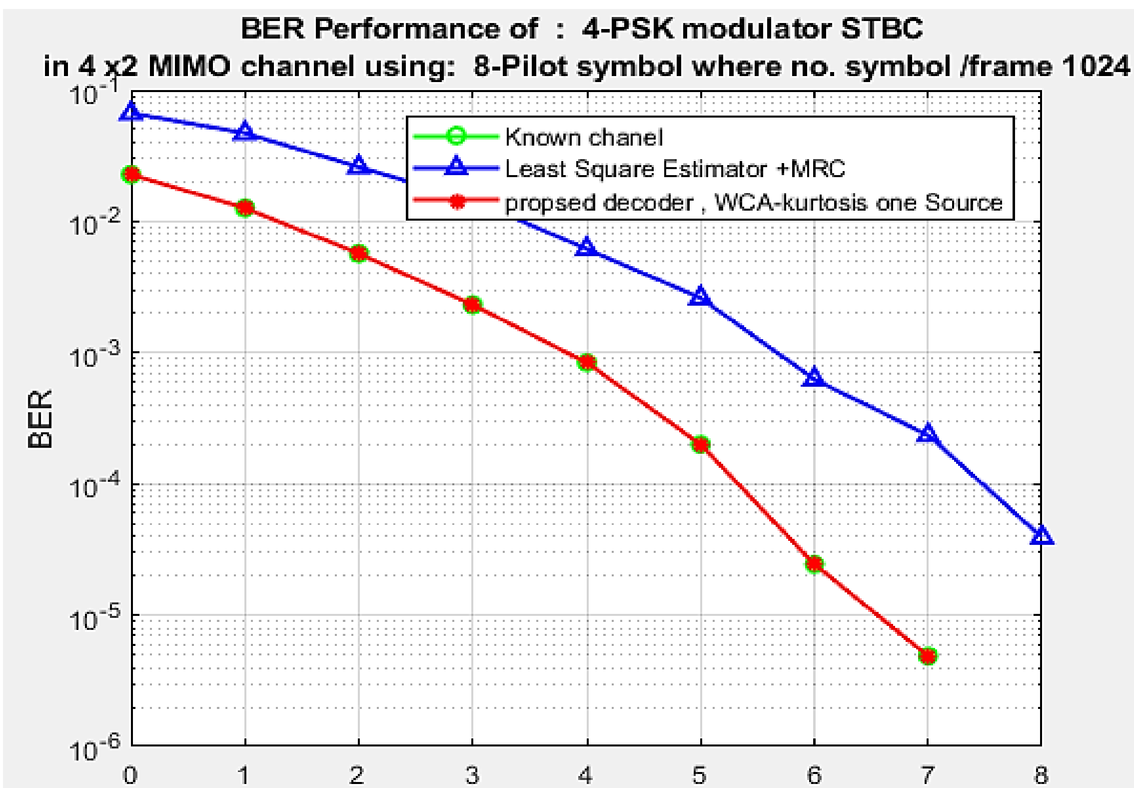
(b)

Figure (4.12 (a)) 2×4 BER performance of one source WCA-kurtosis based ICA (b) average number of iterations for WCA-kurtosis one source.

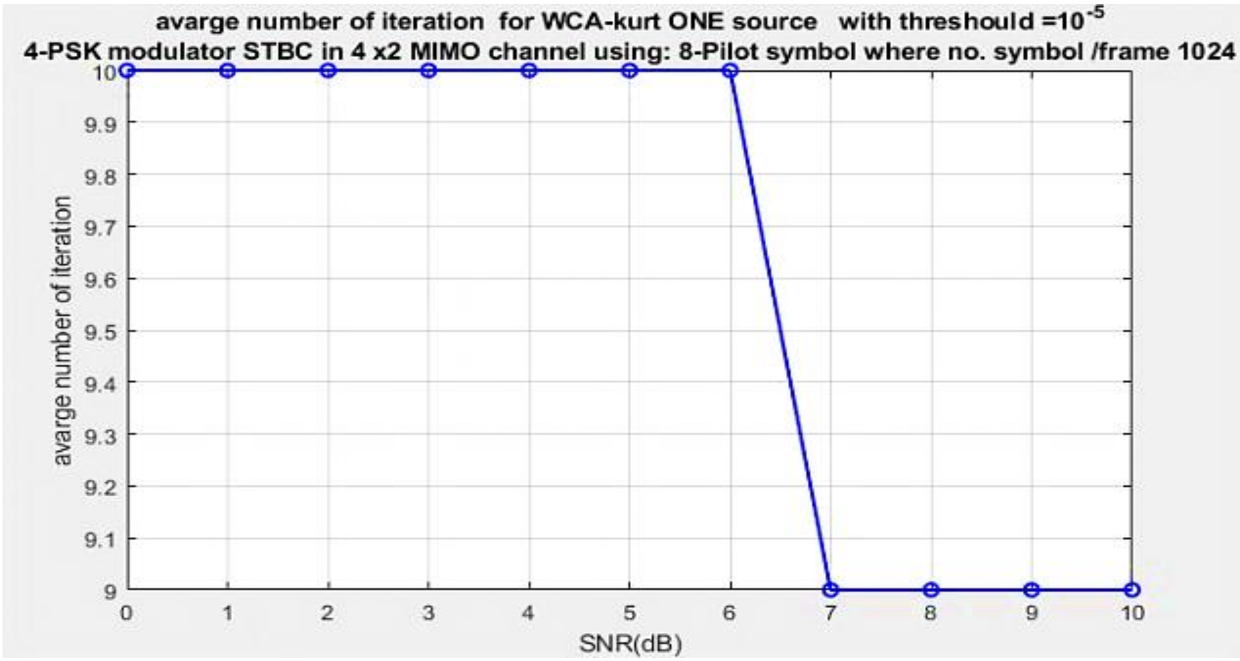
From the calculation of BER optimization at 10^{-4} for the two antennas at the transmitter, we show that the performance of the proposed algorithm using WCA-kurtosis is better than the performance of the LS algorithm by 1dB at the length of the 1024 frame which is shown in Figure (4.12.a). The performance of the proposed algorithm using kurtosis-ICA shows 0.8dB better than the LS algorithm in the 1024 frame length shown in Figure (4.7.a) and the number of iteration in WCA-kurtosis is less than in kurtosis-ICA as shown in Figure (4.12.b).

