

SEMI-BLIND METHODS FOR CHANNEL ESTIMATION AND DATA RECOVERY IN MULTI-CARRIER COMMUNICATIONS

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*With heartfelt gratitude and deep thankfulness, this is dedicated to:
My beloved parents, siblings, daughter Nafisah (Haneefah), and wife
Their unwavering love, prayer, and support have been my most
significant sources of strength.*

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LIST OF ABBREVIATIONS

5G	Fifth Generation
ALS	Alternating Least Squares
BSS	Blind Source Separation
CDMA	Code Division Multiplexing Access
CM	Constant-Modulus
CP	Cyclic Prefix
CRM	Cyclic Repetition Method
CSI	Channel State Information
D-RIS	Double Reflective Intelligence Surface
EDGE	Enhanced Data Rates for Global Evolution
FBM	Forward-Backward Method
FFT	Fast Fourier Transform
GPRS	General Packet Radio System
GSM	Global System for Mobile Communications
HOS	High Order Statistic
HSDPA	High-Speed Downlink Packet Access

i.i.d	Independent and Identically Distributed
LTE	Long-Term Evolution
LTE+	Enhanced Long-Term Evolution
LTE-A	Advanced Long-Term Evolution
MIMO	Multiple-Input Multiple-Output
MISO	Multiple-Input Single-Output
MM	Multi-Modulus
mm-wave	millimeter-wave
M-RIS	Multiple Reflective Intelligence Surface
OFDM	Orthogonal Frequency Division Multiplexing
RIS	Reflective Intelligence Surface
Rx	Receiver
SIMO	Single-Input Multiple-Output
SISO	Single-Input Single-Output
SNR	Signal-to-Noise Ratio
SOS	Second Order Statistic
S-RIS	Single Reflective Intelligence Surface
SS	Subspace
ST	Superimposed Training
STBC	Space-Time Block Coded
TDD	Time-Division Duplexing

TDM	Time-Division Multiplexed
Tx	Transmitter
UMTS	Universal Mobile Telecommunications System
ZP	Zero-Padding

THESIS ABSTRACT

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TITLE OF STUDY: SEMI-BLIND METHODS FOR CHANNEL ESTIMATION AND DATA RECOVERY IN MULTI-CARRIER COMMUNICATIONS

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Multiple Input Multiple Output (MIMO) communication systems and their more advanced counterpart, Reflective Intelligent Surface (RIS) assisted MIMO communications, are regarded as promising technologies for both current and next-generation wireless communication systems due to their exceptional ability to enhance overall system performance.

In this research, we focused on addressing channel estimation and channel equalization using a source separation approach for multicarrier communication systems. Therefore, by employing semi-blind approaches, the thesis emphasizes performance-bound evaluation and developing efficient semi-blind algorithms for MIMO and RIS-assisted MIMO systems, while addressing key challenges such as carrier frequency offset (CFO).

Initially, we focus on developing a global cost function that utilizes the orthogonality properties between the covariance matrix and noise subspace. This approach enables the channel coefficient estimation for each subcarrier in a parallel scheme. As a result, an accurate channel estimation is guaranteed with reduced computational complexity.

To enhance the bandwidth utilization in the system, this thesis employs an embedded pilot scheme, in which the pilot sequence and data symbols are embedded (superimposed) during transmission to conserve additional bandwidth. Further, we introduce a new semi-blind-based algorithm for joint source separation and CFO estimation. In this approach, a block gradient descent optimization method is adopted to minimize the proposed hybrid cost function. We also present a method of optimizing the step size, which improves the estimation process and convergence rate of the proposed algorithm.

In addition, the emergence of Reflective Intelligence Surface (RIS) introduces new challenges in channel estimation, especially when there is more than one RIS in the system, due to the cascading effect of the channel. Current double RIS (D-RIS) systems rely on pilot-based estimation, which is bandwidth inefficient; there is a need for a semi-blind approach to improve the estimation. We present a semi-blind algorithm for D-RIS-assisted systems, where two RISs are considered, and the received signal is presented in the form of a 3-way Tucker-2 tensor model. We adopt a Tucker factorization method for a semi-blind technique to estimate all the channels effectively.

The performance evaluation of the proposed semi-blind algorithms is analyzed using the Cramer-Rao Bound (CRB), and the results highlight the effectiveness of the proposed semi-blind algorithms for the multicarrier communication systems.

ملخص الرسالة

الاسم: كبيرو ناصرو علي

عنوان الدراسة: طرق شبه عمياء لتقدير القنوات واستعادة البيانات في الاتصالات متعددة الموجات

التخصص: الهندسة الكهربائية

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تعتبر أنظمة الاتصالات متعددة المدخلات والمخرجات (MIMO) ونظيرتها الأكثر تقدمًا، اتصالات MIMO بمساعدة السطح الذكي العاكس (RIS)، من التقنيات الواعدة لأنظمة الاتصالات اللاسلكية الحالية والجيل القادم نظرًا لقدرتها الاستثنائية على تحسين الأداء العام للنظام. في هذا البحث، ركزنا على معالجة تقدير القنوات ومعادلتها باستخدام نهج فصل المصدر لأنظمة الاتصالات متعددة الموجات الحاملة. لذلك، ومن خلال استخدام مناهج شبه عمياء، تُركز هذه الرسالة على تقييم حدود الأداء وتطوير خوارزميات شبه عمياء فعالة لكل من أنظمة MIMO وأنظمة MIMO المدعومة بـ RIS، مع معالجة تحديات رئيسية مثل إزاحة تردد الموجة الحاملة (CFO). في البداية، نركز على تطوير دالة تكلفة شاملة تستخدم خصائص التعمد بين مصفوفة التغاير وفضاء الضوضاء. يُمكن هذا النهج من تقدير معامل القناة لكل موجة حاملة فرعية في مخطط متوازي. ونتيجةً لذلك، يُضمن تقدير دقيق للقناة مع تقليل التعقيد الحسابي. لتحسين استخدام عرض النطاق الترددي في النظام، تستخدم هذه الأطروحة مخططًا تجريبيًا مُدمجًا، حيث يتم تضمين تسلسل الدليل ورموز البيانات (تراكيبها) أثناء الإرسال للحفاظ على عرض نطاق ترددي إضافي. علاوةً على ذلك، نُقدم خوارزمية جديدة شبه عمياء لفصل المصدر المشترك وتقدير CFO. في هذا النهج، تُعتمد طريقة تحسين انحدار التدرج الكلي لتقليل دالة التكلفة الهجينة المقترحة. كما نُقدم طريقةً لتحسين حجم الخطوة، مما يُحسن عملية التقدير ومعدل التقارب للخوارزمية المقترحة. يتم تحليل تقييم أداء الخوارزميات شبه العمياء المقترحة باستخدام حدود كرامر-راو (CRB)، مما يسلط الضوء على فعالية الخوارزميات شبه

العمياء المقترحة لأنظمة الاتصالات متعددة الموجات.

أُلهمت هذه الدراسة تطوير خوارزمية جديدة لتقدير القنوات شبه العمياء لأنظمة الاتصالات المدعومة بتقنية MIMO ثنائية الاتجاه (D-RIS).

في هذه الأنظمة، يُؤخذ بعين الاعتبار نظامان من أنظمة RIS، حيث تُعرض الإشارة المستقبلية على شكل نموذج موتر تاكر ثلاثي الاتجاهات ثنائي

الاتجاه. وتُستخدم طريقة تحليل تاكر لعواملها لتقدير جميع القنوات بفعالية.

CHAPTER 1

INTRODUCTION

1.1 Overview

Mobile and wireless communications technologies have significantly advanced in various fields [2], enabling continuous access to voice or data information in a state where it is impractical to install physical equipment. As a result, wireless devices have become increasingly convenient and affordable, resulting in the necessity and expansion of wireless communication technology. Public welfare agencies, such as police, fire safety, and ambulance services, use mobile communications devices extensively for daily operations. Other agencies, such as airline staff, use wireless devices for ticketing, flight scheduling, and luggage handling tasks. Consumers can receive and pay electronic bills via phones using Wireless Application Protocol (WAP). Courier companies like Saudi Post, SMSA, UPS, and DHL have adopted wireless and mobile communication devices for tracking parcels and managing emergency drop-offs or pickups services. In addition to the critical need for precise real-time transmission of voice, data, and video, security personnel increasingly prioritize adopting cutting-

edge wireless technologies. These technologies are intended to enable the creation of a digitally interconnected network using wearable computers and wireless radios to establish a comprehensive surveillance network.

Furthermore, in modern times, mobile cellular communications have emerged as the most widely used technology for wireless communications. The incredible growth of this mobile technology from the first generation (1G) to the sixth generation (6G) has indeed occurred across several technological generations [4]. The first generation (1G) communications standard emerged in the 1980s and was dominated by analog audio transmission, marking a significant leap forward in telecommunications. On the other hand, the emergence of digital technologies resulted in second generation (2G) mobile communications, primarily the Code Division Multiplexing Access (CDMA) and the Global System for Mobile Communications (GSM) have been standardized as 2G technologies and have spread worldwide due to their high system capacity and quality of service[6]. Subsequently, high throughput demands necessitate the emergence of 2.75G Enhanced Data Rates for Global Evolution (EDGE) standard and the conventional 2.5G General Packet Radio System (GPRS). Due to this success, the third generation (3G) and 3.5G was developed using the Universal Mobile Telecommunications System (UMTS) standard and the High-Speed Downlink Packet Access (HSDPA) protocol. However, to facilitate applications that require high bandwidth of capacity 150 Mbps such as high-definition virtual conferencing and the Internet of Things, the fourth generation (4G) was released in 2012 and sought to deliver high-speed communication with increased security. The technological foundation needed to meet 4G standards was provided by Long-Term Evolution (LTE). However, only Ad-

vanced Long-Term Evolution (LTE-A), or Enhanced Long-Term Evolution (LTE+), has achieved 4G standards. The concepts of Orthogonal Frequency Division Multiplexing (OFDM) and Multiple-Input Multiple-Output (MIMO) were the cornerstones of 4G systems [7]. The fifth generation (5G) technology standard for cellular networks was introduced globally by cellular phone companies starting in 2019. This technology succeeds in the 4G standard by increasing the bandwidth of the system, connecting more users with a high data rate at multi-gigabit peak data speed, offering vastly low latency and excellent quality of service. It is also expected to virtually connect everyone and everything, including devices, machines, and objects. The Sixth Generation (6G) network standard aims to provide extremely high energy efficiency with ultra-low latency. In addition, the 6G network standard integrates artificial intelligence to enhance services and capacities. The vision for the 6G generation involves providing a common ground for communication between the human and digital worlds.

To significantly improve the quality of service, system spectral efficiency, capacity, and reliability of wireless communication systems, multiple antennas are used either at the transmitter side (Multiple-Input Single-Output (MISO)), at the receiver side (Single-Input Multiple-Output (SIMO)), or at both ends (MIMO) [9, 10]. MIMO architectures provide additional degrees of freedom through the spatial dimension, which can be leveraged to either transmit independent data streams simultaneously (spatial multiplexing) or transmit the same data stream multiple times (spatial diversity).

Orthogonal Frequency Division Multiplexing (OFDM) is a highly efficient data modulation and multiplexing/demultiplexing technique. It achieves high throughput by simultaneously transmitting over numerous subcarriers. Also, it enhances system

robustness against frequency-selective fading by converting the channel into several parallel flat fading channels. Additionally, OFDM mitigates inter-symbol interference and inter-carrier interference through the use of a cyclic prefix and orthogonal transform. Furthermore, the integration of MIMO technology with OFDM, known as MIMO-OFDM systems, has facilitated high-speed data transfer and positioned the system as a viable option for 5G and beyond communications.

In mobile communications, data symbols and pilot sequences are Time-Division Multiplexed (TDM), meaning that pilot sequences and data sequences are transmitted in separate time slots. The TDM scheme significantly reduces the system's spectral efficiency. On the other hand, a Superimposed Training (ST) scheme has been proposed where the pilot symbols are superimposed to the data signals during transmission to enhance the system's spectral efficiency [7], [8], [9]. In the ST scheme, the data Signal-to-Noise Ratio (SNR) is reduced because the transmitted energy is shared between the pilot sequences and the data sequences.

The embedded pilots scheme has various practical applications in wireless communication systems. These applications include channel estimation, which is utilized in New Radio 5G (5G NR) [10]. It is also employed to fix subcarriers in Wi-Fi (802.11 standards) [11]. Additionally, this scheme is used for Doppler correction and beam tracking in Low Earth Orbit (LEO) and Geostationary Orbit (GEO) satellite communications [12]. Moreover, the embedded pilots scheme aids in balancing accuracy and spectrum usage in cognitive radio systems [13].

Effective system identification and channel equalization are essential for maximizing the potential of the aforementioned technologies. System identification involves

estimating the Channel State Information (CSI), which is used for coherent detection of transmitted signals at the receiver end, and designing efficient precoding schemes to cancel inter-user interference at the transmitter end. Channel equalization compensates for the distortion caused by the communication channel on transmitted signals, enabling the recovery of the transmitted data. In this context, source separation techniques, primarily used in multi-user scenarios, offer an alternative method for detecting transmitted data without direct reliance on CSI.

Recently, significant attraction has been shifted toward the Reflective Intelligence Surface (RIS) architecture. RIS is a novel technology that has a strong potential to be viable for a 6G wireless system. However, effective signal processing techniques are essential to realize the performance and advantage of the RIS technology in radio localization, channel estimation, and transmitted signal recovery.

1.2 Channel Estimation

A communications channel is any medium through which information is transmitted from a transmitter to a receiver. The literature discusses various models and techniques for estimating these channels. The methods for channel estimation are generally categorized into: pilot-based, blind, and semi-blind (SB) approaches.

1.2.1 Pilot-based Approach

The pilot-based approach involves the use of well-known pilot sequence by both the transmitter and receiver. These sequences are appended to the data frames in a time-

frequency grid in two well-known arrangements: block or comb type. This method is often utilized in wireless communication systems due to its simplicity, stability, and high accuracy. Thus, it uses extra resources to transmit known periodic pilot symbols that decrease the system's spectral efficiency [14].

1.2.2 Blind Approach

Blind technique maintains spectral efficiency by relying entirely on a probabilistic model or the statistical properties of the transmitted data, eliminating the need for pilot symbols. The existence of cyclo-stationarity properties in the transmitted signal allows the successful use of Second Order Statistic (SOS) to exploit the non-minimum phase characteristics of the channels, resulting in the devising of numerous blind algorithms like subspace-based algorithms.

However, most SOS approaches depend on diversity conditions and tend to perform poorly when there is channel overestimation, highlighting the limitations of blind techniques in communication systems.

In addition to the SOS approach, High Order Statistic (HOS) provides another blind technique that does not require diversity conditions. HOS offers both amplitude and phase information using a Fourier transform known as poly-spectra. This approach can be applied to both Gaussian and non-Gaussian processes and is categorized into implicit and explicit methods. The implicit HOS approach includes algorithms such as the Sato algorithm, the Godard-2 technique (Constant-Modulus (CM)), and the Multi-Modulus (MM) algorithm.

However, the SOS-based approaches require less data sequence compared to HOS-

based methods. The long data in HOS-based methods is needed for the sample averaging method to result in a minimum variance in estimating higher-order moments. The comprehensive report of HOS techniques provided in [15], [16] and references therein.

1.2.3 Semi-blind Approach

The shortcomings associated with blind and pilot-based approaches are addressed using a semi-blind approach.

The main objective is to utilize the few pilot sequences and receive data to estimate the channel coefficients effectively. This not only reduces the number of pilots needed in a pilot-based approach but also mitigates the ambiguities in a blind-based approach. Additionally, these strategies enable estimating a more extended impulse response using fewer pilots. This approach is particularly suitable for wireless communications in challenging environments.

Furthermore, in the context of SOS approaches, any channel can be estimated with only one pilot. Additionally, the semi-blind approaches are highly appealing in performance compared to the pilot-based or blind approaches, making them increasingly promising for next-generation wireless communications.

1.3 Source Separation

Source separation is a prominent area in digital signal processing research focusing on recovering statistically independent signals from mixed received signals. In digital

signal processing, source separation techniques are employed for channel equalization, which involves retrieving unknown data from different sources propagated through a distorting medium called a communications channel.

Several source separation techniques for communication systems have been documented in the literature, such as Blind Source Separation (BSS), which completely depends on statistical properties of the received signal. Numerous BSS techniques, such as Sparse Component and Independent Component Analysis have been proposed in [17]. CM and MM based approaches are among the BSS. These approaches can be optimized by either an iterative or a closed-form approach. Some of the iterative methods are gradient descent, Newton's method, or Givens and Shears rotations approaches while the closed-forms are Analytical Constant power Algorithm and the Analytical CM Algorithm [18] However, the BSS technique exhibits significant complexity and ambiguity. This can be mitigated using a semi-blind approach.

1.4 Reflective Intelligent Surface

A reflective intelligent surface (RIS) is a cutting-edge communication technology for 5G and beyond that manipulates the communication channel [19]. An RIS consists of a real-time controllable reflective array made up of numerous inexpensive passive elements that control the amplitude, frequency, phase, and polarization of incoming signals from the transmitter before they reach the receiver. RIS is considered as smart, which extends network coverage, increases capacity, and enhances system performance [20].

The performance improvements in the RIS system rely heavily on the number and positions of deployed RIS in the system, as well as the quality of the CSI [21]. In this system, the medium for communication between the transceivers consists of two or three cascaded channels, depending on the number and orientation of RISs considered in the system. As such, the estimation of the CSI becomes very challenging due to the cascading effect of the channels in the systems, as opposed to the conventional communication systems with a single-channel setup [22], [23].

1.5 Thesis Motivations and Organization

This thesis focuses on channel estimation, source separation, and data recovery for multicarrier communications. The thesis primarily concentrates on developing effective Semi Blind solutions for direct channel estimation, equalization, or channel shortening. Additionally, the thesis investigates various factors that the systems performance depends on, such as carrier frequency offset.

Besides, the thesis investigates an embedded pilot scheme that, to our knowledge, has not been studied in the context of MIMO-OFDM communications. This scheme involves superimposing the pilot sequence and data during transmission to enhance the spectral efficiency of the systems.

Furthermore, a focus is given to developing a new performance evaluation metric for the embedded pilot scheme based on the introduced semi-blind algorithms, explicitly based on the analytical Cramer-Rao Bound (CRB).

In addition, the thesis introduces a new Semi-blind channel estimation for the

recent technology, Reflective Intelligent Surfaces using the Tucker-2 tensor decomposition method. The summary and flowchart of the thesis are presented in Fig. 1.1.

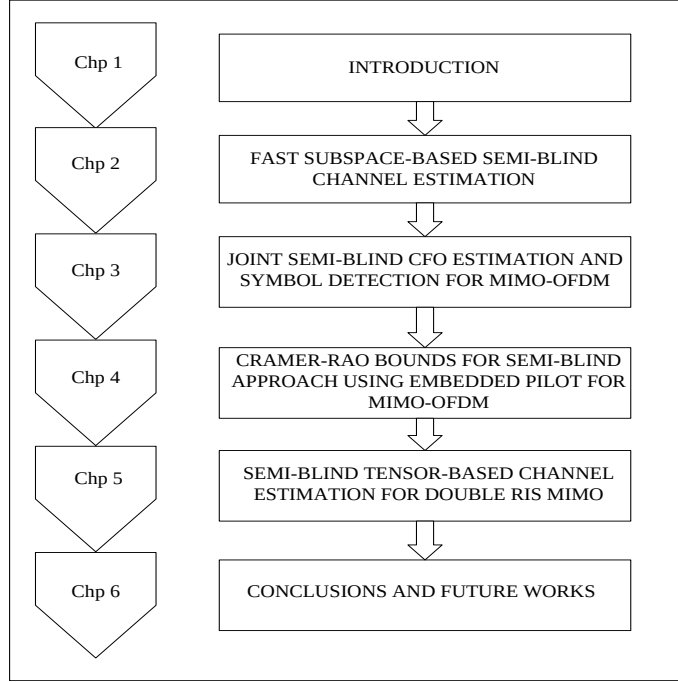


Figure 1.1: The summary of the Thesis presented in the flowchart.

The rest of the dissertation is structured as follows: Chapter 2 presents an algorithm that exploits the orthogonality properties between the signal and the noise subspace of the OFDM systems for each subcarrier in a parallel approach. Subsequently, the global cost function is devised and minimized to estimate the channel coefficients. The algorithm is named a fast subspace-based semi-blind channel estimation algorithm. In addition, the chapter includes a detailed investigation of the computational complexity analysis and the minimum number of useful subcarriers required for the uniqueness of the solution. Chapter 3 introduces a new semi-blind joint CFO estimation and source separation method using the multi-modulus approach for both Time-division Multiplexed pilots (i.e., block pilot arrangement) and embedded

pilots in MIMO-OFDM communications. A joint hybrid objective function incorporating the Least Squares (LS) and Multi-Modulus (MM) is devised for semi-blind source recovery and CFO estimation. The devised objective function is optimized for each iteration using the batch gradient descent optimization method along the search direction. Furthermore, an efficient initialization procedure is introduced to simplify the complexity of the algorithm with ease of convergence. Subsequently, a method for optimizing the step size is presented to enhance the rate of convergence of the proposed approach. Finally, an efficient adaptive equalization and CFO estimation method is proposed for the slow-varying channels and CFO. In Chapter 4, we present a new performance evaluation of a semi-blind algorithm for the superimposed pilot scheme. The primary objective is to evaluate the efficacy of the proposed techniques in the case of an embedded pilot in MIMO-OFDM systems. We derive the CRB for a semi-blind approach that employs embedded pilots for MIMO-OFDM systems. Moreover, we use different data models to investigate and evaluate the derived CRB. Chapter 5 presents a new semi-blind joint (coupled) Tucker-2 decomposition method for channel identification in a Double Reflective Intelligence Surface (D-RIS)-assisted MIMO communications. We demonstrate that the received signals D-RIS-assisted systems can be effectively constructed as a Tucker-2 tensor model. By utilizing the Tucker factorization on the Tucker-2 received signals model, all three cascaded channels can be estimated effectively. Furthermore, the proposed algorithm is compared with a Single Reflective Intelligence Surface (S-RIS) and the Multiple Reflective Intelligence Surface (M-RIS). Lastly, the conclusion and future work are presented in the chapter 6.

1.6 Research Outputs

The following publications are based on the research findings from the presented thesis and have been published or submitted for publication to journals and conferences:

- K. N. Aliyu, A. Lawal, K. Abed-Meraim, and A. Zerguine, “Fast Subspace-based Semi-Blind Channel Estimation for MIMO-OFDM Communications,” EUSIPCO, pp. 1460–1463, 2023, Helsinki, Finland, September 2023.
- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, “Semi-Blind Multi-Modulus Approach using Embedded Pilot for MIMO-OFDM Communications,” ASILOMAR, Pacific Grove, CA, USA, October 2024.
- K. N. Aliyu, T. T. Le, K. Abed-Meraim, and A. Zerguine, “Semi-Blind Tensor-Based Channel Estimation for Double RIS MIMO Systems,” MECOM, Abu Dhabi, UAE, November 2024.
- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, “Joint Semi-Blind Multi-Modulus for CFO Estimation and Symbol Detection in MIMO-OFDM,” IWCMC, Abu Dhabi, UAE, May 2025.
- O. Rekik, K. N. Aliyu, B. M. Tuan, K. Abed-Meraim, and N. L. Trung, “Fast Subspace-Based Blind and Semi-Blind Channel Estimation for MIMO-OFDM Systems,” IEEE Transactions on Wireless Communications, vol. 23, no. 8, pp. 10247–10257, 2024.
- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, “Semi-Blind Joint

CFO Estimation and Symbol Detection for Embedded Pilot in MIMO-OFDM,”

Submitted to IEEE Transactions on Wireless Communications.

- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, “Cramer-Rao Bounds for Semi-Blind Approach using Embedded Pilots for MIMO-OFDM System,” Submitted to IEEE Communications Letters.

CHAPTER 2

FAST SUBSPACE-BASED SEMI-BLIND CHANNEL ESTIMATION

This chapter deals with the problem of semi-blind subspace-based channel estimation when considering MIMO-OFDM communications systems. The proposed solution offers a reduced computational complexity, mainly by a factor of the number of subcarriers, while guaranteeing accurate channel estimation as compared to state-of-the-art techniques. By exploiting the orthogonality property of the OFDM modulation, the covariance matrix and noise subspace are estimated for each subcarrier in a parallel scheme, and then a global cost function is minimized to obtain channel coefficient estimates. Besides, conditions for channel identifiability as well as the minimum number of subcarriers to be used for the uniqueness of the solution, are investigated with various numerical simulations to corroborate our analysis.

2.1 Introduction

Combining the Multiple-Input Multiple-Output (MIMO) technology with the Orthogonal Frequency Division Multiplexing (OFDM), in a MIMO-OFDM architecture has been widely used in wireless communications systems as in 802.11n wireless network [24], LTE and LTE-A [25]. Such a combination has enabled high-speed data transmission and broadband multimedia services over wireless links [26], [27]. Indeed, MIMO architectures allow increasing substantially the data throughput and radio communications reliability [28], [29]. It offers more degrees of freedom provided by the spatial dimension that can be exploited to either transmit simultaneously independent data streams, i.e. spatial multiplexing, or perform multiple transmissions of a single data stream, i.e. spatial diversity. On the other hand, it has been demonstrated that OFDM is a very efficient modulation technique that can achieve very high throughput by transmitting on a great number of carriers simultaneously and improve the system robustness against frequency-selective fading channels by converting the overall channel into a number of parallel flat fading channels [26]. Besides, it helps to eliminate the inter-symbol interference and inter-carrier interference thanks to the use of a Cyclic Prefix (CP) and an orthogonal transform.

Nevertheless, in order to fully exploit the potential of the aforementioned technologies, the knowledge of CSI is most often required. Hence, channel estimation is paramount in wireless communications, where several approaches have been proposed in the literature. Basically, two main classes of channel estimation approaches have been adopted. The first class refers to pilot-based channel estimation, which is per-

formed by using training sequences, called pilots, that are inserted in the data frames and are known *a priori* by both the transmitter and the receiver. Such an approach is the most commonly used in communications standards [24] for its low computational complexity and high robustness. However, its main drawback is the bandwidth consumption induced by the use of pilots, since a relatively important number of pilots is needed for accurate CSI. Alternatively, where no pilots are available, blind channel estimation approaches are adopted. They are fully based on the statistical properties of the unknown transmitted symbols [30], [31]; and hence allow reducing the overhead and enhancing spectral efficiency. But, this technique is associated with ambiguity problems and increased computational cost [3]. On the other hand, the semi-blind (SB) approach incorporates a few pilot samples with a blind method to correct the ambiguity developed in the blind technique and improve the estimation accuracy [1], [32].

SOS-based blind and SB channel estimation, for MIMO-OFDM communications systems, has been widely used in literature, where Subspace (SS)-based blind techniques (e.g. [33], [34], [35]) have shown to be attractive approaches since reliable estimates can be often obtained, in a simple form, by optimizing a quadratic cost function. However, the main drawback of such techniques is often the need for a high amount of received symbols to guarantee an ‘adequate’ estimation accuracy. For the purpose of overcoming such an issue, many works proposed solutions to enhance the speed convergence of SS methods, e.g., [1], [2], [36]. Nevertheless, they still use sub-blocks of the frequency-domain received symbols with relatively high size; which requires a large number of symbols for accurate covariance matrix estimation. More-

over, in the case of SB, [3], [37] proposed the use of virtual carriers and CP to enhance the estimation accuracy. Also, [4] proposed a windowing approach that increases the convergence rate of the algorithm using a circular Toeplitz matrix given in the time domain. However, these algorithms are efficient in the presence of a large OFDM sample size. Compared to them, our solution relies on the small size $N_r \times N_r$ covariance matrices, which reduces the computational cost and also improves the estimation accuracy.

In this context, the aim of this chapter is to propose reduced cost SB SS-based techniques for channel estimation when considering MIMO-OFDM communications systems. The main advantage of the proposed algorithm is to further reduce the computational complexity (as compared to the state of the art), to speed up convergence and to guarantee accurate channel estimation with reduced sample size. Actually, the proposed solution takes advantage of the orthogonality property of OFDM modulation to treat the received symbols, at each subcarrier, in a parallel scheme. Accordingly, covariance matrix and noise subspace estimation, which are basic processing for subspace methods, are estimated for each subcarrier and then used to minimize a global cost function to estimate the channel coefficients. Besides reduced complexity and faster convergence, which is the main contribution of the paper, a parallel processing can be easily adopted for additional numerical cost gain. Also, another important contribution is the identifiability analysis that supports the proposed solution and provides new insights on the minimum number of subcarriers to be used for the channel estimation consistency.

2.2 Existing Subspace Algorithms

Many SS-based channel estimation techniques for OFDM communications systems have been proposed in the literature. All these techniques rely on the orthogonality of the signal and noise subspaces, e.g., [2], [33], [34], [35], [37], [38], [39], [40], [41], as well as the specific structure of the channel matrix (which span the signal subspace) that characterizes ‘uniquely’ the channel coefficient vector. The authors in [2], proposed a novel subspace-based blind algorithm with a reduced time averaging. Thus, a sub-carrier grouping of the frequency-domain received symbols is performed by exploiting the frequency correlation among adjacent subcarriers. The proposed method in [33] unifies and generalizes the existing subspace-based methods for blind channel estimation in Single-Input Single-Output (SISO)-OFDM systems to the MIMO-OFDM case and assessed the performance when exploiting jointly all the subcarriers as well as the CP samples. In [34], [35], the authors proposed an efficient SS method that can be applied to the CP-based MIMO-OFDM system through an appropriate re-modulation on the received signal blocks; and by utilizing non-redundant linear block precoding. The techniques in [42] exploit the space diversity of MIMO systems and use the properties of the entire received symbol to achieve the channel estimation for various OFDM systems such as CP-OFDM, Zero-Padding (ZP)-OFDM and CP-free OFDM systems. In [37], a blind and SB subspace method has been introduced for channel estimation in OFDM systems, exploiting the redundancy of the cyclic prefix and specific structure of the channel matrix. This solution has the advantage of being applied to SISO systems but involves large covariance matrix estimation, which suf-

fers from computational complexity and slow convergence. Authors in [39] relied on redundant linear precoding to develop an SS blind and SB based channel estimation algorithm for Space-Time OFDM systems with Alamouti's block code applied on each subcarrier.

More recent subspace-based blind and SB channel estimation algorithms known as "fast techniques" have been proposed. Authors in [1] proposed a block matrix scheme based on the Toeplitz structure of the channel matrix. So that, each received symbol is re-arranged into many equivalent symbols through a windowing process, leading to a blind subspace channel estimation that can converge within a small amount of received OFDM symbols. In the same context, authors in [36] proposed a fast blind subspace channel estimation using a circular property of the channel matrix for Space-Time Block Coded (STBC) MIMO-OFDM systems. Accordingly, they proposed the Cyclic Repetition Method (CRM) and the Forward-Backward Method (FBM) in order to generate N times of equivalent signals for each STBC-OFDM symbol, with N being the Fast Fourier Transform (FFT) operation size. Also, authors in [4] proposed an SB approach in which the blind part takes advantage of the circulant property of the channel matrix in the time domain by subdividing each OFDM symbol into many OFDM subvectors of reduced length, according to a specific shift. By comparison, in our solution, the received signal of each subcarrier is directly processed in a parallel scheme leading to a gain in terms of convergence and computational complexity. Further comparison with the aforementioned techniques will be given in section 2.6.

By inspecting the proposed literature works, one can notice that exploiting the orthogonality property of the OFDM structure to further reduce computational com-

plexity, has not yet been fully investigated. Therefore, such a lack motivates us to assess the effect of the aforementioned property on the performance of SB subspace-based channel estimation for MIMO-OFDM communication systems. Indeed, by exploiting the orthogonality property allowed by the OFDM system, one can obtain a noise subspace basis in a block-diagonal form, where the diagonal blocks correspond to the noise subspaces associated with the different subcarriers. Consequently, in the proposed solution, these subspaces are estimated independently and in a parallel scheme from the received signal covariance matrix associated with each subcarrier.

2.3 Proposed Subspace Algorithm

This section introduces the multi-carrier communications (MIMO-OFDM) system model adopted in this chapter, then details the proposed SS-based channel estimation algorithm.

2.3.1 Multi-carrier Communications (MIMO-OFDM) System Model

Figure 2.1 presented a MIMO-OFDM system composed of N_t , N_r transmit and receive antennas employing K sub-carriers, whereby $N_r > N_t$. The data symbol transmitted comprises of K samples after carrying out K -point inverse FFT, and it is extended by adding the last L samples as CP in its front. The maximum multipath channel delays N are assumed to be smaller than the CP size, i.e., ($N \leq L$). At the receiving end, the r -th antenna receives OFDM symbols, after taking out the CP and performing

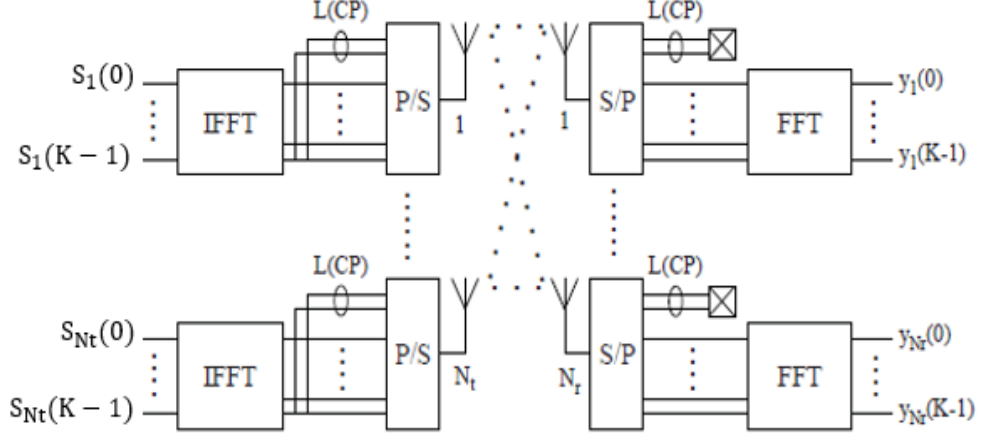


Figure 2.1: MIMO-OFDM communications system

the K -point FFT, the received symbol at the k -th subcarrier can be written as:

$$\mathbf{y}_k(t) = \mathcal{H}_k \mathbf{s}_k(t) + \boldsymbol{\omega}_k(t), \quad t = 1, \dots, N_s \quad (2.1)$$

where $\mathcal{H}_k \in \mathbb{C}^{N_r \times N_t}$ is the channel matrix written as:

$$\mathcal{H}_k = \sum_{l=0}^{N-1} \mathbf{H}(l) e^{-j2\pi \frac{k}{K} l} = \mathbf{H}(\mathbf{e}_k^T \otimes \mathbf{I}_{N_t}), \quad (2.2)$$

where $\mathbf{e}_k = \left[1, e^{-j2\pi \frac{k}{K}}, \dots, e^{-j2\pi \frac{k(N-1)}{K}}\right]$, $\mathbf{H} = [\mathbf{H}(0), \mathbf{H}(1), \dots, \mathbf{H}(N-1)]$ and $\mathbf{H}(l) \in \mathbb{C}^{N_r \times N_t}$

is the l -th channel's tap matrix of the considered MIMO system written as:

$$\mathbf{H}(l) = \begin{pmatrix} h_{1,1}(l) & \cdots & h_{1,N_t}(l) \\ \vdots & \vdots & \vdots \\ h_{N_r,1}(l) & \cdots & h_{N_r,N_t}(l) \end{pmatrix} \quad (2.3)$$

where $\{h_{i,j}(l)\}$ being the channel taps between the j -th transmitter and the i -th receiver, of the MIMO system.

The $N_t \times 1$ OFDM transmitted data $\mathbf{s}_k$ of the k -th subcarrier is considered to be Independent and Identically Distributed (i.i.d) and has a covariance $\mathbf{R}_s = E[\mathbf{s}_k(t)\mathbf{s}_k^H(t)] = \delta_{kl} \text{diag}(\sigma_{s,1}^2, \dots, \sigma_{s,N_t}^2)$ where δ_{kl} is the Kronecker delta operator and the i.i.d. $\boldsymbol{\omega}_k(t)$ is additive white Circular Gaussian (CG) noise having covariance $\mathbf{R}_\omega = E[\boldsymbol{\omega}_k(t)\boldsymbol{\omega}_k^H(t)] = \sigma_{\omega,k}^2 \delta_{kl} \mathbf{I}_{N_r}$. We assume that for all z , $\mathcal{H}(z) = \sum_{l=0}^{N-1} \mathbf{H}(l)z^{-l}$ is a full rank matrix. This condition is met with probability one when the channel taps are drawn from a continuous probability distribution.