D- 4×2, N_t=8:

By using WCA-kurtosis based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.13.a,b)



(a)



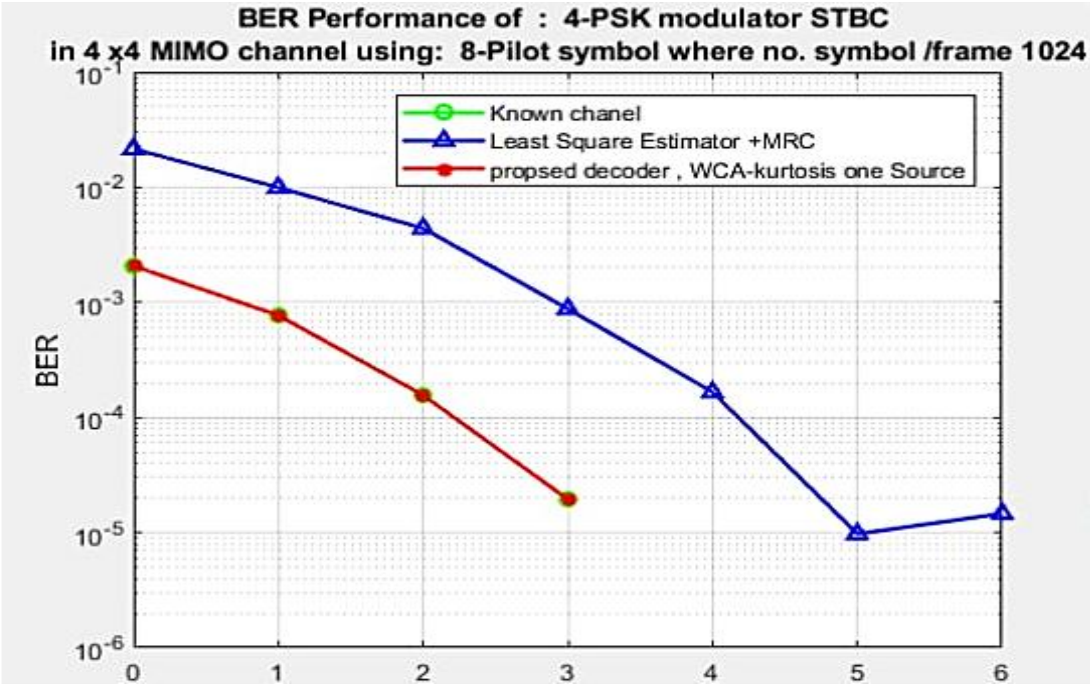
(b)

Figure (4.13(a)) 4×2 BER performance of one source WCA-kurtosis based ICA (b) average number of iterations for WCA-kurtosis one source.

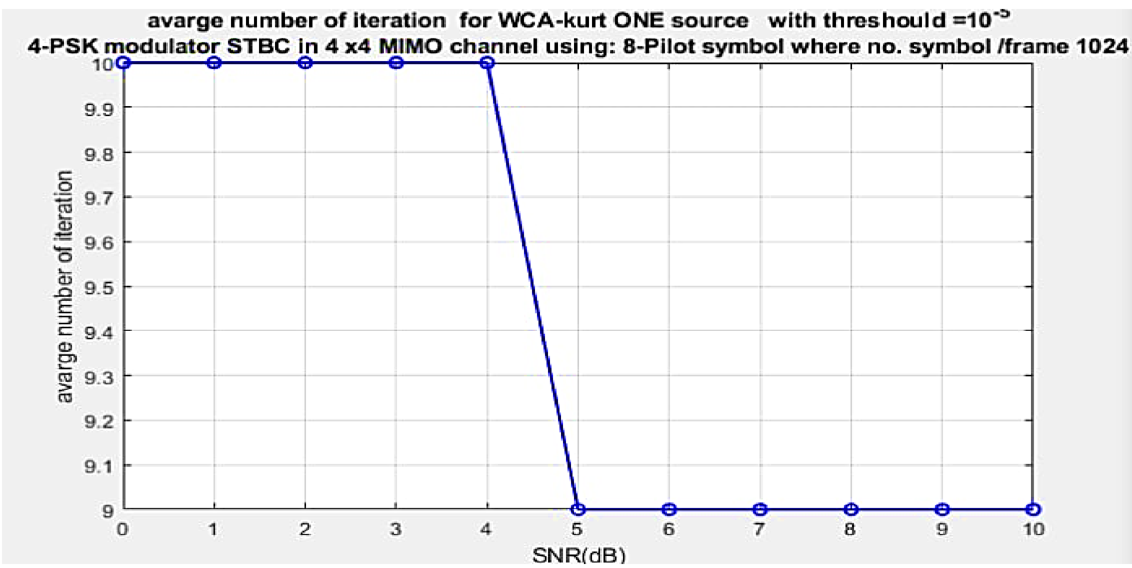
From the calculation of BER optimization at 10^{-4} for the four antennas at the transmitter, it show that the performance of the proposed algorithm using WCA-kurtosis is better than the performance of the LS algorithm by 2 dB at the length of the 1024 frame which is shown in (4.13.a). The performance of the proposed algorithm using kurtosis-ICA shows 1.5dB better than the LS algorithm in the 1024 frame length shown in Figure (4.8.a).

E- 4×4, N_t=8:

By using WCA-kurtosis based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.14 a,b)



(a)



(b)