By collecting N_s symbols, one can write the received signal at the k -th subcarrier as follows:

$$\mathbf{Y}_k = [\mathbf{y}_k(0), \dots, \mathbf{y}_k(N_s - 1)] = \boldsymbol{\mathcal{H}}_k \mathbf{S}_k + \boldsymbol{\Omega}_k \quad (2.4)$$

where $\mathbf{Y}_k \in \mathbb{C}^{N_r \times N_s}$, $\mathbf{S}_k \in \mathbb{C}^{N_t \times N_s}$, and $\boldsymbol{\Omega}_k \in \mathbb{C}^{N_r \times N_s}$.

Remark: It is important to note that when $N_r < N_t$, subspace approaches cannot be applied to the problem of channel estimation unless other diversities, such as time diversity or polarization diversity, are considered to address this issue. Additionally, the condition $N_r > N_t$ typically occurs only at the base station. In this context, using Time-Division Duplexing (TDD) mode and assuming channel reciprocity, the CSI is estimated only in the uplink direction (at the base station) and then utilized for processing in the downlink direction.

2.4 Identifiability Results

Blind estimation of MIMO channels using SOS is prone to inherent indeterminacy [38].

Therefore, the ‘uniqueness’ of the proposed subspace solution should be understood

up to this SOS-based blind processing ambiguity. More precisely, with the SOS only, the blind estimation of the MIMO channel transfer function $\mathcal{H}(z)$ can be achieved up to an unknown $N_t \times N_t$ constant matrix; that is, any solution of the form $\mathcal{H}(z)\mathbf{A}$, where $\mathbf{A}$ is an $N_t \times N_t$ (unknown) constant matrix, is admissible.

Having said that, based on the data model and the channel ‘diversity’ assumption given in subsection 2.3.1, one can prove (see Appendix A) the following identifiability result:

Proof. Assuming (i) the transfer function $\mathcal{H}(z)$ is irreducible and (ii) $\mathbf{H}(N-1)$ is full column rank, the solution of Equation (2.18) is admissible. |

In addition, due to the channel coherence, adjacent subcarriers carry nearly similar channel information [2]. Hence, it is not necessary to use all K subcarriers as in Equation (2.17), but only a selected subset of them, i.e., K_s subcarriers, with $K_s < K$ (In many communications standards we use few tens or few hundreds of frequency bins, so moving from K to K_s might represent a significant computational gain). Next, we provide a sufficient condition on the minimum number of subcarriers K_s that preserves the previous identifiability result, given in Proposition 2.4. The proof of this condition is given in Appendix A.

Proof. A sufficient condition on the minimum number of subcarriers K_s to be used to build criterion (2.15) while preserving the ‘admissibility’ of our subspace-based estimate is given by

$$K_s > (N-1)(N_t+1).$$
|

Now, if we use only K_s subcarriers instead of all K subcarriers, the channel estimation quality might be degraded. We provide here a way to select such K_s subcarriers in order to preserve a ‘good’ estimation performance, as will be illustrated in the next section. The basic idea of our selection procedure is to consider subcarriers for which the corresponding quadratic form estimates $\hat{\mathbf{Q}}_k$ have minimum error variance. That is, we select the K_s subcarriers for which the estimation error variance of $\|\delta\mathbf{Q}_k\|^2$ is minimum, where $\delta\mathbf{Q}_k = \hat{\mathbf{Q}}_k - \mathbf{Q}_k$. Indeed, the estimation error on the channel coefficients is directly impacted by the error on the quadratic forms $\hat{\mathbf{Q}}_k$. This choice is also motivated by the fact that the asymptotic estimation error variance of $\|\delta\mathbf{Q}_k\|^2$ is relatively easy to compute, as compared to that of the channel parameter vector $\mathbf{h}$. In other words, we select the most reliable subcarriers when calculating the matrix $\mathbf{Q}$ according to the following result (proof is given in Appendix B):

Proof. The estimation error $\delta\mathbf{Q}_k$ related to each subcarrier reduces asymptotically to

$$N_s E(\|\delta\mathbf{Q}_k\|^2) \xrightarrow{N_s \rightarrow \infty} 2N^2 N_t (N_r - N_t) \sum_{i=1}^{N_t} \frac{\sigma_{n,k}^2 \lambda_{i,k}}{(\lambda_{i,k} - \sigma_{n,k}^2)^2},$$

where $\lambda_{i,k}$ is the i -th principal eigenvalue of the k -th subcarrier covariance matrix $\mathbf{C}_k$. I

2.4.1 Proposed Semi-blind Approach Description

This section begins by reviewing the well-known pilot-based estimator, which is based on pilot symbols that are known on the receiver side. Following this, we introduce an efficient subspace blind estimator, which leads to the development of the proposed SB

estimation solution. This solution is achieved by minimizing a hybrid cost function that combines a pilot-based and subspace-blind estimator. The aim is to improve the performance of the proposed algorithm by eliminating the indeterminacy inherited in the blind processing while reducing the size of the pilot sequence.

2.4.2 Pilot-based Channel Estimation

The pilot-based technique relies on the training sequence and can be derived from the vectorized form of equation (2.1) when considering all subcarriers as:

$$\mathbf{y} = \tilde{\mathbf{S}}\mathbf{h} + \boldsymbol{\omega}, \quad (2.5)$$

where $\mathbf{h} = [\mathbf{h}_1^T \cdots \mathbf{h}_{N_r}^T]^T$ with $\mathbf{h}_i = [\mathbf{H}_{:,i}^T(0), \dots, \mathbf{H}_{:,i}^T(N)]^T$, is a MIMO channel taps with a size $(N_r N_t N \times 1)$. $\mathbf{S}_i = \text{diag}\{s_i\}$ is a $(K \times K)$ diagonal matrix; $\mathbf{S} = [\mathbf{S}_1 \mathbf{F} \cdots \mathbf{S}_{N_t} \mathbf{F}]$ having $K \times N N_t$ size; and $\tilde{\mathbf{S}} = \mathbf{I}_{N_r} \otimes \mathbf{S}$ with $N_r K \times N N_t N_r$ size, and $\mathbf{F}$ is a submatrix of the Fourier matrix formed by its N first columns. The pilot-based estimator $\hat{\mathbf{h}}_{PB}$ can be found, in our context, by minimizing the least squares cost function:

$$C(\mathbf{h}) = \|\tilde{\mathbf{y}}_p - \tilde{\mathbf{S}}_p \mathbf{h}\|^2, \quad (2.6)$$

where $\tilde{\mathbf{y}}_p = [\mathbf{y}(0)^T \cdots \mathbf{y}(N_p - 1)^T]^T$ (index p stands for 'pilot' and N_p is the number of used pilots), and $\tilde{\mathbf{S}}_p = [\tilde{\mathbf{S}}(0)^T \cdots \tilde{\mathbf{S}}(N_p - 1)^T]^T$. The $\hat{\mathbf{h}}_{PB}$ estimator can be expressed as:

$$\hat{\mathbf{h}}_{PB} = \left(\tilde{\mathbf{S}}_p^H \tilde{\mathbf{S}}_p \right)^{-1} \tilde{\mathbf{S}}_p^H \tilde{\mathbf{y}}_p. \quad (2.7)$$

The latter will be used in the sequel for comparison as well as for the proposed SB approach.

2.4.3 Subspace-based Semi-blind Channel Estimation

Let's begin by introducing the blind part of the proposed SB subspace channel identification method, which stands out against numerous subspace methods presented in the literature for channel equalization in MIMO-OFDM for its low cost, parallelizable architecture, and efficiency for small or moderate sample sizes. As outlined in Section 2.2, subspace-based techniques leverage the orthogonality between the range space of the channel matrix and the noise subspace of the received signal's covariance matrix. By utilizing the orthogonality property provided by the OFDM system, a noise subspace basis (a matrix whose columns span the noise subspace) can be obtained in a block-diagonal form. These diagonal blocks correspond to the noise subspaces associated with the different subcarriers.

These subspaces can be estimated in parallel using the eigenvalue decomposition of the received signal covariance matrix for the $k - th$ subcarrier, which is expressed as:

$$\mathbf{C}_k = E(\mathbf{y}_k \mathbf{y}_k^H) = \mathcal{H}_k \mathbf{R}_s \mathcal{H}_k^H + \sigma_{\omega,k}^2 \mathbf{I}_{N_r}, \quad (2.8)$$

This matrix can be estimated using N_s data OFDM symbols as

$$\hat{\mathbf{C}}_k = \frac{1}{N_s} \mathbf{Y}_k \mathbf{Y}_k^H = \frac{1}{N_s} \sum_{t=0}^{N_s-1} \mathbf{y}_k(t) \mathbf{y}_k(t)^H \quad (2.9)$$

Consequently, we can write

$$\mathbf{C}_k = \mathbf{U}_k \mathbf{\Lambda}_k \mathbf{U}_k^H = [\mathbf{U}_{k_s} | \mathbf{U}_{k_\omega}] \begin{bmatrix} \mathbf{\Lambda}_{k_s} & \mathbf{0} \\ \mathbf{0} & \mathbf{\Lambda}_{k_\omega} \end{bmatrix} \begin{bmatrix} \mathbf{U}_{k_s}^H \\ \mathbf{U}_{k_\omega}^H \end{bmatrix}, \quad (2.10)$$

where $\mathbf{\Lambda}_k$ is a diagonal matrix with eigenvalues arranged in descending order. The signal subspace matrix $\mathbf{U}_{k_s} \in \mathbb{C}^{N_r \times N_t}$ contains the eigenvectors corresponding to the largest eigenvalues, while the noise subspace $\mathbf{U}_{k_\omega} \in \mathbb{C}^{N_r \times (N_r - N_t)}$ is associated with the smallest $(N_r - N_t)$ eigenvalues.

Subsequently, based on the orthogonality relationship between the noise and signal subspaces, it can be expressed as:

$$\mathbf{U}_{k_\omega}^H \mathbf{H}_k = \mathbf{0}. \quad (2.11)$$

However, using the following properties:

$$\text{vec}(\mathbf{U}_{k_\omega}^H \mathbf{H}_k) = (\mathbf{I}_{N_t} \otimes \mathbf{U}_{k_\omega}^H) \text{vec}(\mathbf{H}_k), \quad (2.12)$$

where, based on (2.2),

$$\text{vec}(\mathbf{H}_k) = (\mathbf{e}_k \otimes \mathbf{I}_{N_t} \otimes \mathbf{I}_{N_r}) \mathbf{h}, \quad (2.13)$$

therefore, substituting (2.13) in (2.12) and $\mathbf{h} = \text{vec}(\mathbf{H})$, we can write

$$\text{vec}(\mathbf{U}_{k_\omega}^H \mathbf{H}_k) = (\mathbf{e}_k \otimes \mathbf{I}_{N_t} \otimes \mathbf{U}_{k_\omega}^H) \mathbf{h} = \mathbf{A}_k \mathbf{h}. \quad (2.14)$$

Henceforward, solving (2.11) using the least squares approach while taking into account the K subcarriers, involves minimizing the following cost function:

$$C(\mathbf{h}) = \sum_{k=0}^{K-1} \|\mathbf{U}_{k\omega}^H \boldsymbol{\mathcal{H}}_k\|_F^2 = \sum_{k=0}^{K-1} \|(\mathbf{e}_k \otimes \mathbf{I}_{N_t} \otimes \mathbf{U}_{k\omega}^H) \mathbf{h}\|_F^2, \quad (2.15)$$

which can be written in simple form as:

$$C(\mathbf{h}) = \mathbf{h}^H \mathbf{Q} \mathbf{h}, \quad (2.16)$$

where

$$\mathbf{Q} = \sum_{k=0}^{K-1} \mathbf{E}_k \otimes \mathbf{I}_{N_t} \otimes \mathbf{\Pi}_k, \quad (2.17)$$

where $\mathbf{\Pi}_k = \mathbf{U}_{k\omega} \mathbf{U}_{k\omega}^H$ is the projection matrix onto the noise subspace of the k -th subcarrier, and $\mathbf{E}_k = \mathbf{e}_k^H \mathbf{e}_k$. Thus, the channel coefficients are estimated in blind approach as follows:

$$\hat{\mathbf{h}} = \arg \min_{\mathbf{h}} \mathbf{h}^H \mathbf{Q} \mathbf{h}. \quad (2.18)$$

Thus, by combining the blind subspace-based cost function presented in (2.15) with the pilot-based cost function presented in (2.6), the overall hybrid cost function for the SB technique is formulated as:

$$C(\underline{\mathbf{h}}) = \|\tilde{\mathbf{y}}_p - \tilde{\mathbf{S}}_p \mathbf{h}\|^2 + \alpha \sum_{k=0}^{K-1} \|(\mathbf{e}_k \otimes \mathbf{I}_{N_t} \otimes \mathbf{U}_k^H) \mathbf{h}\|_F^2 \quad (2.19)$$

where $\alpha > 0$ is a weighting factor. The SB channel estimation solution is obtained by

minimization of (2.19) leading to:

$$\hat{\mathbf{h}} = \left(\tilde{\mathbf{S}}_p^H \tilde{\mathbf{S}}_p + \alpha \mathbf{Q} \right)^{-1} \tilde{\mathbf{S}}_p^H \tilde{\mathbf{y}}_p. \quad (2.20)$$

Remark: To prevent degenerate solutions in the blind solution, various constraints on $\mathbf{h}$ can be applied, such as the unit-norm constraint. For this constraint, the solution to (2.18) is given by the smallest eigenvector of $\mathbf{Q}$. Also, based on (2.18), $\hat{\mathbf{h}}$ is estimated with a certain indeterminacy inherent to blind processing. This can be eliminated by applying constraints to the solution or by utilizing additional pilot sequence known at transmitter and receiver. Specifically, with only the second-order statistics (SOS), the blind estimation of the MIMO channel transfer function $\mathcal{H}$ can be determined up to an unknown $N_t \times N_t$ constant matrix. This means any solution of the form $\mathcal{H}(z)\mathbf{A}$, where $\mathbf{A}$ is an unknown non-singular $N_t \times N_t$ constant matrix, is acceptable. One way to ensure this matrix is non-singular is to impose a structure-based constraint on the

channel coefficients $\mathbf{H}(0)$, guaranteeing its full rank property. Therefore, let's consider

$$\mathbf{H}(0) = \begin{pmatrix} 1 & 0 & \cdots & \cdots & 0 \\ * & 1 & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ \vdots & \vdots & \ddots & \ddots & 1 \\ \vdots & \vdots & \vdots & \ddots & * \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ * & \cdots & \cdots & \cdots & * \end{pmatrix} \quad (2.21)$$

where $*$ means the unknown complex channel coefficients. Consequently,

$$\text{vec}(\mathbf{H}) = [\text{vec}(\mathbf{H}(0))^T \text{vec}(\mathbf{H}(1))^T \cdots \text{vec}(\mathbf{H}(N-1))^T]^T. \quad (2.22)$$

Also, by utilizing the triangular structure of $\mathbf{H}(0)$ and an proper permutation matrix $\mathbf{P}$, $\text{vec}(\mathbf{H}(0))$ can be re-arranged as follows:

$$\mathbf{P} \text{vec}(\mathbf{H}(0)) = [\mathbf{0}^T \mathbf{1}^T \tilde{\mathbf{h}}_0^T]^T,$$

where $\mathbf{0}$ is an all-zero vector corresponding to the upper diagonal entries of $\mathbf{H}(0)$, $\mathbf{1}$ is an $N_t \times 1$ all one vector corresponding to the diagonal entries of $\mathbf{H}(0)$, and $\tilde{\mathbf{h}}_0$ is a vector containing the lower diagonal entries of $\mathbf{H}(0)$. Therefore, one can rewrite the column-wise channel coefficients $\text{vec}(\mathbf{H})$ as $\mathbf{h} = [\mathbf{0}^T, \mathbf{1}^T, \tilde{\mathbf{h}}^T]^T$ where $\tilde{\mathbf{h}}$ contains all

unknown coefficients of $\text{vec}(\mathbf{H})$, to be estimated. In such a case, the cost function given in (2.15) can be re-expressed as

$$C(\mathbf{h}) = \sum_{k=0}^{K-1} \|\mathbf{A}_k \mathbf{h}\|_F^2 = \sum_{k=0}^{K-1} \|[\mathbf{A}_{0,k}, \tilde{\mathbf{A}}_k][\mathbf{1}^T, \tilde{\mathbf{h}}^T]^T\|_F^2. \quad (2.23)$$

Finally, one can write

$$\tilde{\mathbf{h}} = -\left(\sum_{k=0}^{K-1} \tilde{\mathbf{A}}_k^H \tilde{\mathbf{A}}_k\right)^\# \mathbf{a}_0 = -\tilde{\mathbf{Q}}^\# \mathbf{a}_0, \quad (2.24)$$

with $\mathbf{a}_0 = \sum_{k=0}^{K-1} \tilde{\mathbf{A}}_k^H \mathbf{A}_{0,k} \mathbf{1}$.

2.4.4 Computational Complexity Analysis

The main steps of the proposed solution, performed independently for each subcarrier, are given in Table 2.1, with the corresponding computational complexity. Also for comparison, the corresponding computational complexity of solutions proposed in [33], [1], [2] and [4] where G refers to the window length used in the algorithms in [1], in [2] and in [4].

When comparing with a subspace technique using all subcarriers at a time, as in [33], or sub-blocks, as in [1], [2] and [4], one can easily notice the large gain, in terms of computational complexity, obtained with the proposed solution by using reduced-size matrices. Indeed, a gain of factor K (respectively, G^2) is obtained when computing covariance matrix $\mathbf{C}_k$, and of factor K^2 (respectively, G^3/K) when finding the eigenvectors of $\mathbf{C}_k$. Note that this difference becomes more significant when the number of

Table 2.1: Computational Complexity

Main step	Proposed	[1]	[4]
Computing $\mathbf{C}_k$	$KN_s N_r^2$	$KN_s (GN_r)^2$	$N_g N_s (GN_r)^2$
Finding $\mathbf{C}_k$ eigenvectors	$O(KN_r^3)$	$O((GN_r)^3)$	$O((GN_r)^3)$
Forming $\mathbf{Q}$ matrix	$K(N_r - N_t + N^2)(N_r)^2$	$G^3(N_r - N_t)(NN_r)^2$	$G^3(N_r - N_t)(GN_r)^2$

subcarriers K increases. For example, when using $K = 1024$ subcarriers, the number of arithmetic operations (mainly multiplications) needed for computing the covariance matrix $\mathbf{C}_k$ is divided by 1024, while the number of arithmetic operations needed for finding the eigenvectors of $\mathbf{C}_k$ is divided by 1024^2 . Also, by increasing the number of vectors (through the windowing method) used in time averaging in [1], the covariance matrix estimation is for sure enhanced but with an increased computational complexity. Moreover, for our method, it is possible to perform the previous subcarriers matrix calculations simultaneously if a parallel computational architecture is used. Further performance gain will be revealed through computer simulations provided in Section 2.6.

Remark: The optimal choice of the parameter α in (2.19) is tedious and leads to high computational complexity. Fortunately, studies in (e.g., [43]) have demonstrated that the channel estimation accuracy stays nearly optimal for a wide range of α values. This implies that fine-tuning this parameter is not essential; typically, one can use $\alpha \propto (N_s/N_p)$.

2.5 Discussion

In this subsection, we provide some comments to get more insights on the proposed SB method:

- The blind approach provides an estimate of the channel transfer function up to an unknown constant matrix [15], i.e., $\mathcal{H}_B(z) = \mathcal{H}(z)\mathbf{A}$ where $\mathcal{H}_B(z)$ denotes the blindly estimated transfer function and $\mathbf{A}$ is an unknown $(N_r - N_t) \times (N_r - N_t)$ constant matrix. Hence, the SB solution allows us to get rid of this indeterminacy with only $(N_r - N_t)^2$ pilot samples. Note that one OFDM symbol corresponds to K samples.
- Another advantage of the SB approach resides in its computational cost gain. Indeed, the blind method needs to minimize cost function (2.15) under appropriate constraints to avoid spurious undesired solutions (see [15], [44] for details), while the SB one relies simply on the LS solution in (2.20).
- In addition, the SB method allows us to reduce the number of subcarriers considered in the cost function (2.19) without compromising the solution uniqueness, which significantly reduces the cost.
- Contrary to other existing subspace methods for MIMO-OFDM, the considered approach relies on small size covariance matrices (of size $N_r \times N_r$) which helps not only reducing the cost but also improving the estimation accuracy when the number of OFDM symbols is relatively small (usually, the 'accurate' estimation of a $N \times N$ matrix by sample averaging requires at least few tens of N i of

samples.).

- Finally, the SB methods are robust to channel order overestimation errors [45] and help to reduce the pilot size (hence increasing the information throughput) without affecting the estimation quality [14].

2.6 Simulation Results

This section is dedicated to the performance analysis of the proposed SB subspace-based solution for system identification when considering MIMO-OFDM systems.

The estimation performance is evaluated in terms of the Normalized Mean-Square Error (NMSE) given by:

$$\text{NMSE} = \frac{1}{N_{\text{mc}}} \sum_{mc=1}^{N_{\text{mc}}} \frac{\|\hat{\mathbf{h}}_{mc} - \mathbf{h}_{\text{exact}}\|^2}{\|\mathbf{h}_{\text{exact}}\|^2}, \quad (2.25)$$

where $N_{\text{mc}} = 500$ represents the number of independent Monte-Carlo runs, $\hat{\mathbf{h}}_{mc}$ is the vector of estimated channel parameters at the mc -th run (Note that we removed the inherent ambiguity of the considered blind channel estimate before its use in the least squares criterion.), while $\mathbf{h}_{\text{exact}}$ contains the true (exact) values of the channel coefficients, which are generated as i.i.d., unit-power, zero-mean complex Gaussian random variables. The transmitted data symbols are drawn from 4-QAM modulation. The Signal-to-Noise Ratio (SNR) is defined as the average value

$$\text{SNR} = \frac{1}{K} \sum_{k=1}^K \|\mathcal{H}_k \mathbf{X}_k\|_F^2 / \|\mathbf{N}_k\|_F^2.$$

Table 2.2: Simulation Parameters

Parameter	Specification
Number of transmit antennas	$N_t = 2$
Number of receive antennas	$N_r = 4$
Number of channel taps	$N = 3$
Number of OFDM subcarriers	$K = 64$

The number of used pilots is $N_p = 4$. Simulation parameters are summarized in Table 2.2, unless otherwise specified.

For comparison, we compare the proposed SB solution with its blind solution and other blind subspace-based solutions proposed in [2] which considers sub-blocks of $P = 32$ adjacent subcarriers, and in [1] which relies on increasing the number of OFDM symbols by considering windowed versions of each received OFDM symbol, augmented by a CP, with $G = 55$ being the length of the sliding window.

Figure 2.2 illustrates the performance of the proposed solution when considering a small number of received OFDM symbols, e.g., $N_s = 30$ symbols. One can notice that the solutions of [2] do not perform well because the small value of N_s does not allow a proper averaging; hence, for a correct subspace estimation, a large size covariance matrices is needed in these method. Moreover, all methods fail to provide good channel estimates at low SNRs due to the lack of averaging in such a noisy context. By comparing the blind part of the proposed solution with that of [1], which is basically designed for cases when only a few received symbols are available, one can notice that the blind part of proposed solution still has approximately the same channel estimation performance at moderate and high SNRs while being computationally much cheaper.

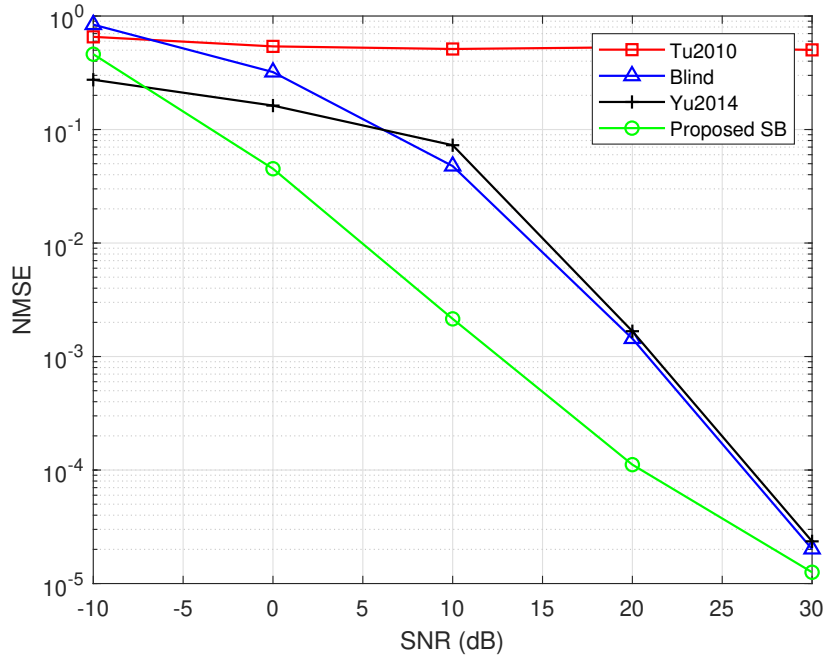


Figure 2.2: NMSE v.s. SNR with $N_s = 30$, $G = 55$ for Ref [1] (Yu2014) and $P = 32$ for Ref [2] (Tu2010).

Remark: The blind part of the proposed solution performance is close to [1]. Nevertheless, it is important to highlight the significant computational complexity gain of our solution by considering matrices of size $N_r \times N_r$ for each subcarrier, compared to that of [1], which involves matrices of size $GN_r \times GN_r$. Indeed, according to section 2.4.4, a reduction of computational complexity of factor $G^2 = 55^2$ is obtained for calculating the covariance matrix and of factor $G^3/K = 55^3/64$ for finding the corresponding eigenvectors.

Figure 2.3 depicts the comparison between the proposed SB method with SB methods presented in [3] and [4] as well as the 'Ideal case', considered just for benchmarking, where all N_s OFDM symbols are assumed to be known and used for channel estimation using the LS cost function in (2.6). In this experiment, $N_t = 2$ transmitting

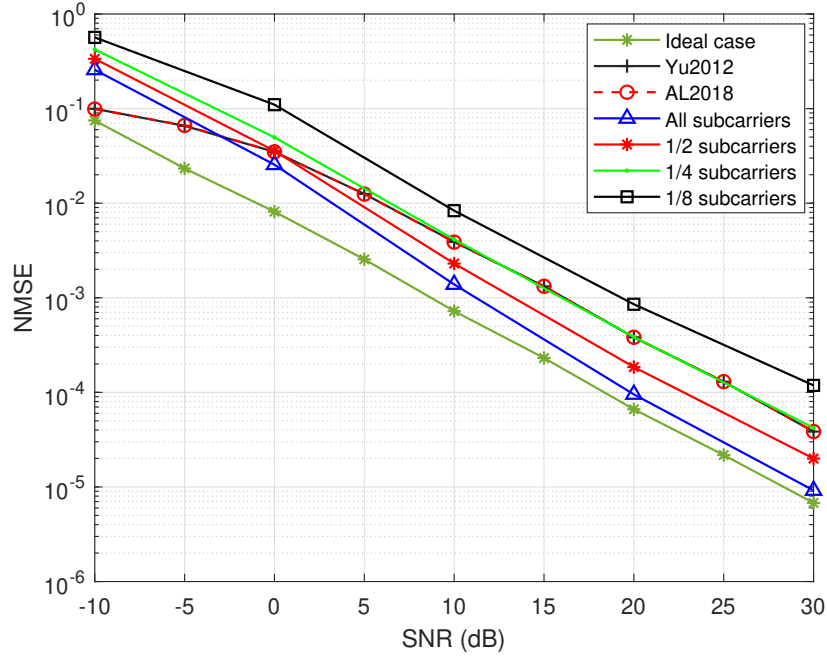


Figure 2.3: Comparison of proposed SB algorithm with existing SB algorithms for NMSE v.s. SNR with $N_s = 150$, $G = 45$ for both Ref [3] (Yu2012) and Ref [4] (AL2018).

antennas and $N_r = 3$ receiving antennas are used. The number of channel taps used is $N = 4$ and the total OFDM subcarriers are $K = 64$. In this experiment, we used all subcarriers for our method and the number of OFDM pilots considered for all the algorithms is 4. The figure presents the NMSE against SNR for all the algorithms considered. Several observations can be drawn from this experiment. Firstly, when comparing both SB described in reference [3] and [4] using a windowing scenario where $G = 45$, they demonstrate the same estimation performance. However, our proposed SB algorithm outperforms the other algorithms in reference [3] and [4] due to reliance on small size covariance matrices (of size $N_r \times N_r$), which helps not only reduce the cost but also improve the estimation accuracy. Secondly, when comparing the algorithms presented in [3] and [4] with the proposed SB algorithm, it can be seen that

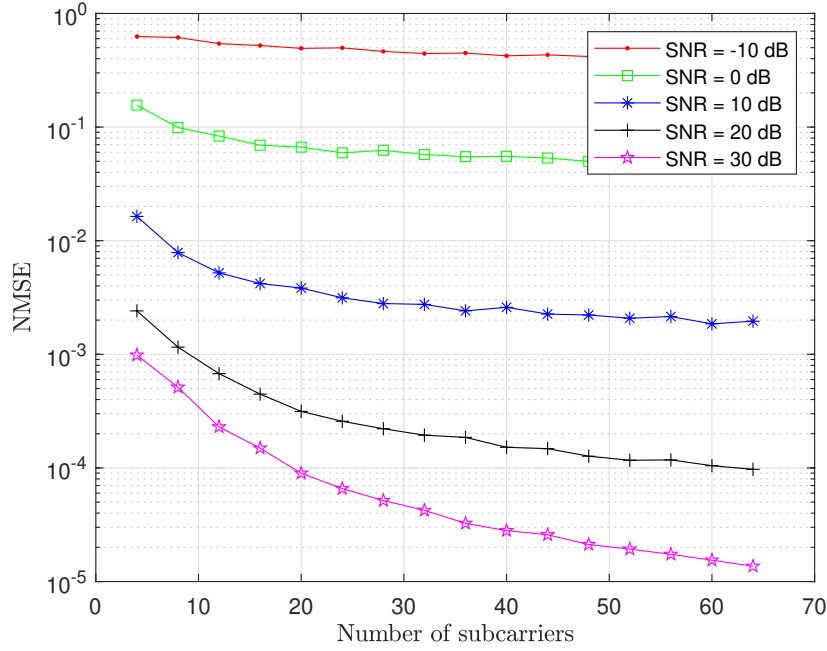


Figure 2.4: Performance evaluation of proposed SB algorithm using NMSE vs. number of used subcarriers K for different SNR with $N_s = 30$.

with half of the available subcarriers, our algorithm still outperforms the other ones. Meanwhile, with one-fourth of the available subcarriers, all the considered algorithms displayed similar performance at SNR higher than 5 dB. Thirdly, upon comparing the obtained results with the 'ideal case', we observe a small discrepancy of a few decibels (dBs) with respect to this benchmark.

Figure 2.4 depicts that the increase in the number of used subcarriers affects the algorithm's performance when the SNR is above 20 dB. However, one can see that for low or moderate SNRs, one can decrease the number of used subcarriers without much affecting the estimation accuracy.

Figure 2.5, presents the performance of both the blind and proposed SB algorithms for NMSE w.r.t SNR; the dashed line represents the blind, and the solid line represents

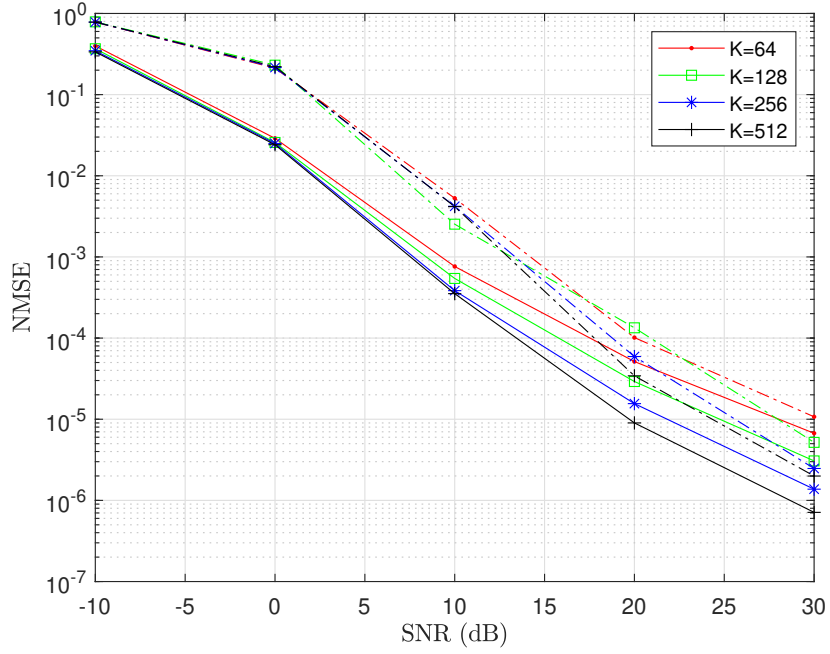


Figure 2.5: Performance evaluation using NMSE vs. SNR for the proposed blind (dashed line) and SB (solid line) solutions with different K values and $N_s = 50$.

the SB. We can observe that when increasing the OFDM symbol size (i.e., the number of subcarriers K) while keeping the number of received data symbols relatively small (e.g., $N_s = 50$), both algorithms perform relatively similarly. However, when the SNR is above 20 dB the algorithm's performance improves significantly.

Figure 2.6 shows the performance of the proposed solution w.r.t. the sample size compared to the SB approach in Ref [4] (AL SB). In the legend of the figure, AL SB $G = 45$ represents SB approach in Ref [4] considering the windowing approach with window size $G = 45$, and AL SB WG denotes the case without windowing. It can be noticed that the proposed SB solution still performs well as compared to the SB approach in Ref [4], in addition to reduced computational cost as shown in table 2.1.

To further reduce the computational complexity, Figure 2.7 shows the performance

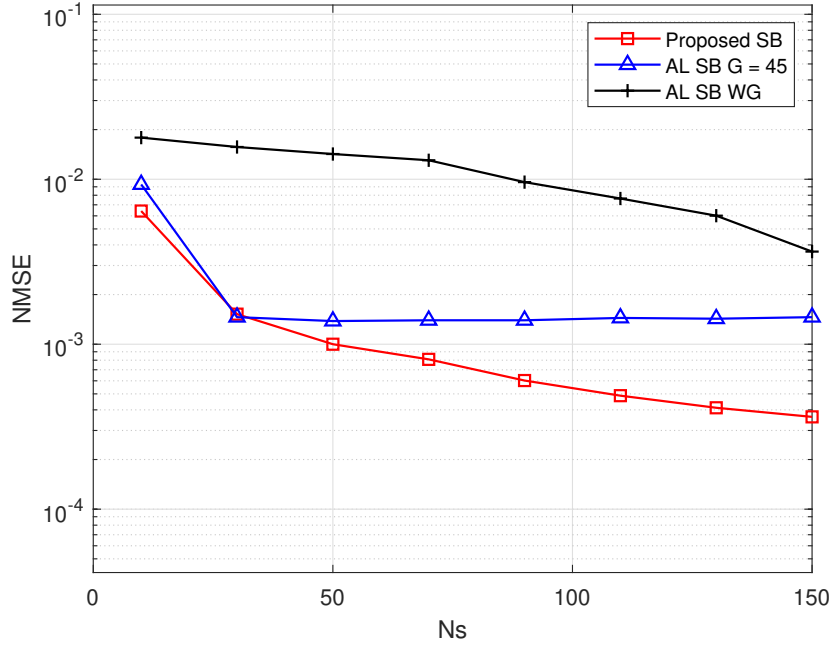


Figure 2.6: Performance comparison for the proposed SB algorithm with Ref [4] using NMSE vs. number of OFDM symbols N_s with $SNR = 10$ dB and $G = 45$ for .

of the proposed solution for both blind and SB, in terms of NMSE w.r.t SNR, when not exploiting all the subcarriers for calculating the matrix $\mathbf{Q}$ given by Equation (2.17). In the legends, “1/x subcarriers” refers to the use of one subcarrier out of x subcarriers, and the dashed lines represent the blind while solid lines represents the SB. Accordingly, one can rely only on some subcarriers for estimating the channel coefficient with acceptable estimation accuracy, in comparison with the case of using all the available subcarriers (“all subcarriers”). Note that, since the pilots are arranged in block-type mode, i.e., the pilots are represented along all subcarriers, reducing the number of subcarriers can be seen as reducing the size of pilots, which leads to a degradation in channel estimation for the SB case, especially in the low-SNR region.

Finally, from Table 2.3, one can notice that when using only the required minimum

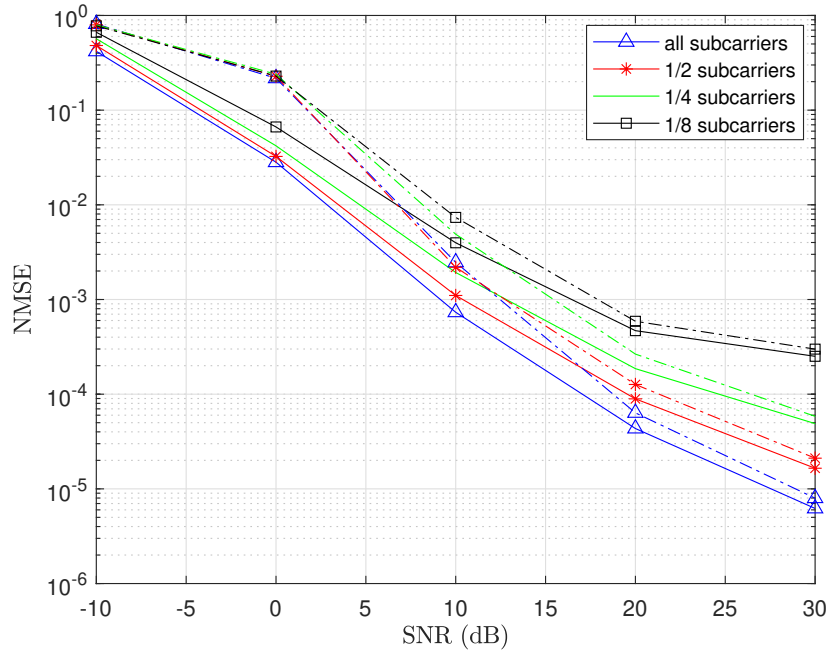


Figure 2.7: Performance evaluation using NMSE vs. SNR for the proposed blind (dashed line) and SB (solid line) solutions when exploiting parts of the available subcarriers, with $K = 64$ and $N_s = 50$.

Table 2.3: NMSE With the Minimum Number of Subcarriers $K_s = (N - 1)(N_t + 1) + 1$

SNR(dB)	∞	100	50	10
NMSE	$5 \cdot 10^{-29}$	$1.3 \cdot 10^{-11}$	$1.5 \cdot 10^{-6}$	$1.2 \cdot 10^{-2}$

number of subcarriers, according to the sufficient condition given in Proposition ??, it is possible to estimate the channel coefficients and, hence, achieve the desired channel identifiability.

2.7 Concluding Remarks & Perspectives

In this chapter, a new SB subspace-based technique for channel estimation is proposed when considering MIMO-OFDM communications systems. The proposed solution aims to further reduce the computational complexity and to speed up convergence

while guaranteeing accurate channel estimation with a reduced number of received symbols, as compared to similar techniques proposed in the literature. In fact, the proposed solution takes advantage of the orthogonality property of OFDM-based systems to estimate the covariance matrix and noise subspace for each subcarrier independently. After that, a global cost function is defined and minimized, leading to channel coefficient estimates. Conditions for channel identifiability, along with numerical simulations, corroborated the effectiveness of the proposed solution.

CHAPTER 3

JOINT SEMI-BLIND CFO ESTIMATION AND SYMBOL DETECTION FOR MIMO-OFDM

In this chapter, we present new joint semiblink CFO estimation and source separation method for both Time-division Multiplexed pilots (i.e., block pilot arrangement) and embedded pilots in MIMO-OFDM systems. The devised semi-blind objective function utilizes the LS and MM to jointly estimate the CFO and recovery data. The objective function is optimized iteratively using a batch gradient descent optimization approach. Furthermore, an efficient initialization procedure is introduced to reduce the complexity of the algorithm with ease of convergence. Consequently, a method for optimizing a step size is presented to speed up the convergence of the proposed approach. Finally, a competitive adaptive algorithm for CFO estimation and equalization in a slow-varying channel and CFO is proposed. The simulation result shows

that our method improves the bandwidth of the system with fast convergence.

3.1 Introduction

MIMO technology has emerged as a promising technology for enhancing data rates, link reliability, and spectral efficiency [46]. Further, OFDM is well known for its effective high-rate simultaneous transmission of multiple data symbols. These symbols are unaffected by frequency-selective fading channels [47]. Integrating MIMO and OFDM technologies offers state-of-art communication systems appropriate for LTE, LTE-A, 802.11n wireless networks, and beyond 5G communications systems [48].

In mobile communications, pilot sequences are appended to the frame of data symbols, meaning they are transmitted in separate time slots (time-division multiplexed (TDM),). The TDM approach significantly reduces the spectral efficiency of the systems. On the other hand, an embedded pilot or superimposed training (ST) scheme has been considered, in which the data signals and the pilot symbols are added during transmission to preserve the bandwidth and enhance the spectral efficiency [7], [8], [9]. In the ST scheme, part of the transmitted energy is assigned to the pilot sequences. This leads to a reduction in the data signal-to-noise ratio (SNR). For instance, the authors in [7] proposed adding a data signal with a low-power periodic sequence prior to transmission. Also, the authors in [8] and [9] proposed a data-dependent superimposed pilot sequence technique in which the unknown sequences (data-dependent sequence) are superimposed to the pilot sequences. Nevertheless, the authors in [49] proposed embedding an orthogonal pilot-constant Zero Auto-correlation Code for space-time

block code in MIMO-OFDM systems. Equally, the authors in [50] embedded pilot and data signals in a doubly selective channel.

Accurate source separation & symbol detection and accurate CFO estimation and synchronization are the two critical factors that determine the performance of systems:

a. Different source separation techniques have been adopted, including pilot-based, blind, and semi-blind approaches [51]. The pilot-based approach requires more bandwidth and power resources for pilot transmission, as in the case of TDM. In the blind source separation (BSS) technique, no pilot sequence is required (bandwidth is preserved); only the transmitted signals properties are exploited and used [15]. However, semi-blind allows the reduction of the pilot size and improves performance by combining data and pilots[52]. Numerous BSS techniques, such as Sparse Component Analysis and Independent Component Analysis, have been mentioned in the literature, e.g., [53]. Constant-modulus (CM) and Multi-Modulus (MM) based approaches are among the most effective BSS solutions utilized for communication signals [54], [55]. These approaches can be optimized either using an iterative algorithm or using closed-form approaches [52]. Among the semi-blind methods, one can cite the work in [56], which proposes an approach for an ST scheme in MIMO-OFDM using whitening and unitary decomposition. Similarly, semi-blind channel estimation for superimposed equi-spaced pilot symbols in multipath fading channels is proposed in [5]. The authors of [52] demonstrated semi-blind for a TDM scheme in MIMO-OFDM using CM and MM criterion. On the other hand, OFDM is vulnerable to CFO due to the instabilities of Doppler shifts or oscillators, causing subcarrier orthogonality loss and severe performance degradation. Fortunately, various literature has discussed the

techniques to estimate and compensate for the impact of CFO, as discussed in [57], [58], [59], [60]. Most of the aforementioned literature addresses source detection and CFO estimation separately. However, the authors in [61] demonstrated that jointly estimating the source and CFO can improve performance with increased computational complexity. In addition, the authors in [62] proposed a Bayesian receiver for joint equalization, CFO, and signal detection for multiuser MIMO-OFDM systems.

This chapter presents a new semi-blind MM source separation and CFO estimation technique based on the MM approach for both ST and TDM schemes in MIMO-OFDM systems. In the case of the ST scheme, the training sequence is superimposed on the data signal to improve the system's spectral efficiency. A hybrid semi-blind objective function combining both MM and LS criteria is developed to enable simultaneous source separation and CFO estimation. This objective function is optimized alternatively using a gradient descent iterative method, employing a full batch-based estimation process to jointly separate all sources and estimate the CFO. In addition, an efficient initialization process is employed to estimate the separation matrix and the CFO at the initial stage and to reduce the complexity of the proposed algorithm. Furthermore, a step size optimization method is introduced to enhance the convergence speed. Finally, considering a slow-varying channel and CFO, a stochastic gradient optimization is applied for symbol-by-symbol equalization and CFO estimation and tracking. The performance assessment of the proposed approach is presented in terms of the joint symbol error rate and the mean square error of the estimated CFO.

3.2 Embedded Pilot Scheme CFO-free MIMO-OFDM

This section presents a semi-blind MM source separation for a superimposed pilot sequence in CFO-free MIMO-OFDM communication systems.

3.2.1 CFO-Free Embedded Pilot MIMO-OFDM Model

Consider a MIMO-OFDM system having N_t and N_r transmit and receive antennas, respectively, whereby $N_r > N_t$. The known pilot sequence $\mathbf{P} \in \mathbb{C}^{N_t \times N_s}$ is superimposed to the data signals $\mathbf{S} \in \mathbb{C}^{N_t \times N_s}$, (i.e., $\mathbf{D} = \mathbf{S} + \mathbf{P}$) during transmission. Thus, the data and the pilots share the total transmitted power as $\sigma_t^2 = \sigma_s^2 + \sigma_p^2$. The superimposed data and pilot consist of K point samples obtained by the K -point inverse Fast Fourier Transform (IFFT) and then preceded in its front with L length CP. The length of the CP L is greater than or equal to a maximum delay N of the multipath channel, i.e., ($N \leq L$). After removing the CP and performing K -point FFT, the received N_s OFDM symbols at the k^{th} subcarrier can be expressed as:

$$\mathbf{X}_k = \mathcal{H}_k \mathbf{D}_k + \mathbf{\Omega}_k, \quad (3.1)$$

where $\mathbf{X}_k \in \mathbb{C}^{N_r \times N_s}$, $\mathbf{D}_k \in \mathbb{C}^{N_t \times N_s}$, and $\mathbf{\Omega}_k \in \mathbb{C}^{N_r \times N_s}$ is the additive white Circular Gaussian (CG) noise with variance σ_ω^2 . The received signals at the k^{th} subcarrier can be expressed as:

$$\mathbf{X}_k = \mathcal{H}_k \mathbf{S}_k + \mathcal{H}_k \mathbf{P}_k + \mathbf{\Omega}_k, \quad (3.2)$$

where $\mathbf{H}_k$ is the channel matrix defined as:

$$\mathbf{H}_k = \sum_{l=0}^{N-1} \mathbf{H}(l) \exp(-j2\pi \frac{k}{K} l), \quad (3.3)$$

where $\mathbf{H}(l) \in \mathbb{C}^{N_r \times N_t}$ is the l^{th} channel matrix of the MIMO transfer function and assumed to be a full-rank matrix, i.e., $N_r > N_t$.

Subsequently, by utilizing a separation matrix $\mathbf{Q}$ on the received signals, all the transmitted signals can be recovered effectively. The separating matrix $\mathbf{Q}$ is obtained such that $\mathbf{Q}(z)\mathbf{H}(z) = \mathbf{I}_{N_t}$ for all z . Furthermore, it's assumed that the condition for the existence of the inverse of $\mathbf{H}(z)$ is satisfied and $\mathbf{H}(z)$ is irreducible [15], so that within the unit circle $\mathbf{Q}(\exp(-j2\pi f_k))\mathbf{H}(\exp(-j2\pi f_k)) = \mathbf{I}_{N_t}$, $\forall k$, where $\mathbf{I}_{N_t}$ is the $(N_t \times N_t)$ identity matrix and $f_k = \frac{k}{K}$. The separation matrix for the k^{th} sub-carrier is expressed as:

$$\mathbf{Q}_k = \sum_{l=0}^{N-1} \mathbf{Q}(l) \exp(-j2\pi \frac{k}{K} l), \quad (3.4)$$

where $\mathbf{Q}(l) \in \mathbb{C}^{N_t \times N_r}$. Hence, the recovered signal at the k^{th} sub-carrier is:

$$\mathbf{Y}_k = \sum_{l=0}^{N-1} \mathbf{Q}(l) \exp(-j2\pi \frac{k}{K} l) \mathbf{X}_k = \mathbf{Q} \bar{\mathbf{V}}_k \mathbf{X}_k, \quad (3.5)$$

where $\mathbf{Q} = [\mathbf{Q}(0), \mathbf{Q}(1), \dots, \mathbf{Q}(N-1)]$, $\bar{\mathbf{V}}_k = \mathbf{v}_k^T \otimes \mathbf{I}_{N_r} \in \mathbb{C}^{NN_r \times N_r}$, $\mathbf{v}_k = [1, \exp(-j2\pi \frac{k}{K}), \dots, \exp(-j2\pi \frac{k}{K}(N-1))]$ is the k^{th} row of the $\mathbf{V}$ and $\mathbf{Q} \in \mathbb{C}^{N_t \times NN_r}$, whereby each source signal is recovered using each row of $\mathbf{Q}$ matrix. In fact, instead of estimating $\bar{\mathbf{V}}_k$, one is required to estimate one $\mathbf{Q}$ matrix, independent of the sub-carriers, as stated in (3.5).

Additionally, in the superimposed pilot type, both pilots and data have the same size, i.e., $N_s = N_p = N_d$. In the block-pilot arrangement, the pilot sequence is transmitted at the beginning of the frame, followed by data N_d , resulting in a total transmitted symbols of $N_s = N_p + N_d$.

3.2.2 CFO-Free Semi-Blind Approach

This section describes the introduced CFO-free semi-blind technique for the ST scheme. The jointly hybrid semi-blind cost function $J_{SB}(\mathbf{Q})$ is expressed as:

$$J_{SB}(\mathbf{Q}) = (1 - \alpha)J_{LS}(\mathbf{Q}) + \alpha J_{MM}(\mathbf{Q}), \quad (3.6)$$

where $J_{MM}(\mathbf{Q})$ is a MM based blind cost function, $J_{LS}(\mathbf{Q})$ is the least squares cost function, and α is a real-valued weighing factor in $[0, 1]$. This factor determines the assigned weight between the two objective functions in the semi-blind cost function.

The hybrid cost function defined in (3.6) is minimized based on the iterative gradient descent method in accordance with:

$$\mathbf{Q}_{n+1} = \mathbf{Q}_n - \mu \mathbf{G}_n, \quad n = 0, 1, \dots, \quad (3.7)$$

with a stopping criterion defined as [52]:

$$\frac{\|\mathbf{G}_n\|}{\|\mathbf{Q}_n\|} < \frac{0.1}{\sqrt{N_s}}, \quad (3.8)$$

where $\mathbf{G}_n$ is the gradient of the joint objective function at n^{th} iteration, μ is a small

real-valued that controls the rate of convergence of the algorithm known as step size, $\mathbf{Q}_n$ and $\mathbf{Q}_{n+1}$ are the past and the present value of the separation matrix $\mathbf{Q}$, respectively. The gradient of the joint objective function $\mathbf{G}_n$ is obtained as follows:

$$\begin{aligned}\mathbf{G}_n &= \nabla J_{SB}(\mathbf{Q}_n) \\ &= (1 - \alpha)\nabla J_{LS}(\mathbf{Q}_n) + \alpha\nabla J_{MM}(\mathbf{Q}_n).\end{aligned}\tag{3.9}$$

Remark: It is important to mention that a fixed number of iterations can be set as a stopping criterion. Also, during the estimation process, a batch-based processing approach is utilized. This approach involves considering a group of data during each gradient iteration to enhance the convergence speed and accuracy of the algorithm. Moreover, this method reduces the potential error accumulation associated with deflation-based approaches [63], [64]. In the ensuing, the LS and the MM algorithms are formulated, and the optimal step size is devised.

3.2.3 Least Squares (Pilot-based) Formulation

The cost function for the pilot-based technique mentioned in (3.6) uses a LS criterion defined as:

$$J_{LS}(\mathbf{Q}) = \sum_{i=1}^{N_t} \sum_{k=1}^K E|y_{k,i}(n) - p_{k,i}(n)|^2,\tag{3.10}$$

where $y_{k,i}(n) = \mathbf{q}_i \bar{\mathbf{V}}_k \mathbf{X}_k(n)$ is the k^{th} estimated signal, and $p_{k,i}(n)$ is the k^{th} transmitted pilot. The gradient of (3.10) with respect to $\mathbf{q}_i$ for the i^{th} user can be expressed as:

$$\nabla J_{LS}(\mathbf{q}_i) = 2E[(\bar{\mathbf{V}}_k \mathbf{X}_k(n))^* (y_{k,i}(n) - p_{k,i}(n))]. \quad (3.11)$$

3.2.4 Multi-Modulus (MM) Formulation

The blind approach utilized in this study aims to recover the source signal by employing the MM criterion. This criterion considers the variation in both the in-phase and quadrature components of the equalized symbols of the square-shaped constellation, and it is defined as follows:

$$J_{MM}(\mathbf{Q}) = \sum_{i=1}^{N_t} \sum_{k=1}^K E[(y_{k,i,R}^2(n) - R_R)^2 - (y_{k,i,I}^2(n) - R_I)^2], \quad (3.12)$$

where $y_{k,i,R}(n) = \Re(\mathbf{q}_i \bar{\mathbf{V}}_k \mathbf{X}_k(n) - p_{k,i}(n))$ and $y_{k,i,I}(n) = \Im(\mathbf{q}_i \bar{\mathbf{V}}_k \mathbf{X}_k(n) - p_{k,i}(n))$ are the real and imaginary components of the $(i, k)^{th}$ of the estimated signal, respectively. The dispersion constants, denoted as $R_R = E[s_R^4(n)]/E[s_R^2(n)]$ and $R_I = E[s_I^4(n)]/E[s_I^2(n)]$, are the real and imaginary components which are influenced by the constellation considered in the $\mathbf{s}$.

The gradient of the blind-based MM with respect to $\mathbf{q}_i$ for the i^{th} user is expressed as:

$$\begin{aligned} \nabla J_{MM}(\mathbf{q}_i) &= \sum_{k=1}^K 4E[(\bar{\mathbf{V}}_k \mathbf{X}_k(n))^* ((y_{k,i,R}^2(n) - R_R)y_{k,i,R}(n) \\ &\quad - j(y_{k,i,I}^2(n) - R_I)y_{k,i,I}(n))]. \end{aligned} \quad (3.13)$$

Note that the step size includes all the multiplicative constants in the above expression [65].

3.2.5 Optimal Step Size

The accuracy and convergence speed of the devised gradient descent algorithm are highly influenced by the step size μ considered. Thus, choosing the optimal μ would not only significantly enhance the convergence of (3.7) but also improve the overall estimation accuracy in the system. Therefore, the optimal step size choice is considered as an optimization problem defined as follows:

$$\mu_{opt} = \arg \min_{\mu} J_{SB}(\mathbf{Q}_{n+1}), \quad (3.14)$$

where $J_{SB}(\mathbf{Q}_{n+1}) = J_{SB}(\mathbf{Q}_n - \mu \nabla J_{SB}(\mathbf{Q}_n))$ is a polynomial function in variable μ . Hence, the derivative of $J_{SB}(\mathbf{Q}_{n+1})$ w.r.t. μ is a 3rd order polynomial. Therefore, the root of $\nabla J_{SB}(\mathbf{Q}_{n+1})$ is the μ_{opt} which is a real-valued expression that minimizes $J_{SB}(\mathbf{Q}_{n+1})$. The updating rule for the separating matrix can be written as:

$$\mathbf{Q}_{n+1} = \mathbf{Q}_n - \nabla J_{SB}(\mathbf{Q}_n) \text{diag}(\boldsymbol{\mu}), \quad (3.15)$$

where $\boldsymbol{\mu} = [\mu_1, \dots, \mu_{N_t}]$ contains the optimal μ values of all sources.

3.2.6 Performance Evaluation

Here, we present the evaluation of the proposed semi-blind method for the ST scheme. The proposed ST scheme is compared with the TDM scheme (specifically the block-pilot arrangement) using the metric Symbol Error Rate (SER) and bandwidth efficiency. The SNR is defined as the average value: $\text{SNR} = \frac{1}{K} \sum_{k=1}^K \|\mathbf{H}_k \mathbf{D}_k\|_F^2 / \|\mathbf{\Omega}_k\|_F^2$.

The transmitted signal and the pilot data are based on 4-QAM modulation system in which $N_r = 4$, $N_t = 2$, $N_s = 100$, $N = 4$, and $K = 64$. Also, 500 Monte Carlo runs are considered, and the channel coefficients are characterized as unit power i.i.d. with zero-mean Gaussian distribution. The initialization of the equalizer is based on a conventional LS-based approach since some training pilots are available. The fixed step size $\mu = 0.01$ and $\alpha = 0.5$ were used. In the ST scheme, N_p pilot sequences have the same size as the data N_s , while in the block-type pilot arrangement, $N_p = 5$. The pilot symbols power (σ_p^2) in the embedded pilot case is set to $\sigma_p^2 = 0.1$ to minimize the interference considering $\sigma_s^2 + \sigma_p^2 = 1$.

Furthermore, the influence of superimposing pilot and data on the system's throughput is investigated, which is mathematically represented as:

$$R_{\text{Throughput}} = \lambda \cdot \frac{N_s}{N_s + N_p} \cdot (1 - \text{SER}), \quad (3.16)$$

where $\lambda = \log_2(M)$ is the transmitted bits per symbol in M -ary levels. Note that $\frac{N_s}{N_s + N_p}$ is 1 for the ST scheme.

Figure 3.1 presents the SER versus different power allocated to the embedded pilots sequence (σ_p^2) for an SNR = 8 dB. In the legend, the BP stands for block-pilot

arrangement, EP for the embedded pilot, and EP-OSS refers to the embedded pilot with an optimal step size. We can observe that EP-OSS outperforms EP, and both

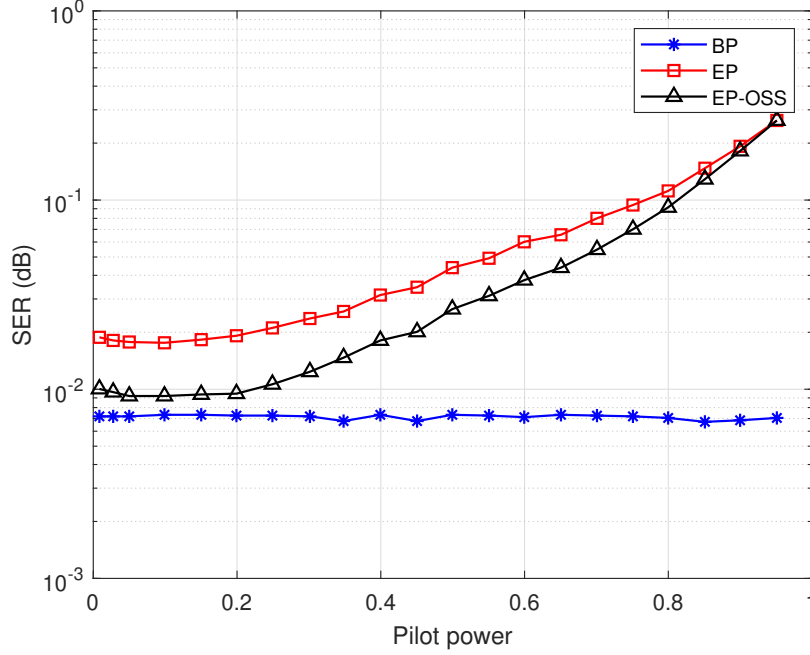


Figure 3.1: SER versus pilot symbols power, SNR = 8 dB, $N_s = 100$.

improve significantly as the value of σ_p^2 increases until it reaches an optimal value of $\sigma_p^2 = 0.1$. However, their performance deteriorates afterward. This determines the optimal power allocated to the embedded pilots, resulting in minimum interference between the data and the superimposed sequence for the SNR values considered. Additionally, with the optimal step size and a good choice of σ_p^2 , the performance of the proposed EP scheme is close to that of the BP scheme. Remember that in the EP case, the data and the pilots share the total transmitted power i.e., $\sigma_t^2 = \sigma_s^2 + \sigma_p^2$ this means as σ_p^2 increases the σ_s^2 decreases and vice-versa. However, in the BP case, no power is shared between the data and pilot sequences, i.e., $\sigma_t^2 = \sigma_s^2 = \sigma_p^2$.

Figure 3.2 depicts the comparison of the proposed EP scheme and block-type pilot

arrangement (i.e., TDM scheme). We can see that the proposed semi-blind approach for the EP scheme shows excellent SER performance. Additionally, with the good choice of optimal step size, the EP-OSS performance closely approaches that of the BP scheme. It's important to note that the TDM method wastes bandwidth, unlike the EP scheme. Furthermore, we can observe that the proposed semi-blind approach for EP displays a distinct performance compared to the semi-blind approach (EP-WY2007) for EP presented in [5]. This highlights the robustness of the proposed approach.

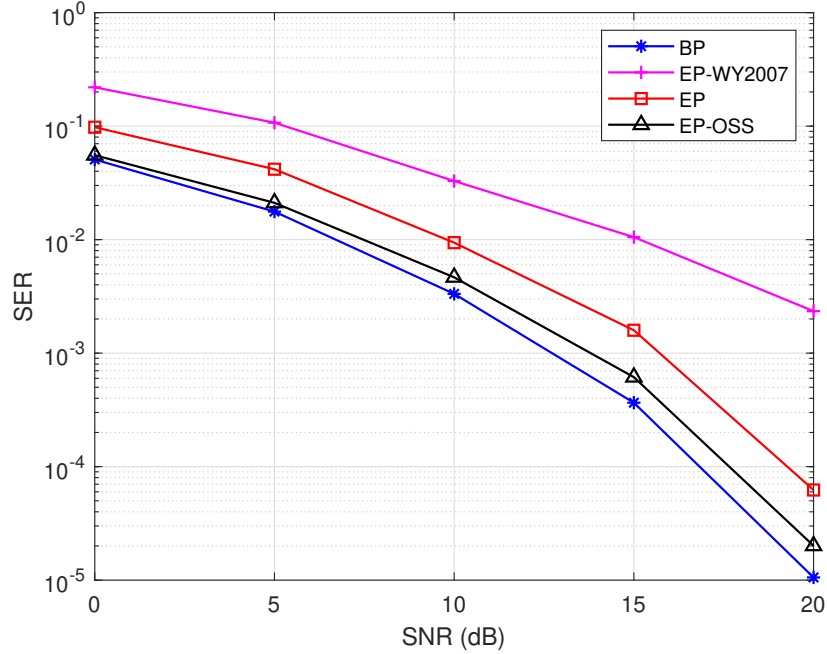


Figure 3.2: Performance evaluation of the proposed algorithm for EP and BP scheme compared with semi-blind EP presented in [5] using SER versus SNR.

Figure 3.3 presents the spectral efficiency comparison for the block-type pilot arrangement and the superimposed pilot scheme for different SNR values. The spectral efficiency is computed using the throughput presented in (3.16). We can clearly see

how the bandwidth is preserved by superimposing the pilots and the data. This is because, for the block-type pilot throughput, $\frac{N_s}{N_s+N_p} < 1$, whereas for the ST scheme throughput, $\frac{N_s}{N_s+N_p} = 1$. In addition, a significant improvement in spectral efficiency is achieved using a good choice of step size (i.e, optimal step size). This demon-

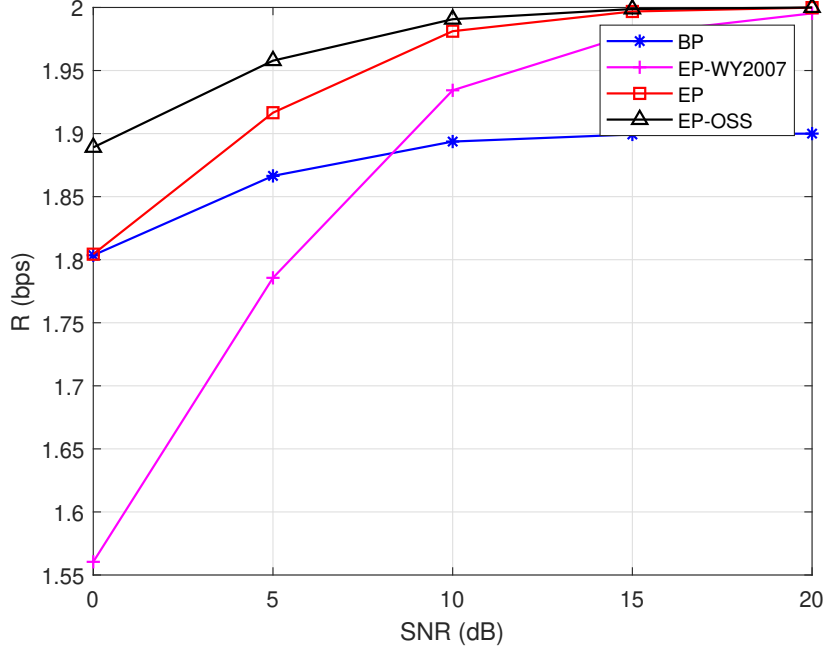


Figure 3.3: Performance evaluation of the proposed algorithm for EP and BP scheme compared with semi-blind EP presented in [5] using Throughput R(bps) versus SNR.

strates that superimposing the pilot symbols and data during transmission enhances the spectral efficiency of the MIMO-OFDM system.

Figure 3.4 depicts the NMSE performance for 10 dB SNR. The NMSE is defined as:

$$\text{NMSE} = \frac{1}{N_{iter}} \sum_{i=1}^{N_{iter}} \frac{\|\hat{\mathbf{d}}_i - \mathbf{d}\|^2}{\|\mathbf{d}\|^2},$$
 where $\hat{\mathbf{d}}_i$ is the estimated symbols, $\mathbf{d}$ is the transmitted symbols and N_{iter} is the number of iterations, It can be observed that the block-type pilot arrangement converges faster than the superimposed pilot scheme. However, the convergence rate of EP improves with the optimal step size.

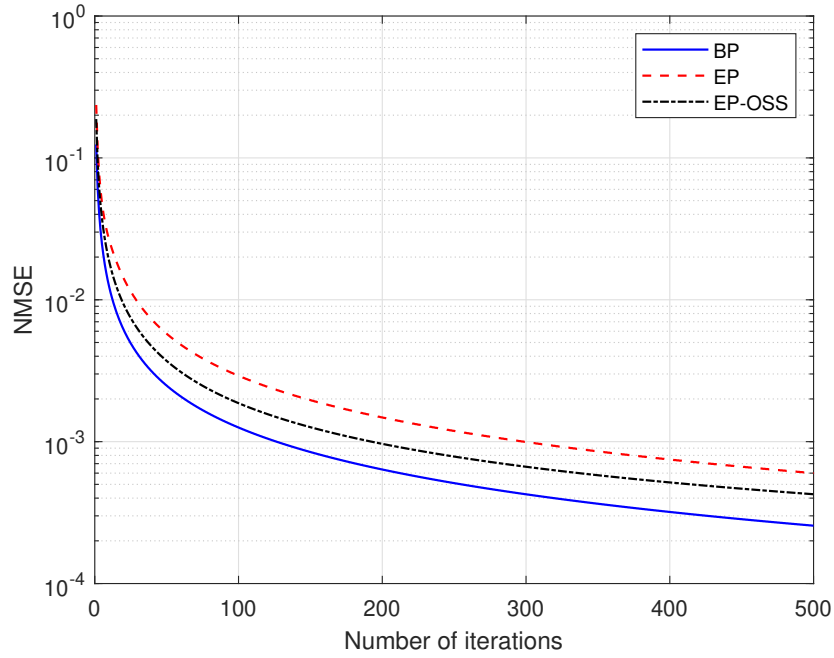


Figure 3.4: NMSE versus number of iterations, for an SNR 10dB.

3.2.7 Conclusion

This work presented a semi-blind source separation approach for embedded pilots in free-CFO MIMO-OFDM communications. A jointly hybrid cost function is devised by employing MM and LS criteria for a source separation scenario. A full batch OFDM symbol estimation is performed using a gradient descent optimization process. Simulation results revealed that significant spectral efficiency is achieved considering the embedded pilot scheme. Furthermore, an excellent performance accuracy in equalization and estimation is achieved with fast convergence using an optimized step size.

3.3 Block Pilot Scheme with CFO in MIMO-OFDM

This section presents a semi-blind MM approach for joint source separation and CFO estimation for BP Scheme in MIMO-OFDM communication systems.

3.3.1 MIMO-OFDM Systems Model

Consider an uplink transmission configuration of the MIMO-OFDM system as presented in Fig. 3.5. The system has N_t transmit, and N_r receive antennas, whereas $N_r \geq N_t$. At the transmitter, a K sample of OFDM symbols is created using a K -point Inverse Fast Fourier Transform (IFFT) and is preceded with a cyclic prefix (CP) of length L . The maximum delay N of the multipath channel is assumed to be smaller than the length of CP (i.e., $L \geq N$) to prevent inter-block interference at the receiver. Upon receiving the OFDM symbols, the CP is removed, and the K -point FFT is employed. The n^{th} OFDM symbol received at the k^{th} subcarrier can be expressed as:

$$\mathbf{y}_k(n) = \mathbf{H}_k \mathbf{\Phi}_k(n) \mathbf{s}_k(n) + \boldsymbol{\omega}_k(n), \quad n = 1, \dots, N_s, \quad (3.17)$$

where $\mathbf{y}_k(n) = [y_{1,k}(n), \dots, y_{N_r,k}(n)]^T$, $\mathbf{s}_k(n) = [s_{1,k}(n), \dots, s_{N_t,k}(n)]^T$ is the n^{th} transmitted OFDM symbol, $\boldsymbol{\omega}_k(n)$ is the additive white symmetric complex Gaussian noise of variance σ_ω^2 , $\mathbf{\Phi}_k(n) = \text{diag}(\phi_{1,k}(n), \dots, \phi_{N_t,k}(n))$ with $\phi_{i,k}(n) = e^{j2\pi f_i(k+(n-1)(K+L))}$, where f_i is a carrier frequency offset for the i^{th} user, and $\mathbf{H}_k$ is the channel matrix

defined as:

$$\mathbf{H}_k = \sum_{l=0}^{N-1} \mathbf{H}(l) e^{-j2\pi \frac{k}{K} l}, \quad (3.18)$$

where $\mathbf{H}(l) \in \mathbb{C}^{N_r \times N_t}$ is the l -th channel coefficient. Furthermore, the overall N_s received OFDM symbols at the k^{th} subcarrier can be written as follows:

$$\mathbf{Y}_k = \mathbf{H}_k(\Phi_k \odot \mathbf{S}_k) + \mathbf{\Omega}_k, \quad (3.19)$$

where $\odot$ denotes the Hadamard (elementwise) product, $\mathbf{S}_k = [\mathbf{P}_k, \mathbf{D}_k] \in \mathbb{C}^{N_t \times N_s}$ in which $\mathbf{P}_k \in \mathbb{C}^{N_t \times N_p}$ is the pilot sequence, $\mathbf{D}_k \in \mathbb{C}^{N_t \times N_d}$ is the data sequence, $\mathbf{\Omega}_k \in \mathbb{C}^{N_r \times N_s}$, $\mathbf{Y}_k = [\mathbf{Y}_{k,p}, \mathbf{Y}_{k,d}] \in \mathbb{C}^{N_r \times N_s}$ and $\Phi_k \in \mathbb{C}^{N_t \times N_s}$ defined as:

$$\Phi_k = \begin{bmatrix} \phi_{1,k}(0) & \cdots & \phi_{1,k}(N_s - 1) \\ \vdots & & \vdots \\ \phi_{N_t,k}(0) & \cdots & \phi_{N_t,k}(N_s - 1) \end{bmatrix}.$$

The chosen pilot sequence $\mathbf{P}_k$ is well-designed to satisfy the orthogonality condition $\mathbf{P}_k \mathbf{P}_k^H = N_p \sigma_p^2 \mathbf{I}_{N_t}$.

Subsequently, an $N_t \times N_r$ separation (deconvolution) filter $\mathbf{W}(z)$ is applied to the received signals to effectively recover all the transmitted signals. The separating filter is designed to satisfy the condition $\mathbf{W}(z)\mathbf{H}(z) = \mathbf{I}_{N_t}$ for all z . Accordingly, it's assumed that the condition for the existence of inverse of $\mathbf{H}(z)$ exists and $\mathbf{H}(z)$ is irreducible [15]. The deconvolution filter for the k^{th} subcarrier can be defined as

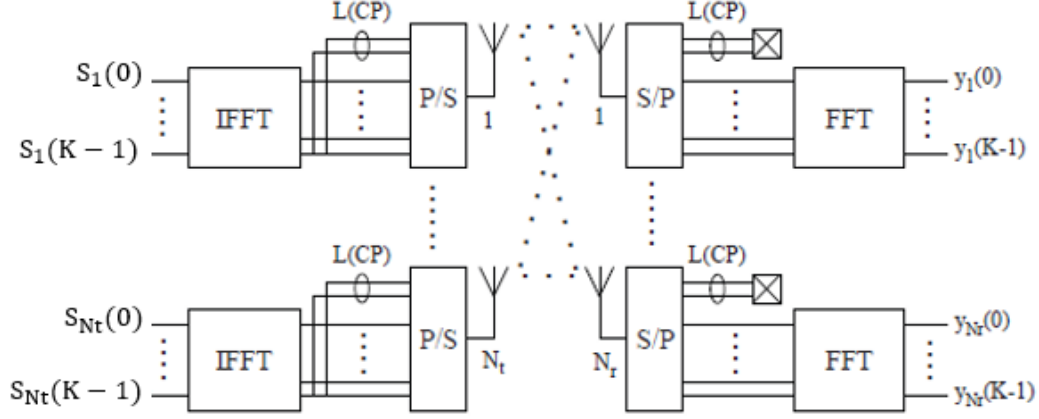


Figure 3.5: Time-division Multiplexing MIMO-OFDM communications system

follows:

$$\mathbf{W}_k = \sum_{l=0}^{N_q-1} \mathbf{W}(l) e^{-j2\pi \frac{k}{K} l}. \quad (3.20)$$

here N_q is the length of the deconvolution filter (chosen in this work as $N_q = N$).