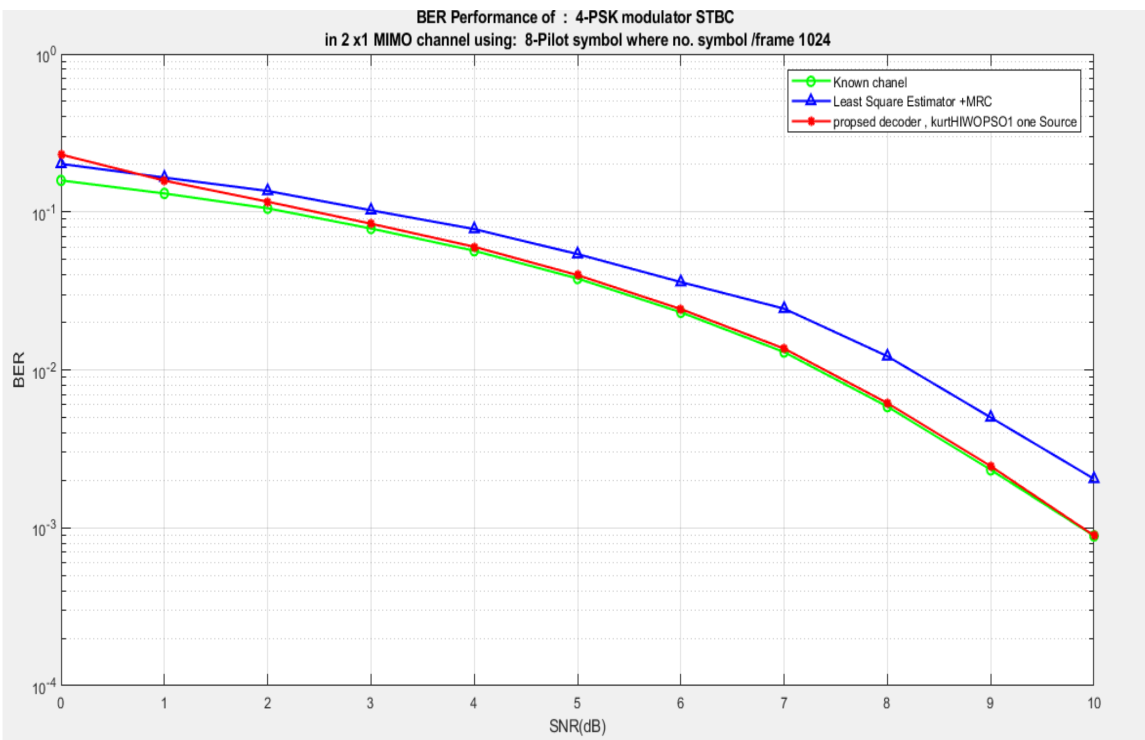
Figure (4.14 (a)) 4×4 BER performance of one source WCA-kurtosis based ICA (b) average number of iterations for WCA-kurtosis one source.

From the calculation of BER optimization at 10^{-4} for the four antennas at the transmitter, it shows that the performance of the proposed algorithm using WCA-kurtosis is better than the performance of the LS algorithm by 2dB at the length of the 1024 frame which is shown in Figure(4.14.a) The performance of the proposed algorithm using kurtosis-ICA shows 1.2 dB better than the LS algorithm in the 1024 frame length shown in Figure (4.9.a) and the number of iteration in WCA-kurtosis is less than in kurtosis-ICA as shown in Figure (4.14.b)

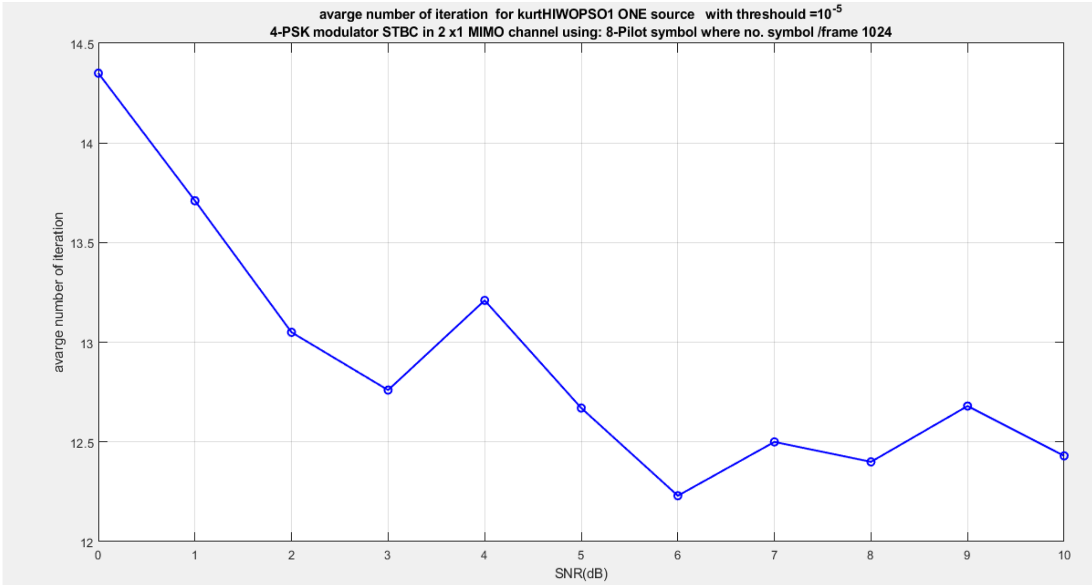
4.5 Comparison between BER performance of HIWOPSO-Kurtosis and Kurtosis

A- 2×1, N_t =8:

By using HIWOPSO-kurtosis based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.15.a,b)



(a)



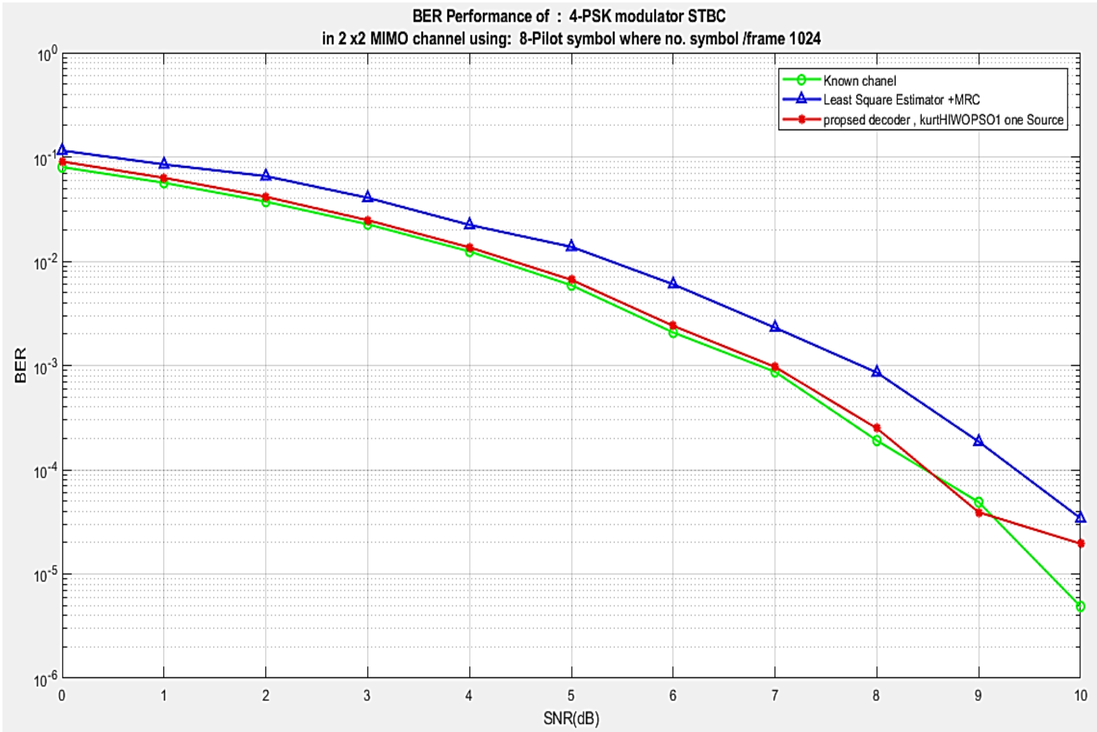
(b)

Figure (4.15 (a)) 2×1 BER performance of one source HIWOPSO-kurtosis based ICA (b) average number of iterations for HIWOPSO-kurtosis one source.