Thus, the recovered signal at the k^{th} subcarrier is:

$$\begin{aligned} \mathbf{x}_k(n) &= \mathbf{\Phi}_k^*(n) \mathbf{W}_k \mathbf{y}_k(n) = \mathbf{\Phi}_k^*(n) \mathbf{W} \bar{\mathbf{V}}_k \mathbf{y}_k(n) \\ &= \mathbf{\Phi}_k^*(n) \mathbf{z}_k(n), \end{aligned} \quad (3.21)$$

where $\mathbf{z}_k(n) = \mathbf{W}_k \mathbf{y}_k(n)$, $\mathbf{Z}_k = [\mathbf{z}_k(0), \dots, \mathbf{z}_k(N_s - 1)]$, $()^*$ denotes the complex conjugate, $\mathbf{W} = [\mathbf{W}(0), \mathbf{W}(1), \dots, \mathbf{W}(N_q - 1)]$, $\bar{\mathbf{V}}_k = \mathbf{v}_k \otimes \mathbf{I}_{N_r} \in \mathbb{C}^{N_q N_r \times N_r}$, and $\mathbf{v}_k = [1, e^{j2\pi \frac{k}{K}}, \dots, e^{j2\pi \frac{k}{K} (N_q - 1)}]^H$. According to equation (3.21), instead of estimating matrices $\mathbf{W}_k$, $k = 0, \dots, K - 1$, it is sufficient to estimate a single matrix $\mathbf{W}$ that is common to all sub-carriers.

3.3.2 Semi-blind Source Separation and CFO Estimation

This section presents the formulation of the proposed joint semi-blind equalization and CFO estimation. The weighted semi-blind cost function $J_{SB}(\mathbf{W}, \mathbf{f})$ can be written as:

$$J_{SB}(\mathbf{W}, \mathbf{f}) = \alpha J_{MM}(\mathbf{W}, \mathbf{f}) + (1 - \alpha) J_{LS}(\mathbf{W}, \mathbf{f}), \quad (3.22)$$

where $J_{MM}(\mathbf{W}, \mathbf{f})$ is a MM-based blind cost function governed by data, $J_{LS}(\mathbf{W}, \mathbf{f})$ is a LS cost function governed by pilots, $\mathbf{f} = [f_1, \dots, f_{N_t}]$, and α is a weighting parameter, with $\alpha \in [0, 1]$. This parameter determines the weight allocated to the blind (data) and pilot-based parts of the hybrid cost function. In this work, we employ the alternating gradient descent optimization technique for solving (3.22). This method alternates iteratively solving one 'bloc' variable while keeping the other fixed. The following recursive equation guides the optimization process:

$$\mathbf{v}_{m+1}(\mathbf{W}, \mathbf{f}) = \mathbf{v}_m(\mathbf{W}, \mathbf{f}) - \mu \mathbf{g}_m, \quad m = 0, 1, \dots, \quad (3.23)$$

The iteration stops when the following criterion is satisfied as follows [52]:

$$\frac{\|\mathbf{g}_m\|}{\|\mathbf{v}_m\|} < \frac{0.1}{\sqrt{N_s}}, \quad (3.24)$$

where $\mathbf{g}_m$ is the gradient of the cost function w.r.t. either $\mathbf{W}$ or $\mathbf{f}$ depending on the parameter under consideration at m -th iteration and $\mu > 0$ is a step size usually small real-valued scalar that determines the convergence rate of the algorithm. Also, $\mathbf{v}_m$

and $\mathbf{V}_{m+1}$ are the old and the updated value of either the deconvolution filter $\mathbf{W}$ or CFO vector $\mathbf{f}$, respectively.

3.3.3 Pilot-based (Least Squares) Formulation

The cost function $J_{LS}(\mathbf{W}, \mathbf{f})$ is based on an LS criterion and can be defined as:

$$J_{LS}(\mathbf{W}, \mathbf{f}) = \sum_{k=0}^{K-1} \|\bar{\mathbf{Z}}_k - \mathbf{P}_k\|^2, \quad (3.25)$$

where $\mathbf{P}_k \in \mathbb{C}^{N_t \times N_p}$ and $\bar{\mathbf{Z}}_k = \Phi_k^* \odot \mathbf{Z}_{k,p} = \Phi_k^* \odot \mathbf{W} \bar{\mathbf{V}}_k \mathbf{Y}_{k,p} \in \mathbb{C}^{N_t \times N_p}$ are the transmitted and estimated pilot sequences, with

$$\Phi_k = \begin{bmatrix} \phi_{1,k}(0) & \cdots & \phi_{1,k}(N_p - 1) \\ \vdots & & \vdots \\ \phi_{N_t,k}(0) & \cdots & \phi_{N_t,k}(N_p - 1) \end{bmatrix}.$$

The gradient of $J_{LS}(\mathbf{W}, \mathbf{f})$ with respect to $\mathbf{W}$ and $\mathbf{f}$ can be written, respectively, as:

$$\nabla J_{LS}(\mathbf{W}) = 2 \sum_{k,n} (\bar{\mathbf{z}}_k(n) - \mathbf{p}_k(n)) (\bar{\mathbf{V}}_k \mathbf{y}_k(n))^H, \quad (3.26)$$

and

$$\nabla J_{LS}(\mathbf{f}) = \sum_{k,n} \alpha_{k,n} \Im(\bar{\mathbf{z}}_k^*(n) \odot \mathbf{p}_k(n) \odot \boldsymbol{\varphi}_k(n)), \quad (3.27)$$

here $\alpha_{k,n} = 4\pi(k + (n-1)(K+L))$, $\boldsymbol{\varphi}_k(n) = [\phi_{1,k}(n), \dots, \phi_{N_t,k}(n)]^T$, $n = 0, \dots, N_p - 1$,

and $\Re(z)$ (resp. $\Im(z)$) stands for the real part (resp. the imaginary part) of z .

3.3.4 Multi-Modulus (MM) Formulation

The blind approach adopted in this study utilizes the MM criterion to recover the source signal¹ and the CFO simultaneously. The data cost function is defined as follows:

$$J_{MM}(\mathbf{W}, \mathbf{f}) = \sum_{k,n} [\|\mathbf{x}_{k,R}(n) \odot \mathbf{x}_{k,R}(n) - R_R\|^2 + \|\mathbf{x}_{k,I}(n) \odot \mathbf{x}_{k,I}(n) - R_I\|^2], \quad (3.28)$$

where

$$\mathbf{x}_{k,R}(n) = \Re(\Phi_k^*(n)\mathbf{z}_k(n)), \quad (3.29)$$

and

$$\mathbf{x}_{k,I}(n) = \Im(\Phi_k^*(n)\mathbf{z}_k(n)), \quad (3.30)$$

where $R_R = E[s_R^4(n)]/E[s_R^2(n)]$ and $R_I = E[s_I^4(n)]/E[s_I^2(n)]$ are the dispersion constants, while $(s(n))$ refers to the input QAM-modulated symbol, $n = N_p, \dots, N_s - 1$.

After derivations simplifications, the gradient of $J_{MM}(\mathbf{W}, \mathbf{f})$ w.r.t. $\mathbf{W}$ is expressed as:

$$\begin{aligned} \nabla J_{MM}(\mathbf{W}) = 2 \sum_{k,n} [& (\mathbf{x}_{k,R}(n) \odot \mathbf{x}_{k,R}(n) - R_R) \odot \mathbf{x}_{k,R}(n) \odot \boldsymbol{\varphi}_k(n) + \\ & j(\mathbf{x}_{k,I}(n) \odot \mathbf{x}_{k,I}(n) - R_I) \odot \mathbf{x}_{k,I}(n) \odot \boldsymbol{\varphi}_k(n)] (\bar{\mathbf{V}}_k \mathbf{y}_k(n))^H, \end{aligned} \quad (3.31)$$

Similarly, the gradient of $J_{MM}(\mathbf{W}, \mathbf{f})$ w.r.t. $\mathbf{f}$ is given by:

$$\begin{aligned} \nabla J_{MM}(\mathbf{f}) = \sum_{k,n} \alpha_{k,n} [& (\mathbf{x}_{k,R}(n) \odot \mathbf{x}_{k,R}(n) - R_R) \odot \mathbf{x}_k(n) + (\mathbf{x}_{k,I}(n) \odot \mathbf{x}_{k,I}(n) \\ & - R_I) \odot \mathbf{x}_k(n)], \end{aligned} \quad (3.32)$$

where $\mathbf{x}_k(n) = \mathbf{x}_{k,R}(n) \odot \mathbf{x}_{k,I}(n)$.

3.3.5 Initialization Process

This section outlines the procedure for initializing the deconvolution filter $\mathbf{W}$ and CFO used in our proposed method. The conventional LS approach is used to initialize deconvolution filter $\mathbf{W}$ assuming that the CFO is zero (i.e., Φ is the identity matrix at the initial stage). The initial $\mathbf{W}$ is used to roughly recover the transmitted pilots for all subcarriers $\bar{\bar{\mathbf{Z}}}_p \in \mathbb{C}^{N_t \times N_p \times K}$. The recovered pilot signals $\bar{\bar{\mathbf{Z}}}_p$ is then rearranged into a matrix $\mathbf{A}_p$ with dimensions of $N_t \times KN_p$. Similarly, a matrix $\mathbf{B}_p$, of size $N_t \times KN_p$, is created from the pilot sequence $\bar{\bar{\mathbf{P}}} \in \mathbb{C}^{N_t \times N_p \times K}$.

The following process is performed to estimate the CFO for the i^{th} antenna: the conjugate of the i^{th} row of $\mathbf{B}$ is multiplied element-wise by the i^{th} row of $\mathbf{A}$, resulting in a vector $\mathbf{u}$. The FFT is then applied to create $\bar{\mathbf{u}}$, which is the frequency components of $\mathbf{u}$. Subsequently, The amplitude of each frequency component of $\mathbf{u}$ is determined by taking the absolute value of the $\bar{\mathbf{u}}$. The index with the maximum amplitude indicates the position of the estimated CFO. Note that the size M of the FFT should be large enough to avoid inaccurate CFO estimation. This procedure is repeated to estimate the CFO of all transmit antennas. Then, a matrix containing all the estimated CFO is created as matrix $\bar{\Phi}$ and then multiplied element-wise with the pilot sequences $\mathbf{P}$ for a subcarrier and then, repeated across all subcarriers to have a new pilot sequence $\bar{\mathbf{P}}$ with an estimated CFO.

The new equalizer is created using the $\bar{\mathbf{P}}$ followed by estimating CFO, and the procedure is repeated for a few numbers of iterations.

Algorithm 3.1: Initialization based on Least Squares (LS)

Initialize CFO: $f_i^{(0)} = 0 \quad i = 0, \dots, N_t - 1$, $\Phi_k^{(0)}(n) = \mathbf{I}_{N_t}$

$\mathbf{P} = [\mathbf{P}_0, \cup_3, \dots, \cup_3, \mathbf{P}_{K-1}] \in \mathbb{C}^{N_t \times N_p \times K}$

$\mathbf{P}^{(0)} = \text{reshape}(\mathbf{P}, N_t, KN_p) \in \mathbb{C}^{N_t \times KN_p}$; $\mathbf{B}_p^{(0)} = \mathbf{P}^{(0)}$

$\mathcal{Y} = [\bar{\mathbf{V}}_0 \mathbf{Y}_{0,p}, \cup_3, \dots, \cup_3, \bar{\mathbf{V}}_{K-1} \mathbf{Y}_{K-1,p}] \in \mathbb{C}^{N_r N_q \times N_p \times K}$

$\bar{\mathcal{Y}} = \text{reshape}(\mathcal{Y}, N_r N_q, KN_p) \in \mathbb{C}^{N_r N_q \times KN_p}$

Initialize equalizer: $\mathbf{W}^{(0)} = \mathbf{P}^{(0)} \bar{\mathcal{Y}}^\#$

where $\bar{\mathcal{Y}}^\# = (\bar{\mathcal{Y}} \bar{\mathcal{Y}}^H)^{-1} \bar{\mathcal{Y}}$,

Initialize: $t_{\max}$

for $t = 1$ to $t_{\max}$ **do**

$\mathbf{Z}_{k,p}^{(t-1)} = \mathbf{W}^{(t-1)} \bar{\mathbf{V}}_k \mathbf{Y}_{k,p} \in \mathbb{C}^{N_t \times N_p}$

$\bar{\bar{\mathbf{Z}}}_p^{(t-1)} = [\mathbf{Z}_{0,p}^{(t-1)}, \cup_3, \dots, \cup_3, \mathbf{Z}_{K-1,p}^{(t-1)}] \in \mathbb{C}^{N_t \times N_p \times K}$

$\mathbf{A}_p^{(t-1)} = \text{reshape}(\bar{\bar{\mathbf{Z}}}_p^{(t-1)}, N_t, KN_p) \in \mathbb{C}^{N_t \times KN_p}$

for $i = 1$ to N_t **do**

$\mathbf{a}_i^{(t-1)} = \mathbf{A}_p^{(t-1)}(i, :)$; $\mathbf{b}_i^{(t-1)} = \mathbf{B}_p^{(t-1)}(i, :)$

$\mathbf{u} = \text{conj}(\mathbf{b}_i^{(t-1)}) \odot \mathbf{a}_i^{(t-1)}$

$f_i^{(t)} = \arg \max_{f_i} |\text{FFT}_M(\mathbf{u})|$

end for

$\hat{\phi}_{i,k}(n) = e^{j2\pi f_i^{(t)}(k+(n-1)(K+L))}$

$\bar{\Phi}_k^{(t)}(n) = \text{diag}(\hat{\phi}_{1,k}(n), \dots, \hat{\phi}_{N_t,k}(n))$

$\bar{\mathbf{p}}_k^{(t)}(n) = \bar{\Phi}_k^{(t)}(n) \mathbf{p}_k^{(t-1)}(n)$, $n = 0, \dots, N_p - 1$

$\bar{\mathbf{P}}^{(t)} = [\bar{\mathbf{P}}_0^{(t)}, \cup_3, \dots, \cup_3, \bar{\mathbf{P}}_{K-1}^{(t)}] \in \mathbb{C}^{N_t \times N_p \times K}$

$\bar{\bar{\mathbf{P}}}^{(t)} = \text{reshape}(\bar{\mathbf{P}}^{(t)}, N_t, KN_p) \in \mathbb{C}^{N_t \times KN_p}$

$$\mathbf{B}_p^{(t)} = \bar{\bar{\mathbf{P}}}^{(t)}$$

$$\mathbf{W}^{(t)} = \bar{\bar{\mathbf{P}}}^{(t)} \bar{\mathbf{Y}}^\#$$

end for

Note that: In the Algorithm 3.1, $\cup_j$ represents the concatenation along the j^{th} dimension, $(i, :)$ is informal MATLAB notations denoting i^{th} row, all columns and $\bar{\mathbf{Y}}^\#$ is the pseudo inverse of $\bar{\mathbf{Y}}$.

3.3.6 Performance Evaluation

Here, the performance of the proposed joint semi-blind equalization and CFO estimation is presented. The assessment is carried out using SER, normalized mean square error of the channel (NMSE), and the NMSE of the CFO estimate.

The transmitted signals are based on a 4-QAM modulation in which $N_r = 4$, $N_t = 2$, $N_s = 100$, $N = 3$, and $K = 64$. An orthogonal pilot sequence is considered throughout the experiments with $N_p = 6$ and the results obtained are the average of 500 Monte Carlo runs, while 4 Iterations are used for the initialization stage, unless otherwise stated. the fixed step size is set to $\mu = 0.01$ for the $\mathbf{W}$, $\mu = 0.001$ for the $\mathbf{f}$ and the channel coefficients are i.i.d. zero-mean with unit power Gaussian distribution. The normalized CFO is randomly chosen for each transmit antenna within the range $[-0.5, 0.5]$, with a slight CFO difference between the users.

The first experiment examines the effect of increasing the number of pilot sequences in the systems on the performance of the proposed method at various SNR levels, as illustrated in Fig. 3.6. As expected, increasing the pilot sequences and SNR results

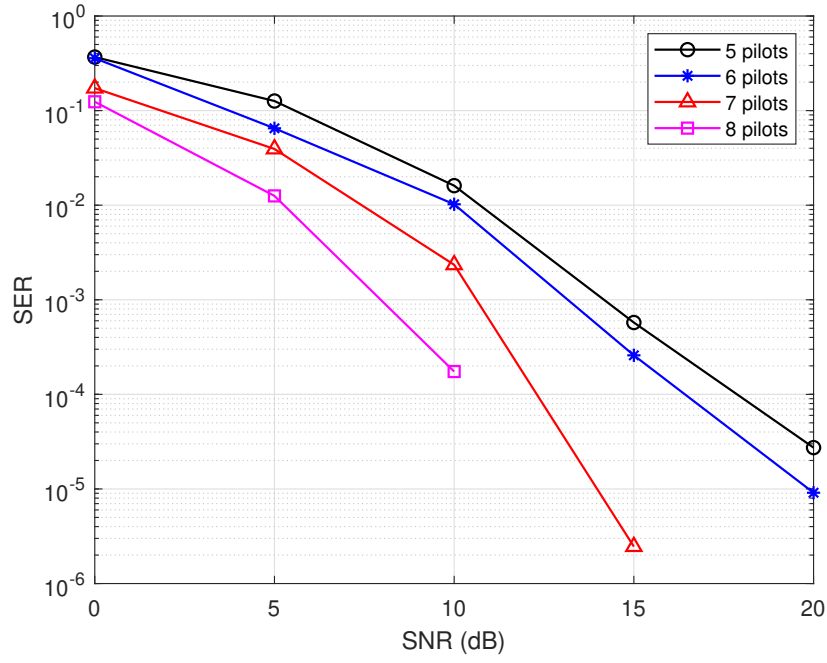


Figure 3.6: Performance evaluation of the proposed algorithm using SER versus SNR for different pilots.

in a more accurate CFO estimate and compensation.

Figure 3.7 presents the comparative evaluation of the proposed algorithm under scenarios of perfect CFO synchronization and Rayleigh channel model (characterized by power delay profile $E\{h_i^* h_j\} = e^{-\beta i} \delta(i - j)$ with $\beta = 1/5$) [58]. In the legend, SB-MM-G represents semi-blind MM with i.i.d. zero mean, unit power, Gaussian distributed channel taps, SB-MM-R denotes semi-blind MM with Rayleigh channel model, and SB-MM CFO = 0 stands for semi-blind MM with perfect CFO synchronization (zero CFO). We can observe that the proposed algorithm achieves a significant performance as compared to the case of perfect CFO synchronization. Note that adding one or two pilots can compensate for the loss in SB-MM-G. However, in the presence of the Rayleigh channel model, the algorithm performance deteriorates due

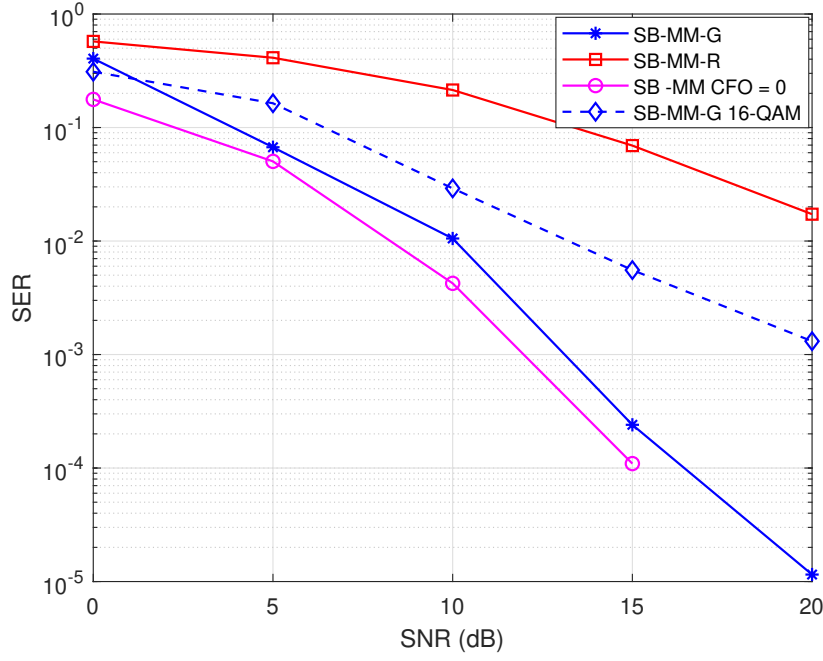


Figure 3.7: SER performance evaluation for the proposed algorithm considering different channel model.

to the severe fading effect of the model.

Figure 3.8 illustrates the channel estimation performance for SB-MM-G, SB-MM-R, and perfect CFO synchronization scenarios using the NMSE. The NMSE is defined as $E[\|\mathbf{h}_{est} - \mathbf{h}\|^2] / \|\mathbf{h}\|^2$, where $\mathbf{h}_{est}$ is the estimated channel and $\mathbf{h}$ is the actual channel. One can notice that the difference between SB-MM-G and the perfect CFO synchronization scenario is relatively small. This demonstrates the robustness of the proposed algorithm. On the other hand, a significant difference between the SB-MM-G and SB-MM-R is observed, which highlights the severe fading effects present in the Rayleigh model.

Figure 3.9 presents the NMSE of the estimated CFO versus the SNR. The NMSE of SB-MM-G and SB-MM-R is compared with the MSE CFO estimator presented in [58]. We can see that the proposed algorithm displays a significant performance in

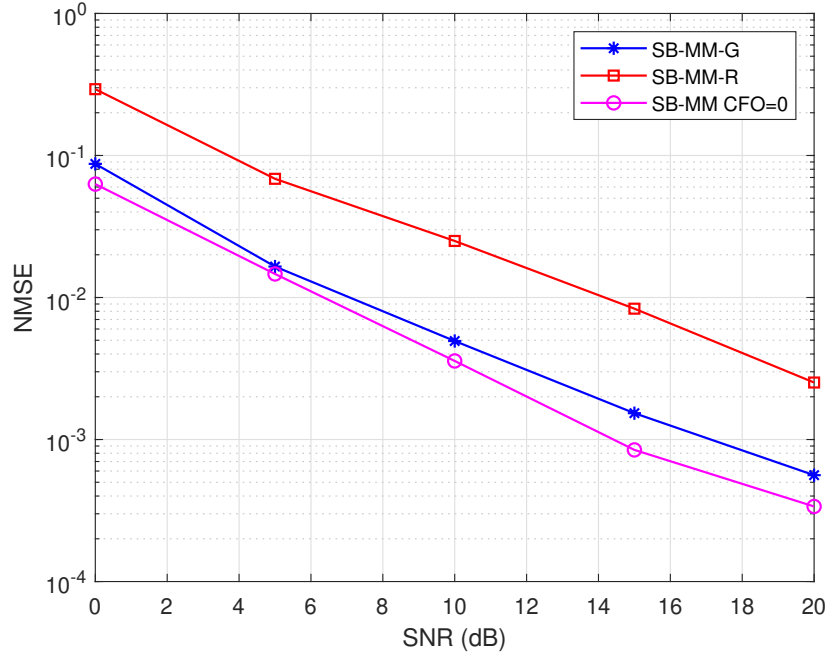


Figure 3.8: Channel NMSE performance evaluation.

terms of CFO estimation accuracy.

3.3.7 Conclusion

This work presented a joint semi-blind MM source separation and CFO estimation for the TDM schemes in uplink MIMO-OFDM communications. A hybrid objective function is designed based on MM and LS criteria for joint source separation and CFO estimation. A full batch-based process is adopted in the estimation and cost function optimization using an iterative alternating gradient descent procedure. In addition, an efficient initialization process is proposed to simplify the algorithm's complexity and improves its convergence. Simulation results demonstrate that the proposed joint semi-blind algorithm shows significant accuracy in data recovery and CFO estimation.

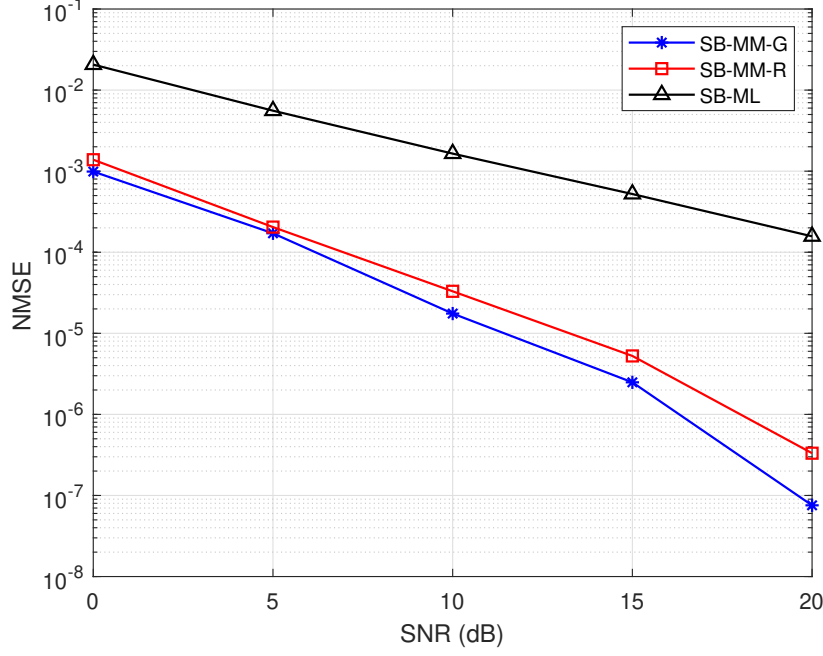


Figure 3.9: NMSE of CFO versus SNR for different channel models compared to the Maximum Likelihood estimator.

3.4 Embedded Pilot Scheme with CFO in MIMO-OFDM

This section presents a semi-blind MM approach for joint source separation and CFO estimation for embedded pilot Scheme in MIMO-OFDM communication systems.

3.4.1 System Model

Consider a MIMO-OFDM system shown in Fig. 3.5 with N_t transmit antennas and $N_r \geq N_t$ receive antennas. For each subcarrier, a known pilot sequence $\mathbf{P}_k \in \mathbb{C}^{N_t \times N_s}$ (N_s being the sample size) is added to the data signals $\mathbf{S}_k \in \mathbb{C}^{N_t \times N_s}$ during transmis-

sion, resulting in a superimposed signal

$$\mathbf{D}_k = \mathbf{S}_k + \mathbf{P}_k, \quad k = 0, \dots, K-1 \quad (3.33)$$

Consequently, the total transmitted power is shared between the data and the pilots, with $\sigma_t^2 = \sigma_s^2 + \sigma_p^2$. The OFDM symbol consists of K samples obtained through K -point Inverse Fast Fourier Transform (IFFT) and preceded by a cyclic prefix (CP) of length $L \geq N$ where N denotes the maximum delay of the multipath channel. Upon removing the CP and performing K -point FFT, the received n^{th} OFDM symbol at the k^{th} subcarrier can be represented as:

$$\mathbf{x}_k(n) = \mathbf{H}_k \mathbf{\Phi}_k(n) \mathbf{d}_k(n) + \boldsymbol{\omega}_k(n), \quad n = 1, \dots, N_s, \quad (3.34)$$

where $\mathbf{x}_k(n) = [x_{1,k}(n), \dots, x_{N_r,k}(n)]^T$, $\mathbf{d}_k(n) = [d_{1,k}(n), \dots, d_{N_t,k}(n)]^T = \mathbf{s}_k(n) + \mathbf{p}_k(n)$, $\boldsymbol{\omega}_k(n)$ is the additive white complex Gaussian noise of variance σ_ω^2 , $\mathbf{\Phi}_k(n) = \text{diag}(\phi_{1,k}(n), \dots, \phi_{N_t,k}(n))$ with $\phi_{i,k}(n) = e^{j2\pi f_i(k+(n-1)(K+L))}$, where f_i is a carrier frequency offset for the i^{th} user, and $\mathbf{H}_k$ is the channel matrix defined as:

$$\mathbf{H}_k = \sum_{l=0}^{N-1} \mathbf{H}(l) e^{-j2\pi \frac{k}{K} l}, \quad (3.35)$$

where $\mathbf{H}(l) \in \mathbb{C}^{N_r \times N_t}$ is the l -th channel coefficient.

Embedding pilot sequences and data signals enables effective bandwidth use, but might encounter interference due to the presence of the pilot sequence. As such, the authors in [8] proposed to add a distortion matrix to the data signal to make the data

orthogonal to the pilot sequence. The suggested distortion matrix can be defined as:

$$\mathbf{\Gamma} = \mathbf{I}_{N_s} - \mathbf{J}, \quad (3.36)$$

where $\mathbf{J} = \frac{N_t}{N_s} \mathbf{1}_{\frac{N_s}{N_t}} \otimes \mathbf{I}_{N_t}$ (it's assumed that $\frac{N_s}{N_t}$ is integer-valued), $\otimes$ is the Kronecker product, and $\mathbf{1}_Q$ denotes the $Q \times Q$ matrix of all ones. The overall transmitted N_s OFDM symbols at the k^{th} subcarrier can be expressed as:

$$\mathbf{D}_k = \mathbf{S}_k \mathbf{\Gamma} + \mathbf{P}_k \quad (3.37)$$

where $\mathbf{S}_k \in \mathbb{C}^{N_t \times N_s}$. The chosen pilot sequence $\mathbf{P}_k$ is designed in such a way to satisfy two criteria [9]: First, it should satisfy the orthogonality condition $\mathbf{P}_k \mathbf{P}_k^H = N_s \sigma_{p_k}^2 \mathbf{I}_{N_t}$. Second, it should be orthogonal to the distortion matrix $\mathbf{\Gamma}$, as indicated by $\mathbf{\Gamma} \mathbf{P}_k^H = 0$. According to [8], a pilot sequence $\mathbf{P}$ satisfying these two conditions can be designed as:

$$p_i(n) = \sigma_p e^{j2\pi i n / N_t}, \quad (3.38)$$

where $i = 0, \dots, N_t - 1$, and $n = 0, \dots, N_s - 1$. However, the latter design is primarily intended for single-carrier systems. In multi-carrier systems, the orthogonality condition for the selected pilots has to be maintained across all subcarriers, but different pilots should be used at different subcarriers. To design these pilots effectively, the pilot sequence in (3.38) is rotated for each subcarrier to mitigate the Peak-to-Average Power Ratio (PAPR) [66], i.e. $\mathbf{P}_k = \mathbf{R}_k \mathbf{P}$, where $\mathbf{R}_k$ is a given diagonal rotation matrix. In this work, this rotation is obtained by conducting numerous trials with

randomly chosen rotations. Among these trials, the one that results in the minimum PAPR for the pilot has been selected.

Afterward, by utilizing an $N_t \times N_r$ separation (deconvolution) filter $\mathbf{Q}(z)$ on the received signals, all the transmitted signals can be recovered effectively. The separating filter is derived to satisfy the equation $\mathbf{Q}(z)\mathbf{H}(z) = \mathbf{I}_{N_t}$ for all z . Furthermore, it's assumed that the condition for the existence of inverse of $\mathbf{H}(z)$ is satisfied and $\mathbf{H}(z)$ is irreducible [67]. The separation matrix for the k -th subcarrier is expressed as:

$$\mathbf{Q}_k = \sum_{l=0}^{N_q-1} \mathbf{Q}(l) e^{-j2\pi \frac{k}{K} l}. \quad (3.39)$$

N_q being the deconvolution filter length (chosen in this paper as $N_q = N$). Therefore, the recovered signal at the k -th subcarrier is:

$$\begin{aligned} \mathbf{y}_k(n) &= \mathbf{\Phi}_k^*(n) \mathbf{Q}_k \mathbf{x}_k(n) = \mathbf{\Phi}_k^*(n) \mathbf{Q} \bar{\mathbf{V}}_k \mathbf{x}_k(n) \\ &= \mathbf{\Phi}_k^*(n) \mathbf{z}_k(n) \end{aligned} \quad (3.40)$$

where $\mathbf{z}_k(n) = \mathbf{Q}_k \mathbf{x}_k(n)$, $\mathbf{Z}_k = [\mathbf{z}_k(0), \dots, \mathbf{z}_k(N_s - 1)]$, $()^*$ denotes the complex conjugate, $\mathbf{Q} = [\mathbf{Q}(0), \mathbf{Q}(1), \dots, \mathbf{Q}(N_q - 1)]$, $\bar{\mathbf{V}}_k = \mathbf{v}_k \otimes \mathbf{I}_{N_r} \in \mathbb{C}^{N_q N_r \times N_r}$, and $\mathbf{v}_k = [1, e^{j2\pi \frac{k}{K}}, \dots, e^{j2\pi \frac{k}{K} (N_q - 1)}]^H$. In fact, instead of estimating matrices $\mathbf{Q}_k$, $k = 0, \dots, K - 1$, one is required to estimate one matrix $\mathbf{Q}$, common to all sub-carriers, as stated in equation (3.40). Additionally, in the ST scheme, both pilots and data have the same size, i.e., $N_s = N_p = N_d$. In the block-pilot arrangement, the N_p pilot symbols are transmitted at the beginning of the frame, followed by N_d data symbols,

resulting in a total of $N_s = N_p + N_d$ transmitted symbols.

3.4.2 Semi-blind Source Separation and CFO Estimation

This section describes the proposed semi-blind source separation and CFO estimation for the ST scheme. The jointly hybrid semi-blind cost function $J_{SB}(\mathbf{Q}, \mathbf{f})$ is expressed as:

$$J_{SB}(\mathbf{Q}, \mathbf{f}) = (1 - \alpha)J_{LS}(\mathbf{Q}, \mathbf{f}) + \alpha J_{MM}(\mathbf{Q}, \mathbf{f}), \quad (3.41)$$

where $\mathbf{f} = [f_1, \dots, f_{N_t}]$, $J_{MM}(\mathbf{Q}, \mathbf{f})$ is a MM-based blind cost function, $J_{LS}(\mathbf{Q}, \mathbf{f})$ is a LS cost function, and α is a weighting factor, with $\alpha \in [0, 1]$. This factor determines the weight assigned to the blind (data) and pilot-based parts of the hybrid cost function. To solve (3.41), we use the alternating gradient descent optimization approach. This method involves solving for one variable iteratively while keeping the other variable constant, alternating between the two, as governed by the following recursion:

$$\mathbf{Q}_{l+1}(\mathbf{Q}, \mathbf{f}) = \mathbf{Q}_l(\mathbf{Q}, \mathbf{f}) - \mu \mathbf{g}_l, \quad l = 0, 1, \dots, \quad (3.42)$$

with an iteration stopping criterion defined as[52]:

$$\frac{\|\mathbf{g}_l\|}{\|\mathbf{Q}_l\|} < \frac{0.1}{\sqrt{N_s}}, \quad (3.43)$$

where $\mathbf{g}_l$ is the gradient of the cost function w.r.t. the parameter under consideration at l -th iteration and $\mu > 0$ is a small real-valued scalar that determines the convergence rate of the algorithm, known as step size. $\mathbf{Q}_l$ and $\mathbf{Q}_{l+1}$ are the old and the updated

value of either the separation matrix $\mathbf{Q}$ or CFO vector $\mathbf{f}$, respectively.

3.4.3 Least Squares (Pilot-based) Formulation

Taking advantage of the pilot-data orthogonality and the properties of the orthogonal projectors $\mathbf{\Gamma}$ and $\mathbf{J}$, one can separate the two terms according to:

$$\begin{aligned}\mathbf{D}_k \mathbf{\Gamma} &= \mathbf{S}_k \mathbf{\Gamma}^2 = \mathbf{S}_k \mathbf{\Gamma} \\ \mathbf{D}_k \mathbf{J} &= \mathbf{P}_k \mathbf{J} = \mathbf{P}_k\end{aligned}\tag{3.44}$$

Hence, the cost function for the pilot-based technique mentioned in (3.41) based on a LS criterion, can be defined as:

$$J_{LS}(\mathbf{Q}, \mathbf{f}) = \sum_{k=0}^{K-1} \|\bar{\mathbf{Z}}_k - \mathbf{P}_k\|^2\tag{3.45}$$

where $\bar{\mathbf{Z}}_k = \mathbf{Y}_k \mathbf{J} = (\mathbf{\Phi}_k^* \odot \mathbf{Z}_k) \mathbf{J}$ ($\odot$ denotes the Hadamard (element-wise) product) with

$$\mathbf{\Phi}_k = \begin{bmatrix} \phi_{1,k}(0) & \cdots & \phi_{1,k}(N_s - 1) \\ \vdots & & \vdots \\ \phi_{N_t,k}(0) & \cdots & \phi_{N_t,k}(N_s - 1) \end{bmatrix}.$$

To find the minimizer of (3.45), we consider the alternating optimization method. The gradient of (3.45) with respect to $\mathbf{Q}$ and $\mathbf{f}$ for the users can be expressed, respectively, as:

$$\nabla J_{LS}(\mathbf{Q}) = \sum_k [(\bar{\mathbf{Z}}_k - \mathbf{P}_k) \odot \mathbf{\Phi}_k] (\bar{\mathbf{V}}_k \mathbf{X}_k)^H\tag{3.46}$$

and

$$\nabla J_{LS}(\mathbf{f}) = \sum_k \Im \left([\mathbf{Y}_k^* \odot (\bar{\mathbf{Z}}_k - \mathbf{P}_k)] \boldsymbol{\alpha}_k \right) \quad (3.47)$$

where $\boldsymbol{\alpha}_k = [\alpha_{k,0}, \dots, \alpha_{k,N_s-1}]^T$ with $\alpha_{k,n} = 4\pi(k + (n-1)(K+L))$, and $\Re(z)$ (resp. $\Im(z)$) stands for the real part (resp. the imaginary part) of z .

3.4.4 Multi-Modulus (MM) Formulation

The blind approach utilized in this study aims to recover both the source signal (Here, we consider square QAM-modulated input signals) and CFO by employing the MM criterion. The MM cost function is defined as follows:

$$J_{MM}(\mathbf{Q}, \mathbf{f}) = \sum_{k=0}^{K-1} [\|\bar{\mathbf{Y}}_{k,R} \odot \bar{\mathbf{Y}}_{k,R} - R_R\|^2 + \|\bar{\mathbf{Y}}_{k,I} \odot \bar{\mathbf{Y}}_{k,I} - R_I\|^2] \quad (3.48)$$

where

$$\bar{\mathbf{Y}}_{k,R} = \Re[\mathbf{Y}_k \boldsymbol{\Gamma}] \quad \text{and} \quad \bar{\mathbf{Y}}_{k,I} = \Im[\mathbf{Y}_k \boldsymbol{\Gamma}] \quad (3.49)$$

The dispersion constants are defined as $R_R = E[s_R^4(n)]/E[s_R^2(n)]$ and $R_I = E[s_I^4(n)]/E[s_I^2(n)]$ ($s(n)$ refers to the input QAM-modulated symbol).

After straightforward derivations, the gradient of (3.48) w.r.t. $\mathbf{Q}$ is expressed as:

$$\nabla J_{MM}(\mathbf{Q}) = 2 \sum_k ((\mathbf{B}_{k,R} + j\mathbf{B}_{k,I})\boldsymbol{\Gamma} \odot \boldsymbol{\Phi}_k) (\bar{\mathbf{V}}_k \mathbf{X}_k)^H \quad (3.50)$$

where $\mathbf{B}_{k,R} = (\bar{\mathbf{Y}}_{k,R} \odot \bar{\mathbf{Y}}_{k,R} - R_R) \odot \bar{\mathbf{Y}}_{k,R}$ and $\mathbf{B}_{k,I} = (\bar{\mathbf{Y}}_{k,I} \odot \bar{\mathbf{Y}}_{k,I} - R_I) \odot \bar{\mathbf{Y}}_{k,I}$. On

the other hand, the gradient of (3.48) w.r.t. $\mathbf{f}$ is expressed as:

$$\begin{aligned} \nabla J_{MM}(\mathbf{f}) = 2 \sum_k \text{diag} \left(\Im[\mathbf{1}_{N_t} \boldsymbol{\alpha}_k^T \odot \boldsymbol{\Phi}_k^* \odot \mathbf{Z}_k] \boldsymbol{\Gamma} \mathbf{B}_{k,R}^T \right) - \text{diag} \left(\Re[\mathbf{1}_{N_t} \boldsymbol{\alpha}_k^T \odot \right. \\ \left. \boldsymbol{\Phi}_k^* \odot \mathbf{Z}_k] \boldsymbol{\Gamma} \mathbf{B}_{k,I}^T \right) \end{aligned} \quad (3.51)$$

where $\mathbf{1}_{N_t}$ is the $N_t \times 1$ all-ones vector and $\text{diag}(\mathbf{M})$ is the vector formed by the diagonal entries of matrix $\mathbf{M}$.

Note that the proof of minimization of (3.46), (3.47), (3.50), and (3.50) is given in appendix C.1

3.4.5 Optimal Step Size

The accuracy and convergence speed of the gradient descent algorithm heavily depends on the chosen step size μ . Therefore, selecting the optimal μ would substantially improve the convergence of (3.42). Consequently, determining the optimal step size, at the l -th iteration, is viewed as an optimization problem, formulated as follows:

$$\mu_{opt} = \arg \min_{\mu} J_{SB}(\mathbf{Q}_{l+1}), \quad (3.52)$$

where $J_{SB}(\mathbf{Q}_{l+1}) = J_{SB}(\mathbf{Q}_l - \mu \nabla J_{SB}(\mathbf{Q}_l))$ is a 4-th order polynomial function in the variable μ . Hence, μ_{opt} is the real-valued root of the derivative of $J_{SB}(\mathbf{Q}_{l+1})$ w.r.t. μ (denoted J'_{SB}) which minimizes $J_{SB}(\mathbf{Q}_{l+1})$.

Note that: In the same way, the optimal step size for the up-dating of the CFO $\mathbf{f}$ is

obtained by solving $\mu_{opt} = \arg \min_{\mu} J_{SB}(\mathbf{f}_{l+1})$.

The expressions of the coefficients of the third order polynomials $J'_{SB}(\mathbf{Q}_{l+1}) = a_0 + a_1\mu + a_2\mu^2 + a_3\mu^3$ are given in the appendix C.2.

3.5 Initialization Process

This section describes the process for initializing the separation matrix $\mathbf{Q}$ and CFO in our proposed method. The separation matrix $\mathbf{Q}$ is initialized using the conventional LS technique, which assumes perfect CFO synchronization (i.e., no CFO in the system, Φ is an identity matrix at the initial setting). The transmitted pilots are approximately recovered for all subcarriers $\bar{\mathbf{Z}} \in \mathbb{C}^{N_t \times N_s \times K}$ using the initial $\mathbf{Q}$. The recovered pilot signals $\bar{\mathbf{Z}}$ are rearranged into a matrix $\mathbf{A}$ of size $N_t \times KN_s$. Similarly, the transmitted pilot sequences for all subcarriers $\bar{\mathbf{P}} \in \mathbb{C}^{N_t \times N_s \times K}$ are rearranged into a matrix $\mathbf{B}$ of size $N_t \times KN_s$.

To estimate the CFO for the i^{th} antenna, the conjugate of the i^{th} row of $\mathbf{B}$ is multiplied element-wise by the i^{th} row of $\mathbf{A}$, creating a vector $\mathbf{u}$. The M length FFT is utilized to generate the frequency component of $\mathbf{u}$; subsequently, the amplitude of each frequency component of $\mathbf{u}$ is determined by calculating the absolute value of $\mathbf{u}$. The index exhibiting the highest amplitude signifies the location of the estimated CFO. The size M of the FFT must be sufficiently large to prevent erroneous CFO estimation. This technique is reiterated to estimate all the CFO of the users. A matrix $\bar{\Phi}$ containing all estimated CFOs is constructed and multiplied element-wise with the pilot sequences $\mathbf{P}$ for a subcarrier and then, repeated over all subcarriers to generate

a new pilot sequence $\bar{\mathbf{P}}$ with the estimated CFOs.

The new separation matrix is created using $\bar{\mathbf{P}}$, then estimating CFO. The procedure is repeated for a few numbers of iterations.

The initialization process is summarized in **Algorithm 3.2**.

Algorithm 3.2 Initialization based on Least Squares (LS)

Initialize CFO: $f_i^{(0)} = 0 \quad i = 0, \dots, N_t - 1, \quad \Phi_k^{(0)}(n) = \mathbf{I}_{N_t}$

$\mathbf{P} = [\mathbf{P}_0, \cup_3, \dots, \cup_3, \mathbf{P}_{K-1}] \in \mathbb{C}^{N_t \times N_s \times K}$

$\mathbf{P}^{(0)} = \text{reshape}(\mathbf{P}, N_t, KN_s) \in \mathbb{C}^{N_t \times KN_s}; \quad \mathbf{B}_p^{(0)} = \mathbf{P}^{(0)}$

$\mathcal{X} = [\bar{\mathbf{V}}_0 \mathbf{X}_0, \cup_3, \dots, \cup_3, \bar{\mathbf{V}}_{K-1} \mathbf{X}_{K-1}] \in \mathbb{C}^{N_r N_q \times N_s \times K}$

$\bar{\mathcal{X}} = \text{reshape}(\mathcal{X}, N_r N_q, KN_s) \in \mathbb{C}^{N_r N_q \times KN_s}$

Initialize equalizer: $\mathbf{Q}^{(0)} = \mathbf{P}^{(0)} \bar{\mathcal{X}}^\#$

where $\bar{\mathcal{X}}^\# = (\bar{\mathcal{X}} \bar{\mathcal{X}}^H)^{-1} \bar{\mathcal{X}}$,

Initialize: $t_{\max}$

for $t = 1$ to $t_{\max}$ **do**

$\mathbf{Z}_k^{(t-1)} = \mathbf{Q}^{(t-1)} \bar{\mathbf{V}}_k \mathbf{X}_k \in \mathbb{C}^{N_t \times N_s}$

$\bar{\mathbf{Z}}^{(t-1)} = [\mathbf{Z}_0^{(t-1)}, \cup_3, \dots, \cup_3, \mathbf{Z}_{K-1}^{(t-1)}] \in \mathbb{C}^{N_t \times N_s \times K}$

$\mathbf{A}^{(t-1)} = \text{reshape}(\bar{\mathbf{Z}}^{(t-1)}, N_t, KN_s) \in \mathbb{C}^{N_t \times KN_s}$

for $i = 1$ to N_t

$\mathbf{a}_i^{(t-1)} = \mathbf{A}^{(t-1)}(i, :); \quad \mathbf{b}_i^{(t-1)} = \mathbf{B}_p^{(t-1)}(i, :)$

$\mathbf{u} = \text{conj}(\mathbf{b}_i^{(t-1)}) \odot \mathbf{a}_i^{(t-1)}$

$f_i^{(t)} = \arg \max_{f_i} |\text{FFT}_M(\mathbf{u})|$

end for

$\hat{\phi}_{i,k}(n) = e^{j2\pi f_i^{(t)}(k+(n-1)(K+L))}$

$$\begin{aligned}
\bar{\Phi}_k^{(t)}(n) &= \text{diag}(\hat{\phi}_{1,k}(n), \dots, \hat{\phi}_{N_t,k}(n)) \\
\bar{\mathbf{p}}_k^{(t)}(n) &= \bar{\Phi}_k^{(t)}(n) \mathbf{p}_k^{(t-1)}(n), \quad n = 0, \dots, N_s - 1 \\
\bar{\mathbf{P}}^{(t)} &= [\bar{\mathbf{P}}_0^{(t)}, \cup_3, \dots, \cup_3, \bar{\mathbf{P}}_{K-1}^{(t)}] \in \mathbb{C}^{N_t \times N_s \times K} \\
\bar{\bar{\mathbf{P}}}^{(t)} &= \text{reshape}(\bar{\mathbf{P}}^{(t)}, N_t, KN_s) \in \mathbb{C}^{N_t \times KN_s} \\
\mathbf{B}_p^{(t)} &= \bar{\bar{\mathbf{P}}}^{(t)} \\
\mathbf{Q}^{(t)} &= \bar{\bar{\mathbf{P}}}^{(t)} \bar{\mathcal{X}}^\#
\end{aligned}$$

end for

Note that: In the Algorithm 3.2, $\cup_j$ represents the concatenation along the j^{th} dimension, $(i, :)$ is informal MATLAB notations denoting i^{th} row, all columns and $\bar{\mathcal{X}}^\#$ is the pseudo inverse of $\bar{\mathcal{X}}$.

3.5.1 Performance Evaluation

Here presents the performance evaluation of the proposed joint semi-blind CFO estimation and symbol detection for the ST scheme. The performance of the proposed ST scheme is compared with that of the BP scheme using the SER, NMSE, and bandwidth efficiency. The transmitted signals are based on a 4-QAM modulation in which $N_r = 4$, $N_t = 2$, $N_s = 100$, $N = 4$, and $K = 64$. The results obtained are the average of 1000 Monte Carlo runs. The channel coefficients are an i.i.d. zero-mean Gaussian distribution with unit power, and the fixed step size is set to $\mu = 0.01$ for $\mathbf{Q}$ and $\mu = 0.001$ for $\mathbf{f}$. The normalized CFO is randomly chosen for each transmit antenna within the range $[-0.5, 0.5]$, with a slight difference between users. The orthogonal pilot sequences are considered throughout the experiments, and the size of pilots in

the ST scheme is the same as the data, i.e., $N_p = N_s$, while in the BP scheme, $N_p = 7$. The initialization process stated in Algorithm 1 is adopted using 4 iterations to initialize the separation matrix and CFO in the estimation process. In the legend, the BP stands for block-pilot arrangement, EP for the embedded pilot, DD-EP stands for the data-dependent embedded pilot, and DD-EP-OSS refers to the data-dependent embedded pilot with an optimal step size.

First, Fig. 3.10 presents the SER versus different power allocated to the embedded pilots sequence (σ_p^2) for an SNR = 10 dB. We can observe that DD-EP-OSS outperforms DD-EP, and both improve significantly as the value of σ_p^2 increases until it reaches an optimal value of $\sigma_p^2 = 0.15$. However, their performance deteriorates afterward. This determines the optimal power allocated to the ST scheme, resulting in a minimum interference between the data and the superimposed pilot sequence for

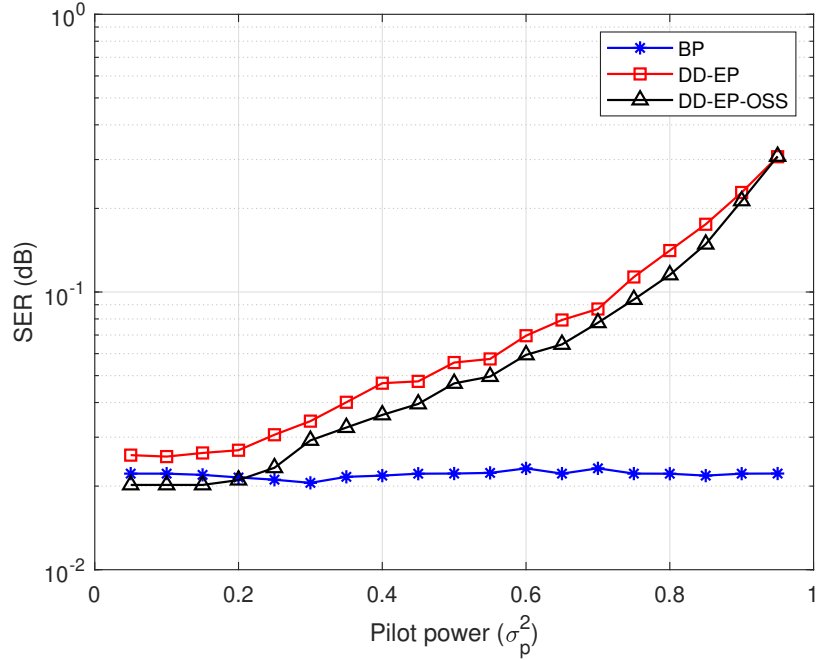


Figure 3.10: SER versus pilot symbols power, SNR = 10 dB, $N_s = 100$.

the SNR values considered. Additionally, with the optimal step size and good choice of σ_p^2 , the proposed DD-EP scheme outperforms that of the BP scheme. Remember that in the DD-EP scheme, the pilots and data are designed to be orthogonal to each other. This means that the presence of pilot and data within the same bandwidth has minimal or no interference effect on one another. In contrast, in the EP scheme, the data and the pilots experience a form of interference that causes performance deterioration. Furthermore, in both DD-EP and EP scheme, the pilots and the data share the total transmitted power i.e., $\sigma_t^2 = \sigma_s^2 + \sigma_p^2$, this means as σ_p^2 increases the σ_s^2 decreases and vice-versa. However, in the BP scheme, both data and pilots have the same power, i.e., $\sigma_t^2 = \sigma_s^2 = \sigma_p^2$.

Second, the effect of mixing factor α on the performance of the proposed semi-blind MM-based approach for the ST scheme and the BP scheme is investigated. The results

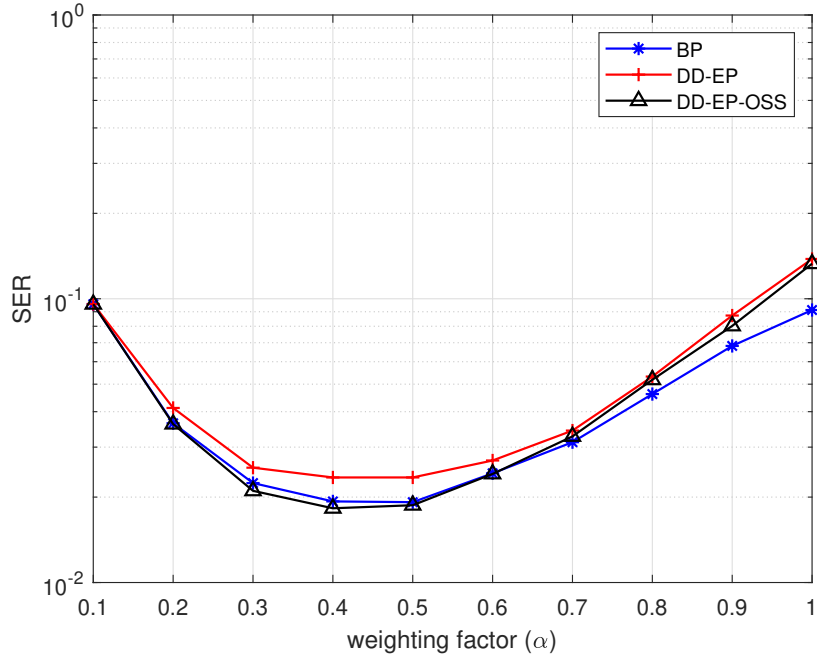


Figure 3.11: SER versus α , for an SNR = 10 dB.

of this study are reported in Fig. 3.11. We can see that with the ad-hoc fine-tuning of the parameter α without using a complex technique or algorithm, a close-to-optimal value of α that gives excellent performance is within the interval $[0.3, 0.6]$. Therefore, in the ensuing, α will be set to 0.35 unless otherwise stated.

Furthermore, the influence of superimposing pilot and data on the throughput of the system is investigated, which is defined mathematically as:

$$R_{\text{Throughput}} = \lambda \cdot \frac{N_s}{N_s + N_p} \cdot (1 - \text{SER}), \quad (3.53)$$

where $\lambda = \log_2(M)$ is the number of transmitted bits per symbol in M -ary levels.

Note that $\frac{N_s}{N_s + N_p}$ is 1 for the superimposed case.

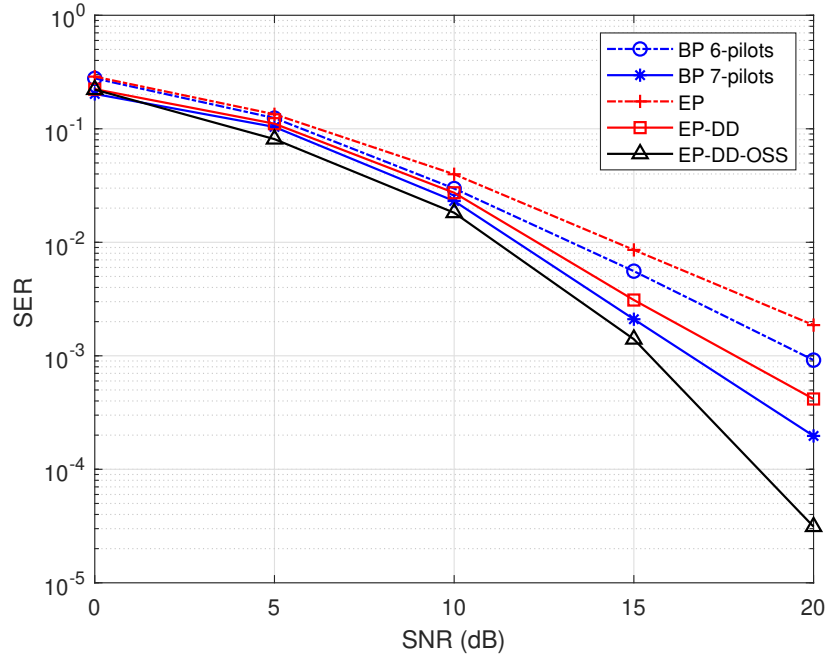


Figure 3.12: SER performance evaluation of the proposed EP-DD, EP-DD-OSS compared to BP scheme.

Third, Fig. 3.12 illustrates the performance comparison of the SER against the

SNR for the proposed semi-blind MM-based approach for the ST scheme and the BP scheme. We can observe that the proposed semi-blind MM approach exhibits an excellent SER performance for the EP. However, for anything above 10 dB SNR, the DD-EP scheme performs better than the BP scheme with 6 pilots. Furthermore, the BP scheme needs more than 7 pilots to outperform the DD-EP with optimal step size, i.e., the DD-EP-OSS method. It is crucial to highlight here that, apart from the improvement gain in the SER in the DD-EP-OSS, the TDM method needs additional bandwidth, which is not the case for the proposed ST scheme.

Next, Fig. 3.13 demonstrates the spectral efficiency comparison for the BP and the ST scheme based on the SER. The spectral efficiency is computed using the throughput defined in (3.53). It can be seen that the throughput of the ST scheme is higher than

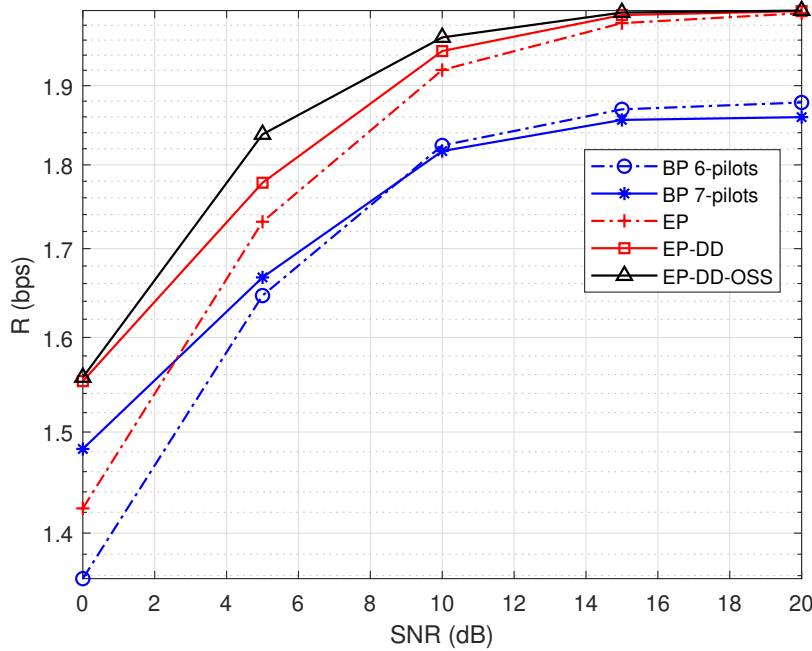


Figure 3.13: Throughput $R(\text{bps})$ performance evaluation of the proposed EP-DD, EP-DD-OSS compared to the BP scheme.

that of the BP scheme. This is because, for the BP scheme throughput, $\frac{N_s}{N_s+N_p} < 1$, where for the ST scheme throughput, $\frac{N_s}{N_s+N_p} = 1$. In addition, improvement in the spectral efficiency is achieved using the DD-EP compared to the EP and BP schemes. Furthermore, a significant increase in the spectral efficiency is observed using a DD-EP-OSS scenario. This proves that the spectral efficiency of the MIMO-OFDM systems can be enhanced by superimposing the pilot symbols and the data

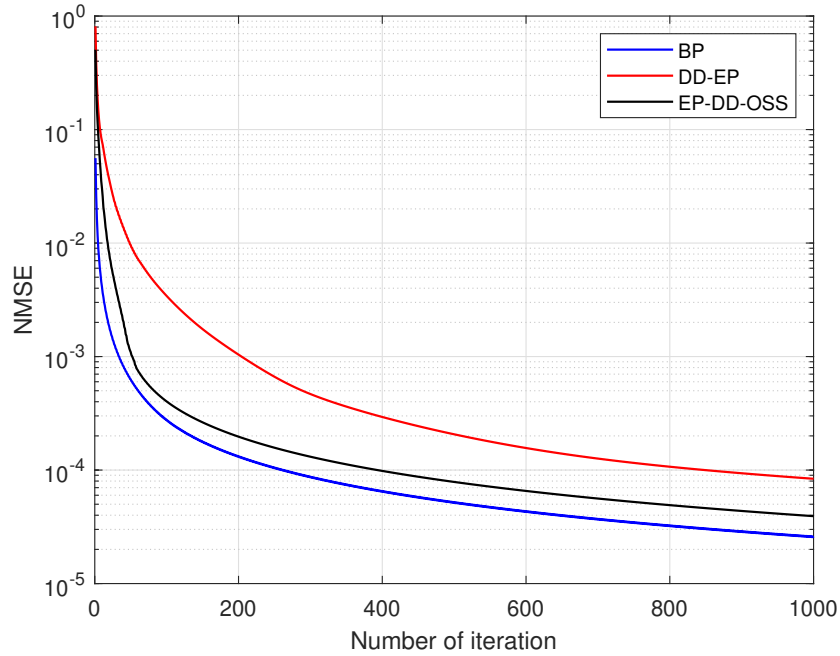


Figure 3.14: NMSE versus Number of iterations, for the proposed EP-DD, EP- DD-OSS compared to the BP scheme at SNR = 10 dB.

during the transmission stage.

Next, Fig. 3.14 illustrates the normalized mean square error (NMSE) performance, defined as $\text{NMSE} = \frac{1}{N_{iter}} \sum_{i=1}^{N_{iter}} \frac{\|\hat{\mathbf{d}}_i - \mathbf{d}\|^2}{\|\mathbf{d}\|^2}$, where $\hat{\mathbf{d}}_{iter}$ is the estimated symbols, $\mathbf{d}$ is the transmitted symbols and N_{iter} is the number of iterations for an SNR of 10 dB. It can be depicted that the BP scheme converges faster than the ST scheme. However, the

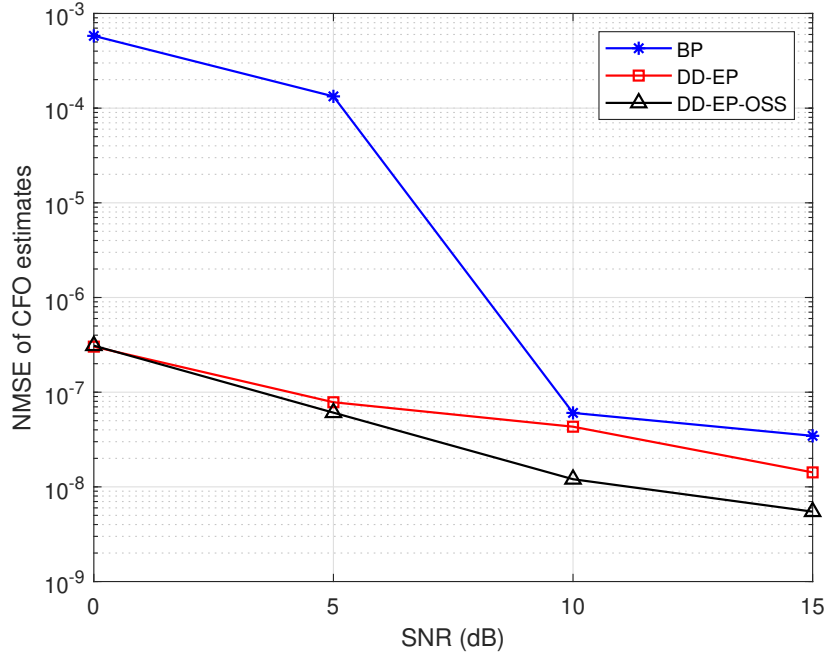


Figure 3.15: NMSE of the CFO performance for the DD-EP, DD-EP-OSS compared to the BP scheme.

convergence rate of the ST scheme improves with the optimal step size.

Again, Fig. 3.15 presents the NMSE versus different SNR values of the CFO. The NMSE in this experiment is defined as: $\text{NMSE} = \frac{1}{N_{iter}} \sum_{i=1}^{N_{iter}} \frac{\|\hat{\phi}_i - \phi\|^2}{\|\phi\|^2}$, where $\hat{\phi}$ is the estimated CFO and ϕ is the exact CFO. It can be observed that the proposed semi-blind MM algorithm for the CFO estimation shows good performance for the DD-EP scheme. We can observe the robustness of the proposed algorithm for the DD-EP and DD-EP-OSS schemes compared to the BP scheme, regardless of the SNR value.

Finally, Fig. 3.16 depicts the performance evaluation for a slowly varying channel and CFO over each OFDM symbol for both the BP and ST schemes. The variation in the CFO is adapted as in [68], whereas the slow varying channel is modeled as a

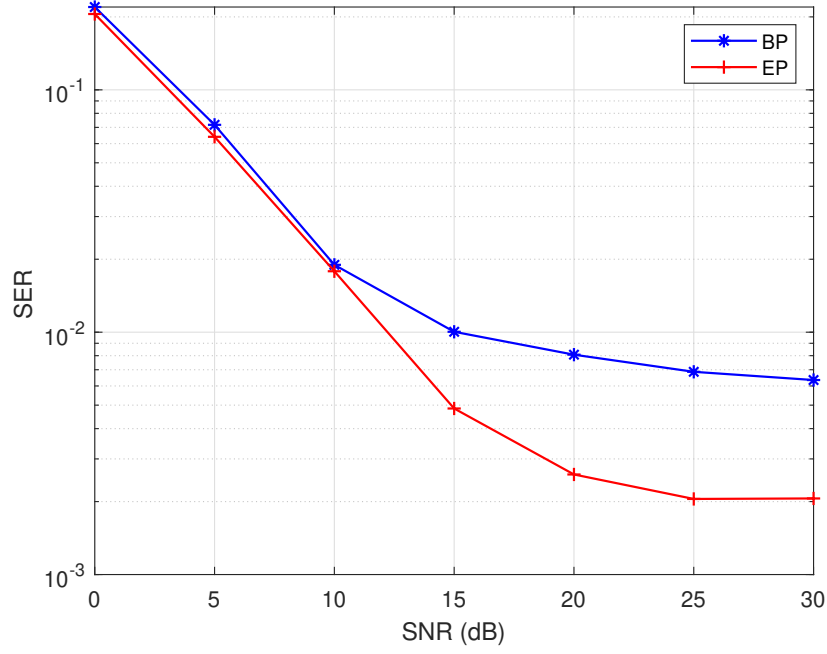


Figure 3.16: SER versus SNR; slow varying channel and CFO per each OFDM symbol.

specular channel defined as:

$$\mathbf{h}(t) = \sum_{l=1}^L \rho_l \mathbf{a}(\theta_l(t)) g(t - \tau), \quad (3.54)$$

where $g(t - \tau)$ is the raised cosine function, ρ_l is the path loss component with Gaussian distribution $\rho_l \sim \mathcal{C}(0, 1)$, and $\mathbf{a}(\theta_l(t))$ is the steering vector with angle of arrival $\theta_l(t)$ uniformly distributed in $[-\pi, \pi]$.

This experiment adopts initial setups as stated with $\alpha_p^2 = 0.15$, $\mu = 10^{-4}$, $\alpha = 0.5$, and hence, a symbol-by-symbol stochastic gradient approach is used to optimize the proposed algorithm. We can see that the proposed algorithm shows a distinct performance in the ST scheme. This is mainly because it is fully Semi-blind due to the presence of both pilot and data throughout the transmission and reception. On

the other hand, in a BP scheme, 80 OFDM symbols are received per frame, where the first 6 symbols are pilots, followed by 74 data symbols. In the equalization stage and CFO estimation, only the pilot-based approach can be used at the beginning of each frame due to the absence of data, followed by the MM approach during the reception of the remaining data symbols. This means that at the beginning of the frame, only the LS approach is used, while later, the MM approach is used at the end of the frame corresponding to $\alpha = 0$ and $\alpha = 1$ in (3.41), respectively.

3.5.2 Conclusion

This work presented a semi-blind MM source separation and CFO estimation for the ST schemes in MIMO-OFDM communications. A jointly hybrid cost function is devised based on MM and LS criteria for source separation and CFO estimation. A full batch gradient descent optimization process is utilized for the source separation and CFO estimation. In addition, a step size optimization method is introduced to enhance the accuracy and convergence speed of the proposed algorithm. Moreover, a slowly varying channel and CFO per each OFDM symbol is considered, where a stochastic gradient is used for optimization. Simulation results reveal that significant spectral efficiency is achieved by superimposing pilots and data during transmission, and the proposed semi-blind algorithm shows good performance accuracy in the equalization and estimation process with a high convergence rate. In addition, the proposed algorithm exhibits accuracy in data recovery and CFO estimation in the presence of slow variation of both channel and CFO.

CHAPTER 4

CRAMER-RAO BOUNDS FOR SEMI-BLIND APPROACH USING EMBEDDED PILOT FOR MIMO-OFDM SYSTEMS

In this chapter, we present the performance evaluation of a semi-blind algorithm using a superimposed pilot scheme. Channel estimation is necessary in most wireless communication systems to ensure effective channel estimation and equalization. This is achieved using a dedicated pilot sequence inserted in the system, either in time-division multiplexed (i.e., a block pilot arrangement scheme), which reduces the bandwidth or the spectral efficiency of the system, or an embedded pilot scheme that preserves the bandwidth or improves the spectral efficiency. The primary purpose of the work is to devise an efficient tool for performance-bound analysis to evaluate

the efficacy of semi-blind channel estimation techniques in the case of an embedded pilot in MIMO-OFDM systems. We derive the CRB for a semi-blind approach that utilizes embedded pilots. Moreover, different data models are used to evaluate the performance of the derived CRB and compare it with that of the CRB in pilot-based and block-pilot arrangements. Furthermore, the results demonstrate that the derived CRB for the embedded pilot achieves excellent performance, comparable to the CRB of the block-pilot arrangement.

4.1 Introduction

MIMO technology combined with OFDM technique, termed as MIMO-OFDM systems, stands as a favorable technology for beyond 5G communications and is widely used in LTE, LTE-A, and 802.11n wireless networks [69], [70]. Certainly, using MIMO-OFDM technology in wireless communications increases communications reliability and channel capacity. Specifically, authors in [46] have shown that the system can significantly enhance the data rate, link reliability, throughput and power efficiency with substantial interference cancellation.

The design arrangements and insertion pattern of the pilot sequence in wireless systems is a long-standing issue that numerous studies have examined [71], [70], [8], [72]. Authors in [73] considered an optimal pilot sequence for the pilot-based estimator that provides excellent performance, whereas [52], [74], [75] considered BP arrangement for SB channel estimation. In [9], [8], the authors utilize an embedded pilot (EP) design to improve channel estimation and minimize BER. However, the performance

gain of the aforementioned channel estimators has been investigated using the well-known efficient lower bound, i.e., CRB. The authors in [76] provide a derivation of the CRB for training sequence, blind, and Semi-blind approaches, applicable to both deterministic and Gaussian models. This work is recognized as the first to establish the CRB for evaluating SB estimator performance. The authors in [71] derived CRB expressions for both SISO and MIMO systems for a Semi-blind estimator to optimize pilot design and insertion. Furthermore, the authors in [77] introduced a CRB as a function of the channel to assess the imperfect channel estimation on the achievable rate of the MIMO system. Meanwhile, [78], a stochastic CRB is derived to evaluate SB channel estimation for both the time-division multiplexed (TDM) pilot and EP scheme in a MIMO system. Moreover, the authors in [70] utilize the CRB to compare the minimum achievable error bounds for both pilot-based and SB channel estimators in MIMO-OFDM systems. Their study explores various data models and pilot arrangements to determine the minimum pilot sequences necessary for an effective semi-blind approach.

This work evaluates the effectiveness of semi-blind channel estimation techniques using the EP in MIMO-OFDM systems. We derive the first CRB expression for a Semi-blind channel estimation approach utilizing the EP scheme for MIMO-OFDM systems. The derived CRB is then compared to the CRBs of pilot-based and SB channel estimation techniques employing BP arrangements using Gaussian and finite alphabet sequence models. The results reveal that the derived CRB for the EP demonstrates excellent performance, comparable to the CRB of the BP arrangement presented in [70].

This chapter is structured as follows: the system model, which includes pilot sequence design, is presented in Section 4.2. Section 4.3 presents general CRB formulations. Section 4.4 presents CRB for SB channel estimation using EP for various data models. Section 4.5 contains a performance evaluation of the derived CRB expressions. Lastly, section 4.6 presented the conclusion.