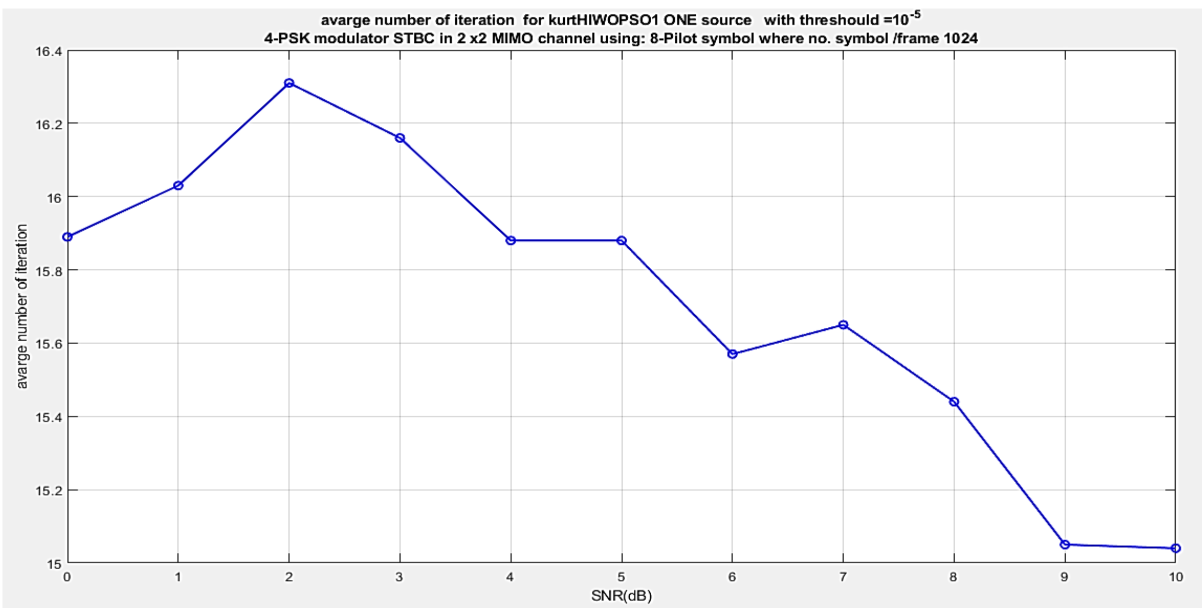
From the calculation of BER optimization at 10^{-2} for the two antennas at the transmitter, it shows that the performance of the proposed algorithm using HIWOPSO -kurtosis is better than the performance of the LS algorithm by 0.8 dB at the length of the 1024 frame which is shown in Figure (4.15.a) The performance of the proposed algorithm using kurtosis-ICA shows 0.6 dB better than the LS algorithm in the 1024 frame length shown in Figure (4.5.a).

B- $2 \times 2, N_t = 8$:

By HIWOPSO -kurtosis based ICA and number of samples/frames =1024, the simulation results are shown in Figure (4.16.a,b)



(a)



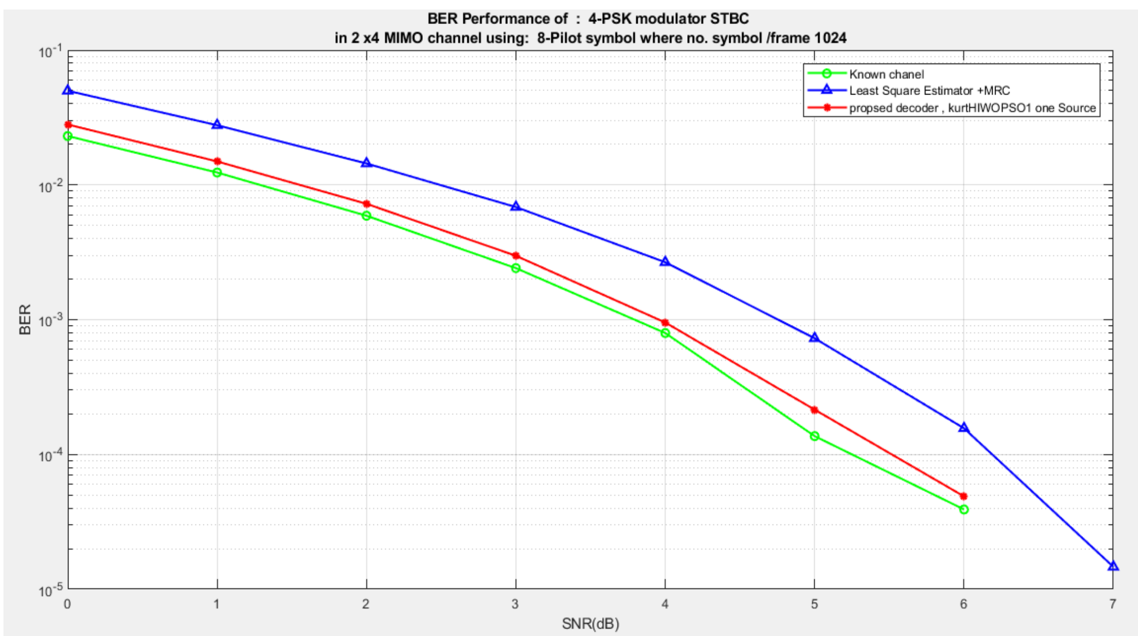
(b)

Figure (4.16 (a)) 2 ×2 BER performance of one source HIWOPOS-kurtosis based ICA (b) average number of iterations for HIWOPSO-kurtosis one source.