4.2 System Model

Consider a MIMO-OFDM system shown in Fig. 3.5 with N_t transmit antennas and N_r receive antennas, where $N_r > N_t$. The transmitted signal is the superimposed pilot and data, which consist of K point samples obtained by the K -point Inverse Fast Fourier Transform (IFFT) and then extended in its front with L length CP. The size of the CP is assumed to be greater than or equal to a maximum delay of the multipath channel N , i.e., ($N \leq L$). The received OFDM symbols at the r -th antenna after removing the CP and applying K -point FFT can be expressed as:

$$\mathbf{y}_r = \sum_{i=1}^{N_t} \mathbf{W} \mathcal{F}(\mathbf{h}_{i,r}) \frac{\mathbf{W}^H}{K} \mathbf{x}_i + \mathbf{n}_r \quad K \times 1, \quad (4.1)$$

where $\mathbf{n}_r$ is $K \times 1$ representing additive white Circular Gaussian (CG) noise with covariance $E[\mathbf{n}_r(k)\mathbf{n}_r(i)^H] = \sigma_n^2 \mathbf{I}_K \delta_{ki}$, $\mathbf{I}_K$ is a $K \times K$ identity matrix, δ_{ki} is the Kronecker delta operator, $\mathbf{x}_i$ is a K length i^{th} OFDM transmitted data, $\mathbf{W}$ is the K -point Fourier matrix, $\mathbf{h}_{i,r}$ represent the $N \times 1$ channel taps of the i^{th} transmit and r^{th} received antenna. The $\mathcal{F}(\mathbf{h}_{i,r})$ represents the circulant matrix with eigenvalue decomposition

expressed as:

$$\mathcal{F}(\mathbf{h}_{i,r}) = \frac{\mathbf{W}^H}{K} \text{diag}\{\mathbf{F}\mathbf{h}_{i,r}\}\mathbf{W}, \quad (4.2)$$

where $\mathbf{F}$ is a $K \times N$ submatrix of the first columns of the $\mathbf{W}$ Fourier matrix. The overall received signal in (5.3) can be rewritten as a single vector of size $N_r K \times 1$ as follows:

$$\mathbf{y} = \boldsymbol{\gamma}\mathbf{x} + \mathbf{n}, \quad (4.3)$$

here $\mathbf{y} = [\mathbf{y}_1^T, \dots, \mathbf{y}_{N_r}^T]^T$, $\mathbf{x} = [\mathbf{x}_1^T, \dots, \mathbf{x}_{N_t}^T]^T$, $\mathbf{n} = [\mathbf{n}_1^T, \dots, \mathbf{n}_{N_r}^T]^T$ with $\mathbf{n} \sim \mathcal{N}(0, \sigma_n^2 \mathbf{I}_{N_r K})$ and $\boldsymbol{\gamma} = [\boldsymbol{\gamma}_1, \dots, \boldsymbol{\gamma}_{N_t}]$ with $\boldsymbol{\gamma}_i = [\boldsymbol{\gamma}_{i,1}, \dots, \boldsymbol{\gamma}_{i,N_r}]^T$ where $\boldsymbol{\gamma}_{i,r} = \text{diag}\{\mathbf{F}\mathbf{h}_{i,r}\}$.

For easy derivations of analytical CRB in term of $\mathbf{h}$, equation (4.3) can be rewritten as:

$$\mathbf{y} = \tilde{\mathbf{X}}\mathbf{h} + \mathbf{n}, \quad (4.4)$$

where $\mathbf{h} = [\mathbf{h}_{1,1}^T, \dots, \mathbf{h}_{N_t,1}^T, \dots, \mathbf{h}_{N_t,N_r}^T]^T$ is a vector of $N_r N_t N \times 1$, $\tilde{\mathbf{X}} = \mathbf{I}_{N_r} \otimes \mathbf{X}$ is a matrix of size $N_r K \times N_r N_t N$ with $\mathbf{X} = [\mathbf{X}_1 \mathbf{F} \dots \mathbf{X}_{N_t} \mathbf{F}]$ of size $K \times N_t N$ and $\mathbf{X}_i$ is a diagonal matrix of size $K \times K$ (i.e., $\mathbf{X}_i = \text{diag}(\mathbf{x}_i)$) and $\otimes$ is a Kronecker product.

4.2.1 Pilot Sequence Design

In channel estimation, it is essential to use known pilot symbols in SB and training-based channel estimation algorithms. These pilot symbols can be placed at the beginning of each frame, time-division multiplexed with a data signal. This means that pilots and data are transmitted in different time slots, which leads to a decrease in the spectral efficiency of the system (see Fig. 4.1a). Alternatively, pilot symbols can be

superimposed with the data symbols, resulting in a significant increase in the spectral efficiency of the system. This technique is referred to as an EP scheme (see Fig. 4.1b).

The k^{th} superimposed transmitted signal can be expressed as:

$$\mathbf{x}_k = \mathbf{p}_k + \mathbf{s}_k \quad (4.5)$$

where $\mathbf{s}_k$ are the finite independent identically distributed sequence with zero mean

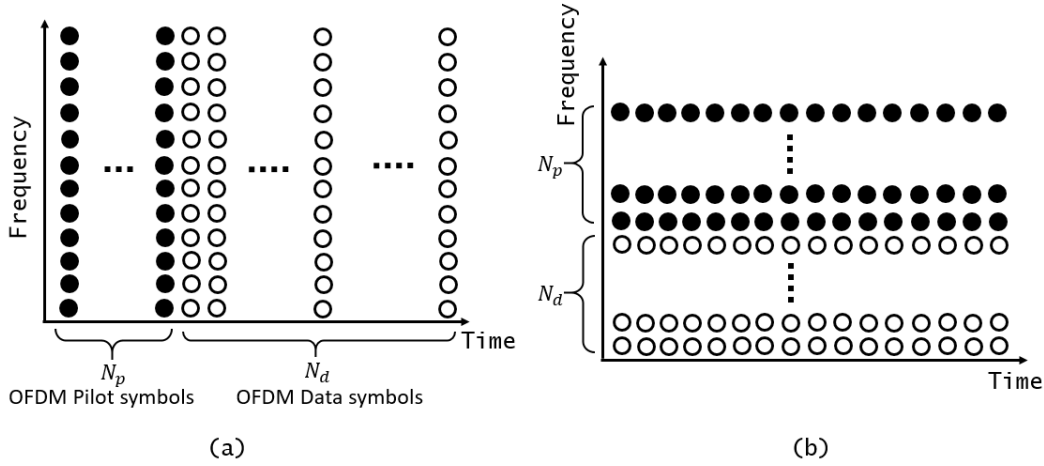


Figure 4.1: (a) Time-multiplexed pilot scheme, (b) Embedded pilot scheme

and variance σ_s^2 and $\mathbf{p}_k$ are the pilot sequence with variance σ_p^2 . Accordingly, the transmitted power σ_t^2 is allocated between the pilots and data as $\sigma_t^2 = \sigma_s^2 + \sigma_p^2$. Thus, the received signal given in (4.4) can be rewritten as:

$$\mathbf{y} = \tilde{\mathbf{X}}\mathbf{h} + \mathbf{n} = (\tilde{\mathbf{P}} + \tilde{\mathbf{S}})\mathbf{h} + \mathbf{n} \quad (4.6)$$

4.3 General Cramer-Rao Bound

The Cramer-Rao Bound is the lower bound criterion that gives the highest achievable performance of the unbiased estimator in a set of real parameters θ . The CRB can be defined as follows:

$$CRB \leq E\{[(\hat{\theta} - \theta)(\hat{\theta} - \theta)^T]\}, \quad (4.7)$$

The CRB is determined by the inverse of the Fisher Information Matrix (FIM) $\mathbf{J}(\theta)$, which can be expressed for a real parameter θ as follows:

$$\mathbf{J}(\theta) = E \left\{ \left(\frac{\partial \ln p(\mathbf{y}|\theta)}{\partial \theta} \right) \left(\frac{\partial \ln p(\mathbf{y}|\theta)}{\partial \theta} \right)^T \right\}, \quad (4.8)$$

However, for a given complex parameter θ , the FIM can be expressed in relation to the vector of real parameter $\theta_R = [\Re(\theta) \ \Im(\theta)]$ and complex entries $\mathbf{J}_{\theta\theta}$ and $\mathbf{J}_{\theta\theta^*}$ as follows:

$$\mathbf{J}_R(\theta_R) = 2 \begin{bmatrix} \Re(\mathbf{J}_{\theta\theta} + \mathbf{J}_{\theta\theta^*}) & -\Im(\mathbf{J}_{\theta\theta} - \mathbf{J}_{\theta\theta^*}) \\ \Im(\mathbf{J}_{\theta\theta} + \mathbf{J}_{\theta\theta^*}) & \Re(\mathbf{J}_{\theta\theta} - \mathbf{J}_{\theta\theta^*}) \end{bmatrix} \quad (4.9)$$

where $\mathbf{J}_{\phi\varphi} = E_{\mathbf{y}|\theta} \left(\frac{\partial \ln p(\mathbf{y}|\theta)}{\partial \phi^*} \right) \left(\frac{\partial \ln p(\mathbf{y}|\theta)}{\partial \varphi^*} \right)^H$ using $\frac{\partial}{\partial \theta} = \frac{1}{2} \left(\frac{\partial}{\partial \mathbf{a}} - j \frac{\partial}{\partial \mathbf{b}} \right)$ where $\theta = \mathbf{a} + j\mathbf{b}$.

4.4 Cramer-Rao Bound for SB Channel Estimation

In this section, we focus on determining the CRB for SB channel estimation using EP for the MIMO-OFDM system. The derivation of the FIM takes into account both data and pilots. We will first examine the performance limits of the SB scheme when

only the second-order statistic (SOS) is taken into account, using a Gaussian data model. After that, we will expand our study to include scenarios where higher-order statistic (HOS)-based data, i.e., a finite alphabet source signal, is considered.

4.4.1 Gaussian Data Cramer-Rao Bound

This subsection considers the SOS, which corresponds to the Gaussian CRB. The data symbols are therefore considered to be i.i.d. Gaussian distributed with zero mean and a diagonal covariance matrix made up of the transmit powers of the users, i.e., $\mathbf{R}_{ss} = \text{diag}(\sigma_{s_i}^2)$ with $i = 1, \dots, N_t$. The received OFDM signal comprises a data symbol superimposed with a pilot sequence, i.e., $\mathbf{y} \sim \mathcal{NC}(\mathbf{P}\boldsymbol{\gamma}, \mathbf{R}_{yy})$ with covariance matrix written as:

$$\mathbf{R}_{yy} = \sum_{i=1}^{N_t} \sigma_{s_i}^2 \boldsymbol{\gamma}_i \boldsymbol{\gamma}_i^H + \sigma_n^2 \mathbf{I}_{KN_r}, \quad (4.10)$$

where σ_s^2 , σ_n^2 are considered known parameters. In the embedded pilot scheme, the MIMO-OFDM FIM for SB estimation with unknown parameter $\boldsymbol{\theta} = \mathbf{h}$ can be expressed as [78]:

$$\mathbf{J}_{hh}(i, j) = \mathbf{J}_{h^*h^*}^H(i, j) = (\tilde{\mathbf{P}}^H \mathbf{R}_{yy}^{-1} \tilde{\mathbf{P}})(i, j) + \bar{\mathbf{J}}_{hh}(i, j) \quad (4.11)$$

here

$$\bar{\mathbf{J}}_{hh}(i, j) = \text{tr} \left\{ \mathbf{R}_{yy}^{-1} \left(\frac{\partial \mathbf{R}_{yy}}{\partial \mathbf{h}_i^*} \right) \mathbf{R}_{yy}^{-1} \left(\frac{\partial \mathbf{R}_{yy}}{\partial \mathbf{h}_j^*} \right)^H \right\}, \quad (4.12)$$

$$\begin{aligned}
\mathbf{J}_{\mathbf{h}\mathbf{h}^*}(i, j) &= \mathbf{J}_{\mathbf{h}^*\mathbf{h}}^H(i, j) \\
&= \text{tr} \left\{ \mathbf{R}_{\mathbf{y}\mathbf{y}}^{-1} \left(\frac{\partial \mathbf{R}_{\mathbf{y}\mathbf{y}}}{\partial \mathbf{h}_i^*} \right) \mathbf{R}_{\mathbf{y}\mathbf{y}}^{-1} \left(\frac{\partial \mathbf{R}_{\mathbf{y}\mathbf{y}}}{\partial \mathbf{h}_j^*} \right) \right\} \\
&1 \leq i, j \leq N_t N_r N,
\end{aligned} \tag{4.13}$$

where $\frac{\partial \mathbf{R}_{\mathbf{y}\mathbf{y}}}{\partial \mathbf{h}_i^*} = \sigma_{\mathbf{s}_{iN_t}}^2 \gamma_{iN_t} \left(\frac{\partial \gamma_{iN_t}}{\partial \mathbf{h}_i} \right)^H$.

Remark: The pilot and the channel information are contained in the first and the second term of (4.11). The $\mathbf{R}_{\mathbf{y}\mathbf{y}}^{-1}$ in the first term contains data that is considered as noise, while the second term is associated with the blind channel identification.

4.4.2 Embedded Pilot Cramer-Rao Bound

In this subsection, a finite alphabet data model, specifically 4-QAM, is used to explore the non-Gaussian nature of communications signals. The received OFDM signal at the k -th sub-carrier can be expressed as:

$$\mathbf{y}_k = \gamma_k \mathbf{x}_k + \mathbf{n}_k, \tag{4.14}$$

where $\gamma_k = [(\mathbf{F}\mathbf{h}_{1,1})_k, \dots, (\mathbf{F}\mathbf{h}_{1,N_r})_k]^T$ represents the k^{th} Fourier element of $\mathbf{h}$. The sequence $\mathbf{x}_k$ consists of i.i.d. values $\pm 1 \pm j$, each with equal probabilities for 4-QAM.

The likelihood function can be expressed as follows:

$$p(\mathbf{y}_k, \theta) = \frac{1}{Q^{N_t}} \sum_{q=1}^{Q^{N_t}} \frac{1}{(\pi \sigma_n^2)^{N_r}} e^{-\left(\|\mathbf{y}_k - \gamma_k(\mathbf{p} + \mathbf{s}_q)\|^2\right)/\sigma_n^2}, \tag{4.15}$$

here $Q = 4$, $\mathbf{s}_q = \pm 1 \pm i$, for 4-QAM modulation, $\mathbf{p}$ is deterministic pilot sequence and $\boldsymbol{\theta} = [\mathbf{h}^T (\mathbf{h}^*)^T]^T$. The likelihood function in (4.15) can be written as following:

$$\begin{aligned}
p_{4-QAM}(\mathbf{z}_k, \theta) &= \frac{1}{(\pi\sigma_n^2)^{N_r}} e^{-\left(\|\mathbf{z}_k\|^2 - \|\boldsymbol{\gamma}_k\|^2\right)/\sigma_n^2} \\
&\times \cosh\left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k)\right) \\
&\times \cosh\left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k)\right),
\end{aligned} \tag{4.16}$$

where $\mathbf{z}_k = \mathbf{y}_k - \boldsymbol{\gamma}_k \mathbf{p}$, $g_1(\mathbf{z}_k) = 2\Re(\mathbf{z}_k^H \boldsymbol{\gamma}_k)$, and $g_2(\mathbf{z}_k) = -j2\Im(\mathbf{z}_k^H \boldsymbol{\gamma}_k)$. The natural logarithmic of the (4.16) can be written as:

$$\begin{aligned}
\ln p_{4-QAM}(\mathbf{z}_k, \theta) &= -N_r \ln(\pi\sigma_n^2) - \frac{1}{\sigma_n^2} (\|\mathbf{z}_k\|^2 + \|\boldsymbol{\gamma}_k\|^2) \\
&+ \ln \cosh\left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k)\right) + \ln \cosh\left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k)\right).
\end{aligned} \tag{4.17}$$

The embedded pilot FIM is defined as:

$$\mathbf{J}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{EP} = \begin{bmatrix} \mathbf{J}_{\mathbf{h}\mathbf{h}} & \mathbf{J}_{\mathbf{h}\mathbf{h}^*} \\ \mathbf{J}_{\mathbf{h}^*\mathbf{h}} & \mathbf{J}_{\mathbf{h}^*\mathbf{h}^*} \end{bmatrix} \tag{4.18}$$

where the elements of $\mathbf{J}_{\boldsymbol{\theta}\boldsymbol{\theta}}^{EP}$ is a block matrix of size $N_r N_t N$ given as follows:

$$\begin{aligned}
[\mathbf{J}_{\mathbf{h}\mathbf{h}}]_{i,j} &= [\mathbf{J}_{\mathbf{h}^*\mathbf{h}^*}]_{i,j}^H = E \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial \boldsymbol{\theta}^*} \right) \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial \boldsymbol{\theta}^*} \right)^H \\
&= -E \frac{\partial}{\partial \boldsymbol{\theta}^*} \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial \boldsymbol{\theta}^*} \right)^H
\end{aligned} \tag{4.19}$$

$$\begin{aligned}
[\mathbf{J}_{\mathbf{h}\mathbf{h}^*}]_{i,j} &= [\mathbf{J}_{\mathbf{h}^*\mathbf{h}}]_{i,j}^H = E \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial \boldsymbol{\theta}^*} \right) \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial \boldsymbol{\theta}} \right)^H \\
&= -E \frac{\partial}{\partial \boldsymbol{\theta}} \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial \boldsymbol{\theta}^*} \right)^H
\end{aligned} \tag{4.20}$$

Furthermore, the derivative in (4.19) and (4.20) can be computed as follows:

$$\begin{aligned}
\frac{\partial}{\partial h_i^*} \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial h_j^*} \right)^H &= -\frac{1}{\sigma_n^2} \left(\frac{\partial \mathbf{z}_k^H}{\partial h_i^*} \left(\frac{\partial \mathbf{z}_k^H}{\partial h_j^*} \right)^H + \frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_i^*} \left(\frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_j^*} \right)^H \right) \\
&\quad + \frac{1}{\sigma_n^2} g_1''(\mathbf{z}_k)_{i,j} \tanh \left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k) \right) + \frac{1}{\sigma_n^4} \|g_1'\|^2 f_1 \\
&\quad + \frac{1}{\sigma_n^2} g_2''(\mathbf{z}_k)_{i,j} \tanh \left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k) \right) + \frac{1}{\sigma_n^4} \|g_2'\|^2 f_2,
\end{aligned} \tag{4.21}$$

$$\frac{\partial}{\partial h_i} \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial h_j^*} \right)^H = 0, \tag{4.22}$$

where $g_1'(\mathbf{z}_k)_i = \frac{\partial g_1(\mathbf{z}_k)}{\partial h_i^*}$, $g_2'(\mathbf{z}_k)_i = \frac{\partial g_2(\mathbf{z}_k)}{\partial h_i^*}$, $g_1''(\mathbf{z}_k)_{i,j} = \frac{\partial}{\partial h_j^*} \left(\frac{\partial g_1(\mathbf{z}_k)}{\partial h_i^*} \right)$, $g_2''(\mathbf{z}_k)_{i,j} = \frac{\partial}{\partial h_j^*} \left(\frac{\partial g_2(\mathbf{z}_k)}{\partial h_i^*} \right)$, $f_1 \stackrel{\text{def}}{=} \frac{1}{\cosh^2 \left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k) \right)}$, $f_2 \stackrel{\text{def}}{=} \frac{1}{\cosh^2 \left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k) \right)}$, with, $\frac{\partial g_1(\mathbf{z}_k)}{\partial h_i^*} = \frac{\partial \mathbf{z}_k^H}{\partial h_i^*} \boldsymbol{\gamma}_k + \mathbf{z}_k \frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_i^*}$, $\frac{\partial g_2(\mathbf{z}_k)}{\partial h_i^*} = -j \left[\frac{\partial \mathbf{z}_k^H}{\partial h_i^*} \boldsymbol{\gamma}_k - \mathbf{z}_k \frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_i^*} \right]$, $\frac{\partial \mathbf{z}_k^H}{\partial h_i^*} = -\mathbf{P}^H \frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_i^*}$.

However, considering the regularity condition and assuming high SNR (i.e., $\text{SNR} > 0$), as adopted in [70], the two functions f_1 and f_2 vanish to 0. Therefore, (4.19) can be rewritten by taking the negative expectation of (4.21), as follows:

$$\begin{aligned}
[\mathbf{J}_{\mathbf{h}\mathbf{h}}]_{i,j} &= [\mathbf{J}_{\mathbf{h}^*\mathbf{h}^*}]_{i,j}^H = -E \frac{\partial}{\partial h_i^*} \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial h_j^*} \right)^H \\
&= \frac{1}{\sigma_n^2} \left(\mathbf{P}^H \frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_i^*} \left(\frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_j^*} \right)^H \mathbf{P} + \frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_i^*} \left(\frac{\partial \boldsymbol{\gamma}_k^H}{\partial h_j^*} \right)^H \right)
\end{aligned} \tag{4.23}$$

$$[\mathbf{J}_{\mathbf{h}\mathbf{h}^*}]_{i,j} = [\mathbf{J}_{\mathbf{h}^*\mathbf{h}}]_{i,j}^H = -E \frac{\partial}{\partial h_i} \left(\frac{\partial \ln p(\mathbf{z}_k, \mathbf{h})}{\partial h_j^*} \right)^H = 0 \tag{4.24}$$

Note that: due to the odd nature of the tanh function and z_k is zero mean variable, the expectation of the two functions $E \left[\tanh \left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k) \right) \right]$ and $E \left[\tanh \left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k) \right) \right]$ can be expressed as follows:

$$E \left[\tanh \left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k) \right) \right] = \int \tanh \left(\frac{1}{\sigma_n^2} g_1(\mathbf{z}_k) \right) p(\mathbf{z}_k, \boldsymbol{\theta}) d\mathbf{z}_k = 0, \quad (4.25)$$

$$E \left[\tanh \left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k) \right) \right] = \int \tanh \left(\frac{1}{\sigma_n^2} g_2(\mathbf{z}_k) \right) p(\mathbf{z}_k, \boldsymbol{\theta}) d\mathbf{z}_k = 0. \quad (4.26)$$

4.5 Performance Evaluation

This section presents the performance assessment of the derived semi-blind CRB for the embedded pilot in the context of the MIMO-OFDM system. We compare the performance of the derived CRB with that of the unbiased Mean Square Error (MSE) estimator and semi-blind CRB for block-pilot arrangements presented in [70]. The MSE estimate utilizes only pilot sequences to estimate the channel as $\text{CRB}_{\text{OP}} = \sigma_n^2 \text{tr}\{(\tilde{\mathbf{P}}^H \tilde{\mathbf{P}})^{-1}\}$ with $\tilde{\mathbf{P}} = [\tilde{\mathbf{P}}(1)^T, \dots, \tilde{\mathbf{P}}(N_p)^T]^T$. The best performance in CRB_{OP} is achieved when the orthogonal pilots are considered i.e., $\tilde{\mathbf{P}}^H \tilde{\mathbf{P}} = N_p \sigma_p^2 \mathbf{I}_{N_r N_t N}$. All results presented are in the form of normalized $\text{CRB} = \left\{ \frac{\text{tr}\{\text{CRB}\}}{\|\mathbf{h}\|^2} \right\}$. The channels are randomly i.i.d, with unit variance and zero-mean having a Gaussian distribution. The transmitted symbols are modulated using the 4-QAM modulation scheme, employing $N_t = 2, N_r = 4$, and channel taps $N = 4$. The pilot sequences have the same size as the data symbols, i.e., $N_s = N_p = 40$ for the embedded pilot scheme with a total of $K = 64$ subcarriers.

Figure 4.2 presents the normalized CRB versus SNR using Gaussian data. Note that in the BP arrangement, the data and pilots have the same power, i.e., $\sigma_t^2 = \sigma_s^2 = \sigma_p^2 = 1$, while in the embedded pilot scheme, the data and the pilots share the total transmitted power, i.e., $\sigma_s^2 = 0.9$ and $\sigma_p^2 = 0.1$. We can observe that the proposed semi-blind CRB for the embedded pilot, i.e., CRB_{SB}^{EBP} , depicts excellent performance. Furthermore, the performance closely matches the BP scheme, i.e., CRB_{SB}^{BP} at high SNR. It's important to remember that the embedded pilot scheme preserves bandwidth, unlike the TDM method. Figure 4.3 illustrates the impact of

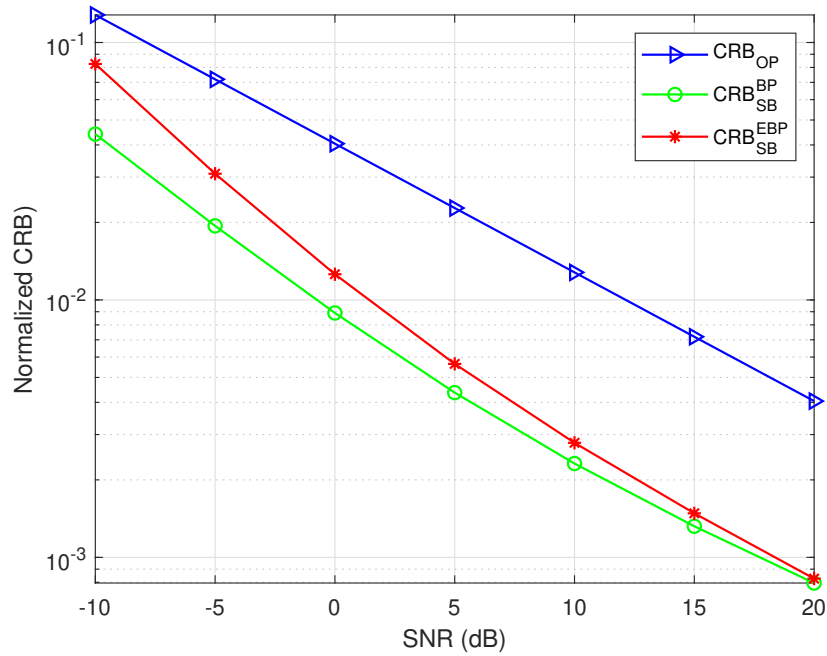


Figure 4.2: Normalized CRB versus SNR for a Gaussian data model for the pilot-based, BP, and EP scheme.

increasing the number of data OFDM symbols (N_s) on the CRB for a specific SNR of 10 dB for both the EP and BP schemes. We can see that the performance improves significantly with the increase in data symbols. Figure 5.5 presents a comparison

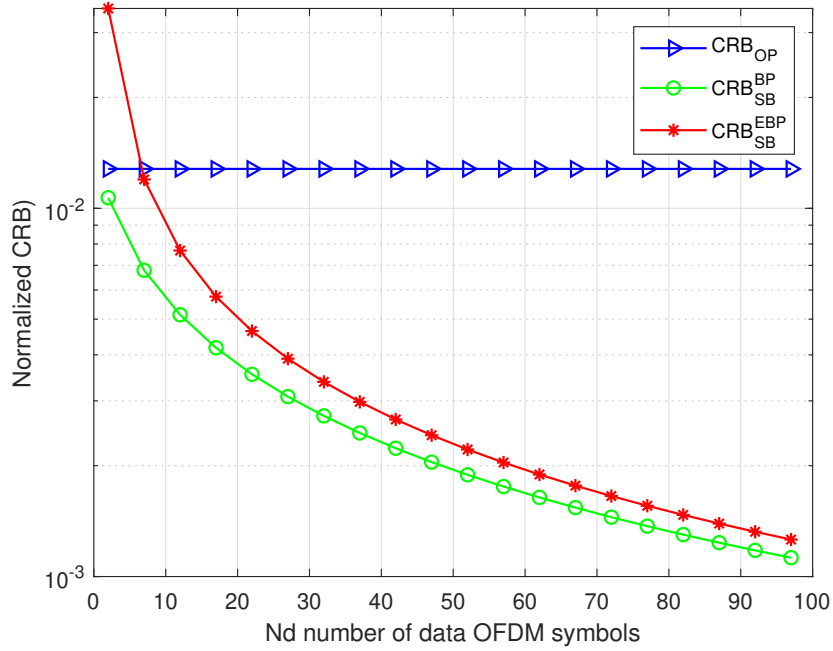


Figure 4.3: Normalized CRB versus number of OFDM symbols at SNR = 10 dB for a Gaussian data model for the pilot-based, BP, and EP scheme.

of the normalized CRB for only pilot sequence, BPSK, QPSK, and EBP using a 4-QAM signal. It is evident that the semi-blind CRB of the embedded pilot (i.e., $\text{CRB}_{\text{SB}}^{\text{EBP}}$) closely aligns with the performance bounds of BPSK and QPSK across all considered SNR. This indicates that by utilizing the embedded pilot scheme, it is possible to achieve performance similar to that of the TDM scheme. Thus, no additional bandwidth is required for transmitting pilot sequences when implementing an embedded pilot scheme. However, a significant performance increase can be noticed for an increase in OFDM data until the symbols reach 40 symbols; henceforth, a slight increase is depicted for BPSK, QPSK, and EP (see Fig. 5.8).

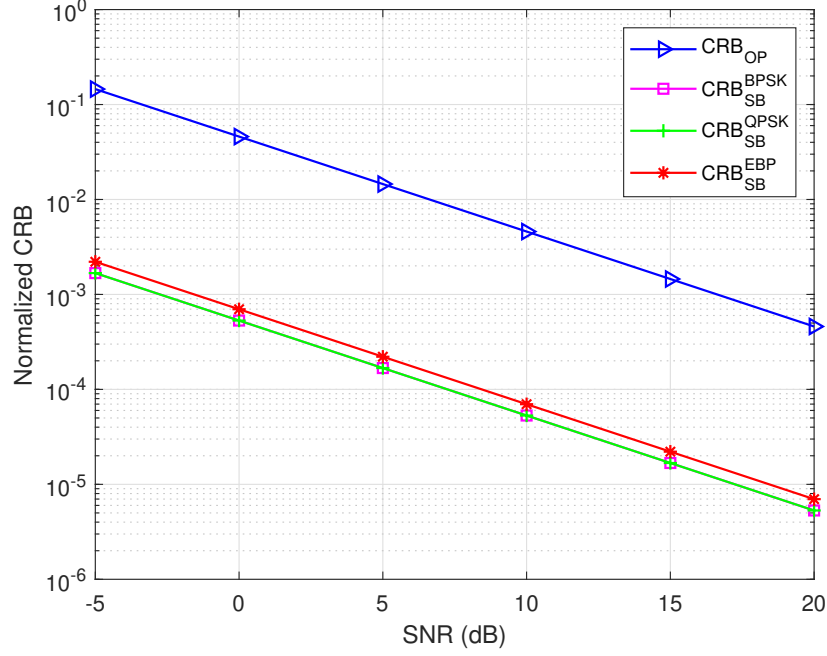


Figure 4.4: Normalized CRB versus SNR for a Finite data model for the pilot- based, BP, and EP scheme with $N_r = 2, N_t = 2$.

4.6 Conclusion

This work presents a performance-bound analysis based on semi-blind channel estimation for embedded pilots in MIMO-OFDM communications. We derived the first analytical semi-blind CRB expressions for the embedded pilot scheme by considering both Gaussian and 4-QAM data models in the MIMO-OFDM systems. Simulation results indicate that, when using the Gaussian data model, it is possible to achieve a performance similar to that of TDM at high SNR. Furthermore, an increase in the number of OFDM data symbols enhances the performance of channel estimations. Additionally, when considering the 4-QAM data model, the embedded pilot CRB closely matches the performance bounds of BPSK and QPSK across all considered SNR levels. This demonstrates that a semi-blind channel estimation technique utilizing embedded

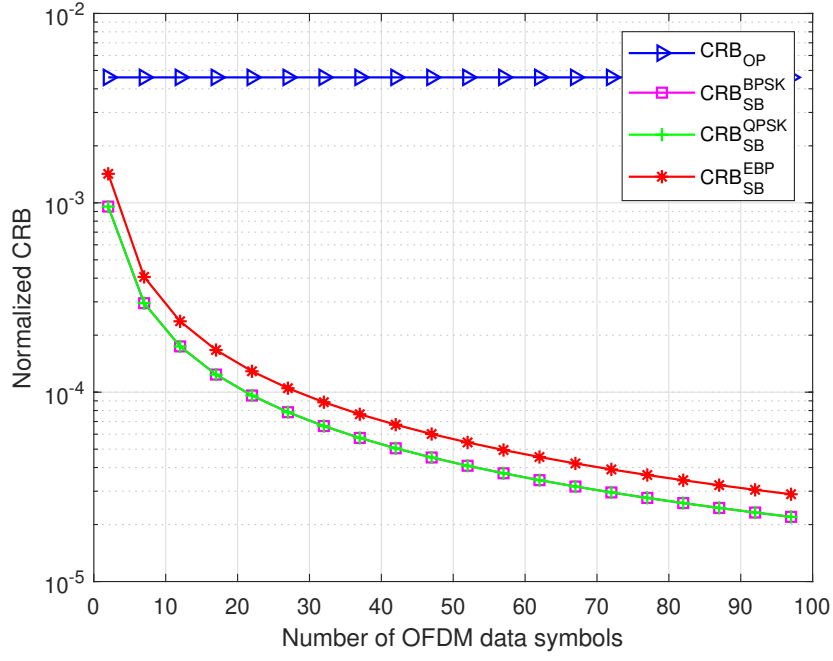


Figure 4.5: Normalized CRB versus number of OFDM symbols for a Finite data model for the pilot-based, BP, and EP scheme at SNR = 10 dB, with $N_r = 2$, $N_t = 2$.

pilots can achieve a performance comparable to that of TDM.

CHAPTER 5

SEMI-BLIND TENSOR-BASED CHANNEL ESTIMATION FOR DOUBLE RIS MIMO SYSTEMS

In this chapter, we propose a new joint (coupled) Tucker-2 decomposition method for semi-blind channel estimation in a D-RIS-assisted MIMO communications system. In the D-RIS-assisted system, two RISs are considered; where the first RIS is placed close to the transmitter, and the other is placed close to the receiver for optimal performance. We demonstrate that the received signals in flat fading D-RIS-assisted MIMO systems can be effectively constructed using a 3-way Tucker-2 tensor model. By utilizing the Tucker factorization on the Tucker-2 received signals model, all the three channels i.e., $\mathbf{H}_T$ channel between Transmitter (Tx)-to-RIS 1, the $\mathbf{H}_S$ channel between RIS 1-to-RIS 2, and the $\mathbf{H}_R$ channel between RIS 2-to-Receiver (Rx) can be estimated effectively. Furthermore, compared with a S-RIS and the M-RIS case, we

demonstrate how the system's performance is influenced by parameters related to the transceiver, training overhead, and the number of elements considered in the RISs. A numerical performance evaluation depicts a fast convergence and underscores the improvement in the spectral efficiency of the D-RIS system compared to S-RIS and M-RIS systems.

5.1 Introduction

The Fifth Generation (5G) and beyond wireless communication standards hold the potential to deliver improved wireless broadband and extensive connectivity with extremely low latency through advanced technology such as massive MIMO and millimeter-wave (mm-wave) communication systems. Nevertheless, these advancements come with significant power consumption and path loss challenges in ensuring users a consistent quality of service, particularly in challenging propagation environments [20]. In response to these limitations, potential and cost-effective remedies like developing RISs have been introduced [79]. The RIS is a 2D surface structure comprising a set of electrically tunable reflecting antenna arrays that adjust their radiation patterns dynamically to improve the efficiency and capacity of the communications system.

The majority of previous research proposed the use of a S-RIS-assisted system where the Tx and the Rx communicate through an S-RIS-aided channel. Additionally, it has been demonstrated that optimal performance gain is achieved when the RIS is positioned in close proximity to the Tx/Rx [80]. On the other hand, some applications,

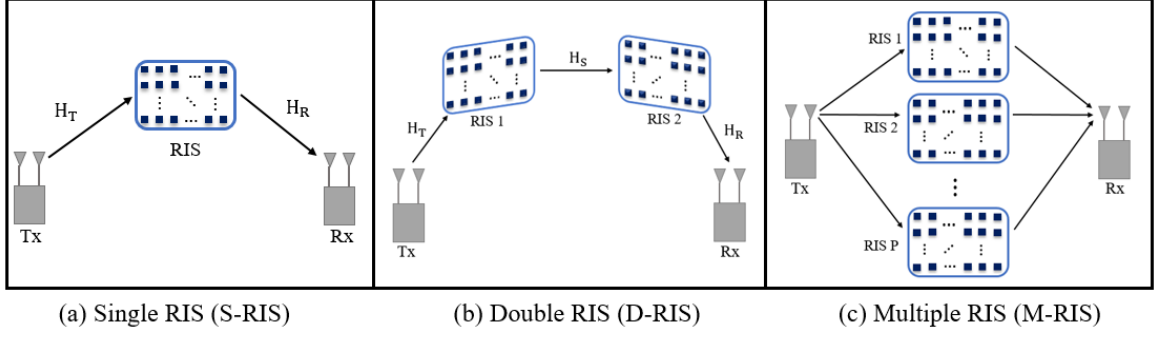


Figure 5.1: S-RIS, D-RIS, and M-RIS aided MIMO communications

like satellite-to-indoor communications, may require multiple deployments of RIS. Multiple deployments of RIS can be D-RIS-assisted where one RIS is positioned close to Tx and the other close to the Rx (see Fig. 5.1a) [81], [6] or a situation in which all the RISs are positioned at precise locations of the channel scatterers (see Fig. 5.1b) named M-RIS-assisted [82]. The performance of the S-RIS, D-RIS, or M-RIS-aided system significantly relies on the number of the array elements on the RIS, the deployed position, and the quality of CSI estimation. This becomes challenging, particularly in a D-RIS-aided system where the channel contains three cascaded channels compared to two in a S-RIS-aided system.

A plethora of recent references, such as [83], [84], [6], [85], have focused on Alternating Least Squares (ALS)-based channel estimation for both S-RIS and D-RIS systems. The authors in [83] proposed an ALS-based channel estimation for an S-RIS system, and their algorithm relied on the parallel tensor model of the received signal. Also, the authors in [84] consider ALS-based in S-RIS under a quasi-static block fading channel by controlling the training sequence overhead using a spatial correlation. Furthermore, the authors in [6], [85] proposed an ALS-based for D-RIS to exploit the 4-way tensor of the D-RIS system using a low-complexity Khatri-Rao

factorization in [85] and using Tucker-2 tensor decomposition in [6]. Their method achieved a remarkable performance with a minimum overhead sequence. Also, the authors in [82] consider channel estimation and joint beamforming design for both the S-RIS and M-RIS systems, whereby all RISs were positioned in a precise location of channel scatterers see Fig 5.1c. However, blind and semi-blind channel estimation maintain the system's spectral efficiency [74], [86] and have recently been proposed for RIS-aided systems. In [87], authors consider S-RIS and proposed a blind data recovery with the help of ALS using a constrained factor tensor decomposition. In [88], a generalized Parallel factor and Tucker tensor decomposition using Khatri-Rao and Kronecker factorization is presented for joint semi-blind equalization in RIS, respectively. Also, the authors in [89] proposed a semi-blind approach for the S-RIS-aided channel, which helps enhance the data rate of the system.

In this work, we develop a new joint (coupled) Tucker-2 factorization for a semi-blind approach in D-RIS-assisted MIMO communication systems. We demonstrate that the received signals can be formulated as a joint Tucker-2 tensor model, enabling a joint coupled Tucker-2 decomposition. By employing the coupled Tucker-2 factorization on the Tucker-2 received signals model, effective estimation of all three channels – Tx-to-RIS 1 ($\mathbf{H}_T$), the channel between RIS 1-to-RIS 2 ($\mathbf{H}_S$), and the channel between RIS 2-to-Rx ($\mathbf{H}_R$) can be achieved. Additionally, in comparison to both S-RIS and M-RIS scenarios, we illustrate how transmit and receive antennas, training overhead, and the number of elements in the RISs impact the system's performance. Furthermore, numerical performance evaluation shows fast convergence and highlights enhancements in spectral efficiency within the D-RIS system compared to both S-RIS

and M-RIS configurations.

5.2 Problem Formulation

5.2.1 System Model

In this work, we consider a MIMO communication systems equipped with a D-RIS between N_t transmit antennas and N_r receive antennas as shown in Fig. 5.1a. The RIS 1 has M_1 reflecting elements and is placed near the Tx, hereas the RIS 2 has M_2 reflecting elements and is placed near the Rx. It is assumed that L symbol frames were transmitted, such that $L = I \cdot K$, and there are no direct communications between Tx-to-Rx, Tx-to-RIS 2, and RIS 1-to-Rx owing to the high propagation pathloss phenomena.

The received signal $\mathbf{y}_{i,k}$ at the (i,k) -th subframe with $i = 1, 2, \dots, I$ and $k = 1, 2, \dots, K$ can be expressed as:

$$\mathbf{y}_{i,k} = \mathbf{H}_R \mathbf{\Phi}_i \mathbf{H}_S \mathbf{\Psi}_i \mathbf{H}_T \mathbf{x}_k + \mathbf{n}_{i,k} \in \mathbb{C}^{N_r \times 1}, \quad (5.1)$$

where $\mathbf{x}_k \in \mathbb{C}^{N_t \times 1}$ is the transmitted signal; $\mathbf{n}_{i,k} \in \mathbb{C}^{N_r \times 1}$ is the additive white Gaussian circularly symmetric complex-valued noise with zero mean and variance σ_n^2 ; $\mathbf{H}_T \in \mathbb{C}^{M_1 \times N_t}$ is the channel between Tx to RIS 1; $\mathbf{H}_R \in \mathbb{C}^{N_r \times M_2}$ is the channel between RIS 2 to Rx; and $\mathbf{H}_S \in \mathbb{C}^{M_2 \times M_1}$ is the channel between RIS 1 to RIS 2, respectively. Let $\mathbf{\Psi}_i = \text{diag}(\boldsymbol{\psi}_i) \in \mathbb{C}^{M_1 \times M_1}$ with $|\boldsymbol{\psi}_i|_{m_1}| = 1/\sqrt{M_1}$ and $\mathbf{\Phi}_i = \text{diag}(\boldsymbol{\phi}_i) \in \mathbb{C}^{M_2 \times M_2}$ with $|\boldsymbol{\Phi}_i|_{m_2}| = 1/\sqrt{M_2}$ be the i -th diagonal reflection matrix of RIS 1 and RIS 2,

respectively; where $\boldsymbol{\psi}_i \in \mathbb{C}^{M_1 \times 1}$ and $\boldsymbol{\phi}_i \in \mathbb{C}^{M_2 \times 1}$, respectively. From (5.1), we stack the vectors $\{\mathbf{y}_{i,k}\}_{k=1}^K$ into a matrix $\mathbf{Y}_i = [\mathbf{y}_{i,1}, \dots, \mathbf{y}_{i,K}] \in \mathbb{C}^{N_r \times K}$ and expressed as:

$$\mathbf{Y}_i = \mathbf{H}_R \boldsymbol{\Phi}_i \mathbf{H}_S \boldsymbol{\Psi}_i \mathbf{H}_T \mathbf{X} + \mathbf{N}_i, \quad (5.2)$$

$$\mathbf{Z}_i \triangleq \mathbf{Y}_i \mathbf{X}^H = \mathbf{H}_R \boldsymbol{\Phi}_i \mathbf{H}_S \boldsymbol{\Psi}_i \mathbf{H}_T + \mathbf{N}_i \mathbf{X}^H \in \mathbb{C}^{N_r \times N_t}, \quad (5.3)$$

where $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_K] \in \mathbb{C}^{N_t \times K}$ and it is assumed that $\mathbf{X} \mathbf{X}^H = \mathbf{I}_{N_t}$ for $K \geq N_t$ (under the assumption that the pilot matrix $\mathbf{X}$ is orthogonal). Our primary target in the following section is to estimate the channels $\mathbf{H}_T$, $\mathbf{H}_S$, and $\mathbf{H}_R$.

5.2.2 Tensor-based Model

If we stack I matrices $\{\mathbf{Y}_i\}_{i=1}^I$ and $\{\mathbf{Z}_i\}$ into two third-order tensors $\boldsymbol{\mathcal{Y}} \in \mathbb{C}^{N_r \times K \times I}$ (i.e., $\boldsymbol{\mathcal{Y}}(:, :, i) = \mathbf{Y}_i \in \mathbb{C}^{N_r \times K}$) and $\boldsymbol{\mathcal{Z}} \in \mathbb{C}^{N_r \times N_t \times I}$ (i.e., $\boldsymbol{\mathcal{Z}}(:, :, i) = \mathbf{Z}_i \in \mathbb{C}^{N_r \times N_t}$), then $\boldsymbol{\mathcal{Y}}$ and $\boldsymbol{\mathcal{Z}}$ admit the following Tucker representations:

$$\boldsymbol{\mathcal{Z}} = \boldsymbol{\mathcal{G}} \times_1 \mathbf{H}_R \times_2 \mathbf{H}_T^T, \quad (5.4)$$

$$\boldsymbol{\mathcal{Y}} = \boldsymbol{\mathcal{G}} \times_1 \mathbf{H}_R \times_2 (\mathbf{X}^T \mathbf{H}_T^T), \quad (5.5)$$

where

$$\boldsymbol{\mathcal{G}} = [\boldsymbol{\mathcal{G}}_1, \cup_3, \dots, \cup_3, \boldsymbol{\mathcal{G}}_I] \in \mathbb{C}^{M_2 \times M_1 \times I}, \text{ and } \boldsymbol{\mathcal{G}}_i = \boldsymbol{\Phi}_i \mathbf{H}_S \boldsymbol{\Psi}_i, \quad i = 1, 2, \dots, I \quad (5.6)$$

Accordingly, taking the Tucker-2 decomposition of $\boldsymbol{\mathcal{Z}}$ can result in $\mathbf{H}_S$, $\mathbf{H}_R$ and $\mathbf{H}_T$

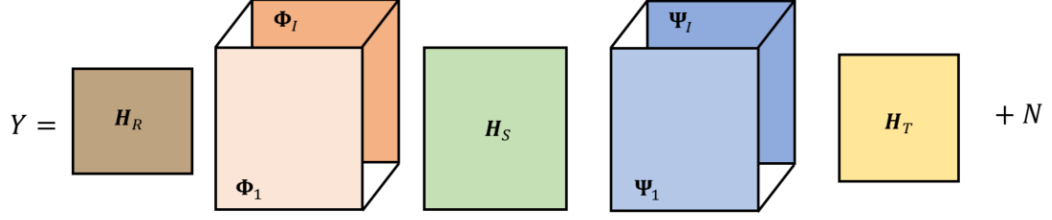


Figure 5.2: Graphical tensor representation of the received signal

as presented in [6] which is expressed as follows;

$$\{\hat{\mathbf{H}}_R, \hat{\mathbf{H}}_T, \hat{\mathbf{H}}_S\} = \arg \min_{\mathbf{H}_R, \mathbf{H}_T, \mathbf{H}_S} \left\| \mathcal{Z} - \mathcal{G} \times_1 \mathbf{H}_R \times_2 \mathbf{H}_T^\top \right\|_F^2, \quad (5.7)$$

The above problem involves joint optimization, which is nonconvex in nature and can be solved using an alternating minimization method where one variable is solved at a time while the others remain fixed. The individual channel estimate can be represented as:

$$\hat{\mathbf{H}}_R = \arg \min_{\mathbf{H}_R} \left\| [\mathcal{Z}]_{(1)} - \mathbf{H}_R \mathbf{F}_R(\mathbf{H}_T, \mathbf{H}_S) \right\|_F^2, \quad (5.8)$$

$$\hat{\mathbf{H}}_T = \arg \min_{\mathbf{H}_T} \left\| [\mathcal{Z}]_{(2)} - \mathbf{H}_T^\top \mathbf{F}_T(\mathbf{H}_R, \mathbf{H}_S) \right\|_F^2, \quad (5.9)$$

$$\hat{\mathbf{h}}_S = \arg \min_{\mathbf{h}_S} \left\| \mathbf{z}_{(3)} - \mathbf{F}_S(\mathbf{H}_T, \mathbf{H}_R) \mathbf{h}_S \right\|_2^2, \quad (5.10)$$

where $\mathbf{F}_R(\mathbf{H}_T, \mathbf{H}_S) = [\mathcal{G}]_{(1)}(\mathbf{I}_I \otimes \mathbf{H}_T^\top)^\top \in \mathbb{C}^{M_2 \times IN_t}$; $\mathbf{F}_T(\mathbf{H}_R, \mathbf{H}_S) = [\mathcal{G}]_{(2)}(\mathbf{I}_I \otimes \mathbf{H}_R^\top)^\top \in \mathbb{C}^{M_1 \times IN_r}$; $\mathbf{F}_S(\mathbf{H}_T, \mathbf{H}_R) = ((\mathbf{H}_T^\top \otimes \mathbf{H}_R) \odot (\Psi \odot \Phi)^\top) \in \mathbb{C}^{IN_r N_t \times M_1 M_2}$; $\hat{\mathbf{h}}_S = \text{vec}\{\hat{\mathbf{H}}_S\} \in \mathbb{C}^{M_1 M_2}$; $\mathbf{z}_{(3)} = \text{vec}\{[\mathcal{Z}]_{(3)}\} \in \mathbb{C}^{IN_t N_r}$ and $[\mathcal{Z}]_{(n)}, n \in \{1, 2, 3\}$ is the n -mode unfolding of $\mathcal{Z}$ which is written as:

$$[\mathcal{Z}]_{(1)} = \mathbf{H}_R [\mathcal{G}]_{(1)} (\mathbf{I}_I \otimes \mathbf{H}_T^\top)^\top + [\mathcal{N}]_{(1)} \in \mathbb{C}^{N_r \times IN_t}, \quad (5.11)$$

$$[\mathbf{Z}]_{(2)} = \mathbf{H}_T^T [\mathbf{G}]_{(2)} (\mathbf{I}_I \otimes \mathbf{H}_R)^T + [\mathbf{N}]_{(2)} \in \mathbb{C}^{N_t \times I N_r}, \quad (5.12)$$

$$[\mathbf{Z}]_{(3)} = [\mathbf{G}]_{(3)} (\mathbf{H}_T^T \otimes \mathbf{H}_R)^T + [\mathbf{N}]_{(3)} \in \mathbb{C}^{I \times N_t N_r}. \quad (5.13)$$

However, for a unique solution of (5.8), (5.9) and (5.10) this requires that $\mathbf{F}_R$ and $\mathbf{F}_T$ have a full column-rank such that $I N_t \geq M_2$ and $I N_r \geq M_1$; whereas $\mathbf{F}_S$ has full row-rank implying $I M_1 M_2 \geq N_r N_t$. Therefore, authors in [6] concluded that the number of channel coefficients for S-RIS and D-RIS denoted as $\mathcal{H}_{\text{S-RIS}}$ and $\mathcal{H}_{\text{D-RIS}}$ can be written as:

$$\mathcal{H}_{\text{S-RIS}} = N_t M + N_r M \quad (5.14)$$

$$\mathcal{H}_{\text{D-RIS}} = N_t M_1 + M_1 M_2 + N_r M_2. \quad (5.15)$$

The work in [6] recasts (5.4) to the PARAFAC model in [85].

5.3 Proposed Semi-Blind Channel Estimation

This section presents our new proposed coupled Tucker-2 received signal model and semi-blind channel estimation algorithm based on a new coupled Tucker-2 tensor decomposition. Assume that we have $\mathbf{X} = [\mathbf{X}_p \ \mathbf{X}_{d,i}] \in \mathbb{C}^{N_t \times (K_p + K_d)}$ where $\mathbf{X}_p \in \mathbb{C}^{N_t \times K_p}$ is the pilot matrix and $\mathbf{X}_{d,i} \in \mathbb{C}^{N_t \times K_d}$ is the unknown matrix. From (5.5), the received pilots and signal can be expressed as follows:

$$\mathbf{Y}_p = \mathbf{G} \times_1 \mathbf{H}_R \times_2 (\mathbf{X}_p^T \mathbf{H}_T^T) + \mathbf{N}_p \in \mathbb{C}^{N_r \times K_p \times I}, \quad (5.16)$$

$$\mathbf{Y}_{d,i} = \mathbf{G}_i \times_1 \mathbf{H}_R \times_2 (\mathbf{X}_{d,i}^T \mathbf{H}_T^T) + \mathbf{N}_{d,i} \in \mathbb{C}^{N_r \times K_d \times I}. \quad (5.17)$$

where $\mathcal{G}_i = \Phi_i \mathbf{H}_S \Psi_i$ is the i^{th} frontal slice of $\mathcal{G}$.

For short, let denote $\mathbf{U}_{T_p} = \mathbf{X}_p^T \mathbf{H}_T^T \in \mathbb{C}^{K_p \times M_1}$, $\mathbf{P}_{d,i} = \mathbf{X}_{d,i}^T \mathbf{X}_p$, and $\mathbf{U}_{T_{d,i}} = \mathbf{P}_{d,i} \mathbf{U}_{T_p} \in \mathbb{C}^{K_d \times M_1}$. Expressions (5.16) and (5.17) can be recast into the following joint (coupled) Tucker-2 decomposition of $\mathcal{Y}_p$ and $\mathbf{Y}_{d,i}$

$$\begin{cases} \mathcal{Y}_p = \mathcal{G} \times_1 \mathbf{H}_R \times_2 \mathbf{U}_{T_p} + \mathcal{N}_p, \\ \mathbf{Y}_{d,i} = \mathcal{G}_i \times_1 \mathbf{H}_R \times_2 \mathbf{U}_{T_{d,i}} + \mathbf{N}_{d,i}, \quad i = 1, 2, \dots, I. \end{cases} \quad (5.18)$$

Here, $\mathcal{G}$ and $\mathbf{H}_R$ represent the common core tensor and the common loading factor, respectively. Two matrices $\mathbf{U}_{T_p}$ and $\mathbf{U}_{T_{d,i}}$ are the individual factors of $\mathcal{Y}_p$ and $\mathbf{Y}_{d,i}$, respectively. Figure 5.3 presents the graphical representation of a 3rd-order Tucker tensor of the received signal. By performing the joint Tucker-2 decomposition of (5.18), we can obtain the matrices $\mathbf{H}_R$, $\mathbf{U}_{T_p}$, $\mathbf{U}_{T_{d,i}}$ and common core $\mathcal{G}$ directly. This can be reformulated as an optimization problem:

$$\arg \min_{\mathcal{G}, \mathbf{H}_R, \mathbf{U}_{T_p}, \mathbf{U}_{T_{d,i}}} \left\| \mathcal{Y}_p - \mathcal{G} \times_1 \mathbf{H}_R \times_2 \mathbf{U}_{T_p} \right\|_F^2 + \sum_{i=1}^I \left\| \mathbf{Y}_{d,i} - \mathcal{G}_i \times_1 \mathbf{H}_R \times_2 \mathbf{U}_{T_{d,i}} \right\|_F^2. \quad (5.19)$$

To solve (5.19), we propose the following iterative optimization procedure

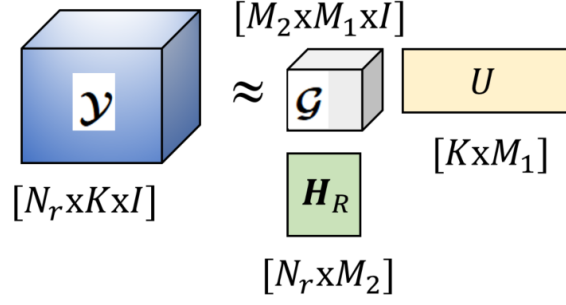


Figure 5.3: Graphical representation of a 3rd-order Tucker tensor of the received signal

$$\begin{aligned} \mathbf{H}_R^{(j)} = \arg \min_{\mathbf{H}_R} & \left\| [\mathbf{Y}_p]_{(1)} - \mathbf{H}_R [\mathbf{G}]_{(1)}^{(j-1)} (\mathbf{I} \otimes \mathbf{U}_{T_p}^{(j-1)})^\top \right\|_F^2 \\ & + \sum_{i=1}^I \left\| \mathbf{Y}_{d,i} - \mathbf{H}_R \mathbf{G}_i^{(j-1)} (\mathbf{U}_{T_{d,i}}^{(j-1)})^\top \right\|_F^2, \end{aligned} \quad (5.20)$$

$$\mathbf{U}_{T_p}^{(j)} = \arg \min_{\mathbf{U}_{T_p}} \left\| [\mathbf{Y}_p]_{(2)} - \mathbf{U}_{T_p} [\mathbf{G}]_{(2)}^{(j-1)} (\mathbf{I}_K \otimes \mathbf{H}_R^{(j)})^\top \right\|_F^2, \quad (5.21)$$

$$\mathbf{U}_{T_{d,i}}^{(j)} = \arg \min_{\mathbf{U}_{T_{d,i}}} \left\| \mathbf{Y}_{d,i}^\top - \mathbf{U}_{T_{d,i}} (\mathbf{G}_i^{(j-1)})^\top \mathbf{H}_R^{(j)} \right\|_F^2, \quad (5.22)$$

$$\begin{aligned} [\mathbf{G}^{(j)}]_{(1)} = \arg \min_{\mathbf{G}} & \left\| [\mathbf{Y}_p]_{(1)} - \mathbf{H}_R^{(j)} [\mathbf{G}]_{(1)} (\mathbf{I} \otimes \mathbf{U}_{T_p}^{(j)})^\top \right\|_F^2 \\ & + \left\| \mathbf{Y}_d^\top - \text{repmat}(\mathbf{H}_R^{(i)}, [I, 1]) \text{blkdiag}([\mathbf{G}]_{(1)}) [\mathbf{U}_{T_{d,1}}^\top \mathbf{U}_{T_{d,2}}^\top \dots \mathbf{U}_{T_{d,I}}^\top]^\top \right\|_F^2. \end{aligned} \quad (5.23)$$

where $\mathbf{Y}_d = [\mathbf{Y}_{d,1}, \mathbf{Y}_{d,2}, \dots, \mathbf{Y}_{d,I}]$.

Note that, we obtain the common core $\mathbf{G}^{(j)}$ by reshaping the matrix $[\mathbf{G}^{(j)}]_{(1)}$ at each iteration. Their closed-form solutions are provided in Algorithm 1. Subsequently, upon obtaining $\hat{\mathbf{H}}_R, \hat{\mathbf{U}}_{T_p}, \hat{\mathbf{U}}_{T_{d,i}}$ and $\hat{\mathbf{G}}$, we proceed to estimate $\hat{\mathbf{H}}_T = \hat{\mathbf{U}}_{T_p}^\top \mathbf{X}_p^\top$ and $\hat{\mathbf{H}}_S \approx \Phi^{-1} \hat{\mathbf{G}} \Psi^{-1}$. Ultimately, the cascaded end-to-end channel estimate can be expressed as:

$$\hat{\mathbf{H}}_e = \hat{\mathbf{H}}_R \Phi \hat{\mathbf{H}}_S \Psi \hat{\mathbf{H}}_T \in \mathbb{C}^{N_r \times N_t}. \quad (5.24)$$

Remarks: The individual channel estimates can be expressed in relation to the actual channels as: $\hat{\mathbf{H}}_R \approx \mathbf{H}_R \mathbf{\Delta}_R$, $\hat{\mathbf{H}}_T \approx \mathbf{\Delta}_T \mathbf{H}_T$, $\mathbf{H}_S \approx \mathbf{\Delta}_R^{-1} \hat{\mathbf{H}}_S \mathbf{\Delta}_T^{-1}$, where $\mathbf{\Delta}$ is the diagonal matrix containing the scaling ambiguities which normally disappear in the end-to-end cascaded channel $\hat{\mathbf{H}}_e = \hat{\mathbf{H}}_R \hat{\mathbf{H}}_S \hat{\mathbf{H}}_T \in \mathbb{C}^{N_r \times N_t}$ because the reflection matrices $\mathbf{\Phi}$ and $\mathbf{\Psi}$ are known at the receiver side and the permutation ambiguities disappeared [85]. Additionally, the proposed method presents an approach to estimate the unknown data matrix $\mathbf{X}_{d,i}$ from $\mathbf{U}_{T_{d,i}}$ and $\mathbf{U}_{T_p}$. Specifically, we first determine the matrix $\mathbf{P}_{d,i} = \mathbf{U}_{T_{d,i}} \mathbf{U}_{T_{d,i}}^+$ and then simply estimate $\mathbf{X}_{d,i} = (\mathbf{P}_{d,i} \mathbf{X}_p^+)^T$.

Algorithm1: Joint (Coupled) Tucker-2 Decomposition

Input: $\mathcal{Y}_p$, $\mathbf{Y}_d$, and a small regularized parameter ρ

Output: $\mathcal{G}$, $\mathbf{H}_R$, $\mathbf{U}_{T_p}$, and $\mathbf{U}_{T_{d,i}}$

Initialization:

$\mathcal{G}^{(0)}$, $\mathbf{H}_R^{(0)}$, $\mathbf{U}_{T_p}^{(0)}$, and $\mathbf{U}_{T_{d,i}}^{(0)}$ are generated at random

$$\mathbf{Z}_p^{(0)} = (\mathbf{I} \otimes \mathbf{U}_{T_p}^{(0)})^\top; \mathbf{Z}_{d,i}^{(0)} = (\mathbf{I} \otimes \mathbf{U}_{T_{d,i}}^{(0)})^\top$$

Main Program:

For $i = 1, 2, \dots$ **do**

// Estimate the common factor $\mathbf{H}_R$

$$\mathbf{W}_p^{(j)} = [\mathcal{G}^{(j-1)}]_{(1)} \mathbf{Z}_p^{(j-1)}$$

$$\mathbf{W}_{d,i}^{(j)} = \mathcal{G}_i^{(j-1)} (\mathbf{U}_{d,i}^{(j-1)})^\top$$

$$\mathbf{Y}^{(j)} = [\mathcal{Y}_p]_{(1)} (\mathbf{W}_p^{(j)})^\top + \sum_{i=1}^I \mathbf{Y}_{d,i} (\mathbf{W}_{d,i}^{(j)})^\top$$

$$\mathbf{H}_R^{(j)} = \mathbf{Y}^{(j)} (\mathbf{W}_p^{(j)} (\mathbf{W}_p^{(j)})^\top + \sum_{i=1}^I \mathbf{W}_{d,i}^{(j)} (\mathbf{W}_{d,i}^{(j)})^\top + \rho \mathbf{I}_{M_2})^{-1}$$

// Estimate two factors $\mathbf{U}_{T_p}$ and $\mathbf{U}_{T_{d,i}}$

$$\mathbf{Q}^{(j)} = [\mathcal{G}^{(j-1)}]_{(2)} (\mathbf{I}_K \otimes \mathbf{H}_R^{(j)})^\top$$

$$\mathbf{U}_{T_p}^{(j)} = [\mathcal{Y}_p]_{(2)} (\mathbf{Q}^{(j)})^+$$

$$\mathbf{U}_{T_{d,i}}^{(j)} = \mathbf{Y}_{d,i} (\mathbf{H}_R^{(j)} \mathcal{G}_i^{(j-1)})^+$$

// Estimate the common core $\mathcal{G}$

$$\mathbf{Z}_p^{(j)} = (\mathbf{I} \otimes \mathbf{U}_{T_p}^{(j)})^\top$$

$$\mathbf{Z}^{(j)} = (\mathbf{H}_R^{(j)})^+ ([\mathbf{Y}_p]_{(1)} (\mathbf{Z}_p^{(j)})^\top + \sum_{i=1}^I \mathbf{Y}_{d,i} (\mathbf{U}_{T_{d,i}}^{(j)})^\top)$$

$$[\mathcal{G}^{(j)}]_{(1)} = \mathbf{Z}^{(j)} (\mathbf{Z}_p^{(j)} (\mathbf{Z}_p^{(j)})^\top + \sum_{i=1}^I \mathbf{U}_{T_{d,i}}^{(j)} (\mathbf{U}_{T_{d,i}}^{(j)})^\top + \rho \mathbf{I})^{-1}$$

End For

5.4 Numerical Evaluation

This section presents a performance assessment of the proposed semi-blind coupled Turker-2 approach for a D-RIS-aided compared to the model proposed in [82] based on spectral efficiency which is defined as:

$$\text{SE (bps/Hz)} = \log 2 \left[\det \left(\mathbf{I} + \text{SNR} \cdot \hat{\mathbf{H}}_e^H \hat{\mathbf{H}}_e \right) \right], \quad (5.25)$$

where P is the number of RIS considered in the system; $\hat{\mathbf{H}}_e$ is the cascaded end-to-end channel estimate. The channel matrices $\mathbf{H}_R$, $\mathbf{H}_S$, and $\mathbf{H}_T$ are generated randomly and assumed to be Gaussian independent and identically distributed (i.i.d.)

with zero mean and unit variance. A finite alphabet sequences are considered as transmitted information. The Signal-to-Noise Ratio (SNR) is defined as: $\text{SNR} = \mathbb{E}\{\|\mathbf{Z} - \mathcal{N}\|_F^2\} / \mathbb{E}\{\|\mathcal{N}\|_F^2\}$. The reflection matrices $\mathbf{\Psi} \in \mathbb{C}^{I_1 \times M_1}$ and $\mathbf{\Phi} \in \mathbb{C}^{I_2 \times M_2}$ are updated by random selection of the I_1 and I_2 rows of the normalized M_1 and M_2 -DFT matrices, such that $I_1 \leq M_1$ and $I_2 \leq M_2$ as in [6].

Figures 5.4 and 5.5 illustrate the performance evaluation of the proposed joint Tucker-2 decomposition of $\mathbf{Y}_p$ and $\mathbf{Y}_d$ using the following metric:

$$\text{Error}(\mathbf{Z}_{gt}, \mathbf{Z}_{es}) = \|\mathbf{Z}_{gt} - \mathbf{Z}_{es}\|_F / \|\mathbf{Z}_{gt}\|_F, \quad (5.26)$$

where $\mathbf{Z}_{gt}$ and $\mathbf{Z}_{es}$ are ground truth and estimate, respectively. The convergence of the algorithm is decided based on the threshold δ (i.e., $\text{Error}(i) - \text{Error}(i-1) \leq \delta$).

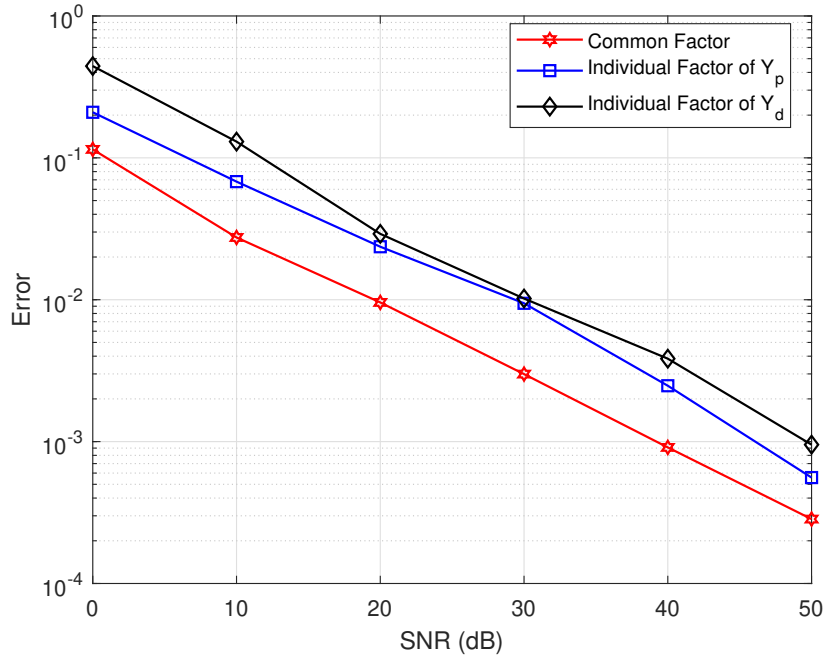


Figure 5.4: Error versus SNR performance of the Common factor $\mathbf{G}$, Individual factor $\mathbf{Y}_p$ and Individual factor $\mathbf{Y}_d$.

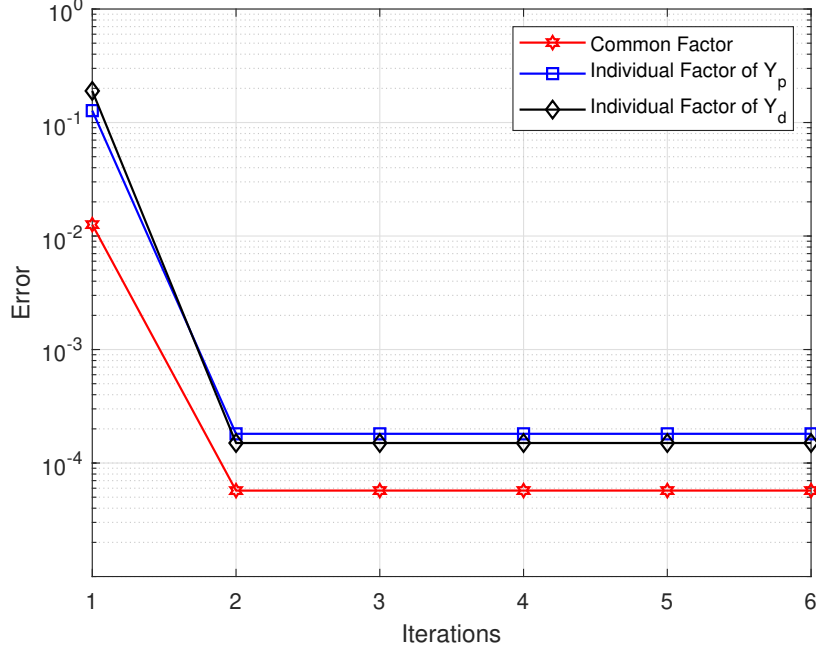


Figure 5.5: Error versus number of iterations.

The setup considered in this experiment consists of $I = 40$ training overhead; $N_r = 4$, $N_t = 2$, $M_1 = 20$, $M_2 = 10$ and $\delta = 10^{-4}$. The legends of Fig. 5.4 and Fig. 5.5 depict the common core $\mathcal{G}$; individual factor of $\mathcal{Y}_p$ and individual factor of $\mathcal{Y}_d$. As can be observed from Fig. 5.4, the proposed algorithm performs very well and effectively in the presence of noise. Moreover, in terms of convergence, as depicted in Fig. 5.5, the proposed algorithm attains a steady state in almost two iterations.

Figure 5.6 shows the results of the proposed joint Tucker-2 approach for D-RIS in terms of the normalized mean square error (NMSE) of the effective channels defined as $\text{NMSE} = \mathbb{E}\{\|\mathbf{H}_e - \hat{\mathbf{H}}_e\|_F^2\} / \mathbb{E}\{\|\mathbf{H}_e\|_F^2\}$. In this experiment, the setup consists of $I = 20$ training overhead, $N_r = 4$, $N_t = 2$, and different elements distributions for M_1 and M_2 in the RIS 1 and RIS 2 in D-RIS as indicated in the legend of the Fig. 5.6. We can observe a significant NMSE performance improvement when $M_1 = M_2 = 20$

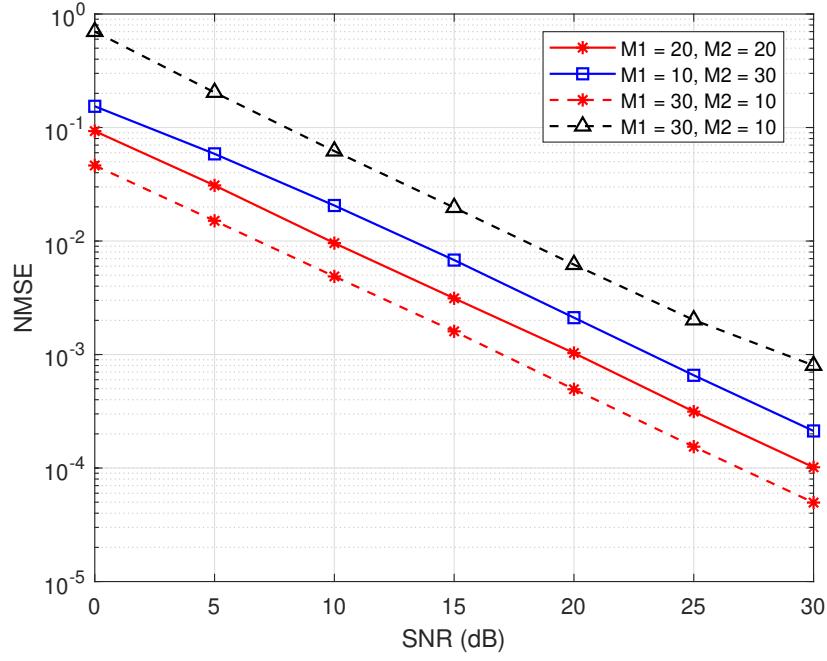


Figure 5.6: NMSE versus SNR, $N_r = 4$, $N_t = 2$, $I = 20$ training overhead for solid line, $N_r = 8$, $N_t = 2$, $I = 40$ training overhead dashed line. The Black dashed line is the work presented by [6]

compared to when $M_1 = 10, M_2 = 30$. This indicates that excellent performance can be achieved with careful distribution of elements between RIS 1 and RIS 2 of the D-RIS system.