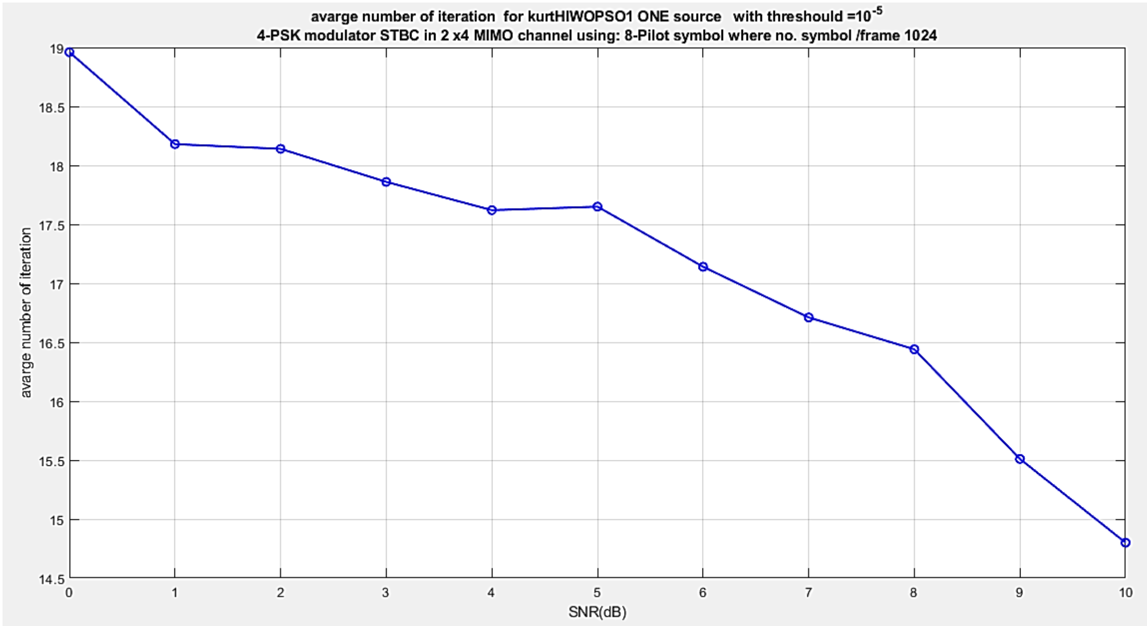
From the calculation of BER optimization at 10^{-4} for the two antennas at the transmitter, it shows that the performance of the proposed algorithm using HIWOPOS-kurtosis is better than the performance of the LS algorithm by 1dB at the length of the 1024 frame which is shown in Figure (4.16.a). The performance of the proposed algorithm using kurtosis-ICA shows 0.8dB better than the LS algorithm in the 1024 frame length shown in Figure (4.6.a), and the number of iterations in HIWOPOS-kurtosis is less than in kurtosis-ICA.

C- $\mathbf{2 \times 4}, \boldsymbol{N_t} = \mathbf{8}$

By using HIWOPSO-kurtosis based ICA and number of samples/frames = 1024, the simulation result is shown in Figure (4.17.a,b)



(a)



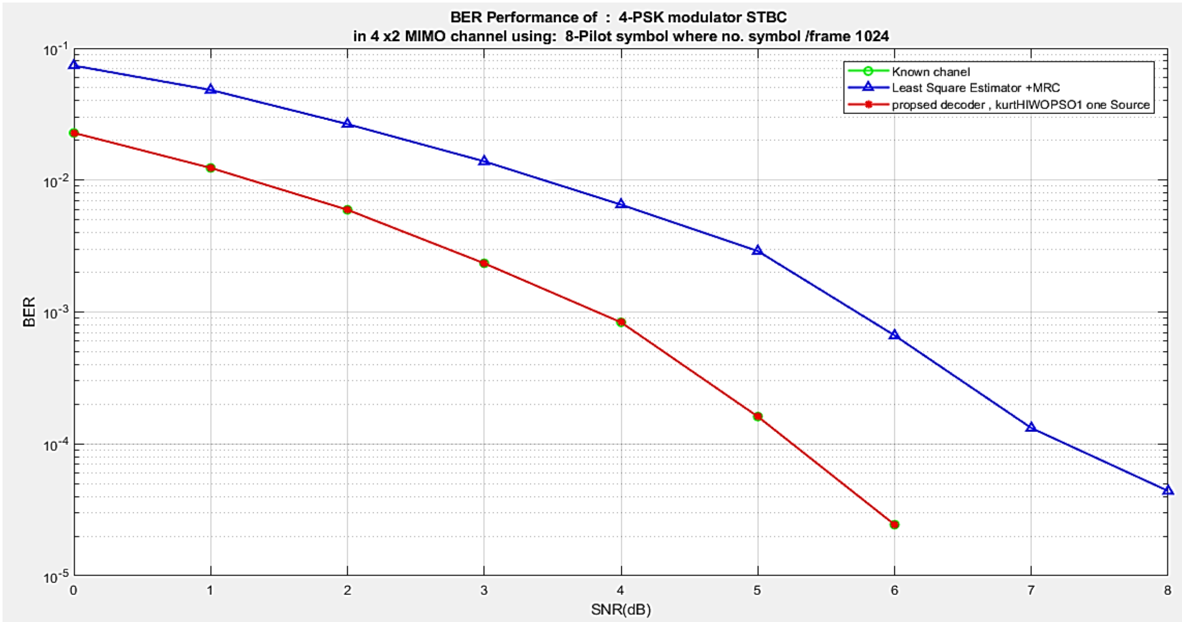
(b)

Figure (4.17(a)) 2×4 BER performance of one source HIWOPSO-kurtosis based ICA (b) average number of iterations for HIWOPSO-kurtosis one source.