As far as the spectral efficiency is concerned, Fig. 5.7 presents the performance of the proposed joint Tucker-2 semi-blind approach for D-RIS compared to the work presented in [82] for S-RIS and M-RIS systems, whereby all RISs were positioned in same scenario as reported in [82]. In this experiment, $I = 20$ training overhead is used for all cases. Furthermore, the number of S-RIS elements, M , is considered to be distributed between RIS 1 and RIS 2 in both the D-RIS and M-RIS scenarios, i.e., $M = M_1 + M_2$. As an example, assume that $M = 40$ elements, then from (5.14) and (5.15), S-RIS has channel coefficient $\mathcal{H}_{\text{S-RIS}} = 240$, whereas D-RIS and M-RIS

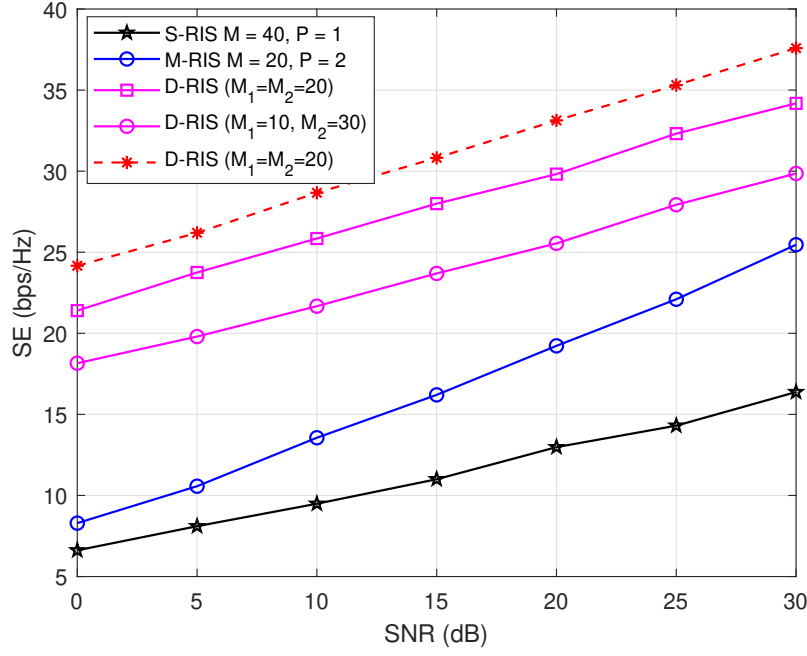


Figure 5.7: SE versus SNR for $I = 20$ training overhead for all cases. $N_r = 4, N_t = 2$ for solid line, $N_r = 6, N_t = 2$ dashed line.

have channel coefficients $\mathcal{H}_{\text{D-RIS}} = 520$ with $M_1 = M_2 = M/2 = 20$ elements. This shows that the D-RIS and M-RIS systems have more channel coefficients than the S-RIS system. Moreover, as highlighted in [6], when $N_r \approx N_t$ and $\mathcal{H}_{\text{D-RIS}} > \mathcal{H}_{\text{S-RIS}}$, the S-RIS requires less training overhead. However, with less training overhead (in this case, $I = 20$), we can observe that the proposed semi-blind algorithm displays a better SE of about 35.9 bps/Hz than S-RIS and M-RIS scenarios with a SE of 16 bps/Hz and 25 bps/Hz, respectively, for an SNR= 30 dB. Also, the performance of our algorithm improves to SE 37 bps/Hz with an increase in N_r (see Fig. 5.7). Nevertheless, considering $M_1 = 10$, and $M_2 = 30$, the D-RIS channel number of coefficients decreases ($\mathcal{H}_{\text{D-RIS}} = 440$), which affects our algorithm's performance but still achieves SE of 30 bps/Hz better than its counterpart (see Fig. 5.7). In Fig. 5.8,

we can see that an increase in training overhead ($I = 40$) has no significant impact on S-RIS performance compared to M-RIS and D-RIS, which shows a remarkable performance improvement.

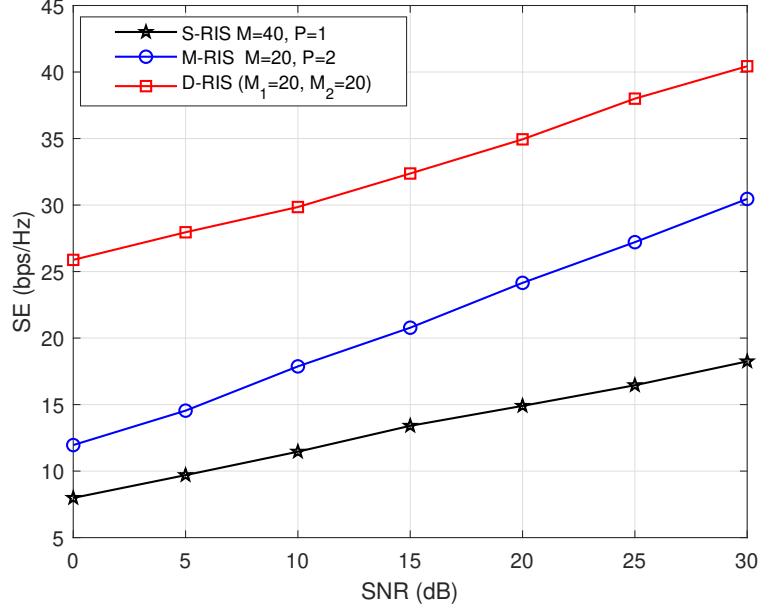


Figure 5.8: Spectral efficiency evaluation for different RIS configuration using SE versus SNR. $N_r = 4, N_t = 2$.

5.5 Conclusion

This chapter considers a new semi-blind channel estimation technique based on a new joint (coupled) Tucker-2 tensor decomposition approach for D-RIS-aided MIMO systems. We demonstrated that our proposed algorithm performs better in the presence of noise and converges in a few iterations. Moreover, we demonstrated that a perfect end-to-end channel can be estimated with a small training overhead, which results in improved spectral efficiency of a D-RIS system in comparison with S-RIS and M-RIS scenarios.

CHAPTER 6

CONCLUSIONS AND FUTURE WORKS

6.1 Conclusions

In this thesis, we primarily developed efficient semi-blind algorithms for channel estimation, equalization, and source separation in MIMO-OFDM communication systems. Moreover, this work addresses the problem of CFO estimation and compensation for both block pilot and embedded pilot schemes in the context of MIMO-OFDM systems.

Initially, we developed a new semi-blind subspace-based algorithm that leverages the orthogonality properties between the covariance matrix and noise subspace for channel estimation. This algorithm demonstrates accurate channel estimation with less computational complexity and a faster convergence rate compared to the existing algorithms. Furthermore, detailed computational complexity and uniqueness of the solution are provided.

Secondly, the thesis explores an embedded pilot scheme that has not been pre-

viously investigated in the context of multicarrier communications. We introduced a new source separation and carrier frequency estimation method for TDM and the embedded pilot scheme based on the hybrid semi-blind cost function. In addition, a new initialization procedure and a method of optimizing a step size are introduced to enhance the performance of the devised algorithm. Moreover, a slow-varying channel and CFO per each OFDM symbol are considered and optimized using a stochastic gradient method. The simulation results indicate a good estimation accuracy and data recovery along with significant spectral efficiency improvement.

Further, the performance of the proposed techniques is evaluated using a devised theoretical CRB, and the CRB metric points out the effectiveness of the developed algorithms in MIMO-OFDM systems.

This thesis motivates the development of a new semi-blind tensor-based channel estimation algorithm for D-RIS MIMO-assisted communication systems. A numerical evaluation shows a fast convergence and underscores the improvement in the spectral efficiency of the D-RIS system compared to the S-RIS and M-RIS systems.

6.2 Future Works

This thesis investigates semi-blind channel estimation and source separation for multi-carrier communication systems. Additionally, several methods can be explored to extend this research further in the future as follows:

- The proposed CRB performance analysis for the embedded pilot can be extended to the data-dependent embedded pilot method in the MIMO-OFDM system.

- Explore the feasibility of developing an analytical solution for source separation based on a multi-modulus criterion using embedded pilots in MIMO-OFDM systems.
- Develop a deep learning method for a joint semi-blind source separation and CFO estimation in MIMO-OFDM systems.
- Develop a deep learning method for semi-blind channel estimation in RIS MIMO-assisted systems.

APPENDIX A

PROOF OF IDENTIFIABILITY

This appendix provides proof of the propositions 2.4 and 2.4 in chapter 2, section 2.4.

In [38], it has been established that the subspace method is implicitly based on an orthogonality relation between rational subspaces. In fact, since $\mathcal{H}(z)$ is (i) irreducible and (ii) column-reduced, which means that $\text{rank}(\mathbf{H}(N-1)) = N_t$, its column vectors span a rational subspace of dimension N_t . The noise vectors and orthogonality relation represent a way to estimate a basis $\mathcal{U}(z)$ of the orthogonal rational subspace, whose dimension is $(N_r - N_t)$, and to characterize the desired channel matrix via the orthogonality relation $\mathcal{U}(z)^H \mathcal{H}(z) = 0$, for all z . The latter relation, under the data model assumptions, allows us to estimate the polynomial channel matrix up to a constant $N_t \times N_t$ matrix $\mathbf{D}$, i.e. in the noiseless case, the estimated channel matrix $\hat{\mathcal{H}}(z)$ is given by $\hat{\mathcal{H}}(z) = \mathcal{H}(z)\mathbf{A}$ where $\mathbf{A}$ is an unknown $N_t \times N_t$ matrix.

In addition, it is shown in [38] that the orthogonal rational subspace admits a ‘minimal’ polynomial basis, denoted as $\mathcal{U}_{\min}(z)$, which is irreducible and whose column vector degrees $N_1, \dots, N_{N_r-N_t}$ satisfy $N_1 + \dots + N_{N_r-N_t} = N_t(N-1)$ (see [38], [90] for details).

Now, let us reconsider the orthogonality relations in (2.15) using this new conceptual insight. Since both $\mathbf{U}_{n_k}$ and $\mathbf{U}_{\min}(e^{-j2\pi k/K})$ span the noise subspace of $\mathbf{C}_k$, there exists a non-singular transform matrix $\mathbf{P}_k$ such that $\mathbf{U}_{n_k} = \mathbf{U}_{\min}(e^{-j2\pi k/K})\mathbf{P}_k$. Hence, the orthogonality relation becomes

$$\mathbf{U}_{n_k}^H \mathbf{H}(e^{-j2\pi k/K}) = 0,$$

which is equivalent to

$$\mathbf{U}_{\min}^H(e^{-j2\pi k/K}) \mathbf{H}(e^{-j2\pi k/K}) = 0.$$

The equivalence comes from the fact that $\mathbf{P}_k$ is non-singular and hence can be disregarded. Note that $\mathbf{U}_{\min}^H(z) \mathbf{H}(z)$ is a polynomial matrix of degree M satisfying

$$\begin{aligned} M &\leq \max_{1 \leq i \leq N_r - N_t} N_i + N - 1 \\ &\leq \left(\sum_{i=1}^{N_r - N_t} N_i \right) + N - 1 \\ &= (N_t + 1)(N - 1). \end{aligned}$$

Finally, a polynomial of degree M with strictly more than M roots is the null polynomial, that is

$$\mathbf{U}_{\min}^H(z) \mathbf{H}(z) = 0$$

for $z = e^{-j2\pi k/K}$, $k = 0, \dots, K - 1$. Hence,

$$\mathbf{U}_{\min}^H(z) \mathbf{H}(z) = 0,$$

for all z , if the number of subcarriers $K > (N_t + 1)(N - 1)$, which is the case in practice. This ends the proof of the two propositions.

APPENDIX B

PROOF OF PROPOSITION 3

The proof of our third proposition relies on the following two lemmas:

Lemma B.1 *The sample averaged estimates of the data covariance at two different frequency bins are statistically independent, i.e. $\mathbf{R}_k$ and $\mathbf{R}_l$ are independent if $k \neq l$, and satisfy*

$$N_s E(\text{tr}(\delta \mathbf{C}_k \mathbf{M} \delta \mathbf{C}_k \mathbf{N})) \xrightarrow{N_s \rightarrow \infty} \text{tr}(\mathbf{C}_k \mathbf{N}) \text{tr}(\mathbf{C}_k \mathbf{M}) \quad (\text{B.1})$$

where $\delta \mathbf{C} = \hat{\mathbf{C}}_k - \mathbf{C}_k$, with $\mathbf{C}_k$ being the exact covariance matrix, and $\mathbf{N}$ and $\mathbf{M}$ are any given matrices.

Proof. This lemma is a special case of [91, Lemma 1] for i.i.d. input signals. ■

Lemma B.2 *The first order Taylor expansion of the noise subspace projector estimate is given by:*

$$\delta \mathbf{\Pi}_k = -\Gamma_k \delta \mathbf{C}_k \mathbf{\Pi}_k - \mathbf{\Pi}_k \delta \mathbf{C}_k \Gamma_k \quad (\text{B.2})$$

where, $\delta \mathbf{\Pi}_k = \hat{\mathbf{\Pi}}_k - \mathbf{\Pi}_k$ with $\mathbf{\Pi}_k$ being the exact noise projection matrix, and $\Gamma_k = (\mathbf{C}_k - \sigma_{n,k}^2 \mathbf{I}_{N_r})^\#$.

Proof. The proof is given by [38, Theorem 6]. I

Using Lemma B.2, the first order expansion of $\delta \mathbf{Q}_k$ can be expressed as

$$\begin{aligned}\delta \mathbf{Q}_k &= \mathbf{E}_k \otimes \mathbf{I}_{N_t} \otimes \delta_k \\ &= -\mathbf{E}_k \otimes \mathbf{I}_{N_t} \otimes (\Gamma_k \delta \mathbf{C}_k \Pi_k + \Pi_k \delta \mathbf{C}_k \Gamma_k).\end{aligned}$$

Hence,

$$\begin{aligned}E(\|\delta \mathbf{Q}_k\|^2) &= E(\text{tr}(\delta \mathbf{Q}_k^2)) \\ &= \text{tr}(\mathbf{E}_k^2 \otimes \mathbf{I}_{N_t}) \text{tr}((\Gamma_k \delta \mathbf{C}_k \Pi_k + \Pi_k \delta \mathbf{C}_k \Gamma_k)^2) \\ &= N^2 N_t (\text{tr}(\delta \mathbf{C}_k \Gamma_k^2 \delta \mathbf{C}_k \Pi_k) + \text{tr}(\delta \mathbf{C}_k \Pi_k \delta \mathbf{C}_k \Gamma_k^2)),\end{aligned}$$

where we used $\mathbf{E}_k^2 = N \mathbf{E}_k$, the Kronecker property $\text{tr}(\mathbf{A} \otimes \mathbf{B}) = \text{tr}(\mathbf{A}) \text{tr}(\mathbf{B})$ and the orthogonality relation $\Pi_k \Gamma_k = 0$. Finally, by using Lemma C.1, we obtain

$$N_s E(\|\delta \mathbf{Q}_k\|^2) \xrightarrow{N_s \rightarrow \infty} 2N^2 N_t \text{tr}(\mathbf{C}_k \Gamma_k^2) \text{tr}(\mathbf{C}_k \Pi_k).$$

To conclude, we use

$$\text{tr}(\mathbf{C}_k \Gamma_k^2) = \sum_{i=1}^{N_t} \frac{\lambda_{i,k}}{(\lambda_{i,k} - \sigma_{n,k}^2)^2}$$

and

$$\text{tr}(\mathbf{C}_k \Pi_k) = \sigma_{n,k}^2 (N_r - N_t).$$

This, finally, leads to

$$N_s E(\|\delta \mathbf{Q}_k\|^2) \xrightarrow{N_s \rightarrow \infty} 2N^2 N_t (N_r - N_t) \sum_{i=1}^{N_t} \frac{\sigma_{n,k}^2 \lambda_{i,k}}{(\lambda_{i,k} - \sigma_{n,k}^2)^2},$$

which ends the proof of Proposition B.

APPENDIX C

PROOF OF PROPOSITION 4

C.1 Proof of Proposed Semi-blind Cost Function

This section describes the derivation of our proposed jointly semi-blind cost function for source separation and CFO estimation. The LS cost function is given as follows:

$$J_{LS}(\mathbf{Q}, \mathbf{f}) = \sum_{k=0}^{K-1} \left\| \bar{\mathbf{Z}}_k - \mathbf{P}_k \right\|^2, \quad (\text{C.1})$$

The LS cost function w.r.t the $\mathbf{Q}$ can be written in first-order expansion form as:

$$J_{LS}(\mathbf{Q} + \delta\mathbf{Q}) = \sum_{k=0}^{K-1} \left\| \bar{\mathbf{Z}}_k - \mathbf{P}_k + \delta\bar{\mathbf{Z}}_k \right\|^2 = J(\mathbf{Q}) + \delta J_k(\mathbf{Q}), \quad (\text{C.2})$$

where

$$\delta J_k(\mathbf{Q}) = 2 \sum_{k=0}^{K-1} \Re \left(\left\langle \bar{\mathbf{Z}}_k - \mathbf{P}_k, \delta\bar{\mathbf{Z}}_k \right\rangle \right) 2 \sum_{k=0}^{K-1} \Re \left(\text{Tr} \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) \delta\bar{\mathbf{Z}}_k^H \right) \right),$$

and

$$\delta \bar{\mathbf{Z}}_k = (\Phi_k^* \odot \delta \mathbf{Z}_k) \mathbf{J} = (\Phi_k^* \odot \delta \mathbf{Q} \bar{\mathbf{V}}_k \mathbf{X}_k) \mathbf{J}.$$

However, $\delta J_k(\mathbf{Q})$ can be expanded as follows:

$$\begin{aligned} \delta J_k(\mathbf{Q}) &= 2\Re \left(Tr \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) \mathbf{J} (\Phi_k^* \odot \delta \mathbf{Q} \bar{\mathbf{V}}_k \mathbf{X}_k)^H \right) \right) \\ &= 2\Re \left(Tr \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) (\Phi_k^* \odot \delta \mathbf{Q} \bar{\mathbf{V}}_k \mathbf{X}_k)^H \right) \right). \end{aligned} \quad (\text{C.3})$$

Using the following Lemma C.1:

Lemma C.1

$$Tr \left(\mathbf{A} (\mathbf{B}^* \odot \mathbf{X} \mathbf{C})^H \right) = Tr \left((\mathbf{A} \odot \mathbf{B}) \mathbf{C}^H \mathbf{X}^H \right) \quad (\text{C.4})$$

Employing the Lemma C.1, equation (C.3) can be rewritten as:

$$\delta J_k = 2\Re \left(Tr \left([(\bar{\mathbf{Z}}_k - \mathbf{P}_k) \odot \Phi_k] (\bar{\mathbf{V}}_k \mathbf{X}_k)^H \delta \mathbf{Q}^H \right) \right). \quad (\text{C.5})$$

Therefore, (C.2) leads to:

$$J_{LS}(\mathbf{Q} + \delta \mathbf{Q}) = J(\mathbf{Q}) + 2\Re \left(Tr \left(\mathbf{M} \delta \mathbf{Q}^H \right) \right), \quad (\text{C.6})$$

where $\mathbf{M} = \nabla J(\mathbf{Q})$,

Hence

$$\nabla J_{LS}(\mathbf{Q}) = \sum_k [(\bar{\mathbf{Z}}_k - \mathbf{P}_k) \odot \Phi_k] (\bar{\mathbf{V}}_k \mathbf{X}_k)^H. \quad (\text{C.7})$$

Similarly, the LS cost function w.r.t the $\mathbf{f}$ can be expressed in first-order expansion as follows:

$$J_{LS}(\mathbf{f} + \delta \mathbf{f}) = J(\mathbf{f}) + \delta J_k(\mathbf{f}), \quad (\text{C.8})$$

where

$$\delta J_k(\mathbf{f}) = 2 \sum_{k=0}^{K-1} \Re \left(\text{Tr} \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) \delta \bar{\mathbf{Z}}_k^H \right) \right), \quad (\text{C.9})$$

and

$$\begin{aligned} \delta \bar{\mathbf{Z}}_k &= (\delta \Phi_k^* \odot \delta \mathbf{Z}_k) \mathbf{J} \\ \delta \Phi_k^* &= -\frac{j}{2} \text{diag}(\delta \mathbf{f}) (\mathbf{1}_{N_t} \alpha_k^T \odot \Phi_k^*) \end{aligned} \quad (\text{C.10})$$

Nevertheless, $\delta J_k(\mathbf{f})$ can be written as follows:

$$\begin{aligned} \delta J_k(\mathbf{f}) &= -\Re \left(j \text{Tr} \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) [\mathbf{1}_{N_t} \alpha_k^T \odot \Phi_k^* \odot \mathbf{Z}_k]^H \text{diag}(\delta \mathbf{f}) \right) \right), \\ &= \Im \left(\text{Tr} \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) [\mathbf{1}_{N_t} \alpha_k^T \odot \Phi_k^* \odot \mathbf{Z}_k]^H \text{diag}(\delta \mathbf{f}) \right) \right), \\ &= \Im \left(\text{diag} \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) [\mathbf{1}_{N_t} \alpha_k^T \odot \Phi_k^* \odot \mathbf{Z}_k]^H \right)^T \delta \mathbf{f} \right). \end{aligned} \quad (\text{C.11})$$

with

$$\text{diag}(\mathbf{x}) = \begin{bmatrix} x_1 & 0 & \cdots & 0 \\ 0 & x_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & x_n \end{bmatrix} \quad \text{if} \quad \mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix},$$

$$\text{diag}(\mathbf{X}) = \begin{bmatrix} x_{11} \\ x_{22} \\ \vdots \\ x_{nm} \end{bmatrix} \quad \text{if} \quad \mathbf{X} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix},$$

accordingly,

$$\text{diag} \left((\bar{\mathbf{Z}}_k - \mathbf{P}_k) [\mathbf{1}_{N_t} \boldsymbol{\alpha}_k^T \odot \Phi_k^* \odot \mathbf{Z}_k]^H \right) = \Phi_k \odot \mathbf{Z}_k^* \odot (\bar{\mathbf{Z}}_k - \mathbf{P}_k) \boldsymbol{\alpha}_k. \quad (\text{C.12})$$

Hence,

$$\nabla J(\mathbf{f}) = \Im \left(\Phi_k \odot \mathbf{Z}_k^* \odot (\bar{\mathbf{Z}}_k - \mathbf{P}_k) \boldsymbol{\alpha}_k \right) \quad (\text{C.13})$$

we use

$$J(\mathbf{f} + \delta \mathbf{f}) = J(\mathbf{f}) + \mathbf{M}^T \delta \mathbf{f}$$

where

$$\nabla J(\mathbf{f}) = \mathbf{M}, \quad (\mathbf{f} \text{ being a real-valued vector})$$

Conversely, considering only the real-part term, the MM cost function can be derived as follows:

$$J_{MM,k}^{(R)}(\mathbf{Q}) = \left\| \bar{\mathbf{Y}}_{k,R} \odot \bar{\mathbf{Y}}_{k,R} - R_R + 2\bar{\mathbf{Y}}_{k,R} \odot \delta\bar{\mathbf{Y}}_{k,R} \right\|^2 \quad (\text{C.14})$$

Thus, (C.14) can be expanded as:

$$\begin{aligned} J_{MM,k}^{(R)}(\mathbf{Q}) &= J_k^{(R)}(\mathbf{Q}) + 4\Re \left(\langle \bar{\mathbf{Y}}_{k,R} \odot \bar{\mathbf{Y}}_{k,R} - R_k, \bar{\mathbf{Y}}_{k,R} \odot \delta\bar{\mathbf{Y}}_{k,R} \rangle \right), \\ &= 4\Re \left(\text{Tr} \left((\bar{\mathbf{Y}}_{k,R} \odot \bar{\mathbf{Y}}_{k,R} - R_k) (\bar{\mathbf{Y}}_{k,R} \odot \delta\bar{\mathbf{Y}}_{k,R})^H \right) \right), \\ &= 4\text{Tr} \left(\mathbf{B}_{k1,R} \delta\bar{\mathbf{Y}}_{k,R}^H \right), \end{aligned} \quad (\text{C.15})$$

where $\mathbf{B}_{k,R} = (\bar{\mathbf{Y}}_{k,R} \odot \bar{\mathbf{Y}}_{k,R} - R_k) \odot \bar{\mathbf{Y}}_{k,R}$, $\bar{\mathbf{Y}}_{k,R} = \Re(\mathbf{Y}_k \Gamma) = \Re((\Phi_k^* \odot \mathbf{Z}_k) \Gamma)$ and $\delta\bar{\mathbf{Y}}_{k,R} = \Re((\Phi_k^* \odot \delta\mathbf{Q} \bar{\mathbf{V}}_k \mathbf{X}_k) \Gamma)$. Furthermore, $\delta\bar{\mathbf{Y}}_{k,R}$ can be expanded as:

$$\delta\bar{\mathbf{Y}}_{k,R} = \frac{1}{2} \left((\Phi_k^* \odot \delta\mathbf{Q} \bar{\mathbf{Z}}_k \mathbf{X}_k^*) + (\Phi_k \odot \delta\mathbf{Q}^* (\bar{\mathbf{V}}_k \mathbf{X}_k)^*) \Gamma \right)$$

and

$$\delta\mathbf{Y}_{k,R}^H = \delta\mathbf{Y}_{k,R}^T = \frac{1}{2} \left((\Phi_k^* \odot \delta\mathbf{Q} \bar{\mathbf{Z}}_k \mathbf{X}_k^*) + (\Phi_k \odot \delta\mathbf{Q}^* (\bar{\mathbf{V}}_k \mathbf{X}_k)^*) \Gamma \right)^T$$

Therefore

$$\begin{aligned}
\delta J(\mathbf{Q}) &= 2\text{Tr}\left(\mathbf{B}_{k,R}\left[(\Phi_k^* \odot \delta\mathbf{Q}\bar{\mathbf{V}}_k\mathbf{X}_k)^T + (\Phi_k \odot \delta\mathbf{Q}^* (\bar{\mathbf{V}}_k\mathbf{X}_k)^*)^T\right]\right) \\
&= 2\Re\left(\text{Tr}\left(\mathbf{B}_{k,R}\Gamma(\Phi_k \odot \delta\mathbf{Q}^* (\bar{\mathbf{V}}_k\mathbf{X}_k)^*)^T\right)\right) \\
&= 2\Re\left(\text{Tr}\left((\mathbf{B}_{k,R}\Gamma \odot \Phi_k)(\bar{\mathbf{V}}_k\mathbf{X}_k)^H \delta\mathbf{Q}^H\right)\right)
\end{aligned} \tag{C.16}$$

C.2 Proof of Optimal Step-size

This appendix describes the derivation of the proposed optimal step size.

The least squares cost function for the optimal step size is expressed as follows:

$$J_{LS}(\mathbf{Q} - \mu\delta\mathbf{Q}) = \sum_k \left\| (\Phi_k^* \odot (\mathbf{Q} - \mu\delta\mathbf{Q})\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J} - \mathbf{P}_k \right\|^2, \tag{C.17}$$

which can be simplified as follows:

$$\begin{aligned}
J_{LS}(\mathbf{Q} - \mu\delta\mathbf{Q}) &= \sum_k \text{Tr}\left(\left((\Phi_k^* \odot (\mathbf{Q} - \mu\delta\mathbf{Q})\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J} - \mathbf{P}_k\right)\left((\Phi_k^* \odot (\mathbf{Q} - \mu\delta\mathbf{Q})\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J} - \mathbf{P}_k\right)^H\right),
\end{aligned} \tag{C.18}$$

the above quadratic terms can be simplified as:

$$\begin{aligned}
J_{LS}(\mathbf{Q} - \mu\delta\mathbf{Q}) &= \sum_k \left[\text{Tr}(((\Phi_k^* \odot (\mathbf{Q} - \mu\delta\mathbf{Q})\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J}) \right. \\
&\quad \left. ((\Phi_k^* \odot (\mathbf{Q} - \mu\delta\mathbf{Q})\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J})^H) - 2\Re(\text{Tr}((\Phi_k^* \odot (\mathbf{Q} - \mu\delta\mathbf{Q})\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J}\mathbf{P}_k^H)) \right. \\
&\quad \left. + \text{Tr}(\mathbf{P}_k^H\mathbf{P}_k) \right], \tag{C.19}
\end{aligned}$$

The derivative of $J_{LS}(\mathbf{Q} - \mu\delta\mathbf{Q})$ w.r.t. μ is expressed as:

$$J'_{LS} = a_0 + a_1\mu \tag{C.20}$$

where $\frac{\partial}{\partial\mu}\text{Tr}(\mathbf{P}_k^H\mathbf{P}_k) = 0$, $\delta\mathbf{Q}$ is the gradient, $a_0 = 2\sum_k \Re(\text{Tr}((\Phi_k^* \odot \delta\mathbf{Q}\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J}\mathbf{P}_k^H))$ and $a_1 = -2\sum_k \text{Tr}(((\Phi_k^* \odot \delta\mathbf{Q}\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J})((\Phi_k^* \odot \delta\mathbf{Q}\bar{\mathbf{V}}_k\mathbf{X}_k)\mathbf{J})^H)$.

The MM cost function for the optimal step size can be calculated using the following polynomial function given as follows:

$$J_{MM,R}(\mathbf{Q} - \mu\nabla\mathbf{Q}) = \alpha_0 + \alpha_1\mu + \alpha_2\mu^2 + \alpha_3\mu^3 + \alpha_4\mu^4, \tag{C.21}$$

where

$$\begin{aligned}
\alpha_0 &= J_{MM,R}(\mathbf{Q}), \\
\alpha_1 &= -4 \sum_k \text{Tr}((\bar{\mathbf{Y}}_k \odot \bar{\mathbf{Y}}_k - R_R)(\bar{\mathbf{Y}}_k \odot \delta \bar{\mathbf{Y}}_k)^H), \\
\alpha_2 &= 2 \sum_k \text{Tr}((\bar{\mathbf{Y}}_k \odot \bar{\mathbf{Y}}_k - R_R)(\delta \bar{\mathbf{Y}}_k \odot \delta \bar{\mathbf{Y}}_k)^H) \\
&\quad + 4 \|\bar{\mathbf{Y}}_k \odot \delta \bar{\mathbf{Y}}_k\|^2, \\
\alpha_3 &= -4 \sum_k \text{Tr}((\bar{\mathbf{Y}}_k \odot \delta \bar{\mathbf{Y}}_k)(\delta \bar{\mathbf{Y}}_k \odot \delta \bar{\mathbf{Y}}_k)^H), \\
\alpha_4 &= \sum_k \|\delta \bar{\mathbf{Y}}_k \odot \delta \bar{\mathbf{Y}}_k\|^2.
\end{aligned} \tag{C.22}$$

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Objective	To positively contribute to the development of any organization that I am called upon to serve, work with existing staffs to the best of my ability to improve the organization objective and achieve managerial goals and targets.

POST SECONDARY EDUCATION

May, 2025	PhD in Electrical Engineering King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia Thesis title: Semi-blind Methods for Channel Estimation and Data Recovery in Multi-carrier Communications Advisor: Prof. Azzedine Zerguine CGPA: 3.556/4.00
May, 2020	M.Sc in Electrical Engineering King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia Thesis title: Direction of Arrival (DOA) Estimation Using Deep Learning with Application to Seismic Acquisition Advisor: Prof. Ali Muqaibel CGPA: 3.286/4.00
February, 2016	Bachelor of Science in Electronics Bayero University Kano, Nigeria Thesis title: Design of Closed-Circuit Television (CCTV) Networks Advisor: Dr. Anas Abubakar Bisu CGPA: 4.50/5.00
December, 2010	National Diploma (ND), Science Laboratory Technology Kano State Polytechnic (School of Technology), Nigeria

CERTIFICATION

August, 2020	Introduction to Computer Networks (CCNA1) ITN-192 CISCO Academy, KFUPM
June, 2020	Artificial Intelligence Fundamentals KnowledgeHut

RESEARCH EXPERIENCE

October- November, 2023	Visiting Graduate Researcher PRISME lab University of Orléans Orléans, France Host: Prof. Karim Abed-Meriam
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WORK HISTORY

Teaching Activities
(2019-2025) EE 235 Electronics and Microcontrollers Lab
EE 271 Electrical Circuits II
EE 204 Fundamentals of Electric Circuits

National Service
(2016–2017) Fundamentals of Electric/Electronics Circuit I

Intern
(2014-2015) BSS/Transmission Engineer, Huawei Technologies Co., NIG. LTD

Grants and Funding

"Semi-blind methods for channel estimation and data recovery in multi-carrier communications", funded by Deanship of Research Oversight and Coordination at KFUPM under the Interdisciplinary Research Center for Communication Systems and Sensing, Project No. INCS2404.

"Smart Seismic Data Acquisition", funded by CeGP under KFUPM/Georgia Tech Collaboration, Project No. GTEC1601.

SKILLS AND INTERESTS

Research Interests Statistical Signal Processing for Communications
Blind and Semi-blind Source Separation
Blind and Semi-blind Equalization
Machine Learning
Electronics

Technical Software Cisco Packet Tracer (Networking Simulation Tool)
Multisim (Electronic Instrumentation Lab)
MIDE-51 Studio (Assembly Lang for 8051 Microcontroller)
Optisystem (Optical Communication Simulation Software)
Powerworld Simulator
Overleaf, Online LaTeX Editor
Microsoft Office

Mathematical Software MATLAB

Programming Language Python

Hobbies Reading, Football, Swimming, Travelling

CONFERENCES PRESENTED

May 12–16, 2025	The 21 st International Wireless Communications Mobile Computing Conference (IWCMC 2025), Marriott Hotel Downtown, Abu Dhabi, UAE
January 22–23, 2025	The First Edition of the Saudi Next-G Summit, KFUPM, Dhahran 31261, Saudi Arabia
November 17–20, 2024	25 th IEEE Middle East Conference on Communications and Networking (MECOM 2024), Abu Dhabi, United Arab Emirates
October 27–30, 2024	The 58 th Asilomar Conference on Signals, Systems, and Computers (Asilomar 2024), Asilomar Grounds in Pacific Grove, CA, USA
September 4–8, 2023	31 st European Signal Processing Conference (EUSIPCO 2023), Helsinki, Finland
February 20–23, 2023	20 th International Multi-Conference on Systems, Signals and Devices (SSD 2023), Mahdia, Tunisia

AWARDS/SCHOLARSHIPS

2025	1 st position in Saudi Next-G Summit Poster Competition
2020	Ph.D in Electrical Engineering King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
2017	M.Sc in Electrical Engineering King Fahd University of Petroleum and Minerals, Dhahran 31261, Saudi Arabia
2016	Best Graduating Student in Electronics Department, Bayero University Kano, Nigeria
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- Published Articles** K. N. Aliyu, A. Lawal, S. A. Alawsh, A. Zerguine, A. Muqaibel, and N. Iqbal, "Robust DOA Estimation using Hybrid 1-D Convolutional Neural Network and Long Short-Term Memory Deep Learning Algorithm," in *Arabian Journal of Science and Engineering (AJSE)*. Springer, Accepted, pp. 1-13, 2025.
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- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, "Cramer-Rao Bounds for Semi-blind Approach using Embedded Pilot for MIMO-OFDM Systems," Submitted to *IEEE Communications Letters*.
- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, "Semi-Blind Multi-Modulus Source Separation and CFO Estimation for Embedded Pilot in MIMO-OFDM Systems," Submitted to *IEEE Transactions on Signal Processing*.
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- K. N. Aliyu, I. Habiballah, S. Rehman, "Technological assessment of grid-connected solar photovoltaic system; review," *Int J Eng Res Technol*, vol. 9, no. 11, pp. 245, 2020.
- K. N. Aliyu, A. Lawal, S. A. Alawsh, S. Al-Dharrab, A. Zerguine, and A. Muqaibel, "Robust direction of arrival estimation using deep learning algorithms," Available at SSRN 4421607.
- Conferences** K. N. Aliyu, A. Zerguine, K. Abed-Meraim, and L. T. Nguyen, "Semi-blind DFE for MIMO Optical Communications," *The 33rd European Signal Processing Conference (EUSIPCO)*, IEEE, Accepted, 2025.
- A. Lawal, K. N. Aliyu, A. Zerguine, and A. Muqaibel, "Direction of Arrival Estimation using hybrid CNN-GRU," In: *2025 IEEE 22nd International Multi-Conference on Systems, Signals & Devices (SSD)*, pp. 574–577, 2025.
- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, "Semi-Blind Multi-Modulus Algorithm for Joint CFO Estimation and Symbol Detection in MIMO-OFDM," In: *2025 IEEE 21st International Wireless Communications & Mobile Computing Conference (IWCMC)*, Accepted, 2025.

- K. N. Aliyu, T. T. Le, K. Abed-Meraim, and A. Zerguine, "Semi-Blind Tensor-Based Channel Estimation For Double RIS MIMO Systems," In: 2024 IEEE Middle East Conference on Communications and Networking (MECOM), pp. 291–296, 2024.
- K. N. Aliyu, K. Abed-Meraim, A. Zerguine, and A. Lawal, "Semi-blind multi-modulus approach using embedded pilot for MIMO-OFDM communications," In: 2024 IEEE 58th Asilomar Conference on Signals, Systems, and Computers, pp. 1547–1551, 2024.
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