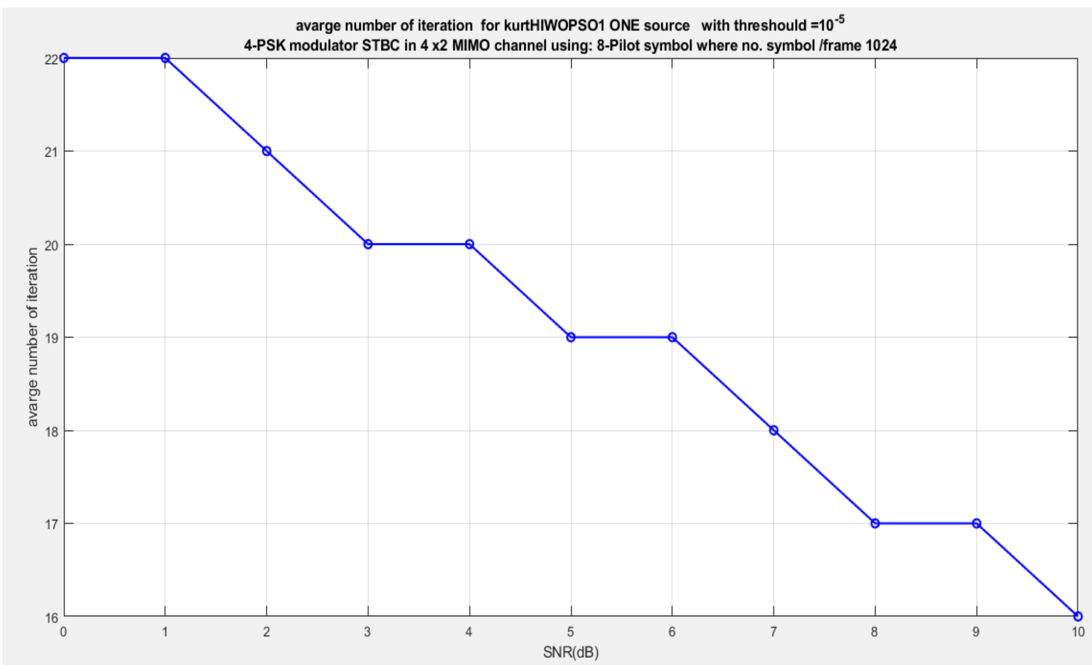
From the calculation of BER optimization at 10^{-4} for the two antennas at the transmitter, it shows that the performance of the proposed algorithm using HIWOPSO-kurtosis is better than the performance of the LS algorithm by 0.8dB at the length of the 1024 frame which is shown in Figure (4.17.a). The performance of the proposed algorithm using kurtosis-ICA shows is also 0.8dB in the 1024 frame length shown in Figure (4.7.a).

D- 4×2, N_t=8:

By using HIWOPSO-kurtosis based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.18.a,b)



(a)



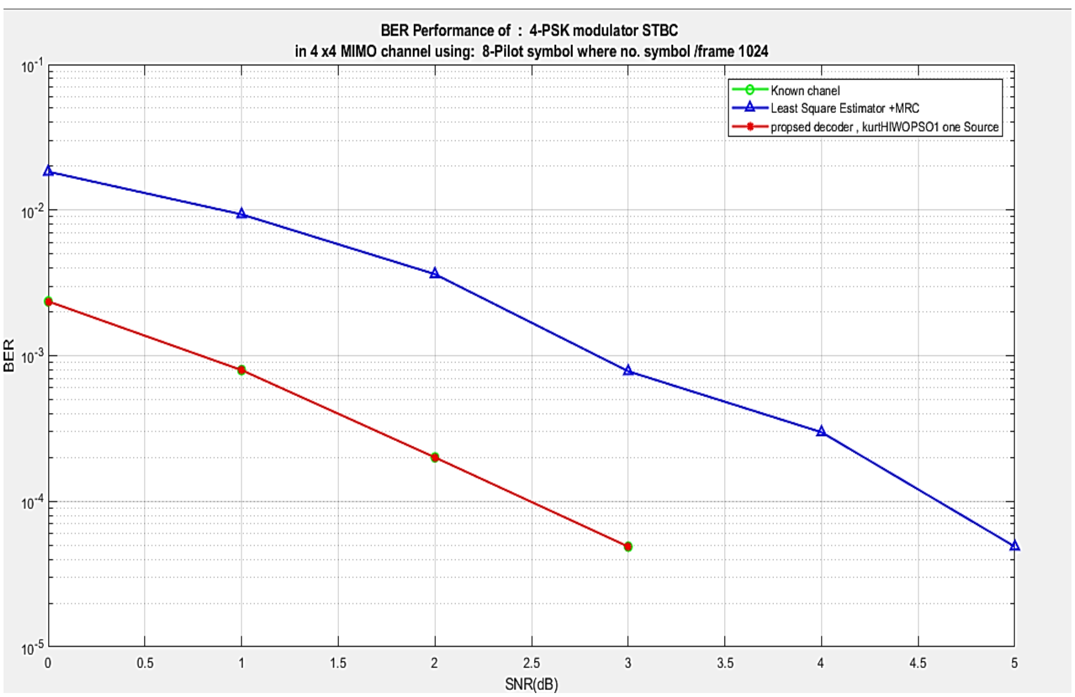
(b)

Figure (4.18) (a) 4 × 2 BER performance of one source HIWOPSO-kurtosis based ICA (b) average number of iterations for HIWOPSO-kurtosis one source.

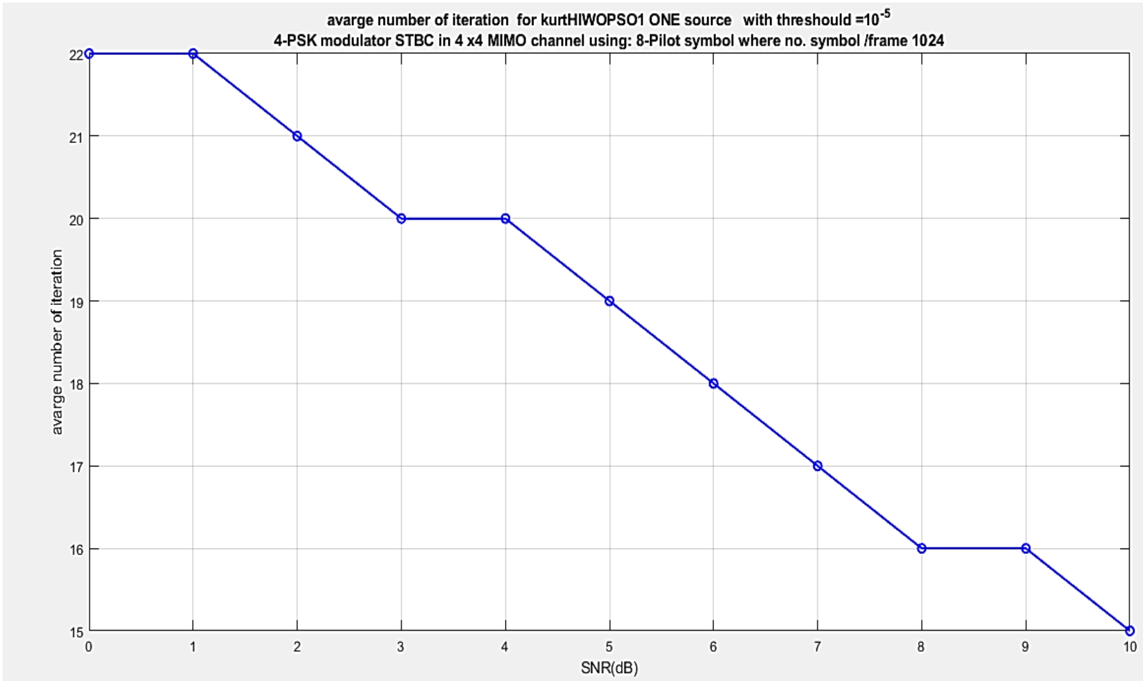
From the calculation of BER optimization at 10^{-4} for the four antennas at the transmitter, it shows that the performance of the proposed algorithm using HIWOPSO-kurtosis is better than the performance of the LS algorithm by 2.1 dB at the length of the 1024 frame which is shown in (4.18.a). The performance of the proposed algorithm using kurtosis-ICA shows 1.5dB better than the LS algorithm in the 1024 frame length shown in Figure (4.8.a).

E- 4×4, N_t=8:

By using HIWOPSO-kurtosis based ICA and number of samples/frames = 1024, the simulation results are shown in Figure (4.19.a,b)



(a)



(b)

Figure (4.19) (a) $\mathbf{4} \times \mathbf{4}$ BER performance of one source HIWOPSO-kurtosis based ICA (b) average number of iterations for HIWOPSO-kurtosis one source.

From the calculation of BER optimization at 10^{-4} for the four antennas at the transmitter, it shows that the performance of the proposed algorithm using HIWOPSO-kurtosis is better than the performance of the LS algorithm by 4.2dB at the length of the 1024 frame which is shown in Figure (4.19.a) The performance of the proposed algorithm using kurtosis-ICA shows 1.2 dB better than the LS algorithm in the 1024 frame length shown in Figure (4.9.a).

4.6 Comparison between BER performance of Kurtosis, WCA-Kurtosis and HIWOPSO-Kurtosis

Table 4.5 the Comparison between BER performance of kurtosis, WCA-Kurtosis and HIWOPSO-Kurtosis:

	Kurtosis		WCA-Kurtosis		HIWOPSO-Kurtosis	
	coding gain	Number of iterations	Coding gain	Number of iterations	coding gain	Number of iterations
$\mathbf{2 \times 1}$	0.6 dB	17	0.8 dB	9	0.8 dB	13
$\mathbf{2 \times 2}$	0.8 dB	19	1.6 dB	9	1 dB	15
$\mathbf{2 \times 4}$	0.8 dB	25	1 dB	9	0.8 dB	15
$\mathbf{4 \times 2}$	1.5 dB	32	2 dB	9	2.1 dB	16
$\mathbf{4 \times 4}$	1.2dB	42	2dB	9	4.2dB	15

Conclusion

This work proposed a new technology for decoding Multiple Input Multiple Output Space Time Block Code (MIMO-STBC) by utilized blind source separation (BSS), to enhance the BER performance for MIMO STBC channel estimator by using semi-blind independent component analysis (ICA) method, The kurtosis-based source extraction technique is achieved by using real imaginary decomposition (R-Im) of maximum ratio combiner (MRC)in order to solve the problem of source sign and sign ambiguity , Finally, by applying the water cycle(WCA) and A Hybrid Algorithm based on Invasive Weed Optimization and Particle Swarm Optimization (HIWOPSO) for Global Optimization, we were able to increase the work speed and performance of channel estimation using the ICA technique.

When WCA and HIWOPSO are combined independently with a single source extraction kurtosis based ICA, a low complexity, fast speed, good BER performance decoder that can operate with any MIMO STBC is produced, Where it resulted that the performance of WCA-Kurtosis is better than the performance of the LS algorithm for transmit and receive antennas in 2×1, 2×2, 4×2, and 4×4 by 0.8,1.6, 1, 2, and 2 dB, respectively, at the frame length of the 1024,and the performance of the HIWOPSO-Kurtosis is better than the performance of the LS algorithm for transmit and receive antennas in 2×1, 2×2, 4×2, and 4×4 by 0.8 , 1 , 0.8 , 2.1 and 4.2

The result show that at 4×4 the HIWOPSO is the best algorithm because the proposed channel approaching to the known channel and get away the LS at a rate of 4.2dB, and also the WCA algorithm achieved the best result at 4 × 4 at a rate of 2 dB than the LS, but HIWOPSO has more iterations than the WCA, whereas the Kurtosis-ICA achieved the best result at 2 × 2 and the worst result at 4 × 4, and this indicates that the proposed algorithms (WCA and HIWOPSO) can deal with matrices of large dimensions and with high accuracy and small iteration to reach the optimal solution.

Table 4.6 represent the compression between this work and the previous work.

Table 4.6 Compression the proposed work with the previous works

Reference	Decoding technique	Optimization Methods	No. of transmit and received antennas	Estimation	Result
[14]	MIMO-	----	(2 × 2)	The performance of Alamouti scheme and Maximum ratio combining technique(MRC) are evaluated under the assumption of BPSK signals affected by reflection, detraction and scattering environment	It is shown that in wireless MIMO system based on Alamouti diversity technique and Maximum ratio combining technique can help to combat and mitigate against Rayleigh fading channel and approach AWGN channel performance with constant transmit power.
[25]	MIMO STBC-	PSO	(2×2)	Simi-blind MMI-ICA	The result show that a good performance achieved with only 1.2 to 1.4 dB and shows the number of iteration gradually decrease
[26]	MIMO STBC-	OPSO	(4×4)	FastICA,	The simulation results show that at (Nr = 2 and 4) As compare with classical decoding algorithm, it is found that the new decoder provides coding gain (at BER =10-6) equal to 1 dB and 1.45 dB when Nr = 2 and 4 respectively
proposed work	QPSK-STBC	WCA	(2×1),(2×2,(2×4),(4×2),(4×4)	Simi-blind Kurtosis-WCA	The result shows that the WCA algorithm achieved the best result at 4 × 4 at a rate of 2 dB than the LS with less number of iteration.

	QPSK-STBC	HIWOPSO	(2×1),(2×2,(2×4),(4×2),(4×4)	Simi-blind Kurtosis-HIWOPSO	The result show that at 4×4 the HIWOPSO is the best algorithm because the proposed channel approaching to the known channel and get away the LS at a rate of 4.2dB with less number of iteration.

Chapter Five

Conclusions and Future Works

Chapter Five
Conclusions and Future Works

5.1 Conclusion Remarks

In this thesis, the BER performance of a standard MRC decoder in a MIMO STBC system is evaluated using an LS channel estimator with a variable number of receivers. The main goal of this thesis is to provide STBCs for multiple transmit antennas and multiple receive antennas using semi-blind of channel estimation, improve BER performance, reduce decoding time and solve the ambiguities of BSS by combined the kurtosis based on ICA with WCA and HIWOPSO independently to get a low complexity, fast speed, good BER performance decoder that can operate with any MIMO STBC is produced. During this work it is found that:

1. Despite the fact that the new decoder is more sophisticated than standard MRC, the new methods allow for combined estimate and decoding at the same time.
2. The problem of sign and source ambiguity is resolved by utilizing appropriate initialization for the de-mixing vector based on pilot symbols.
3. By combining the given criteria for single source extraction with a single unit ICA,
4. The decoding time has been decreased by $\frac{1}{n_s}$.
5. The performance of all ICA algorithms is mostly determined by the frame length of the transmitted block. High frame length is related with higher BER performance.
6. Kurtosis-based ICA is one of the finest algorithms since it can work with both long and short frame lengths and has a straightforward computation.
7. Combining WCA and HIWOPSO algorithms with a single source extraction kurtosis-based ICA results in a low complexity, high speed, and

good BER perforce joint decoder and estimator that can be used in any MIMO STBC.

5.2 Future Works

The suggested points could be used to improve or complete this work are:
1- In this work WCA and HIWOPSO are used as search algorithm, other evolutionary search algorithms (like: GWO, BAT, GSA, HCA, …) could be used to reduce decoding latency.

2- In this thesis this algorithm is built to decode MIMO- STBC system. One can re-construct this algorithm to decode other MIMO system like MIMO- OFDM, LTE, etc.

3- In this thesis only kurtosis ICA algorithm is used. Other ICA algorithms like (Info MAX, kernel ICA, FICA and MMI …) could be also tested and they may be providing better performance.

4- Complex based ICA algorithms could be used to illuminate the need of (**R-Im**) decomposition.

5- In this thesis quasi-static, frequency non-selective, Rayleigh fading as model for MIMO channel is used to test the decoder performance. Suitable strategy must be combining with the algorithm to illuminate the other bad effect of MIMO channel like ISI, ICA and multipath effect and pursuit to eliminate non linearity of fast fading frequency selective channel.

6- In the thesis, the PSO and IWO algorithms are combined in order to design a new hybrid method for seeking the global solution, the other algorithms can be hybridization with IWO also to get a new hybrid method to get the optimal solution like: the grey wolf optimization (GWO), Artificial bee colony algorithm (ABC), Ant Colony optimization (ACO) and the and the other new algorithms.

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الخلاصة

تُستخدم أنظمة متعددة المدخلات ومخرجات (MIMO) في معظم أنظمة الاتصالات اللاسلكية الحديثة ، بما في ذلك WiMAX و DVB-NGH و WiFi و HSPA + و LTE و G4 و G5. تعد أنظمة MIMO مع تشفير وقت الفراغ تقنية محتملة لزيادة معدلات البيانات وتحسين موثوقية الاتصالات اللاسلكية.

الهدف الرئيسي من هذ البحث هو توفير (STBC) لهوائيات إرسال متعددة وهوائيات استقبال متعددة باستخدام تقدير شبه أعمى للقنوات ، وتحسين أداء BER ، وتقليل وقت فك التشفير.

اقترح هذا العمل تقنية جديدة لفك ترميز رمز الكتلة الزمني متعدد المدخلات والمخرجات (MIMO-STBC) باستخدام فصل المصدر الأعمى (BSS) ، لتعزيز أداءنسبة خطأ البت(BER) لمقدر قناة MIMO STBC باستخدام طريقة تحليل المكون المستقل شبه الأعمى (ICA) ،حيث يتم تحقيق تقنية استخراج المصدر القائمة على التفرطح باستخدام التحلل التخيلي الحقيقي (R-Im) لمجمع النسبة القصوى (MRC) لحل مشكلة غموض الإشارة والمصدروايضا من خلال دمج تقنية المصدر القائمة على التفرطح(Kurtosis)مع تقنيتي WCA و HIWOPSO بشكل منفصل للحصول على تعقيد منخفض وسرعة عالية واداء افضل لنسبة خطأ البت(BER)و التي يمكن أن تعمل مع أي MIMO STBC يتم إنتاجها.

تم استخدام برنامج MATLAB لنمذجة أداء النظام. تظهر نتائج المحاكاة أن أداء -WCA Kurtosis أفضل من أداء خوارزمية LS لهوائيات الإرسال والاستقبال في 2 × 1 ، 2 × 2 ، 4 × 2, 2 × 4 و 4 × 4 بمقدار 0.8 ، 1.6 و 1 و 2 و 2 ديسيبل على التوالي ,في طول الإطار 1024 ، وأداء HIWOPSO-Kurtosis أفضل من أداء خوارزمية LS لهوائيات الإرسال والاستقبال في 2 × 1 ، 2 × 2 ، 4 × 2, 2 × 4 و 4 × 4 بمقدار 0.8 و 1 و 0.8 و 2.1 و 4.2 ديسيبل على التوالي. توضح نتائج المحاكاة أن تقنية تقدير القناة المقترحة مجدية وفعالة ، مع وجود اختلاف بسيط فقط في الأداء بين معلمات القناة المقدرة والمعروفة ، وأظهرت النتيجة أنه عند 4 × 4 فإن HIWOPSO هي أفضل خوارزمية لأن القناة المقترحة تقترب من القناة المعروفة وتبتعد عن LS بمعدل 4.2 ديسيبل ، وكذلك حققت خوارزمية WCA أفضل نتيجة عند 4 × 4 بمعدل 2 ديسيبل من LS, لكن عدد التكرارات في HIWOPSO أكثر مقارنة مع WCA ، بينما حققت Kurtosis-ICA أفضل نتيجة عند 2 × 2 وأسوأ نتيجة عند 4 × 4 وهذا يشير إلى

أن الخوارزميات المقترحة (WCA و HIWOPSO) يمكنها التعامل مع مصفوفات ذات أبعاد كبيرة وبدقة عالية وتكرار صغير للوصول إلى الحل الأمثل.

وزارة التعليم العالي والبحث العلمي

جامعة بابـل / كلية الهندسة

قسم الهندسة الكهربائية

تحسين معدل الخطأ للترميزالزماني المكاني بناءا على مخمن القناة

رســـالـــة

مقدمة الى كلية الهندسة في جامعة بابل

كجزء من متطلبات نيل درجة الماجستير في الهندسة الكهربائية / اتصالات

من قبل

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بأشـــراف

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